Global linkages, trade network and development

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THÈSE DE DOCTORAT
DE L'UNIVERSITÉ PARIS 1 PANTHÉON SORBONNE

ÉCOLE DOCTORALE D'ÉCONOMIE N° 465

par

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Global Linkages, Trade Network and Development

Thèse présentée et soutenue à Paris, le 25 septembre 2018

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Il n'y a de bonnes affaires que celles qui sont terminées.

Théodore Leclercq

Acknowledgements

First and before all, I would like to thank Lionel Fontagné for having been my advisor. His comments from the very first proposal to the final version of the dissertation have always been clear, rigorous, consistent and to the point. Each of our conversations were dense and of a high quality. I highly appreciated his support and his guidance through all the process. It took me a while, but Bloningen is finally referenced in this dissertation! Merci, vraiment merci.

I feel lucky to have in my dissertation committee people whose work I admire. Many thanks to Luca de Benedictis and Raja Kali to have accepted the role of referees. Both have been pioneers in trade network analysis, and I am honored they accepted to review my work. Many thanks to Anne-Celia Disdier and Jose de Sousa for being part of the committee. Their very constructive comments during the pre-defense have contributed to greatly improve this dissertation. Many thanks to Angelo Secchi for chairing the committee. Hopefully I was able to make the dissertation clearer as he suggested. Also a special thanks to Jean-Christophe Fouillé who made the administrative process *so* much smoother during these three years and to Loïc Sorel who has been of a great help in the final line.

Completing a PhD is a long journey and life follows its path in parallel. I was lucky enough to get through it with Gabriel on my side. He taught me the principle of roller-coaster of emotions a PhD student goes through, and remind me at each down that the upside will always come again. Elisa, our little bundle of joy, joined the journey right in the middle. Thank you for giving me a worry-free pregnancy, considering sleeping over some nights, and being the most adorable human being on Earth. More importantly, thanks to both of you for making me so happy. These acknowledgements are dedicated to those who contributed to the completion of my dissertation, and having a truly happy life outside of the PhD was perhaps the main reason of success.

Unfortunately, educational achievements are still very correlated to the familiar environment. Fortunately, I was born in a family that have always been supportive, backing up any of my educational decisions. Merci Maman for all your support, for being on my side, for not sharing all the worries you surely had, and for always supporting my decisions, even if they include building my life in the other side of the Atlantic. Merci too for proof-reading the French sum up of my dissertation – a role that only a mother could have accepted! Merci also to my grand-mother, my Mamichou, for the strong inspirational role she had in my life.

While completing my PhD, I worked in parallel in several offices, and met many very supportive colleagues. Tatiana Didier, my first boss, who become my true friend deserves a huge thank for the empowerment she gave me and the example she has been for me. My dissertation benefited from long conversations with Tito Cordella, Joaquin Urrego, and Anderson Ospina. Two of the four chapters of my dissertation are co-authored papers. Thank you Tatiana Didier, Yevgneyia Korniyenko, Brian Dew and Sebastian Herrádor for having contributed to this journey.

My PhD is also the fruit of a voyage across different institutions that contributed to my formation in economics: University Paris Dauphine, Universidad Católica de Chile, Paris School of Economics, University Paris 1 Sorbonne, the World Bank and the International Monetary Fund. On my way, there was one important high school professor, who detected my early interest in economics. Merci Mireille Kral. I was for the first time exposed to international economics as a research assistant of a Paris Dauphine professor. Merci Jean-Marc Siroën. A professor at the PSE triggered a full change in my life just after I finished my master. Merci Romain Rancière. A boss taught me how important is talking clearly about complex subjects. Gracias Augusto de la Torre.

I had also been supported by a team of close friends. Arthur Poirier deserves a special thanks for being during these three years my one-stop for questions relative to a PhD. I shared my fears and roller coaster emotions with my close friend Nathaly Rivera while we were both going through the PhD. I benefited from the longstanding support of Yacine Rouimi who has always believed more in my work than I do. I will forever remember assisting to the PhD defense of my cheRRYshed friend Amandine *Vecina* Issautier, a PhD in quantic *red clouds* physic, and not understanding anything beside the opening slide. It is a great honor to join the club Vecina! My dear friends Alexandre Deyieux and David Gonzalez de Cabo, early proof-readers of some of my research and travel companions across the world, have highlighted all my PhD-related trips to Paris. Merci les ami.e.s.

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Résumé

Le système économique mondial n'est plus ce qu'il était au XXe siècle, lorsque les économies avancées (AE[1]) opéraient en tant que « centre » d'une « périphérie » d'économies émergentes et en développement (EMDE[2]). La dynamique des EMDE amène à penser au-delà de cette dichotomie. Les caractéristiques des AE et EMDE ont évolué, suggérant l'émergence d'une économie mondiale beaucoup plus multipolaire. En particulier, l'association traditionnelle entre « centre » et « AE » versus « périphérie » et « EMDE » s'érode, certains pays émergents devenant des acteurs majeurs du paysage économique mondial.

Quelques statistiques mettent en lumière l'ampleur et la rapidité de ces changements (cf. graphique 1). En 1980, le produit intérieur brut (PIB) des EMDE (défini comme l'ensemble des pays n'appartenant pas à l'OCDE en 1980[3]) représentait environ 20% du PIB mondial. En 2016, les EMDE ont capturé plus de 40% du PIB mondial. L'expansion des EMDE est tout aussi frappante en termes de flux commerciaux et financiers. Les pays EMDE représentaient environ 30% des flux commerciaux mondiaux en 1980, alors qu'en 2016 ils représentaient environ 47%. De même, les EMDE ont capturé environ 13% des entrées de capitaux mondiaux en 1980 ; en 2016, ils ont reçu plus de 40% du total. Ils sont également devenus plus représentatifs en

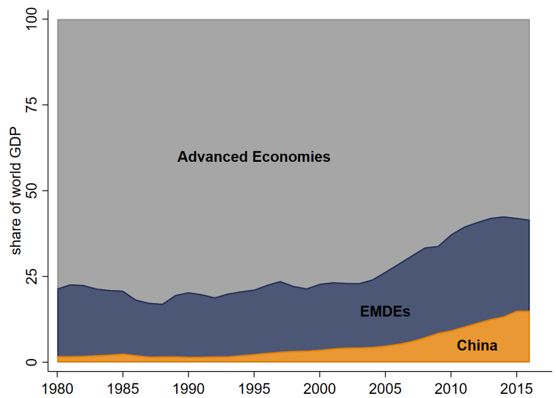
[1] Acronyme en anglais correspondant aux Advanced Economies.

[2] Acronyme en anglais correspondant aux Emerging Markets and Developing Economies.

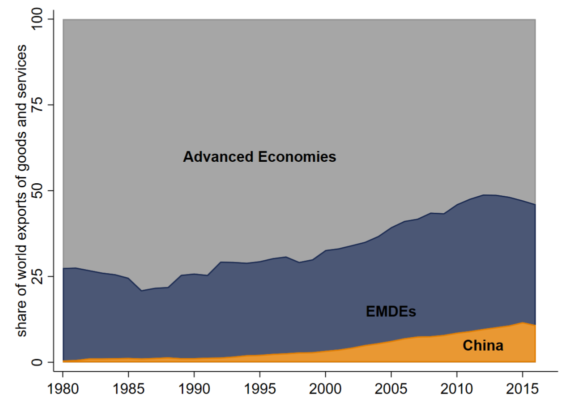
[3] Les pays de l'OCDE en 1980 comprennent : Australie, Autriche, Belgique, Canada, Danemark, Finlande, France, Allemagne, Grèce, Islande, Irlande, Italie, Japon, Luxembourg, Pays-Bas, Nouvelle-Zélande, Norvège, Portugal, Espagne, Suède, Suisse, Turquie, Royaume-Uni et les États-Unis.

Figure 1: Part mondiale du PIB et des exports

(a) Part mondiale du PIB



(b) Part mondiale des exports



Source: WDI.
Note: Le graphique de gauche présente l'évolution de la part du PIB mondial ; le graphique de droite montre la part mondiale des exportations de biens et de services.

tant que pays d'origine, en étant à l'origine de 30% des capitaux mondiaux en 2016, contre 6% en 1980. Bien que la Chine ne soit pas la seule économie EMDE derrière ces tendances, elle a joué un rôle important depuis son accession à l'Organisation mondiale du commerce en 2001. Au cours des dernières années, le processus de rattrapage a été freiné dans certaines grandes économies émergentes —les économies brésilienne, russe et sud-africaine ont ralenti ou sont entrées en récession alors que l'économie chinoise s'est rééquilibrée vers une consommation intérieure plus forte avec un rythme plus lent.

Cette reconfiguration radicale du paysage économique mondial - en particulier l'abandon du modèle traditionnel des pays à revenu élevé au centre et des pays en développement à la périphérie - a également apporté des changements significatifs à l'analyse traditionnelle du commerce et de la finance internationale. Cette thèse doctorale contribue à l'analyse de l'impact des développements récents des structures des réseaux commerciaux et financiers sur la diffusion internationale de la technologie (chapitre 1), la vitesse d'adoption des nouvelles technologies (chapitre 2), la probabilité d'investir dans un nouveau pays (chapitre 3), et le risque de perturbation de la production (chapitre 4). Avant de passer au contenu de la thèse, ce chapitre introductif expose les changements récents dans la structure des réseaux commerciaux et financiers dont les impacts seront analysés dans les prochains chapitres.

Comme point de départ de cette analyse, ce chapitre introductif présente quatre faits [4] liés à la montée des EMDE :

1. Plusieurs pays émergents sont désormais au centre du réseau commercial mondial.

2. Les communautés de commerce ont changé au fil du temps.

3. Le réseau financier mondial n'a pas été fondamentalement restructuré, mais les EMDE sont maintenant plus intégrées que par le passé.

4. La production des biens est plus fréquemment impactée que par le passé après une catastrophe naturelle dans un pays fournisseur de biens intermédiaires.

Fait n°1 : Plusieurs économies émergentes ont rejoint les AE au centre du réseau commercial mondial.

Cet important changement est visible sur les figures du graphique 2, qui montrent les réseaux commerciaux mondiaux en 1980 et en 2012. Chaque nœud représente un pays, tandis que les couleurs différencient les économies avancées (en orange) des économies émergentes (en bleues). Chaque lien correspond à l'existence d'une connexion bilatérale active, correspondant aux exportations d'un pays vers un autre, comme indiqué par les flèches. Les pays qui captent une plus grande part des exportations d'autres pays et qui sont liés à un plus grand nombre de partenaires commerciaux

[4] Les faits 1 et 2 sont tirés d'un document de travail co-écrit avec Augusto de la Torre et Tatiana Didier (De la Torre et al. (2014).

(c'est-à-dire les pays les plus importants du réseau mondial) apparaissent à droite dans le graphique 2.

En 1980, un ensemble d'économies avancées se situait à ce qui peut être empiriquement caractérisé comme le centre du réseau commercial mondial : les États-Unis, l'Allemagne (et quelques autres pays d'Europe occidentale) et le Japon étaient au cœur du réseau. En 2012, plusieurs pays émergents, comprenant non seulement la Chine mais aussi le Brésil, l'Inde, la Fédération de Russie, l'Afrique du Sud, la Turquie et d'autres, se sont déplacés vers le centre. À la suite de ces changements, les EMDE ne sont plus synonyme de périphérie et les AE ne sont plus synonymes de centre du commerce mondial.

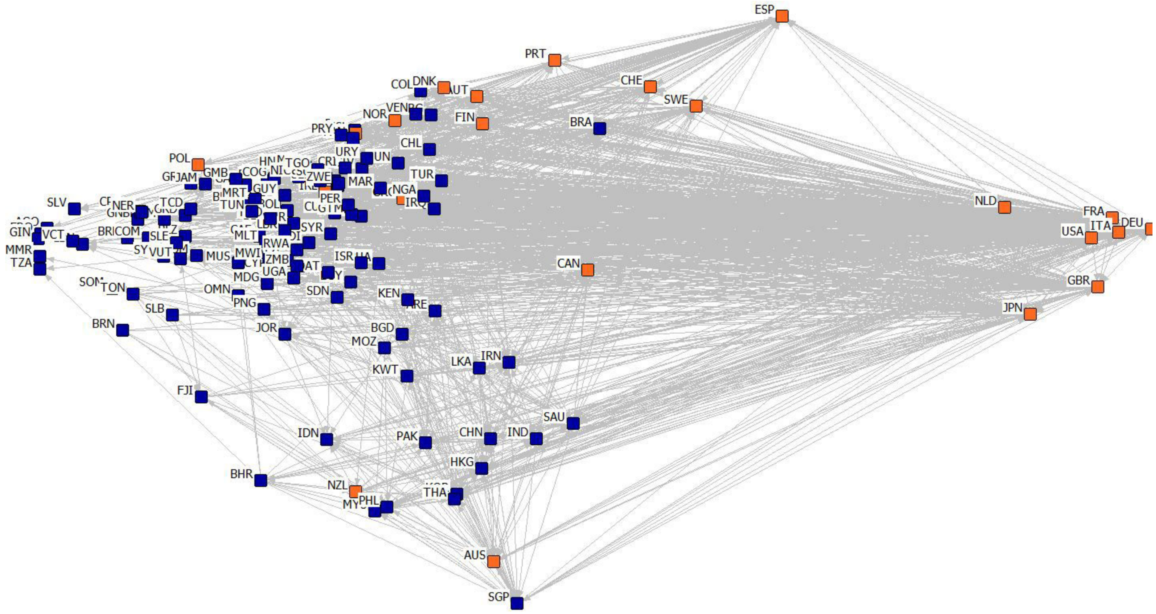
Fait n°2 : Les pôles commerciaux ont changé au fil du temps.

Le graphique 2 illustre également la similarité de la structure des relations commerciales entre les pays : plus proches sont deux pays sur le graphique, plus ils ont des parts d'exportations similaires avec le reste du monde. Au cours des années 1980 et 1990, les pays centraux du réseau (situés à droite) sont très proches les uns des autres, ce qui reflète un degré élevé de similitude dans la structure de leurs relations commerciales avec les autres pays du réseau. Le réseau commercial mondial en 1980 avait donc tendance à afficher une « polarité unique », les économies avancées agissant comme un seul pôle (c'est-à-dire jouant le même rôle) dans le commerce mondial.

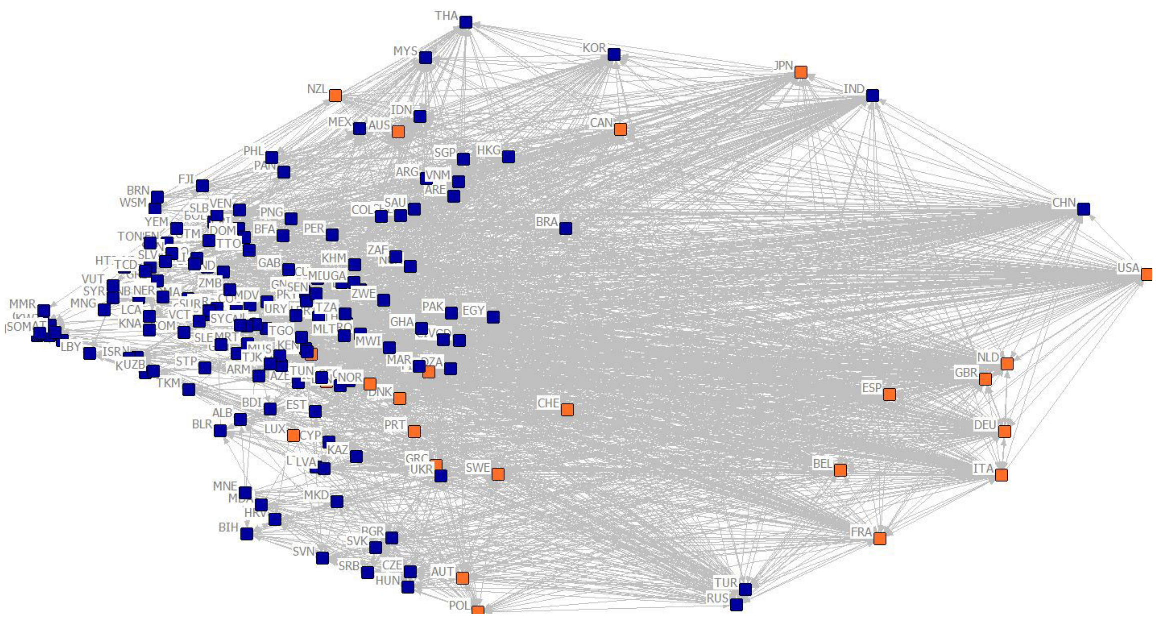
Le réseau commercial mondial en 2012 révèle un changement radical : plusieurs pays parmi les EMDE apparaissent sur la partie droite en bas du graphique 2, ce qui indique leur pertinence accrue pour le commerce mondial. Cependant, ils restent éloignés (le long de la dimension verticale) des économies avancées sur le côté droit de la figure. Ce côté du graphique ressemble à une étoile, avec de petits groupes de pays centraux placés à une certaine distance les uns des autres. La Russie et la Turquie, par exemple, ne sont pas situées à proximité des économies avancées européennes, et

Figure 2: Centralité et communautés de commerce

(a) 1980



(b) 2012



Source: Calculs basés sur la base de données DOTs.

Note: Le graphique estime l'ampleur et la direction des exportations. Un algorithme de composante principale est ensuite appliqué à la matrice de part des exportations afin de déterminer la position de chaque pays dans le réseau commercial. Le long de l'axe horizontal, les pays sont répartis en fonction de leur centralité dans le réseau commercial. Les pays les plus centraux sont situés à la droite du graphique. L'axe vertical indique la similarité de la structure des exportations entre les pays. Une distance plus faible entre deux pays indique une structure plus similaire, en termes d'exportations vers le reste du monde et d'importance relative pour les autres partenaires commerciaux.

le Japon n'est proche ni de la Chine ni de la Corée. Le paysage commercial mondial est devenu plus hétérogène et « multipolaire ».

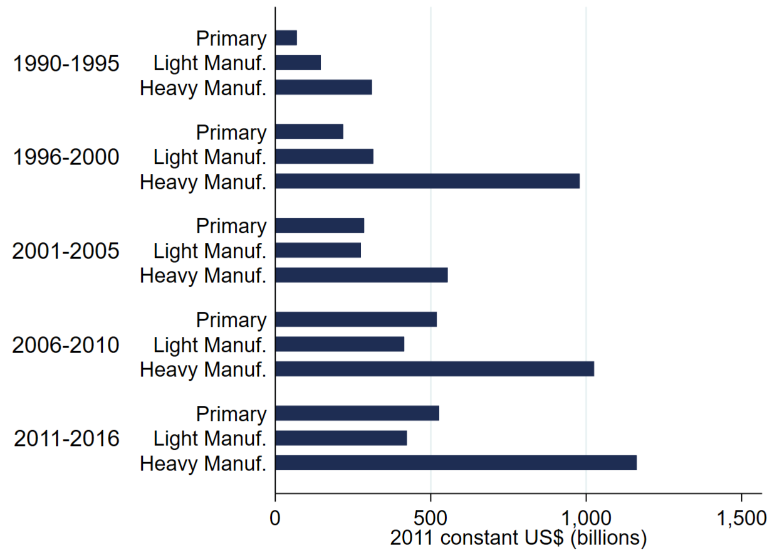
La dispersion du processus de production entre les pays soutient ces schémas de regroupement autour de pôles. Les chaînes mondiales de valeur sont en effet issues d'un nombre limité de pays qui se groupent pour produire un bien. Hernández et al. (2014) mettent en évidence le cas du secteur laitier en Amérique centrale. Des entreprises au Salvador ont établi des partenariats avec le Nicaragua pour produire du fromage qui est ensuite vendu aux États-Unis ; Morris et al. (2011) soulignent le développement des chaînes régionales de valeur parmi les fabricants de vêtements, dirigées par l'Afrique du Sud et étendues au Lesotho et au Royaume du Swaziland.

Fait n°3 : Contrairement au réseau commercial mondial, le réseau financier n'a pas été fondamentalement restructuré ; mais les EMDE sont maintenant plus intégrées que par le passé.

Une caractéristique clé de la nouvelle dynamique de l'économie mondiale a été l'asymétrie dans la structure des changements entre le commerce mondial et les réseaux financiers. Dans le domaine du commerce, la correspondance traditionnelle entre les AE et le centre, et les EMDE et la périphérie, a été reconfigurée. En revanche, dans le domaine de la finance, les Aes restent seules au centre des réseaux financiers mondiaux, bien que les EMDE aient accru leur connectivité.

La croissance des EMDE a été généralisée. Au fur et à mesure que les EMDE prenaient de l'importance dans l'économie mondiale, le nombre de leurs connexions internationales bilatérales a augmenté. Les flux de fusions et acquisitions sont particulièrement importantes dans l'industrie lourde (55% depuis 2011, graphique 3). L'investissement dans le secteur primaire a augmenté et est maintenant plus important que les investissements dans l'industrie légère (25% contre 20% depuis 2011).

Figure 3: Composition sectorielle des flux de fusions et acquisitions transfrontalières



Source: Calculs basés sur la base de données SDC platinium.
Note: Le secteur primaire comprend l'agriculture, la chasse, la foresterie, la pêche, l'exploitation minière, le pétrole brut et le gaz naturel. L'industrie légère comprend les produits alimentaires, les boissons, le tabac, le textile, les vêtements (y compris le cuir), et les produits liés au bois et au papier. L'industrie lourde comprend le pétrole raffiné et les produits connexes, les produits chimiques et les plastiques, les minéraux non métalliques, les métaux, les machines et le matériel et les équipements de transport.

Fait n°4 : L'internationalisation des processus de production a accru l'interdépendance des pays.

La dispersion des processus de production, évoquée dans le fait n°2, a accru l'interdépendance entre les pays. Les estimations suggèrent l'existence de points d'étranglement spécifiques dans le réseau commercial mondial qui deviennent particulièrement saillants après une catastrophe naturelle. Le tremblement de terre au Japon en 2011 est maintenant un événement très étudié qui met en lumière la façon dont une catastrophe localisée peut avoir un effet de contagion important sur de nombreux pays à travers le monde. Les pays qui importaient des facteurs de productions de la zone touchée à Fukushima ont dû interrompre leur production pendant des jours, voire des mois, en raison du retard pris en amont par les entreprises japonaises. Cela s'est produit dans le cas de l'entreprise Apple, qui importait le verre de son écran tactile de l'iPad 2 exclusivement d'Asahi Glass, une entreprise située dans la province de Fukushima. Après le tremblement de terre, l'entreprise a retardé de cinq semaines la livraison du verre de l'écran tactile, ce qui a provoqué un retard de deux mois du lancement de l'iPad 2.

L'augmentation de l'importance des chaînes internationales de valeur a conduit à une plus haute interdépendance des pays. Une catastrophe naturelle dans un des pays fournisseurs de biens intermédiaires a maintenant une forte probabilité de perturber la production dans d'autres pays.

Énoncé de la question de recherche

Les relations internationales sont traditionnellement étudiées à travers l'analyse des liens bilatéraux. Cependant, l'intensification et la complexification des liens internationaux exigent une analyse plus globale, dans laquelle non seulement les caractéristiques au niveau du pays et entre deux pays sont prises en compte, mais où les relations sont également considérées du point de vue du réseau. Cette dissertation porte sur la manière dont les réseaux affectent les relations économiques internationales, en particulier le commerce et la finance, et évalue leurs impacts sur les trajectoires de développement des pays.

Comment la structure du réseau influence-t-elle les relations internationales ?

- Quelles sont les conséquences de la dynamique des réseaux pour la croissance économique, la diffusion de la technologie, les processus de production et le développement ?
- Comment les caractéristiques du réseau telles que la centralité, les communautés de commerce et la transitivité importent-elles ?
- Quelles sont les fragilités du processus de production à la lumière des caractéristiques du réseau ?

Pourquoi étudier les relations internationales en utilisant l'analyse de réseau ?

L'objectif de cette thèse est de revisiter certaines questions d'économie internationale, en utilisant les outils d'analyse de réseau. Les outils d'analyse de réseau sont de plus en plus utilisés pour étudier le commerce et la finance internationale pour de multiples raisons.

En se référant à leur utilisation pour analyser les données du commerce international, De De Benedictis et al. (2014) déclarent : « L'analyse de réseau est fondamentalement liée aux analyses des relations. » De nombreux aspects des relations internationales sont étudiés en fonction des caractéristiques individuelles des pays (comme la population ou le PIB) ou en fonction des caractéristiques de leurs relations (comme la distance géographique). Cependant, une troisième composante de ces relations a été moins étudiée, et De Benedictis et al. (2014) la décrit comme la « dimension structurelle ». Les relations entre deux pays ne peuvent pas être analysées indépendamment des effets des pays tiers. La notion d'interdépendance est centrale dans l'analyse de réseau.

Des études ont tenté de mesurer l'interdépendance et les effets des pays tiers sur le commerce et la finance. Dans l'article publié dans l'*American Economic Review*, Anderson and Van Wincoop (2003) tentent d'identifier les barrières non observables au commerce international en estimant une résistance commerciale multilatérale (MRT) entre deux partenaires commerciaux. Leurs résultats théoriques montrent comment les exportations du pays i vers le pays j sont déterminées par le coût du commerce du pays i par rapport à sa « résistance » globale aux importations (toutes choses égales par ailleurs, plus le coût commercial général et la résistance moyenne des exportateurs du pays i sont hauts, plus les exportateurs du pays i sont poussés à commercer avec le pays j).

Il est difficile d'estimer la résistance commerciale multilatérale. Anderson et Van Wincoop (2003) utilisent des méthodes itératives pour estimer les effets d'une hausse de la résistance commerciale multilatérale, mais cette procédure n'est pas souvent utilisée car elle nécessite une approche non linéaire utilisant la méthode des moindres carrés ordinaires. Des alternatives plus simples incluent l'utilisation d'une variable d'éloignement ou d'effets fixes (Rose and Van Wincoop (2001); Feenstra (2005); Baldwin and Taglioni (2006)).

Une autre tentative théorique et empirique importante d'introduire des effets de réseau à l'analyse du commerce international a été faite dans Chaney (2014). Dans son article, une entreprise exportant vers un pays i durant l'année t est plus susceptible d'entrer en $t + 1$ dans le pays j, un pays géographiquement proche de i, et ce même si j n'est pas proche du pays d'origine de l'entreprise. Ce résultat est dû à la dynamique informationnelle. Chaney (2014) prouve cette prédiction théorique en utilisant des données d'entreprises françaises. La littérature sur les « plateformes d'exportation » (Ekholm et al. (2007), Yeaple (2003), Bergstrand and Egger (2007)) souligne également l'importance des partenaires dans le choix de nouvelles destinations d'exportation. Les plateformes d'exportation font références aux situations dans lesquelles un pays investit dans un pays hôte avec l'intention de desservir des marchés « tiers ».

L'analyse de réseau permet d'analyser l'impact de la structure sur le réseau que la littérature existante n'étudie pas systématiquement. Dans cette approche, les effets des pays tiers ne sont pas réduits à un effet moyen, masquant l'hétérogénéité entre les pays tiers. À mesure que les économies deviennent plus globalisées, les analyses des relations internationales à travers les lentilles de réseau deviennent plus nécessaires.

Pendant longtemps, les auteurs manquaient d'outils pour mesurer correctement l'intégration économique internationale (Kali and Reyes (2007)). Les progrès de la théorie des réseaux et de l'économétrie, la disponibilité de nouvelles bases de données bilatérales et l'augmentation de la capacité informatique ont ouvert de nouveaux horizons de recherche et donné de nouveaux outils aux économistes pour étudier les liens entre les pays (Albert and Barabási (2002); Newman (2005); Galeotti et al. (2010); De Martí and Zenou (2009); Jackson (2010); Newman (2010)).

Cette dissertation permet d'inclure l'hétérogénéité des effets des pays tiers dans les relations commerciales et financières. L'analyse de réseau y est appliquée à différentes bases de données bilatérales de commerce et de finance afin d'étudier le système en tant que réseau interconnecté. L'approche en réseau permet d'étudier la pertinence de certaines caractéristiques du réseau, telles que la centralité des partenaires commerciaux, l'impact des communautés de commerce et l'importance des relations triangulaires sur la diffusion de nouvelles technologies, l'augmentation de la productivité et le développement des investissements, ainsi que sur l'augmentation des risques de disruption de la production.

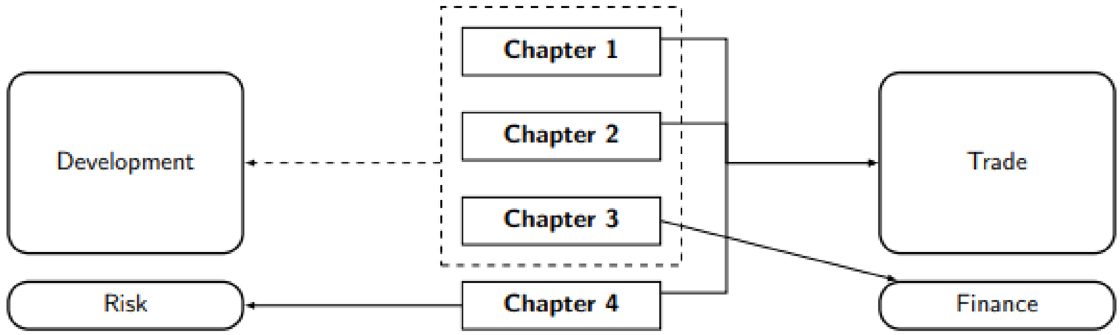
Plan de la thèse

Cette thèse est composée de quatre chapitres. Comme illustré dans le graphique 4, les chapitres 1 à 3 proposent d'étudier l'impact des réseaux commerciaux et financiers sur le développement des pays, tandis que le chapitre 4 met en évidence les risques émergeant de la structure du réseau. Les chapitres 1, 2 et 4 étudient le commerce international, tandis que le chapitre 3 se penche sur la finance internationale.

Chapitre 1 : Diffusion des idées et centralité dans le réseau commercial

Le chapitre 1 analyse la diffusion des idées à travers le commerce international. Dans ce chapitre, la notion d'impact des partenaires commerciaux est essentielle : si la diffusion des connaissances par le biais du commerce est bilatérale (un pays apprend de son partenaire commercial), l'impact économique de cette diffusion dépend

Figure 4: Plan de la thèse



de la pertinence du partenaire dans le réseau commercial. Dans Coe et al. (1997), les auteurs établissent qu' « en échangeant avec un pays industriel disposant d'un 'stock de connaissances' plus important, un pays en développement a plus à gagner à la fois en terme de produits qu'il peut importer et des connaissances directes qu'il peut acquérir ». Ce chapitre fait valoir que l'association entre pays industrialisés et larges stocks de connaissances n'est plus pertinente, car la frontière entre le niveau de développement et la position dans le réseau commercial est plus floue que par le passé (graphique 2). Au lieu des pays industrialisés, le chapitre fait valoir que les pays les plus centraux sont ceux qui ont les plus grands stocks de connaissances. Plus un partenaire est important (central) dans le réseau commercial, plus les connaissances acquises grâce au commerce avec ce partenaire affecteront la croissance d'un pays.

La première contribution du chapitre 1 est théorique. Le modèle ricardien multi-pays du commerce international d'Alvarez et al. (2017) et Buera and Oberfield (2017) est réinterprété en utilisant l'analyse de réseau. Les pays centraux d'un réseau commercial ont tendance à être à la frontière des idées. Ces pays sont les principaux moteurs de la diffusion des connaissances. Les pays qui développent des liens étroits avec les pays du centre sont plus susceptibles d'acquérir des technologies récentes, d'améliorer leur productivité et d'augmenter leurs revenus.

Le chapitre se tourne ensuite vers l'évaluation empirique de la théorie. Pour la première fois dans la littérature sur le commerce, le chapitre utilise la mesure de la centralité d'intermédiarité par marche aléatoire (RWBC[5]) développée par Newman (2005) et Fisher and Vega-Redondo (2006). La mesure de la centralité d'intermédiarité est mieux adaptée à la notion de flux d'idées dans le réseau. Cette mesure souligne l'influence d'un pays sur les autres pays. Un pays avec une centralité élevée a une forte influence dans la transmission des idées et des technologies à travers le réseau.

Troisièmement, dans le cadre d'un système de méthodes généralisées des moments (S-GMM[6]), les estimations confirment que les pays qui ont développé plus de liens avec les partenaires commerciaux centraux ont eu une croissance plus forte. L'importance du canal d'apprentissage est confirmée. Les pays où l'éducation de la population active est la plus élevée bénéficient davantage des échanges avec les pays du centre que ceux qui ont des travailleurs moins instruits. Les gains potentiels pour les pays à forte intensité de main-d'œuvre peuvent atteindre 2 points de croissance du PIB.

Chapitre 2 : Timing de l'adoption des nouvelles technologies et communauté de commerce

Le chapitre 2 explore les déterminants d'une adoption plus rapide des nouvelles technologies. Dans les études théoriques et empiriques antérieures, l'importance du commerce avec les partenaires était un facteur clé d'une adoption plus rapide des nouvelles technologies. Cette étude prolonge cette idée et conclut que les partenaires commerciaux ne contribuent pas de manière égale. Plus précisément, les partenaires commerciaux appartenant aux mêmes communautés commerciales sont plus susceptibles de favoriser l'adoption de nouvelles technologies.

La première contribution du chapitre est l'utilisation de l'algorithme de détection des communautés de Rosvall and Bergstrom (2008) (RB) pour identifier les groupes de

[5]Acronyme en anglais correspondant à la Random Walk Betweeness Centrality.
[6]Acronyme en anglais correspondant au System Generalized Method of Moments

pays dans le réseau commercial. Les recherches antérieures ont utilisé des définitions basées sur des similitudes dans la matrice des exportations qui ne garantissent pas que les pays qui font du commerce appartiennent à la même communauté ou à des méthodologies telles que la moyenne k, qui requièrent l'imposition du nombre de communautés a priori. L'algorithme RB utilise la marche aléatoire comme proxy des flux commerciaux et décompose le réseau en communautés de pays en « compressant une description du flux de probabilité ». L'algorithme RB vise à identifier la colonne vertébrale du réseau en regroupant les pays en communautés représentant sa structure principale. Il ne requiert pas l'imposition du nombre de communautés a priori.

Deuxièmement, ce chapitre décrit le mécanisme de formation des communautés dans le réseau commercial. Après avoir montré que les variables de gravité ne permettent pas de déterminer les limites des communautés commerciales, les résultats indiquent que les intentions de développer une chaîne de valeur conduisent à la formation de nouvelles communautés. L'analyse des pays qui changent de communauté montrent que ceux qui changent reçoivent plus d'entrées d'investissements et augmentent leur commerce de biens intermédiaires avec les membres de leur nouveau groupe.

Troisièmement, cette étude offre une contribution théorique en fournissant un aperçu de la façon dont les communautés influencent le processus de diffusion de la technologie, en imitant la possibilité d'une cascade complète. Dans ce cadre, les pays adoptent une nouvelle technologie lorsqu'un nombre suffisant de partenaires commerciaux l'ont déjà adoptée. Contrairement à la littérature théorique sur l'adoption de la technologie, l'existence de communautés implique que la technologie est adoptée dans le groupe de l'innovateur, mais pas plus loin. Une augmentation du nombre de communautés dans un réseau a deux implications théoriques sur le processus de diffusion de la technologie : un impact négatif lorsque le nombre de pays dans le cluster d'innovateurs diminue, mais aussi un impact positif car il y a plus de communautés.

La quatrième contribution est l'estimation empirique de l'impact des pôles commerciaux sur l'adoption de la technologie. Alors qu'une technologie se diffuse parmi les partenaires commerciaux (en adéquation avec les contributions passées), le processus d'adoption est plus rapide parmi les pays d'une même communauté (conformément aux implications du modèle théorique). La première approche utilise la méthode groupée des moindres carrés ordinaires pour tester si le fait d'avoir un partenaire commercial au sein d'une même communauté favorise l'adoption d'une technologie par un pays. Les résultats indiquent un effet causal statistiquement significatif. Le résultat est robuste à diverses spécifications et variables de contrôle.

Ensuite, cette étude explore l'influence du nombre de communautés et de leur composition sur le timing de l'adoption d'une nouvelle technologie. L'augmentation du nombre des communautés favorise l'adoption de la technologie, mais simultanément, la réduction du nombre de pays dans les communautés a un impact négatif. Ce double effet conduit à l'existence d'un nombre optimal de communautés. Si l'évolution au cours des dernières décennies a eu un effet positif sur la diffusion de la technologie, cela pourrait ne pas être le cas si le nombre de communautés continue d'augmenter.

Chapitre 3 : Les déterminants de réseau des décisions de fusions-acquisitions

Le chapitre 3 évalue si les décisions de fusions-acquisitions sont basées sur des effets de réseau. Conformément à la littérature sur les plates-formes d'exportation et les obstacles informationnels, le chapitre conclut sur l'importance des pays tiers dans la création de nouveaux investissements.

La première contribution de ce chapitre est d'utiliser des outils économétriques de réseau pour intégrer l'impact des pays tiers. Des modèles de graphe aléatoire exponentiel (ERGM[7]) et de graphe aléatoire exponentiel temporel (TERGM[8]) sont

[7]Acronyme en anglais correspondant aux Exponential Random Graph Models.
[8]Acronyme en anglais correspondant aux Temporal Exponential Random Graph Models.

utilisés pour estimer les déterminants des investissements de fusions-acquisitions au niveau sectoriel. À la différence des modèles d'estimations traditionnels, les ERGM et TERGM permettent l'analyse de dépendances plus élevées. Le réseau de fusions-acquisitions observé est considéré comme l'un des nombreux qui pourraient avoir eu lieu. Il représente la réalisation d'un tirage au sort à partir d'une distribution de tous les réseaux de fusions-acquisitions possibles. Les inférences statistiques donnent des informations sur les déterminants du réseau réalisé, en particulier la probabilité de transitivité dans la réalisation de nouveaux investissements.

La deuxième contribution de ce chapitre est dans les résultats empiriques. Les estimations montrent que la transitivité est importante : un pays est plus susceptible d'investir dans une destination où l'un de ses partenaires a déjà réalisé une fusion-acquisition. Cet effet de réseau est considérable, et elle est plus importante que certains des déterminants traditionnels des fusions-acquisitions. Les chances d'un investissement sont 4,2 fois plus élevées dans l'industrie légère, 4,5 fois plus élevée dans l'industrie primaire et 6,2 fois plus élevée dans l'industrie lourde, lorsqu'un pays partenaire a déjà investi dans le nouveau pays. Ces probabilités sont plus grandes que certains des déterminants traditionnels des fusions- acquisitions, tels que l'ouverture commerciale.

Chapitre 4 : Évaluation de la fragilité du commerce mondial : l'impact des catastrophes naturelles au travers de l'analyse de réseau

Le chapitre 4 prend un angle différent du chapitre précédent. Au lieu de montrer le rôle que les réseaux jouent dans le développement, l'adoption de la technologie ou de nouvelles décisions d'investissements, il évalue les risques qui émergent de la connectivité des pays. Ce chapitre fait valoir que les conséquences d'un choc d'approvisionnement situé dans un pays d'origine des imports dépendent de la structure du réseau du bien importé.

La première contribution du chapitre 4 est de construire une mesure de la fragilité des importations. La mesure est basée sur l'évaluation du risque des produits échangés en analysant le réseau de biens exportés et en basant le choix des composants de l'indice sur la littérature. En particulier, le chapitre souligne le risque lié à la présence d'acteurs centraux dans le réseau d'un produit, à l'existence de communautés et à la faible substituabilité internationale des partenaires commerciaux. La méthodologie développée permet d'identifier les produits les plus vulnérables dans le commerce mondial et détecte les principaux exportateurs et importateurs de ces produits. La méthodologie permet de comparer les vulnérabilités potentielles des différents pays importateurs et fournit un nouvel ensemble de données utilisé pour l'analyse transnationale.

La deuxième contribution du chapitre est l'estimation du pouvoir prédictif de l'indicateur. La méthodologie est testée pour deux cas particuliers de catastrophe naturelle : le tremblement de terre au Japon en 2011 et les inondations en Thaïlande en 2011. Sur la base des données de 2010, l'indicateur permet de détecter 5 des 6 produits qui ont perturbé les chaînes de valeur mondiales après les catastrophes naturelles. Le test est généralisé à une régression entre pays. Une augmentation de 1% de la part des importations de produits fragiles d'une économie touchée par une catastrophe est associée à une réduction de 0,7% des exportations du pays importateur.

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Introduction

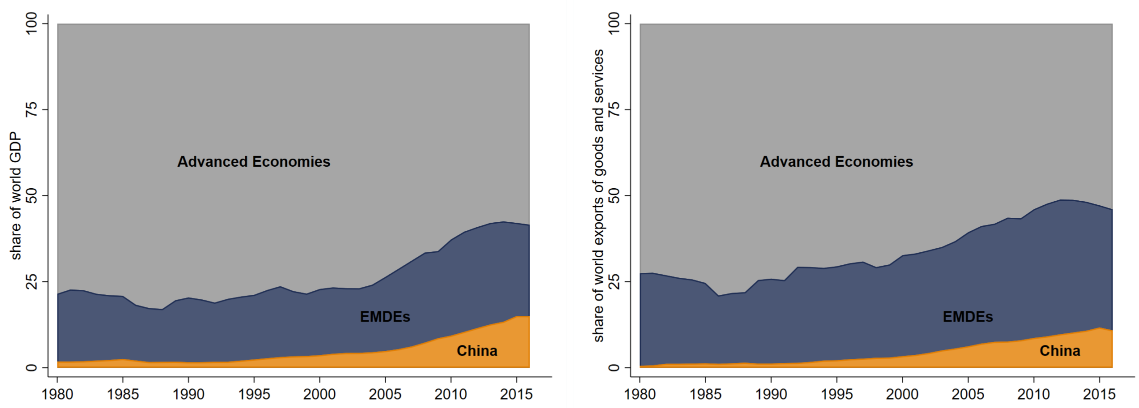
The world economic system is not what it used to be in the 20th century, when advanced economies (AEs) were acting as "center" for a "periphery" of emerging market and developing economies (EMDEs). The rise of EMDEs advocates for the need to go beyond this dichotomy. The previous AE–EMDE dynamics are diversifying and changing, suggesting the emergence of a much more multipolar world economy. In particular, the traditional overlap between "center" and "AEs" versus "periphery" and "EMDEs" is eroding, as some emerging countries are becoming major players on the global economic landscape.

A few statistics shed light on the magnitude and speed of these changes (Figure 5). Back in 1980, the gross domestic product (GDP) in current dollars of the EMDEs (defined as all the countries outside of OECD in 1980[9]) was around 20 percent of the global GDP. By 2016, EMDEs captured more than 40 percent of the global GDP. The EMDEs' expansion is similarly striking in terms of trade and financial flows. EMDEs accounted for about 30 percent of global trade flows in 1980, whereas in 2016 they represented around 47 percent. Similarly, EMDEs captured around 13 percent of global capital inflows in 1980; by 2016, they received more than 40 percent of the total. They also became more representative as source countries, sending 30 percent of global capital outflows in 2016, up from 6 percent in 1980. Although China

[9]OECD countries in 1980 include Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Japan, Luxemburg, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, Turkey, United Kingdom, and the United States.

Figure 5: World share of GDP and exports of goods and services

(a) World share of GDP (b) World share of exports



Source: WDI.
Note: The left-hand panel presents the evolution of the world share of current GDP; the right-hand panel shows the world share of exports of goods and services.

is not the only EMDE behind these trends, it has played an important role in their development since its accession to the World Trade Organization in 2001. In the most recent years, the process of catch-up held back in major emerging economies —Brazil, Russia and South Africa slowed down or fell into recession while the Chinese economy was rebalancing toward more domestic consumption with a lower growth rate.

This tectonic reconfiguration of the global economic landscape—particularly the move away from the traditional pattern of high-income countries at the center and developing countries at the periphery—has also brought significant changes to the traditional analysis of trade and finance. The present dissertation contributes to the understanding of the impact of recent developments in trade and finance network structures on the international diffusion of technology (chapter 1), the timing of technology adoption (chapter 2), the likeliness to invest in a new country (chapter 3), and the risk of production disruption (chapter 4). Before turning to the content of the dissertation, this introductory chapter exposes the recent changes in the structure of the trade and finance networks that will be analyzed in the forthcoming chapters.

As a starting point for this analysis, this introductory chapter outlines four sets of facts[10] related to the rise of the EMDEs:

1. Several emerging countries are now at the center of the global trade network.

2. Trade clusters have changed over time.

3. The global finance network has not been fundamentally restructured but EMDEs are now more integrated than in the past.

4. Large disruptions in trade production are occurring more frequently after a disaster in a source country.

Fact 1: Several EMDEs have joined the AEs at the center of the global trade network.

This momentous change stands out clearly in Figure 6, which shows the global trade networks in 1980 and in 2012. Each node represents a country, while colors differentiate between AEs (in orange) and EMDEs (in blue). Each link corresponds to the existence of an active bilateral connection, corresponding to exports from one country to another, as indicated by the arrows. Countries that capture a larger share of other countries' exports and that are connected with a larger number of trading partners (that is, countries that are more important in the global network) appear to the right in Figure 6.

In 1980, a set of AEs stood at what can be empirically characterized as the center of the global trade network: the United States, Germany (and a few other Western European countries), and Japan were at the core of the network. By 2012, several emerging countries, including not only China, but also Brazil, India, the Russian Federation, South Africa, Turkey, and others, had moved to the center. As a result of

[10]Sets of facts 1 and 2 are drawn from a co-authored working paper, De la Torre et al. (2014).

these changes, EMDE is no longer a synonym for the periphery, and AE is no longer a synonym for the center of global trade.

Fact 2: Trade clusters have changed over time.

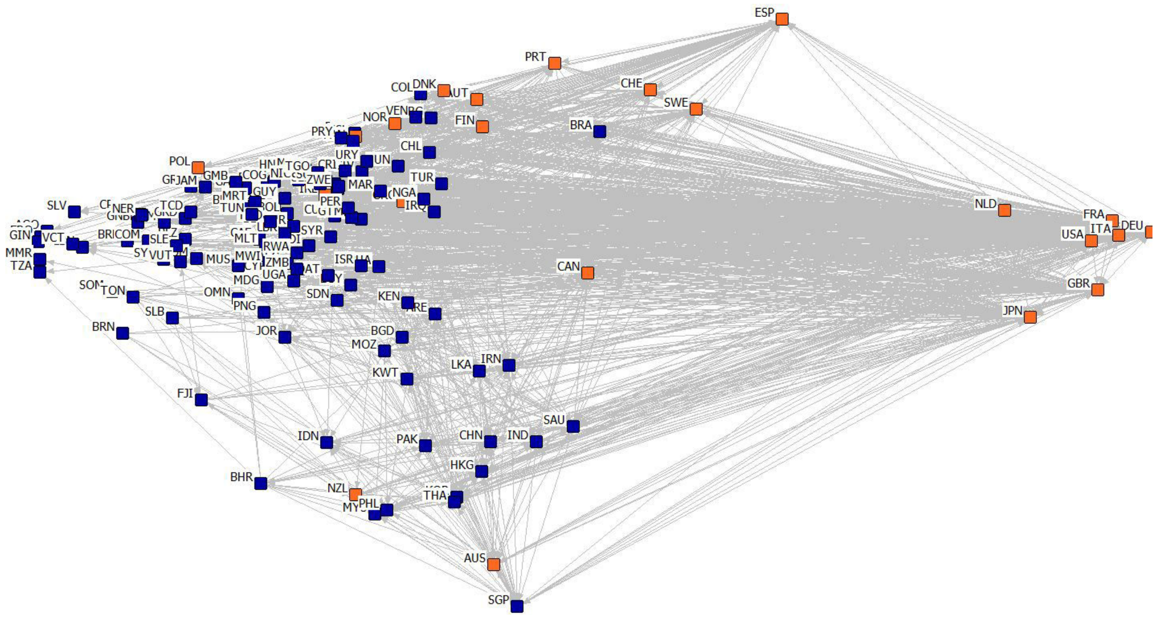
Figure 6 also illustrates the similarity in the structure of trade connections among countries: the closer countries are to one another, , the more alike they are in terms of export shares with the rest of the world. During the 1980s and 1990s, countries central to the network (situated on the right) are very close to one another, reflecting a high degree of similarity in the structure of their trade connections with other countries in the network. The global trade network in 1980 thus tended to display a sort of "single polarity," with some North countries acting as a single pole (that is, playing the same role) within world trade.

The global trade network in 2012 reveals a tectonic shift: several countries among the EMDEs appear on the right-hand side of panel b of Figure 6, indicating their increased relevance to world trade. However, they remain somewhat distant (along the vertical dimension) from the other AEs on the right-hand side of the figure. This side of the figure resembles a star, with small groups of central countries placed at a certain distance from one another. Russia and Turkey, for example, are not located near any core AEs countries from Europe, and Japan is not close to either China or Korea. The global trading landscape has become more heterogeneous and "multipolar."

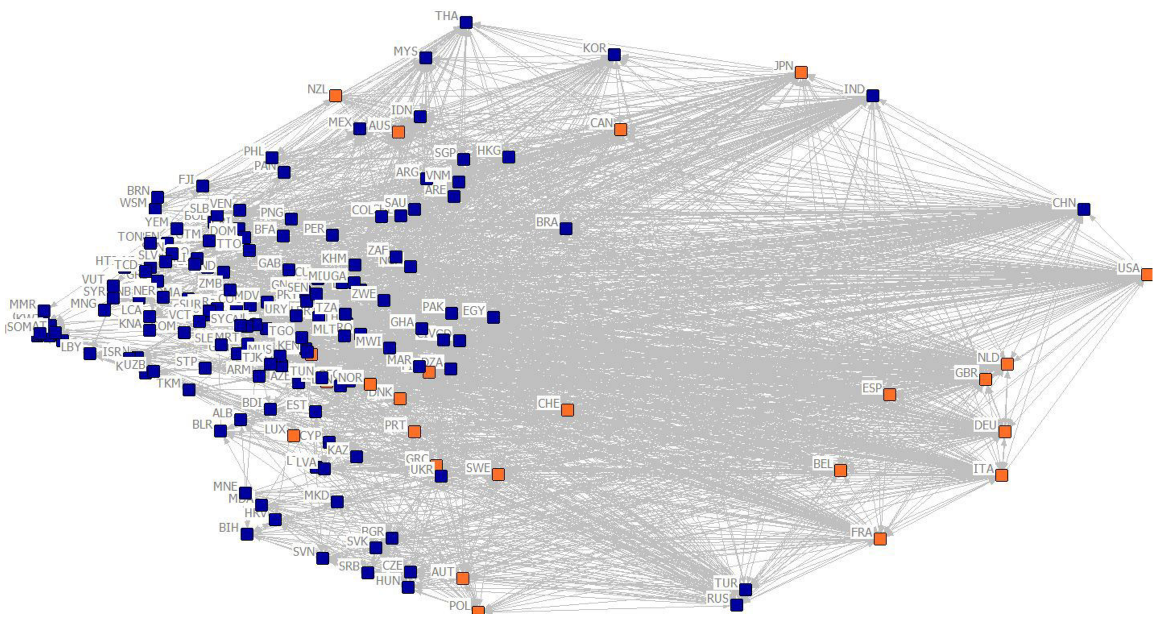
The dispersion of production stages and processes across countries supports these clustering patterns to some degree. So-called global value chains (GVCs) are indeed arising among a limited set of countries, rather more regionally than truly worldwide. Hernández et al. (2014) highlight the case of the dairy sector in Central America. Companies in El Salvador have developed partnerships in Nicaragua to produce cheese that is then sold in the United States; Morris et al. (2011) highlight the development

Figure 6: Centrality and clusters

(a) 1980



(b) 2012



Source: IMF's DOTs.

Note: The figure estimates the magnitude and the direction of the exports. A principal component algorithm is then applied to the matrix of share of exports in order to determine the position of each country in the trade network. Along the horizontal axis, countries are distributed according to their centrality to the trade network. More relevant countries to the network are situated to the right of the plot. The vertical axis indicates the similarity of trade structure between countries, with a smaller distance between two countries indicating a more similar structure of trade connections, in terms of exports to the rest of the world and relative importance to other trade partners.

of regional value chains among clothing manufacturers, led by South Africa in Lesotho and the Kingdom of Swaziland.

Fact 3: Unlike the global trade network, the global finance network has not been fundamentally restructured; but EMDEs are now more integrated than in the past.

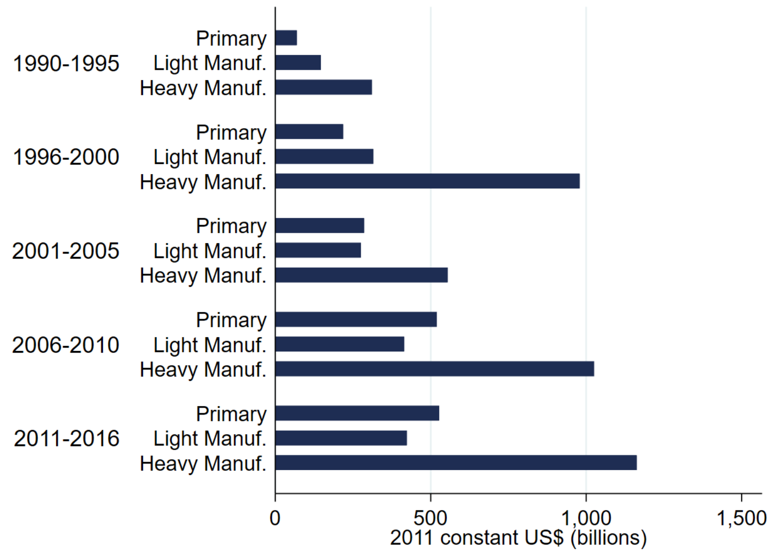
A key feature of the new dynamics of the global economy has been the asymmetry in the pattern of changes between the global trade and financial networks. In the sphere of trade, the traditional correspondence between the AEs and the center, and the EMDEs and the periphery, has been reconfigured. In contrast, in the sphere of finance, AEs still stand alone at the center of the global financial networks, though the EMDEs have increased their connectivity within these networks.

