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Cross-border Patenting, Globalization, and Development

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Cross-border Patenting, Globalization, and Development[*†]

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Abstract

We build a model of cross-border patent filing, technology diffusion, and development. Our theory delivers a 'structural gravity' equation for cross-border patent flows that disentangles the effects of technology diffusion from policy-driven changes in IPR protection. To test the model's predictions, we compile the International Patent and Citations across Sectors (INPACT-S) database that tracks patents within and between countries and industries over time. The econometric analysis reveals that while policy efforts have effectively promoted cross-border patent flows, the surge in patents from developed (North) to developing (South) countries between 1995 and 2018 was primarily driven by increased technology diffusion. A numerical analysis shows these North-South flows benefited both regions but generated larger gains in the South, thus reducing global income inequality.

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1 Introduction

In recent decades, globalization has led to a significant increase in cross-border patenting, both in absolute terms and also relative to domestic patent applications. Between 1995 and 2018, foreign patent applications grew by 136% compared to just 27% growth in domestic applications, with flows from developed ("North") to developing ("South") countries increasing by 542%.[1] Since patents are national rights granted by individual countries' patent offices, innovators must file separately in each jurisdiction where they seek protection, incurring local fees, translation costs, and enforcement expenses.[2] While international systems like the Patent Cooperation Treaty (PCT) can facilitate this process, the territorial nature of patents means that expanding into foreign markets requires significant investment in intellectual property protection.

The surge in cross-border patenting, particularly from developed to developing countries, could reflect different underlying forces. Innovators may be seeking protection in new markets due to fears of imitation (Eaton and Kortum, 1999). However, the rise could also be driven by increased diffusion of technologies, with developing countries becoming more capable of adopting and implementing foreign innovations, or developed country firms wanting to enter these markets and protecting their ideas along the way (Kortum and Lerner, 1999). Understanding which factors drive the increase in cross-border patenting is crucial for assessing its implications for global development. If this trend is primarily driven by technology diffusion, with developing countries increasingly able to adopt and implement foreign technologies, this could foster innovation and growth in technology-importing countries. However, if the increase is mainly due to policy changes, such as trade agreements requiring stronger intellectual property (IP) provisions, this might actually increase inequality by granting greater monopoly power to innovators from developed nations.

As highlighted by the World Bank:

> "Today, FDI is not only about capital, but also—and more important—about technology and know-how, [...] International patterns of production are leading to new forms of cross-border investment, in which foreign investors share their intangible assets such as know-how or brands in conjunction with local capital or tangible assets of domestic investors." (The World Bank, 2015)

This paper investigates the determinants of cross-border patenting in a globalized world and its consequences for economic development. We begin by examining the factors driving cross-border patent filings, guided by economic theory and empirical analysis. Then, we leverage these findings to assess the impact of cross-border patenting

[1] These calculations exclude China as the origin of patenting activity.

[2] The European Patent Office (EPO) offers a centralized application process—inventors can file a single European patent application that, if granted, can be validated in multiple EPO member states, though post-grant validation still requires translations and fees in each chosen country.

on economic development across countries, and we make three main contributions to understanding what drives the increase in cross-border patenting. First, we compile a dataset that tracks cross-border and domestic patent flows across countries and industries over time. By tracking where innovators seek protection for their ideas, we can identify emerging destinations for technology, such as the rise of Asia as a key market for patent protection. For instance, our data reveal the rise of Eastern Asia not just as a source but increasingly as a destination for patent applications, with countries like China, South Korea, and Taiwan becoming important markets where inventors seek protection. The shift of patents toward Asia suggests a gradual transfer of technology from established innovation centers, which may support technological development in the region. Second, guided by theory, we develop a gravity framework for cross-border patents that allows us to estimate the effects of various policy determinants on patent flows, as well as broader impacts of diffusion beyond observable policies. In addition to using average treatment effect (ATE) methods to mitigate potential endogeneity concerns with our policy variables, an important advantage of our new dataset is that its domestic dimension enables us to capture the impact of technology diffusion with a flexible set of dummy variables, which are exogenous by construction. Finally, to understand how different drivers of cross-border patenting might affect development, we conduct a numerical analysis. Our results suggest that if the observed increase in patent flows is driven by diffusion rather than policy changes, this could lead to reduced income inequality between developed and developing countries.

Our *International Patent and Citations across Sectors* (INPACT-S) database contributes to existing efforts to track patent flows by including both cross-border and domestic patents across industries.[3] The database allows us to examine where innovators are seeking protection for their ideas over time, revealing important trends in the global innovation landscape. The domestic dimension of INPACT-S is particularly useful for our analysis, as it enables us to obtain estimates of diffusion effects that go beyond policy and which cannot be identified with data on cross-border patents only. Using these data, we document that between 1995 and 2018, cross-border patenting has experienced faster growth compared to domestic applications, with China being an outlier, showcasing an unprecedented surge in domestic patents. Most cross-border patents are from developed to developing countries.[4]

Motivated by the patterns in the data, we develop an empirical approach that incorporates both domestic and international patent flows to understand the significant increase in cross-border patenting relative to domestic patenting. This approach is novel in its application to patent data and the diffusion of technology across countries. Leveraging our dataset, we first construct a multi-country model of cross-border patenting that yields a

[3] The INPACT-S dataset is available upon request by filling this questionnaire.

[4] The partition into North and South is based on the income classification of the World Bank for 2000.

structural gravity equation. Our theoretical framework builds on a multi-country model of innovation and technology diffusion where countries trade differentiated goods. For analytical tractability, we assume full depreciation of ideas in our baseline specification. While this assumption is stark, we show in a Supplementary Appendix that a model with partial depreciation yields similar insights on the balanced growth path but comes at the cost of analytical tractability when studying time-varying diffusion patterns and short-run dynamics. The full depreciation assumption allows us to derive a period-by-period gravity equation for patent flows that can accommodate time-varying diffusion rates—a key feature for our empirical analysis of how globalization affects international patent flows.[5] We then estimate this structural gravity model using established econometric techniques, allowing us to quantify the impacts of diffusion trends and specific policies on patent flows. By incorporating domestic flows, which are crucial for identifying diffusion trends in a gravity setting, we aim to provide estimates of those trends on cross-border patenting. This approach not only provides insights into the drivers of increased cross-border patenting but also allows us to disentangle the relative importance of technology diffusion and policy-driven changes in IPR regimes, which has implications for economic development across countries.

Our estimation analysis uses four nested specifications to highlight key aspects of our data and identification strategy. We start with a simple cross-sectional model using standard gravity variables and time-invariant border effects. This initial analysis shows that distance reduces patent flows, common language increases them, and borders present significant frictions. Second, we allow for border effects to vary across four country-pair income groups, revealing substantial heterogeneity in patent frictions. The smallest frictions are observed between "North" countries, while the largest occur in flows from "South" to "North" and "South" to "South" countries.

Our third specification uses panel data with country-pair fixed effects and time-varying border effects to capture the impact of technology diffusion and other non-policy factors on patent flows across income groups over time. This analysis reveals that diffusion has significantly increased patenting from "North" to "South" countries, with flows growing by about 300% between 1995 and 2018. This accounts for approximately 55% of the observed increase in cross-border patenting from "North" to "South" that we observe in the data. However, patenting originating from the "South" has not experienced similar growth. These findings help us understand why cross-border patenting has increased so dramatically, especially relative to domestic patenting, and highlight the differential impacts of technology diffusion on patent flows between developed and developing countries.

[5] In a Supplementary Appendix, we also demonstrate that both our model and an Eaton and Kortum (1999) framework with trade and Bertrand competition generate isomorphic gravity equations for patent flows, but they achieve this through distinct microfoundations. This feature of our gravity model of patents is akin to the isomorphic feature of the gravity model of trade (Arkolakis, Costinot, and Rodriguez-Clare, 2012; Allen, Arkolakis, and Takahashi, 2020).

The strong effect on North-South flows, combined with weak effects on South-originating patents, suggests that the increase in cross-border patenting may reflect developing countries becoming more capable of adopting and implementing foreign technologies, rather than just stronger IPR enforcement.

Our fourth and main specification introduces policy variables such as regional trade agreements (RTAs), the Trade-Related Aspects of Intellectual Property Rights (TRIPS) agreement, and the PCT, allowing for heterogeneous effects across bilateral income groups. This analysis is crucial as it allows us to disentangle two potential drivers of increased cross-border patenting: technology diffusion from policy-driven changes in IPR protection. Key findings include: (1) Policy efforts, particularly those strengthening IPR protection, have effectively promoted cross-border patent flows; (2) Policy effects vary significantly across different types of policies and directions of patent flows, with RTAs having stronger effects on North-North flows; and (3) While policies explain most changes in patent flows between developed economies, they account for only part of the surge in patents from "North" to "South". This last finding suggests that the dramatic increase in North-South patent flows is driven more by technology diffusion and market opportunities in developing countries than by policy changes strengthening IPR protection.

We then conduct a battery of robustness exercises. Our results remain stable across various modifications, including controlling for trade flows, using an alternative quality-corrected dependent variable, dropping China from the sample, altering country groupings, and other variations in model specification. Importantly, we find that when we control for trade flows in our main specification, trade positively affects patenting; however, controlling for trade flows does not significantly alter our main findings: policy estimates and diffusion effects remain largely unchanged. This suggests that the impact of diffusion on cross-border patenting is primarily direct, rather than mediated through trade. Detailed results of these robustness checks are reported in a Supplementary Appendix.

Since our empirical analysis points to technology diffusion, rather than policy changes, as the key driver of increased North-South patent flows, we use our model and partial equilibrium estimates to explore two questions about the implications for development: "What would have been the trajectory of cross-border patenting from North to South between 1995 and 2018 if the diffusion trends that we estimated had remained at their 1995 levels?" and "What might this imply for income per capita differences?" For simplicity, and consistent with our empirical results, we partition the world into two groups—North and South. To provide some quantitative guidance on these questions, we calibrate our model using data on cross-border patenting flows, R&D intensity, and bilateral trade flows.

The numerical results suggest that, in the absence of the estimated diffusion effects, cross-border patenting would have been 38% lower on average between 1995 and 2018.

While both North and South appear to have benefited from increased technology flows, the gains for the South were more substantial, particularly after the 2000s. This pattern is consistent with the interpretation that increased cross-border patenting, when driven by diffusion, may help narrow the real income gap between poor and rich countries. However, our estimates also suggest that policy changes like stronger IPR protection may have partially offset these convergence effects by disproportionately benefiting innovators in the North.

Related Literature. Our paper contributes to several strands of literature. First, we build upon work on patent dynamics and diffusion. Kortum and Lerner (1999) investigate factors driving the surge in US patenting during the 1980s and 1990s, providing key insights through their decomposition of patent applications into source and destination country effects. Our research extends the multi-country models of innovation and diffusion developed by Eaton and Kortum (1996, 1999), which explore how factors like imitation probability influence foreign patenting decisions, to study the broader interplay between globalization, diffusion, and cross-border patenting.

Second, we contribute to the growing empirical literature using patent data to analyze cross-border innovation and technology diffusion. While several studies have developed similar datasets, our approach offers several advantages. Liu and Ma (2021) construct a dataset focused on cross-sector R&D spillovers using Google Patents data, emphasizing sectoral innovation efficiencies within a closed-economy network model. Our dataset, in contrast, emphasizes cross-border patent flows and uses a broader array of patent offices, enabling us to employ a structural gravity framework that captures the effects of globalization on international patenting. Similarly, while Berkes, Manysheva, and Mestieri (2022) analyze long-term global patent data from PATSTAT to study the productivity impact of international knowledge spillovers, their focus is primarily on how knowledge flows affect growth over a long time horizon. Our analysis instead emphasizes recent globalization trends, examining how policy changes and income group differences affect cross-border patenting patterns. Uniquely, our dataset incorporates both domestic and international patent flows consistently across sectors, which proves crucial for identifying globalization effects beyond what can be captured with cross-border patents alone. Related empirical work by Brunel and Zylkin (2022) and De Rassenfosse et al. (2022) finds that innovators patent where they anticipate more trade, while Gong et al. (2023) suggest cross-border patenting serves as a quality signal for emerging economies. Impullitti and Ates (2021) explore how firms use foreign patenting to escape competition.

Third, our work connects to research on IPR, patents, and development. A key debate concerns whether stronger patent protection benefits developed nations at the expense of developing ones (Helpman, 1993; Grossman and Lai, 2004) or can increase growth in developing countries (Kwan and Lai, 2003). Important contributions include Lai (1998);

Lai and Qiu (2003); Yang and Maskus (2001); Branstetter et al. (2007, 2011); Tanaka and Iwaisako (2014); Diwan and Rodrik (1991); Kanwar and Evenson (2003). Hoekman and Saggi (2007) study how North-South trade agreements with technology provisions benefit the South, while Bond and Saggi (2020) examine the South's patent protection incentives. Recent work by Santacreu (2024) and Hémous et al. (2023) analyzes IP improvements' impact on technology transfer and optimal policy. This connects to broader research on IPR and technology transfer, with Maskus (2000) examining IPR's relationship with trade and growth, Keller (2004) studying diffusion's impact on innovation, and Glass and Saggi (1998) exploring how technology transfer closes development gaps. Related empirical work by Martínez-Zarzoso and Chelala (2021), Arregui and Martínez-Zarzoso (2024), Coleman (2022) and Howard, Maskus, and Ridley (2023) examines how trade agreements and IPR provisions affect bilateral patent flows.

Fourth, our empirical strategy builds on the gravity model literature in international trade, which examines border effects on flows (McCallum, 1995; Anderson and van Wincoop, 2003; Hillberry and Hummels, 2003; Balistreri and Hillberry, 2007). While early work was skeptical of gravity models' ability to capture globalization—as noted by Coe, Subramanian, and Tamirisa (2007)'s observation that "globalization is everywhere but in estimated gravity models" (p.3)—recent research shows these effects are present and important for unbiased policy estimates (Bergstrand, Larch, and Yotov, 2015).

Finally, we contribute to the literature on appropriate technology and North-South technology transfer. Building on theoretical foundations from Acemoglu and Zilibotti (2001) and Caselli and Coleman (2006), this work highlights how technologies from advanced economies may not suit developing country needs. Recent empirical evidence from Moscona and Sastry (2022) documents this mismatch in agriculture. The arrival of Northern technologies also shapes Southern innovation and adoption in complex ways, as shown by de Souza (2022)'s analysis of labor market impacts and Choi and Shim (2024)'s examination of optimal technology policy evolution. Our analysis of where innovators seek patent protection provides new insights into these dynamics, suggesting firms increasingly view developing markets as viable technology destinations—though whether this reflects greater diffusion capabilities or simply stronger IP enforcement has important implications for development.