The growth of the EMDEs has been widespread. As the EMDEs gained prominence in the global economy, the number of their bilateral international connections proliferated. M&A flows are particularly large in the heavy manufacturing sector (55 percent since 2011, Figure 7). Investment in the primary sector has been growing and is now larger than investments in light manufacturing (25 percent versus 20 percent since 2011).

Fact 4: The internationalization of production processes has increased countries' interconnectedness.

The dispersion of production stages and processes across countries, evoked in Fact 2, has increased the interdependence across countries. Anecdotal evidence suggests the existence of specific choke points in the global trade network that become especially salient after natural disasters occur. The 2011 Japanese earthquake is now a well-studied event that shed light on how a localized disaster can have a significant contagion effect on many countries around the world. Countries importing inputs

Figure 7: Sectoral composition of cross-border mergers and acquisitions (M&A) flows



Source: Calculations based on SDC platinium database.
Note: The primary sector includes agriculture, hunting, forestry, and fishing; mining; and crude petroleum and natural gas. The light manufacturing sector includes food, beverages, and tobacco; textiles and apparel (including leather); and wood and paper-related products. The heavy manufacturing sector includes refined petroleum and related products, chemicals and plastics, nonmetallic minerals, metals, machinery and equipment, and transport equipment.

for their production from the impacted area of Fukushima had to interrupt their production for days or even months, because the lack of key inputs for their production. This occurred in the case of Apple, which was importing overlay glass for its iPad 2 touchscreen exclusively from Asahi Glass, a firm located in the province of Fukushima. After the earthquake, the firm delayed its delivery of overlay glass for five weeks, generating a two-month delay in launching the iPad 2.

With trade becoming more integrated into international value chains, any disaster located within providers of key intermediary goods now has a large probability to disrupt production in other countries.

Statement of the research question

International relationships are traditionally studied through the analysis of bilateral ties. However, the intensification and complexification of international links call for a more global analysis, in which not only the characteristics at the country level and between two countries are taken into account, but the situation is also considered from a network perspective. This dissertation deals with how the networks affect international economics relationships, in particular trade and finance, and assesses their impact on countries' development paths.

How does the network structure impact on international relationships?

- What are the consequences of network dynamics for economic growth, diffusion of technology, production processes, and development?
- How do network characteristics such as centrality, clusters, and transitivity matter?
- How fragile is the production process in light of network characteristics?

Why analyze international relationships using network analysis?

The focus of this dissertation is to revisit some questions researchers have been working on, using network analysis tools. The use of network analysis tools for the analysis of international trade and finance is increasing for multiple reasons. Referring to the use of network analysis tools to analyze international trade data, De Benedictis et al. (2014) stated: "Networks are about relations." Many aspects of international relationships are studied based on individual characteristics —i.e., country-level characteristics —or the nature of their connections —i.e., observables ties, such as common language or geographical distance. However, a third component to these relationships has received less attention, and is described by De Benedictis et al. (2014) as the "structural dimension." Relations between two countries cannot be analyzed in isolation of third-country effects. The notion of interdependence is key in network analysis.

The trade and finance literature has attempted to proxy countries' interdependence and third-country effects. In their *American Economic Review* paper, Anderson and Van Wincoop (2003) attempt to identify unobserved barriers to trade by estimating a multilateral trade resistance (MRT) between two trading partners. Their theoretical results show how the exports of country i to country$j$ are determined by country j's trade cost toward i relative to its overall "resistance" to imports (everything else equal, the higher the general trade cost and the average "resistance" exporters face in country i, the more they are pushed to trade with country j).

Estimation of MRT is challenging. Anderson and Van Wincoop (2003) use iterative methods to construct estimates of the price-raising effects of MRT barriers, but this procedure is not often used, as it requires a non-linear least squares approach. Simpler alternatives include the use of a remoteness variable or fixed effects (Rose and Van Wincoop (2001); Feenstra (2005); Baldwin and Taglioni (2006))[11].

Another important theoretical and empirical attempt has been made by Chaney (2014)'s studies on informational friction in trade. In his paper, a firm exporting to country i in year t is more likely to enter in year $t + 1$ in country j , a country

[11] Other attempts include the gravity literature, which assesses the impact of cultural ties on trade. Rauch and Trindade (2002) shows first that proximity and a common language or colonial ties are more important for differentiated products than for homogenous ones, and that search barriers to trade are higher for differentiated than for homogeneous products. Rauch and Trindade (2002) show that Chinese ethnic networks represent an influential facilitator of trade. Felbermayr and Toubal (2010) find a positive correlation between trade and a measure of cultural similarity based on a European singing competition.

geographically close to i, even if j is not close to the origin country of the firm. The reason behind this is an informational dynamic. Chaney (2014) finds empirical evidence for this prediction using French firm data. The "export platform" literature (Ekholm et al. (2007), Yeaple (2003), Bergstrand and Egger (2007)) also emphasizes the importance of partners in choosing new export destinations. Export platform refers to situations where a parent country invests in a particular host country with the intention of serving "third" markets with exports of final goods from the affiliate companies in the host country.

Network analysis allows to approach more systematically particular impacts that the existing literature does not capture, such as the impact of the structure on the network, or the role of individual countries or groups of countries within it. In this approach, third-country effects are not reduced to an average effect, thus masking heterogeneity across third countries. As economies become more globalized, analyses of international relationships though network lenses become more necessary.

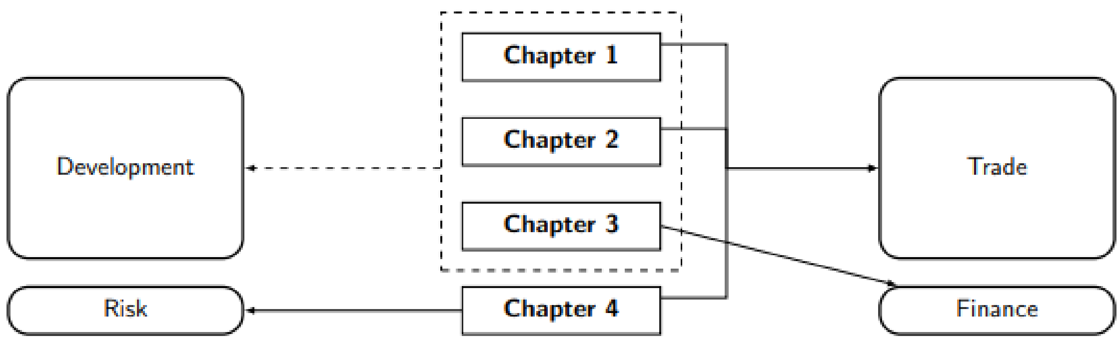
For a long time, authors lacked the tools to measure international economic integration correctly (Kali and Reyes (2007)). Progress in network theory and econometrics, the availability of newer bilateral databases, and increases in computer capacity opened new areas of research and gave new tools to international economists to study the patterns of linkages that connect countries together (Albert and Barabási (2002); Newman (2005); Galeotti et al. (2010); De Martí and Zenou (2009); Jackson (2010); Newman (2010)).

This dissertation takes a step toward including the heterogeneity of third-country effects in trade and finance relationships. Network analysis is applied to different bilateral trade and finance databases in order to study the system as an interconnected network. The network approach allows to study the relevance of certain characteristics of the network, such as the centrality of trade partners, the impact of clusterization, and the importance of triangular relationships on the likeliness of diffusing new technologies, increasing productivity, and developing investment, as well as on the development of risks emerging from the structure.

Outline of the dissertation

This dissertation is composed by four chapters. As depicted in Figure 8, Chapter 1, 2, and 3 study the impact of trade and finance networks on countries' development, while 4 highlights the risks emerging from the structure of the network. Chapter 1, 2, and 4 investigate trade while 3 looks into finance.

Figure 8: Sectoral composition of cross-border mergers and acquisitions (M&A) flows



Chapter 1: Diffusion of ideas and centrality in the trade network

Chapter 1 explores the diffusion of ideas through international trade. In this chapter, the notion of the impact of trade partners is key: if the diffusion of knowledge through trade is bilateral (a country learns from its trade partner), the economic impact of this diffusion depends on the relevance of the partner in the trade network. In Coe et al. (1997), the authors state that "by trading with an industrial country that has a larger 'stock of knowledge,' a developing country stands to gain more in terms of both the products it can import and the direct knowledge it can acquire than it would by trading with another developing country." This chapter argues that the association between industrial countries and larger stocks of knowledge is no longer relevant, as the line between level of development and position in the trade network is more blurred than in the past (Figure 6). In lieu of industrial countries, the chapter argues that the most central countries are those that have the largest stocks of knowledge. The more important (central) a partner is in the trade network, the more the knowledge gained from trade with this partner will affect a country's growth.

The first contribution of chapter 1 is theoretical. The multi-country Ricardian model of international trade of Alvarez et al. (2017) and Buera and Oberfield (2017) is reinterpreted using network analysis. Countries central to a trade network tend to be at the frontier of ideas. These countries are the main drivers of knowledge diffusion. Countries that develop strong ties with central countries that are innovators are more likely to acquire recent technologies, improve their productivity, and boost their income.

The chapter then turns to the empirical assessment of the theory. For the first time in the trade literature, the chapter uses the random walk betweenness centrality (RWBC) measure developed by Newman (2005) and Fisher and Vega-Redondo (2006). The measure of betweenness centrality is better suited to fit the notion of idea flows in the network. In turn, the concept of a random walk is more relevant for networks where the concept of shortest path is not meaningful, as it is the case of densely connected network such as the trade network. This measure emphasizes the role of a country in its relations in acting between other countries. A country with high betweenness centrality has a key influence in the transmission of ideas and technologies through the network.

Third, in a system-GMM framework, estimations confirm that countries that developed more ties with central trade partners were more likely to grow faster. The importance of the learning channel is confirmed. Countries with higher labor force education benefit more from trading with central countries than do those with less-educated workers. Potential gains for countries with high labor force education can be as high as 2 percentage points of GDP growth.

Chapter 2: Timing of technology adoption and clustering in trade networks Chapter 2 explores the determinants of faster adoption of new technologies. In earlier theoretical and empirical studies, the amount of trade with partners was a key determinant of faster adoption of new technology. Expanding on this idea, this study finds that trade partners do not contribute equally. More precisely, trade partners belonging to the same trade clusters are more likely to foster new technology adoption.

The chapter's first contribution is its use of the Rosvall and Bergstrom (2008) (RB) community detection algorithm to identify clusters in the trade network. Previous trade research has used definitions based on similarities in the export matrix that do not guarantee that countries trading together belong to the same cluster, or methodologies such as the k-mean, which require the imposition of the number of cluster a priori. The RB algorithm uses random walks as a proxy of the trade flows and decomposes the network into clusters by "compressing a description of the probability flow." The RB algorithm aims to identify the backbone of the network by grouping countries into clusters representing the main structure of the network. The intuition behind the RB algorithm is that the longer the random walk remains among a group of countries, the more likely those countries form a cluster. Furthermore, the algorithm has the advantage of not requiring the imposition of the number of clusters a priori.

Second, this chapter describes the mechanism behind trade cluster formation. After showing that gravity variables fail to determine the boundaries of trade clusters, the results indicate that value chain motives drive cluster formation. The analyses of countries switching clusters shows that "switchers" receive more inflows of M&A investment and increase their trade in intermediary goods from members of their new cluster, compared with their former cluster.

Third, this study offers a theoretical contribution by providing some insight into how clusters influence the technology diffusion process, by imitating the possibility of a complete cascade. In this framework, countries adopt a new technology when a sufficient number of trade partners have adopted it. In contrast with the theoretical literature on technology adoption, the existence of clusters implies that the technology is adopted within the innovator's cluster, but not further. An increase in the number of clusters in a network has two theoretical implications on the technology diffusion process: a negative impact as the number of countries in the innovator's cluster decreases, but a positive impact if the smaller clusters are denser than the larger ones.

The fourth contribution is the empirical estimation of the impact of trade clusters on technology adoption. While a technology diffuses among trade partners (in line with previous literature), the adoption process is faster among countries within the same cluster (following the implications of the theoretical setup). The first approach uses a pooled OLS regression over time to test whether having a trade partner within the same cluster in a previous period fosters a country's technology adoption. The results indicate evidence of causality with a statistically significant effect. The result is robust to various specifications and control variables. In particular, controlling for the country and trading partners in the same region, Regional Trade Agreement (RTA), or the intensity of intra-industry trade, do not offset the effect.

Next, this study explores the influence of the number of clusters and their composition on the technology adoption process. An increase in the number of clusters fosters technology adoption, but simultaneously, a reduction in the number of countries in the cluster has a negative impact. This dual effect leads to the existence of an optimal number of clusters. However, if the evolution over the past decades had a positive effect on technology diffusion, this might not be the case if the number of clusters continues to increase.

Chapter 3: Network determinants of merger and acquisition decisions

Chapter 3 assesses whether M&A decisions reflect network effects. In line with the literature on export platforms and informational barriers, a sizable impact is found of third countries on the creation of new investments.

The first contribution of this chapter is to use network econometric tools for finance variables. An exponential random graph models (ERGMs) and a temporal exponential random graph models (TERGMs) are estimated to find the determinants of cross-country M&A investments at the sectorial level. In lieu of the traditional setup, ERGM and TERGM allows the analysis of higher-level dependencies in M&A networks. The observed M&A network is considered one of the many that could have happened. It represents a realization of a random draw from a distribution of all the possible M&A networks. Statistical inferences give information on the determinant of the realized network, in particular the likeliness of transitivity in the realization of new M&As.

The second contribution of this chapter lies in the empirical results. The findings show that transitivity matters: a country is more likely to invest in a certain destination where one of its existing partners has already made some investments. This network effect is sizable, being larger than some of the more traditional M&A determinants. The odds of an M&A investment are 4.2 times higher in light manufacturing, 4.5 times higher in primary, and 6.2 times higher in heavy manufacturing, when a partner country has already invested in the new location. These odds are larger than some of the more traditional M&A determinants, such as trade openness.

Chapter 4: Assessing the fragility in global trade: the impact of natural disasters using network analysis Chapter 4 takes a different angle than previous chapters. Instead of showing the role that networks play in development, adoption of technology, or new M&A decisions, the chapter assesses the risks that emerge from countries' connectedness. International trade structure of production is key in explaining how country-specific shocks are transmitted across economies. Carvalho (2014) find that localized disturbances of individual production lead to global shocks. As international value chains lead to the synchronization of business cycles across countries, firms from several countries might be impacted by one country's shock due to the lack of a key input. This chapter argues that the consequences of a localized supply shock in a trade partner country depend on the structure of the network of the good imported.

The first contribution of chapter 4 is to construct a measure of fragility of countries' imports to a possible future localized supply shock. The measure is based on the evaluation of the riskiness of the products traded by analyzing the network of goods exported, basing the choice of index components on the literature. In particular, it underscores the riskiness arising from the presence of central players in the network of a product, the tendency to cluster, and the low international substitutability of trade partners. The methodology developed helps to identify the most vulnerable products in global trade and tracks top exporters and importers of these products. The methodology allows the benchmarking of potential import basket vulnerabilities against different countries, country groups, and across regions, and provides a new dataset that is used for cross-country analysis.

The second contribution of the chapter is to evaluate the predictive power of the indicator for a particular case of localized supply shock: natural disaster. The methodology is tested for two case studies: the 2011 Japan earthquake and the 2011 Thailand floods. Based on 2010 data, the indicator achieves the detection of 5 out of 6 goods that disrupted other countries' value chains after the natural disasters. The test is generalized to a cross-country regression. An increase of 1 percent of the share of imports of fragile products from an economy that is impacted by a disaster is associated with a reduction of 0.7 percent of country exports.

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Chapter 1

Diffusion of Ideas and Centrality in the Trade Network[1]

[1]This chapter has a a policy-oriented companion paper, Didier and Pinat (2017), that was part of the 2015 World Bank Regional Flagship Report for Latin America and the Caribbean. This version focuses on the theory, the implementation and the results of the impact of trade partners' centrality. I received very helpful comments from Lionel Fontagné, Luca De Benedictis, participants at presentations held at the 18th Annual Meeting of the LACEA (Mexico City), 16th Annual Conference on Global Economic Analysis (Shanghai), PSE International Economics Seminar (Paris), the World Bank (Washington, DC), 12th edition of the ACDD (Strasbourg), and the 17th edition of the ETSG (Paris).

1.1 Introduction

Most cross-country income differences have been attributed to differences in the Total Factor Productivity (TFP)[2]. An important question, then, is to understand how countries can increase their TFP in order to raise their long-term income. Traditional determinants of TFP explored in the literature include technological innovations, trade openness, quality of government policies and institutions[3], flow of investments[4], and misalocation of resources across heterogeneous firms[5] among others.

This chapter revisits the role of technology and trade in increasing TFP. The terminologies *technologies* and *ideas* will be used indifferently in this chapter. In line with the Eaton and Kortum (1999) and Coe et al. (1997), they refer to all production-related knowledge, that contribute to the increase of a country's productivity. This includes production methods, products, design, organizational methods and market conditions. Despite the generalization of the access to internet, there is no indication that a global source of technology exists. As described by Keller (2004), an important component of (technology diffusion) is tacit by nature. Trade, and imports in particular, is a factor of transmission of ideas internationally as it makes products that embodied foreign technologies available to other countries. By importing, firms and countries get exposed to foreign technologies.

In Coe et al. (1997), the authors state that "by trading with an industrial country that has a larger' stock of knowledge' a developing country stands to gain more in terms of both the products it can import and the direct knowledge it can acquire than it would by trading with another developing country." This chapter argues that the association between industrial countries and largest stock of knowledge is no longer relevant. As the line between level of development and position in the trade network

[2]see for instance Hall and Jones (1999), Klenow and Rodriguez-Clare (1997), Caselli (2005), and Hsieh and Klenow (2009).

[3]see for instance Dollar and Kraay (2003) and Rodrik et al. (2004)

[4]see for instance Borensztein et al. (1998) and Alfaro et al. (2010)

[5]see for instance Syverson (2004), Hsieh and Klenow (2009) and Petrin and Levinsohn (2012).

is blurrier than in the past (see the introductory chapter). In lieu of industrial countries, the chapter argues that the most central countries are the one that have the largest stock of knowledge. Central countries in the sense of betweenness centrality, both import from many countries (and are thus exposed to many countries' technologies) and export to many countries (they are also relevant in terms of technology accumulation). At the difference of industrial countries, central countries were and are still at the technology frontier.

In this chapter, the notion of other countries' impact is key: if the diffusion of knowledge through trade is bilateral (a country learns from its trade partner), the economic impact of this diffusion depends on the relevance of the partner in the trade network. The more important a partner is in the trade network, the more the knowledge gained from trade will affect a country's growth.

In a multi-country Ricardian model of international trade, this chapter studies the diffusion of ideas. It uses a model based on Alvarez et al. (2017) and Buera and Oberfield (2017). According to this model, endogenous growth is driven by agents learning from their trading partners. Long-term growth depends on the search for current ideas and the concentration of high-productivity elements in the economy. Trade openness affects the creation and diffusion of technologies because more open countries have a wider range of partners to learn from.

This chapter focuses on the relevance of the network centrality of trade partners in the diffusion of technologies across countries. A theoretical model emphasizes that in certain circumstances, countries that are central to the trade network are at the frontier of ideas. In that case, these innovative countries are the main driver of knowledge diffusion. While a central country is defined based on its relevance to other countries' imports, a country that became central due to low cost exports based on low wages would not be expected to foster a positive learning spillover on the rest of the network. Countries that develop strong ties with central countries that are innovators are more likely to learn recent technologies, improve their TFP, and ultimately their income.

In a System-GMM framework, results indicated that countries trading with central countries helped increased their income. Results confirm the importance of the learning channel, as countries with higher labor force education benefit more from trading with central countries than those with less-educated workers. Potential gains for countries with high labor force education can be as high as 2 percentage points of GDP per capita growth. This result is confirmed by the differentiated impact of increasing trade with core and inner-peripherical countries. The more educated the labor force, the more that is gained from trading with core countries.

Taken together, the theoretical and empirical frameworks allow for an understanding of the evolution of countries within the trade network. For a concrete application, this chapter examines the experiences of South Korea and Colombia in Annex 1.A. South Korea was a peripheral country in the 1960s, but it cultivated commercial ties with Japan, a country that had become central due to its production and export of technological goods. South Korea learned more efficient technologies to produce by importing from Japan, increasing its productivity and its income. As a result, it became more central to the trade network. In a lesser extend, the exposure of Colombia to the technology embedded in imports from the United States have contributed to its productivity and economic growth. This chapter concludes with some policy recommendations at the country level and some implications for multilateral organizations.

The remainder of this chapter is as follows: Section 1.2 of this chapter presents the relevant theoretical and empirical literature. Section 1.3 describes the theoretical model and highlights the role of central trade partners in the diffusion of knowledge.

Section 1.4 examines the estimation strategy, the data, and the results of this chapter. Section 1.5 concludes the chapter.

1.2 Literature review

Theoretical sections from this chapter draw from the endogenous growth theory and Ricardian model for international trade; empirical sections build on papers analyzing the determinants of economic growth and network analysis applied to international trade. This section reviews the main references the chapter borrows from.

1.2.1 Growth theory, idea flow literature and trade

In endogenous growth theory, long-term economic growth comes either from knowledge spillovers that reduce the relative cost of entry into an expanding varieties framework (Romer (1990)) or from productivity spillovers that allow entrants to improve the technological frontier in a quality ladders framework (Aghion and Howitt (1992)).

The idea flow literature describes the evolution of production efficiency through the meeting of one agent with another of higher productivity[6]. Agents improve their productivity either by imitating an existing technology (when they meet an agent with higher productivity) or inventing one (stochastically). In a closed economy model, Kortum (1997) adds a standard theory of results to this framework: invention depends on the past research efforts $K(t)$ and has a Poisson distribution between two points in time. The most efficient process to produce a good at time t is called the 'technological frontier,' and it has a Fréchet distribution. Nevertheless, unlike this chapter's model, there is no insight from trade partners.

[6] Earlier sources Jovanovic and Rob (1989) and Jovanovic and MacDonald (1994).

Grossman and Helpman (1991) formalized trade as a key determinant for adopting new technology through the diffusion of ideas embedded in imported and exported goods[7]. The authors model the importance of foreign R&D in sustaining growth within a small open economy framework. The technology flows through trade in goods; the higher the volume of trade with the rest of the world, the more knowledge can be accumulated. This framework does not account for the level of knowledge of the foreign country. It only assumes a linear relation between the exposure to foreign trade and the accumulation of outside knowledge.

In a perfectly competitive Ricardian model of international trade, Eaton and Kortum (2002) use the idea flow literature in an international context. Their insights are drawn from the distribution of potential producers in each country according to exogenous diffusion rates, which are estimated to be country-pair specific (although countries are assumed to be in autarky otherwise). In this model, freer trade replaces inefficient domestic producers with more efficient foreign producers. Changes in trade costs do not affect the diffusion of ideas. Alvarez and Lucas (2007)[8] expand this model to show the existence and uniqueness of an equilibrium with balanced trade. Both of these models integrate only static effects at the difference with this chapter.

[7]An alternative view on trade's influence on productivity comes from the microeconomic literature. Income differences across countries are based on differences in productivity across firms that may be explained by a suboptimal allocation of resources (Hsieh and Klenow (2009), Alfaro et al. (2008), and Midrigan and Xu (2010)). Melitz (2003) asserts that larger firms are also the more productive. This result is contradicted by the empirical literature, mainly because of the imperfect mobility of resources. For instance, Syverson (2004) shows that the biggest firms produce more with the same input and compared with the US, plants at the 90th percentile of the productivity distribution make twice as much output with the same inputs as the plants in the 10th percentile. Hsieh and Klenow (2009) find even larger ratios in China and India. Bartelsman et al. (2013) finds that the within-industry dispersion of labor productivity is larger than the within-industry dispersion of total factor productivity. They find that the US is doing 50 percent better than their input would predict, while some Western European countries are performing at only 20 percent. The main reason proposed for this is policy-induced distortion (as first proposed by Banerjee and Duflo (2005)).

[8]Alvarez and Lucas (2007) is a note paper extending the mathematics of Kortum (1997) diffusion of ideas.

Alvarez et al. (2017) is based on Eaton and Kortum (2002) and Alvarez and Lucas (2007). They add a theory of endogenous growth in which agents receive new production-related ideas by learning from the agents with whom they do business or compete (Lucas Jr and Moll (2014) and Perla and Tonetti (2014)). Trade then has the effect of putting domestic producers in contact with the most efficient foreign and domestic producers. The authors use a continuous arrival of ideas instead of a Poisson distribution. More advanced technologies used for one product are adapted to others. One result of this is that long term growth depends on the search for innovative ideas and the concentration of high-productivity elements in the economy. Buera and Oberfield (2017) allow for a more general distribution of productivity. Productivities follow a Fréchet distribution, where the evolution of the scale parameter in each country is governed by a system of differential equations.

Alvarez et al. (2017) and Buera and Oberfield (2017) are the main theoretical reference of this chapter. Their models are merged (using the law of motion of the productivity from Alvarez et al. (2017) and the learning from seller section from Buera and Oberfield (2017)) and reinterpreted through network analysis lenses. Trade partners at the center of the network are the most likely to foster learning when those countries are also at the frontier of learning. Doing so can reveal the imperfect convergence across countries, the existence of non-linearity growth, and the existence of clubs of convergence.

1.2.2 Import openness, economic growth and network effect

A number of case studies highlighted the importance of imports[9] in the international diffusion of ideas. Cases of Asian countries have been particularly studied as they represent example of success. Fransman (1986), Freeman (1988) and Amsden (1989) present evidence that Japan and Korea learned foreign technology by importing machinery and equipment, and components. Fukasaku (2005) provides evidence on how Japan could develop super tankers, after having absorbed knowledge from imports of machinery and equipment from UK, Ireland and Germany. Westphal et al. (1981) stresses the selectivity of Korean firms in their imports to acquire new technologies and develop local capabilities. Firms in these countries often used imitation to learn the technology embedded in imports, as exposed by Kim (1997). Sjöholm (1996) studies a more formal technology diffusion by analyzing patent citations of Swedish firms by foreign firms. He finds a positive correlation between Swedish patent citations and bilateral imports.

Cross-country literature have also explored the link between import and economic/productivity growth. Coe and Helpman (1995) finds that a country's total factor productivity (TFP) depends not only on domestic R&D capital but also on foreign R&D capital, conditional on imports from that foreign country. Acharya and Keller (2009) show that the productivity impact of international technology transfer often exceeds that of domestic technological change, especially in high-technology industries. Coe et al. (1997) finds that developing countries benefit from developed countries' R&D. Developing countries can boost their productivity by importing a larger variety of intermediate products and capital equipment that contains foreign knowledge, allowing them to acquire useful information that would otherwise be costly or difficult to obtain. Acharya and Keller (2009) show that the productivity impact of

[9]While this is not the focus of this chapter, there is also a process of learning-by-exporting. Exporters might gain access to new technologies and knowledge from the feedback they receive by global buyers (Lucas Jr (1988), Lall (1992), Blundell et al. (1995), Gereffi (1999), Castellani (2002)).

international technology transfer often exceeds that of domestic technological change, especially in high-technology industries. This chapter argues that the association between industrial countries and largest stock of knowledge is no longer relevant as the line between level of development and position in the trade network is blurrier than in the past (see the introductory chapter).

Integrating network analysis measures into examinations of empirical trade and economic growth is still not a widespread practice, even if numerous papers have described network properties in the trade data. Serrano and Boguná (2003) present a detailed topology of the World Trade Web (WTW). The authors show that the WTW displays some topological differences with respect to the random-graph as well as properties specific to complex networks, including scale-free degree distribution, small-world property, a high clustering coefficient, and degree-degree correlation between different nodes (i.e. highly connected nodes tend to connect to other highly connected ones). Garlaschelli and Loffredo (2004) extend this work to more countries. Analyzing a weighted WTW, Fagiolo et al. (2010) demonstrated the presence of a core-periphery structure. Richer countries tend to trade with poorer ones among highly interconnected clusters. Those characteristics appear to be stable over time. Fagiolo et al. (2009) showed that the distribution of link weights moves from a log-normal density towards a power law.

Bhattacharya et al. (2008) comes one step closer to an economic analysis by showing that the main features of the real-world WTW have been reproduced using a simple non-conservative dynamical model based on the well-known gravity model from the social and economic sciences. A lack of integrating network measures could lead to important misspecifications in the study of WTW. De Benedictis and Tajoli (2011) present evidence that countries have a non-normal distribution in choosing their trade partners. Without this heterogeneity, models would end up referring to a misperceived "average country." Squartini et al. (2011) show that country-specific information is not enough to characterize higher-order moments of the distribution of trade relationships, such as the trade behavior a given country's partners or the likelihood of clustering.

Closer to the empirical framework of this chapter, some studies integrate trade network measures with a growth framework. Ward et al. (2013) adds trade network properties to the classical gravity model, and the results outperform the classical model. If the classical trade openness indicator does not help in understanding differences in economic development, trade network centrality does.Duernecker et al. (2014) finds that a country's integration has a sizable and significant effect on per capita income and GDP per capita growth rate. Their Bayesian model-averaging analysis finds a very high inclusion probability of 76 percent, indicating that this measure has an important role in explaining cross-country income differences. Kali and Reyes (2007) finds that the position of a country in the network have implications for its development: an increase in the degree centrality ranking by 10 units at the 2 percent trade-link threshold is associated to an increase of the average growth rate by 1.1 percentage points. Fagiolo et al. (2008) analyze the successful development in East Asian countries versus the stagnation of Latin American economies through the lens of trade network centrality. They assess that the performance of East Asian countries is linked to their betweenness centrality in the trade network. These studies focus on the impact of countries' centrality on their own GDP per capita growth; while this chapter examines the impact on their trade partner growth. Kali et al. (2007) finds that the number of trading partners is positively correlated with growth across countries, and this effect is more pronounced for rich countries. This chapters follows this line of research digging into the impact on development of trade partners' connectivity.

Beaton et al. (2017) revisits an earlier version of this chapter and finds similar impact using a similar empirical setup but eigenvalue centrality instead of RWBC. Their results suggest that increasing the share of trade with the most central importers from 25th percentile countries to 75th percentile would increase average per capita growth by 0.8 percentage points. Deng (2016) reports on the top ten country/industry pairs' contributions to global knowledge diffusion. The list comprises four high-tech industries (vehicles, machinery, electronics, and measurement) from three major knowledge creators: the USA, Japan, and Germany. It is skewed: the top ten country/industry pairs contribute more than one quarter of global productivity growth. This chapter reaches a similar conclusion; the USA, Japan, and Germany are core countries in every trade network. Deng (2016) also notes that China plays an increasingly significant role in global knowledge diffusion and has surpassed major industrialized economies like the United Kingdom, Italy, and France, over the last two decades. This matches one result of this chapter, since China is now at the core of the trade network.

1.3 Theoretical framework

The models developed in Alvarez et al. (2017) and Buera and Oberfield (2017) are used to present the importance of the trade network on the diffusion of technologies and countries' long-term growth. The law of motion of the productivity is obtained from Alvarez et al. (2017) and the process of learning from seller from Buera and Oberfield (2017)). Their models are merged and reinterpreted through network analysis lenses. Section 1.3.1 gives the main equations of the model; section 1.3.2 describes the network analysis interpretation.

1.3.1 Framework

In a closed economy

Consumers have identical preferences over a continuum of $s \in [0,1]$ goods. $c(s)$ denotes the consumption of an agent of each of the goods for each period t[10]. The period t utility function is $C = \left[\int_0^1 c(s)^{1-1/\eta} ds\right]^{\eta/(\eta-1)}$ so goods enter in a symmetrical and exchangeable way. Each consumer is endowed by one unit of labor which he supplies inelastically.

Each product s can be made by many producers, with each producer using the same labor-only linear function $y(s) = l(s)z(s)$ where $l(s)$ is the labor input and $z(s)$ the productivity associated with product s. All producers of good s behave competitively.

Using the symmetry of the utility function and the competitive framework, products are grouped by their productivity and the utility at time t is $C_t = \left[\int_{\mathbb{R}+} c(z)^{1-1/\eta} f(z,t) dz\right]^{\eta/(\eta-1)}$ where $c(z)$ is the consumption of any good s that has the productivity z and $f(z,t)$ the productivity density, derived from the cdf of the productivity $F(z,t)$ as $f(z,t) = \delta F(z,t)/\delta z$.

In a competitive equilibrium, the price of any good z will be $p(z) = w/z$ and the price index $p(t) = \left[\int_{\mathbb{R}+} p(z)^{1-\eta} dF_t(z)\right]^{1/(1-\eta)}$ and real per capital GDP equal real wage, $y(t) = w/p(t) = \left[\int_{\mathbb{R}} z^{\eta-1} dF_t(z)\right]^{1/(1-\eta)}$.

In an open economy

In this section, the model moves from autarky to a world of n countries. Icebergs trade costs[11] and populations are given. The static trade equilibrium is constructed under the assumption of continuous trade balance, meaning that at any time t, $p_i.C_i = w_i.L_i$.

[10]Time t subscripts are omitted in order to streamline the writing.

[11]Trade cost between country i and j are assumed to be $\kappa_{ij} \geqslant 1$ and are symmetric so $\kappa_{ij} = \kappa_{ji}$. Note that $\kappa_{ii} = 1$

This model is an adaptation of Eaton and Kortum (2002) and it builds on Alvarez and Lucas (2007) development of the diffusion of ideas. It is closely related to Alvarez et al. (2017) and Buera and Oberfield (2017). Each country under autarky is identical to the closed economy described in Section 1.3.1. The same notation is used, adding the country subscript i to the variables $c_i(s), z_i(s), y_i(s)$, and $l_i(s)$. As utility functions are symetrical and the market competitive, goods s with the same profile of productivities $\mathbf{z} = (z_1, ..., z_n)$ can be grouped across the n countries; production technology for goods with productivity $\mathbf{z}$ is $y_i = z_i l_i$. Productivities are distributed independently across countries. $f(\mathbf{z}) = \prod_{i=1}^{n} f_i(z_i)$ denote the joint density of productivities. Using this notation, the period utility is [12]

$$C_i = \left[\int_0^n c(\mathbf{z})^{1-1/\eta} f(\mathbf{z}) d\mathbf{z} \right]^{\eta/(\eta-1)} \tag{1.1}$$

where $c(\mathbf{z})$ is country i's consumption of goods that have the productivity profile $\mathbf{z}$.

Each product of productivity profile $\mathbf{z} = (z_1, ..., z_n)$ is available in i at the unit price, $\dfrac{w_1 \kappa_{i1}}{z_1}, ..., \dfrac{w_n \kappa_{in}}{z_n}$ which replace both production and transportation costs. The equilibrium prices is solved given wages. Let $p_i(\mathbf{z})$ be the prices paid for good $\mathbf{z}$ in i, so $p_i(\mathbf{z}) = min_j \left[\dfrac{w_j \kappa_{ij}}{z_j} \right]$ since agent i buys the good at the lowest price. Given prices $p_i(\mathbf{z})$, the ideal price index is the minimum cost of providing one unit of aggregate consumption C_i to buyers in i:

$$p_i = \left[\sum_{j=1}^{n} (w_j \kappa_{ij})^{1-\eta} \int_0^\infty z^{\eta-1} f_j(z) \prod_{k \neq j} F_k \left(\frac{w_k \kappa_{ik}}{w_j \kappa_{ij}} z \right) dz \right]^{1/(1-\eta)} \tag{1.2}$$

[12]Since the analysis is static, time subscripts are omitted. The implied dynamics will be studied in the next section.

The minimum cost of providing one unit of aggregate depends on the cost of production of j (wages and iceberg cost) times the probability that j is providing the product of productivity z at the lowest cost (i.e. the probability that any other k countries is not producing it at a lower cost).

Consumption of good $\mathbf{z}$ in country i equals:

$$c_i(\mathbf{z}) = \left(\frac{p_i}{p_i(\mathbf{z})}\right)^{\eta} \frac{w_i L_i}{p_i} \tag{1.3}$$

Process of the diffusion of ideas

Each countries has a (cdf) productivity distribution $F_{i,t}$ at date t. The technological profile $F = (F_1, ..., F_n)$ is the function determining the state variables of the economy. It evolves as a function of the countries' productivity distribution. The evolution of technological profile $F_{i,t}$ depends on the arrival of new ideas from producers outside the country, y_G, with distribution $G_{i,t}$ that differs across countries, over time, and on the likeliness of the producer/country to adopt it, shows as y_H with distribution $H(.)$ constant across countries and over time.

The mechanism is as follows: a producer in country i with productivity z meets a producer from trade partner country j with productivity y without any cost[13]. The producer in i adopts the technology y if $y > z$. y, the productivity of country j, is a combination of $y_G^{\beta} + y_H^{(1-\beta)}$. After a producer in country i adopts the technology y, all the producers of goods with z productivity in the country adopt instantaneously the new technology[14].

The law of motion of the productivity distribution is:

[13] In a similar process to search and matching

[14] Perfect and instantaneous diffusion of technology is assumed across the producers of goods with a certain level of productivity inside a country. The chapter focuses exclusively on the international diffusion of learning, and not on the domestic.

$$\frac{d}{dt}ln\left(F_{i,t}(z)\right) = -\delta\int_0^\infty\left[1 - G_{i,t}\left(\frac{z^{1/\beta}}{x^{1-\beta/\beta}}\right)\right]dH(x) \tag{1.4}$$

$H(.)$ follows a Pareto distribution and $H(z) = 1 - (z/z_0)^{-\tilde{\theta}}$ for $z > z_0$ with simplifying notation $\theta = \tilde{\theta}/(1-\beta)$ and $\delta \equiv \tilde{\delta}z_0^{\tilde{\theta}}$ constant.

To the limit:

$$\lim_{z_0\to\infty}\frac{d}{dt}lnF_{i,t}(z) = -\delta z^{-\theta}\int_0^\infty x^{\beta\theta}dG_{i,t}(x) \tag{1.5}$$

$$\lim_{x\to\infty}\left[1 - G_{i,t}(x)\right]x^{\beta\theta} = 0 \tag{1.6}$$

As in Eaton and Kortum (2002), the country level productivity z is obtained and has a Fréchet distribution. In equation:

$$F_i(z,t) = e^{-\lambda_{i,t}z^{-\theta}} \tag{1.7}$$

where $\lambda_{i,t}$ is the state variable, country-specific and time-varying, and θ the parameter of concentration, constant across country and over time. As developed in Eaton and Kortum (2002), $\lambda_{i,t}$ can be interpreted as the efficiency of each country; the higher is $\lambda_{i,t}$, the higher is the probability that country i will produce any good s efficiently. It refers to the traditional concept in the literature of *absolute advantage*. θ is the variation across distribution of productivity z and it relates to the heterogeneity across goods. The lower is θ, the higher is the variability of goods in terms of productivity. The potential effect of the *comparative advantage* against trade cost is stronger.

The parameter of motion λ_{it} evolves as follows:

$$\begin{aligned} \frac{d\lambda_{i,t}}{dt} &= \delta \int_0^\infty x^{\beta\theta} dG_{i,t}^{\beta} \\ &= \delta \sum_{j\neq i} \pi_{ij,t}^{1-\beta}.\lambda_{j,t}^{\beta} \\ &= \Gamma\left(1-\beta\right)\delta \sum_{j\neq i} \pi_{ij,t} \left(\frac{\lambda_{ij,t}}{\pi_{ij,t}}\right)^{\beta} \end{aligned} \tag{1.8}$$

with $\Gamma(.)$, the gamma function and $\pi_{ij,t}$, the share of country i's expenditure that is spent on goods from country j. The evolution of the stock of knowledge of country i is dependent on the knowledge of country i trade with them.

In equilibrium, the expenditure share π_{ij} corresponds to the maximization of Equation 1.8 subject to $\sum \pi_{ij} = 1$ at each point in time. Mathematically:

$$\frac{\pi_{ij}}{\sum_{j=1}^{n} \pi_{ij}} = \frac{\lambda_j \left(w_{ij}\kappa_{ij}\right)^{-\theta}}{\sum_{j=1}^{n} \lambda_j \left(w_{ij}\kappa_{ij}\right)^{-\theta}} \tag{1.9}$$

The expenditure share depend positively on the amount of technology imbedded in imports and negatively on trade costs.

Nevertheless, to maximize learning from trade, countries must bias their trade toward countries with high productivity. Mathematically, they need to maximize π_{ij} in Equation 1.8 subject to $\sum \pi_{ij} = 1$ at each point in time. The expenditure share that provide the country with the best insight is:

$$\frac{\pi_{ij}}{\sum_{j=1}^{n} \pi_{ij}} = \frac{\lambda_j}{\sum_{j=1}^{n} \lambda_j} \tag{1.10}$$

which corresponds to the fact that the weight of trade partners in a country's trade basket equals the weight of the partners in global knowledge.

Equations 1.9 and 1.10 match if and only if the differences in trade costs are offset by the differences in wages.

1.3.2 Maximizing the diffusion of ideas and centrality of trade partners

The implication of the maximization process and the optimum learning for the network position of country j corresponds to the generalization of the results of Equation 1.9 and 1.10 for all the countries. The position of country j in the network is then:

$$\sum_{i=1}^{i \neq j} \frac{\pi_{ij}}{\sum_{j=1}^{n} \pi_{ij}} \tag{1.11}$$

This equation corresponds to the weighted outdegree centrality measure, developed by Barrat et al. (2004). The higher the outdegree centrality, the higher the relevance of the country in the trade network. Following this definition, the most central country is the one the most relevant in the basket of imports of most of the other countries.

In the optimum, Equation 1.10 shows that the centrality of countries in the trade network correspond to the distribution of efficiency of countries. Most central countries are also at the technology frontier. At equilibrium (Equation 1.9), the equation of the optimum stays true if, and only if, the wage differential between countries does not offset this ranking. Countries can be central because they are at the technology frontier or because their low wages give them a comparative advantage[15]. Only being connected to central countries at the technology frontier leads to the diffusion of technology.

1.4 Empirical strategy

This section contains an empirical evaluation of the theoretical model and an estimation of its quantitative impact. The baseline regression and its extension is presented in section 1.4.1. The estimation strategy is developed 1.4.2. The data are presented in section 1.4.3. The results are shown in section 1.4.4.

1.4.1 Baseline regression equations and extensions

The following baseline regression is used to examine the influence of trade partners' centrality in diffusing technology and affecting GDP per capita growth:

$$\begin{aligned} y_{i,t} - y_{i,t-1} =& \beta_1 C_{i,t} + \beta_2 y_{i,t-1} + \beta_3 TO_{i,t} + \beta_4 HK_{i,t} + \\ & \beta_5 K_{i,t} + \beta_6 \sigma(\pi_{i,t}) + \mu_t + \eta_i + \epsilon_{i,t} \end{aligned} \tag{1.12a}$$

with $y_{i,t}$ as the GDP per capita of country i in time t, and $C_{i,t}$ as the share country i trades with countries central to the trade network at time t. The baseline regression also includes some variables commonly considered affecting GDP per capita growth $y_{i,t-1}$ which is the level of GDP per capita at the beginning of the period to account for the convergence effect, $TO_{i,t}$ or the trade openness of country i's GDP to take into account the global effect of trade on GDP growth, or $HK_{i,t}$ the level of human capital $K_{i,t}$ which is the development of public infrastructure, and $\sigma(\pi_{i,t})$ the stability of

[15]Some insights on the dynamic of the evolution of countries toward the center of the network is developed in Annex 1.B

relative price to account for the volatility of the economy. Estimations are controlled by μ_t (unobserved) time-specific effects and η_i (unobserved) country-specific effects. Finally, $\epsilon_{i,t}$ account for the error term.

Non-linearities can be inferred from the theoretical model as the impact of trading with central partners depends fundamentally on the level of openness to trade. To capture this potential non-linearity in the effects of trade openness on growth that depends on the trade partners' country centrality, interaction terms are added between trade openness and the centrality of trade partners.

$$\begin{aligned} y_{i,t} - y_{i,t-1} = &\beta_1 C_{i,t} + \beta_2 y_{i,t-1} + \beta_3 TO_{i,t} + \beta_4 HK_{i,t} + \\ &\beta_5 K_{i,t} + \beta_6 \sigma(\pi_{i,t}) + \beta_7 C_{i,t} TO_{i,t} + \mu_t + \eta_i + \epsilon_{i,t} \end{aligned} \tag{1.12b}$$

where $C_{i,t}TO_{i,t}$ represents the interaction between trade openness and the centrality of trade partners in country i at time t. In addition, one must also consider an extension of this specification including a quadratic interactive term.

$$\begin{aligned} y_{i,t} - y_{i,t-1} = &\beta_1 C_{i,t} + \beta_2 y_{i,t-1} + \beta_3 TO_{i,t} + \beta_4 HK_{i,t} + \\ &\beta_5 K_{i,t} + \beta_6 \sigma(\pi_{i,t}) + \beta_7 C_{i,t} TO_{i,t} + \beta_8 \left(C_{i,t} TO_{i,t}\right)^2 \\ &+ \mu_t + \eta_i + \epsilon_{i,t} \end{aligned} \tag{1.12c}$$

Also, the theoretical model shows that trading with central partners impacts domestic economies though a knowledge channel. To illustrate this point, an interaction term between labor force education (proxy for the knowledge channel) and the centrality of trade partners is added to the regression model to assess whether the network position of trade partners affects countries differently in relation to their level of education:

$$y_{i,t} - y_{i,t-1} = \beta_1 C_{i,t} + \beta_2 y_{i,t-1} + \beta_3 TO_{i,t} + \beta_4 HK_{i,t} + \beta_5 K_{i,t} + \beta_6 \sigma(\pi_{i,t}) + \beta_7 C_{i,t} HK_{i,t} + \mu_t + \eta_i + \epsilon_{i,t} \tag{1.12d}$$

where $C_{i,t}TO_{i,t}$ represents the interaction between trade openness and the centrality of trade partners in country i at time t. Finally, this extension is extended to include a quadratic interactive term.

$$y_{i,t} - y_{i,t-1} = \beta_1 C_{i,t} + \beta_2 y_{i,t-1} + \beta_3 TO_{i,t} + \beta_4 HK_{i,t} + \beta_5 K_{i,t} + \beta_6 \sigma(\pi_{i,t}) + \beta_7 C_{i,t} HK_{i,t} + \beta_8 \left(C_{i,t} HK_{i,t}\right)^2 + \mu_t + \eta_i + \epsilon_{i,t} \tag{1.12e}$$

1.4.2 Empirical methodology

The trade-growth regression specifications presented above pose several challenges for estimation. Empirical studies of the growth literature have typically used the system generalized method of moments (S-GMM) procedure developed in Arellano and Bover (1995) and Blundell and Bond (2000)[16]. The S-GMM procedure estimates a system of equations that combines the regression specification in levels, as described above in Equation 1.12a, and the same specification in differences[17]. This method allows for dealing with both the unobserved country-specific effects in this dynamic setup and the potential biases arising from the endogeneity of explanatory variables. Differencing the regressions allows for control of unobserved country-specific effects.

[16] See for example Dollar and Kraay (2004), Loayza et al. (2005), Chang et al. (2009) in the trade-growth literature, and Beck et al. (2000) and Beck and Levine (2004) in the finance-growth literature.

[17] S-GMM is used instead of the difference GMM estimator, which relies solely on the difference equation, because the explanatory variables are persistent over time and could thus render instruments weak. In addition, Bond et al. (2001) show that for small sample periods, S-GMM performs better than the difference GMM

This creates an additional problem: the error term of the differentiated equation is correlated with the lagged dependent variable.

Taking advantage of the panel structure of the dataset, the so-called internal instruments are used to account for this issue as well as the potential endogeneity of the explanatory variables. More specifically, for the equation in levels, the instruments are given by the lagged differences of the explanatory variables. For the equation in differences, the instruments are lagged observations of both the explanatory and the dependent variables[18].

It is worth pointing out that the set of instruments grows with the number of explanatory variables and time periods. As the time frame of the sample size is limited, a restricted set of moment conditions is used to avoid over-fitting bias[19]. Only the first appropriate lag of each time-varying explanatory variable is used as an internal instrument.

This S-GMM procedure relies on four key assumptions: (i) the error term is not serially correlated; (ii) shocks to growth are not predictable given the past values of the explanatory variables, (iii) the explanatory variables are uncorrelated with future realizations of the error term; and (iv) the correlation between the explanatory variables and the country-specific effects is constant over time. Nonetheless, the method allows for current and future values of the explanatory variables to be affected by growth shocks; it is exactly this type of endogeneity that the method is designed to handle.

In addition, the consistency of the S-GMM estimates and their asymptotic variance-covariance matrix depends on whether lagged values of the explanatory

[18] Bazzi and Clemens (2013) and Kraay (2015) alert on the weaknesses of internal instruments. The chapter includes several procedures to test the strength of the instruments, while acknowledging the limitations and assumptions of the estimation. However, internal instruments remain the most powerful instruments currently used in the literature.

[19] See Roodman (2009).

variables are valid instruments in the growth regression. To evaluate these potential issues, three specification tests are considered here, beginning with the Hansen test of over-identifying restrictions on the full set of instruments. This " Full Hansen" tests the validity of the instruments by analyzing the sample analog of the moment conditions used in the estimation process. Second, the Hansen test of over-identifying restriction is conducted on the additional instruments that are introduced in the levels equations. This " Incremental Hansen" tests the stationarity assumption on which these instruments are based. And third, it is tested whether the error term is serially correlated.[20]. In all three tests, a failure to reject the null hypothesis validates the estimated regression specification.

1.4.3 Data

To assess whether the structural features of the trade network affect the trade-income nexus, the panel dataset is unbalanced. It covers the 110 countries corresponding to countries for which trade data is available for at least 8 out of the 10 periods studied: 25 from Africa, 26 from America, 22 from Asia and the Pacific, 22 from Europe, and 15 from the Middle East and North Africa. Full sample of countries is presented in Table 1.4. For robustness, a smaller (and more standard in the literature) sample of 82 countries is also considered[21]. Within each panel, the dataset includes at most 10 observations consisting of non-overlapping 5-year averages spanning the 1960-2010 period.

As pointed out above, the dependent variable is the average rate of growth in real GDP per capita within a 5-year period. As is standard in the literature, the regressions are controlled for the initial economic condition by including the GDP per

[20]In the S-GMM system specification, the test is whether the residual of the equation indifferences is second-order serially correlated, which would indicate that the original error term is serially correlated and follows a moving average process of at least order one. In this case, it would reject the validity of the proposed set of instruments and would call for higher order lags to be used as instruments.

[21]See for example Beck et al. (2000), Loayza and Ranciere (2006), and Chang et al. (2009).

capita at the beginning of each period as a regressor. The degree of trade openness is included to the regression, defined as imports plus exports as a share of GDP. The rate of the active population's tertiary school enrollment at the beginning of the period is also included to account for human capital investment. The number of main telephone lines per capita is used as a proxy for the development of the public infrastructure in each country and the absolute value of inflation minus 3 percent is included as a proxy for relative price stability and exchange rate fluctuations. All variables are measured as averages over 5-year periods.

The measure of betweenness centrality is better suited to fit the notion of idea flow in the network. This measure emphasizes the role of a node in its relation between other nodes. The betweenness centrality of a node measures the number of shortest paths from all nodes to all others that pass through it. A node with high betweenness centrality has a key influence in the transmission of ideas and technologies through the network. In the context of trade networks, where many countries are connected to others, the unweighted notion of a short path does not work. For the empirical section, the Random-Walk Betweenness Centrality (RWBC)[22] is used.

To calculate the imports from central countries, first the average of RWBC score of countries' partners is calculated, weighted by the value of imports. This measure considers each country's share in world trade, their number of trading partners, and the position of their partners in the global network[23]. On the same model, the impact of trading with core countries (defined as those in the 95th percentile and above of most central countries in the network) and with the inner-periphery (defined as the 70th-94th percentile of the centrality distribution) is then evaluated.

Table 1.5 contains descriptive statistics.

[22] See Appendix 1.C for a detailed description of the methodology used.

[23] This measure is a widely used measure in network analysis and has been applied to the global trade and financial networks. See for example Newman (2005), Fisher and Vega-Redondo (2006), Reyes et al. (2008).

1.4.4 Results

This section explores the impact of trade with central countries on GDP per capita growth more deeply. Section 1.4.4 estimates alternative baseline regressions to explore the consistency of the S-GMM. Section1.4.4 examines the continuous value of trade partners' centrality in imports. Section 1.4.4. Finally, Section 1.4.4 explores whether the origin of trade partners' centrality matters for growth.