A few remarks are in order: While cross-border patenting is not a direct measure of technology diffusion, the surge in North-South patent flows may signal increased potential for transfer. Our analysis suggests these flows are driven by developing countries' growing technological capabilities rather than policy shifts—consistent with innovators seeking protection where their technologies can be implemented. While actual diffusion involves factors beyond our scope, our findings complement other studies examining direct measures of diffusion through citations (Cai, Li, and Santacreu, 2022; Liu and Ma, 2021; Berkes, Manysheva, and Mestieri, 2022; Pauly and Stipanicic, 2021) and patent characteristics (Kalyani, 2024; Bloom et al., 2021) by identifying where technology transfer is becoming more viable.

The rest of the paper is organized as follows. Section 2 describes the INPACT-S dataset. In Section 3, we develop our theoretical model (in Subsection 3.1), and we translate it into an estimating equation (in Subsection 3.3). Section 4 presents our main estimation findings (in Subsection 4.1) and offers numerical analysis for the impact of patents on welfare and income inequality (in Subsection 4.2). Section 5 concludes with directions for future work. A Supplementary Appendix includes results and discussion from a series of robustness experiments and additional specifications. The Supplementary Appendix also includes details on the model, a comprehensive description of the data construction process, and several salient features of our novel dataset.

2 The INPACT-S Database

Our *International Patent and Citations across Sectors* (INPACT-S) database documents international and domestic patent flows and citations across countries and industries from 1980 to 2018.[6]

To construct INPACT-S, we rely primarily on the PATSTAT Global Autumn 2021. Using patent-level data from PATSTAT, we compute the number of patent applications from a country of origin (i.e., the residence of the inventor or the owner of the technology) to an application authority at the International Patent Classification (IPC) level — 4-digit IPC codes — for the period 1980-2019. We account for both the applicant and the inventor, respectively.[7] We then use concordance tables developed by Lybbert and Zolas (2022) to transform IPC codes into industry codes—ISIC Rev 3, at 2-digit. The result is a dataset that contains 91 patent authorities, 213 countries of origin, 40 years, and 31 ISIC codes. Next, we summarize the main features of INPACT-S. In the Supplementary Appendix, we describe in detail the steps taken to construct our dataset.

INPACT-S offers several key advantages over other publicly available datasets. It provides a more comprehensive view of global patent activity by encompassing a wider array of patent authorities. The dataset also includes industry-specific bilateral data, enabling detailed sectoral analysis. Through imputation methods, INPACT-S captures a

[6]The database includes citation patterns between country-sector pairs, facilitating analysis of international knowledge flows in the spirit of Cai, Li, and Santacreu (2022). Related work includes Liu and Ma (2021), who construct sector-level citation networks using Google Patents data, and Berkes, Manysheva, and Mestieri (2022), who analyze sectoral knowledge spillovers using PATSTAT data over an extended time period.

[7]The inventor country of residence reflects the country of origin of the innovation, whereas the applicant country of residence reflects the ownership of the intangible. Not all applicants are necessarily inventors, as the inventor may simply develop a new technology while ownership resides with the firm that employs or funds her. For the same reason, being an inventor does not automatically make one an applicant. Importantly, in PATSTAT, firms can be applicants but cannot be inventors.

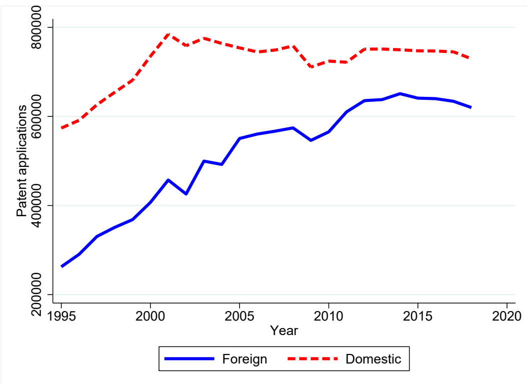
greater number of patent applications, enhancing its coverage. Additionally, it includes comprehensive data on cross-country and cross-sector citation patterns. Importantly, INPACT-S uniquely incorporates consistently constructed data on both cross-border and domestic patents, allowing for more robust comparative analyses. These features collectively make INPACT-S a powerful tool for studying global patenting trends and their economic implications.

INPACT-S uncovers several interesting features of patent flows across countries over time. We summarize the main findings for the purpose of this paper here, and leave details on other interesting facts in the Supplementary Appendix. Among other facts, we find that international patent applications have grown faster than domestic patent applications, especially from developed to developing countries. We highlight the rise of Asia as both an origin and a destination of patent applications over the past decades. Asian countries increasingly becoming destinations for patent applications suggests a flow of technology from traditionally innovative countries. This exchange has the potential to drive development in Asia, as the countries gain access to advanced knowledge, methodologies, and technologies from developed countries. Indeed, we also observe that more Asian countries are becoming origins of patents, implying they are becoming more innovative themselves.

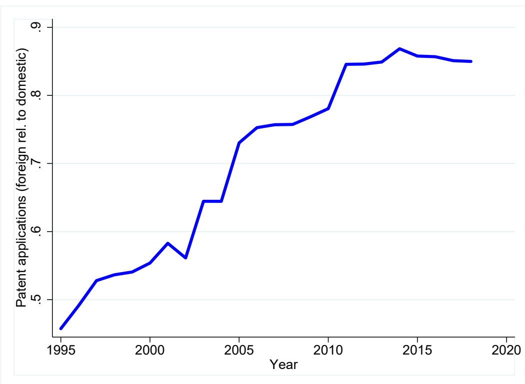
Figure 1 illustrates the evolution of domestic and foreign patent applications over time, excluding China.[8] Foreign patent applications have grown faster than domestic applications. Specifically, between 1995 and 2018, foreign patent applications (excluding those from China) grew by 136%, significantly outpacing the 27% growth in domestic applications. The right panel of Figure 1 shows the ratio of foreign to domestic patent applications, which has steadily increased from 0.5 in 1995 to nearly 0.9 in 2018, indicating that innovators are increasingly seeking patent protection in foreign markets.

Figure 1: Patent Applications: Domestic vs Foreign (excluding China)

(a) Patent Applications



(b) Ratio Foreign vs Domestic



[8]When including China, results are influenced by its unprecedented growth in domestic patent applications (162-fold increase from 1995 to 2018), likely due to generous subsidy programs set to be phased out by 2025 (CNIPA, 2021).

Figure 1 reveals three distinct periods in the evolution of cross-border patenting versus domestic patenting. Before 2000, foreign and domestic patent applications grew at a similar pace, with a relatively stable ratio of foreign to domestic applications around 0.5 to 0.6, indicating a balanced distribution of patenting activities. From 2000 to 2010, foreign patent applications grew at a faster rate than domestic ones, leading to a narrowing of the gap between the two, even though domestic applications remained larger in absolute numbers. This faster growth of foreign applications is reflected in the steady increase in the ratio of foreign to domestic applications during this period, signaling a shift towards internationalization in patenting activities. After 2010, both foreign and domestic applications continued to grow at a more similar rate compared to the previous decade, leading to a stabilization in the ratio of foreign to domestic applications around 0.8 to 0.9, suggesting a more balanced growth in recent years, albeit with a higher level of internationalization compared to the pre-2000 era.

This faster growth of foreign patent applications can be attributed to several factors, such as diffusion or policy (i.e., the harmonization of patent laws through the PCT, TRIPS, and the improvement of IP protection as part of regional trade agreements). Diffusion has led to increased international trade and foreign direct investment, which has incentivized companies to protect their IP in foreign markets. Moreover, the PCT has streamlined the process of filing international patent applications, making it easier for innovators to seek protection in multiple countries. Lastly, the inclusion of IPR chapters in trade agreements has strengthened patent protection in participating countries, encouraging more cross-border patent filings.

The INPACT-S database reveals several important patterns about the origins and destinations of global patent flows. Innovation is concentrated in Europe, the United States, and Eastern Asia, with the rise of East Asian countries as significant new innovators. While China shows unprecedented growth in domestic patent applications (increasing 162-fold from 1995-2018), Japan, South Korea, Taiwan and China have also emerged as important sources of cross-border patents, though China's international patenting has not matched its domestic surge. On the destination side, the US and China dominated as recipients of cross-border patents by the 2010s, with both countries attracting over a million foreign patent applications that decade. South Korea and Taiwan have also become increasingly important destinations, ranking 4th and 7th respectively in attracting foreign patents. The emergence of these Asian economies as key destinations for patent protection suggests they are becoming important markets for technology deployment.

3 Cross-border Patenting and Globalization: Theory and Empirics

Building on patterns revealed in the INPACT-S database, this section analyzes the drivers and determinants of cross-border patent flows. Subsection 3.1 develops a model of cross-border patenting that incorporates technology diffusion, trade, and development dynamics. A key theoretical contribution is the derivation of a gravity model for cross-border patent flows, which enables us to disentangle the roles of technology diffusion and policy changes in driving international patent activity. This decomposition is crucial because, as our empirical analysis demonstrates, the surge in North-to-South patent flows appears to be driven more by increased technology diffusion than by policy changes. In Subsection 3.3, we develop an empirical framework to separately identify these diffusion and policy effects.

3.1 A Theory of Cross-border Patenting and Globalization

We develop a multi-country model of innovation and technology diffusion to analyze the patenting decisions of innovators that want to maximize their returns to R&D investment, while minimizing the risk of imitation. There are M countries, indexed by i and n. Time is discrete and indexed by $t \in \{0, \infty\}$. Countries trade and exchange ideas. The trade model consists of an Armington framework where each country produces differentiated intermediate goods that are traded internationally, subject to trade costs. Technology is determined by innovation and technology diffusion and subject to imitation and patenting decisions.

Innovators invest in R&D to create new ideas, which serve as blueprints for differentiated goods. These ideas can diffuse in foreign countries and be used to produce intermediate goods there, generating profits and payments for the innovators. While increased diffusion can enhance R&D returns, unpatented ideas face imitation. Innovators therefore file patents in jurisdictions where their ideas have diffused to protect against imitation.[9] While patented ideas have a positive but lower probability of imitation, unpatented ideas are imitated with certainty. Following Romer (2005) and Grossman and Lai (2004), a country's technological level is determined by the number of ideas used in production.

We present a model with full depreciation of ideas, which allows us to derive clean analytical expressions for patent flows that hold period-by-period rather than just on the balanced growth path. In the Appendix, we show that a more general version of the model with partial depreciation delivers similar insights about the relationship between

[9] This resembles a world in which innovators license their technology to a foreign firm and file a patent application prior to licensing.

trade costs, technology diffusion, and patent flows, but requires restricting attention to balanced growth paths where diffusion rates are constant. Since our empirical work emphasizes the role of time-varying diffusion patterns in explaining patent flows, we opt for the more tractable full depreciation specification in our baseline model. This choice enables us to study how changes in diffusion rates affect patenting decisions outside of balanced growth paths, while still capturing the key economic mechanisms driving cross-border patent flows.

3.1.1 Production and Trade: Static Equilibrium

Given the level of technology and trade costs at time t, an Armington trade model determines the static equilibrium.

Final Production. A final producer in each country n uses intermediate goods, both domestic and foreign, to produce a final good, Y_{nt}, with a CES technology

$$Y_{nt} = \left(\sum_{i=1}^{M} \int_{j=1}^{T_{it}} X_{ni,t}(j)^{\frac{\sigma-1}{\sigma}} dj \right)^{\frac{\sigma}{\sigma-1}}, \tag{1}$$

where T_{it} is the number of products being produced in country i, $X_{ni,t}(j)$ is the amount of good j from country i demanded by country n, and σ is the elasticity of substitution across varieties. The demand for intermediate goods from country i by final producers in country n is given by

$$X_{ni,t}(j) = \left(\frac{p_{ni,t}(j)}{P_{nt}} \right)^{-\sigma} Y_{nt}, \tag{2}$$

where $p_{ni,t}(j)$ is the price charged by each intermediate producer j in country i selling to country n and P_{nt} is the aggregate price level in country n, given by

$$P_{nt} = \left(\sum_{i=1}^{M} \int_{1}^{T_{it}} p_{ni,t}(j)^{1-\sigma} dj \right)^{\frac{1}{1-\sigma}}.$$

Intermediate Production. Each intermediate good j in country i is produced by a monopolistic competitive firm according to

$$y_{it}(j) = \Omega_{it} l_{it}(j), \tag{3}$$

where $y_{it}(j)$ is the amount of intermediate good j produced in country i, Ω_{it} represents fundamental productivity in country i, and $l_{it}(j)$ is the amount of labor used to produce intermediate good j. The firms choose labor and prices taking as given the demand by final producers. Prices are set as a constant markup of the cost, which is given by wages.

The mark up is given by $\bar{m} = \frac{\sigma}{\sigma-1}$ and prices are given by

$$p_{ni,t}(j) = \bar{m} W_{it} d_{ni}, \tag{4}$$

where W_{it} is the wage, and d_{ni} is an iceberg transport cost for selling goods from country i to country n. In a symmetric equilibrium, the resulting price of the final good producer is given by

$$P_{nt} = \left(\sum_{i=1}^{M} \Omega_i^{\sigma-1} T_{it} p_{ni,t}^{1-\sigma} \right)^{\frac{1}{1-\sigma}} \tag{5}$$

Trade Shares. Given technology, T_{nt}, and trade costs, d_{in}, the share of goods that are imported by country i from country n, $\pi_{in,t}$, is given by

$$\pi_{in,t} = \Omega_{nt}^{\sigma-1} T_{nt} \frac{(\bar{m} W_{nt} d_{in})^{1-\sigma}}{P_{it}^{1-\sigma}}. \tag{6}$$

The previous equation is a version of the standard gravity model of trade.

3.1.2 Growth Model: Innovation, Diffusion, and Cross-border Patenting

Technology evolves endogenously through two processes: innovation and technology diffusion. Innovators invest resources to create new ideas, which then diffuse across countries through an exogenous process. These diffused ideas can be used to produce intermediate goods. As technologies are non-rivalrous, firms in different countries can utilize the same technology; however, the same idea produces different goods in each country due to the Armington structure. Innovators receive a payment for their diffused ideas, but imperfect enforcement of IPR means that a fraction of these ideas may be imitated, resulting in no compensation for the innovators. To mitigate imitation and increase the return on R&D, innovators may file patent applications. Since patenting is a costly activity, innovators choose to patent only a share of their technologies, arriving at an interior solution that balances the benefits and costs of patenting.