Baseline results

First, the model described above is estimated using the fixed-effect or within estimator ordinary least square (OLS). Column 1 Table 1.1 reports the results of the estimation. The coefficient associated with the trade network centrality of the import country is positive and statistically significant, suggesting that economies benefit from expanding imports from a central country. The results associated with the control variables are comparable to those reported in the existing empirical literature. Trade openness is positive and statistically significant, indicating a positive impact on economic growth on average. Initial GDP per capita has a negative and statistically significant coefficient, which is interpreted as evidence in favor of conditional convergence across countries. That is, more developed countries grow less on average than developed ones. The coefficient associated with human capital investment (initially proxied by the share of the population that reached tertiary education) is not statistically significant[24]. The estimated coefficient on public infrastructure, a proxy for capital accumulation, is also positive and statistically significant. Economic volatility, which is proxied by the absolute value of the inflation minus 3 percent and captures the adverse effects of relative price in-stability on growth outcomes, has a negative and statistically significant impact on economic growth. Column 2 Table 1.1

[24]This differs from typical results in the literature, in part due to the non-treatment of the endogeneity araising from the estimation process. Note that the coefficient associated to the labor force is generally more positive and statistically significant in other regressions.

presents the results of a simple pooled OLS regression. The sign of the coefficient are consistent with Column 1, but coefficients are typically smaller and statistically less significant. As exposed by Nickell (1981), Bond (2002), Bond (2002) and Roodman (2009), while the within-estimator reported in column 1 the lagged dependent variable was positively correlated with the error, biasing its coefficient estimate upward, it is the opposite in the pooled OLS. A good estimate of the true parameter should lie in the range between these two values.

Column 3 Table 1.1 reports the results from a S-GMM regression with the two-step estimation procedure, one lag for the variables measured as initial values (initial GDP per capita and labor force education) and two lags for the variables measured as an average of the period (trade openness, public infrastructure, economic volatility, and the variables of interest linked to network centrality). The coefficient associated with import partners' centrality is positive, statistically significant and lies between the pooled OLS (column 2) and the Within-Group estimators OLS (column 1) coefficient, except for labor force education for the reasons mentioned in the previous paragraph. The three specification tests presented at the bottom of the table, namely the two Hansen tests and the serial correlation test, support the estimation results. They indicate that the null hypothesis of a correct specification of the estimated model cannot be rejected. This is also the case for most estimations presented in the rest of this chapter. The chapter will return to them only when different results are obtained. Nevertheless, in this specification the number of instruments is larger than the number of countries in the sample, which is a potential bias according to Roodman (2009).

Column 4 Table 1.1 reports the preferred estimation protocol. It discards the problem of over-instrumentation by increasing the number of lags to two for variables measured as initial value and to three for variables measured as an average of the

Table 1.1: Baseline Results and Alternative Estimation Strategies

	Within-Estimator OLS	Pooled OLS	Two-Step S-GMM	Two-Step S-GMM	One-Step S-GMM	Two-Step S-GMM: Collapse
	(1)	(2)	(3)	(4)	(5)	(6)
Partners' centrality (M weighted)	23.338**	9.152	18.190***	10.084**	9.358	-20.065
	(11.030)	(7.734)	(2.815)	(4.409)	(15.169)	(38.922)
Trade Openness	1.193***	0.313	0.790***	0.903***	0.660	0.633
	(0.342)	(0.225)	(0.112)	(0.163)	(0.443)	(1.692)
Initial GDP per capita	-5.079***	-2.076***	-2.712***	-2.492***	-2.449***	-3.209***
	(0.395)	(0.237)	(0.084)	(0.121)	(0.380)	(0.961)
Labor Force Educ.	-0.026	0.155	1.063***	0.182**	0.176	0.595
	(0.272)	(0.182)	(0.084)	(0.083)	(0.312)	(0.609)
Public Infrastructure	0.954***	1.223***	1.157***	1.710***	1.834***	2.206***
	(0.232)	(0.171)	(0.062)	(0.095)	(0.257)	(0.479)
Econ. Volatility	-0.769***	-0.695***	-1.221***	-0.410***	-0.505**	-0.866*
	(0.109)	(0.103)	(0.031)	(0.074)	(0.208)	(0.459)
Period 1966-1970	0.736	-0.039				
	(0.455)	(0.463)				
Period 1971-1975	1.327***	-0.173	0.191*	-0.431**	-0.563	-0.605
	(0.513)	(0.481)	(0.106)	(0.168)	(0.413)	(0.890)
Period 1976-1980	1.821***	-0.185	-0.157	-0.722***	-0.759	-0.833
	(0.566)	(0.494)	(0.128)	(0.199)	(0.495)	(1.329)
Period 1981-1985	-0.201	-2.752***	-2.725***	-3.108***	-3.355***	-3.622***
	(0.608)	(0.495)	(0.142)	(0.222)	(0.511)	(1.306)
Period 1986-1990	0.686	-1.805***	-2.063***	-2.369***	-2.468***	-2.888**
	(0.634)	(0.493)	(0.161)	(0.150)	(0.523)	(1.319)
Period 1991-1995	0.402	-2.301***	-2.585***	-2.938***	-3.075***	-3.861**
	(0.699)	(0.516)	(0.202)	(0.196)	(0.615)	(1.635)
Period 1996-2000	0.534	-2.375***	-3.116***	-3.131***	-3.308***	-4.719**
	(0.779)	(0.549)	(0.196)	(0.207)	(0.707)	(2.047)
Period 2001-2005	0.775	-2.472***	-3.374***	-3.329***	-3.457***	-5.134**
	(0.852)	(0.583)	(0.217)	(0.225)	(0.808)	(2.365)
Period 2006-2010	1.583*	-1.998***	-2.896***	-3.065***	-3.034***	-4.874*
	(0.910)	(0.610)	(0.275)	(0.238)	(0.888)	(2.589)
Constant	42.715***	24.464***	27.264***	27.003***	28.375***	38.608***
	(3.580)	(2.598)	(0.898)	(1.637)	(4.143)	(9.230)
Parameters of the regressions:						
# of Observations	892	892	892	892	892	892
# of countries	110	110	110	110	110	110
# of instruments			117	97	97	21
# Lags S-GMM (a/b)§			1/2	2/3	2/3	2/3
Specification Test (p-values):						
Hansen J-test			0.440	0.424		0.471
Incremental Hansen Test			0.855	0.815	0.005	0.007
AR(2) statistic			0.721	0.469	0.508	0.589

Notes: This table reports the regressions of GDP per capita growth on the centrality of trade partners, trade openness, initial GDP per capita, labor force education, infrastructure, and economic volatility. Robust standard errors are shown in parentheses. *, **, and *** denote statistical significance at 10, 5, and 1 percent, respectively. §: 'a' refers to number of lags for initial variables (initial GDP per capita and Labor Force Education), 'b' refers to number of lags for other variables.

period. Results are statistically very close to the Column 3 estimation. The next part of the empirical section of this chapter will be built on this framework.

Arellano and Bond (1991) and Blundell and Bond (1998) argue that the two-step procedure produces asymptotically efficient estimates of the S-GMM given a large enough sample (in the cross-sectional dimension) and proper instruments. The resulting standard error estimates are consistent in the presence of heteroskedasticity and autocorrelation within panels. However, when these conditions are not met, the two-step procedure may produce biased estimates and may lead to underestimation of standard errors. For robustness, some alternative estimations of this benchmark model are presented: one-step S-GMM estimates and the collapsed two-step estimates. The one-step procedure estimates a variance-covariance matrix consistent with a homoscedastic error term in the levels regression. The results in 1.1 column 5 are comparable to those of the two-step procedure; the coefficient of interest is statistically significant only at 1 percent. Nevertheless, the Hansen test of over-identifying restrictions on additional instruments is not rejected, and the stationarity assumption is not guaranteed.

Finally, the collapsed two-step S-GMM reported in column 6 restricts the instrument matrix so that it contains one instrument for each lag depth instead of one instrument for each period and lag depth as in the conventional S-GMM instrument matrix. At the cost of the reduced efficiency, this procedure uses fewer instruments, thus accommodating cases in which many explanatory variables and the presence of several time-series periods lead to many instruments. In this benchmark case, the number of instruments is reduced significantly and the Hansen incremental test rejects the null of under-identification, indicating that the instruments used are not jointly valid. This is therefore not an appropriate specification for this model.

Evaluation of the importance of partner's centrality

Table 1.2 reports the estimations associated with the impact of the centrality of trade partner on countries economic growth. Column (1) reproduces Column (4) of Table 1.1. Trade partners' centrality has a positive and statistically significant impact on growth. Increasing the centrality of import partners by one standard deviation can lead to a 0.21 percentage-point impact on countries' economic growth. This is in line with the positive and significant impact found in Arora and Vamvakidis (2005), Duernecker et al. (2014), and Beaton et al. (2017). Note that the degree of trade openness stays positive and statistically significant.

Table 1.3 presents the potential gain in economic activity that the 20 countries with highest potential gain would obtain by increasing their imports from central countries. Several Sub-Saharan Africa countries would be the greatest beneficiaries. They could increase their GDP growth up to 0.6 percentage points.

In Column (2) and (3) of Table 1.2 show the regression estimates associated with Equation 1.12b and 1.12c. They present the estimations on the interactions between trade openness and the trade with central countries[25]. The coefficients associated with the interaction terms are positive, though when the quadratic term is included in the regression, it is not statistically significant. In order to infer the total impact of a change in the centrality of trade partners on economic growth, the coefficients on both the interaction terms and on the variable itself (taking as given all the other explanatory variables) need to be considered. The left panel of Figure 1.1 shows that the total growth effect is positive for an increase corresponding to a standard deviation of the centrality of trade partners. Gains in growth can be as large as 0.5 percentage points when the country had previously been poorly integrated into global trade. In

[25] Instruments are not used for the interacted terms as each individual term within the interaction has already been instrumentalized. A similar approach has been followed by Chang et al. (2009).

Table 1.2: Influence of the centrality of import partners on economic growth

	(1)	(2)	(3)	(4)	(5)
Partners' centrality (M weighted)	10.084**	89.240***	82.533***	-15.537*	-26.058***
	(4.409)	(27.706)	(28.462)	(8.088)	(9.869)
Trade Openness	0.903***	1.962***	1.976***	1.125***	1.098***
	(0.163)	(0.355)	(0.356)	(0.167)	(0.188)
Initial GDP per capita	-2.492***	-2.529***	-2.458***	-2.196***	-2.518***
	(0.121)	(0.115)	(0.129)	(0.178)	(0.193)
Labor Force Educ.	0.182**	0.120	0.118	-0.883***	-0.811***
	(0.083)	(0.098)	(0.098)	(0.233)	(0.280)
Public Infrastructure	1.710***	1.723***	1.708***	1.511***	1.649***
	(0.095)	(0.097)	(0.098)	(0.145)	(0.155)
Econ. Volatility	-0.410***	-0.471***	-0.465***	-0.476***	-0.564***
	(0.074)	(0.084)	(0.084)	(0.073)	(0.091)
Partners' centrality x TO		-19.030***	-24.457***		
		(5.998)	(7.309)		
(Partners' centrality x TO)^2			12.467		
			(9.991)		
Partners' centrality x HK				20.896***	14.582**
				(4.764)	(5.995)
(Partners' centrality x HK)^2					50.201***
					(13.226)
Constant	27.003***	22.842***	23.148***	24.560***	28.602***
	(1.637)	(2.085)	(2.105)	(1.990)	(2.236)
Parameters of the regressions:					
# of Observations	892	892	892	892	892
# of countries	110	110	110	110	110
# of instruments	97	97	97	97	97
# of Lags S-GMM (a/b)§	2/3	2/3	2/3	2/3	2/3
Period Dummies	Yes	Yes	Yes	Yes	Yes
Specification Test (p-values):					
Hansen J-test	0.424	0.422	0.421	0.300	0.373
Incremental Hansen Test	0.815	0.732	0.770	0.738	0.795
AR(2) statistic	0.469	0.503	0.466	0.464	0.535

Note: This table reports the regressions of GDP per capita growth on the centrality of trade partners, trade openness, initial GDP per capita, labor force education, infrastructure, and economic volatility. Robust standard errors are shown in parentheses. *, **, and *** denote statistical significance at the 10, 5, and 1 percent, respectively. §: 'a' refers to number of lags for initial variables (initial GDP per capita and Labor Force Education), 'b' refers to number of lags for other variables.

Table 1.3: Potential gain of increasing imports from central countries

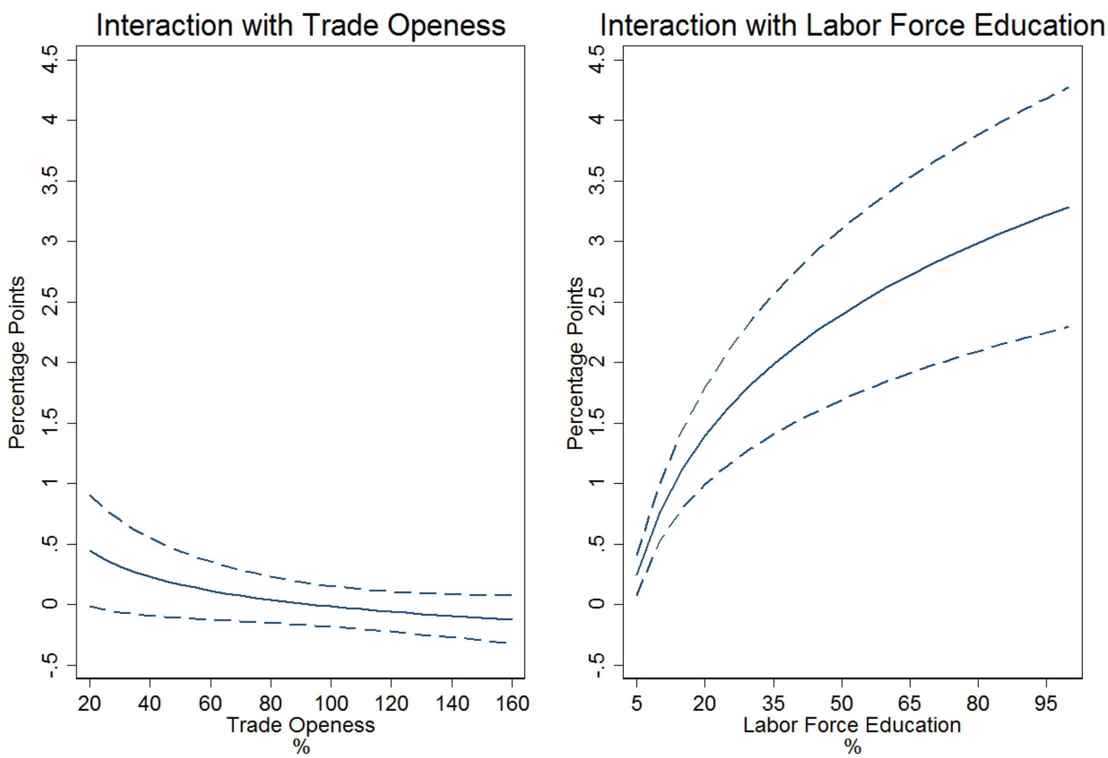
Rank	Country	GDP gain	Rank	Country	GDP gain
1	Zambia	0.624	**11**	Uganda	0.536
2	Zimbabwe	0.620	**12**	Côte d'Ivoire	0.530
3	Bolivia	0.582	**13**	Sri Lanka	0.526
4	Malawi	0.582	**14**	Syria	0.525
5	Fiji	0.580	**15**	Papua New Guinea	0.524
6	Rwanda	0.571	**16**	Bulgaria	0.506
7	Mozambique	0.558	**17**	Iraq	0.506
8	Laos	0.556	**18**	Sudan	0.503
9	Burundi	0.540	**19**	Cyprus	0.501
10	Mali	0.537	**20**	Uruguay	0.496

Note: This table reports the potential gain in GDP per capita growth that a country would earn by increasing their trade to the country with the highest level of trade with central countries. In 2001-2006, the latest period of the study, Mexico was the country with the highest level of imports from central countries, with an import-weighted average partner centrality of 0.8. The gain is calculated based on Column (1) of Table 1.2, setting an import-weighted average partner centrality of 0.8 for all the countries.

contrast, the point estimates indicate that increasing the share of trade with very central countries with high trade openness is no longer associated with a significant impact on growth. While the effect can be large for countries that are closed from a trade point of view, the impact of trading more with central countries is no longer positive for level of openness above 110 percent. For closed countries, an increase of imports from central countries can boost technological transfer, as countries learn only from a small sample of goods. As trade openness increases, partner's centrality matters less because of the increasing number of options.

Analogously, columns 4 and 5 correspond to the estimates of Equations 1.12d and 1.12e and show the estimates of the effects increase the trade with central partners interacted with the level of labor force education. For ease of exposure, the analysis focuses on the total growth effects of increasing the centrality of partners by one standard deviation. The right panel of Figure 1.1shows that increasing the share of trade with central partner from its sample mean, is associated with positive effects on per capita income growth. The effect increases with labor force education —the more educated the labor force is, the greater the growth effects that are associated with an increase in the centrality of the trade partners. This increase reaches almost

Figure 1.1: Total Growth Effects of Increasing the Share of Trade with Central Countries by a SD



Note: This figure offers a graphical display of the total growth effects associated with an increase in the share of trade with central countries (C) in the global trade network by a standard deviation from their sample mean. The estimates are based on the regressions in columns 3 (left panel) and 5 (left panel)of Table 1.2. The total growth effects shown in the left panel is given by $Growth = (\beta_C + \beta_{CxTO} * TO + 2 * \beta_{(CxTO)^2} * TO^2 * C) * \delta C$. β_C, β_{CxTO}, and $\beta_{(CxTO)^2}$ are respectively the estimated regression coefficients on the share of trade with central countries weighted by imports, the interaction with trade openness, and the interaction with trade openness squared.δC is a constant equal to a standard deviation of the sample mean of the centrality of trade partners. Trade openness takes different possible values starting at 20 percent (the lowest value of TO in my sample) to 160 percent (the highest value of TO in my sample). Analogously, The total growth effects shown in the left panel is given by $Growth = (\beta_C + \beta_{CxHK} * TO + 2 * \beta_{(CxHK)^2} * HK^2 * C) * \delta C.\beta_C$, β_{CxHK}, and $\beta_{(CxHK)^2}$ are respectively the estimated regression coefficients on the centrality of trade partners, the interaction labor force education, and the interaction labor force education squared. δC is a constant equal to a standard deviation of the sample mean of centrality of trade partners. Dash lines correspond to confidence bands at 90 percent.

2 percentage points for countries with highly educated labor force[26]. Those results fit with the theory: the more the country learns from its partners (i.e. the more educated the labor force) the more it benefits from trading with central countries. Those results are in line with Deng (2016). findings.

The differentiated effect of the countries at the core of the trade network

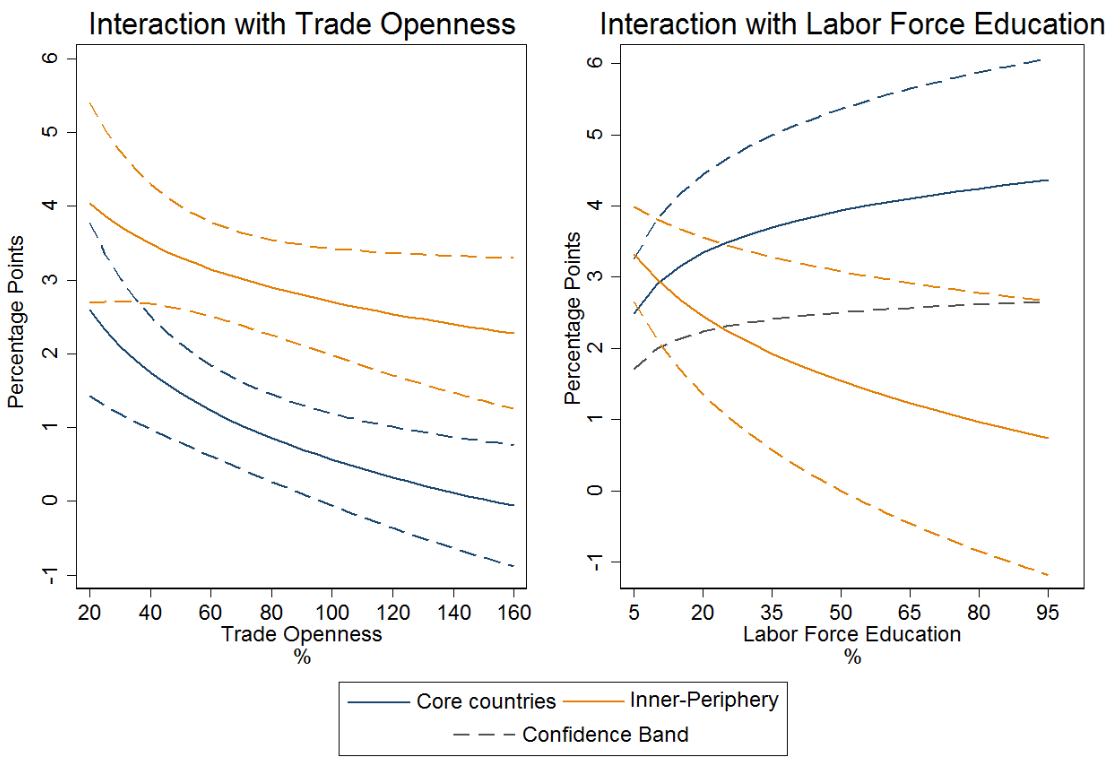
Table 1.7 contrasts the share of imports from countries in the 95th percentile of the trade network and above (the so-called *core countries*) with the share of imports with countries in the 70th-94th percentile (the so-called *inner-periphery* countries). Column 1 of Table 1.7 shows that the coefficient on the share of imports from core countries is positive and statistically significant, but significantly lower than the coefficient associated with share of imports from countries in the inner-periphery[27]. The linear effect of an increase of a standard deviation in the share of trade with core countries is associated with an increase in growth of about 1.25 percentage points for the average country, while the effect reaches almost 1.66 percentage points for a similar increase in the share of trade with countries in the inner-periphery. This result occurs because inner-periphery countries typically have a higher growth rate than core countries. The result must also be put in perspective with the peripheral countries, third groups of countries that are not included in the regressions, and that have by deduction a negative impact on economic growth.

When the factor of interactions with trade openness is added to these regression specifications, the results show strong non-linearity in the total growth effect associated with increases in trade shares with these central countries. The left panel of

[26]This gain correspond to the highest value of labor force education in the sample, which is 55 percent in the sample. Nevertheless, we report the full range of potential value of tertiary education of the labor force.

[27]A Ward test confirm the statistical difference between both coefficient.

Figure 1.2: Total Growth Effects of Increasing the Share of Trade with Core and Inner-Periphery by a SD



Note: This figure offers a graphical display of the total growth effects associated with an increase in the share of trade with core countries (Co) or inner periphery (IP) in the global trade network by a standard deviation from their sample mean. The estimates are based on the regressions in columns 3 (left panel) and column 5 (left panel)of Table 1.7. The total growth effects shown in the left panel is given by $Growth = (\beta_{C/IP} + \beta_{C/IP*TO} * TO + 2 * \beta_{(C/IP*TO)^2} * TO^2 * C/IP) * \delta C/IP$. $\beta_{C/IP}$, $\beta_{C/IP*TO}$, and $\beta_{(C/IP*TO)^2}$ are respectively the estimated regression coefficients on the share of trade with core or inner periphery countries weighted by imports, the interaction with trade openness, and the interaction with trade openness squared.$\delta C/IP$ is a constant equal to a standard deviation of the sample mean of Core or Inner Periphery countries. Trade openness takes different values starting at 20 percent (the lowest value of TO in my sample) to 160 percent (the highest value of TO in the sample). Analogously, The total growth effects shown in the left panel is given by $Growth = (\beta_{C/IP} + \beta_{C/IP*HK} * TO + 2 * \beta_{(C/IP*HK)^2} * HK^2 * C/IP) * \delta C/IP. \beta_{C/IP}$, $\beta_{C/IP*HK}$, and $\beta_{(C/IP*HK)^2}$ are respectively the estimated regression coefficients on the centrality of trade partners, the interaction labor force education, and the interaction labor force education squared. $\delta C/IP$ is a constant equal to a standard deviation of the sample mean of centrality of trade partners. Dash lines correspond to confidence bands at 90 percent.

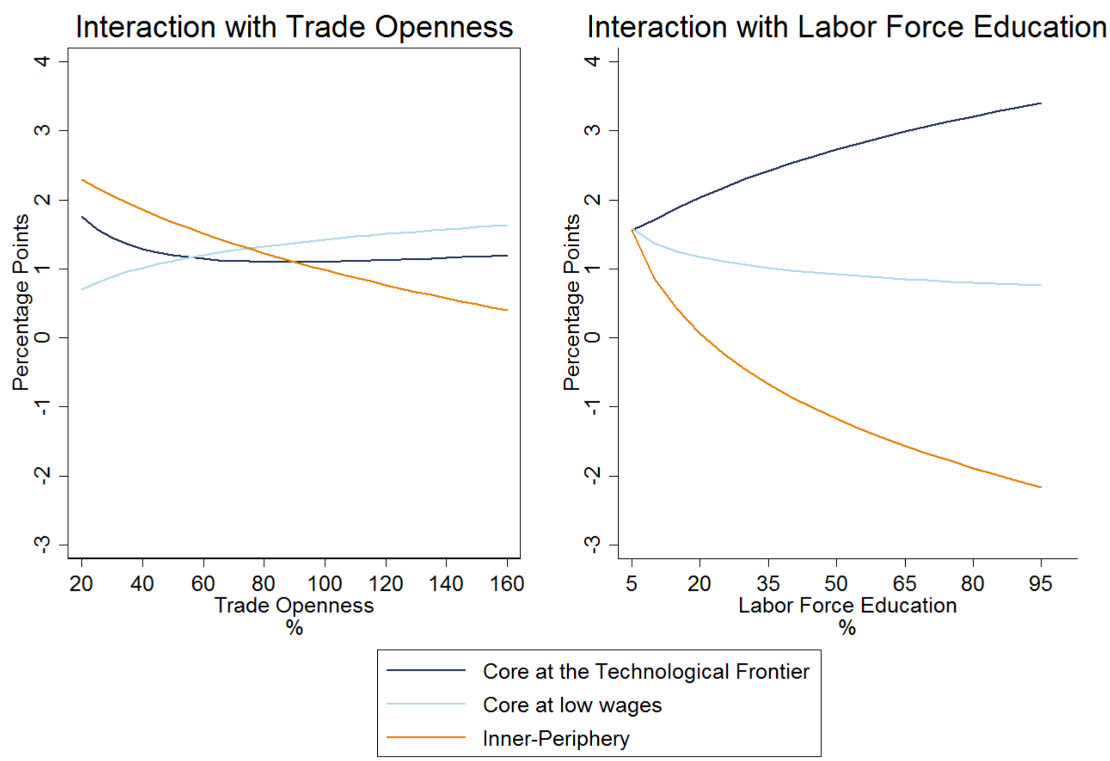
Figure 1.2 shows the economic size of the effects implied by the results in 1.7. For levels of trade openness above 40 percent, the impact of trading more with inner-periphery countries is almost 2 percentage points of GDP per capita growth more than increasing the trade with core countries. The more open a country is, the more it will benefit from trading with the inner-periphery relative to core countries, as their growth rate is higher.

These trading shares interact with labor force education (columns 4 and 5 of Table 1.7) in the left panel of Figure 1.2. The total growth effects associated with an increase of a standard deviation in the share of trade with inner-periphery countries are typically positive, but they decrease as labor force education increases. Interestingly, the growth effects associated with a similar increase in the share of trade with core countries can surpass 2 percentage points for levels of tertiary enrollment above 10 percent. When focusing on the interaction with labor force education, the impact of increasing the trade with central countries on growth is greater than the impact of increasing the trade with inner-periphery countries. This fits with the theoretical conclusions; trade with core countries brings knowledge spillover if the country is able to process it (i.e., the labor force is well-educated).

Does the source of trade partners' centrality matter?

This section explores a final element of the theoretical model: the idea that central partners foster knowledge diffusion through trade if, and only if, their centrality results from being at the technological frontier and not from low wages. This idea is tested by separating the core countries into two subcategories: core countries at the technological frontier, and other core countries. High income World Bank historical classification is used as a proxy for being at the technological frontier.

Figure 1.3: Total Growth Effects of Increasing the Share of Trade with Core at the technological frontier, other Core and Inner-Periphery by a SD



Note: This figure offers a graphical display of the total growth effects associated with an increase in the share of trade with core countries at the technological frontier (TF-C), other core countries (O-C) or inner periphery (IP) countries in the global trade network by a standard deviation from their sample mean. The estimates are based on the regressions in columns 3 (left panel) and column 5 (left panel) of Table 1.8. The total growth effects shown in the left panel are given as a function of the partner p that corresponds alternatively to TF-C, O-C, or IP by $Growth = (\beta_p + \beta_{p*TO} * TO + 2 * \beta_{(p*TO)^2} * TO^2 * p) * \delta p$. β_p, β_{p*TO}, and $\beta_{(p*TO)^2}$ are respectively the estimated regression coefficients on the share of trade with TF-C, O-C, or IP countries weighted by imports, the interaction with trade openness, and the interaction with trade openness squared.δp is a constant equal to a standard deviation of the sample mean of TF-C, O-C, or IP countries. Trade openness takes different values starting at 20 percent (the lowest value of TO in my sample) to 160 percent (the highest value of TO in the sample). Analogously, the total growth effects shown in the left panel is given by $Growth = (\beta_p + \beta_{p*HK} * TO + 2 * \beta_{(p*HK)^2} * HK^2 * p) * \delta p.\beta_p$, β_{p*HK}, and $\beta_{(p*HK)^2}$ are respectively the estimated regression coefficients on the centrality of trade partners, the interaction labor force education, and the interaction labor force education squared. δp is a constant equal to a standard deviation of the sample mean of centrality of trade partners. Dash lines correspond to confidence bands at 90 percent.

Table 1.8 contrasts the share of imports from core countries at the technological frontier with the share of imports from other core countries and countries at the inner-periphery of the global trade network. Column 1 of shows that the coefficient on the share of imports from core countries at the technological frontier is positive and statistically significant but significantly lower than the coefficient associated with share of imports from other core countries. The differential effect is confirmed when the interactions with trade openness is added to these regression specifications (column 2 and 3 of Table 1.8). Left panel of Figure 1.3 shows the economic size of the effects implied by the results in column 3 of Table A6. For levels of trade openness above 50 percent, the impact of trading more with core countries at the technological frontier is lower than with core countries with low wages, but this effect is not statistically significant.

Nevertheless, when these trading shares interact with the labor force education (columns 4 and 5 of Table 1.8 and left panel of 1.2) the picture is different. The total growth effect associated with an increase of a standard deviation in the share of trade with core countries at the technological frontier is positive and statistically larger than a similar increase with other core countries and inner-periphery countries, and it increases with higher labor force education. The growth effect is above 2 percentage points for levels of tertiary enrollment above 5 percent. This result confirms the theoretical assessment that only core countries whose centrality relies on being at the technological frontier diffuse knowledge and generate economic growth in their trade partners.

1.5 Conclusion

Network characteristics of trade partners are key to understanding the benefits a given country can receive from trade. Borrowing from the idea flow theoretical literature, this chapter shows the importance of trade partners'centrality and technological position using the models by Alvarez et al. (2017) and Buera and Oberfield (2017). A central country is defined by its relevance to many countries' basket of imports. In certain circumstances, countries at the frontier of ideas coincide with central countries in the trade network, and they are important drivers of knowledge diffusion. Countries that develop strong ties with central trading partners are more likely to learn recent technologies, improve their TFP, and ultimately their income.

This theory is evaluated in an empirical framework. Historically, by tackling endogeneity problems through a S-GMM estimation, countries that developed more ties with central trade partners were more likely to grow faster. The importance of the diffusion of ideas is confirmed by the fact that the better the labor force is trained, the greater the economic benefits to the country. This chapter also finds an effect with the countries in the 95th percentile of the centrality distribution. Independent of their level of sophistication, these core countries may be more exposed to the technology and knowledge frontier because they are more strongly connected to a wider range of countries. Therefore, the quality and intensity of the feedback effects between buyers and sellers in global trade may be greater if one of the countries involved is at the center of the global trade network. For a more peripheral country, the potential for exposure to a wider set of ideas and technologies increases with the strength of its trade ties with these central countries. Increasing the imports from central trade partners could lead to up to 2 percentage points of income growth.

Since individual companies do not integrate the positive externality of technology diffusion across firms into their cost-benefit analysis, there is some room for authorities to create industrial policies. Authorities should develop links with central countries to foster learning. This can materialize through the development of trade agreements or more informally through the fostering of relations with central countries, increasing of overall exposure, and development of diplomatic relations. Increase in labor force education is also key to benefit from trade with central players.

This chapter can be extended along several lines. First, it would be interesting to break down the analysis by industry. In line with Deng (2016) detailing cross-industry spillover can shed light on specific mechanisms of the network. Second, the trade slowdown resulting from the 2008-09 fiscal crisis has deeply modified the structure of the network. Re-estimating the effect found in this chapter for the post-crisis would be of a major interest. However, the empirical framework will need to be changed to consider the short timeframe of available data, and the lack of good input-output data for a large sample of countries constitute an important limitation for this project.

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Appendix 1.A Two illustrative case study: South Korea and Colombia

This appendix provides two real-world illustrations of the chapter's main idea. Acknowledging the limitations of the exercise, it first reinvestigates the well-studied case of South Korea's income rise mainly attributable to trade and highlight the important Japan, a core country, played in this development. Second, it analyses the divergence of evolution between Bolivia and Colombia, that changed over the years their trade relationship with the United States and Western Europe (other core countries).

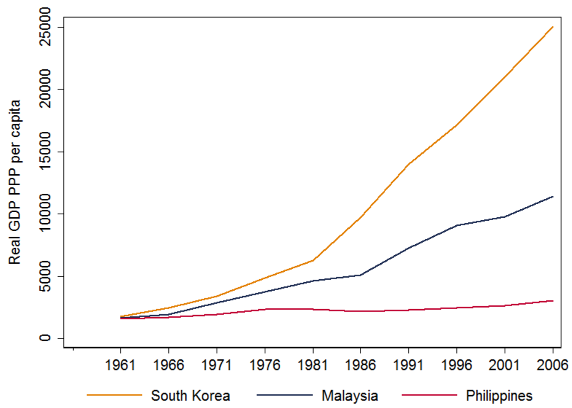
1.A.1 The case of South Korea

This section uses Malaysia and the Philippines, two countries similar to South Korea in 1960, and tracks their evolution. Each are East Asian Pacific countries, and they had a similar real GDP PPP per capita in 1960 (USD$1670, USD$1466, and USD$1453 respectively). During the second half of the 20th century, they all grew at an impressive pace (Figure 1.4a), and the most common explanation for this growth was in the external sector: those countries learned by doing trade. The evolution of these countries' openness is noticeable (Figure 1.4b).

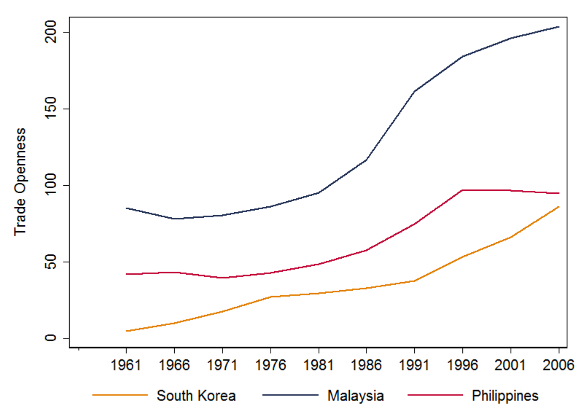
Interestingly, South Korea was not the country with the highest increase in trade openness, but it had the largest economic growth over the period studied. This chapter argues that the degree of openness is important, but the identity of trade partners is equally necessary. This chapter demonstrates that the more central and at the technological frontier a trade partner is, the more a country will benefit from technology diffusion. In East Asia, the country with closest links and highest centrality has historically been Japan. South Korea developed its commercial links with Japan much more than did Malaysia and the Philippines. As presented in Figure 1.5a, at constant US dollars, South Korea is the country that most increased its imports from

Figure 1.4: Selected EAP economies GDP and trade openness evolution

(a) GDP per capita



(b) Trade Openness



Source: WDI.
Note: The left panel presents the evolution of the real PPP GDP per capita; the right panel presents the value of trade openness calculated as the sum of imports and exports as a share of GDP for each country.

Japan over time. Those strong ties to a very central country have led to the economic development of South Korea.

Along with these close links to Japan, South Korea's labor force has become much more educated than either Malaysia or the Philippines (see figure 1.5b). This has made it possible for South Korea to take better advantage of the technological diffusion it gained from trade.

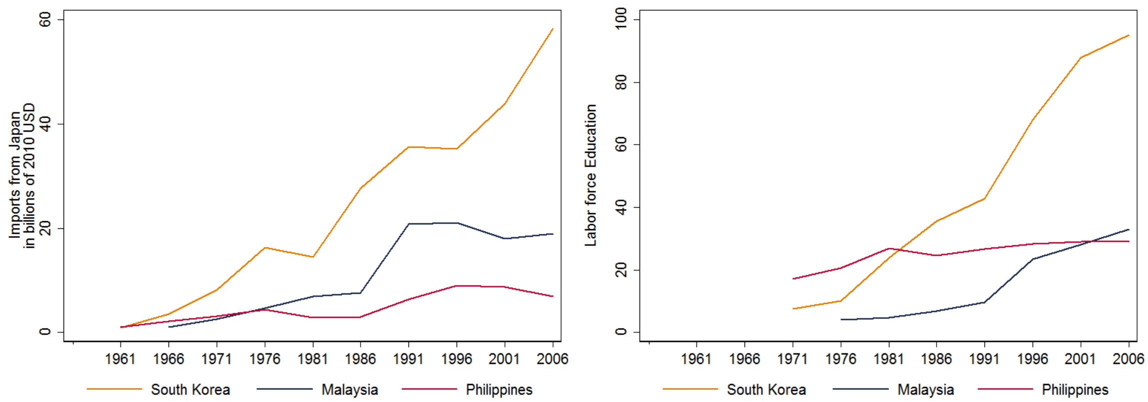
As stated in the theoretical and empirical sections, a country must not only import from a central country, but it must also have the human capital to learn from the technology it imports.

1.A.2 The case of Colombia

The case of South Korea is a telling example of the paper mechanisms, particularly because a long literature as shown that most of its impressive growth since the 1970s

Figure 1.5: Factors that led South Korea to get to develop

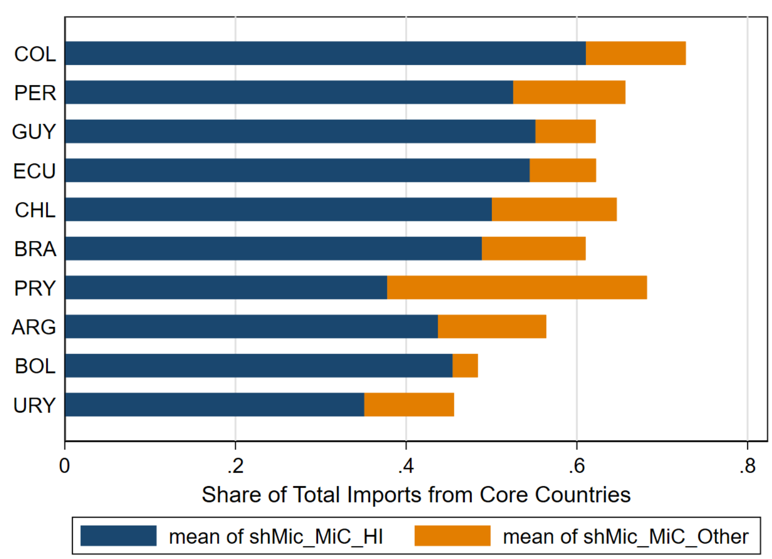
(a) Imports from Japan (b) Labor Force Education



Note: The left figure presents the evolution of Japanese imports for South Korea, Malaysia, and Singapore in billions of 2010 US dollars; the right figure presents the level of the labor force education, calculated as the share of the labor force with tertiary education. Sources: IMF's DOTS and WDI.

has been driven by development in trade. But the centrality of trade partners matters even for countries less exposed to trade than Korea. In regions that benefited less from trade, countries the most connected to central actors have also benefited of higher knowledge diffusion rate.

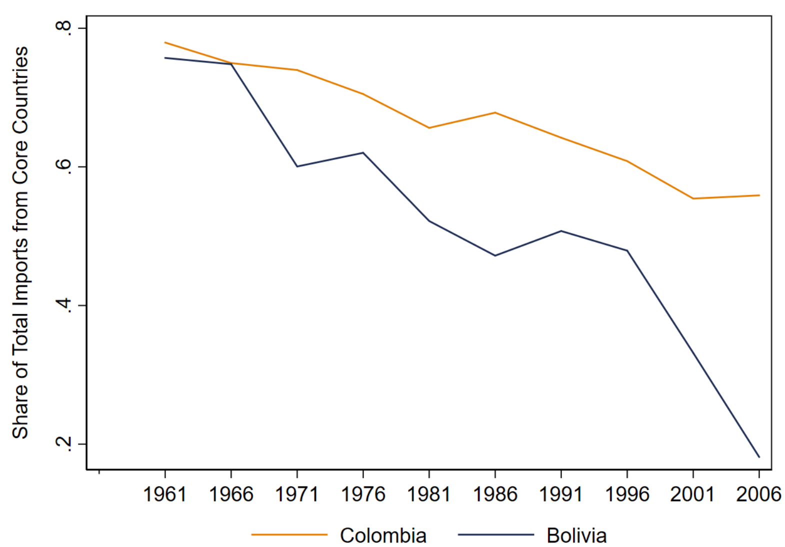
Figure 1.6: Share of South American total imports from core countries in 2010



Source: UNComtrade/WITS database and author calculation.

Figure 1.6 shows the average share of imports from core countries between 2006 and 2010 for South American countries. Based on this graph, the following section will focus on the two extreme cases: Colombia (accounting for a share close to 60 percent) and Bolivia (about 20 percent). Interestingly, this distribution has not always been the case. In 1960-65, the share of total imports from core countries was similar in Colombia and in Bolivia, and close to 80 percent (Figure 1.7). This figure was mainly driven by the large share of trade with the US and Western Europe (Figure 1.8). Over time, while both countries reduced their share of imports with core countries, the share stabilized in Colombia around 60 percent it deacreased in Bolivia to 20 percent.

Figure 1.7: Share of Bolivia and Colombia total imports from core countries



Source: UNComtrade/WITS database and author calculation.

This divergence in the evolution of trade partner have mainly been driven by political factors. Colombia has been actively pursuing trade connections with the United States and Western Europe countries (core countries), particularly through treaties and bilateral agreements. Those agreements generally include specific products with high share of technological component and potential learning. For instance, in its bilateral treaty with the United States, goods with preferential tariff include "almost all products in these sectors: agriculture and construction equipment, *aircraft and parts, auto parts, fertilizers and agro-chemicals, information technology equipment, medical and scientific equipment*, and wood". Many of those products have a high potential of embedded technology.

On the opposite, Bolivia has been actively developing connections with its neighbor countries. As a landlocked country and with a government that prioritizes industrialization, most of its trade connections are with its five neighbors country rather than with this US and Europe. In 2008, Bolivia even lost its preferential trade status with this United States after the US judged the country was not doing enough efforts in terms of drug trafficking combat. This divergence with the Colombian strategy can been seen in the origin of imports countries in 2010.

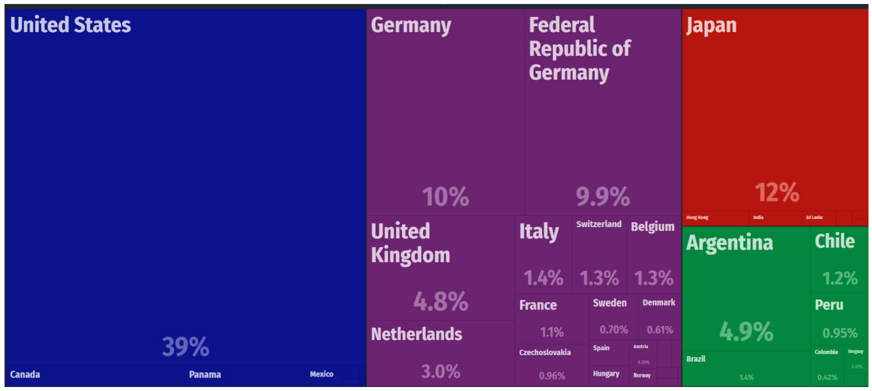
As in the case of South Korea, Colombia real GDP per capita grew faster than its pair, while starting at a relatively similar point (Figure 1.9a). However, at the difference with the South Korean case, labor force education has been growing both in Colombia and Bolivia (Figure 1.9b).

As the link between economic growth and trade is not as strong in Colombia respect to South Korea, Figure 1.10 depicts an additional piece of evidence that the exposure of Colombia to the trade with core countries had contributed to its growth. The figure shows the amount of exports of high tech products[28] over time. While this amount is minimal for both Bolivia and Colombia in the 90s, it has been growing very fast for Colombia.

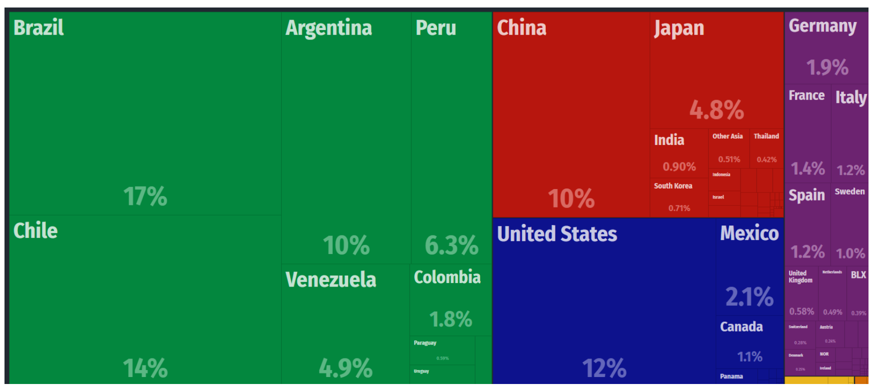
[28]High-technology exports are products with high R&D intensity, such as in aerospace, computers, pharmaceuticals, scientific instruments, and electrical machinery.

Figure 1.8: Imports by origin country

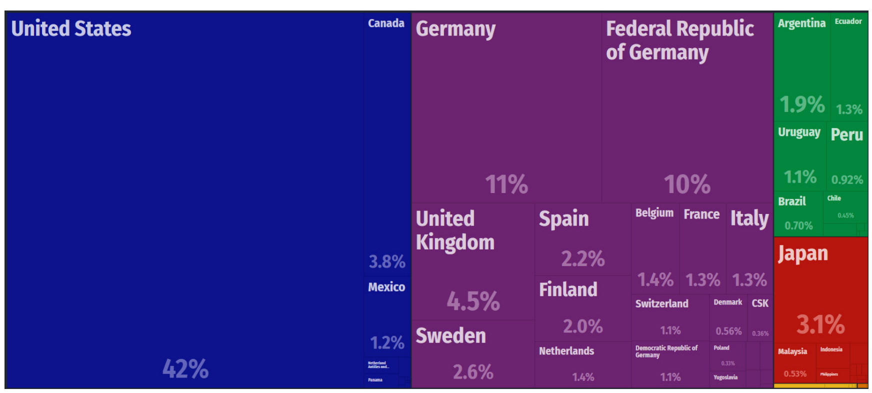
(a) Bolivia - 1965



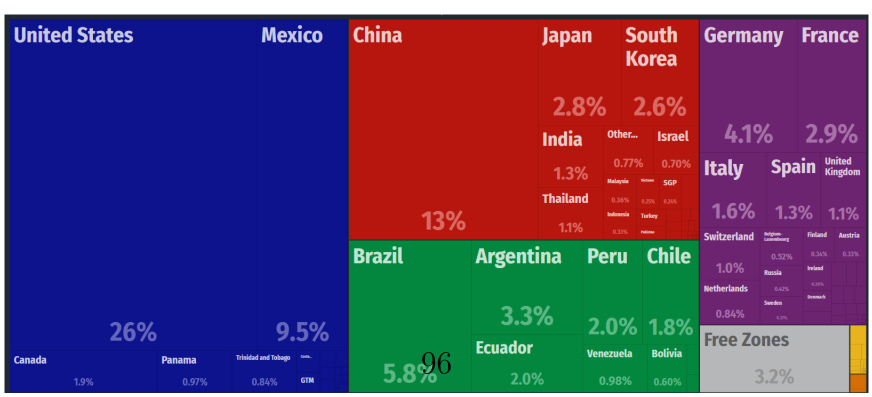
(b) Bolivia - 2010



(c) Colombia - 1965



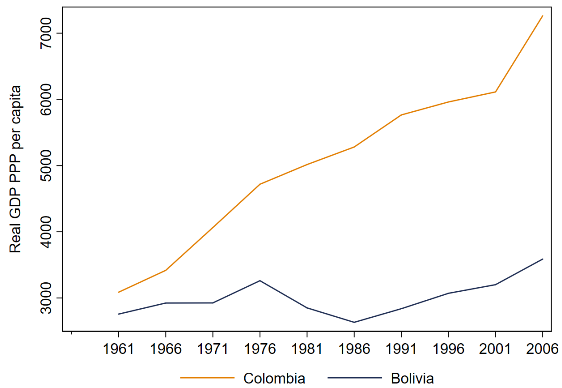
(d) Colombia - 2010



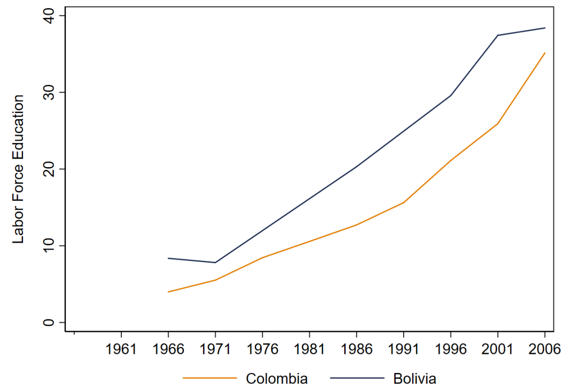
Notes: The share of total imports by Bolivia and Colombia in 1965 and in 2010 is presented in function of the origin country. Sources: OEC representation based on BACI database.

Figure 1.9: Bolivia and Colombia GDP per capita and labor force education evolution

(a) GDP PPP per capita

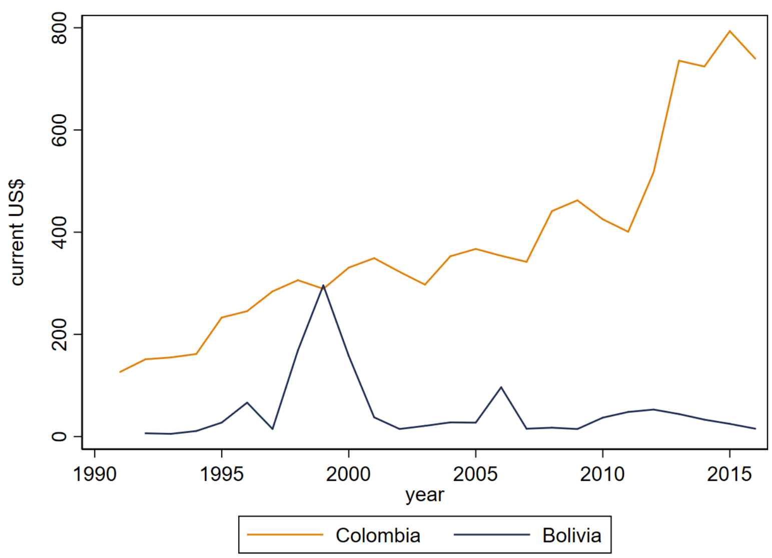


(b) Labor Force Education



Source: WDI.
Note: The left panel presents the evolution of the real PPP GDP per capita; the right panel presents the labor force education for each country.

Figure 1.10: Evolution of high-tech exports in Bolivia and Colombia



Source: UNComtrade/WITS database and author calculation.

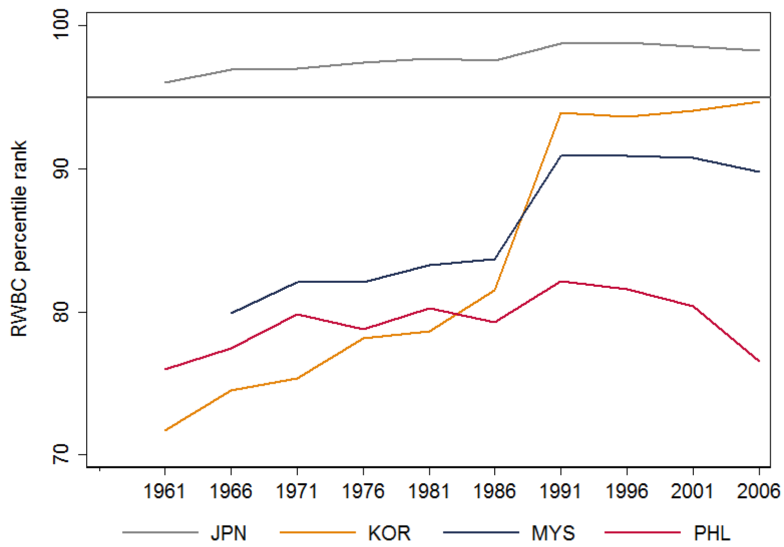
Appendix 1.B Dynamic of the evolution of the central countries

Trade partners' positions in the trade network is key to understanding the dynamic of economic growth. The position of different countries has changed over the last fifty years, moving from a world where the categories of "core countries" and "developed countries" overlapped to a world where some emerging countries are moving into the core of the trade network. This section presents current trends and the underlying dynamic of centrality in the trade network in the theoretical model.