Innovation and International Diffusion. Innovators in n create new technologies at the rate $\gamma_{nt} \left(\frac{H_{nt}}{Y_{nt}}\right)^{\eta}$, with H_{nt} representing investment into R&D. Assuming full depreciation of new technologies, the number of newly created technologies every period is

$$Z_{nt} = \gamma_{nt} \left(\frac{H_{nt}}{Y_{nt}} \right)^{\eta}, \tag{7}$$

where γ_{nt} is a time-varying country-specific parameter capturing the innovation efficiency, and the parameter η represents diminishing returns to R&D investment.

Technology Diffusion. In every period t, a fraction $\varepsilon_{in,t}$ of ideas created by country n diffuses to each other country i. Diffusion increases the likelihood that an idea is used to produce differentiated intermediate goods. The number of intermediate goods produced in country n, with domestic and foreign technology, at time t is equal to:

$$T_{nt} = \sum_{i=1}^{M} \varepsilon_{ni,t} Z_{it}.$$

Cross-border patenting. Due to diffusion and imitation, innovators in country n decide on the fraction of their innovations to patent in each country i. Unpatented ideas are imitated with certainty, while a fraction $(1 - \phi_{in,t})$ of patented ideas from country n are imitated in country i, with $\phi_{in,t}$ representing the bilateral strength of IP protection. This term can be influenced by several factors, such as bilateral or multilateral agreements on IPR protection, harmonization of IP laws and enforcement practices, and explicitly addressed responsibilities in technology transfer agreements or licensing contracts (Hémous et al., 2023; Santacreu, 2024). Faster diffusion and better IP protection increase patenting activity, but patenting is costly.

Innovators from country n choose the fraction $\lambda_{in,t}$ to patent in country i at time t to maximize

$$\underbrace{\lambda_{in,t} V_{in,t}^{\text{pat}} - C(\lambda_{in,t}) P_{it}}_{\text{Value of patenting}} + \underbrace{(1 - \lambda_{in,t}) V_{in,t}^{\text{nopat}}}_{\text{Value of not patenting}},$$

where $C(\lambda_{in,t})$ is the cost of patenting a technology from country n in country i. We assume that the cost of patenting is paid in the destination country i.

The value of a patented technology is given by:

$$V_{in,t}^{pat} = \varepsilon_{in,t} \phi_{in,t} \frac{\Pi_{it}}{T_{it}}, \tag{8}$$

where Π_{it} are the profits of all intermediate goods produced in country i and $\phi_{in,t}$ is the share of patented technologies from country n that are imitated in country i. We assume that $V_{in,t}^{nopat} = 0$, that is, all unpatented technologies are imitated.

The FOC for the share of patented technologies is:

$$C'(\lambda_{in,t}) P_{it} = V_{in,t}^{pat} - V_{in,t}^{nopat}.$$

We assume the following functional form for the cost of patenting:

$$C(\lambda_{in,t}) = \frac{1}{\xi} \tau_{in} (\lambda_{in,t})^{\xi}, \quad \xi > 1, \tag{9}$$

where τ_{in} captures bilateral patenting frictions that increase the cost of patenting, such as language, geography, and ξ captures increasing marginal costs to patenting. This functional form incorporates curvature to ensure an interior solution for the share of diffused ideas that are patented. The underlying assumption is the presence of increasing marginal costs associated with patenting additional technologies; that is, increasing efforts to patent more technologies—more legal and administrative tasks, higher complexity, and higher R&D demands, particularly when overseeing an extensive patent portfolio—incur disproportionately greater resources. In other words, we assume congestion in the patenting process.

We can then express the share of patented technologies as:

$$\lambda_{in,t} = {\tau_{in}}^{-1/(\xi-1)} \left(\frac{V_{in,t}^{pat}}{P_{it}} \right)^{1/(\xi-1)}. \tag{10}$$

Note that if there is no IP protection, i.e., $\phi_{in,t} = 0$, the patent share ($\lambda_{in,t}$) is 0. This means that when imitation is guaranteed to occur, firms have no incentive to patent their innovations, as they would not be able to protect their IP and capture the full value of their invention. However, when there is perfect IP enforcement, that is, if $\phi_{in,t} = 1$, the patent share ($\lambda_{in,t}$) is not necessarily 1. This is because patenting is costly, and firms must weigh the benefits of patenting against the associated costs. Then, the number of patented technologies is given by:

$$\text{Pat}_{in,t} = \lambda_{in,t} \varepsilon_{in,t} Z_{nt}. \tag{11}$$

Substituting equations (8) and (10) into (11), we obtain an expression for the determinants of cross-border patenting:

$$\text{Pat}_{in,t} = \tau_{in}^{-1/(\xi-1)} \varepsilon_{in,t} (\varepsilon_{in,t} \phi_{in,t})^{1/(\xi-1)} \left(\frac{\Pi_{it}}{T_{it} P_{it}} \right)^{1/(\xi-1)} Z_{nt}. \tag{12}$$

Optimal R&D investment The first-order condition for R&D investment is derived from the following problem:

$$Z_{nt} V_{nt} - P_{nt} H_{nt}, \tag{13}$$

subject to the expression for $Z_{nt} = \gamma_{nt} \left(\frac{H_{n,t}}{Y_{nt}} \right)^{\eta}$. The value of innovation can be expressed as

$$V_{nt} = \sum_{i=1}^{M} \varepsilon_{in,t} \lambda_{in,t} \phi_{in,t} \frac{\Pi_{it}}{T_{it}}. \tag{14}$$

The first-order-condition determining R&D investment is

$$H_{nt} = \eta \frac{V_{nt}}{P_{nt}} Z_{nt}. \tag{15}$$

Finally, the profits are given by

$$\Pi_{nt} = (\bar{m} - 1)W_{nt}L_{nt}. \tag{16}$$

Preferences. In each country, there is a representative consumer choosing consumption to maximize lifetime utility

$$\sum_{t=0}^{\infty} \beta^t C_{nt}, \tag{17}$$

where β is the discount factor, C_{nt} is consumption of country n in period t.

Consumers face the budget constraint

$$P_{nt}C_{nt} = W_{nt}L_{nt} + \Pi_{nt}^{all}, \tag{18}$$

where Π_{nt}^{all} are profits of all firms operating in the economy.

Market Clearing Conditions. To close the model, we impose the following market clearing conditions:

(i) Final output: $Y_{nt} = C_{nt} + H_{nt}$;

(ii) Labor market: $\bar{m}W_{nt}L_{nt} = \sum_{i=1}^{M} \pi_{in,t}Y_{it}$;

(iii) Total number of intermediate goods produced using domestic and foreign technology: $T_{nt} = \sum_{i=1}^{M} \varepsilon_{ni,t}Z_{it}$;

(iv) Consumer's budget constraint: $P_{nt}C_{nt} = W_{nt}L_{nt} + \Pi_{nt}^{all}$, where Π_{nt}^{all} includes the profits of intermediate producers and innovators, and it is defined in a Supplementary Appendix.

3.1.3 Structural Gravity Equation for Cross-border patenting

Equation (12) provides a structural gravity equation for cross-border patents.