The case of South Korea presented in section 1.A.1 is interesting because it demonstrates the dynamic nature of centrality in the trade network. As shown in Figure 1.11, South Korea realized a spectacular jump in its betweenness centrality ranking, moving from the lower bound of the inner-periphery in the 1960s to the upper bands in the 2000s. It has even become part of the core since 2010. South Korea is now the most central country among the three East Asian countries featured, although it started from the 71.6th percentile of the centrality ranking, lower than Malaysia (79.9th percentile in the second period of study) and the Philippines (75.9th percentile).

Understanding how South Korea moved from the inner-periphery to the core of the trade network gives important insights on a key implication of this chapter's theoretical and empirical models. The models suggest that the more countries import goods from central partners in the trade network, the more they learn from the technology content of their imports. Central countries are more likely than others to export goods at the technology frontier. Consequently, importing countries are able to increase their productivity, add value to their exports, and in the end, grow more. This increase of productivity and competitiveness has another implication: countries become more attractive in the trade network. This implies that those countries would

Figure 1.11: Evolution of selected countries centrality

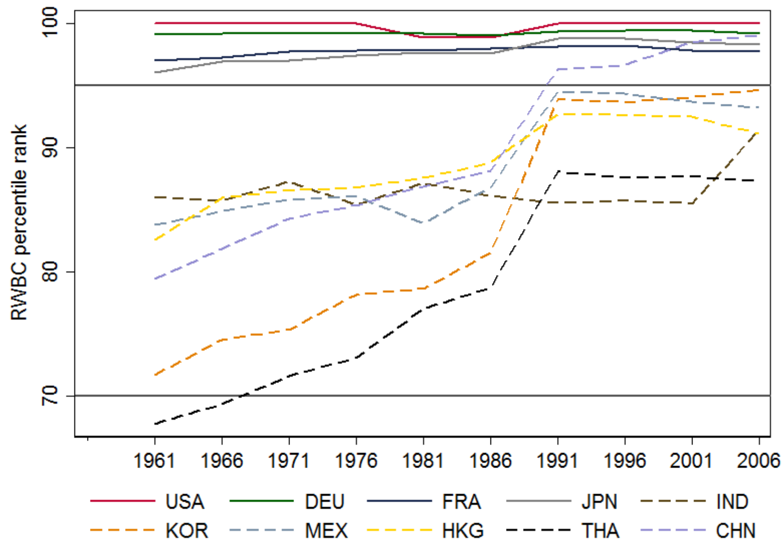


Source: Author's calculation based on the IMF's DOTS database.
Note: The plot displays the percentile rank of the 5-year average of the trade networks' RWBC centrality by country. One hundred indicates the most central country, and 1 is the least central. The x-axis shows first year of the average (1961 correspond to 1961-1966, and so on). The 95-100th percentile corresponds to core countries; the 70-95th percentile to the inner-periphery; and below the 70th percentile is the periphery.

then become more central to the trade network. This has been the case with South Korea. Starting at a lower level of centrality than Malaysia and Thailand, South Korea caught up and accelerated to reach the core of the network in 2010. An important factor that contributed to this evolution was its link to Japan, one of the most central countries at the technological frontier.

South Korea's case is not isolated. In 1960, the core of the trade network was composed of developed countries, including the USA, China, Germany, United Kingdom, Canada, and Japan 1.12). In 2012, the core included the USA, Germany, Japan, France, the Netherlands, United Kingdom, and Italy, but also South Korea and China. Between those two points in time, emerging and developing countries increasingly participated in international trade, and some countries became key in the trade exchanges, such as China and South Korea.

Figure 1.12: Evolution of trade network centrality for selected countries

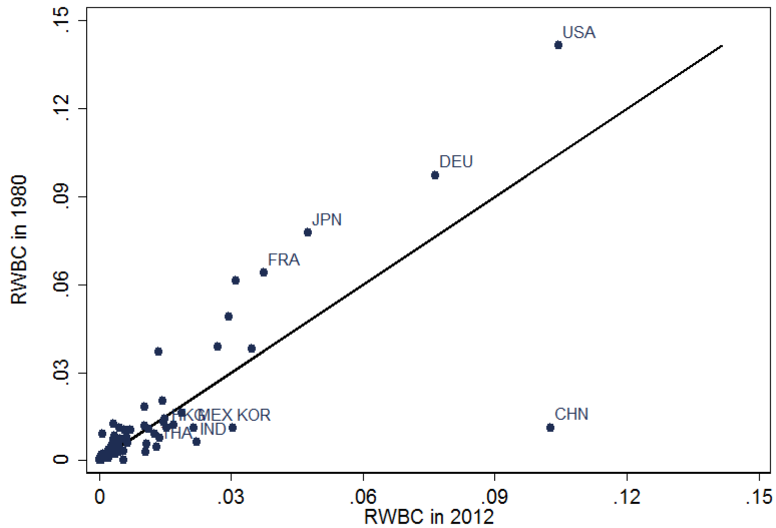


Source: Author's calculation based on IMF's DOTS database.
Note: The plot displays the percentile rank of the 5-year average of trade network's RWBC centrality by country. One hundred is the most central country, while 1 is the least central. The x-axis shows the first year of the average (1961 correspond to 1961-1966, and so on). Countries in the 95-100th percentile are core countries; the 70-95th percentile is the inner-periphery; and below the 70th percentile is the periphery.

Emerging countries' moving toward greater centrality did not lead to a replacement of countries already central to the network. Instead, it resulted in a reduction of the distance between core and periphery. Figure 1.13 shows how the world became more compact in this manner. Emerging countries became more central by taking a share in the more developed countries (placed on the left of the 45 degrees' line, corresponding to a loss of centrality in absolute value). There are fewer countries with high values of centrality in 2012 than in 1980; the lines between core and periphery have blurred.

Peripheral countries have gradually increased their trade with central countries and learned from them. Some of these countries started their move toward the core of the network. Figure 1.14 presents empirical evidence of this evolution by showing the kernel density of the absolute measure of centrality. Over time, the distribution

Figure 1.13: Evolution of the countries' centrality between 1980 and 2012

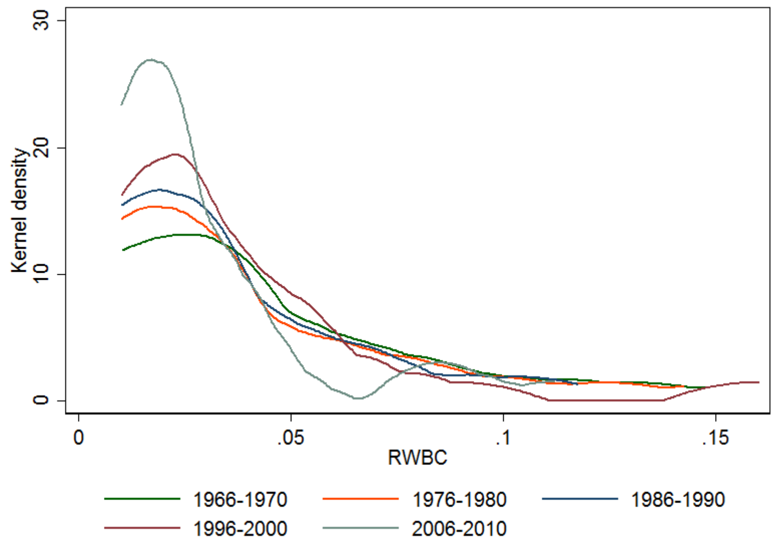


Source: Author's calculation based on IMF DOTS database.
Note: The figure shows the value of the centrality measure in 1980 (last year between structural changes in the network) and on the x-axis the value of the centrality in 2012 (latest year of the sample). Absolute value of the RWBC is shown. RWBC sums to one across countries for each year.

shortens and skews to the left, showing that countries are converging toward a similar value of centrality. Core-periphery distinction becomes blurred as the sum of the centrality measure equals one.

Theoretically, the previously described increase in peripheral countries'centrality could have led to two different outputs. In the first case, the peripheral country might trade evenly with the all the core countries. The country would learn evenly from all of them and move toward the single core in the second period. In the second case, the peripheral country might trade and learn from one of the core countries. In the second period, the country gets to the core, but the core itself is not uniquely defined. A situation of multipolarity appears, and the former peripheral country becomes closer to its mentor country and dissimilar to the other core countries.

Figure 1.14: Distribution centrality measure over time



Source: Author's calculation based on IMF's DOTS database.
Note: his figure presents the distribution of the value of the RWBC centrality for 5 periods of the sample: 1966-1970, 1976-1980, 1986-1990, 1996-2000, and 2006-2010. The sum of RWBC across-country is one for each period. Values of RWBC below 0.01 have been dropped for clarity and readiness purposes.

As documented in 2, the second case has developed over the last 30 years. In 1980, only advanced economies are central to the trade network (they are located to the right of the figure) and the core is similar. In economic terms, this implies that only advanced economies were central to the trade network. Those countries were also similar in the way they were trading, creating a clear division in the trade network between core countries and the periphery.

In 2012 , some developing countries moved toward the right of the picture, meaning that they became more central to the trade network. Moreover, those central countries are not anymore closely located. Roles have changed and clusters of countries begun to appear. The world now appears to be multipolar. The right side of the figure resembles a star with clusters of countries. Japan, India, and South Korea form one, Western Europe another. Note that the implications are similar to the club of convergence described by Quah (1997) among others.

Appendix 1.C Random Walk Betweenness Centrality

This technical appendix presents the concept of "betweenness centrality". It is used in the chapter to define the most central countries in the global trade network.

Measures of network centrality capture the importance of a node within a network. In the context of this chapter, nodes are countries, and edges that connect countries in the network reflect the volume of trade that flows between them. Paths are sequences of nodes and edges connecting two countries. The simplest centrality measure in a network is the degree of the node, i.e. the number of other countries to which one is connected. This measure is not useful in this context because virtually all countries are connected to one another. Such an un-weighted measure of centrality would yield little dispersion in centrality values across countries. A measure based on a weighted average of the number of each country's connections, on the other hand, would lead to a ranking in which the largest traders appear as most central.

Measures of betweenness centrality capture the extent to which a node lies on a path between two other nodes. Nodes with high betweenness centrality influence the network as they 'control' the flow passing through them. Betweenness centrality is measured as the ratio of the shortest paths between node pairs that pass through the node of interest. Mathematically, betweenness centrality for country i is:

$$x_i = \sum_{jk} \frac{n^i_{jk}}{g_{jk}}$$

where n^i_{jk} is equal to 1 if country i lies on the path from country j to k, and zero otherwise; g_{jk} is the total number of alternative paths from j to k. In the case of the global trade network, as many countries are directly connected the shortest path would almost always be the direct connection between j and k, with no stop by i.

Once more, all the countries would have a similar value of betweenness centrality, with little dispersion across countries.

Therefore, a different measure of betweenness must be use that does consider all paths and their weight: the Random-Walk Betweenness Centrality developed by Newman (2005) and Fisher and Vega-Redondo (2006). In this variant, all the paths from country j to county k are considered - not only the shortest one. However, paths have different probabilities. Typically, shorter paths and paths with a high intensity of trade contribute more to the betweenness score of country i. Formally,

$$x_i^{RWBC} = \sum_{jk} r_{jk}^i$$

where r_{jk}^i is a combination of the number of times that the random walk from j to k passes through i and the weight of each path, averaged over many repetitions of the random walk.

Table 1.4: Sample of countries

Africa (25 countries)

Benin	Kenya	Senegal
Burundi	Liberia	Sierra Leone
Cameroon	Malawi	Togo
Central African Rep.	Mali	Uganda
Congo	Mauritania	Tanzania
Côte d'Ivoire	Mauritius	Zambia
Gabon	Mozambique	Zimbabwe
Gambia	Niger	
Ghana	Rwanda	

America (26 countries)

Argentina	Dominican Rep.	Nicaragua
Barbados	Ecuador	Panama
Belize	El Salvador	Paraguay
Bolivia	Guatemala	Peru
Brazil	Guyana	Trinidad and Tobago
Canada	Haiti	United States
Chile	Honduras	Uruguay
Colombia	Jamaica	Venezuela
Costa Rica	Mexico	

Asia and Pacific (22 countries)

Bangladesh	Japan	Sri Lanka
Brunei	Kuwait	Thailand
Cambodia	Lao	Turkey
China	Malaysia	Vietnam
Hong Kong	New Zealand	
Fiji	Papua New Guinea	
India	Philippines	
Indonesia	Rep. of Korea	
Israel	Singapore	

Europe (22 countries)

Australia	Hungary	Spain
Austria	Iceland	Sweden
Bulgaria	Ireland	Switzerland
Cyprus	Italy	United Kingdom
Denmark	Malta	
Finland	Netherlands	
France	Norway	
Germany	Poland	
Greece	Portugal	

Middle East and North Africa (15 countries)

Afghanistan	Pakistan
Algeria	Qatar
Bahrain	Saudi Arabia
Egypt	Sudan
Iran	Syria
Iraq	Tunisia
Jordan	
Libya	
Morocco	

Table 1.5: Descriptive Statistics

	Mean	*Stand. Dev.*	*Min*	*Max*
Growth (in %)	1.88	3.38	-23.13	24.14
Initial GDP per capita	4181.51	3.71	160.80	87217.48
Labor force education (in %)	3.06	4.06	0.03	49.48
Trade openness (in %)	50.90	2.01	3.52	418.36
Public infrastructure	0.03	7.20	0.00	0.72
Economic volatility	6.63	3.09	1.22	8501.58
Partners' centrality (M weighted)	0.06	0.02	0.01	0.14
Sh. Import from Core (in %)	43.82	9.97	11.48	65.18
Sh. Import from IP (in %)	29.24	11.34	3.76	61.84

Table 1.6: Source variables

Variable	Description	Source
Growth in GDP per capita	Growth rate of GDP per capita based on real GDP per capita measured at 2005 constant dollars.	Penn World Table 7.1
Initial GDP per Capita	GDP per capita measured in 2005 constant dollars on the first year of each 5-year period.	Penn World Table 7.1
Trade Openness	Calculated as the sum of exports and imports, scaled by GDP.	Penn World Table 7.1
Labor Force Education	Percentage of the population older than 15 years that attained tertiary schooling.	Updated database from Barro-Lee (2010)
Public Infrastructure	Average number of telephone lines per capita.	World Development Indicators.
Economic volatility	Absolute value of annual (inflation minus 3%)	World Development Indicators
Partners' centrality (M weighted)	Calculated as centrality of a country trade partners, weighted by the imports. Centrality of countries is defined by the random walk betweenness centrality measure developed by Newman (2005) and Fisher and Vega-Redondo.	Author's calculations based on DOTS.
Share of Imports from Core and Inner-Periphery Countries	Calculated as the share of a country's imports from countries in the core and in the inner-periphery of the global trade network. Core countries are those ranked in the top-5 percentile of the cross-country ranking given by the random walk betweenness centrality measure developed by Newman (2005) and Fisher and Vega-Redondo (2006), whereas inner-periphery countries are those ranked between percentiles 70 to 95. This classification is conducted separately for every year in the sample period.	Author's calculations based on DOTS.
Share of Imports from Core at the Technological Frontier	Calculated as the share of a country's imports from countries in the core belonging to the high income historical classification of the World Bank.	Author's calculations based on DOTS and World Bank.

Table 1.7: Influence of the centrality of import partners on economic growth

	(1)	(2)	(3)	(4)	(5)
Sh. Import from Core countries	11.779***	30.025***	43.537***	15.910***	15.737***
	(0.965)	(6.711)	(9.526)	(1.907)	(2.279)
Sh. Import from Inner-Periphery	13.870***	31.609***	52.087***	21.702***	22.868***
	(1.071)	(7.387)	(10.703)	(1.552)	(2.084)
Sh. Import from C x TO		-4.169***	-10.998***		
		(1.427)	(3.016)		
Sh. Import from IP x TO		-4.157**	-10.896***		
		(1.670)	(3.075)		
(Sh. Import from C x TO)^2			1.230***		
			(0.398)		
(Sh. Import from IP x TO)^2			0.723**		
			(0.351)		
Sh. Import from C x HK				0.650	-3.571***
				(1.032)	(1.297)
Sh. Import from IP x HK				-5.010***	-2.567*
				(0.823)	(1.393)
(Sh. Import from C x HK)^2					2.092***
					(0.214)
(Sh. Import from IP x HK)^2					-3.298***
					(0.562)
Trade Openness	1.137***	4.244***	6.791***	1.219***	0.852***
	(0.083)	(1.138)	(1.431)	(0.107)	(0.132)
Initial GDP per capita	-2.405***	-2.393***	-2.579***	-2.137***	-2.152***
	(0.114)	(0.116)	(0.127)	(0.122)	(0.138)
Labor Force Educ.	-0.017	0.030	0.080	0.984	1.917**
	(0.043)	(0.048)	(0.088)	(0.605)	(0.820)
Public Infrastructure	1.541***	1.481***	1.563***	1.445***	1.419***
	(0.077)	(0.082)	(0.119)	(0.096)	(0.105)
Econ. Volatility	-0.353***	-0.342***	-0.323***	-0.402***	-0.467***
	(0.052)	(0.056)	(0.057)	(0.050)	(0.051)
Constant	16.619***	2.816	-2.929	10.128***	11.095***
	(1.400)	(5.548)	(6.988)	(1.738)	(2.531)
Parameters of the regressions:					
# of Observations	891	891	891	891	891
# of countries	110	110	110	110	110
# of instruments	111	111	111	111	111
# of lags S-GMM (a/b)	2/3	2/3	2/3	2/3	2/3
Period Dummies	Yes	Yes	Yes	Yes	Yes
Specification Test (p-values):					
Hansen J-test	0.460	0.438	0.521	0.363	0.492
Incremental Hansen Test	0.707	0.678	0.745	0.607	0.737
AR(2) statistic	0.389	0.359	0.391	0.317	0.446

Note: This table reports the regressions of GDP per capita growth on the share of total imports from core and inner periphery, trade openness, initial GDP per capita, and labor force education. Core countries are defined as those ranked in the 95th percentile or higher in terms of centrality to the global trade network; inner periphery countries are those ranked within the 70th and 95th percentiles. All other countries are considered periphery countries. The share of trade with periphery countries is excluded from the regressions. Robust standard errors are shown in parentheses. *, **, and *** denote statistical significance at 10, 5, and 1 percent, respectively. §: 'a' refers to number of lags for initial variables (initial GDP per capita and Labor Force Education), 'b' refers to number of lags for other variables.

Table 1.8: Differentiated impact of the core partners in function of dynamic

	(1)	(2)	(3)	(4)	(5)
Sh. Import from Tech-F. Core	8.739***	38.714***	62.172***	12.427***	16.695***
	(1.693)	(8.927)	(7.580)	(2.283)	(2.721)
Sh. Import from Other Core	33.618***	1.649	-15.103	46.450***	46.871***
	(3.006)	(13.959)	(18.093)	(4.078)	(5.007)
Sh. Import from Inner-Periphery	13.665***	43.641***	17.852*	19.680***	24.891***
	(1.306)	(8.526)	(10.378)	(1.538)	(2.175)
Sh. Import from Tech.-F C x TO		-7.505***	-23.379***		
		(1.982)	(2.342)		
Sh. Import from Other C x TO		5.993*	10.420**		
		(3.298)	(4.943)		
Sh. Import from IP x TO		-7.243***	6.633**		
		(1.936)	(3.248)		
(Sh. Import from Tech.-F C x TO)^2			3.123***		
			(0.367)		
(Sh. Import from Other C x TO)^2			-1.596		
			(1.113)		
(Sh. Import from IP x TO)^2			-3.119***		
			(0.426)		
Sh. Import from Tech.-F C x HK				1.564	-4.414**
				(1.306)	(1.850)
Sh. Import from Other C x HK				-4.087**	-7.957**
				(1.952)	(3.378)
Sh. Import from IP x HK				-3.139***	-4.856***
				(1.014)	(1.682)
(Sh. Import from Tech.-F C x HK)^2					1.935***
					(0.414)
(Sh. Import from Other C x HK)^2					5.768
					(3.977)
(Sh. Import from IP x HK)^2					-1.830**
					(0.782)
Initial GDP per capita	-2.088***	-2.159***	-1.820***	-1.474***	-1.421***
	(0.152)	(0.141)	(0.114)	(0.128)	(0.130)
Labor Force Educ.	-0.142**	-0.044	-0.250**	0.039	2.678**
	(0.059)	(0.078)	(0.105)	(0.801)	(1.106)
Trade Openness	1.110***	6.583***	6.780***	1.283***	0.861***
	(0.074)	(1.394)	(1.241)	(0.100)	(0.159)
Public Infrastructure	1.408***	1.379***	1.264***	1.027***	1.026***
	(0.111)	(0.104)	(0.084)	(0.115)	(0.111)
Econ. Volatility	-0.321***	-0.408***	-0.477***	-0.302***	-0.381***
	(0.052)	(0.060)	(0.061)	(0.060)	(0.061)
Constant	15.205***	-6.212	-6.815	4.767**	2.417
	(2.052)	(6.578)	(5.490)	(2.099)	(1.952)
Parameters of the regressions:					
# of Observations	891	891	891	891	891
# of countries	110	110	110	110	110
# of instruments	111	111	111	111	111
# of lags S-GMM (a/b)	2/3	2/3	2/3	2/3	2/3
Period Dummies	Yes	Yes	Yes	Yes	Yes
Specification Test (p-values):					
Hansen J-test	0.370	0.345	0.269	0.378	0.418
Incremental Hansen Test	0.449	0.329	0.199	0.504	0.587
AR(2) statistic	0.374	0.279	0.154	0.300	0.352

Note: This table reports the regressions of GDP per capita growth on the share of total imports from core and inner periphery, trade openness, initial GDP per capita, and labor force education. Core countries are defined as those ranked in the 95th percentile or higher in terms of centrality to the global trade network; inner periphery countries are those ranked within the 70th and 95th percentiles. All other countries are considered periphery countries. The share of trade with periphery countries is excluded from the regressions. The core is separated into the countries at the core of the central network because they are at the technological frontier and the other. Robust standard errors are shown in parentheses. *, **, and *** denote statistical significance at 10, 5, and 1 percent, respectively. §: 'a' refers to number of lags for initial variables (initial GDP per capita and Labor Force Education), 'b' refers to number of lags for other variables.

Chapter 2

Timing of Technology Adoption and Clustering in Trade Network

2.1 Introduction

Given the cost of innovation, only a few firms in a limited number of countries innovate. However, if innovation is costly, Romer (1990) highlights that technology is a non-rival good. Once produced, multiple agents can use it simultaneously, without preventing others from accessing it. A vast majority of economic actors actually adopt or imitate existing technologies. Keller (2010) estimates the share of domestic productivity due to foreign technology at 90 percent. Technology adoption through imitation alsp has a cost (Saggi (2002)). Teece (1977) surveys 29 technology transfer projects and finds that, on average, technology adoption costs were approximately 20 percent of the total project cost and up to 60 percent in some case.

Extensive literature on the determinants of technology adoption exists. Rogers (1986) provides in its seminal work the five stages potential adopters go through to adopt a new technology: (1) they learn about the innovation (*knowledge*), (2) they must be persuaded about its value (*persuasion*), (3) they decide to adopt (*decision*), (4) they implement the innovation (*implementation*), and (5)finally they confirm their use (*confirmation*).

This chapter focuses on how clusters impact the *decision* process in the adoption of a new technology. The process of international technology diffusion is key for a country to adopt a new technology, but the mechanisms behind diffusion and adoption differ (Eaton and Kortum (1999)). A technology diffuses to a country when agents discover it; however agents adopt it only when they actually begin using it. This chapter argues that in addition to the traditional arguments described in section 2.3, the role of trade clusters affect the timing of new technology adoption.

For most of the 20th century, global trade activities were concentrated within developed countries. Trade was organized in a core-periphery framework: core countries, composed exclusively of advanced economies, traded among each other heavily, while the periphery, composed of developing countries, was mainly oriented toward the core. However, since the dawn of the 21st century, developing countries, led by China and other large emerging economies, rapidly emerged as major players in the global trade network. This impressive change is associated with significant structural transformations in the world trade network. As the introductory chapter documents, the world moved from the *core-periphery* framework prevalent in the 1980s, in which only advanced economies were central to the trade network in similar capacities, to a *multipolar* world, with emerging economies at the core, but not to the same extent as advanced economies (see the introductory chapter). Convergence to a multipolar world increased the number of trade clusters.

The chapter's first contribution is its use of the Rosvall and Bergstrom (2008) (RB) algorithm to detect clusters in the trade network. Previous trade research has used definitions based on similarities in the export matrix (e.g. blockmodeling in Smith and White (1992) and Rašković et al. (2011)) or methodologies such as the k-mean (e.g. Bjornskov and Lind (2002) and Costantini et al. (2007)). The former methods do not guarantee that countries with a similar trade structure are even trade partners, while the latter methods require that researchers impose the number of clusters a priori. This study uses Rosvall and Bergstrom (2008)'s community detection algorithm. The RB algorithm uses random walks as a proxy of the trade flows and decomposes the network into clusters by "compressing a description of the probability flow." The RB algorithm aims to identify the backbone of the network by grouping countries into clusters representing the main structure of the network. The intuition behind the RB algorithm is that the longer the random walk remains among a group of countries, the more likely those countries form a cluster. Furthermore, the algorithm has the advantage of not requiring the imposition of the number of clusters a priori.

Second, this chapter describes the mechanism behind trade network formation. After showing that gravity variables fail to determine the boundaries of trade clusters, the results indicate that value chains motives drive cluster formation. The analyses of countries switching clusters shows that Switchers receive more inflows of M&A investment and increase their trade in intermediary goods from members of their new cluster compared to their former cluster. While using the RB algorithm to analyze an export matrix as a proxy for value chain is beyond the scope of this paper, it represents an interesting research avenue and a solid alternative to the much criticized MRIO database[1].

Third, this study offers a theoretical contribution by providing some insight into how clusters influence the technology diffusion process by imitating the possibility of a complete cascade. In this framework, countries adopt a new technology when a sufficient number of trade partners have adopted it. In contrast to the theoretical literature on technology adoption (Grossman and Helpman (1991), among many others), the existence of clusters implies that the technology is adopted within the innovator's cluster, but not further. An increase in the number of clusters in a network has two theoretical implications on the technology diffusion process: a negative impact as the number of countries in the innovator's cluster decreases, but a positive impact if small clusters are denser than larger ones are.

The fourth contribution is the empirical estimation of the impact of trade clusters on technology adoption. While a technology diffuses among trade partners (in line with previous literature), the adoption process is faster among countries within the same cluster (implications of the theoretical setup). The first approach uses a pooled

[1]The MRIO database of input-output data for more than 190 countries between 1990 and 2015 is criticized principally due to the many interpolations made to complete the database and the approximation that homogenizes sectors across countries.

OLS regression over time to test whether a trade partner within the same cluster in a previous period fosters a country's technology adoption. The results indicate evidence of causality with a statistically significant effect. The result is robust to various specifications and control variables. In particular, controlling for the country and trading partners in the same region, Regional Trade Agreement (RTA), or the intensity of intra-industry trade does not offset the effect.

Next, this study explores the influence of the number of clusters and their composition on the technology adoption process. An increase in the number of clusters fosters technology adoption, but simultaneously, a reduction in the number of countries in the cluster has a negative impact. This dual effect leads to the existence of an optimal number of clusters. However, if the evolution over the past decades had a positive effect on technology diffusion, this might not be the case if the number of clusters continues to increase.

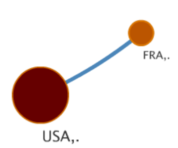
The remainder of this chapter proceeds as follows. Section 2.2 describes the notion of trade clusters and the determinants of their boundaries. Section 2.3 presents the relevant theoretical and empirical literature. Section 2.4 describes the theoretical framework of technology diffusion in a network. Section 2.5 presents the estimation strategy, data, and results. Section 2.6 concludes.

2.2 Definition and determinants of clusters' boundaries

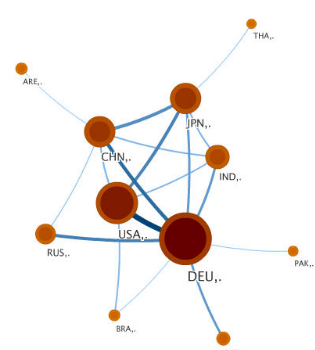
As described in the introduction, world trade relationships are now multipolar, implying that the network has shifted from a unilateral system of core-periphery to a more fragmented core. The increasing dissimilarity in trade connections among countries at the core of the network led to the multiplication of clusters, meaning a group of countries with trade connections relatively more intense than their trade with the rest of the world. Figure 2.1 provides a simplified representation of the communities in the trade network in 1960 (panel a) and 2012 (panel b) according to Rosvall and Bergstrom (2008)'s algorithm, which groups countries into the same cluster if the trade among them is important. In Figure 2.1, each node represents a cluster and the label corresponds to the most central country of the cluster. The thickness of the link indicates the strength of these connections. Panel (a) of Figure 2.1 shows the results for 1960. Two coexisting clusters represent virtually all world trade. Panel (b) of Figure 2.1 provides a starkly different representation: it indicates eleven coexisting clusters. From 1960 to present date, the trade network clustered toward various poles of increasingly equivalent importance. In the Annex, Figure 2.9 provides the corresponding geographical representation of the multiplication of the number of clusters.

Figure 2.1: Clusters in global networks

(a) 1960



(b) 2012



Source: Author's calculation by applying Rosvall and Bergstrom (2008)'s algorithm to the IMF DOTS database.
Notes: Each node correspond to a cluster of countries and is labeled by a three-letter ISO code of the country that is most central to the cluster. The larger the node, the more important is the cluster size. The ties between the nodes indicate the connection between the clusters and their size represents their strength.

2.2.1 Trade cluster algorithm

A cluster is a group of countries with trade connections that are relatively more intense than those with the rest of the world. As the introduction states, defining trade clusters is not straightforward. Previous research adopted definitions based on export matrix similarities or methodologies such as the k-mean, which requires the imposition of the number of clusters a priori [2]. First, the block modeling methodology, which groups countries by similarity, does not guarantee that countries with a similar trade structure become trade partners. For instance, assume that two small economies have a trade structure oriented toward a third economy. These two small economies might not trade with each other, even though their trade matrix is similar given that both trade heavily with the same country. In the block modeling methodology, the two countries would be in the same cluster. Other methodologies, such as the k-mean, require the input of the number of clusters a priori, thus maximizing the representation of the trade network. However, there is no good model to determine the optimal number of clusters. Since this study analyzes the evolution of the number of clusters and the phenomenon of multipolarization in particular, the number of clusters should then be the output of the methodology and not a requirement.

This study adopts the RB algorithm to reveal the communities in the the trade networks (weighted and undirected ties) for each year between 1960 and 2012. The RB algorithm uses random walks as a proxy of the trade flows and decomposes the network into clusters by "compressing a description of the probability flow." The RB algorithm aims to identify the backbone of the network by grouping countries into clusters representative of the main structure of the network. Because it does not impose the number of clusters (this emerges from the data), there is a trade-

[2] In particular, see the use of blockmodeling in Snyder and Kick (1979) and Smith and White (1992) and more recently, Everett and Borgatti (1999) and Fagiolo et al. (2009)

off between maintaining many links to derive the correct representation of the data and addressing the scarcity of information that can provide a useful and intelligible representation. Intuitively, the longer the random walk among a group of countries, the more probable it is that those countries will form a cluster. Annex 2.B.1 presents the algorithm in more detail and is based on a network that treats countries as nodes and the share of total trade between two countries as the links.

2.2.2 Determinants of cluster boundaries

Cluster boundaries emerge directly from applying the RB algorithm to the matrix of exports. Because trade patterns are determined by gravity variables, cluster boundaries should also depend on them. However, clusters also include the concept of value chain that is more independent to the gravity variables. This study first shows that gravity variables alone cannot boundaries and then provides evidence on the key role of cross national value chains in shaping trade clusters.

Cluster boundary predictability with gravity variables

Since clusters emerge directly from the matrix of exports, a legitimate question is whether the boundaries depend only on gravity variables or something more. This section reports the predictability in determining cluster boundaries by gravity variables and RTA following Baier and Bergstrand (2004)'s methodology[3].

Baier and Bergstrand (2004)'s econometric framework is based on the qualitative choice model of McFadden (1975) and McFadden (1976), executed by Wooldridge (2010). The variable $CLUSTER$ takes the value 1 if two countries belong to the

[3]Baier and Bergstrand (2004) estimate the economic determinants of the formation of FTAs. Compared to the variable of interest in this chapter (the formation of a cluster), their variable of interest is a dummy.

same clusters, and 0 otherwise. The response probability, P, for $CLUSTER$ is:

$$P(CLUSTER = 1) = G(\beta_0 + x\beta) \tag{2.1}$$

where $G(.)$ is the standard normal cumulative distribution function, which ensures that $P(CLUSTER = 1)$ lies between 0 and 1. The standard errors of the estimates of β are asymptotically normally distributed and the z-statistics indicate the statistical significance of the probit estimates. The economic characteristics x integrated in the model are based on the traditional literature on the gravity model and free trade agreements (FTA).

Table 2.1 presents the results of the analysis of the relationship between the likelihood of belonging to a cluster and various economic characteristics for 2001-2006[4]. The first testable hypothesis is that the probability of belonging to the same cluster is higher as the distance between two countries decreases. Column (1) shows that the results support this hypothesis across the period. The likelihood of forming a cluster is higher the distance between two countries decreases.

Column (2) tests whether a cluster is more likely to form among two countries when they have larger economies. This is a key determinant in the trade literature because the larger the potential market is, the larger the expected trade is. $RGDP_{ij}$ variable measures the sum of the logs of countries i and j. The coefficient associated with this variable is positive and statistically significant in all columns. The larger the economies are, the more likely it is that they are part of the same cluster.

The third testable hypothesis is that two countries belonging to the same cluster are more likely to be of similar sizes. $D - RGDP_{ij}$ measures the absolute value of the difference between the logs of the GDP of countries i and j. Column (3) shows that the coefficient is positive and statistically significant, revealing that the smaller

[4]Other periods in the sample give similar results, which are available upon request

the difference in GDP between trade partners is, the more likely they are to belong to the same cluster.

Column (4) includes a dummy variable equal to 1 if both countries have the same language. Sharing the same language increases the probability of being part of the same cluster. Column (5) adds a dummy variable equal to 1 if there is a former colonization relationship between the two countries. The coefficient on this variable is positive and statistically significant, suggesting that past colonial links increase the likelihood of being part of the same cluster.

Finally, Column (6) adds a dummy variable equal to 1 if both countries are part of the same RTA. The coefficient on this variable is positive and statistically significant; belonging to the same RTA increases the likelihood of belonging to the same cluster.

Results in this section lead to the conclusion that gravity variables and RTA are important determinants of cluster boundaries, but fail to determine them fully. The R^2, which is a better metric to determine the predictive power of the model (Wooldridge (2010)) is below 0.2. For comparison, and with the same methodology, Baier and Bergstrand (2004) find a superior predictive power of the gravity variables and endowments to determine the formation of an FTA with a value of 0.7.

Countries' motivation to switch clusters

The last section showed that gravity model variables explain only about one fifth of the formation of a trade cluster. In this section, the study delves into the drivers of cluster boundaries. Three reasons are tested: inclusion to a value chain, imperialism, and search for new markets.

To focus on the drivers that determine cluster boundaries, this section focuses on a country's switching clusters. To determine which countries change clusters, it is first necessary to identify clusters consistently over time. Because the RB algorithm is run every year, it does not assure consistent clusters over time. A rule is set so that

Table 2.1: Predictability of cluster formation based on gravity and RTA variables

	(1)	(2)	(3)	(4)	(5)	(6)
$DIST$	-0.203***	-0.208***	-0.209***	-0.206***	-0.206***	-0.183***
	(0.0059)	(0.0059)	(0.0061)	(0.0061)	(0.0061)	(0.0062)
$RGDP$		0.124***	0.124***	0.125***	0.124***	0.117***
		(0.0041)	(0.0041)	(0.0041)	(0.0041)	(0.0041)
$D-RGDP$			0.0152**	0.0175**	0.0146*	0.0297***
			(0.0077)	(0.0077)	(0.0078)	(0.0077)
$LANG$				0.246***	0.233***	0.208***
				(0.0350)	(0.0355)	(0.0362)
COL					0.282**	0.212*
					(0.1151)	(0.1130)
RTA						0.726***
						(0.0481)
Constant	-0.0823***	-6.136***	-6.124***	-6.249***	-6.207***	-6.081***
	(0.0279)	(0.1968)	(0.1974)	(0.1990)	(0.1995)	(0.1989)
Pseudo R^2	0.199	0.252	0.252	0.255	0.255	0.278
Log likelihood	-6133	-5516	-5514	-5490	-5488	-5293
Observations	21,170	20,022	20,022	20,022	20,022	19,740

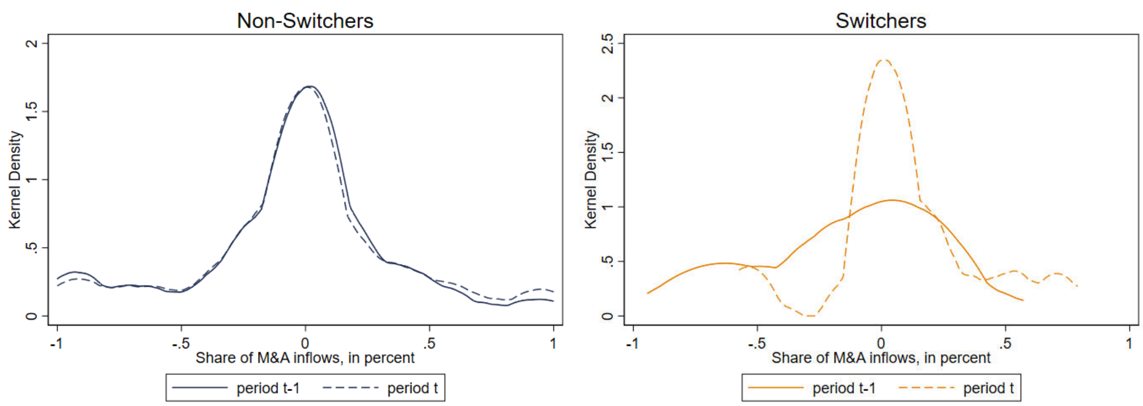
Notes: The table displays the probit results for the probability of a cluster.

in case more than one country separates, the identifier of the cluster belongs to the group with the larger number of countries. Once the cluster identification is set, it is possible to construct a database of countries switching from one cluster to another and to analyze the determinants.

Value chain. First, information on M&A inflows is used to assess the long-term engagement of cluster members with the new countries joining the cluster, the "Switchers" compared to their counterpart "Non-Switchers." If the creation of a value chain is a determinant of cluster boundaries, one should observe an increase in the inflows of M&A from countries in the new cluster. For the Non-Switchers, the share of total inflows from cluster members is close to the median of 64 percent. For the Switchers, the median value of M&A inflows from countries in the cluster move from 23 percent in the previous cluster (in $t-1$) to 47 percent in the new one (in t).

Figure 2.2 presents the Kernel density of the year-on-year (y-o-y) growth of M&A inflows from cluster partners, both for Switchers and Non-Switchers. While the distribution is similar for the $t-1$ and t clusters for Non-Switchers, the distribution is skewed to the right for Switchers in $t-1$, indicating that countries changing clusters received in influx of M&A in from members of its new cluster. M&A investment is then linked to the determination of the cluster. This argument supports the idea that value chains drive cluster boundaries.

Figure 2.2: Kernel density of M&A inflows growth among countries in the same cluster



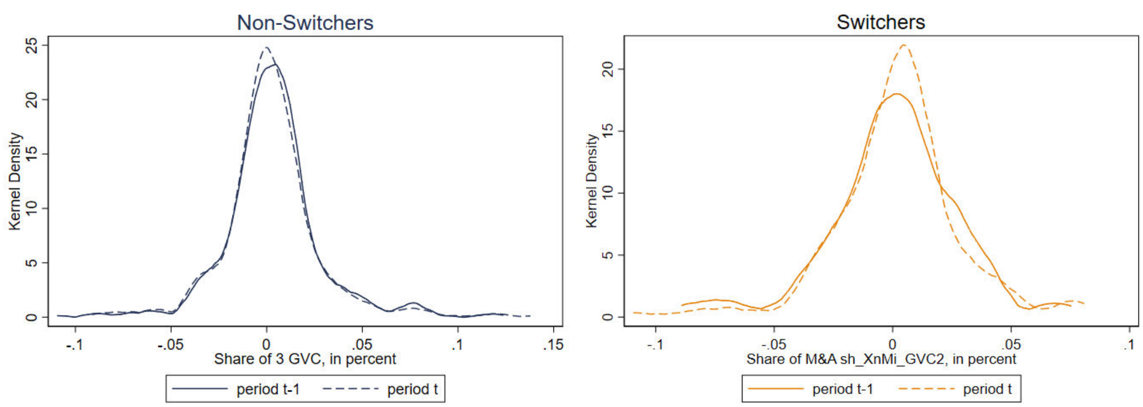
Source: Thompson M&A database.
Note: The figure presents the Kernel distribution of y-o-y growth of M&A inflows from partners in the cluster. The left panel shows the countries that do not change cluster between $t-1$ and t. Difference between the two lines are due only to the one-period difference. The right panel illustrates countries that switch clusters.

An other indicator of the link between value chains and trade clusters is the increase of trade in intermediary goods between the Switchers and members of their new cluster. Measuring the integration of a country into GVCs is a challenge. Given the paucity of suitable data[5], proxies must be used. In this section, trade of GVC-relevant intermediate goods defined at 5-digit dis-aggregation is used. Figure XX documents the rise of exports of intermediate goods that are relevant for GVCs in three industries: apparel and footwear, electronics, and automobiles and motorcycles following the methodology of Sturgeon and Memedović (2011).Figure 2.3 shows an increase of the trade in intermediary goods among countries in the same cluster

[5]The international input-output database MRIO is criticized due to the many interpolations made to complete the database and the approximation that homogenizes sectors across countries.

between t and $t-1$ for countries switching cluster. More precisely, for Switchers, the median of trade in intermediaries with the member of its cluster is 3.7 percent in $t-1$ and it increases to 5 percent after changing cluster in t. For the Non-Switchers, the value in $t-1$ and t is 5.3 percent.

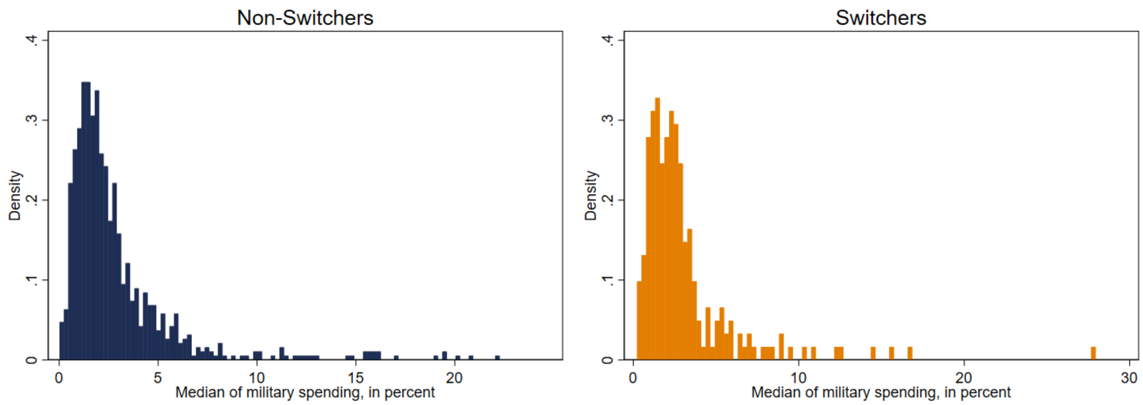
Figure 2.3: Kernel density of intermediary good trade growth among countries in the same cluster



Source: Calculations based on data from WITS/Comtrade (SITC Rev.1 5-digit); classification of intermediate goods into three major global value chains (apparel and footwear, electronics, and automobiles and motorcycles) is from Sturgeon and Memevodic 2010.
Note: The figure presents the Kernel distribution of y-o-y growth of intermediary trade between partners in the cluster. The left panel shows the countries that do not change cluster between $t-1$ and t. Difference between the two lines are only due to the one-period difference. The right panel illustrates countries that switch clusters.

Imperialism. Military spending is used as a proxy to assess test whether imperialism is a determinant of cluster extension. Figure 2.4 shows the median military spending of countries in the same cluster for Non-Switchers and Switchers. The distribution is wider for Switchers than for Non-Switchers. The countries switching clusters tend to join a cluster with a median military spend of 2 percent of total expenditure, while that for Switchers is 2.3 percent.

Figure 2.4: Histogram of military spending from countries in the same cluster

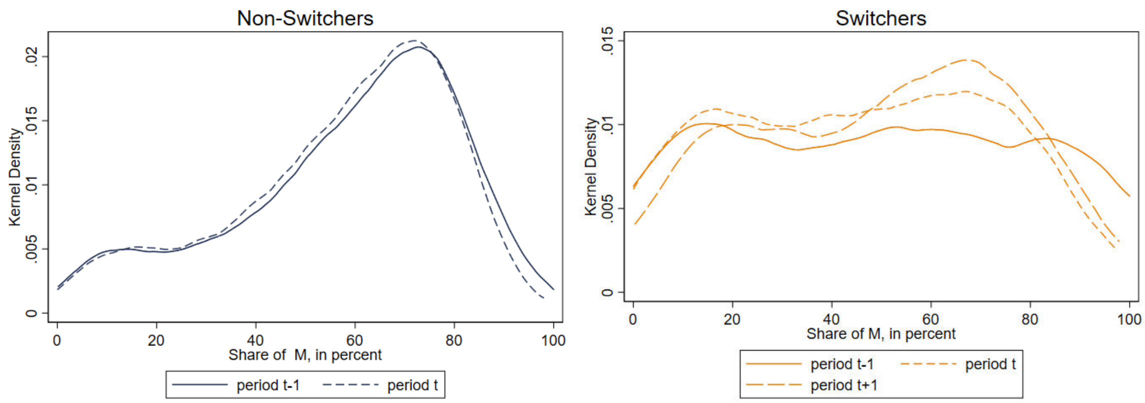


Source: IMF DOTs database.

Securing new markets. To assess whether market seeking is a determinant of cluster formation, Figure 2.5 shows the share of total imports from countries belonging to the same cluster. If market access is a motivation, then one should observe an increase in imports from countries belonging to the cluster for Switchers. Figure 2.5 presents the kernel density of imports from countries belonging to the same clusters. For Non-Switchers, the distribution picks around 70 percent of total imports; for Switchers, share of total inflows is slightly higher, but the median remains unchanged. Only in $t + 1$ is the distribution slightly more toward the right. From this evidence, searching for new markets as a reason to extend a cluster is not conclusive.

To conclude, this section provides some evidence that willingness to develop an international value chain may be the most important driver determining cluster boundaries. Imperialism motives are neither discarded as a potential driver. The next section actually exposes It is worth mentioning that securing new markets and imperialism are not necessarily disconnected and could drivers in the development of value chains.

Figure 2.5: Kernel density of the share of total imports from countries in the same cluster



Source: IMF DOTs database.

2.3 Literature Review on Technology Adoption and Network Effects

This section first reviews prior general arguments on the process of technology adoption, with a focus on timing. Next, it discusses the five determinants of technology adoption: knowledge, geography, institutions, aggregate demand, and trade. It gives a special emphasis on the role of value chains to echo the conclusion of the previous section. Finally, this section approaches the angle of networks with a focus on the Industrial Organization (IO) literature, empirical works using network measures, and small-world networks to justify the interest in analyzing clusters.

2.3.1 Process of technology adoption

In their seminal book, Hall and Khan (2003) state that the process of technology adoption results from the sum of individual decisions, from both the supply and demand sides. Individuals adopting a new technology weight the incremental benefit against the cost of change, the uncertainty of the new process, and the limited information they might have. The suppliers affect the benefits, cost, and how they share information on the new technology. In keeping with the interest of this chapter, this review will focus on the demand side.

Of particular import for this chapter, Hall and Khan (2003) argue that rather than analyzing whether the technology is adopted of not, the timing of adoption is what matters. As this chapter discusses later, countries converge *in fine* to the adoption of major technologies such as the internet. The question is the determinants that might foster this adoption.

2.3.2 Traditional determinants of technology adoption

The level of knowledge is a determinant in the adoption of a technology because innovations are generally not straightforward to implement (Comin and Hobijn (2007)). Banerjee and Duflo (2005) argue that a cause of lack of access to the latest technology is the lack of suitable human capital to use it. Nelson and Phelps (1966) define a coutnry's knowledge as human capital, typically proxied by the educational attainment of formal workers. Caselli and Coleman (2001) and Riddell and Song (2012) study the role of human capital in the first adoption of computers at a macro level for the former and micro-level for the later. Both find that years of schooling is associated with an increase in computer adoption. Benhabib and Spiegel (1994) find that the stock of human capital is also positively correlated with a higher productivity growth rate. The notion of knowledge gained in the work place is also relevant for new technology adoption (Manuelli and Seshadri (2014) and Erosa et al. (2010)). Empirical estimates below will be controlled by a measure of human capital.

A firm's capability to adopt a technology may depend on the decisions of other companies within the same geographic area (Porter (1998)) because a technology might have a higher value when two countries adopt it rather than only one (for instance, railways) and because some technologies are geography-specific and are more likely to be adopted in neighboring countries. Diamond and Ford (2000) cite the specificity of crops to particular climates that lead to the adoption of technology along similar latitudes. In the micro-economic literature, the adoption of some new technology, particularly in agriculture, depends on neighbors' decisions. Conley and Udry (2010) find that pineapple farmers tend to adopt fertilizer when they observe success among their neighboring producers. Using data on twenty technologies from CHAT, Comin et al. (2013) find a strong and significant correlation between closeness and a country's adoption of a technology. The estimates imply that spatial interactions that facilitate technology adoption decline by 73 percent every 1000 Kms. This chapter argues that not only does geographical closeness matter, but also clusters based on trade partners. The regression will have a control for a measure of geographic distance.

The quality of institutions also impacts the adoption of technology. Bad institutions can impede new technology adoption. The risk of expropriation, a common syndrome of bad institutions, threatens agents' investments and adoption of new technology. In addition, the elite may shun some technologies that can increase political transparency, such as communication technologies (Acemoglu and Robinson (2000)). Comin and Hobijn (2004) find that having an ineffective executive or having a military regime are associated with a lower level of technology adoption in a country. This is consistent with the notion that property rights protection is a necessary condition for technology adoption.

The level of demand is another important determinant of new technology adoption because it impacts estimated returns. By increasing the profitability of the investment, higher demand allows adopters to cover the sunk costs of adoption much faster. Griliches (1991), Fatas (2000) and Comin and Gertler (2006) finds a positive co-movement between R&D activities and output. Barlevy (2007) confirms this result with firm-level and 4-digit sector data. Comin and Hobijn (2004) find that the elasticity of technology with respect to income is around 1, even after controlling for potential omitted variables. The regression will include a proxy for demand.

Trade openness is another factor of technological adoption. Comin and Hobijn (2004) find that countries with higher trade openness are more likely to adopt new technologies than closed countries are. The authors find that countries that are 15 percent more open are 1 percent more likely to be ahead in new technology adoption. This chapter confirms the importance of trade partners in adopting technologies and finds an additional impact thought the trade cluster effect.

2.3.3 Value chain and technology diffusion

The origins of Global Value Chains (GVC) go back to the 1960s when US firms started to slice their production process (Timmer et al. (2014)). Transnational corporations began to restructure their operations to keep in the home country only high-value activities (including research, design, marketing, ownership of intellectual property rights and patents (Gereffi et al. (2011)). For activities with lower value, these firms moved from a "in house" production to a transnational contraction or outsourcing in lower cost countries, where rules and methods of productions were nevertheless following closely the contractor specifications.

Process get complexified over time but the rational remained the same, the lead firms taking decision on where subcontracting the required part of the production process. Corporates are reinforced at the top of the value chains by national and international patent law that leverage their position of owning high-value activities and are able to push further down the price on the value chain.

Cox and Wartenbe (2018) states that it is the rights to intellectual property that provide to these firms at the top of the GVCs both economic and political power relative to other entities. Lev (2000) shows an acceleration of this phenomena with the development of GVC. Between 1982 and 1998, the share of intangible assets of S&P 500 corporations went from 38 percent of the corporation value to 85 percent.

The extend of learning opportunities inside value chains is an ongoing debate. On one side, joining a value chain requires countries to receive specific knowledge transfers from the lead firm as well to use the same similar broad technologies. Studies find that local producers learn from joining GVC by improving their production processes, reaching consistent and high quality output and increasing the speed of their response (Lall (1992), Piore and Ruiz Durán (1998), andSchmitz and Knorringa (2000)). There is also scope for improving quality products by working for different lead firm with different quality requirements (Gereffi (1999)). On the other end, local producers are often limited to the production of a small part of the final product, limiting the possibility of upgrading position in the structure of the value chain. Governance structures are key to disentangle among both argument as they are the "authority and power relationships that determine how financial, material, and human resources are allocated and flow within a chain"(Gereffi (1994)).