Proposition 1. ***(Structural Gravity for Cross-border Patents.)*** *Cross-border patenting from country n to country i at time t is given by*

$$Pat_{in,t} = \underbrace{\frac{H_{nt}P_{nt}}{\eta V_{nt}}}_{\textit{Source innovation}} \underbrace{\left(\frac{\Pi_{it}}{P_{it}T_{it}}\right)^{1/(\xi-1)}}_{\textit{Destination attractiveness}} \underbrace{\left(\tau_{in}\right)^{-1/(\xi-1)}}_{\textit{Bilateral patenting frictions}} \underbrace{\left(\phi_{in,t}\right)^{1/(\xi-1)}}_{\textit{Policy}} \underbrace{\varepsilon_{in,t}^{\frac{\xi}{\xi-1}}}_{\textit{Diffusion}}. \tag{19}$$

Cross-border patent flows obey the law of gravity, i.e., the "closer" and the ''larger" two countries are, the more cross-border patents they would exchange.

More specifically, according to our theoretical gravity model, cross-border patenting depends on several determinants. First, they depend on the characteristics of the origin country, $\frac{H_{nt}P_{nt}}{\eta V_{nt}}$, which reflect the source country's innovative capacity. We label this term "Source innovation". Second, they depend on the characteristics of the destination country, $\left(\frac{\Pi_{it}}{P_{it}T_{it}}\right)^{1/(\xi-1)}$, which determine the attractiveness of the host country, based on size and productivity. We label this term "Source attractiveness". Finally, they depend on country-pair specific characteristics, $(\tau_{in})^{-1/(\xi-1)}(\phi_{in,t})^{1/(\xi-1)}\varepsilon_{in,t}^{\frac{\xi}{\xi-1}}$, which we label "Bilateral patenting frictions" (e.g., distance, language), "Diffusion", and "Policy" (i.e., trade and patenting policies—e.g., international agreements and treaties, harmonization of patent laws).

The gravity equation for cross-border patenting shares some similarities with the gravity equation for trade flows, but also exhibits important differences. The determinants of bilateral patent flows in our gravity equation include bilateral patent frictions, technology diffusion barriers, trade and patent-related policies, the attractiveness of the destination market, and the innovation capacity of the source country. However, unlike the gravity equation for trade flows, the outward multilateral resistance term only indirectly enters our system through trade in intermediates. This difference can be attributed to the non-rival nature of patents, which allows for the simultaneous use of a patented invention in multiple countries. Consequently, the decision to patent in a particular market is less influenced by the relative barriers to patenting in other markets. Instead, it depends on factors such as market size, the strength of IP protection, and the potential for local enforcement. In contrast, the presence of outward multilateral resistance terms in the gravity equation for trade flows captures the idea that exports to one country come at the opportunity cost of not exporting to other markets, as determined by the relative trade barriers across destinations.

Our structural gravity equation for cross-border patenting captures the complex interplay between diffusion ($\varepsilon_{in,t}$) and policy effects ($\phi_{in,t}$) through country-pair-time specific border effects. While both parameters increase cross-border patenting, their implications for economic development can differ substantially depending on which force dominates, as we explain next.

3.2 Mechanism: Technology Diffusion vs Policy Changes

To understand the drivers of the increased international patent flows and their implications for economic development, it is crucial to disentangle the effects of diffusion from policy-driven changes in IPR enforcement. Our model captures this interplay through two key parameters: $\varepsilon_{in,t}$, which represents the diffusion of ideas from country n to country i, and $\phi_{in,t}$, which reflects the quality of IP enforcement in the destination country. The interaction between these parameters is central to determining the incentives for cross-border patenting.

This interaction is captured by equation (12), which describes the number of patented technologies. A higher value of $\varepsilon_{in,t}$ indicates greater diffusion of ideas from country n to country i, whereas a higher $\phi_{in,t}$ captures a better IP enforcement, which can be influenced by policy.

When diffusion ($\varepsilon_{in,t}$) is high, innovators have a greater incentive to patent their ideas in country i to protect their IP and receive payments for the use of their technology. However, the strength of this incentive also depends on the level of IPR enforcement ($\phi_{in,t}$). When IPR enforcement is weak (i.e., $\phi_{in,t}$ is low), the risk of imitation is high, and innovators from n may be less inclined to patent their ideas in country i, even if diffusion is high. Conversely, if IPR enforcement is strong (i.e., $\phi_{in,t}$ is high), innovators may have a greater incentive to patent their ideas in country i, as the risk of imitation is lower.

Hence, the impact of diffusion and policy on cross-border patenting and inequality operates through changes in the diffusion of ideas ($\varepsilon_{in,t}$) and the strength of IPR protection ($\phi_{in,t}$), respectively. While both factors can increase cross-border patenting, their effects on development and inequality can differ significantly. An increase in $\varepsilon_{in,t}$ directly facilitates more technology transfer from country n to country i by increasing the diffusion of ideas. This tends to benefit country i by giving them access to more advanced technologies. There is also an indirect effect of an increase in $\varepsilon_{in,t}$, which comes from an increase in the value of an innovation, hence an increase in the number of ideas that are created by country n through innovation, Z_{nt}. In contrast, an increase in $\phi_{in,t}$ allows innovators in country n to charge higher prices for their technologies, potentially widening the income gap. The ultimate effect on income per capita differences depends on the interaction between these two forces.

In our empirical analysis, we estimate the effects of various policy measures and diffusion trends that influence both $\varepsilon_{in,t}$ and $\phi_{in,t}$. These estimates inform our quantitative analysis, where we simulate counterfactual scenarios to disentangle the impacts of changes in diffusion and IPR protection. This approach allows us to quantify the relative importance of these factors in driving cross-border patenting and their implications for global income inequality.

3.3 Estimating Gravity for Cross-border Patent Flows

The objective of this section is to set an econometric model for cross-border patent flows. Guided by our theory (as summarized by equation 19), we specify the following estimating equation:

$$\begin{aligned} \text{Pat}_{ni,t} &= \exp[\chi_{i,t} + \pi_{n,t} + \overrightarrow{\mu}_{ni} + \sum_{t=1996}^{2018} \beta_t \times BRDR_{ni,t} \\ &\quad + POLICY_{ni,t} \times \alpha] \times \epsilon_{ni,t}, \forall\, i, n. \end{aligned} \tag{20}$$

The dependent variable in equation (20), $\text{Pat}_{ni,t}$, denotes the total number of patents from source i to destination n at time t.[10] To take full advantage of our dataset and to improve estimation efficiency, we allow for patent flows from any source i to any destination n.

Since our dependent variable is based on count data, Poisson is the natural choice for our estimator. Moreover, owing to the seminal work of Santos Silva and Tenreyro (2006), the Poisson Pseudo Maximum Likelihood (PPML) has become the workhorse estimator for trade gravity models because of two properties that also apply to our analysis of patent flows. First, due to its multiplicative form, the PPML estimator would enable us to include and take advantage of the information contained in the zeros in our sample; i.e., when there is no patent flow from a given country to another. Second, and probably more important, Santos Silva and Tenreyro (2006) demonstrate that the PPML estimator successfully handles heteroskedasticity in trade flows data, which, due to Jensen's inequality, actually renders the corresponding OLS estimates inconsistent.[11]

In addition to cross-border ($i \neq n$) patent flows, our dependent variable also includes domestic ($i = n$) patents. This is important for our analysis for two related reasons. First, the use of domestic patents allows us to estimate the impact of (de-)globalization, defined broadly as the effects of factors not explicitly captured in our model, on international relative to domestic patent flows. To capture such effects, we introduce to our specification a series of time-varying border indicators, which are defined and discussed in more detail below. In addition, the use of domestic patents allows us to obtain estimates of the diffusion effects for different groups of countries (e.g., poor vs. rich, or South vs. North in our notation), country-specific diffusion effects (e.g., for China vs. US), and directional estimates of the effects of diffusion (e.g., for patents moving from North to South, from North to North, etc.). The latter is particularly important for our purposes because we would be able to isolate the impact of diffusion on cross-border patent flows from North to South.[12]

Turning to the variables on the right-hand side of our estimating equation, specification (20) includes three sets of fixed effects. The term $\chi_{i,t}$ denotes a full set of source-time

[10] In the robustness analysis, we also obtain estimates at the industry level.