2.3.4 Network effects in adopting new technologies

The importance of network effects in new technology adoption is central in the IO literature. Technologies are increasingly interdependent and often encompass a network effect in which the value of a technology increases with the number of users in the network. The network effect can be direct or indirect. Direct effect arises when the utility of use depends directly on the number of technology adopters, such as for telephones or e-mail, where the utility increases directly with the number of person the user can reach. Indirect network effect emerges from the wider availability of complementary goods. The "hardware / software" paradigm applies in the case of Macintosh computers; users are better off with the increase in adopters because this will foster demand (and then offers) of new software for these computers. The indirect network effect is central to the idea of this chapter. Network effects are particularly important for general technology adoption. They explain for instance the relatively slow introduction of dynamo and internet (David (1990), Brynjolfsson and Hitt (2000)).

Recent empirical literature includes network trade effects in the determinants of new technology adoption. Lumenga-Neso et al. (2005) distinguish between "produced" and "available" R&D. While a country creates the former and may transmit it to others through direct trade, it transforms into the latter when other countries, which do not necessarily have a direct trade connection with the creator country, have access to related knowledge. The authors find that indirect technology diffusion is almost as important for domestic total factor productivity (TFP) as direct technology transmission. Using a sample of 20 OECD countries, Franco et al. (2011) find that the impact of foreign R&D stock is greater than that of domestic stock when accounting for indirect effects. The authors calculate the average propagation length by country to reflect the economic distance between two countries to measure the length of trade it takes to "propagate" knowledge flows across countries. Using both technology adoption and trade data, Ferrier et al. (2015) show that countries better connected to the trade network have higher technology intensities. Their work is more closely related to this study's framework because it does not use TFP (an outcome measure of technology) or R&D (an input measure of technology) as a proxy for innovation, but adopts a direct measure of innovation using Comin and Hobijn (2009) database[6].

The presence of clusters is a trade network aspect that prior studies did not investigate as a determinant of technology adoption. Nonetheless, the network literature predicts that the diffusion of information across nodes is fostered in a small world network (Watts and Strogatz (1998)). Small world networks are networks in which all nodes are connected (Travers and Milgram (1967)), as is the case for export networks, which are characterized by small average path lengths and high clustering indicators. Bridging ties between clusters eventually allows diffusion across clusters. Prior studies find empirical links between the flow of information and small world networks in technology alliance networks (Verspagen and Duysters (2004)) and innovation across firms (Schilling and Phelps (2007) and Fleming et al. (2007)).

2.4 Modeling technology adoption in a clustered network

This section presents a model of technology adoption on the basis of a more general model of game theory decision making in a network-coordinated game. In this framework, players are countries and the relationship between players is based on trade. Countries decide to adopt a new technology in function of their trade partners' decision. The choice is based on direct benefit, that is, the benefits of adopting a new technology increase as others adopt it (Blume (1993), Ellison (1993), Morris (2000), Young (2001), Easley and Kleinberg (2010))[7]. Consequently, a country adopts a new technology when a sufficient proportion of its trade partners have done so.

[6]See section 2.5 for more detail.

[7]Other sources of decision making by partners in a network might be based on an informational effect.

Consider that countries have a choice between two communication strategies: fax (F) and email (E). If countries i and j are trade partners, they have an incentive to use the same technology. This can be represented as a game in which countries i and j are players and F and E are possible strategies. The pay-offs are defined as follows:

- if i and j adopt technology F, each gets a payoff of f > 0;
- if i and j adopt technology E, each gets a payoff of e > 0; and
- if i and j adopt different technologies, each gets a payoff of 0.

Country i plays this game with each of its trade partners in the network. Its total pay-off is the sum of the pay-offs of the game played with all its trade partners. Country i's final decision to adopt a technology will depend on its partners' decision. Formally, q is the fraction of country i's trade partners that have adopted technology E and $(1 - q)$ is the fraction that has adopted technology F. If i has N neighbors, qN uses emails and $(1 - q)N$ uses fax; i gets qNe if it adopts E and $(1 - q)Nf$ if it chooses F. As a final decision, E is chosen if $qNe \geqslant (1 - q)Nf$ or if $q \geqslant f/(e + f)$.

The threshold rule is as follows: if $q \geqslant f/(e + f)$ adopts emails, then country i should adopt it as well. The threshold depends on (1) the number of countries that adopted emails and (2) the expected gain e of using emails.

Equilibria There are two obvious equilibria: one in which all the countries adopt emails and other in which all the countries use fax. Interestingly, this raises the question of how to move from one equilibrium to another and highlights the need to understand how intermediate cases could occur.

Consider an equilibrium in which all the countries have fax. Some "early-adopters" adopt email for some reason outside of the game [8]. Each country decides to maintain fax technology or switch to emails during each period of a game. The process stops when all countries use emails (complete cascade) or no other country has the incentive to switch to emails (incomplete cascade that generates an equilibrium with the coexistence of emails and fax[9]).

Clusters Clusters can cause a cascading effect of a new technology to stop. They are a densely connected community of commercial partners. For ease of presentation, let's define a cluster as a set nodes, such that each node in the cluster has at least p of its partners in the cluster [10].

Consider an arbitrary network in Figure 2.6 and for simplicity, an equal payment of both technologies ($e = f$). Clusters are defined for p=3/5 and distinguished in the figure by the shape of the node. In period 1, countries 5 and 7 are early adopters of emails (E), while all the other countries continue to use fax (F). In period 2, 8 will adopt emails as two-third of its partners has already adopted it. In periods 3, 4, and 5, respectively, countries 9, 6, and 4 will adopt emails. At this point, the cascade stops. No other country shows interest in adopting emails as more of their trade partners use fax.

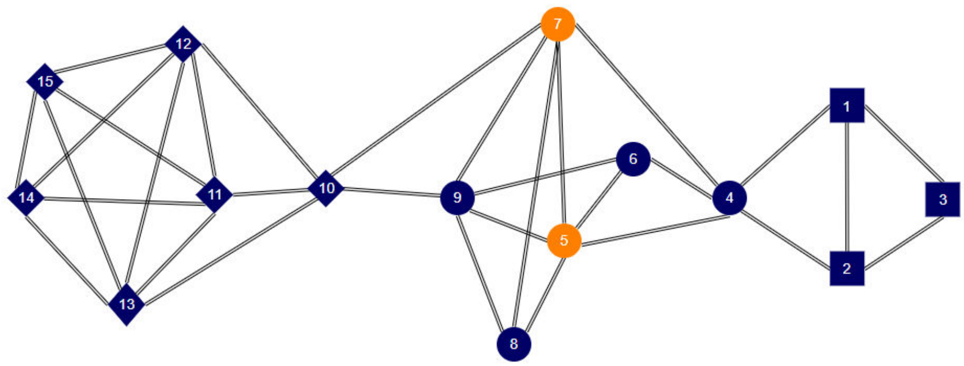
The adoption of emails is limited to countries in cluster B. The existence of clusters limits the proliferation of emails. This is because the density of the cluster that is yet to gain access to the technology is higher than that of links with countries in clusters

[8] They may do so because they are innovators, expect a high return, or consider emails as superiors to fax; however, this does not occur in the pay-off function.

[9] The coexistence of two technologies with the same purpose is a frequently occurring phenomenon; for example, consider the coexistence of Apple Macintosh and Windows computers. Some firms in certain industries almost exclusively use Apple, even if Windows is more widely used. These industries often include architects and designers and may be part of a cluster.

[10] The limitation of this method in describing clusters will be presented later in this study and the RB detection of a community algorithm will be used

Figure 2.6: Adoption of emails across a network with clusters

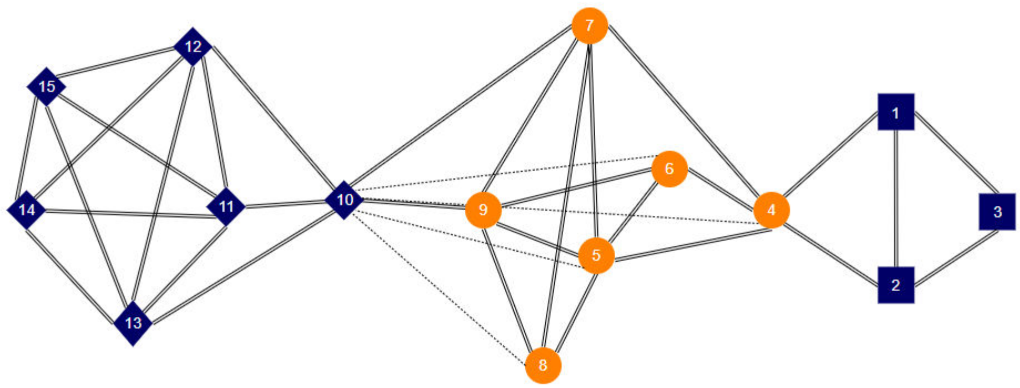


Note: Nodes represent countries and undirected ties, that is, a commercial link between two countries. The shapes of the nodes distinguish between three clusters of density threshold $p = 3/5$. Cluster A is denoted by squares and comprises countries from (1) to (3), cluster B are represented by circles and includes countries from (4) to (9); and cluster C is in the form of diamonds and comprises countries from (10) to (15). Nodes (5) and (7) in orange are the early innovators and the first countries to adopt emails E.

using the new technology. Only an increase in the pay-off of emails $e$or new trade connections between countries from different clusters could further email adoption over fax.

Switchers. Dash line in Figure 2.7 shows new connections in the trade network. Consider for instance (10) join a value chain associated to the round shape cluster. By developing its trade links with countries (4), (5), (6), and (8), (10) changes cluster from the diamond-sahpe to the circle shape and adopts emails as two-third of its partners have adopted it.

Figure 2.7: Adoption of emails in a clustered network with switching countries



Note: Nodes represent countries and undirected ties, that is, a commercial link between two countries. The shapes of the nodes distinguish between three clusters of density $p = 3/5$. Cluster A is denoted by squares and comprises countries from 1 to 3, cluster B are represented by circles and includes countries from 4 to 9; and cluster C is in the form of diamonds and comprises countries from 10 to 15. Dash line represent new trade links.

2.5 Empirical approach

This section presents the empirical strategy used to test the implications of the presence of clusters in a trade network and to assess the impact of the multiplication of the number of clusterson technology adoption across countries.

2.5.1 Importance of clusters in technology adoption

Methodology and Data This section evaluates the influence of clusters on technology adoption using pooled OLS regressions with the following specifications:

$$A_{ikt} = \beta_1 A^p_{ik(t-1)} + \sum_{k\neq}^{m} \beta_k X_{it} + \delta_{ik} + e_{itk}, \tag{2.2}$$

where A_{ikt} denotes the adoption of technology k by country i at time t; $A^p_{ik(t-1)}$ is the trade weighted average of a partner's adoption of technology, which will be split among partners belonging to the same cluster, $A^{p=}_{ik(t-1)}$, and partners that do not belong to the same cluster, $A^{p\neq}_{ik(t-1)}$); X_{it} is the different control variables for country i at period t; δ_{ik} is the technology time-specific dummy; and e_{itk} is the error of specification.

The variable of interest and dependent variable is the adoption of technology by countries. Data are taken from the Cross-country Historical Adoption of Technology (CHAT) database constructed by Comin and Hobijn (2004) and Comin and Mestieri (2013). The database includes technologies from eight industries: steel (2), telecommunications (7), textiles (1), transportation (6), and various other industries using technologies (3)[11]. While the CHAT database is the best currently available to analyze the adoption of specific technologies for a large number of countries over a long period, it is important to highlight the limitation of the technologies available. The reader is invited to read the Annex for more details on which innovations the empirical section is based on. Since this study focuses on the adoption of *new* technology, the data are censored when the technology becomes obsolete or dominated by another. In the preferred regression sets, technology adoption data are censored for the year in which *a country's* use of a technology begins to decline. Results for when years in which *the world's* use of technology begins to decline are reported in the Annex.

To deal with the evolution of frontiers, the rule established by Comin and Mestieri (2013) is followed to make the databases comparable. In case of a reunified country, the economy that was larger prior to the unification and the unified country as a single nation are considered a single nation (e.g., West Germany and Germany). In case of the fragmentation of a country into two nations, the largest economy following the separation and the previous entity are considered a single nation (e.g., USSR and Russia). Four countries are excluded from the sample: Indochina, North Vietnam,

[11] Technologies belonging to agriculture, finance, health, and tourism are excluded owing to the resultant difficulties in conducting a cross-country comparison.

South Vietnam, and South Yemen. In addition, to merge with bilateral trades from DOTS, data since 1960 are used. Annex 2.4 presents the descriptive statistics for the sample on technology adoption considered for this study: 12,078 observations are considered for 157 countries and 19 technologies between 1960 and 2012. As is standard in the literature, data are averaged by a period of five years to reduce the probability of fluctuations affecting the results independent of the technology adoption dynamics.

The basic sets of regressions include the log of the real GDP per capita to control for differences in income and endowments between countries. Alternatively, in robustness regressions reported in the Annex, the share of population that enrolled at least in secondary education was included to account for the level of human capital in each country. Trade openness is also included: when trade openness of a country's partners is included, the average of country i is obtained after weighting the share of the country's total trade with the partner. All variables that are not included in the share are transformed using the logarithm, which allows to interpret the results of the coefficient as elasticities. More details on the data description and sources are presented in the Annex 2.5. The three dimensions of the dependent variable[12] allow to exploit the variation across country and over time, which is considerably helpful as the variable of technology adoption is not a highly volatile one. In the preferred set of regressions, the clusters of errors are at the country-period level. The risk of endogeneity appears to be limited as specific technologies, rather than TFP, are used as the dependent variable. It seems reasonable to assume that the use of a specific technology as a dependent variable should not reversely affect aggregate control variables such as GDP or trade openness (see Comin and Mestieri (2013) and Ferrier et al. (2015)).

[12]The three dimensions include country, year, and technology.

Results Table 2.2 presents the results of the estimation of equation 2.2. Column (1) confirms the results obtained in Comin and Hobijn (2004) on a different sample of countries and periods[13]. The coefficient associated with the log of the GDP per capita is positive and statistically significant, although it is lower than that in the original paper (0.63). Since the left- and right-hand side variables are in log, the coefficient can be interpreted as elasticity: a 1 percent increase in GDP per capita would lead to 0.63 percent greater adoption of technology. Column (2) includes the trade openness of country i and the average of partners' technology adoption weighted by trade in the precedent period. The coefficient associated with trade openness is positive but not statistically significant. With respect to the other variable, an increase in one percent of technology adoption by the country's trade partners in $t-1$ would lead to an expected increase in the country adoption of technology by 0.9 percent in t. This is in line with the literature presented in Section 2.3: the more a country trades with a nation that adopted a technology, the more likely it is to adopt the technology. When separating the variable between partners belonging to the same and different clusters (column 3), only the coefficient associated with the average technology of the countries, weighted by trade belonging to the same cluster, is positive and statistically significant. The technology adoption is stronger across countries belonging to the same cluster as predicted by the theoretical framework (Section 2.4).

Columns 4–7 include complementary controls to discard the misinterpretation of the cluster effect. The coefficient of clusters could mistakenly account for geographical region, particularly in the later years of the sample (see panel (b) of Figure 2.9). Column (4) includes the trade weighted average level of the technology of countries in

[13] Comin and Hobijn (2004) analyze 23 of the most industrially advanced economies but for the period of 1800–2001

the same region. While the coefficient associated with the partners in the same region is positive and statistically significant, the one associated with the trade partners in the same cluster remains statistically significant and of a magnitude similar to that in column (4), leaving the conclusions unchanged.

To increase the confidence of the coefficient associated with the cluster that does not account for any commercial agreement, the average technology adoption of partners within a common RTA is added in column (5). The results of the principal regression hold and the technology adoption positively depends on trades with partners that have adopted the technology and belong to a common trade union.

Column (6) presents the results of the regression controlling for intra-industry trade (IIT). IIT is another factor of technology adoption through trade (Hakura and Jaumotte (2001)). The coefficient associated with the variable is positive and statistically significant. An increase of one percent in IIT is associated with an increase of 0.3 percent in technology adoption. Nevertheless, the coefficient associated with trade among countries belonging to the same cluster remains positive and statistically significant.

Finally, column (7) introduces a measure to evaluate the incidence of geographical interactions in adopting technologies from other countries. The spatial distance from other countries' technology (SDT) is defined as that in Comin et al. (2013), that is, by the interaction between the adoption of technology in other countries and the distance between them [14]. The coefficient associated with the measure of spatial distance from other countries' technology is negative and statistically significant and of a similar

[14]Formally, the spatial distance from other countries' technology is defined as $SDT_{ikt} = \sum d_{ij} A_{jkt}$, where d_{ij} is the distance between country i and j and denoted in thousands of kilometers, and A_{jkt} is the adoption of technology k in j at t.

amplitude to that reported by Comin et al. (2013). This suggests that countries located close to a nation that adopted a technology are more likely to adopt it than a country that is further away. As for the other columns of this table, the coefficient associated with trades among countries belonging to the same cluster remains positive and statistically significant.

Table 2.2: Results of OLS pooled regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
y_{it}	0.738***	0.770***	0.821***	0.718***	0.795***	0.631***	0.819***
	(0.07)	(0.02)	(0.02)	(0.05)	(0.05)	(0.02)	(0.02)
TO_{it}		0.0207	0.0293	0.0608	0.0161	0.0502	0.00220
		(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)
$A^{p=}_{ik(t-1)}$			0.0176***	0.0166***	0.0169**	0.0125**	0.0177***
			(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
$A^{p\neq}_{ik(t-1)}$			-0.0631	-0.0603	-0.0699	-0.0801	-0.0461
			(0.07)	(0.10)	(0.13)	(0.07)	(0.07)
$A^{p}_{ik(t-1)}$		0.898***					
		(0.07)					
$A^{=region}_{ik(t-1)}$				0.207***			
				(0.03)			
$A^{=RTA}_{ik(t-1)}$					0.0206*		
					(0.01)		
$IIT^{4d}_{i(t-1)}$						0.352***	
						(0.02)	
$SDT_{ik(t-1)}$							-0.455***
							(0.00)
Constant	-5.422***	-6.592***	-6.372***	-5.718***	-6.105***	-5.488***	-6.257***
	(0.63)	(0.29)	(0.31)	(0.44)	(0.50)	(0.27)	(0.32)
Observations	10,041	6,915	6,915	6,915	6,915	6,709	6,915
R-squared	0.913	0.928	0.920	0.929	0.920	0.923	0.920
Dummy	A-p	A-p	A-p	A-p	A-p	A-p	A-p
Cluster	cp	cp	cp	cp	cp	cp	cp
Obsolescence	A-p	A-p	A-p	A-p	A-p	A-p	A-p

Notes: The dependent variable is the adoption of technology k in country i at time t. In rows *Dummy*, *Cluster*, and *Obsolescence*, "A," "p," and "c" denote technology, period, and country, respectively. Robust standard errors in parentheses. *** stands for p<0.01, ** for p<0.05, and * for p<0.1

Annex Table 2.6 presents the robustness checks for three potential concerns regarding 2.2's estimations: lack of human capital inclusion, cluster of errors, and definition of technology obsolescence. First, and contrary to Comin and Hobijn (2004), principal regression is controlled for only by the income effect and human capital level (proxied by the share of those who have completed secondary and tertiary education) is not added as both variables are highly correlated (66 percent). Columns (1) and (2) of Table 2.6 present a version of the regression controlling for human capital. The coefficient associated with the variable is positive and statistically significant. All other coefficients of interest remain statistically significant and are of a magnitude similar to that in Table 2.2. The interpretation does not change.

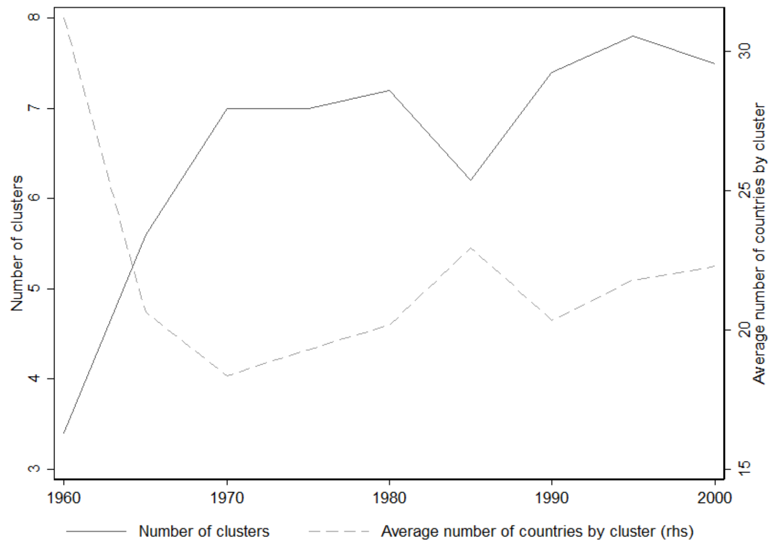
Columns (3) and (4) present an alternative method of clustering errors: the clustering is performed by country (and not country-period as in Table 2.2). $A^{p}_{ik(t-1)}$ remains statistically significant at 1 percent in column (3), while $A^{p=}_{ik(t-1)}$ is now statistically significant at 5 percent only. The magnitude of the coefficient and interpretation remain the same. Finally, in columns (5) and (6), the definition of obsolescence of the variables for technology adoption changes. At the difference with the preferred regression, where the year of obsolescence is defined at the country-technology level, in columns (5) and (6), the obsolescence is defined only at the technology level. A technology is declared as obsolete when its use begins to decline for the mean country in the world. This increases the number of observations but the results are rendered less precise. Nevertheless, the conclusion holds.

Impact of the increase of the number of clusters on technology adoption

This section studies the consequences of the increase in the number of clusters that occurred over the last decade on the technology adoption. Figure 2.8 presents the evolution of the number of trade clusters and the average number of countries within each cluster since 1960. During 1960–1965, the number of clusters was about three and increased to eight between 2000 and 2004 (and was 11 in 2012). By contrast, the number of countries per cluster declined from 31 countries in 1960–1964 to 22 during 2000–2004.

The preceding sections highlight two possible effects: on the one hand, the trade cluster should increase technology adoption as countries have an incentive to reinforce

Figure 2.8: Evolution of clusters overtime



Notes: The data are averaged by a five-year period. Sources: Author's calculations based on IMF DOTS database.Robust standard errors in parentheses. *** stands for p<0.01, ** for p<0.05, and * for p<0.1

knowledge among the cluster's partners; on the other hand, a reduction in the number of countries in the cluster further decreases possible partners from who others can learn. The total effect remains an empirical question that will be addressed in this section.

Methodology The pooled regressions have the following specification:

$$A_{itk} = y_{it} + TO_{it} + A^{p}_{ik(t-1)} + N_{c(t-1)} + N^{c}_{i(t-1)} + e_{ita}, \tag{2.3}$$

where $N_c(t-1)$ is the number of clusters in $t-1$ and $N^c_i(t-1)$ is the average number of countries by cluster in $t-1$.

Results Column (1) in Table 2.3 proposes the estimation result for equation 2.3. As in Table 2.2, the log of GDP per capita and weighted average of technology adoption by partners is positive and statistically significant, while the trade openness of country

i remains positive but it is not statistically significant. The two coefficients of interest are those associated with the effects of the number of clusters in $t-1$ and the average number of countries by cluster in $t-1$ on technology adoption in t. As expected, both are positive and statistically significant. Nevertheless, the effect associated with the number of clusters in $t-1$ is superior to that associated with the number of countries[15] From the two expected effects, an increase in the number of clusters had a net positive effect on the technology adoption over the past decades.

The prediction is confirmed by segregating the data into three sub-periods [16]. Column (2) evaluates the effect of average technology adoption by trade partners in sub-periods 2 and 3 (against sub-period 1). The coefficient associated with sub-period 3 is statistically positive and superior to other sub-periods. The same conclusions are drawn from column (3) when focusing on partners belonging to the same cluster.

The effect is also reaffirmed by the integration of an index for income concentration by cluster with the regression. In column (4), the coefficient associated with the Herfindahl index for GDP per cluster is reported with a negative sign and statistically significant. An increase in the concentration of countries in clusters is associated with a reduction in technology adoption.

In column (5), the integration of the Theil index's components sheds further light on the impact of the clusters' composition on technology adoption. The within-component of the Theil index is not statistically significant, indicating that the difference in income within the cluster does not impact technology adoption. By contrast, the coefficient associated with the between-component of the Theil index is negative

[15] A Wald test confirms the statistical significance of this result.

[16] The three sub-periods are sp_1= 1960–1974, sp_2 = 1975–1989, and sp_3 = 1990–2004

Table 2.3: Influence of multipolarization

	(1)	(2)	(3)	(4)	(5)
y_{it}	0.730***	0.753***	0.802***	0.717***	0.730***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
TO_{it}	0.00801	0.0275	0.103**	0.0273	0.0219
	(0.05)	(0.05)	(0.05)	(0.06)	(0.05)
$A^{p}_{ik(t-1)}$	0.975***	0.652***		0.981***	0.974***
	(0.00)	(0.08)		(0.00)	(0.00)
Num. of clusters $(t-1)$	0.153***				
	(0.04)				
Av. num. of countries by cluster $(t-1)$	0.0376***				
	(0.01)				
$A^{p}_{ik(t-1)} * p_2$		0.335***			
		(0.07)			
$A^{p}_{ik(t-1)} * p_3$		0.591***			
		(0.10)			
$A^{p=}_{ik(t-1)}$			-0.00669		
			(0.01)		
$A^{p=}_{ik(t-1)} * p_2$			0.0304**		
			(0.01)		
$A^{p=}_{ik(t-1)} * p_3$			0.0745***		
			(0.01)		
Herfindhal gdp_{t-1}				-0.465*	
				(0.25)	
Theil-within gdp_{t-1}					0.412
					(0.45)
Theil-between gdp_{t-1}					-2.336*
					(1.23)
Constant	-8.454***	-6.315***	-6.517***	-6.614***	-7.174***
	(0.52)	(0.27)	(0.30)	(0.28)	(0.87)
Observations	6,915	6,886	6,915	5,394	6,915
R-squared	0.911	0.928	0.908	0.912	0.910
Dummy	None	A-sp	A-sp	None	None
Cluster	c-p	c-p	c-p	c-p	c-p
Obsolescence	A-p	A-p	A-p	A-p	A-p

Notes: In rows *Dummy*, *Cluster* and *Obsolescence*, "A," "p," and "c" denote technology, period, and country, respectively. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

and statistically significant. The higher the inequality across clusters, the less likely the technology adoption.

2.6 Conclusion

An extensive literature on the effect of trade on technology adoption exists, with most findings highlighting positive effects. This study contributes to this literature by exploring the effects of trade clusterization on the process of adopting a new technology. It defines clusters as a group of countries with heavy trade between them, and is the first in the trade literature to employ Rosvall and Bergstrom (2008) algorithm, which defines clusters not as a function of the similarity of trade among actors, as in classical and prior algorithms, but as a function of trade intensity. The chapter highlights the links between trade clusters and value chain formation.

Trade with countries within the same cluster fosters technology adoption. This study's results are robust to various specifications and controls. The second round of analysis shows the positive impact of the increase in the number of clusters on technology diffusion over the past decade; however, the process might have approached its end with the decreasing number of countries within each cluster counterbalancing the negative effect.

This chapter provides theoretical and empirical evidence that value chains seen through the lens of clusters contribute to the diffusion of technology. It also offers an alternative tool for future work on value chains that does not require the use of I-O tables.

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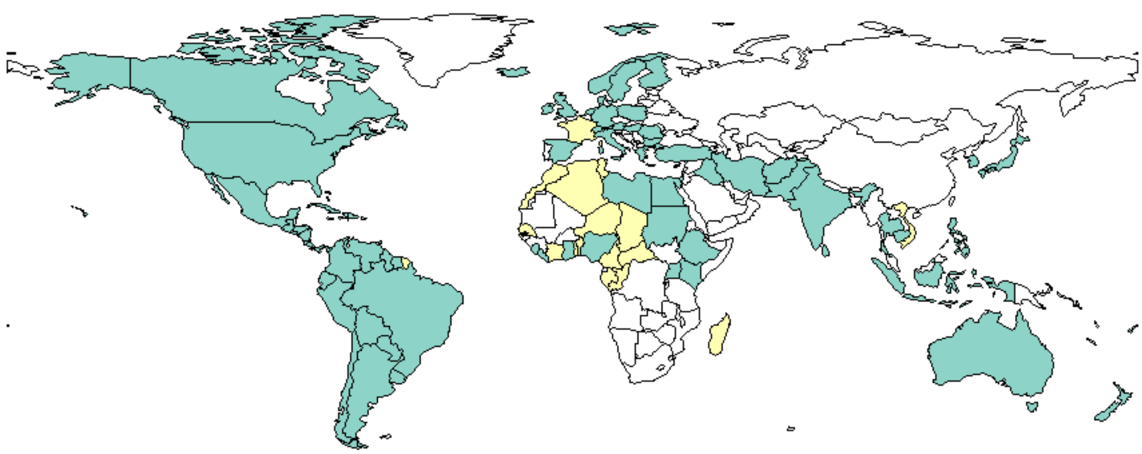
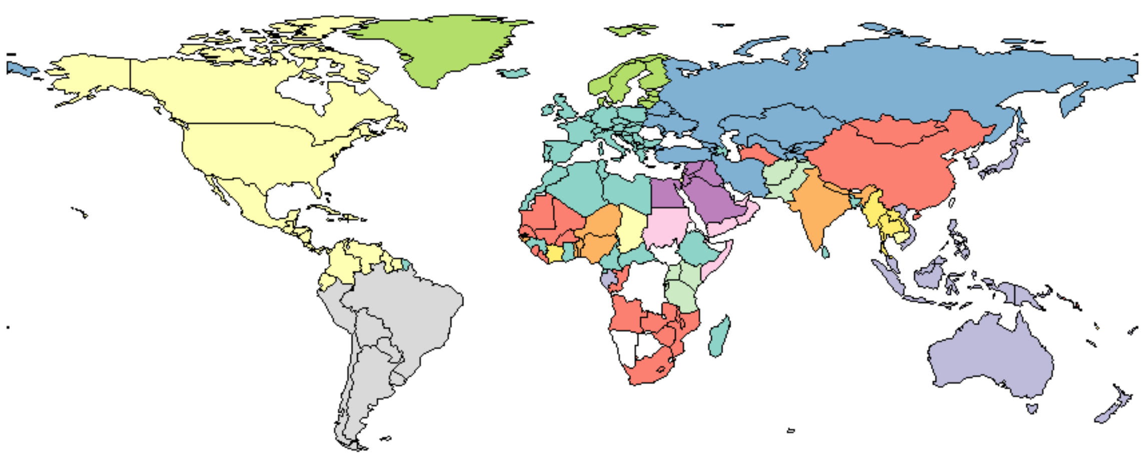
Appendix 2.A Geographical maps

Figure 2.9: Clusters in global networks

(a) 1960



(b) 2012



Source: Author's calculation by applying the RB algorithm to the IMF DOTS database.
Notes: Different colors denote various clusters; for countries in white, no data are available.

Appendix 2.B Methodology

2.B.1 Rosvall and Bergstrom (2008) algorithm on detection of communities

The algorithm developed by Rosvall and Bergstrom (2008) (RB algorithm) allow to reveal communities of flow weighted network. RB algorithm is implemented in C++ language. The algorithm is applied to the trade network for 1960-2012 data in order to find clusters.

The algorithm uses random walks on trade network as a proxy of the trade flows and decompose the network into clusters by "compressing a description of the probability flow". The RB algorithm aims to find the "backbone" of the network, by grouping countries into clusters representatives of the main structure of the network. Finding the structure of the network must be the balance between keeping too many links (and making the structure useable) and omitting important features (by over simplifying). The information-theoretic approach allows to measure the level of representativity of the community.

As no numbers of clusters are imposed (this number will emerge from the data), there is by consequence a trade-off between keeping too many links and making representatitivity and scarceness of the information shown. The methodology is twofold:

- First level of description: Describing in a schematize way flows in a network is a coding/compression problem. The idea is that flow data can be compressed by a code that explode regularities in the process. By using a random walk on the network trade flow, all the information of the network is used and nothing more. A Huffman code is used to describe the random walk on the network. The algorithm assigns letter code to nodes: the more frequent the random walk go through the node, the shorter the length of the code word. This gives the structure of the network.

- Second level of description: another aspect of the random-walk methodology can be used to determined the different communities. Statistically, a random-walk will remains more time within clusters of nodes.

There is then a dual problem to solve: the Huffman coding and the finding of the community structure. RB algorithm finds the module partition $\mathbf{M}$ of n nodes and m modules by minimizing the expected description length of a random walk. The average description length of a random walk is:

$$L(\mathbf{M}) = \underbrace{q \curvearrowright H(\mathfrak{Q})}_{\text{entropy of movement} \textit{between} \text{ cluster}} + \underbrace{\sum_{p=i}^{m} p^{i} \circlearrowleft H(\mathfrak{P}^{\mathrm{i}})}_{\text{entropy of movement} \textit{within} \text{ cluster}} \tag{2.4}$$

with $q \curvearrowright$ is the probability that the random walk changes of community on any given step; $H(\mathfrak{Q})$, the entropy of the module names; $H(\mathfrak{P}^{\mathrm{i}})$, the entropy of the within-module movements, including the exit code for module i. The weight $p^{i} \circlearrowleft$ is the fraction of within-module movements that occur in module i, plus the probability of exiting module i. Both components are weighted by the occurrence in the particular partitioning.

Finally, as trade data network is too big to analyze each possible partition to find the one that minimize the description length of the random-walk, a computational search is applied to restring the set of possibilities.

Appendix 2.C Data

Table 2.4: Data of adoption of technology

	Simple average across countries									Sample size								
Beginning of period	1960	1965	1970	1975	1980	1985	1990	1995	2000	1960	1965	1970	1975	1980	1985	1990	1995	2000
Steel																		
Blast Oxygen furnaces	0.13	0.32	0.32	0.39	0.43	0.46	0.34	0.34	0.36	16	18	59	60	61	62	93	89	84
Electric Arc furnaces	0.27	0.24	0.38	0.4	0.45	0.45	0.57	0.58	0.61	16	18	59	60	61	62	93	89	84
Telecommunication																		
Cable TV				0.01	0.03	0.05	0.04	0.05	0.06	0	0	0	23	30	34	90	109	102
Mobile phones				0	0	0	0.01	0.05	0.2	0	0	0	123	124	124	146	146	146
Mail	71.13	74.22	78.09	88.15	100.36	127.52	156.93			66	67	70	64	56	50	44	0	0
Newspapers	0.09	0.09	0.1	0.09	0.1	0.1	0.1			104	113	116	124	124	124	132	0	0
Radios	0.13	0.16	0.19	0.22	0.27	0.33	0.36			105	117	121	125	126	126	146	0	0
Telephones	0.05	0.06	0.08	0.1	0.12	0.13	0.15	0.15	0.15	108	109	109	119	121	121	100	85	72
Televisions	0.04	0.06	0.09	0.11	0.13	0.14	0.18	0.21	0.28	78	90	97	114	119	128	148	147	67
Textiles																		
Autoloom	0.64	0.73	0.79	0.88						57	61	59	93	0	0	0	0	0
Transportation																		
Railways Passengers	17984	14447	15473	17771	20779	21618	21985			89	88	87	81	78	75	73	0	0
Trucks	2.31	2.54	2.7	3.25	3.82	4.17	4.37	4.694	6.59	107	108	108	104	104	102	99	62	9
Cars Passengers	0.03	0.04	0.05	0.07	0.08	0.09	0.11	0.14	0.22	112	113	114	112	112	108	128	102	39
Aviation Freight	464	818	1540	2516	3242	3626	3216			85	89	90	94	96	94	91	0	0
Aviation Passengers	59.08	104.21	193.45	311.86	423.87	530.88	614.36			93	94	95	102	100	99	106	0	0
Steam or Motorships	0.72	0.72	0.8	0.87	0.85	0.85	1	1		11	11	10	8	7	7	6	2	0
General interest																		
Internet				0	0	0	0	0.03	0.09	0	0	0	5	5	6	76	144	145
Personal Computer					0.01	0.03	0.04	0.07	0.11	0	0	0	0	4	41	82	123	128
MWh of electricity	14.23	17.19	19.94	23.92	27.51	30.66	40.5	45.08	48.13	111	113	116	116	116	116	138	111	75

Notes: Steel variables are the fraction of total steel produced by each method; Telecommunication are per capita as well as Passenger traffic on railways, Passenger cars, Aviation Passengers, Internet and personal Computers; Trucks, Aviation Freight and MWh electricity produced are per $M of real GDP; All the technology not obsolete from the world perspective are presented in this table. The total number of observations is 12,078.

Table 2.5: Description of the variables

Variable	Description	Source
A_{itk}	Adoption of technology k by country i at time t. More detail in Annex Table 2.4	Comin and Hobijn (2009)
y_{it}	Real GDP per capita	World Development Indicators
HK_{it}	Share of population that started have been enrolled in secondary or tertiary education	Barro and Lee (2013)
TO_{it}	Trade openness calculated as sum of Exports plus imports of goods and services as a share of GDP	WDI
A^{p}_{ikt}	Trade weighted average of the adoption of technology k by partners j of country i at time t	DOTS
$A^{p=c}_{ikt}$	Trade weighted average of the adoption of technology k by partners j belonging to the same cluster of country i at time t	DOTS and use of the algorithm Rosvall and Bergstrom (2008) to detect cluster
$A^{p\neq c}_{ikt}$	Trade weighted average of the adoption of technology k by partners j belonging to another cluster of country i at time t	DOTS and use of the algorithm Rosvall and Bergstrom (2008) to detect cluster
$A^{p=region}_{ikt}$	Trade weighted average of the adoption of technology k by partners j belonging to the same geographical region of country i at time t	WDI
$A^{p\neq region}_{ikt}$	Trade weighted average of the adoption of technology k by partners j belonging to another geographical region of country i at time t	WDI
$A^{p=RTA}_{ikt}$	Trade weighted average of the adoption of technology k by partners j having a regional trade agreement with i at time t	De Sousa (2012) based on WTO agreement
$A^{p\neq RTA}_{ikt}$	Trade weighted average of the adoption of technology k by partners j that do not have a RTA with i at time t	De Sousa (2012) based on WTO agreement
IIT_{4d}	Share of intra-industry trade at 4-digit based on Grubel-Lloyd measure	Comtrade 4digit

Appendix 2.D Robustness check

Table A2.6 presents some robustness check of the table 2.2.

Table 2.6: Robustness check of Table 2.2

	(1)	(2)	(3)	(4)	(5)	(6)
y_{it}	0.646***	0.679***	0.738***	0.783***	0.701***	0.743***
	(0.02)	(0.02)	(0.04)	(0.03)	(0.02)	(0.02)
HK_{it}	0.185***	0.212***				
	(0.04)	(0.04)				
TO_{it}	0.0172	0.0448	0.0176	0.0218	0.0297	0.0364
	(0.05)	(0.05)	(0.11)	(0.10)	(0.05)	(0.04)
$A^{p}_{ik(t-1)}$	0.954***		0.900***		0.910***	
	(0.07)		(0.12)		(0.07)	
$A^{p=}_{ik(t-1)}$		0.0144**		0.0141**		0.0101**
		(0.01)		(0.01)		(0.00)
$A^{p\neq}_{ik(t-1)}$		-0.0895		-0.0306		0.0131
		(0.08)		(0.12)		(0.07)
Constant	-5.725***	-5.405***	-6.032***	-5.754***	-5.778***	-5.507***
	(0.29)	(0.30)	(0.51)	(0.54)	(0.26)	(0.27)
Observations	6,462	6,462	6,957	6,957	8,015	8,015
R-squared	0.931	0.922	0.929	0.920	0.932	0.925
Dummy	A-p	A-p	A-p	A-p	A-p	A-p
Cluster	cp-	c-p	c	c	c-p	c-p
Obsolescence	A-p	A-p	A-p	A-p	A	A

Notes: The dependent variable is the adoption of technology k in country i at time t. In rows *Dummy*, *Cluster*, and *Obsolescence*, "A," "p," and "c" denote technology, period, and country, respectively. Robust standard errors in parentheses. *** stands for p<0.01, ** for p<0.05, and * for p<0.1.

Chapter 3

Network Determinants of Mergers and Acquisitions Decisions[1]

[1]This chapter corresponds to an eponym IMF/World Bank mimeo co-written with Tatiana Didier and Sebastián Herrador.

3.1 Introduction

The value of worldwide foreign direct investment (FDI) has increased significantly since the early 1990s, from US$204 billion in 1990 to US$ 1868 billion in 2016[2], with mergers and acquisitions (M&A) representing a large share of total FDI (45 percent in 2016). Many observers view the rising participation of developing countries' economies in global financial flows broadly and FDI, particularly, as a potential driver of these countries' economic growth. FDI flows can not only directly ease financing constraints in recipient economies, but they can also be a major conduit of technology diffusion and learning spillovers.

Indeed, policymakers place attracting FDI high on their agendas. They use incentives such as income tax holidays, tariff exemptions, and subsidies to infrastructure to attract foreign firms[3]. Behind these efforts is the belief that foreign presence benefits the host country by potentially raising aggregate productivity in the economy; introducing advanced technologies (both hard technologies, such as machinery and blueprints, and soft technologies, such as management techniques and information), and fostering positive externalities to local firms through technological diffusion and knowledge spillovers [4].

This chapter makes an in-depth examination of the drivers of FDI, by focusing on cross-border M&A transactions at the sectorial level. We examine the determinants of M&A decisions by building on the gravity model framework. This methodology,

[2]Data from UNCTAD.

[3]According to a census of investment promotion agencies carried out by the World Bank in 2004, 78 of the 110 countries surveyed were offering fiscal or financial concessions to foreign companies that decided to set up production or other facilities within their borders (Harding and Javorcik (2011), Harding and Javorcik (2012)).

[4]Romer (1993) argues that the presence of multinational companies can narrow both the "object gap" (the shortage of physical goods, such as factories and roads) and the "ideas gap" (the shortage of knowledge used to create value added) in developing economies.

commonly used in trade literature, has been used more recently to understand the determinants of cross-border capital flows. We build upon the existing literature by adding a novel aspect to the standard gravity equation. Specifically, we analyze whether the structure of the financial network influences a country's investment decision. In line with the literature on informational barriers, we investigate whether the decision to invest in a certain country depends on the relationship between its financial partners and the targeted country, that is, firms are more likely to invest in countries wherein financial partners have already invested. The motives for foreign investments may vary across sectors. Hence, we separately consider M&As in three different sectors —primary, light manufacturing, and heavy manufacturing. Our study focuses on a large sample of 83 countries, covering more than 94 percent of total flows between 2000 and 2016.

As a first step, we use a logit estimation to provide benchmark results characterizing the drivers of cross-border M&A transactions. However, this methodology is unsuitable for evaluating of potential dependencies among the countries in the network. Indeed, it is likely that M&A decisions between an acquirer and a target are not only dependent on the two countries' characteristics, nor only on the characteristics linking the acquirer with the target with other countries, but also rely on other countries. To account for high degree dependencies, we estimate exponential random graph models (ERGM) for cross-sectional data between 2000 and 2016. We also estimate temporal ERGM models (TERGM) for the 2000-2016 period, though some computational issues arise.

We find that odds of an M&A investment are 4.2 times higher in light manufacturing, 4.5 times higher in the Primary sector, and 6.2 times higher in heavy manufacturing when a partner country has already invested in the new location. These odds are larger than some of the more traditional M&A determinants, such as trade openness.

The remainder of the chapter is organized as follows. Section 3.2 describes the relevant literature. Section 3.3 presents the econometric methodology. Section 3.4 introduces the data and some descriptive statistics. Section 3.5 provides the results. Finally, Section 3.6 summarizes and concludes.

3.2 Literature Review

This section first exposes the traditional determinants of M&A decision and then turns to some elements of network analysis that can be found in the trade and finance literature.

3.2.1 Traditional determinants of M&A investment

A *domestic* M&A typically takes place when the management of a firm perceives the potential gain of acquiring another entity (see for example Jensen and Ruback (1983); Jarrell et al. (1988); Andrade et al. (2001); and Andrade et al. (2001)). These gains can come from production efficiencies such as a reduction in contracting costs across firms. Mergers can be driven by the motive of achieving tax optimization or to gain market power. Furthermore, managers can take value-decreasing acquisitions that increase their individual utility. Research on the determinants of M&As also highlights the importance of intra-industrial flows. Deregulation can also play a role in M&A activity.

Cross-border M&As can be affected by a wider range of factors, in addition to the determinants listed above. For instance, the typical factors used to explain trade in goods can be relevant for cross-border financial investments, such as geographic distance and differences in language, currency[5], legal framework, colonial origin, and time zones. Ahern et al. (2015) argue that these frictions increase the cost associated with cross-border M&As. Information asymmetries can also pose a major obstacle. For instance, an assessment of the valuation of targeted firms can be more difficult for foreign firms. Differences in regulations also impact cross-border M&A decisions; Chari et al. (2009) find that developed-market acquirers benefit more from weaker contracting environments in emerging markets. Additionally, currency fluctuations impact the profitability of investments, independent of firms' fundamentals. Standard gravity model variables will be included in our setup.

Another key factor exposed by Rajan and Zingales (1998) is the importance of the state of development of financial markets. The existence of a well-developed market represents a source of comparative advantage for a country in industries that are more dependent on external finance; conversely, the costs imposed by a lack of financial development can impede the development of a new sector. Therefore, the level of financial development impacts not only the amount of inflow but also determines the developments of certain sectors and its concentration. We will consider the sector in which investment are realized.

There has been a growing interest in understanding the role of trade in goods as a determinant of financial flows. The classic Heckscher-Ohlin-Mundell paradigm predicts that trade is an important factor in international capital flows. It argues that exports are based on endowments —advanced economies export capital. Additionally, the paradigm states that and trade and capital flows are substitutes. Countries invest in locations to which they cannot export their goods, thereby gaining access to their

[5] De Sousa and Lochard (2011) find that the Economic and Monetary Union (EMU) has increased intra-EMU FDI stocks on average by around 30 percent.

domestic markets. Consequently, trade integration reduces incentives for capital to flow to capital-scarce countries.

Recent theoretical work on international investment argues that trade and capital flows can be complements rather than substitutes and that the emerging economies export capital to advanced economies (Antras and Caballero (2009); Ju and Wei (2011); Jin (2012)). A part of these effects may be rooted in firm-level motives to export and invest abroad (Greenaway and Kneller (2007); Alfaro and Charlton (2009)). Empirically, De la Torre et al. (2015) use a cross-country sectoral gravity framework to examine the influence of trade in the decision of financial investment. Particularly, the authors include measures of comparative advantage on traded goods for source and receiver countries as dependent variables on a gravity equation for FDI. They find that advanced economies tend to invest more in sectors wherein the receiver has a comparative advantage, while the emerging and developing markets invest more in countries wherein the receiver has a disadvantage. We integrate comparative advantages of trade into the M&A determinants.

3.2.2 Network determinants of M&A decision

The core of this chapter digs into the importance of the information barrier at the time of investing in a new country. This chapter shares with Chaney (2014) the notion of information as the key friction in international relationships. As per Chaney (2014), if a certain firm exports to country a in year t, then it is more likely to enter in year $t + 1$ into a country b geographically close to a, even if b is not close to the firm. The possibility to use existing contacts to find new ones gives an advantage to firms with many contacts. This generates a fat-tailed distribution for the number of foreign contacts across firms. We apply a similar reasoning to understand factors driving a new oversea M&A investment —if a country had invested in country a in year t, then it is more likely to invest for the first time in country b in year $t+1$, if a had already invested in b.

Empirical work including third-country effect on FDI decision is sparse. The "export-platform" literature (Ekholm et al. (2007), Yeaple (2003), Bergstrand and Egger (2007)) is close to our work. Export-platform refers to a situation wherein a parent country invests in a particular host country with the intention of serving "third" markets with exports of final goods from the affiliate companies in the host country.

Head et al. (1995) use a conditional logit estimate to examine the choice of location of 751 Japanese manufacturing plants built in the US, including a specific variable for interdependence of the location decision across all possible locations. Their estimates support the hypothesis that industry-level agglomeration benefits play an important role in the location decision. Using a sample of Japanese firms' choices of regions within European countries, Head and Mayer (2004) show that not only the potential of the host market but also the potential of markets in adjacent regions holds significance in determining location choice.

While Head et al. (1995) and Head and Mayer (2004) use a discrete choice model to assess the importance of third-country effect, such a framework imposes the independence of all the alternatives. Blonigen et al. (2007) allow a more general setup using spatial econometrics. Their study finds suggestive evidence of export-platform FDI for most industries within the developed European countries.

To estimate the network impact, we need to estimate the determinants at the country, dyad, and network levels simultaneously; this estimation is not possible with the gravity framework. Unlike the spatial model of Blonigen et al. (2007), we use an ERGM that considers the network as a conditional factor on a series of predictor terms (Erdös and Rényi (1959); Frank and Strauss (1986); Hunter and Handcock (2006)). We also use the temporal extension of the ERGM —the discrete TERGM —to analyze the dynamics of the networks (Krivitsky and Butts (2013); Krivitsky and Handcock (2014)). We focus on extra-dyadic interdependencies that arise from an "alliance" network (Cranmer et al. (2012)). When making a decision concerning oversees M&As, firms are likely to consider not only the characteristics of their targeted country (e.g., population and area) or its relationship with them (e.g., size of the bilateral trade, border effects, and potential information asymmetries) but also what happens in other "alliances." To the best of our knowledge, the contemporaneous project of Herman (2017) is the only other paper using ERGM in international economics. Herman (2017) reestimates the traditional trade gravity model, by integrating network variables in a probit model of trade incidence and in an ERGM. He concludes that both modelizations represent a better modeling environment than the classical gravity model.

3.3 Methodology

In lieu of the traditional setup, ERGM and TERGM allow the examination of higher level dependencies in an M&A network. The observed M&A network is considered one of the many networks that had the potential to realize. It represents a realization of a random draw from a distribution of all the possible M&A networks. Statistical inferences will give information on the determinant of the realized network.

3.3.1 Exponential random graph model

To estimate the impact of the network on an M&A decision, we use an ERGM. ERGMs are a general class of models based in exponential-family theory that specify the probability distribution of random networks. Through ERGM, it is possible to identify factors that maximize the probability of the emergence of a network with similar properties as the structure of the observed network.

In an ERGM, the probability to observe a network g depends on an associated vector of statistics $S(g)$ that might include, for instance, the density of the network, number of mutual links, or number of triangles. The general form of the probability of realization of a network is the following:

$$P_\beta(Y = y|\beta) = \frac{exp(\beta.S(y))}{\sum exp(\beta'.S(y'))} \tag{3.1}$$

where Y is the random variable for the state of the network (with realization y), β is a vector of model parameters, $S(y)$ the vector of model statistics for network y, $exp(\beta.S(y))$ the probability of observing y, and the denominator $\sum exp(\beta'.S(y'))$ is the sum of all other possible networks. The value of β should be interpreted as the log-odds impact of the variable on the appearance of a tie between two countries.

There are two main challenges in estimating ERGMs. The first is a computational one. To estimate the likelihood of a given network, we need to estimate the likelihood of other networks as well (denominator in the probability equation). Estimating the universe of all other networks challenges the current computational possibility, as the number of possible networks grows exponentially with the number of nodes. To deal with this issue, we use the Markov Chain Monte Carlo (MCMC) sampling techniques to draw networks and estimate ERGMs (Snijders (2002); Handcock et al. (2003)). MCMC is based on the generation of a distribution of random graphs by stochastic simulation from a starting set of parameters, which are refined through comparison with the observed graph across iterations. The process ends once the parameters are stabilized. However, reaching convergence remains an issue for many ERGM specifications (Handcock et al. (2003); Hunter et al. (2008)).

The second challenge is in the consistency of the estimates. At the difference, with standard models, increasing the number of observations in an ERGM is not necessarily associated with an increase in the accuracy of the results. Following Jackson (2010), a necessary condition for consistency is the "non-conflicted" condition. In some small neighborhoods, the expected value of statistics must be unconstrained, that is, each realization must be jointly feasible. To respect this condition, we exclude and isolate a node from our sample. A first sufficient condition is that different parameters must distinguish themselves with different expected statistics. This is a minimal condition, because if two parameters generate too similar outputs, the realized statistics do not allow to distinguish between them. The second sufficient condition is that statistics must be appropriately normalized and concentrate around their means. If this condition is not realized, observing the statistics would not allow us to back out to a parameter.

To assess the accuracy of our prediction, we compare the structures of the simulated network and the observed network. Following Hunter et al. (2008), we compare the goodness of fit of the degree distribution, distribution of edgewise shared partners, and geodesic distribution. The closer is the simulated distribution of the observed network, the more accurate and reliable is the estimation.

3.3.2 Temporal exponential random graph model

To transition to a TERGM, we need to add a matrix to account for the dynamic. To model the transition from network Y^t at time t to a network $Y^(t+1)$ at time $t+1$, we assume a separable TERGM. The formation and dissolution of ties occur independently from each other within each time step. Both the formation and dissolution processes are modeled as separate ERGMs.

Let us define Y^+ as the formation network generated as an ERGM. Formally,

$$P_\beta(Y^+ = y^+|Y^t;\beta^+) = \frac{exp(\beta^+.S(y^+))}{\sum exp(\beta^{+\prime}.S(y^{+\prime}))} \tag{3.2}$$

Dissolution network Y^- is generated simultaneously. Thus, formally,

$$P_\beta(Y^- = y^-|Y^t;\beta^-) = \frac{exp(\beta^-.S(y^-))}{\sum exp(\beta^{-\prime}.S(y^{-\prime}))} \tag{3.3}$$

The cross-sectional network at time $t+1$ is constructed by applying change Y^+ and Y^- to y^t. Formally,

$$Y^{t+1} = Y^t \mp (Y^+ - Y^t) - (Y^t - Y^-) \tag{3.4}$$

3.3.3 Obtaining convergence

One challenge faced in using ERGM and TERGM estimations is the difficulty to reach convergence. The following are ways to obtain converging results:

- We constrain the set of possible networks to those with the same number of edges as the observed network. This restriction ensures that only reasonable networks are used in the estimation. This eliminates unrealistic networks in which there are no ties or all nodes are connected. The coefficient of bilateral trade is then interpreted as the estimation of which countries invest in M&As, given a fixed prevalence of ties.

- We binarized the matrix of M&A flows and use a dummy for High Income countries instead of their GDPs.

- Using the IMF classification, we limit the set of nodes to high income and emerging/developing countries, and exclude low income economies. The sample is reduced to 83 countries, representing nevertheless more than 94 percent of global flows (see Figure 3.2 and Annex 3.A).

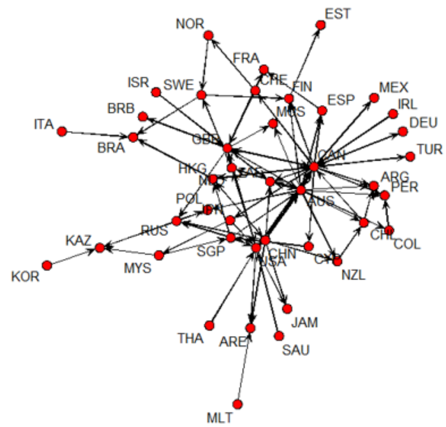
3.4 Data and descriptive statistics

We analyze the cross-border decisions of M&A investment. We choose M&A investments for two reasons: 1) M&As are long-term investments, as they mean that the acquirer takes “control of assets and operations” (UNCTAD 2000). 2) The quality of data is generally better than for other investments.

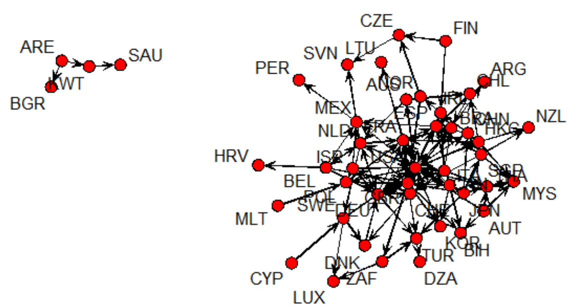
Data on M&As are taken from the Thompson Reuter's Security Data Corporation Platinum database for operations realized between 2000 and 2016. We aggregate the data by country and obtain a bilateral database at the country level. Sectors of investment are classified using the 4-digit Standard Industrial Classification (SIC). Using network analysis terminologies, countries are represented by nodes, and M&A outflows are represented by direct ties linking a pair of nodes. The network is binarized. Moreover, we distinguish three types of investments: in the primary sector (including agriculture, mining, and oil), in the light manufacturing sector (including food, textiles, and wood), and in the heavy manufacturing sector (including chemicals, metals, machinery, and equipment). We construct one network by sector and by year (Figure 3.1).

Figure 3.1: M&A investment network by sector in 2016

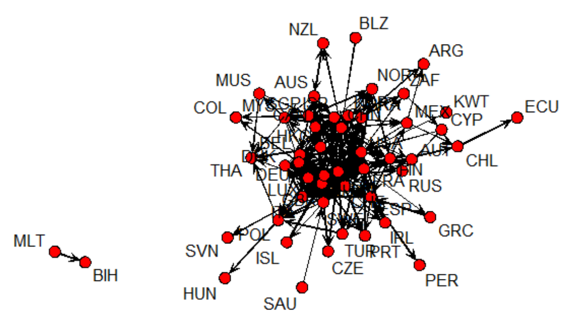
(a) Primary sector



(b) Light manufacturing

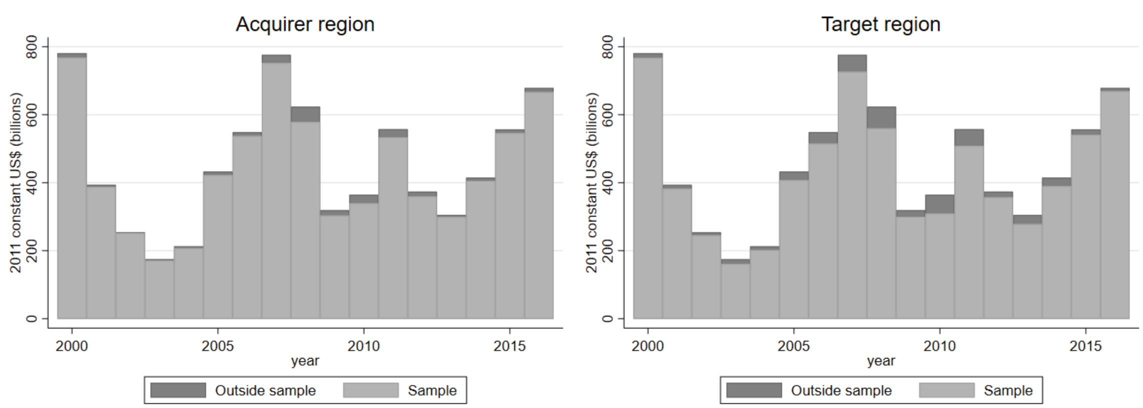


(c) Heavy manufacturing



Source: Thompson Reuter's Security Data Corporation Platinum database and author's calculations.

Figure 3.2: M&A investments sample



Source: Thompson Reuter's Security Data Corporation Platinum database.

3.4.1 Dyad level variables

In recent M&A literature, trade is an essential determinant. In this study, we use the concept of net relative comparative advantage (NRCA) constructed following Vollrath (1991) to understand the impact of trade on investment[6]. Formally,

$$RCA_{i,j,t} = ln \left\{ \frac{X_{i,j,t} / \left(\sum_{\forall j} X_{i,j,t} - X_{i,j,t} \right)}{\frac{\left(\sum_{\forall i} X_{i,j,t} - X_{i,j,t} \right)}{\left[\left(\sum_{\forall i,j} X_{i,j,t} - \sum_{\forall j} X_{i,j,t} \right) - \left(\sum_{\forall i} X_{i,j,t} - X_{i,j,t} \right) \right]}} \right\} \tag{3.5}$$

where $X_(i, j, t)$ refers to the exports of country i in industry j in period t. The dependent variable is specified as $log(1 + flows)$ in order to explicitly account for the large number of observations equal to zero. All regressions control for both fixed source and host-country effects.

We calculate the NRCA at the bilateral level for each sector and year based on bilateral exports from UN Comtrade/World Integrated Trade Solution. The dataset covers the period from 2003 to 2012 for 205 source and recipient countries. We aggregate the database to the bilateral country level using the 4-digit Standard International Trade Classification (SITC). SITC and SIC (for M&A classification) are not directly comparable: SITC is a classification of goods, while SIC is a classification of industries. Thus, we use Eurostat's conversion tables to obtain each SITC code associated with the 4-digit SIC codes. We then aggregate the data in the three aggregate sectors.

[6]Unlike the traditional definition of relative comparative advantage, Vollrath (1991)'s equation considers the market share of exporters.

In our analysis, we control for an exogenous variable that could impact M&A investment. The control variables are both node-specific and dyadic-specific, and they are adapted to finance from the literature on gravity models. The controls variables are obtained from the GeoDist database of Centre d'Etudes Prospectives et d'Informations Internationales, The World Factbook of the Central Intelligence Agency, and World Development Indicators by the World Bank. We include trade openness as the sum of exports and imports. We also include distance, longitude, and latitude (all in km). We control based on differences in time zones (in hours) as they may impact financial transactions. Finally, we consider the common language, common legal origin, and colonial history.

3.4.2 Network level variables

We include two variables at the structural network level. First, we include the edges that corresponds to the number of links in the network. They can be interpreted as intercept parameters in a bilateral framework and are required in ERGM configuration (Snijders et al. (2006); Hunter (2007)).

Second, we include a measure of transitivity to represent the shared partner distribution (Hunter and Handcock (2006); Hunter (2007)). This term adds one network statistic to the model equal to the geometrically weighted edgewise shared partner (GWESP) distribution with weight parameter alpha. It measures how frequently two nodes are connected by a link as well as by an indirect connection of length 2. The significant and positive GWESP coefficient points to transitivity in the network that is beyond the transitivity that may be explained solely by nodal characteristics. This suggests that countries prefer to realize an M&A with countries that are also connected to one another.

3.5 Results

This section empirically estimates the determinants of M&A investments, by testing the trade openness variable and gravity variables in a logit regression before estimating the potential impact of network variables with the ERGM and TERGM procedures.

3.5.1 Logit estimations

The regressions in Table 3.1 explore in more detail the relationship between M&A and trade flows at the country-pair level using logit estimates[7]. Particularly, the regressions link M&A flows with the comparative advantages of the source and receiving countries for each of the following three sectors: primary, light manufacturing, and heavy manufacturing. The regressions also include gravity controls. The first three columns refer to a cross-country regression for 2016, while columns (4) to (6) estimate a cross-country panel extending from 2000 to 2016.

The first pattern that emerges from Table 3.1 is that, even after controlling with gravity variables for common factors that can jointly drive trade and lending decisions, high-income countries tend to invest more in any of the three sector. The high-income variable is set as a proxy for the GDP acquirer because the usage of a continuous variable of GDP prevents convergence in ERGM/TERGM estimations. The countries that are more open also tend to invest more (measured as the sum of exports and imports). In 2016, an increase in one unit of the log of trade openness variable (about 2.8 percentage points increase in trade openness) was associated with a higher probability of an M&A transaction of 0.7 percent in the primary sector, 0.8 in the light manufacturing sector and 0.9 percent in the heavy manufacturing sector.

[7]This procedure is not considered standard in existing literature; M&A is usually estimated with a two-step probit, such as in Di Giovanni (2005), or by using Poisson pseudo-maximum-likelihood (PPML), such as in De la Torre et al. (2015). However, due to computational limitation, the ERGM can currently be run only on the binarized matrix. To facilitate the analysis of the additional effect of network measures, we use a logit procedure as a first step.

Table 3.1: Estimations of M&A determinants using Logit estimates

	2016			**2000-2016**		
	Primary	Light Manuf.	Heavy Manuf.	Primary	Light Manuf.	Heavy Manuf.
	(1)	(2)	(3)	(4)	(5)	(6)
Trade Openness$_i$	0.718***	0.766***	0.885***	0.898***	0.806***	0.946***
	(0.11)	(0.09)	(0.09)	(0.06)	(0.04)	(0.04)
High Income$_i$	0.859**	0.885***	0.758***	1.166***	1.137***	1.425***
	(0.34)	(0.27)	(0.20)	(0.17)	(0.13)	(0.12)
Net RCA$_{ik}$	0.211***	-0.166	-0.351***	0.0873***	0.0667	-0.0743*
	(0.06)	(0.11)	(0.12)	(0.03)	(0.05)	(0.04)
Net RCA$_{jk}$	0.169***	0.383***	0.669***	0.0598***	0.368***	0.790***
	(0.05)	(0.09)	(0.08)	(0.02)	(0.04)	(0.04)
Time difference	0.0883**	-0.0486	0.00255	0.0215	-0.0912***	-0.0437***
	(0.04)	(0.04)	(0.02)	(0.02) (0.02)	(0.02)	
Common language	0.814**	0.892***	0.586**	0.991***	0.820***	0.762***
	(0.34)	(0.30)	(0.30)	(0.27)	(0.21)	(0.22)
Colonial relationship	0.452	0.0638	0.600**	0.807**	0.538**	0.582**
	(0.38)	(0.38)	(0.29)	(0.32)	(0.23)	(0.24)
Currency union	-1.133	-1.395***	-0.192	-1.386***	-0.637***	-0.699***
	(0.79)	(0.49)	(0.28)	(0.35)	(0.21)	(0.19))
Difference in latitude	-0.00809	-0.0163***	-0.0144***	-0.000589	-0.0144***	-0.0115***
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Common legal origin	1.082***	1.171***	1.063***	1.803***	1.956***	1.826***
	(0.29)	(0.24)	(0.19)	(0.20)	(0.13)	(0.13)
Common border	1.612***	1.222***	0.871***	1.895***	1.569***	1.591***
	(0.43)	(0.33)	(0.28)	(0.28)	(0.19)	(0.20)
Constant	-18.93***	-18.82***	-20.39***	-25.32***	-21.07***	-23.26***
	(1.97)	(1.70)	(1.71)	(1.22)	(0.86)	(0.86)
Observations	6,806	6,806	6,806	115,702	115,702	115,702
N. of countries	83	83	83	83	83	83
R-squared	0.2494	0.2558	0.2868	-	-	-
Cluster error	acq-tgt	acq-tgt	acq-tgt	acq-tgt	acq-tgt	acq-tgt

Note: This table explores the relation between M&A flows and trade flows using sector-level data. The dependent variable is dummy variable equals to one when the M&A flow between two countries is positive, and zero otherwise. Total trade is measured as the sum of exports and imports. Relative comparative advantage (RCA) is based on Vollrath (1991). All regressions include gravity control variables that help explain levels of M&A flows between each country pair based on the differences in latitude between countries, differences in time zones, whether they share a common language, whether they have a common legal origin, and whether the receiver (sender) country is (or was) a colony of the sender (receiver). The regressions also control for source- and target-country dummies. The sample includes 83 countries. Standard errors are clustered by country pairs. Sources: Calculations based on data from SDC Platinum and Comtrade.

In all the three sectors, there is a positive relationship between the relative comparative advantage (RCA) of the receiver country and M&As. Countries tend to invest in places with a comparative advantage in the sector they target, thereby securing their provision. This is true for all the sectors, as observed in 2016 and from 2000 to 2016. The evidence is different with respect to the net comparative advantage of the acquirer. Countries with a net comparative advantage in the primary sector tend to invest abroad, while countries with a comparative disadvantage tend to invest in the heavy manufacturing sector of foreign countries. There is no statistical evidence regarding light manufacturing.

At a few exceptions, gravity variables tend to have the expected sign and are statistically significant. Coefficients associated with common languages, colonial relationship, common legal origin, and common border are positive and most of the time statistically significant; coefficients associated with a difference in latitude are negative and statistically significant for the regression where the dependent variable is M&A in the light and heavy manufacturing sectors. The time difference is negative and statistically significant for the light and heavy manufacturing sectors between 2000 and 2016. Otherwise, it is found to be not statistically significant. The negative sign associated with the currency union is unexpected and would require more research.

3.5.2 ERGM estimations

The regressions in Table 3.2 build on the first three columns of Table 3.1 by introducing a network element to the regression and using the ERGM estimation methodology. Results in the ERGM reproduces remarkably well the variables estimated with the logit, both in terms of sign and magnitude.

As for the logit results, even after controlling with gravity variables for common factors that can jointly drive trade and lending decisions, countries tend to invest more in partners with which they have larger trade flows. There is also no statistically significant relationship between the net RCA of source countries and M&A flows, but countries are more likely to invest in countries with a positive net RCA in the heavy manufacturing sector. Results from gravity variables are generally less statistically significant in the ERGM regression when compared to the logit estimation.

Table 3.2: Estimations of M&A determinants using the Exponential Random Graph Model

	2016					
	Primary		Light Manuf.		Heavy Manuf.	
	(1)		(2)		(3)	
GWESP	1.54816	***	1.42276	***	1.82064	***
	0.1811		0.16098		0.17403	
High Income$_i$	0.52982	*	0.67606	*	0.30705	
	0.26591		0.27645		0.19755	
Trade Openness$_i$	0.53991	***	0.53595	***	0.49849	***
	0.08548		0.08006		0.06181	
Net RCA$_{ik}$	0.539	*	0.04858		-0.25272	
	0.21846		0.20151		0.17596	
Net RCA$_{jk}$	0.52178	**	-0.14125		0.50105	***
	0.20173		0.1801		0.13176	
Time difference	0.32651		-0.5492	*	-0.34946	*
	0.38793		0.25096		0.16763	
Common language	0.34351		0.40806		0.11493	
	0.27177		0.28297		0.23589	
Colonial relationship	0.42955		-0.0444		0.49192	
	0.33883		0.37301		0.26584	
Currency union	-0.79079		-1.50295	**	-0.17421	
	0.71188		0.57842		0.25978	
Difference in latitude	0.12954		0.85063		0.1356	
	0.89068		0.86323		0.5868	
Common legal origin	0.85866	***	0.84151	***	0.72245	***
	0.22756		0.20362		0.16275	
Common border	1.72408	***	1.32523	***	0.83294	**
	0.3897		0.36213		0.29289	
Edges	-16.7497	***	-15.9279	***	-14.5744	***
	1.97473		1.87308		1.37028	
Observations	6,806		6,806		6,806	
N. of countries	83		83		83	
Triangles	80		147		940	
AIC criteria	684.6		915.3		1410	
BIC criteria	773.9		1005		1499	

Note: This table explores the relation between M&A flows, trade flows, and network variable using sector-level data. The dependent variable is the M&A flow between two countries. Total trade is measured as the sum of exports and imports. The GWESP indicator stands for geometrically weighted edgewise shared partner distribution and measures the likeliness of a common receiver country for two countries linked with an M&A. Relative comparative advantage (RCA) is based on Vollrath (1991). All regressions include gravity control variables that help explain levels of M&A flows between each country pair based on the differences in latitude between countries, differences in time zones, whether they share a common language, whether they have a common legal origin, and whether the receiver (sender) country is (or was) a colony of the sender (receiver). The sample includes 83 countries. Sources: Calculations based on data from SDC Platinum and Comtrade.

The transitivity variable GWESP measures the influence of a third country in one country's decision to ivest in another country. Precisely, it depicts the likeliness of a country to invest in a destination where one of its financial partners has already invested. This variable is positive and statistically significant for the three sectors, confirming the influence of the network effect on the decision to invest. The odds of an M&A investment are 4.2 times higher in light manufacturing sector, 4.5 times higher in the primary sector, and 6.2 times higher in heavy manufacturing sector in the presence of a triangle. These results are stable over the years, as it can be seen in Annex 3.6, 3.7, and 3.8, which displays the ERGM estimations for every year between 2000 and 2016 for the three sectors.

Annex 3.B presents the goodness-of-fit statistics and horizontal parameter traces for each sectoral regression. The goodness-of-fit compares the parameters predicted by the model with the observed network. Both statistics are closed and the model appears to be a good fit for all the three sectors. Additionally, the trace of the simulated parameter values is relatively stable and these values vary around the mean over the course of the iteration.

3.5.3 TERGM estimations

Computational limitations do not allow the use of all the gravity variables characterizing the relationship between dyads with the TERGM. Nevertheless, we decided to present the results of those regressions, acknowledging the limitation of their interpretation.

The regressions in Table 3.3 build on the last three columns of Table 3.1 by introducing a network element to the regression using the TERGM estimation. As in Table 3.1, the TERGM regression concludes that countries tend to invest more in partners with whom they have larger trade flows, for any sectors. The net RCA of recipient countries are statistically significant for the primary and heavy manufacturing sectors. The variable GWESP is positive and statistically significant in all three sectors, confirming the influence of the network effect on the decision to invest.

Table 3.3: Estimations of M&A determinants using the Temporal Exponential Random Graph Model

	2000-2016					
	Primary		Light Manuf.		Heavy Manuf.	
	(1)		(2)		(3)	
GWESP	1.5142	***	1.28036	***	1.59194	***
	0.1419		0.11597		0.1356	
Trade openness	0.6004	***	0.45575	***	0.26573	***
	0.0815		0.06132		0.04348	
Net RCA of source country	0.571	**	0.09198		0.23558	
	0.208		0.16153		0.1394	
Net RCA of receiver country	0.4607	*	0.30831		0.64273	***
	0.1888		0.16364		0.12648	
Edges	-12.9352	***	-10.63254	***	-8.31684	***
	1.0514		0.77644		0.48243	
Observations	115,702		115,702		115,702	
N. of countries	83		83		83	
Triangles	3535		2347		18093	
AIC criteria	-19195		-18842		-18290	
BIC criteria	-19158		-18804		-18252	

Note: This table explores the relation between M&A flows, trade flows, and network variables using sector-level data. The dependent variable is the M&A flow between two countries. Total trade is measured as the sum of exports and imports. The GWESP indicator stands for geometrically weighted edgewise shared partner distribution and measures the likeliness of a common receiver country for two countries linked with an M&A. Relative comparative advantage (RCA) is based on Vollrath (1991). The sample includes 83 countries. Sources: Calculations based on data from SDC Platinum and Comtrade.

Annex 3.C presents the goodness-of-fit statistics and horizontal parameter traces for each sectoral regression.

3.6 Concluding remarks

Building on bilateral estimates of M&A determinants, the addition of a shared partner variable in a network estimate framework provides meaningful insights regarding the determinants of decisions about M&A investments. From our results, we conclude that M&A decisions depend on trade openness and the traditional gravity variable. Moreover, an M&A is more probable in a country displaying a positive net RCA. Finally, an investment is more likely if a financial partner of the country has already invested in the target location.

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Appendix 3.A Sample and descriptive statistics

3.A.1 Country sample

Algeria
Antigua & Barbuda
Argentina
Australia
Austria
Azerbaijan
Bahamas, The
Barbados
Belgium
Belize
Bosnia & Herzegovina
Botswana
Brazil
Brunei
Bulgaria
Canada
Chile
China
Colombia
Costa Rica
Croatia
Cyprus
Czech Rep.
Denmark
Dominican Rep.
Ecuador
Estonia
Fiji
Finland
France
Macedonia
Gabon
Germany
Greece
Guyana
Hong Kong SAR
Hungary
Iceland
Iran
Iraq
Ireland
Israel
Italy
Jamaica
Japan
Kazakhstan
Korea
Kuwait
Latvia
Lebanon
Lithuania
Luxembourg
Malaysia
Malta
Mauritius
Mexico
Namibia
Netherlands
New Zealand
Norway
Panama
Peru
Poland
Portugal
Russia
Saudi Arabia
Seychelles
Singapore
Slovak Rep.
Slovenia
South Africa
Spain
St. Kit. & Nev.
St. Lucia
Sweden
Switzerland
Thailand
Trin. & Tob.
Turkey
UAE
United Kingdom
United States
Uruguay

3.A.2 Descriptive statistics

Table 3.4: Descriptive statistics for 2016

Primary

	Obs.	Mean	Std. Dev.	Min	Max
Mergers and Acquisitions	6,806	0.01	0.11	0	1.00
High income	6,806	0.42	0.49	0	1.00
Trade openness (in logs)	6,806	17.82	2.11	12.42	21.72
Net RCA of source country	6,806	-0.86	2.34	-9.53	6.85
Net RCA of receiver country	6,396	-0.87	2.34	-10.64	6.85
Time difference	6,806	4.69	3.82	0	18
Common language	6,806	0.07	0.26	0	1
Colonial relationship	6,806	0.02	0.14	0	1
Currency union	6,806	0.04	0.19	0	1
Difference in latitude	6,806	30.26	23.60	0	105
Common legal origin	6,806	0.06	0.24	0	1
Common border	6,806	0.03	0.16	0	1

Light Manufacturing

		Mean	Std. Dev.	Min	Max
Mergers and Acquisitions	6,806	0.02	0.14	0	1.00
High income	6,806	0.42	0.49	0	1.00
Trade openness (in logs)	6,806	17.82	2.11	12.42	21.72
Net RCA of source country	6,806	-0.52	1.13	-7.04	1.66
Net RCA of receiver country	6,396	-0.52	1.13	-7.04	1.91
Time difference	6,806	4.69	3.82	0	18
Common language	6,806	0.07	0.26	0	1
Colonial relationship	6,806	0.02	0.14	0	1
Currency union	6,806	0.04	0.19	0	1
Difference in latitude	6,806	30.26	23.60	0	105
Common legal origin	6,806	0.06	0.24	0	1
Common border	6,806	0.03	0.16	0	1

Heavy Manufacturing

	Obs.	Mean	Std. Dev.	Min	Max
Mergers and Acquisitions	6,806	0.04	0.19	0	1.00
High income	6,806	0.42	0.49	0	1.00
Trade openness (in logs)	6,806	17.82	2.11	12.42	21.72
Net RCA of source country	6,806	-0.98	1.31	-6.65	4.83
Net RCA of receiver country	6,396	-0.98	1.31	-6.65	4.83
Time difference	6,806	4.69	3.82	0	18
Common language	6,806	0.07	0.26	0	1
Colonial relationship	6,806	0.02	0.14	0	1
Currency union	6,806	0.04	0.19	0	1
Difference in latitude	6,806	30.26	23.60	0	105
Common legal origin	6,806	0.06	0.24	0	1
Common border	6,806	0.03	0.16	0	1

Table 3.5: Descriptive statistics for 2000-2016

Primary

	Obs.	Mean	Std. Dev.	Min	Max
Mergers and Acquisitions	115,702	0.02	0.13	0	1.00
High income	115,702	0.42	0.49	0	1.00
Trade openness (in logs)	115,702	12.26	3.80	4.85	21.82
Net RCA of source country	115,702	-0.35	2.51	-13.48	15.72
Net RCA of receiver country	115,702	-0.35	2.51	-13.48	15.72
Time difference	115,702	4.69	3.82	0	18
Common language	115,702	0.07	0.26	0	1
Colonial relationship	115,702	0.02	0.14	0	1
Currency union	115,702	0.04	0.19	0	1
Difference in latitude	115,702	30.26	23.59	0	105
Common legal origin	115,702	0.06	0.24	0	1
Common border	115,702	0.03	0.16	0	1

Light Manufacturing

		Mean	Std. Dev.	Min	Max
Mergers and Acquisitions	115,702	0.02	0.14	0	1.00
High income	115,702	0.42	0.49	0	1.00
Trade openness (in logs)	115,702	12.26	3.80	4.85	21.82
Net RCA of source country	115,702	-0.51	1.40	-11.28	3.59
Net RCA of receiver country	115,702	-0.51	1.40	-11.28	3.59
Time difference	115,702	4.69	3.82	0	18
Common language	115,702	0.07	0.26	0	1
Colonial relationship	115,702	0.02	0.14	0	1
Currency union	115,702	0.04	0.19	0	1
Difference in latitude	115,702	30.26	23.59	0	105
Common legal origin	115,702	0.06	0.24	0	1
Common border	115,702	0.03	0.16	0	1

Heavy Manufacturing

	Obs.	Mean	Std. Dev.	Min	Max
Mergers and Acquisitions	115,702	0.04	0.19	0	1.00
High income	115,702	0.42	0.49	0	1.00
Trade openness (in logs)	115,702	12.26	3.80	4.85	21.82
Net RCA of source country	115,702	-1.26	1.63	-11.78	4.86
Net RCA of receiver country	115,702	-1.26	1.63	-11.78	4.86
Time difference	115,702	4.69	3.82	0	18
Common language	115,702	0.07	0.26	0	1
Colonial relationship	115,702	0.02	0.14	0	1
Currency union	115,702	0.04	0.19	0	1
Difference in latitude	115,702	30.26	23.59	0	105
Common legal origin	115,702	0.06	0.24	0	1
Common border	115,702	0.03	0.16	0	1

Appendix 3.B Goodness of fit for ERGM results

After running the ERGM, we estimate the goodness-of-fit and trace the MCMC plots of the statistically significant variables.

Figure 3.3: Primary sector

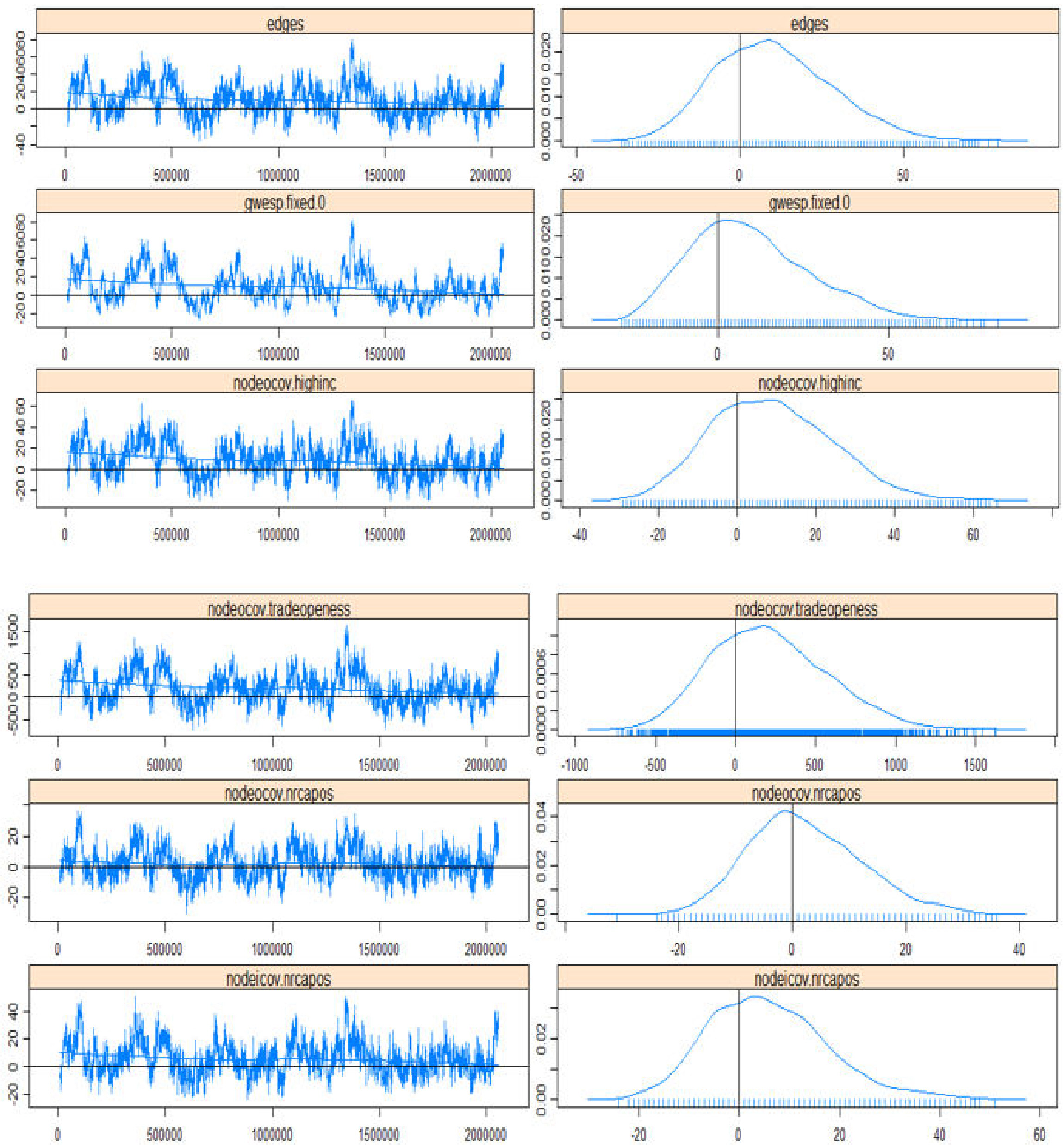


Figure 3.4: Light manufacturing

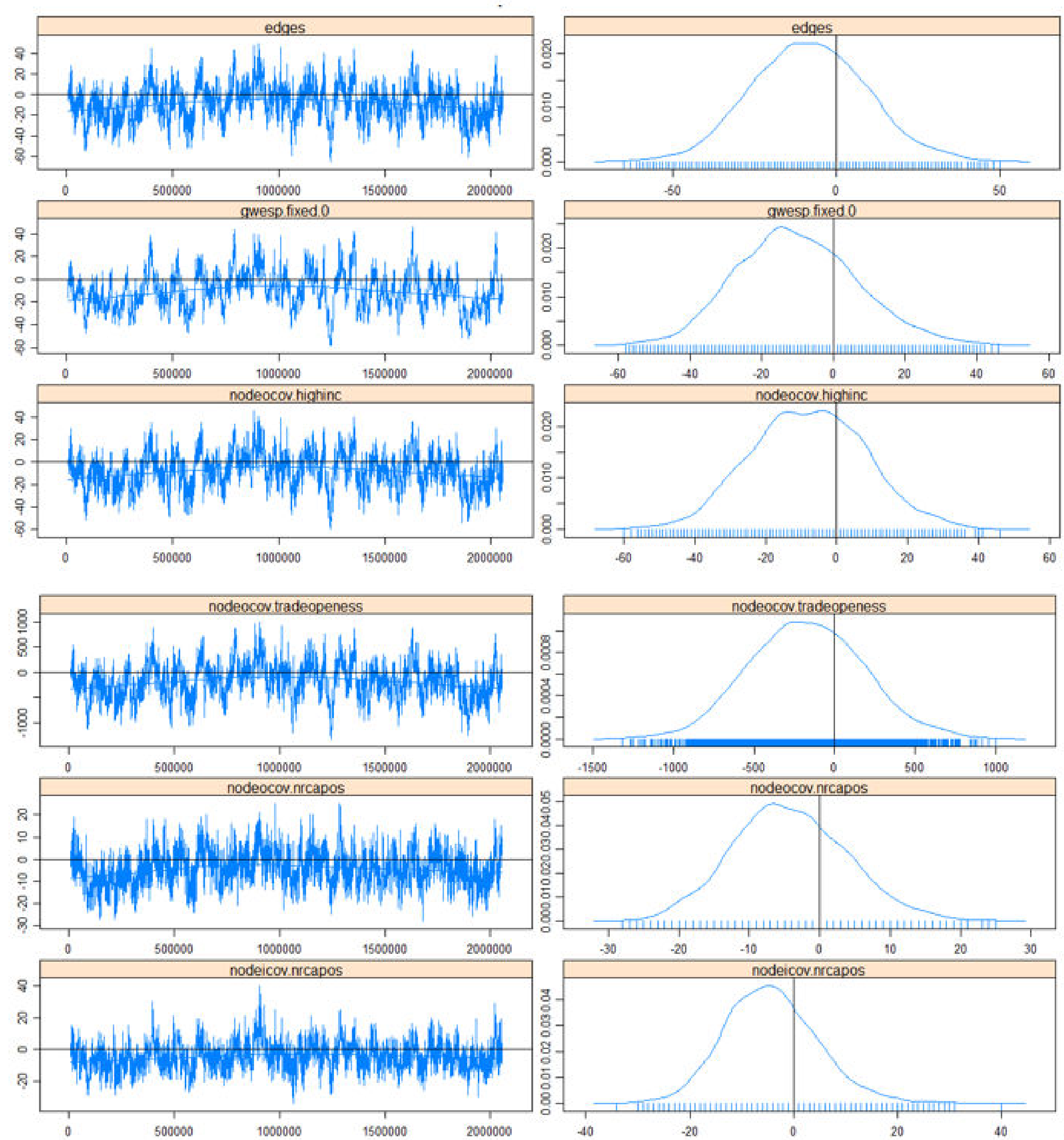


Figure 3.5: Heavy manufacturing

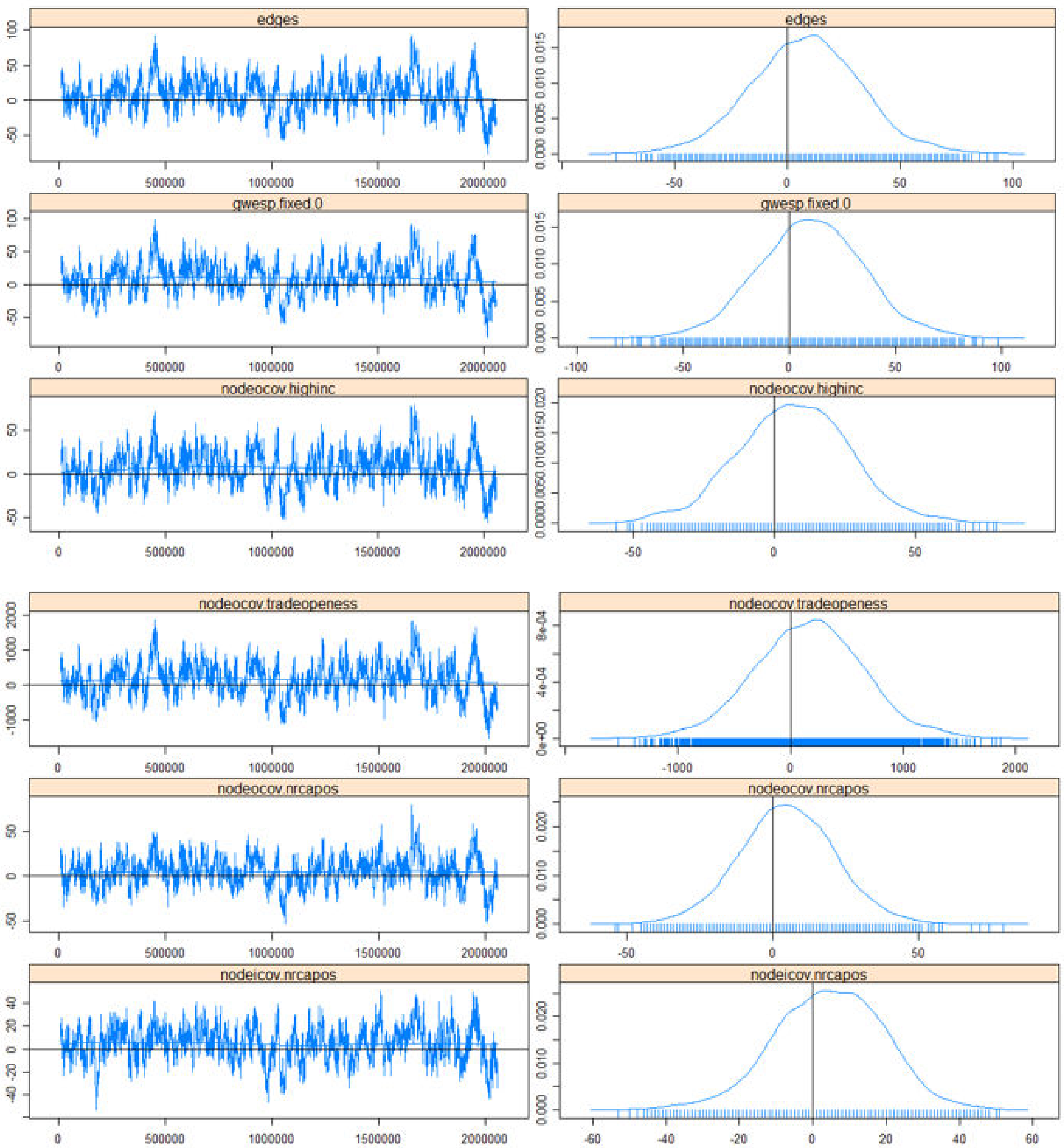


Table 3.6: Estimation of M&A in Primary sector determinants using ERGM procedure

	2000•	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013•	2014	2015•	2016
GWESP	1.532	1.68 ***	2.1 ***	1.42 ***	1.97 ***	2.11 ***	2.13 ***	1.76 ***	2.01 ***	1.81 ***	1.88 ***	1.89 ***	1.73 ***	1.77	1.46 ***	1.91	1.6 ***
High Income$_i$	1.531	1.05 *	0.8 *	0.9 **	0.56 *	0.52 *	0.62 **	0.7 ***	0.63 ***	0.7 ***	0.65 ***	0.49 **	0.63 **	0.73	0.47 *	0.69	0.52
Trade Openness$_i$	0.593	0.65 ***	0.56 ***	0.75 ***	0.82 ***	0.46 ***	0.44 ***	0.53 ***	0.35 ***	0.43 ***	0.45 ***	0.46 ***	0.5 ***	0.47	0.55 ***	0.34	0.54 ***
Net RCA$_{ik}$	0.506	0.87 **	0.62 **	1.25 ***	1.35 ***	0.38	0.56 **	0.77 ***	0.39 *	0.53 **	0.44 *	0.47 **	0.5 *	0.29	0.33	0.31	0.51 *
Net RCA$_{jk}$	0.824	0.78 ***	1 ***	0.87 ***	0.71 **	0.45 *	0.39 *	0.57 ***	0.54 ***	0.47 **	0.6 ***	0.55 ***	0.55 ***	0.77	0.62 ***	0.49	0.51 *
Time difference	-0.644	-0.5	-0.28	-0.27	-0.36	0.14	-0.08	0.04	-0.28	0.03	0.63	0.59	0.02	0.69	0.23	0.9	0.32
Common language	0.085	0.26	-0.07	0.06	-0.15	0.2	0.22	-0.25	0.04	-0.12	-0.12	0.54 **	0.2	0.31	0.18	0.01	0.34
Colonial relationship	0.054	-0.11	-0.3	-0.21	-0.55	-0.04	0.2	0.09	0.54	0.56 *	0.38	0.4	0.53	0.22	0.68 *	0.65	0.49
Currency union	-0.23	-0.11	-0.32	-0.63	-1.24	-0.66	-0.63	-1.1	-1.82 **	-2.33 *	-1.57	-0.22	-1.7	-0.57	-1.71	-1.04	-0.74
Difference in latitude	14.914	-1.28 *	-0.39	0.14	-1.02	-1.02	-0.15	1.08	0.31	0.22	-0.18	-0.54	0.37	15.75	-0.47	15.7	0.19
Common legal origin	0.89	1 ***	1.11 ***	0.9 ***	1.05 ***	0.92 ***	0.78 ***	0.83 ***	0.81 ***	0.79 ***	0.77 ***	0.41 *	0.86 ***	0.68	0.83 ***	0.6	0.83 ***
Common border	0.871	1.17 **	1.07 *	2.24 ***	1.11 *	0.39	0.75 *	1.7 ***	1.04 ***	1.36 ***	1.37 ***	0.94 **	0.69	1.47	1.49 ***	1.59	1.8 ***
Edges	-28.18	-12.72 ***	-12.81 ***	-15.54 ***	-15.38 ***	-10.6 ***	-11.11 ***	-13.68 ***	-10.21 ***	-11.26 ***	-11.72 ***	-11.38 ***	-12.3 ***	-31.47	-15.92 ***	-28.98	-16.87 ***
Observations	6,806	6,806	6,806	6,806	6,806	6,806	6,806	6,806	6,806	6,806	6,806	6,806	6,806	6,806	6,806	6,806	6,806
AIC criteria	637.26	563.95	560.69	662.5	574.15	726.83	848.09	1009.74	1156.77	1034.64	1058.67	1138.24	959.88	876.42	883.95	788.86	685.05
Triangles	76	74	90	86	147	154	207	340	451	309	408	409	241	191	136	136	80
BIC criteria	726.62	653.3	650.05	751.86	663.5	816.19	937.45	1099.1	1246.13	1124	1148.02	1227.6	1049.23	965.77	973.31	878.21	774.41

Note: This table explores the relation between M&A flows , trade flows, and network variable. The dependent variable is the M&A flow in primary sector between two countries. Total trade is measured as the sum of exports and imports. The GWESP indicator stands for geometrically weighted edgewise shared partner distribution and measures the likeliness of a common receiver country for two countries linked with an M&A. Relative comparative advantage (RCA) is based on Vollrath (1991). All regressions include gravity control variables that help explain levels of M&A flows between each country pair based on the differences in latitude between countries, differences in time zones, whether they share a common language, whether they have a common legal origin, and whether the receiver (sender) country is (or was) a colony of the sender (receiver). • indicates the years for which the ERGM estimation did not convergence. Significance levels correspond to *** p<0.001, ** p<0.01, * p<0.05. Standard deviations are not reported. Sources: Calculations based on data from SDC Platinum and Comtrade.

Table 3.7: Estimation of M&A in Light Manufacturing determinants using ERGM procedure

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
GWESP	1.535 ***	1.31 ***	1.24 ***	1.26 ***	1.44 ***	1.49 ***	1.35 ***	1.52 ***	1.51 ***	1.36 ***	1.31 ***	1.29 ***	1.35 ***	1.27 ***	1.37 ***	1.49 ***	1.42 ***
High Income$_i$	1.712 ***	1.16 **	0.63 *	0.49 .	0.69 *	0.9 **	0.43 .	0.71 **	0.27	0.38	0.23	0.37 .	0.79 **	0.3	0.65 *	0.44 .	0.67 *
Trade Openness$_i$	0.408 ***	0.41 ***	0.54 ***	0.47 ***	0.46 ***	0.44 ***	0.53 ***	0.36 ***	0.47 ***	0.66 ***	0.53 ***	0.51 ***	0.5 ***	0.58 ***	0.62 ***	0.65 ***	0.54 ***
Net RCA$_{ik}$	-0.027	-0.09	0.28	0.14	0.04	-0.06	-0.21	0.04	0.2	0.16	-0.04	0.2	0.34 .	0.2	0.28	0.38 .	0.07
Net RCA$_{jk}$	0.067	0.22	0.08	0.2	0.08	0.36 *	0.3 .	-0.08	-0.16	-0.17	-0.08	0.06	-0.07	-0.38 *	-0.22	0.03	-0.12
Time difference	-0.686 ***	-0.71 ***	-0.55 *	-0.33	-0.46 *	-0.19	-0.1	-0.46 *	-0.14	-0.24	-0.43	-0.11	-0.2	-0.3	-0.3	0	-0.51 *
Common language	0.185	0.07	0.5 *	0.54 *	0.38	0.02	0.13	0.21	0.48 .	0.26	0.17	0.59 *	0.68 **	0.49 .	0.42	0.42	0.39
Colonial relationship	0.779 *	0.5	0.5	0.29	0.36	0.28	0.57 .	0.19	0.12	-0.12	0.22	0.22	-0.2	0.08	0.24	0.8 *	0.05
Currency union	-0.614 .	-1.02 **	-0.66 .	-0.68 .	-0.54	-0.44	-0.46	-0.84 *	-0.38	-0.9 *	-1.71 **	-0.78 .	-0.48	-0.53	-0.74	-0.1	-1.52 **
Difference in latitude	-0.658	1.58	-0.54	0.12	1.21	1.16	-0.18	-0.3	-0.07	0.62	0.38	-1.07 *	-0.62	-0.12	-0.15	0.43	0.83
Common legal origin	1.181 ***	1.06 ***	0.99 ***	0.74 ***	0.67 **	0.97 ***	1.03 ***	1.23 ***	1 ***	1.18 ***	1.02 ***	1.06 ***	0.87 ***	1.12 ***	0.81 ***	0.95 ***	0.84 ***
Common border	1.104 ***	1.19 ***	1.21 ***	1.37 ***	1.03 **	1.33 ***	1.41 ***	1.16 ***	1.21 ***	1.06 **	1.5 ***	1.22 ***	0.87 *	1.16 ***	1.14 **	1.23 ***	1.33 ***
Edges	-9.905 ***	-11.46 ***	-10.75 ***	-10.51 ***	-11.64 ***	-11.92 ***	-11.26 ***	-9.02 ***	-10.6 ***	-13.6 ***	-11.34 ***	-10.16 ***	-10.79 ***	-15.88 ***	-16.96 ***	-18.47 ***	-16.09 ***
Observations	6,806	6,806	6,806	6,806	6,806	6,806	6,806	6,806	6,806	6,806	6,806	6,806	6,806	6,806	6,806	6,806	6,806
Triangles	282	119	142	112	109	130	186	201	173	65	71	112	90	140	118	150	147
AIC criteria	904.85	895.87	890.7	967.67	889.63	872.39	960.83	1022.39	948.14	723.01	845.25	981.85	931.11	941.09	858.57	838.86	917.5
BIC criteria	994.2	985.23	980.06	1057.02	978.98	961.75	1050.19	1111.74	1037.49	812.36	934.6	1071.2	1020.47	1030.44	947.93	928.22	1006.86

Note: This table explores the relation between M&A flows , trade flows, and network variable. The dependent variable is the M&A flow in light manufacturing sector between two countries. Total trade is measured as the sum of exports and imports. The GWESP indicator stands for geometrically weighted edgewise shared partner distribution and measures the likeliness of a common receiver country for two countries linked with an M&A. Relative comparative advantage (RCA) is based on Vollrath (1991). All regressions include gravity control variables that help explain levels of M&A flows between each country pair based on the differences in latitude between countries, differences in time zones, whether they share a common language, whether they have a common legal origin, and whether the receiver (sender) country is (or was) a colony of the sender (receiver). Significance levels correspond to *** p<0.001, ** p<0.01, * p<0.05. Standard deviations are not reported. Sources: Calculations based on data from SDC Platinum and Comtrade.

Table 3.8: Estimation of M&A in Heavy Manufacturing determinants using ERGM procedure

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
GWESP	1.982 ***	1.78 ***	2.24 ***	1.67 ***	1.57 ***	2.16 ***	1.77 ***	1.86 ***	1.95 ***	1.88 ***	1.98 ***	1.94 ***	1.75 ***	2.01 ***	2.11 ***	1.83 ***	1.83 ***
High Income$_i$	0.868 ***	1.24 ***	0.65 **	0.7 **	0.75 **	0.39 *	0.7 ***	0.69 ***	0.38 *	0.65 **	0.73 ***	0.52 *	0.59 **	0.71 ***	0.52 *	0.47 *	0.31 .
Trade Openness$_i$	0.536 ***	0.55 ***	0.43 ***	0.57 ***	0.42 ***	0.47 ***	0.42 ***	0.48 ***	0.38 ***	0.4 ***	0.38 ***	0.47 ***	0.42 ***	0.47 ***	0.45 ***	0.55 ***	0.49 ***
Net RCA$_{ik}$	-0.14	-0.23 .	-0.35 *	-0.15	0.05	0.01	-0.26 .	-0.1	0.11	-0.06	-0.15	-0.07	-0.18	-0.25	0	-0.12	-0.24
Net RCA$_{jk}$	0.394 **	0.71 ***	0.48 **	0.7 ***	0.45 **	0.63 ***	0.6 ***	0.61 ***	0.51 ***	0.41 **	0.44 ***	0.63 ***	0.71 ***	0.46 ***	0.49 ***	0.66 ***	0.5 ***
Time difference	-0.36 *	-0.33 .	-0.02	-0.43 *	-0.05	-0.23	-0.29 .	-0.13	0.19	-0.16	-0.12	0.03	-0.11	0.2	-0.03	0.07	-0.33 *
Colonial relationship	0.315	0.68 **	0.49 .	0.45	0.4	-0.01	0.38	0.22	0.36	0.18	0.13	-0.02	0.25	0.3	0.39	0.22	0.53 *
Currency union	-0.823 **	-0.15	-0.24	-1.09 **	-0.72 *	-0.73 **	-1 **	-0.88 **	-0.34	-0.9 **	-0.99 **	-0.68 *	-0.93 **	-0.3	-1.05 **	-0.03	-0.2
Difference in latitude	0.215	0.37	0.83	0.49	0.58	0.59	1.88 *	1.36 .	0.21	1.03	0.49	0.52	0.76	0.23	0.05	-0.08	0.25
Common legal origin	1.04 ***	0.75 ***	0.76 ***	1.03 ***	0.76 ***	1.07 ***	0.86 ***	0.96 ***	0.95 ***	0.81 ***	0.9 ***	0.97 ***	0.85 ***	0.85 ***	0.97 ***	0.86 ***	0.7 ***
Common language	-0.099	-0.01	-0.26	0.19	0.1	0.11	-0.07	0.22	0.03	0.36	0.32	0.38	0.26	-0.1	0.04	0.42 .	0.09
Common border	1.323 ***	1.39 ***	1.77 ***	1.21 ***	1.62 ***	1.52 ***	1.37 ***	1.31 ***	1.49 ***	1.33 ***	1.05 ***	1.2 ***	1.02 ***	1.15 ***	1.51 ***	0.94 **	0.82 **
Edges	-11.831 ***	-12.39 ***	-11.52 ***	-12.37 ***	-10.85 ***	-11.81 ***	-11.95 ***	-12.5 ***	-10.47 ***	-11.21 ***	-10.61 ***	-11.96 ***	-11.23 ***	-15.07 ***	-14.51 ***	-16.18 ***	-14.57 ***
Observations	6,806	6,806	6,806	6,806	6,806	6,806	6,806	6,806	6,806	6,806	6,806	6,806	6,806	6,806	6,806	6,806	6,806
Triangles	1269	1112	826	801	654	1026	1309	1726	1435	769	921	1113	906	876	1288	1122	940
AIC criteria	1376.85	1326.86	1173.76	1197.49	1321.86	1282.44	1653.93	1734.35	1689.91	1369.9	1441.92	1460.81	1468.77	1352.7	1452.03	1387.89	1412.81
BIC criteria	1466.21	1416.21	1263.11	1286.84	1411.22	1371.8	1743.28	1823.71	1779.26	1459.26	1531.28	1550.16	1558.13	1442.06	1541.39	1477.25	1502.17

Note: This table explores the relation between M&A flows , trade flows, and network variable. The dependent variable is the M&A flow in heavy manufacturing sector between two countries. Total trade is measured as the sum of exports and imports. The GWESP indicator stands for geometrically weighted edgewise shared partner distribution and measures the likeliness of a common receiver country for two countries linked with an M&A. Relative comparative advantage (RCA) is based on Vollrath (1991). All regressions include gravity control variables that help explain levels of M&A flows between each country pair based on the differences in latitude between countries, differences in time zones, whether they share a common language, whether they have a common legal origin, and whether the receiver (sender) country is (or was) a colony of the sender (receiver). Significance levels correspond to *** $p<0.001$, ** $p<0.01$, * $p<0.05$. Standard deviations are not reported. Sources: Calculations based on data from SDC Platinum and Comtrade.