[11] We refer the reader to Santos Silva and Tenreyro (2021) for a recent summary and discussion of the benefits of PPML for gravity regressions. We view PPML as the appropriate estimator for our purposes. Therefore, we employ it to obtain our main results. However, in the robustness analysis, we also replicate our main findings with the OLS estimator.

[12] We refer the reader to Yotov (2022) for a summary of the benefits of using domestic flows in trade gravity regressions.

fixed effects, which are motivated by and would absorb the theoretical term $\frac{P_{it}H_{it}}{\eta V_{it}}$. In addition, these fixed effects control for and absorb any other source-time-specific characteristics (e.g., institutional quality, national regulations, taxes, etc.) that may impact patent flows. Similarly, $\pi_{n,t}$ denotes a full set of destination-time fixed effects, which are motivated by the theoretical term, $\left(\frac{\Pi_{nt}}{P_{nt}T_{nt}}\right)^{1/(\xi-1)}$, and control for and absorb any other destination-time-specific characteristics that may impact patent flows. In combination, $\chi_{i,t}$ and $\pi_{n,t}$ will comprehensively account for all possible country-time characteristics on the source and the destination side, thus enabling us to focus on the bilateral determinants of cross-border patents, which are of central interest to us.

The third set of fixed effects that we employ includes country-pair fixed effects, $\overrightarrow{\mu}_{ni}$, which also vary depending on the direction of the patent flows. The use of bilateral fixed effects would, of course, also absorb the theoretical constant term $\left(\frac{\mu}{\rho}\right)^{-1/(\xi-1)}$. Motivated by Baier and Bergstrand (2007), and consistent with the ATE methods of Wooldridge (2010), country-pair fixed effects are typically used in trade gravity models to mitigate potential endogeneity concerns with bilateral policies. The same logic should hold for bilateral policies that impact cross-border patents. On a related note, the country-pair fixed effects would absorb and comprehensively control for all time-invariant bilateral patent frictions that are part of the theoretical term $(\tau_{ni})^{-\frac{1}{\xi-1}}$.[13]

We also allow for the pair fixed effects in our model to vary depending on the direction of the patents. Baier, Yotov, and Zylkin (2019) demonstrate that this has significant implications for the estimates of free trade agreements, which can be very asymmetric and biased if the pair fixed effects are not allowed to vary depending on the direction of trade flows. Applied to our setting, the use of directional pair fixed effects could be crucial for proper identification of the impact of diffusion and liberalization policies for the directional patent flows from North to South.

The next term in specification (20) is particularly important for our analysis. Specifically, $\sum_{t=1996}^{2018} \beta_t \times BRDR_{ni,t}$ denotes a set of time-varying border indicators, which take a value of one for international patents and are equal to zero for domestic patents for each year in our sample. There are several advantages of our dummy-variable approach for current purposes. For example, these indicator variables are exogenous by construction (in effect, these variables are fixed effects). Moreover, by definition, the estimates on

[13]Egger and Nigai (2015) and Agnosteva, Anderson, and Yotov (2019) demonstrate that the 'standard' gravity variables (e.g., distance, contiguity, common official language, etc.) do well in predicting relative bilateral trade costs, however, they fail to capture the level of bilateral trade costs (e.g., they underpredict the bilateral trade costs for the poor countries and overpredict them for the more developed countries). Therefore, and given our focus on the time-varying bilateral determinants of patent flows, we rely on a specification with country-pair fixed effects to obtain our main results. Nevertheless, we start the empirical analysis by estimating our model with a set of 'standard' gravity variables instead of the country-pair fixed effects. On the one hand, this provides benchmark estimates for the effects of the standard gravity variables on cross-border patents. In addition, we will be able to benchmark our findings against those from the trade gravity literature to explore similarities and differences.

these variables will capture the evolution over time of the effects of any forces that are driving a wedge between domestic and cross-border patents.

The flexible definition of the border dummies would enable us to identify the common (across countries) impact of technology diffusion, as well as its differential effects for specific groups of countries and depending on the direction of patent flows (e.g., from North to South). Bergstrand, Larch, and Yotov (2015) demonstrate that failure to control for such time-varying border effects may result in severely biased estimates of the effects of trade agreements on trade in gravity regressions (e.g., because they may erroneously capture other factors). This may also be the case for the effects of policies that target cross-border patents. Moreover, it is possible that the evolution of cross-border patent flows may be driven by factors beyond the observable covariates in our model. As shown in our empirical analysis, the flexible specification with border indicators would enable us to account for such effects. A potential disadvantage of our comprehensive dummy-variable approach is that it does not allow for decomposing the impact of specific individual characteristics. Therefore, as discussed next, we also add to our model a rich set of policy variables that we believe may affect cross-border patenting. As a result, our time-varying border estimates would capture the impact of any additional drivers of cross-border patents beyond our policy variables. Consistent with our theory, we label such unobserved effects diffusion trends.

Before we continue to describe the rest of the covariates in specification (20), we discuss two technical items in relation to the diffusion dummies in our model. First, we cannot obtain estimates of the impact of diffusion without the domestic patents in our sample. If we only had international patents, then the impact of diffusion would be controlled for but buried in the country-time fixed effects. Second, due to perfect collinearity with the pair fixed effects in our preferred specification, we cannot estimate all border effects, so we need to drop one of them. Our choice will be the border dummy for the first year in our sample, 1995. Thus, all diffusion effects that we will obtain would be relative to those in 1995.

In addition to accounting for diffusion trends, we also include in our econometric model several policy variables that were designed to affect international patent flows. Specifically, the vector $POLICY^{k}_{ni,t}$ in equation (20) includes the following time-varying bilateral policy covariates. $RTA_{in,t}$ is an indicator variable that takes a value of one if countries i and n have an RTA in force at time t.[14] In addition, we rely on Martínez-Zarzoso and Chelala (2021) to distinguish between RTAs with and without technology provisions ($RTA\_TECH_{in,t}$ vs. $RTA\_NO\_TECH_{in,t}$, respectively). $TRIPS_{in,t}$ is an indicator for the TRIPS agreement, which has been built using the information provided

[14]Data on RTAs have been updated using the code provided by de Sousa (2012), who coded free-trade agreements using WTO data and complementary national sources.

at the WTO website.[15] Since the generated TRIPS dummy variable is almost collinear with WTO membership, we include only the former in the empirical specification. Finally, $PCT_{in,t}$ is an indicator for membership in the PCT.[16] Similar to our treatment of the effects of diffusion, we would allow for heterogeneous effects of each of the policy variables in our model depending on the direction of patent flows (e.g., from North to South). As previously stated, we use the ATE methods of Baier and Bergstrand (2007) from the trade gravity literature to mitigate potential endogeneity concerns with our policy variables. Moreover, in the sensitivity analysis we also obtain disaggregated estimates at the sectoral level, which should be less subject to endogeneity concerns.