Appendix 3.C Goodness of fit for TERGM results

After running the TERGM, we estimate the goodness-of-fit and trace the MCMC plots of the statistically significant variables.

Figure 3.6: Primary sector

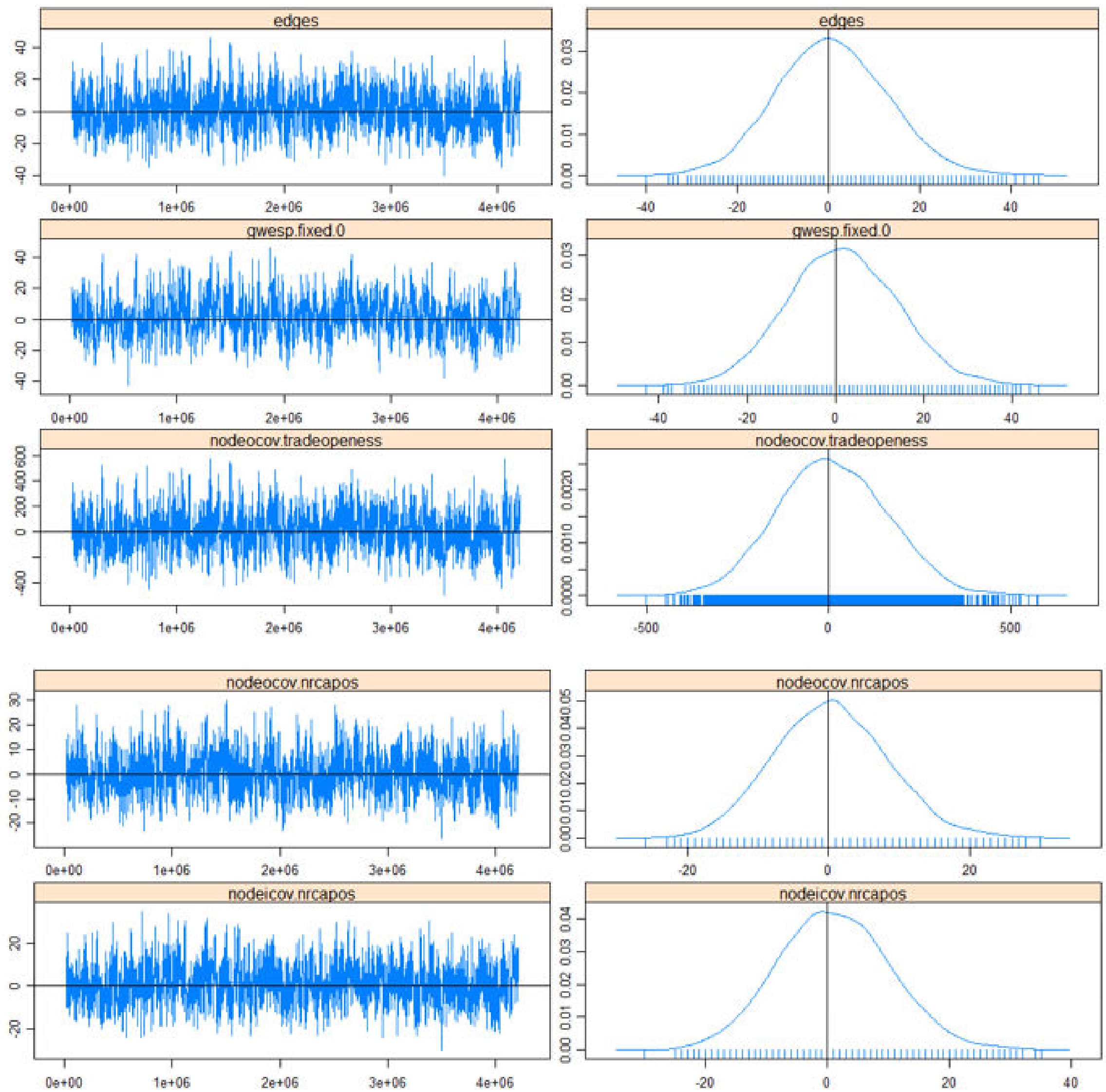


Figure 3.7: Light manufacturing

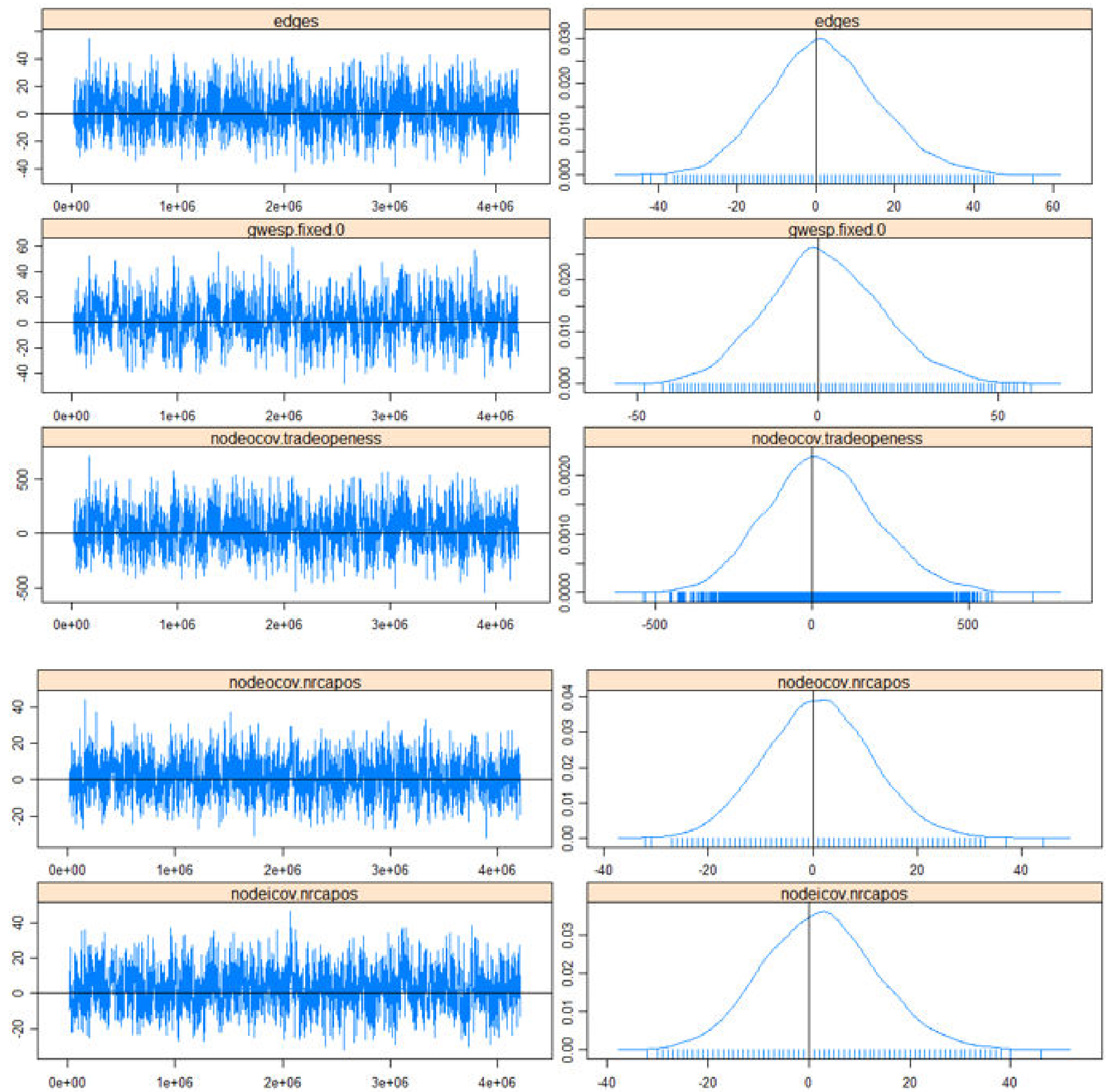
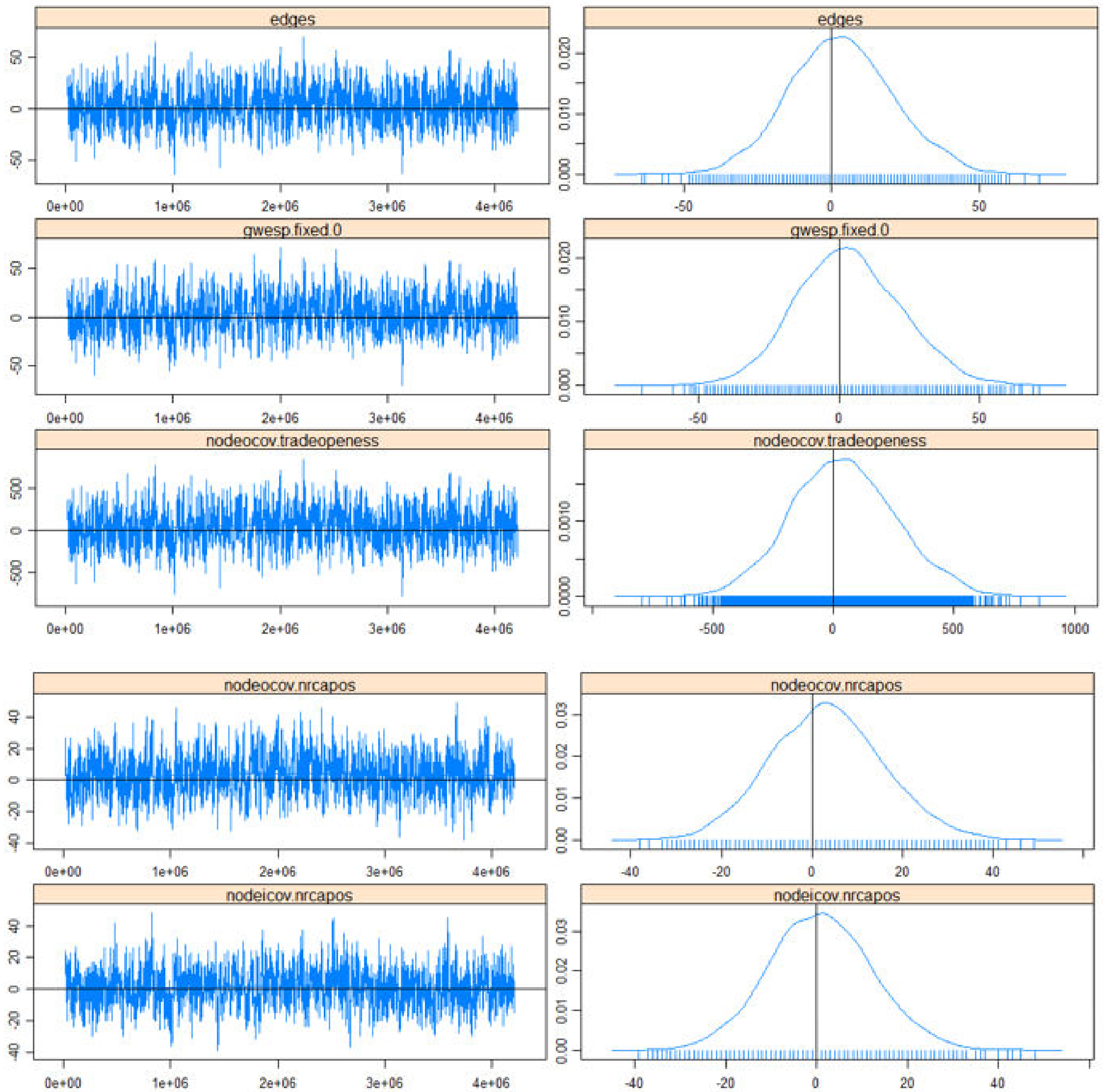


Figure 3.8: Heavy manufacturing



Chapter 4

Assessing the Fragility in Global Trade: The Impact of Natural Disasters Using Network Analysis[1]

[1]This chapter draws heavily on the IMF working paper "Assessing the Fragility of Global Trade: The Impact of Localized Supply Shocks Using Network Analysis" co-written with Yevgeniya Korniyenko and Brian Dew. We would like to thank Vikram Haksar, Tamim Bayoumi, Murtaza Husain Syed, Camelia Minoiu, Christian Henn, Tito Cordella, Tatiana Didier, Lionel Fontagné, Luca de Benedictis, Raja Kali, participants of the IMF SPR seminar, the XXXVI Sunbelt Conference, the GSIE seminar, and the 5th CIRANO Workshop for suggestions and comments. All errors and omissions are our own.

4.1 Introduction

The 2011 Japanese earthquake is now a well-studied event that shed light on how a localized disaster had a significant contagion effect on many countries around the world. Countries importing inputs for their production from the impacted area of Fukushima had to interrupt their production for days, or even months, because of the lack of key inputs for their production. This event is not an exception. Since 2004, 112 natural disasters have been registered with severe economic consequences[2]. Traditional evaluation of the consequences are generally case studies of events. Besedeša and Murshidb (2014) examine the eruption of the Icelandic volcano, Eyjafjallajökull, and find that it negatively impacted exports from the affected countries to the U.S. and Japan. Martincus and Blyde (2013) study the effect of a Chilean earthquake in 2010 on export volumes and find that diminished transportation infrastructure had a significant negative impact on firms' exports. Meanwhile, Escaith et al. (2011) report that the effect of the earthquake in Japan in 2011 on global trade was relatively small and short-lived, despite the devastation in Japan.

The literature studying the dynamic resilience of economies to supply shocks (Rose (2007)) added an important new factor to evaluate the consequences of disasters: the structure of the global value chain (GVC). As GVCs have gained prominence on the international trading scene, exports of final products have become increasingly composed of imports of intermediate inputs[3]. Todo et al. (2015) find that being integrated into a GVC increases a country's resilience, due to a diversification effect working through three channels. First, firms in the impacted region receive support from suppliers located in other regions. Second, the firms that lose suppliers or

[2] Details on the definitions used are provided in section 4.4.2.

[3] Antras et al. (2017) document that increases in firm-level imports from China do not decrease domestic and third-market sourcing, but instead are associated with increased firm-level sourcing from other markets

demand from firms located in the impacted area are able to find new partners through the GVC network. Finally, they benefit from agglomeration through information spillovers and input sharing even after disasters.

Nevertheless, an important majority of the global value chain literature finds that increasing links among economies fosters the propagation of such shocks across economies, through a contagion process called the "cascade effect," coined by Acemoglu et al. (2012). In their theoretical paper, the authors show that the presence of intersectoral I–O linkages lead to the propagation of microeconomic idiosyncratic shocks through the network and generate a "cascade effect" within the aggregate economy[4]. As argued in Carvalho (2014), the international trade structure of production is key in explaining how microeconomic shocks are transmitted across economies. Localized disturbances associated with individual production lead to the synchronization of business cycles across countries, as firms from other countries might be impacted by the lack of a key input. Indeed, Acemoglu et al. (2015) show that network-based propagation is larger than the direct effects of these shocks. Using simulations based on an I–O model, Henriet et al. (2012) find evidence of the negative effects of supply chain disruptions across several regions. In turn, Carvalho et al. (2014) use firm data before and after the 2011 Great East Japan Earthquake to assess empirically whether companies indirectly linked to firms that disrupted their production were affected by the event. They find that firms placed within two or three degrees of separation were in fact negatively affected and experienced lower sales growth. For this same event, Tokui et al. (2012) find that 90 percent of output losses due to the earthquake in Japan were in firms located outside the country, rather than inside, putting in evidence the importance of network consequences. Boehm et al. (2015) find that U.S. affiliates of Japanese multinationals suffered large drops in U.S. output in the months

[4] Ramírez (2017) shows how changes in the propagation of shocks within a network economy affect not only aggregate variables, but also equilibrium asset prices and aggregate risk premia.

following the 2011 earthquake in Japan, roughly one-for-one with the drop in imports and consistent with a Leontief relationship between imported and domestic inputs.

This chapter argues that the consequences of a localized supply shock on the value chain depend on the structure of the network of the good traded. A combination of characteristics in the network of goods leads to the existence of fragilities in the value chain. When an unexpected supply shock occurs, replacement of input is more difficult and a production disruption is more likely.The role of the centrality of actors in propagating shocks has been found in the trade network analysis literature to be an important factor of the network in transmitting shocks. Clauset et al. (2009), Riccaboni and Schiavo (2010), and De Benedictis et al. (2014) show that the out-degree distribution of countries in trade networks follows a power law: only a few countries are very central to the trade network. A fat-tailed distribution leads to the break-off of the central limit theorem. As shown in Gabaix (2011), idiosyncratic shocks to heavily connected countries explain a non-trivial fraction of aggregate world fluctuations. The clusterization of countries also has an important role in the transmission of shocks in the trade network. Fagiolo et al. (2010) put in evidence the presence of a clique structure in the world trade network. Ward et al. (2013) show that the traditional gravity model is misspecified in the absence of third-order dependencies.

This chapter contributes in two ways to the empirical literature. First, a measure of the fragility of countries' imports to localized supply shocks is constructed. The measure is based on the evaluation of the riskiness of the products traded through analyzing the network of goods exported, basing the choice of index components on the previously cited literature. In particular, it underscores the riskiness arising from the presence of central players in the network of a product, the tendency to cluster, and the low international substitutability of trade partners. The methodology developed helps to identify the most vulnerable products in global trade and tracks top exporters and importers of these products. The methodology allows the benchmarking of potential import basket vulnerabilities against different countries and country groups, as well as across regions, and provides a new dataset that is used for cross-country analysis. Second, the chapter estimates evaluate the predictive power of the indicator for a particular case of localized supply shock: natural disaster[5]. The methodology is tested for two case studies: the 2011 Japan earthquake and the 2011 Thailand floods. Based on 2010 data, the indicator achieves the detection of 5 out of 6 goods that disrupted other countries' value chains after these natural disasters. The test is generalized to a cross-country regression. An increase of 1 percent of the share of imports of fragile products from an economy that is impacted by a disaster is associated with a reduction of 0.7 percent of country exports[6].

The chapter proceeds as follows: section 4.2 sets the analytic framework, describes the four components of product vulnerability, and discusses the method of classifying a product's overall fragility. Section 4.3 describes and analyzes the results. Section 4.4 provides a validation of the methodology based on two case studies and a cross-country analysis, while potential applications and extensions of the research are discussed, and concluding remarks are presented, in section 4.5.

[5] A political shock would be another case of localized supply shock.

[6] Early literature such as Helpman and Razin (1978) and Helpman (1988) integrate uncertainty in trade models: when the volatility across sectors is different, exports are determined by comparative advantage and insurance issues. Most of the recent literature on trade and uncertainty actually pays more attention to export riskiness (such as De Sousa et al. (2015); Caselli et al. (2015); Fillat and Garetto (2015)), rather than provisional risk of input for production, even with the increasing importance of global value chains. Along this avenue of research, Novy and Taylor (2014) analyze the response to uncertainty shocks by adjustment of inventories and disproportional cuts in orders from intermediaries. Gervais (2016) shows that the benefits of multi-sourcing—the strategy of buying the same input from multiple suppliers— can be similar to those of portfolio diversification in theoretical finance. The policy implications are interesting, but outside the scope of this chapter, and merit further research.

4.2 Empirical Methodology

The chapter uses detailed BACI bilateral trade data, based on the harmonized system 2002 (HS2002) classification at the 6-digit level, for the period 2003-2014. Data available at this highly disaggregated level are not available for value-added. This raises the possibility that the network of a product is misrepresented because certain countries add very low value in the process of production (for example, only pieces are assembled). This is a common criticism to work on trade networks, such as the seminal work of Hidalgo et al. (2007). The approach of his paper is nevertheless less subject to this criticism. Even if a country is only assembling a good (and not producing it) it is still in the trade network of the product. If the 'assembling' country is hit by a temporary shock, it will (at least in the short term) lead to a supply shock for importing countries. This is also the case for products with low value added. A screw supply shortage from a company located in Italy severely hit the French car manufacturer Peugeot in 2011.

In total, there are 5224 products and 223 countries and self-governed territories in the database. Final goods and consumption goods, defined using the UN BEC classification, are excluded from the dataset in order to focus exclusively on products that are used by other industries and have the potential for negative spillovers[7]. From 2007 onwards some countries started submitting data using only the HS2007 classification. The HS2002 and HS2007 classifications are merged using correspondence tables, and products with a match from multiple products to multiples products or from one products to multiple products are excluded[8]. Finally, products that refer

[7]These are 760 consumer goods (including passenger motor cars) and 429 foods and beverage goods mainly for household consumption. An analysis of the riskiness of those products following the methodology is presented in Annex.

[8]There are 416 products dropped during the process of merging HS2002 and HS2007 classifications; there is not such miscategorization at for the change of classification between HS2007 and HS2012. Two products are dropped due to their classification in miscellaneous products categories 999999 and 9999XX.

to the crude oil and refined oil category and the products that are not reported in all years of the sample[9] are dropped. The sample shrinks to 3578 products after the cleaning process.

4.2.1 The three components of product fragility

For each year and product in the sample, the fragility of the product based on the following three components is calculated:

Presence of central players

The first characteristic identified as important for the analysis of risky products is the presence of central players in the network of traded goods. The presence of central players has a role in the extent to which microeconomic shocks explain aggregate fluctuations (Gabaix (2011))[10]. Using network analysis measures of centrality,products with exporters so important that a shock to their supply may disrupt importers' production are identified. In network analysis terms, goods with star-shape networks are identified (Figure 4.1a), as opposed to a fully connected network (Figure 4.1b), as teh former is riskier from the importer point of view.

The standard deviation of weighted outdegree centrality is used to measure the presence of central players[11]. First, the weighted outdegree centrality is calculated for each country in each product network. As detailed in Annex 4.A.1, weighted outdegree centrality measures the intensity of a country's exports as a share of the

[9]This concerns 37 products.

[10]In networks where the largest firms contribute disproportionately to aggregate output, shocks to these firms contribute to aggregate fluctuations. Similarly, Carvalho (2014) uses the Katz (1953)' Bonacich measure of centrality, which assigns to each sector a centrality score that is the sum of some baseline centrality level (equal across sectors), and the centrality score of each of its downstream sectors, defined in the same way.

[11]Variants of this measure have been deployed in the sociology literature, notably Bonacich (1972) and Katz (1953), in computer science with Google's PageRank algorithm (Brin and Page (1998)), or in social networks literature within economics (for example, Ballester et al. (2006)).

Figure 4.1: Detection of the presence of central players using network analysis

(a) Star-shape network

(b) Fully connected network

Notes: Nodes with letters represent countries and the ties that link the nodes represent trade flows.For the sake of clarity, an undirected and unweighted version of the outdegree measure is presented. Note that a weighted version is used in the calculation. In panel A, the outdegree centrality of node A is equal to one, as country A is exporting to all the countries in the sample. In contrast, the outdegree centrality of countries B, C, D, E, and F is equal to zero, as they are trading to zero countries out of the five possible. The standard deviation of this network is 0.45. In panel B, all of the countries are trading with all other countries in the network. All countries in this fully connected network have an outdegree centrality of one, so the standard deviation is zero.

total value of its partners' imports of the product. Countries with many partners and with a high intensity of exports are more likely to generate negative spillovers in case of a negative supply shock. They are often characterized as influential. Star-shaped networks are characterized by the presence of few central players. The standard deviation of weighted outdegree centrality is calculated for each product network to measure the product's tendency to have few very central exporters; the higher the standard deviation, more likely the star shape and the higher the potential risk[12].

Tendency to cluster

Another characteristic of a product network that increases potential spillover risk is the tendency of groups of countries to cluster to trade more among each other than

[12]Due to data availability across country, a more disaggregated information is not available (such as, for example, HS 10-digit classification or firm level data). A potential concern is the loss of precision in identifying products, as many very similar products would be aggregated to the 6-digit level. There is a possibility that two products at 10-digit disaggregation level would have very different networks (for instance, one being very risky and the other not), and that the aggregation at 6-digit would be misinterpreted. Nevertheless, this would only underestimate the risk associated to the centrality component. Two 10-digit good networks from the same 6-digit category: one star-shaped and the other fully connected, will be fully connected at the 6-digit network. Star-shaped networks detected at the 6-digit level effectively only include star-shaped networks at the 10-digit level. As a consequence, all the categories that are detected as risky contain actually risky products. Case studies reinforce this view.

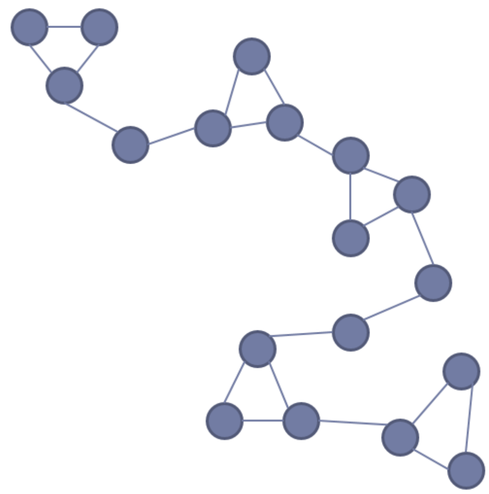
with the rest of the world[13]. Figure 4.2 demonstrates a network with the tendency to cluster. Risk emerges if a cluster is destabilized (for example, after a supply shock to its most central country) as the probability of importers in the cluster finding a new supplier is lower than in product networks where all countries are highly connected (networks with only one cluster).

As detailed in Annex 4.A.2, standard algorithms to detect clusters in the network analysis literature are not applicable to trade data. Two characteristics from cluster analysis are used to detect products for which countries have tendency to cluster: the weighted average local clustering coefficient and the network diameter. The weighted average local clustering coefficient quantifies how close the partners of a country are to others. In other words, this captures the likelihood of the trade partners of a particular country for a particular good also trading the same good among each other. The higher the clustering coefficient the higher the tendency of countries to cluster.

The weighted average local clustering coefficient is then multiplied by the diameter of the product network. The diameter of a network is the size of the longest direct path' the maximum number of steps that separate the two most distant countries. If a country belonging to a cluster needs to find a new provider, it will be easier to connect to a country in a close cluster (i.e. a cluster already connected to other countries in the clusters).

[13]For the relevance and presence of clusters in trade networks, see Fagiolo et al. (2009), Fagiolo et al. (2010), Ward et al. (2013); for the presence of cluster in finance networks, see Hattori et al. (2007) for the network of international bank exposures,Kubelec and Sá (2010) and Sá (2010) for different asset class and Minoiu and Reyes (2013) for the syndicated loans network.

Figure 4.2: Detection of the tendency to cluster using network analysis



Notes: This network is a typical representation of a tendency to cluster. For the sake of clarity, an undirected and unweighted version of the network is presented. The weighted average of the local cluster is high (equal to one on a scale going from zero to one) and the diameter is equal to 12. The measure for tendency to cluster for this particular product is then 1x12=12 (on a scale going from 0 to the maximum value of the parameter.

International substitutability

The final component is the degree of international substitutability of the product. The idea is based on the assumption made byArmington (1969) that products traded internationally are differentiated by country of origin. As such, when a shock hits major suppliers the extent of spillovers will depend on the availability on international markets of substitutes for any affected goods. If there are no close substitutes in the short run, every user is affected by the disturbances at the source country[14]. Data on the Armington elasticity[15] of each product is not available, therefore it is proxied

[14]For example, Tanaka (2012) finds that some Japanese auto parts are less substitutable, which led to the disruptions throughout the global supply chain for the auto industry after the earthquake in Japan in 2011.

[15]The estimates vary significantly depending on the method of estimation and data used. Aspalter et al. (2016), Feenstra (2014), Saito (2004) provide some estimates of simple Armington elasticity using both bilateral and multilateral trade data. Additionally, pioneering work by Feenstra et al. (2014) allows further differentiation between a macro Armington elasticity of substitution between domestic and imported goods and a micro Armington elasticity between different import sources. Their empirical work highlights differences in these micro and macro elasticities. In particular, they find that the macro elasticity is significantly lower than the micro elasticity for up to one-half of the goods considered, relying on both simulation studies and highly disaggregated U.S. data.

with an indicator inspired by Revealed Factor Intensity (RFI) developed by Shirotori et al. (2010), and in particular the level of human capital of each exporter country and its' distribution for each product. In the case of a temporary supply shock, the importing country will look for alternative suppliers with similar characteristics to those who provided the temporally unavailable good. The 'wider' the distribution of human capital of exporting countries, the more heterogeneous the available production methods are for a product. This heterogeneity complicates international substitutability, as a country's substitute supplier must comply with its standard of production. Like the presence of influential players and tendency to cluster, low international substitutability adds to the vulnerability of imports[16][17].

4.2.2 Classifying overall product fragility

Identifying which products are risky at 6-digit disaggregation level can help to track importers' vulnerability to supply shocks from abroad and exporters' potential to originate important negative spillovers from natural disasters. The methodology classifies a product as risky if it scores high in each of the three components described in the previous section. To classify products in different groups, cluster analysis (the k-median procedure) is applied to the standardized scores to group the products into risk categories. From the partition exercise, a cluster for which the value of each component is high is obtained: this group is defined as risky[18] [19]. After categorizing products, the importers and exporters of risky products can be tracked by looking at the risky-product share of total imports or exports in a county's trade basket.

[16]For more details, see Annex 4.A.3

[17]In Annex 4.D, an alternative to this component is proposed.

[18]Note that the partition is not hierarchized, but one group emerges naturally maximizing the value of each of the component.

[19]More details are in Annex 4.A.4

4.3 Results and Analysis

4.3.1 Descriptive statistics

The methodology described in the previous section is applied to the bilateral trade database for each year from 2003-2014 for 223 countries and territories. For each year, products are grouped into four levels of risk (see Annex 4.BII Table A.1.; group 4 is considered the riskiest). Over 2003-2014, an average of 655 products are classified in Group 4, and 421 products are consistently classified in Group 4 in each of the fourteen years of the sample (see Annex 4.B Table A.2.). Table 4.1 presents the ten risky products with the highest global value of imports. Products identified as risky belong mainly to three broad sections: machinery and mechanical appliances (HS codes starting with 84 and 85), and transport equipment (HS codes starting with 87 and 88). Other sections that are overrepresented in Group 4 are pharmaceutical products (30), rubber articles (40), and precision instruments (90).

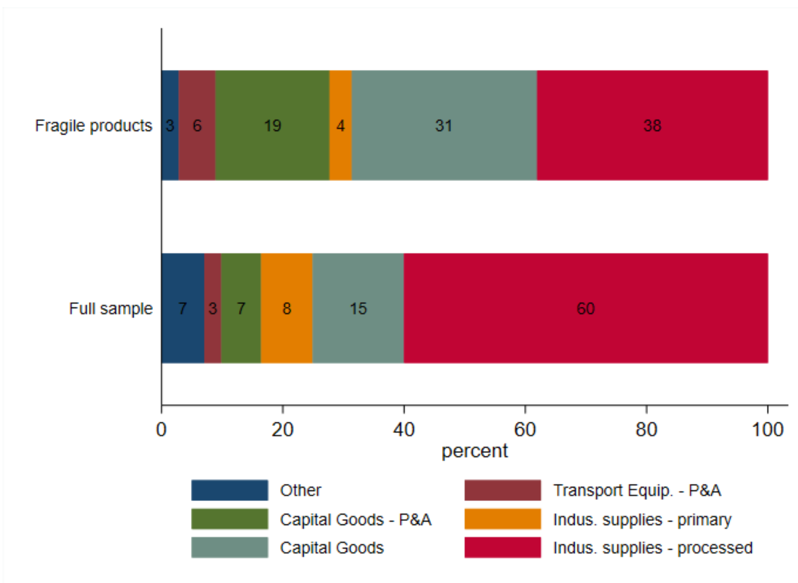
Table 4.1: Top 10 risky import products by their value in trade

	Product HS2002 6-digit	Product Description	Share Value of Imports
1	847170	Storage units (of auto. data processing machines)	0.964%
2	880330	Parts of aeroplanes/helicopters, other than propellers, rotors, under-carri ...	0.761%
3	870829	Parts & accessories of bodies (incl. cabs) of the motor vehicles of 87.01-8 ...	0.717%
4	300210	Antisera & oth. blood fractions & modified immunological prods., whether or ...	0.671%
5	870421	Motor vehicles for the tpt. of gds. (excl. of 8704.10), with C-I int. comb. ...	0.573%
6	848180	Taps, cocks, valves & sim. appls. for pipes/boiler shells/tanks/vats or the ...	0.537%
7	850440	Static converters	0.523%
8	841191	Parts of the turbo-jets/turbo-propellers of 8411.11-8411.22	0.470%
9	401110	New pneumatic tyres, of rubber, of a kind used on motor cars (incl. station ...	0.463%
10	901890	Instruments & appls. used in medical/surgical/veterinary sciences, incl. ot ...	0.455%

Notes: The products shown in the table are consistently classified as risky (cluster Group 4) over 2003-2014. The ranking is by their value in imports. The top 100 most imported goods constantly classified as the risky over time can be found in Annex Table AII.

Comparisons of the set of risky products with the full sample by BEC industry classification (Figure 4.3) and 2-digit HS classification (Figure 4.4) are presented to assist in summarizing which products are identified as risky. The top bar in Figure 4.3 shows the total number of products for each industry in 2014 for the full sample of 3578 products, while the bottom bar shows only the products belonging to the risky group. From Figure 4.3, processed industrial supply and capital goods are the categories of products most represented in global trade. Interestingly, the comparison between the top and bottom bars shows a different picture of the relative importance. The parts and accessories (P&A) of transport equipment represent only 3 percent of products in the full sample (top bar), but 6 percent of the risky products. In contrast, products in the processed industry category are under-represented in the risky group; the category comprises almost 60 percent of the full sample but only 38 percent of the risky group.

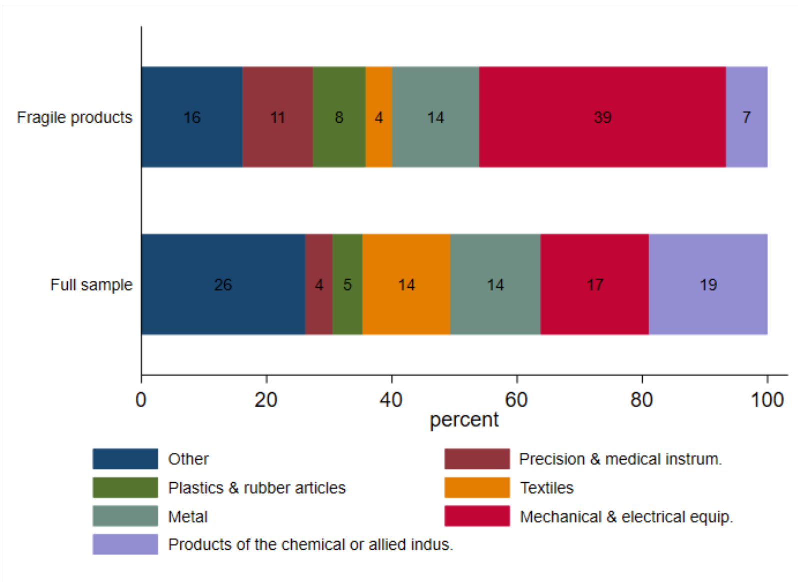
Figure 4.3: Industry classification of products traded in 2014



Notes: Classification corresponds to the Broad Economic categories (BEC).

To further analyze what kind of products are defined as risky, the classification by section is compared for the products in the risky group to the full sample (Figure 4.4). Similar to Figure 4.3, the top bar of Figure 4.4 presents the section composition of goods in the risky products while the bottom bar shows the full sample of 3578 goods. Comparing both panels, mechanical appliances and electrical equipment are over-represented in the risky category. While their share is around 17 percent of the full sample, mechanical appliances and electrical equipment comprise more than 38 percent of the risky group. Precision and medical equipment is also over-represented, claiming only 4 percent of the full sample but 11 percent of the risky products group.

Figure 4.4: HS classification by section of products traded in 2014



Notes: Classification corresponds to the HS 2002 2-digit section classification.

4.3.2 Countries' fragility and origins of risk

After identifying products with fragile trade networks, this section turns to the determination of countries that are importing and exporting these risky products. The group of products identified as risky comprise on average 25 percent of total imports but with a large degree of variation by country (Figure 4.5). A high share of risky products indicates that a country is particularly vulnerable to spillover effects from supply shocks. In 2014, Chad imports the highest share of risky products (43.4 percent), followed by the Republic of Congo (39.4 percent), Gabon (38.9 percent), Equatorial Guinea (37.8 percent), and Turkmenistan (37.6 percent). Many countries with an above average share of risky imports have notably limited domestic economic diversification. Domestic production, consumption, and often transportation, is dependent upon, and therefore vulnerable to, foreign supply shocks of goods.

A second set of countries import a high share of fragile network products due to their role in international supply chains. These countries import raw materials and intermediate products, add value domestically, and then export the assembled or final product for resale and consumption elsewhere. International supply chain countries with more than 30 percent of imports of fragile network products in 2014 include Mexico (37 percent), Hungary (36.2 percent), Romania (34.2 percent), Slovakia (34 percent), the Czech Republic (33.9 percent), Canada (31.5 percent), Germany (30.8 percent), and Austria (30.7 percent). While a supply chain participating country may not be importing a specific good for its domestic consumption, it is vulnerable to spillovers to its domestic labor supply from supply shocks to these imports. Likewise, a domestic disruption may be transmitted elsewhere through the trade network.

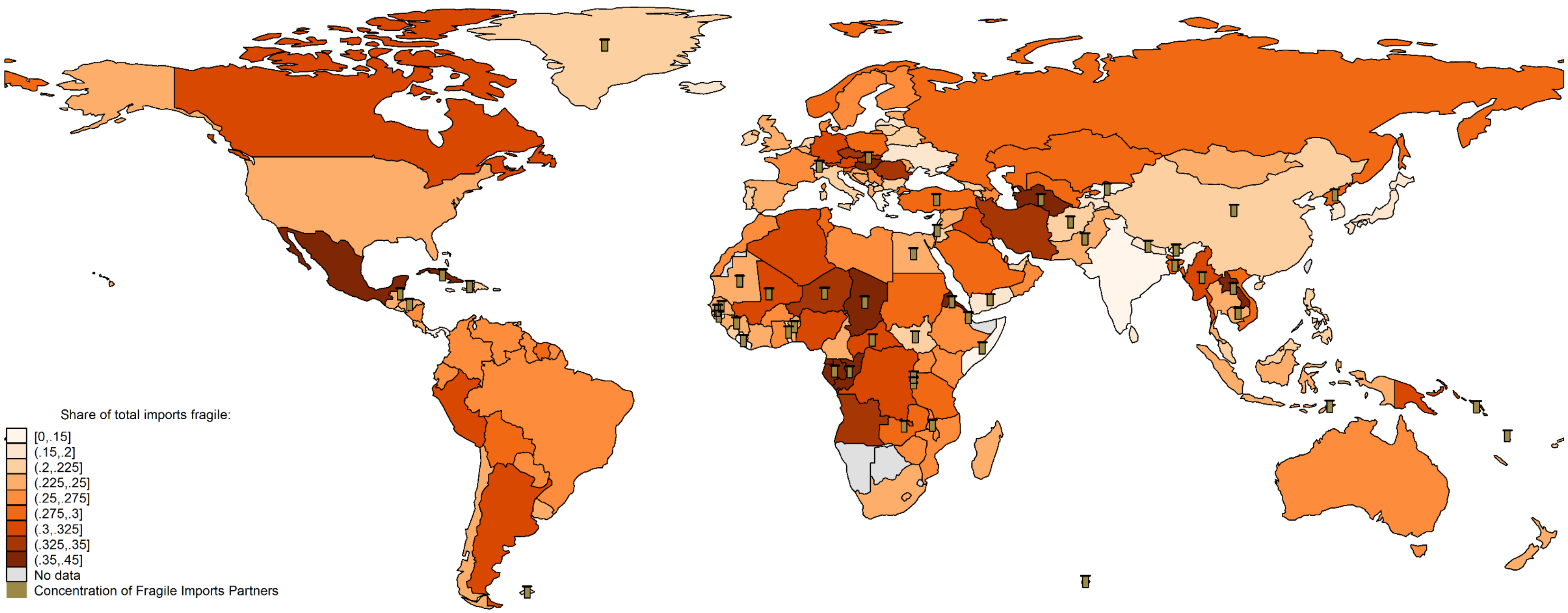
Major economies with a low share of fragile network products in their import baskets include India (13.2 percent) and Japan (16.6 percent), while Korea (17.6 percent) and China (21.2 percent) also have below average vulnerability according to the measure in 2014. The U.S. (24.9 percent), France (27.4 percent), and U.K. (23.9 percent) import baskets are near the mean.

While all countries import fragile products, exporters of such products are very concentrated. Each country's share of world exports of risky products varies dramatically (Figure 4.6), with most countries exporting virtually none, and the G8 countries exporting 59.7 percent of the total. The U.S. exports the largest share (13.1

percent) of all fragile network products, followed by Germany (13 percent), Japan (8.6 percent), and China (7.9 percent). The remaining risky product exporters are all middle-income countries or higher. The African continent is represented among risky product exporters only by South Africa, Egypt, Tunisia, and Morocco, which combined export less than one percent of the world's risky products. Importantly, many countries involved in international supply chains and highly specialized production are also therefore exporters of products that exhibit characteristics identified as risky. In 2014, Mexico exports approximately 3 percent of the world's risky goods, Korea exports 2.4 percent, Austria and Switzerland each export 1.6 percent, Malaysia exports 1.5 percent and Thailand exports 1.2 percent.

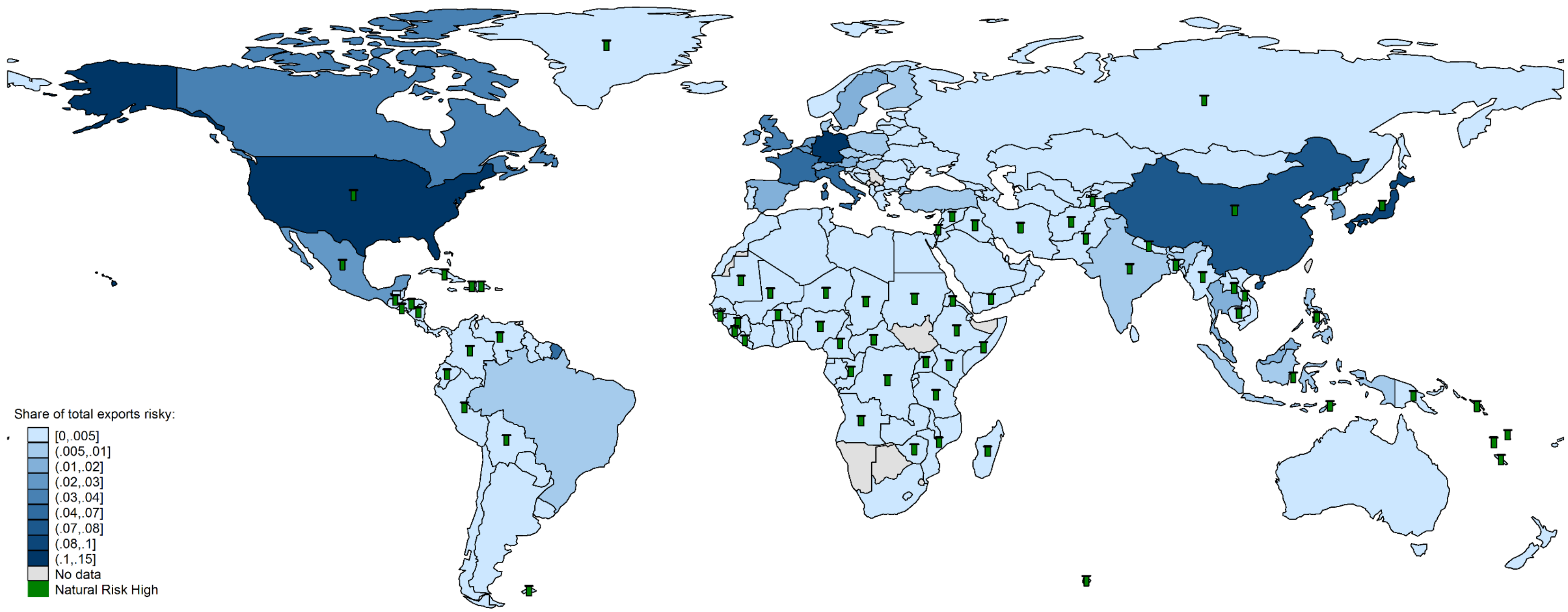
As shown in the methodology, producers of fragile products can serve as origins of risk if the domestic production of exports is severely constrained. A temporary domestic shock, emerging from natural disasters, can thereby be transmitted to other countries through the trade of risky products.

Figure 4.5: Importers of risky products, 2014



Source: Authors' calculation based on BACI database.
Notes: Latest data available is used for this map, 2014.

Figure 4.6: Exporters of risky products and Risk of Supply Shock in 2014



Source: authors calculation based on BACI database and Maplecroft data.
Notes: Latest data available is used for this map: 2014, for the share of imports of fragile products and 2015Q3 for country risks. Risks are displayed only if the information on the data for exports of fragile products is available. The risk is considered high (and displayed on the map) if in the product is in the top third of the sample.

4.4 Validation of the Methodology

Acknowledging the difficulty to validate the methodology, two complimentary approaches are used to support the indicator. First, the case of two recent events is studied (the 2011 Japanese earthquake and nuclear disaster and the 2011 Thailand floods). Business literature and media reports identify products that were temporarily unavailable due to the disaster and in some cases note a resultant disruption of production in other countries. Such products are matched in the data to assess the power of prediction of the index one year before a disaster. Next, a cross-country regression analysis estimates the impact on exports (as a proxy of impact on production emphasizing the risk of multiple steps of negative spillovers) of importing risky products from a country suffering a disaster.

4.4.1 Case studies

2011 Japanese earthquake and nuclear disaster

On March 11, 2011, a magnitude 9.0 earthquake struck 70 km off the eastern coast of Japan. The earthquake and resultant tsunami killed and injured in total more than 21,000 people. Property destruction was enormous with 125,000 buildings totally collapsed and over one million damaged. Manufacturing facilities were damaged or destroyed in three prefectures of the country. The natural disasters were followed by electricity shortages which increased the affected zone and further exacerbated the effect on manufacturing. The economic toll was steep, with 2011 GDP growth figures 2 percentage points below their March 2011 forecast.

In the period following the earthquake, the economic effects of the disasters spread throughout the world through trade and global supply chains, particularly impacting the Asia region[20]. Damage to manufacturing in Japan had been amplified by the riskiness of several key products for which Japan plays a central role in world production. The following products were affected strongly by the disasters: diesel engines, power supply and aluminum capacitors, and LCD screens used in TV sets, notebook computers, smartphones, and tablets (See Table 4.2).

Table 4.2: Selected risky products exported by Japan in 2010, one year before 2011 earthquake and nuclear disaster

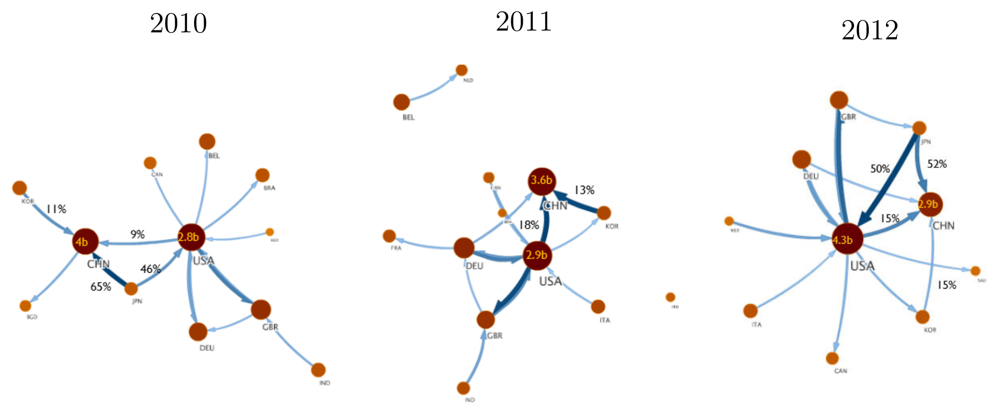
HS2002 6-digit	Risk category in 2010	Products Description (sometimes shortened)	z-score Comp. 1	z-score Comp. 2	z-score Comp. 3
840890	4	Combustion Engines # Other engines *includes diesel engines*	1.39	0.95	1.68
853229	4	Electrical Capacitors # Other *includes power supply capacitors and aluminium capcacitors*	0.89	0.74	0.32
901380	3	LCDs # Other devices, applicances and instruments *includes LCD screens in TV sets, notebook, smartphones, tablets*	1.09	1.10	-0.79

Notes: Column 1 of Table 4.2 present the HS2002 6-digit classification of products identified as having disrupted production in other countries after the 2011 disasters. The category of the product is described in columns 3 and the precise description of the good is shown in italics. Column 2 presents the level of risk found with the methodology, 4 being the highest risk category. Out of three products identified, the methodology categorizes two in the highest risk group one year before the event. Columns 4-6 present the standardized value of each component.

Exports of diesel engines by Japan decreased by nearly 20 percent in 2011, as manufacturers were not able to supply parts. A major French automobile manufacturer, for example, in turn delayed the launch of two car models and was eventually forced to source from another supplier. The chapter identifies diesel engines as a risky product. This category of product is produced by 'central players,' has clusters in the trade network (as shown in Figure 4.7, the Japanese cluster for diesel engines disappears entirely in 2011), are highly systemically relevant, and are not easily substitutable on international markets. The resultant choke point predicted by the methodology proved problematic for importers following the supply shock.

[20] HarvardBusinessReview (2011).

Figure 4.7: Network analysis of diesel engines



Note: This Figure shows trade networks for product 840890 from the HS2002 classification' a category of diesel engines. Community detector of Rosvall and Bergstrom (2008) is used to show the evolution of the network for this product between 2010 and 2012. Countries are grouped by similarity of their trade matrix and the country with the highest Page Rank centrality is displayed below the node[21]. The bigger the share of trade of the countries in each group, the bigger is the node. Above some links, the share of total imports of the destination country from the country at the origin of the arrow is displayed (e.g., in 2010, the USA imports 46 percent of their diesel engines from Japan). On the top of some nodes, the value of imports is displayed (e.g., in 2010, the US had imported 2.8 billion US of diesel engine). The figure shows only the links that reflect the structure of the network. In 2010, Japan is a key player, exporting to both the US and Chinese clusters. In 2011, the year of the Fukushima accident, the Japanese cluster disappears. Korean cluster seems to reinforce exports to China, but not to the US. In 2012, the Japanese cluster is back and the network is more connected than before the earthquake. Iran is omitted from the 2011 algorithm-generated graphic for simplicity of presentation.

Small parts can also cause disruption in production and carry outsized trade risks. Capacitors and resistors are critical to global electronics supply chains and Japan is a major producer of these products. Following the earthquake, prices of the tiny inputs increased, and in importer countries, production of various electronics and automotive parts that used the capacitors slowed. Aluminum capacitors are included in a product grouping with very similar risk characteristics to the diesel engines. An additional risky product, the LCD screens used in many modern devices, was affected by the disaster and has similar risk characteristics, but was not categorized as high-risk.

2011 Thailand Floods

The 2011 monsoon season in Thailand brought severe flooding to 65 of Thailand's 77 provinces, causing more than 815 deaths and 45 billion USD of property damage.

[21]The PageRank algorithm defines the centrality as the popularity of a node, i.e. the more central is a country the higher likelihood a trade connection goes through it. Compared to the outdegree centrality used in the chapter, this algorithm uses recursive equation to compute the centrality.

Triggered by a tropical storm at the end of July, floodwaters spread throughout the northern parts of the country and through the Mekong and Chao Phraya rivers, eventually reaching Bangkok. Efforts made to protect the capital city from the floodwaters were successful to varying degrees.

Industrial estates and manufacturing facilities were badly flooded in many parts of the country, causing production and exports to be adversely affected. Literature on the economic effects of the floods mentions some specific products which had seemingly outsized consequences on global trade and supply chains. Three such products were hard disk drives, semiconductors, and pick-up trucks[22]. All three of these products are listed as risky according to the methodology; two of which display all the risky characteristics.

Thailand is the world's second largest producer of hard disk drives, which serve as the 'long-term' memory and file storage in desktop and laptop computers, tablets, and mobile devices. When factories which produce these hard drives were flooded, exports decreased, prices increased (almost doubling and remaining elevated for two years), and production of the electronic devices which use these intermediate goods slowed in many countries. Hard disk drives are a risky good according to the methodology, which exhibits particularly high levels of out degree centrality and clustering.

Flooding also damaged the manufacturing equipment used to produce semiconductors and pick-up trucks. Suspension of the production of pick-up trucks in Thailand has economic impact in Japan, whose automotive companies produce in Thailand, and in the countries from which source component orders are suspended. Similarly, suspended semiconductor production in Thailand slowed other countries' production

[22] Reuters (2011).

of goods for which semiconductors are an intermediate input. Semiconductors and integrated circuits are valuable exports for which Thailand is a fairly central player, and also register above average in three areas of trade risk (see Table 4.3 for the correspondence with the methodology).

Table 4.3: Selected risky products exported by Thailand in 2010, one year before 2011 floods

HS2002 6-digit	Risk category in 2010	Products Description (sometimes shortened)	z-score Comp. 1	z-score Comp. 2	z-score Comp. 3
847170	4	Computers # Storage units *includes computer hard disk drives*	2.66	1.68	1.40
854121	4	Semiconductor Devices # with a dissipation rate of < 1W *includes semiconductors used in microprocessors*	0.58	1.09	1.38
870421	4	Delivery Trucks # g.v.w. not exceeding 5 tonnes *includes pick up trucks*	2.42	2.72	1.70

Notes: Column 1 of Table 3 present the HS2002 6-digit classification of products identified as having disrupted production in other countries after the 2011 event in Thailand. The category of the product is described in column 3 and the precise description of the good is shown in italic. Column 2 presents the level of risk found with the methodology, 4 being the highest risk category. The methodology categorizes all of the products in the highest risk group one year before the event. Columns 4-6 detail the standardized value of each component.

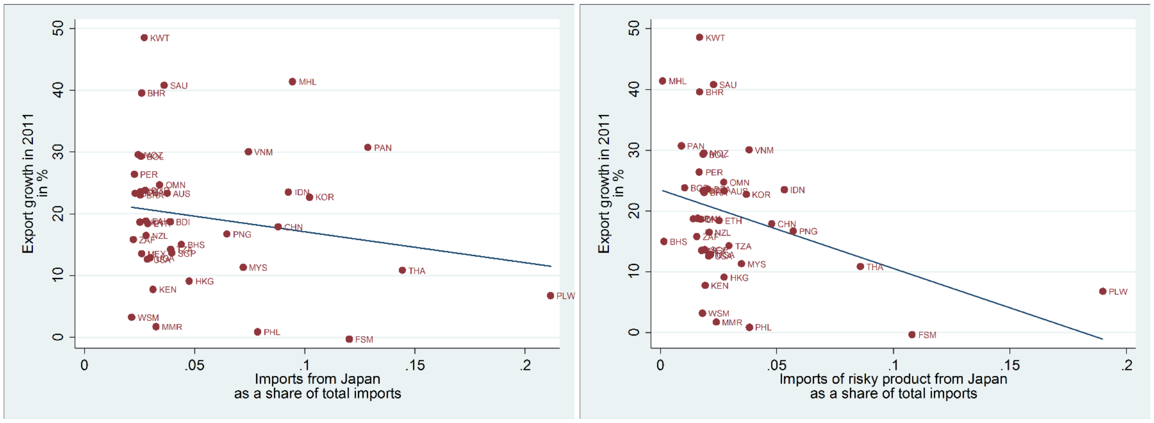
4.4.2 Cross-country past event validity of the index

This section tests the validity of the hypothesis that the more a country imports risky goods from a partner suffering a disaster, the more substantial the impact will be on the economy, particularly the countries' export flows. To introduce the results of this section, the case of the 2011 Japanese earthquake and its negative consequences on its trade partners is used. In Figure 8, the correlation between the reliance on risky products from Japan in 2010 and the exports growth in 2011 is presented. Figure 4.8 panel A plots real export growth in 2011 on the y-axis and the share of imports from Japan in 2010 on the x-axis. The relation is slightly negative and non-statistically significant. In panel B, the x-axis is replaced by the share of imports of the risky goods from Japan, keeping the y-axis unchanged. The relationship is even more negative and significant.

Figure 4.8: Macroeconomic spillovers of importing risky products from Japan

(a) share of imports from Japan and 2011 exports growth

(b) share of imports of risky products from Japan and 2011 exports growth



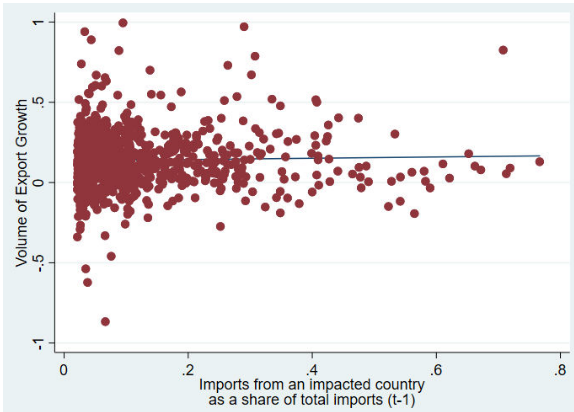
Notes: Equation of the fitted line is $y = -50.4\beta - 22.2^{***}$ for panel A and $y = -129.5^{**}\beta - 23.5^{***}$ for panel B. Only countries for which Japan represents at least 2 percent of the total imports are displayed.

Figure 4.9 generalizes the case study to other disaster events between 2003 and 2014. In panel A, the volume of export growth in t is plotted against the share of imports in $t-1$ from countries impacted by a natural disaster in t. The slope is slightly positive and the coefficient is not statistically significant. In panel B, the volume of export growth in t is plotted against the share of imports of *risky goods* in $t-1$ from countries impacted by a natural disaster in t. As expected, the slope is negative and statistically significant.

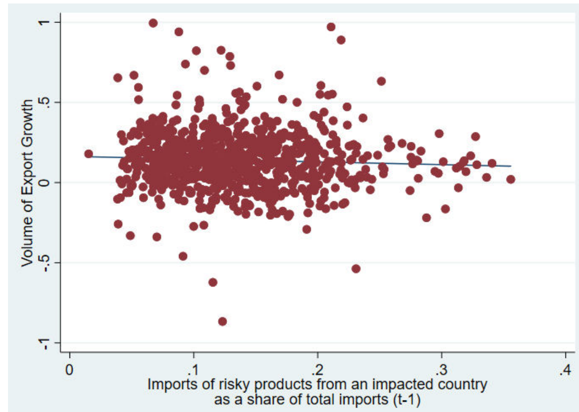
The validity of these correlations is tested using a panel regression. The impact of the measure of import riskiness is assessed on the export growth, when one or more provider(s) is suffering a localized supply shock in $(t-1)$. More formally, a within-group estimation model for the period 2003-2014 is run at the country-year level, following the setup of Freund and Pierola (2012)[23]:

[23] In Freund and Pierola (2012), the short span of the sample due to data limitations does not allow to variables to be averaged over five-year periods. As a consequence, the exercise might be impacted by year-on-year volatility.

Figure 4.9: Macroeconomic spillovers of importing risky products from a country impacted by a disaster, 2003-2014



(a) share of total imports from a country impacted by a disaster in $t-1$ and exports growth in t



(b) share of total imports of risky products from a country impacted by a disaster in $t-1$ and exports growth in t

Notes: Equation of the fitted line is $y = 0.04\beta + 0.135^{***}$ for panel A and $y = -0.173^{**}\beta + 0.164^{***}$ for panel B. Only countries for which the partner country affected by a disaster in t represents at least 2 percent of the total imports are displayed.

$$\hat{X}_{i,t} = \beta_0 ln(REER_{i,(t-1)}) + \beta_1 X_{i,(t-1)} + \beta_2 RM_{i,(t-1)} + \\ \beta_3 MIC_{i,(t-1)} + \beta_4 RMIC_{i,(t-1)} + \delta_{i,t} + \epsilon_{i,t}$$

where $\hat{X}_{i,t}$ is the growth of export volumes of country i in period t, $REER_{i,(t-1)}$ is the lagged growth in the real effective exchange rate (REER) in $t-1$[24], and $RMIC_{(t-1)}$ is the share of total imports of products considered as risky by the methodology in period $t-1$ from countries that suffer a large natural disaster in period t[25]. To assure the validity of the results, regressions are also controlled for the share of total imports that is risky ($RM_{i,(t-1)}$), and the share of total imports from countries suffering a disaster in $t-1$ ($MIC_{i,(t-1)}$). Importing risky products is not an issue as long as there is no disruption of supply. Also, there is no reason to have a prior on the relationship

[24]The coefficient β_0 reflects the effect of an appreciation on export growth.

[25]RMIC stands for Risky Imports (M) from Impacted Country.

between importing non-risky products from a country suffering a disaster and its impact on countries' exports. These two variables can be interpreted as a placebo test.Year fixed effects $\delta_{i,t}$ are included and $\epsilon_{i,t}$ is defined as the error term of the model.

Data on total exports, total imports, and GDP come from the IMF Balance of Payments Statistics (BOPS) database and are adjusted to constant prices using data obtained from the U.S. Federal Reserve Bank of St. Louis FRED database[26]. REER data are obtained from the World Bank and are adjusted from a baseline of 100 in 2010. The BACI database is used in the construction of the country-level measure to calculate the share of products traded. Data on large natural disasters data are constructed based on the EM-DAT database, which collects data on natural disasters and their effects. Natural disasters include among others, hydrological (such as floods), meteorological (such as storms), and geophysical events (such as earthquakes). A disaster is defined as large by the damage it generates as a share of GDP. Specifically, disasters in the 90th percentile by damage are considered large following Cavallo et al. (2013); there were 112 such events during 2004-2014.

Table 4.4 presents the results of the within-group estimations. The coefficient associated with the REER is negative —a currency appreciation is associated with lower export growth—but not statistically different from zero, probably due to the lack of control of the volatility of the variable. As mentioned previously, the small number of years in the sample does not allow for averaging data over periods to control for volatility. The coefficient on the share of total imports in $t-1$ of goods identified as risky in the methodology from a country suffering a large natural disaster

[26]Outliers are excluded by symmetrically dropping one percent of the distribution, as these observations might represent unexpected events and/or mistakes in data that the chapter does not aim to model.

in period t is negative and statistically significant at the 15 percent confidence level. A one percent increase in imports of risky products from a country suffering a natural disaster is associated with a 0.6 percent decrease in exports in the year of the event. The estimated effect is potentially a low estimate the overall economic impact for several reasons. First, the effects of RMIC are measured on total exports; estimation of changes to subsets of export flows (for instance, excluding commodities and true raw products) would be more closely associated with the supply shock's consequences on domestic production. Also, yearly trade flow data are used to keep a large sample of countries and an important disaggregation at the product level. As evidenced in case studies, a supply shock may be relevant for one or two quarters, but disappear for the rest of the year.

To further confirm those results, the regressions are controlled for the share of total imports that are risky and the existing level of trade before the natural disaster. As developed in the chapter, importing goods classified as fragile by the methodology has potential adverse effects if and only if there is a disruption of the supply. Regression results confirm this statement: the coefficient associated with imports of fragile products from countries that do not suffer a natural disaster has no statistical significance in the model. Finally, the share of total imports in period $t-1$ from a country that suffers a disaster in period t is tested; the resultant coefficient is not statistically significant. Column 1 presents regression results for the full sample, while column 2 shows the same estimation applied to a sample that excludes observations corresponding to a country experiencing a disaster in $t-1$.

Table 4.5 presents some robustness tests to the estimation. Column (1) shows that the effect of the imports of risky products in $t-1$ from a country with a disaster in t fades in $t+1$. Columns 2—4 define the riskiness of products based on each component

Table 4.4: Cross-country regressions

	(1)	(2)
$REER_{i,(t-1)}$	-0.117	-0.121
	(0.113)	(0.118)
Risky imports $RM_{i,t-1}$	0.067	0.105
	(0.285)	(0.286)
Imports from an impacted country $MIC_{i,t-1}$	0.017	0.017
	(0.066)	(0.070)
Risky Imports from impacted country $RMIC_{i,t-1}$	-0.608+	-0.676*
	(0.389)	(0.390)
Constant	0.795+	0.810+
	(0.506)	(0.527)
Country-fixed effects	Y	Y
Year-fixed effects	Y	Y
Exclude obs. if disaster in the i	N	Y
Observations	1,718	1,619
Number of country1	169	169
R-squared	0.324	0.315

Notes: The dependent variable is the country annual export growth in t. Estimations report the results of a within-estimators regressions. Robust standard errors in parentheses. Cluster errors are at country-level. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

separately. Riskiness defined only on a component does not impact statistically on export growth in t.

Finally, Table 4.6 assesses the sensibility of the results to the number of clusters of risky products considered. Results for 2, 3, 4 (favorite specification), 5, and 6 clusters are reported. The impact of the coefficients associated with the import of goods in the cluster considered as the riskier is consistently negative across specifications and always with a greater effect than with the placebo variables (share of risky imports from all partners and share of imports from a country with a disaster). Coefficients are statistically significant (except for the results associated with 5 clusters). It is worth mentioning that the coefficient associated with the riskier category of 6 clusters is greater in magnitude than the other coefficient associated with a lower number of cluster (0.859); on the other side, the coefficient associated with only 3 clusters is smaller (0.381). The more restrictive the definition of risk, the larger the impact on export growth after a disaster in a provider.

Table 4.5: Robustness check on cross-country regressions (1)

	(1)	(2)	(3)	(4)
$REER_{i,(t-1)}$	-0.178**	-0.119	-0.123	-0.128
	(0.085)	(0.118)	(0.120)	(0.118)
Risky imports $RM_{i,t-1}$	0.493			
	(0.668)			
Imports from an impacted country $MIC_{i,t-1}$	0.157+	0.019	0.023	0.018
	(0.108)	(0.069)	(0.071)	(0.070)
Risky Imports from impacted country $RMIC_{i,t-1}$	0.233			
	(0.870)			
Risky imports $RM_{i,t-1}$ based on comp.1		0.187		
		(0.270)		
Risky Imports from impacted country $RMIC_{i,t-1}$ based on comp. 1		-0.759		
		(0.755)		
Risky imports $RM_{i,t-1}$ based on comp.2			0.198	
			(0.274)	
Risky Imports from impacted country $RMIC_{i,t-1}$ based on comp. 2			-0.477	
			(0.369)	
Risky imports $RM_{i,t-1}$ based on comp.3				-0.153
				(0.170)
Risky Imports from impacted country $RMIC_{i,t-1}$ based on comp. 3				-0.076
				(0.273)
Constant	0.792***	0.792+	0.771	0.843+
	(0.263)	(0.530)	(0.565)	(0.532)
Observations	1,457	1,619	1,619	1,619
Number of countries	169	169	169	169
R-squared	0.069	0.315	0.313	0.313

Notes: The dependent variable is the country annual export growth in $t+1$ in column (1) and in t in columns 2-4. Estimations report the results of a within-estimators regressions. Robust standard errors in parentheses. Cluster errors are at country-level. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

4.5 Conclusion and Potential Applications

Applying network analysis tools to evaluate and compare the global supply fragility of individual traded goods generates new insight into the supply-side risks of modern international trade. Anecdotal evidence of choke points in the global trade network correspond well with the risky products predicted by network analysis tools. Case study analysis provides some evidence of outsized domestic effects from import supply shocks to risky products (those with the most fragile networks). Using a highly disaggregated international trade database, the chapter examines variation in trade

Table 4.6: Robustness check on cross-country regressions (2)

	(1)	(2)	(3)	(4)	(5)
$REER_{i,(t-1)}$	-0.121	-0.120	-0.121	-0.121	-0.119
	(0.120)	(0.117)	(0.118)	(0.119)	(0.118)
Risky imports $RM_{i,t-1}$	0.038	0.086	0.106	0.158	0.274
	(0.186)	(0.248)	(0.286)	(0.350)	(0.374)
Imports from an impacted country $MIC_{i,t-1}$	0.013	0.012	0.017	0.023	0.024
	(0.070)	(0.069)	(0.070)	(0.071)	(0.070)
Risky Imports from impacted country $RMIC_{i,t-1}$	-0.381+	-0.698**	-0.678*	-0.605	-0.859*
	(0.254)	(0.341)	(0.390)	(0.476)	(0.491)
Constant	0.810+	0.827+	0.810+	0.780+	0.769+
	(0.559)	(0.522)	(0.527)	(0.538)	(0.522)
Country-fixed effects	Y	Y	Y	Y	Y
Year-fixed effects	Y	Y	Y	Y	Y
Exclude obs. if disaster in the country	Y	Y	Y	Y	Y
Observations	1,619	1,619	1,619	1,619	1,619
Number of countryies	169	169	169	169	169
Number of cluster of products	2	3	4	5	6
R-squared	0.315	0.317	0.315	0.313	0.314

Notes: The dependent variable is the country annual export growth in t. Estimations report the results of a within-estimators regressions. Robust standard errors in parentheses. Cluster errors are at country-level. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

networks structure and uses these differences in structure and estimates of international substitutability to identify the riskier products globally. At the country level, the measure can be used to assess potential spillover effects of supply shocks from importing specific goods from specific countries. The methodology additionally can be applied to predict exporters' potential to originate negative spillovers from natural disasters.

By exploring the individual characteristics of riskiness of individual goods, in addition to the overall measure, researchers investigate different dimensions of the fragility of an import or set of imports. Likewise, a country-level indicator can be a useful starting point for undertaking nuanced macro diagnostics and analysis and for identifying specific areas for reform or intervention. Over time, the methodology could be used to evaluate ongoing efforts to improve the resilience of trade to global shocks.

The suggested methodology has a number of potential applications, including (i) as a vigilance tool, (ii) as a tool to evaluate spillovers, and (iii) to assess policies. The country-level share of risky products in import basket can be supplemented by information on main exporters of risky products and the structure of domestic economy to evaluate respective vulnerabilities of countries over time. The data can be used to assess the potential impact of natural disasters, globally and by country. Maps and network graphs can be helpful in visualizing the spillovers.

Additionally, by increasing the sample to all goods, this methodology can be useful for identifying the potential impact of natural disasters on the supply and prices of consumer goods and raw materials, which is particularly important for low income countries and island countries.

There are several potential extensions to this new research, such as cross-country analysis (for example, the analysis of business cycles and localized supply shocks), analysis of interaction with the global value chain, and analysis of permanent supply shocks (technological progress). The same methodology can be used for the analysis of trade in services, FDI, and other financial instruments. Additionally, it can be a powerful tool for micro level research of firms or industries interconnectedness globally (through, for example, input-output tables).

A number of policy implications emerge from the analysis of risky products and countries vulnerabilities from importing them. As demonstrated, better monitoring and more-detailed data provide a more robust understanding of the risks inherent in the modern global trade system. Such risks can be foreseen and mitigated by taking network effects of trade into account. For example, as discussed in this chapter, shock spillovers can be mitigated by macroeconomic policies that influence the properties of the export-import matrices of individual countries by changing their in- and out-degrees, exposure to centrality, tendency to cluster, and other network properties. Efforts to diversify suppliers of risky products might be desirable for some countries with highly concentrated imports[27]. Countries may consider insurance mechanisms or policy instruments capable of mitigating domestic risk from trade in risky goods, such as building up strategic physical reserves of certain risky products (at a country or firm level), trade regulations (for example, tax incentives), and trade promotion agencies, each with the intention of mitigating market volatility while ensuring sufficient supply.

[27]Annex 4.F explores countries' responses after a disaster happen in a trade partner country providing risky goods.

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Appendix 4.A Technical details on the definition of components and the overall product fragility measure

The methodology explores the trade network of individual goods. For each network, the information is used on which countries export and import the good, and the annual value of exports for each resultant pair of countries. Using network analysis terminologies, countries are represented by nodes, and exports will be represented by directed ties linking a pair of nodes. Three network analysis measures are used in the chapter:

4.A.1 Outdegree centrality

Outdegree centrality is a network analysis tool to identify the most influential nodes within a graph. It is defined as the sum of ties that a node directs outward to other nodes as a share of the total number of other nodes. This measure is weighted (the value of the ties is taken into account) and follow the definition of Barrat et al. (2004). The mathematical formulation of the weighted centrality of each country for each product network is:

$$C_i^{out} = \sum_{j=1}^{n-1} \frac{w_{ij}}{\langle w_j \rangle}$$

where C_i^{out} is the weighted outdegree centrality of country i, n is the total number of nodes in the network, w_{ij}, the value of the exports of country i to country j , and $\langle w_j \rangle$ the average value of j's imports. Formally, $\langle w_j \rangle$ is defined for each product by:

$$\langle w_j \rangle = \frac{\sum_i w_{ij}}{k_j}$$

where k_j is the number of nodes j imports from, and w_{ij} the value of the tie between j and i.

The standard deviation of outdegree centrality is used to measure each product's risk arising from having a few very central exporters. Formally:

$$Centrality_k = \sqrt{\frac{C_{ik}^{out} - \bar{C_k^{out}}}{n-1}}$$

where $\bar{C_k^{out}}$ is the average centrality of countries for product k.

4.A.2 Tendency to cluster

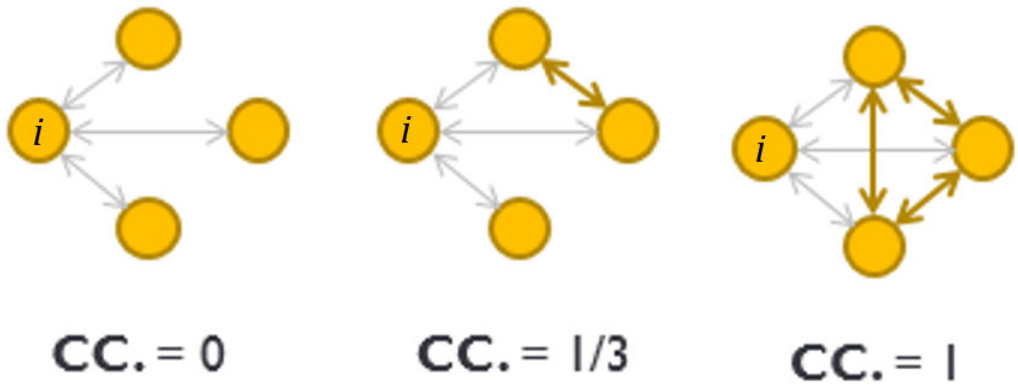
To assess the tendency to cluster of a network of goods, two complementary measures are used:

Weighted average of local cluster coefficient

The clustering coefficient measures the degree to which nodes tend to cluster together. The local cluster coefficient in the sense of Watts and Strogatz (1998) quantifies the tendency of the connected nodes of a country to form a clique, i.e. to trade together.

The local clustering coefficient CC_i for a node i is given by the proportion of ties between i's neighbor, divided by the maximal number of possible connections. In the non-weighted version, possible outcomes range from 0 (no connection among the partners of a country) to 1 (all the neighbor countries are connected). First, the weighted extension proposed by Barrat et al. (2004) is used. A value is assigned to

Figure 4.10: Different level of clustering coefficient



each triplet in the network based on the arithmetic mean. Next, the sum of the value of each closed triplet in the neighbor of each i is calculated and divided by the sum of the value of the triplets.

Formally:

$$CC_i^w = \frac{1}{k_i\left(k_i - 1\right)} \sum_{j,k} \frac{1}{\langle w_i \rangle} \frac{w_{ij} + w_{ik}}{2} T_{ij} T_{ik} T_{jk}$$

where k_i is the number of nodes connected to i, w_{ij} is the value of the tie between i and j (exports from i to j), and $\langle w_i \rangle$ is the average weight of ties connected with i:

$$\langle w_i \rangle = \frac{\sum_j T_{ij}}{k_i}$$

The weighted local cluster coefficient calculates the contribution of each triangle, weighted by the arithmetic average of the two adjacent ties, to the average weight of all the connections of node ii. Note that the direction of the ties is taken into account in this measure.

To obtain a measure at the product-year level, we average across countries.

Diameter

The diameter of a network is the length of the shortest path between the most distant nodes, i.e. the length of the longest geodesic path. It calculates the number of steps necessary for a node to reach the furthest node in the network. This measure is directed (the direction of the ties matter) but not weighted.

Value of the component

The value of the component of tendency to cluster is then equal to:

$$Cluster_k = CC_i^w.Diameter$$

4.A.3 International substitutability

The last component calculates the dispersion of human capital levels of countries exporting a good. The formulation is the following:

$$Int'lSubstituability_k = \sqrt{\frac{L_i^k - \bar{L_i^k}}{n-1}}$$

where L_i^k is the level of human capital of country i exporter of product k. The 'wider' the distribution of human capital of exporting countries, the more difficult it will be for a country to find a substitute supplier that corresponds to its standard.

4.A.4 Classifying overall product fragility

To classify products into groups by riskiness, the values of the three components described in the Section 4.3.1 are first normalized by calculating z-scores for each component, year, and product:

$$z\left(c_{kt}\right)=\frac{c_{kt}-\bar{c_t}}{\sigma\left(c_{kt}\right)}$$

where $z\left(c_{kt}\right)$, the z-score for component c, product k and year t is calculated as the raw score for each component, product, and each year, c_{kt}, minus the average score for all products in that year, $\bar{c_t}$, divided by the standard deviation of the raw score, $\sigma\left(c_{kt}\right)$.

Next, cluster analysis (the k-median procedure) partitions products into mutually exclusive groups, based on their standardized scores for the three components. The algorithm seeks to maximize the variation between clusters and minimize the variation inside. To reach this goal, the algorithm iterates the minimization of the following equation:

$$\sum\sum\left|X_{ck}-\bar{x_C}\right|^2$$

where X_ck is the value of the component c of product k, and $\left|X_{ck}-\bar{x_C}\right|$ is the distance between each product and the "center" of the cluster, in this case the median of the current product in the cluster.

After categorizing products, importers and exporters of risky products are tracked by looking at the risky-product share of total imports or exports in a county's trade basket.

Appendix 4.B Descriptive statistics

4.B.1 Frequency of products

Table 4.7: Number of products in each category over time

	Group 1	Group 2	Group 3	Group 4	Non-classified
2003	887	839	1146	689	0
2004	962	846	1091	656	15
2005	878	783	1247	654	11
2006	969	800	1110	672	24
2007	1029	735	1112	679	21
2008	1036	728	1119	672	21
2009	838	848	1129	700	61
2010	981	766	1112	657	60
2011	983	733	1109	667	84
2012	1043	818	1073	570	74
2013	1079	711	1094	615	79
2014	1040	694	1126	640	78

Notes: The table summarizes the frequency of products over time in the four risk groups, with group 4 being the riskiest. On average across years, 655 products are categorized in the riskier group (Group 4). Products which the algorithm fails to associate to a group are shown in the 'non-classified' column.

4.B.2 List of risky products

Table 4.8: One hundred most traded risky products during 2003-2014

	Product code HS 2002 6-digit	Product Description	Share Value of Imports
1	847170	Storage units (of auto. data processing machines)	0.964%
2	880330	Parts of aeroplanes/helicopters, other than propellers, rotors, under-carri ...	0.761%
3	870829	Parts & accessories of bodies (incl. cabs) of the motor vehicles of 87.01-8 ...	0.717%
4	300210	Antisera & oth. blood fractions & modified immunological prods., whether or ...	0.671%
5	870421	Motor vehicles for the tpt. of gds. (excl. of 8704.10), with C-I int. comb. ...	0.573%
6	848180	Taps, cocks, valves & sim. appls. for pipes/boiler shells/tanks/vats or the ...	0.537%
7	850440	Static converters	0.523%
8	841191	Parts of the turbo-jets/turbo-propellers of 8411.11-8411.22	0.470%
9	401110	New pneumatic tyres, of rubber, of a kind used on motor cars (incl. station ...	0.463%
10	901890	Instruments & appls. used in medical/surgical/veterinary sciences, incl. ot ...	0.455%
11	853400	Printed circuits	0.445%
12	854140	Photosensitive semiconductor devices, incl. photovoltaic cells whether or n ...	0.443%
13	732690	Articles of iron/steel, n.e.s.	0.423%
14	853710	Boards, panels, consoles, desks, cabinets & oth. bases, equipped with 2/mor ...	0.413%
15	840734	Spark ignition recip. piston engines of a kind used for the propulsion of v ...	0.399%
16	853690	Electrical app. for switching/protecting electrical circuits,/for making co ...	0.399%
17	840820	Compression-ignition int. comb. piston engines (diesel/semi-diesel engines) ...	0.392%
18	840999	Parts suit. for use solely/princ. with the engines of 84.07/84.08 (excl. of ...	0.391%
19	840991	Parts suit. for use solely/princ. with spark-ignition int. comb. piston eng ...	0.388%
20	870431	Motor vehicles for the tpt. of gds. (excl. of 8704.10), with spark-ignition ...	0.349%
21	854430	Ignition wiring sets & oth. wiring sets of a kind used in vehicles/aircraft ...	0.348%
22	730890	Structures...& parts of structures...of iron/steel (excl. of 7308.10-7308.4 ...	0.340%
23	870120	Road tractors for semi-trailers (excl. of 87.09)	0.330%
24	390110	Polyethylene having a sp.gr. of <0.94, in primary forms	0.323%
25	853890	Parts suit. for use solely/princ. with the app. of 85.35/85.36/85.37 (excl. ...	0.322%
26	390120	Polyethylene having a sp.gr. of 0.94/more, in primary forms	0.311%
27	870839	Brakes & servo-brakes & parts thereof (excl. mounted brake linings) for the ...	0.311%
28	940190	Parts of the seats of 94.01	0.310%
29	843149	Parts suit. for use solely/princ. with the mach. of 84.26/84.29/84.30 (excl ...	0.301%
30	390210	Polypropylene, in primary forms	0.290%
31	401120	New pneumatic tyres, of rubber, of a kind used on buses/lorries	0.277%
32	854459	Electric conductors (excl. of 8544.11-8544.30), for a voltage 80V but not ...	0.273%
33	842952	Self-propelled mech. shovels & excavators with a 360? revolving superstruct ...	0.265%
34	844359	Printing mach. n.e.s. in 84.43	0.261%
35	870422	Motor vehicles for the tpt. of gds. (excl. of 8704.10), with C-I int. comb. ...	0.256%
36	903289	Automatic regulating/controlling instr. & app., n.e.s. in 90.32	0.245%
37	870190	Tractors n.e.s. in 87.01 (excl. of 87.09)	0.242%
38	760612	Plates, sheets & strip, rect. (incl. square), of a thkns. 0.2mm, of alumin ...	0.242%
39	841199	Parts of the oth. gas turbines of 8411.81 & 8411.82	0.240%
40	841480	Air pumps, air/oth. gas compressors & fans (excl. of 8414.10-8414.59); vent ...	0.234%
41	901839	Catheters, cannulae and the like	0.229%
42	854441	Electric conductors (excl. of 8544.11-8544.30), for a voltage not 80V, fit ...	0.228%
43	151190	Palm oil, other than crude, & fractions thereof , whether or not ref. but n ...	0.227%
44	850300	Parts suit. for use solely/princ. with the machines of 85.01/85.02	0.220%
45	90111	Coffee, not roasted, not decaffeinated	0.220%
46	903180	Measuring/checking instr., app.& machines, n.e.s. in Ch. 90	0.217%
47	853650	Switches other than isolating switches & make-&-break switches, for a volta ...	0.215%
48	870423	Motor vehicles for the tpt. of gds. (excl. of 8704.10), with C-I int. comb. ...	0.208%
49	852190	Video recording/repr. app. other than magnetic tape-type, whether or not in ...	0.201%
50	300220	Vaccines for human medicine	0.201%
51	870870	Road wheels & parts & accessories thereof for the motor vehicles of 87.01-8 ...	0.195%
52	843143	Parts suit. for use solely/princ. with the boring/sinking mach. of 8430.41/ ...	0.192%
53	731815	Screws & bolts (excl. of 7318.11-7318.14), whether or not with their nuts/w ...	0.189%
54	842139	Filtering/purifying mach. & app. for gases, other than intake air filters f ...	0.185%
55	848340	Gears&gearing(excl. toothed wheels, chain sprockets&oth. transmission eleme ...	0.185%
56	841391	Parts of the pumps of 8413.11-8413.81	0.183%
57	848190	Parts of the appls. of 84.81	0.182%
58	841490	Parts of the pumps, compressors, fans & recycling hoods of 8414.10-8414.20	0.180%

One hundred most traded risky products during 2003-2014 (continued)

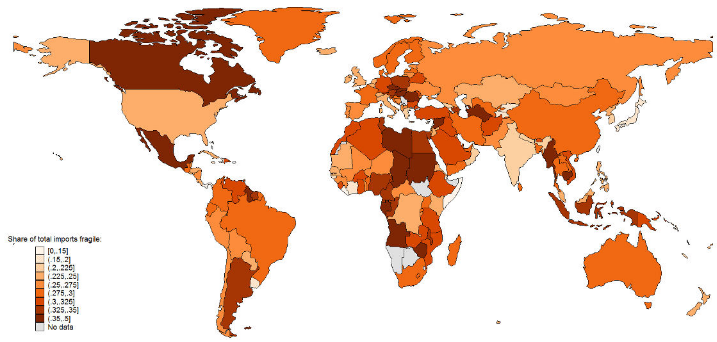
	Product code HS 2002 6-digit	Product Description	Share Value of Imports
59	850780	Electric accumulators, incl. separators therefor, whether or not rect. (inc ...	0.165%
60	841430	Compressors of a kind used in refrigerating equip.	0.163%
61	848210	Ball bearings	0.160%
62	841590	Parts of the air-conditioning machines of 8415.10-8415.83	0.160%
63	870210	Motor vehicles for the tpt. of 10/more persons incl. the driver, with C-I i ...	0.159%
64	330210	Mixtures of odoriferous subs. & mixts. (incl. alcoholic solutions) with a b ...	0.157%
65	761699	Articles of aluminium n.e.s. in Ch.76	0.157%
66	853669	Plugs & sockets for a voltage not 1000V	0.156%
67	392190	Plates, sheets, film, foil & strip (excl. cellular), of plastics, n.e.s. in ...	0.156%
68	854129	Transistors (excl. photosensitive transistors), other than those with a dis ...	0.156%
69	852691	Radio navigational aid app.	0.153%
70	940320	Metal furniture (excl. of 94.01 & 94.02)	0.151%
71	390690	Acrylic polymers other than poly(methyl methacrylate), in primary forms	0.150%
72	850110	Electric motors of an output not 37.5W	0.150%
73	840890	Internal combustion piston engines (diesel/semi-diesel engines) (excl. of 8 ...	0.148%
74	841370	Centrifugal pumps (excl. of 8413.11-8413.40)	0.146%
75	690890	Glazed ceramic flags & paving/hearth/wall tiles (excl. of 6908.10); glazed ...	0.144%
76	940510	Chandeliers & oth. elec. ceiling/wall lighting fittings (excl. those of a k ...	0.144%
77	842951	Self-propelled front-end shovel loaders	0.143%
78	950490	Articles for funfair/table/parlour games (excl. playing cards), incl. pinta ...	0.142%
79	230990	Preparations of a kind used in animal feeding other than dog/cat food put u ...	0.138%
80	851220	Lighting/visual signalling equip. of a kind used for cycles (excl. bicycles ...	0.137%
81	940540	Electric lamps & lighting fittings, n.e.s. in 94.05	0.137%
82	841330	Fuel/lubricating/cooling medium pumps for int. comb. piston engines	0.137%
83	391990	Self-adhesive plates, sheets, film, foil, tape, strip & oth. flat shapes, o ...	0.135%
84	842199	Parts of the filtering/purifying mach. & app. of 84.21 (excl. of centrifuge ...	0.134%
85	401699	Articles of vulcanised rubber other than hard rubber, n.e.s. in Ch.40	0.131%
86	390720	Polyethers other than polyacetals, in primary forms	0.129%
87	848310	Transmission shafts (incl. cam shafts & crank shafts) & cranks	0.122%
88	392310	Boxes, cases, crates & sim. arts., of plastics	0.121%
89	401693	Gaskets, washers & oth. seals of vulcanised rubber other than hard rubber	0.120%
90	854110	Diodes (excl. photosensitive/light emitting diodes)	0.118%
91	392321	Sacks & bags (incl. cones), of polymers of ethylene	0.116%
92	902780	Instruments & app. for physical/chem. analysis, n.e.s. in 90.27	0.116%
93	760429	Bars, rods & profiles (excl. hollow profiles) of aluminium alloys	0.115%
94	850490	Parts of the machines of 85.04	0.115%
95	240120	Tobacco, partly/wholly stemmed/stripped	0.113%
96	848390	Toothed wheels, chain sprockets & oth. transmission elements presented sep. ...	0.111%
97	841950	Heat exchange units, whether or not electrically heated	0.111%
98	902790	Microtomes; parts & accessories of instr. & app. of 90.27	0.109%
99	841459	Fans, other than table/floor/wall/window/ceiling/roof fans, with a self-con ...	0.103%
100	901819	Electro-diagnostic app. used in medical/surgical/dental/veterinary sciences ...	0.103%

Notes: Products are considered as risky if they constantly are classified in Group 4 during 2003-2014. Products are sorted by their relative importance in the world trade between 2003-2014.

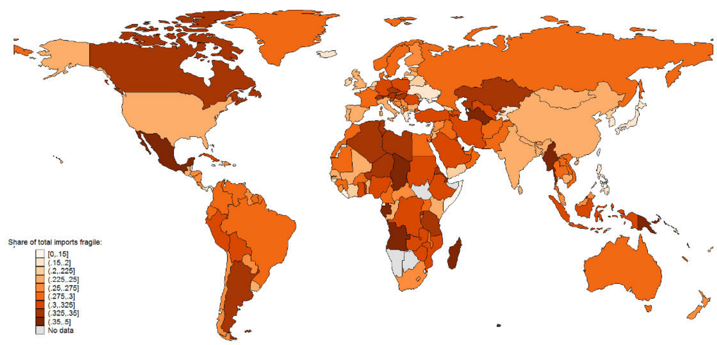
Appendix 4.C Fragility maps over time

Figure 4.11: Share of Total Imports of fragile products

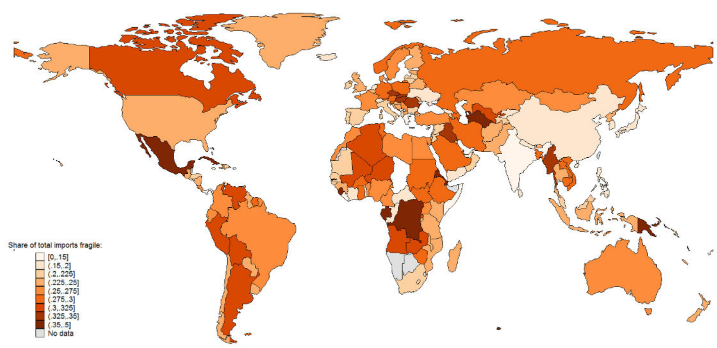
2003



2009



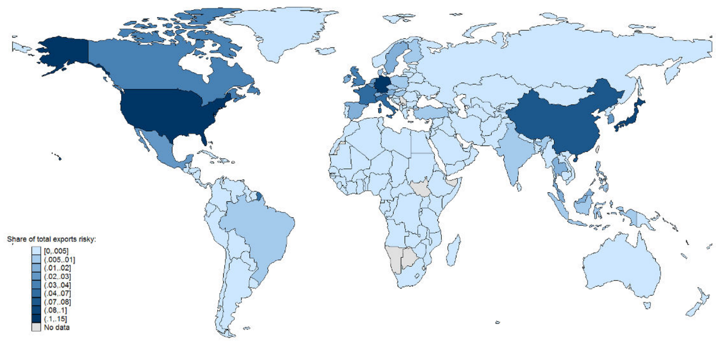
2013



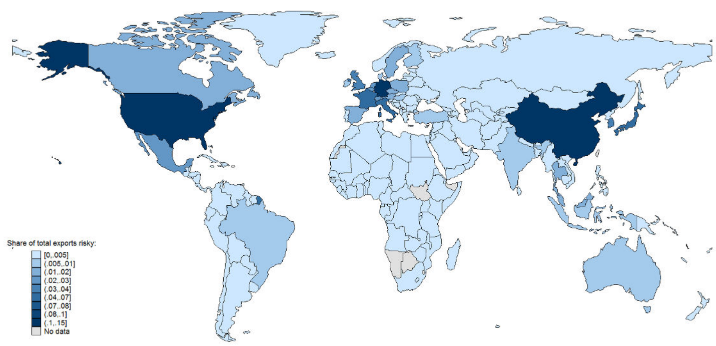
Notes: Over time, the share of imports of risky products have increased in Latin America, Russia and Australia, and decreased in Europe and East Asia.

Figure 4.12: Share of Total Imports of fragile products

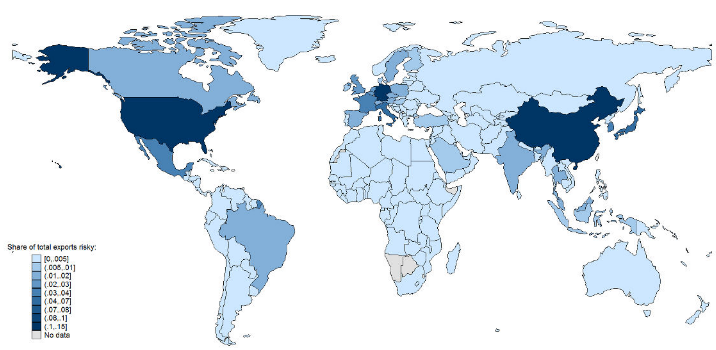
2003



2009



2013



Notes: Regions exporting risky goods are stable over time, and have become more concentrated in recent years.

Appendix 4.D Alternative to the third component

An alternative to the use of the standard deviation of the human capital is to use the measure of product complexity by Hidalgo et al. (2007). Hausmann et al. (2007) develop an index of complexity (based on the basket of goods that higher-income countries typically export) to rank countries' export baskets. They find a statistically significant association between complexity and growth: countries whose export baskets rank high on their complexity index tend to grow more rapidly.

Both measure have then the same spirit: in case of loss of a partner producing an input necessary for a country production, the country will search for an alternative partner with similar characteristics. The larger the variance of human capital across the countries producing the goods (the 3rd component) or the higher the complexity of a products (Product Complexity Index), the more difficult it will be to find an alternative partner. Both alternatives have the same intuition. But similarity in the construction of the complexity measure and of the measure of riskiness exist (particularly of the centrality component) is the reason with use the complexity measure as an alternative.

First, Table 4.9 shows that the correlation between both component is high and statistically significant at 1 percent for each year of the sample.

Table 4.9: Correlation Component 3 and Hausman, Hidalgo and Rodrik 2007's Product Complexity Index (PCI) by year

	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
corr(comp. 3; PCI)	-0.3834*	-0.3687*	-0.3695*	-0.3290*	-0.3747*	-0.3802*	-0.3614*	-0.3185*	-0.3289*	-0.3677*	-0.3630*	-0.3468*

Notes: * denotes a statistical significance at 0.1 percent.

Second, Table 4.10 present the top 10 products considered as risky and with the higher share of imports in the world across the years of the sample. Nine out of ten of the products are similar to the original list. Liquid crystal devices is a product that is detected as risky when the PCI is included in the index instead of HK.

Table 4.10: Top 10 risky import products by their value in trade

	Poduct code HS 2002 6-digit	Product Description	Share Value of Imports
1	847170	Storage units (of auto. data processing machines)	0.964%
2	880330	Parts of aeroplanes/helicopters, other than propellers, rotors, under-carri ...	0.761%
3	870829	Parts & accessories of bodies (incl. cabs) of the motor vehicles of 87.01-8 ...	0.717%
4	300210	Antisera & both. blood fractions & modified immunological prods., whether or ...	0.671%
5	901380	Liquid crystal devices not constituting arts. provided for more specificall ...	0.598%
6	870421	Motor vehicles for the tpt. of gds. (excl. of 8704.10), with C-I int. comb. ...	0.573%
7	848180	Taps, cocks, valves & sim. appls. for pipes/boiler shells/tanks/vats or the ...	0.537%
8	850440	Static converters	0.523%
9	841191	Parts of the turbo-jets/turbo-propellers of 8411.11-8411.22	0.470%
10	401110	New pneumatic tyres, of rubber, of a kind used on motor cars (incl. station ...	0.463%

Notes: The products shown in the table are consistently classified as risky (cluster Group 4) over 2003-2014. The ranking is by their value in imports.

Third, it is worth noting that four out six case studies products are confirmed when using the PCI instead of the chapter original component 3. While Electrical capacitors are considered risky with the original methodology, it is not using PCI. At the opposite, LCD devices are considered as risky using the complexity index and not the standard deviation of human capital. Results are displayed in Table 4.11.

Table 4.11: Case studies with alternative Component 3

Product code HS2002 6-digit	Risk category in 2010	Products Description (sometimes shortened)	z-score Comp. 1	z-score Comp. 2	z-score PCI
Japan Case Study - 2011 Earthquake and Nuclear Disaster					
840890	4	Combustion Engines # Other engines *includes diesel engines*	1.39	0.95	1.12
853229	3	Electrical Capacitors # Other *includes power supply capacitors and aluminium capcacitors*	0.89	0.74	0.00
901380	4	LCDs # Other devices, applicances and instruments *includes LCD screens in TV sets, notebook, smartphones, and tablets*	1.09	1.10	1.59
Thailand Case Study - 2011 Floods					
847170	4	Computers # Storage units *includes computer hard disk drives*	2.66	1.68	0.79
854121	4	Semiconductor Devices # with a dissipation rate of < 1W *includes semiconductors used in microprocessors*	0.58	1.09	0.74
870421	4	Delivery Trucks # g.v.w. not exceeding 5 tonnes *includes pick up trucks*	2.42	2.72	-0.18

Appendix 4.E Alternative using all the products available

In this extension, the methodology on all the products available is used, without excluding final products. The focus of the chapter is to assess the negative spillover risk of importing intermediary products on national production. Nevertheless, and as stated in the core of the chapter, the methodology is applicable to all kind of products, including final products. Keeping the 4798 products available each year, the frequency of number of products by group is displayed in Table 4.12. Around 300 products more are considered as risky.

Table 4.12: Number of products in each category over time

	Group 1	Group 2	Group 3	Group 4	Non-classified
2003	1255	1088	1487	945	0
2004	1160	1122	1486	998	20
2005	1358	1024	1445	947	17
2006	1234	1093	1527	910	29
2007	1324	1016	1481	944	30
2008	1381	946	1462	963	44
2009	1082	1121	1468	1018	107
2010	1246	1006	1488	954	102
2011	1253	1399	999	1016	129
2012	1349	1003	1458	859	129
2013	1445	942	1451	818	142
2014	1345	944	1415	956	138

Notes: The table summarizes the frequency of products over time in the four risk groups, with group 4 being the riskiest. On average across years, 944 products are categorized in the riskier group (Group 4). Products which the algorithm fails to associate to a group are shown in the 'non-classified' column.

In Table 4.13, the list of the 10 products considered as risky is displayed in the final products category and that are the most imported. Medicaments, vehicles and rice are consistently detected as risky products between 2003 and 2014. They are also the final products with most important value imported.

Table 4.13: Top 10 risky import products by their value in trade

	Product code HS 2002 6-digit	Product Description	Share Value of Imports
1	300490	Medicaments (excl. of 30.02/30.05/30.06) consisting of mixed/unmixed prods. ...	6.118%
2	870323	Vehicles (excl. of 87.02 & 8703.10) princ. designed for the tpt. of persons ...	5.792%
3	100630	Semi-milled/wholly milled rice, whether or not polished/glazed	2.873%
4	870332	Vehicles princ.designed for the tpt. of persons (excl. of 87.02 & 8703.10- ...	2.093%
5	870322	Vehicles (excl.of 87.02 & 8703.10) princ. designed for the tpt. of persons ...	2.018%
6	870324	Vehicles (excl.of 87.02 & 8703.10) princ. designed for the tpt. of persons ...	2.010%
7	210690	Food preps.,n.e.s.	1.880%
8	711319	Articles ofjewellery & parts thereof , of oth. precious metal (excl. silve ...	1.390%
9	870333	Vehicles princ.designed for the tpt. of persons (excl. of 87.02 & 8703.10- ...	1.293%
10	220300	Beer made from malt	0.950%

Notes: The final products shown in the table are consistently classified as risky (cluster Group 4) over 2003-2014. The ranking is by their value in imports as a share of total imports of final products.

Appendix 4.F Countries' response after a a disaster in a provider of risky goods

A follow-up question to this paper is whether countries increase their number of providers of risky products after a disaster in one of them. While a more in-depth analysis is needed for a proper assessment, some evidence is provided in this annex. First, Figure 4.7 presents some evidence for diesel engine provided by Japan. In 2010, Japan is a key player, exporting diesel engines to both the Chinese clusters. In 2011, the year of the Fukushima accident, the Japanese cluster disappears; at this time, China reinforces its imports from Korea. In 2012, the Japanese cluster is back, but the Korean cluster remains present; the network is more connected than before the earthquake.

For a more global analysis, Table 4.14 shows the average and median number of providers of a risky good one year before, the year of, and one year after a disaster in a provider country. Table 4.14 is constructed by retaining only the part of the database corresponding to exports of risky goods by a country suffering a disaster in t. Countries importing this or these goods from a provider impacted are then analyzed.

Countries tend to increase the number of providers of risky products, after one of them is impacted by a disaster. Increases in the number of partners happen in t and is sustained in $t+1$. This is particularly accurate the higher risky products represent in the total of imports and the lower the number of initial providers. For instance, countries importing risky goods from only one provider the year before a disaster, tend to import at least from one more after the disaster.

Table 4.14: Number of providers of risky good (Average/Median)

	Obs.	$t-1$	t	$t+1$
Share of Total imports risky >0%	5927	28/25	29/26	29/26
Share of Total imports risky >5%	2660	23/17	23/18	24/18
Share of Total imports risky >10%	2018	21/15	22/16	22/17
Share of Total imports risky >20%	1342	18/12	18/13	19/14

	Obs.	$t-1$	t	$t+1$
Number of providers in $t-1$ <25	2951	12/12	14/13	14/14
Number of providers in $t-1$ <10	1159	5/5	7/6	7/6
Number of providers in $t-1 = 1$	107	1/1	2/2	3/2

Notes: Averages are rounded to the closest unit. Number of observations corresponds to the number of countries importing at least one risky products in $t-1$ from a country experiencing a disaster in t.

Conclusion

This dissertation makes use of network analysis tools to delve into trade and finance problematics. Chapter 1 shows the role of trade partners' centrality in the diffusion of knowledge. Chapter 2 brings evidence of how clusters accelerate the adoption of technologies. Chapter 3 emphasizes the role of current partners in choosing a new destination for investment. Chapter 4 highlights the risks for importers of certain goods in the occurrence of a natural disaster in another country. These chapters represent a step toward integrating networks into international economics and open a promising avenue for further research.

With the increase of computer capacity, digging into higher order of network dependencies networks will become possible. Procedures presented in chapter 3 such as ERGM and TERGM will be able to converge with more nodes, more control variables, and more complex statistics. This will refine the analysis of trade and finance relationships by allowing the detection of higher dependencies and new regularities in the networks in order to understand international relationships better.

Another interesting direction for research is that of multilayer networks. Characterizing the trade and financial networks as a multilayer interdependent network could provide new insights underlying the structure of the international economic system, its vulnerabilities, and its resilience. It could provide evidence and estimate multiple channels of transmission across both networks. It could allow the reconciliation of evidence on the trade–finance nexus that traditional econometrics could not solve.

The availability of international Input–Output tables with high-quality data will also be propitious to do some investigation using network analysis tools. Analyzing the connectivity of countries could reveal choke points in the network and further risk of disruption at the micro level generating macro shock. In particular, key industries in a specific country could be highlighted as highly likely to generate supply chain disruption. Some interesting exercises of contagion analysis could be undertaken (expanding the approach of chapter 4 and allowing impact estimation of such effects).

With the increasing availability of firm-level data, the trade and finance literature has been moving to a more microeconomic analysis. Network analysis performed at the firm level would bring interesting insights, particularly for firms undertaking operations in multiple countries. Nevertheless, much work needs to be conducted to homogenize the identity of such firms. However, the work of cleaning the data is important. Machine learning tools offer several potentially valuable methods for matching firms across datasets and predicting ownership when disagreement occurs or information is missing.

Liens mondiaux, réseau commercial et développement
Cette thèse doctorale étudie l'impact des effets de réseau sur le commerce et la finance internationale. Le premier chapitre évalue le rôle que joue la centralité des partenaires commerciaux dans la diffusion des connaissances et conclut que l'importation de biens provenant de partenaires situés au cœur du réseau est génératrice de croissance économique. Le deuxième chapitre étudie le rôle des communautés de commerce dans la vitesse d'adoption de nouvelles technologies et établit que la diffusion des idées est encouragée au sein des pays appartenant à la même communauté. Le troisième chapitre souligne le rôle que jouent les partenaires financiers dans le choix d'investir dans une nouvelle destination et montre que les pays sont plus susceptibles d'investir dans un nouveau pays si un de leurs partenaires actuels y a déjà investi. Le quatrième chapitre évalue l'impact de l'importation des produits à risque et estime qu'une augmentation d'un pourcent des importations de produits fragiles provenant d'un pays touché par une catastrophe naturelle est associée à une réduction de 0,7 pourcent des exportations nationales.

Mots-clés : Commerce international, analyse de réseau, diffusion des connaissances, chocs d'offre.

Global Linkages, Trade Network and Development
This doctoral dissertation investigates the impact of networks effects on international trade and finance. The first chapter estimates the role a trade partners' centrality plays in the diffusion of knowledge and finds that importing from countries at the core of the network leads to a significant increase in economic growth. The second chapter investigates the role of clusters in the speed of technology adoption and concludes that the diffusion of ideas is fostered among countries belonging to the same cluster. The third chapter emphasizes the role of current partners in choosing a destination for new investments and finds that countries are more likely to invest in a new destination if one of their existing partners have already made some investments in the location. The fourth chapter evaluates the impact of importing risky products on the economy and finds that the elasticity of a country's exports with respect to its import share of fragile products from a partner impacted by a natural disaster is -0.7 percent.

Keywords: International trade, network analysis, knowledge diffusion, supply shocks.