Finally, following the standard approach in the gravity literature, in our main specifications we cluster the standard errors by country pair, i.e., $Cov[\varepsilon_{int}, \varepsilon_{ind}] \neq 0$ for all t, d, and zero elsewhere. However, motivated by Egger and Tarlea (2015) and Pfaffermayr (2019), in the robustness analysis we also experiment with three-way clustering by source, destination, and year.

4 Estimation Results and Comparative Statics

This section presents the findings from our estimation analysis (in Subsection 4.1) and discusses comparative statics results (in Subsection 4.2).

4.1 Estimation Results

This subsection reports our main findings regarding the impact of various determinants of the flow of patents across international borders, including standard gravity variables, diffusion, and various bilateral policies. To highlight several important aspects of our data and identification strategy, we develop the analysis in four specifications, which are nested in equation (20). We start with simple cross-section specifications with standard gravity variables for various years.[17] Second, we allow for the effects of diffusion to vary based on

[15] The agreement states that developing countries and those in the process of transformation from a centrally-planned into a market economy would have a five-year transition period, until 2020. Least-developed countries (LDC) were granted a longer transition period of a total of eleven years (until 1 January 2006), with the possibility of an extension. The transition period has been extended three times, and now runs until 1 July 2034, or until a member ceases to be an LDC, whichever comes first.

[16] The PTC is an international treaty concluded in 1970, which was amended in 1979 and modified twice (in 1984 and 2001) and with 157 members in 2022. The members can obtain patent protection simultaneously in all Contracting States by filling and international patent application in the country of which the applicant is a national or resident and it can also be filled in the International Bureau of WIPO. Additionally, it can also be filled in the European Patent Office (EPO), the African Regional Intellectual Property Organization (ARIPO), the African Intellectual Property Organization (OAPI) or the Eurasian Patent Office (EAPO) if countries are members of the agreements and conventions related to each of those patent offices. See https://www.wipo.int/treaties/en/registration/pct for further information.

[17] While our dataset covers the period from 1980 onward, the empirical analysis focuses primarily on the years from 1995 to 2018. This is due to the limited coverage and reliability of the data on cross-border patent flows and other key variables of interest in the earlier years of the sample period.

development levels and depending on the direction of patents (e.g., from North to South). Third, we move to a panel model, which enables us to comprehensively account for all time-invariant bilateral patent frictions while obtaining heterogeneous estimates of the impact of diffusion on cross-border patent flows. Fourth, in addition to the heterogeneous diffusion effects, we introduce a set of policy variables and allow for their effects to be heterogeneous across the same dimensions as the diffusion effects. We conclude the estimation analysis with a series of sensitivity experiments, which are designed to test the robustness of our main findings to alternative estimators and specifications, to generate richer policy implications, and to highlight the sectoral dimension of our new database.

Our first estimates are obtained from the following naïve cross-section version of specification (20), which only includes exporter and importer fixed effects as well as a set of 'standard' time-invariant gravity variables:

$$\begin{aligned} \text{Pat}_{ni} &= \exp[\beta_1 LN\_DIST_{ni} + \beta_2 CNTG_{ni} + \beta_3 LANG_{ni} + \beta_4 CLNY_{ni}] \times \\ &\quad \exp[\beta_5 BRDR_{ni} + \chi_i + \pi_n] \times \epsilon_{ni}, \quad \forall\, i, n. \end{aligned} \tag{21}$$

Here, following the trade gravity literature, LN_DIST_{ni} is the log of population-weighted bilateral distance between countries n and i, and $CNTG_{ni}$, $LANG_{ni}$, and $CLNY_{ni}$ are indicator variables that capture the presence of a common border, common official language, and any type of colonial relationships between n and i, respectively. Finally, $BRDR_{ni}$ is a dummy variable, which takes a value of one for international transactions, and it is equal to zero otherwise. By construction, $BRDR_{ni}$ is an exogenous variable that captures the average impact of any bilateral factors (apart from those included explicitly in our model, e.g., geography) that drive a wedge between cross-border patent flows and domestic patent flows.

Despite its simplicity, specification (21) serves three important purposes. First, it delivers estimates of the effects of the 'standard' gravity variables with our new bilateral patent data, which can serve as a reference for future studies, depending on their purposes. Second, on a related note, we are able to compare our estimates of the effects of the 'standard' gravity variables on patent flows with those from the trade literature. Finally, we obtain from specification (21) an estimate of the 'border' effects for the first year in our sample, which we combine with the 'globalization' effects from our preferred panel specification–a proxy for the aforementioned diffusion trends—to perform numerical analysis.

Our first set of results appears in Table 1. The estimates in column (1) correspond directly to specification (21) and they are obtained with data for the first year in our sample – 1995. We note the following. First, the estimate of the effect of distance is negative and statistically significant but much smaller than the corresponding effect for trade flows. Given the nature of the patent flows, we find this result to be intuitive.

Second, the estimates on $CNTG_{ni}$ and $CLNY_{ni}$ are not statistically significant, which is another difference from the corresponding trade estimates. Third, we obtain a positive, statistically significant, and very large (much larger than the corresponding index for trade) estimate of the effect of common language ($LANG_{ni}$) on cross border patent flows. We find the results that language is a strong determinant of cross-border patent flows and that its effects are much stronger than those for trade, intuitive as well.

Finally, we find that borders have a large, negative, and statistically significant impact on cross-border patent flows. Specifically, our estimate suggests that, conditional on geography (i.e., distance and contiguity), common language, and colonial relationships, other border frictions in place have decreased cross-border patent flows by about 91 percent (std.err. 3.31) in 1995.[18] While it is true that some of these frictions can probably never be eliminated, our estimates suggest that the frictions in cross-border patent flows are very large and there is significant scope for potential gains from further regional and global integration.

The results in column (2) of Table 1 are obtained after a single modification to the specification from column (1). Specifically, motivated by our theory, we allow for heterogeneous border effects depending on countries' development level and on the direction of patent flows. To this end, we use the 2000 version of the income classification of the World Bank (WB) to categorize the countries in our sample in two groups – "North", which includes the "high-income" countries and the "upper-middle income" countries from the WB classification vs. "South", which includes the "lower-middle income" countries and the "low income" countries from the WB classification.[19] Then, based on the two country-specific income groups ("North" vs. "South") and the direction of patent flows, we construct four bilateral income groups of countries, which allow for heterogeneous border effects depending on whether the patent flows are from "North to North" ($BRDR\_N\_N$), "North to South" ($BRDR\_N\_S$), "South to South" ($BRDR\_S\_S$), and "South to North" ($BRDR\_S\_N$). Thus, in effect, we split the common border effect from column (1) into four categories.[20]

We draw three conclusions based on the results from column (2) of Table 1. First, the

[18]Calculated as $[exp(-2.404) - 1] * 100 = -90.97$, where the standard errors are obtained with the Delta method.

[19]We chose the 2000 WB classification for two reasons (an alternative classification was built for 1990). First, because it is more complete. For instance, using data from 1990 fails to capture the emergence of post-Soviet countries like Russia, Ukraine, and the Baltic states. Second, because the year 2000 is closer to the middle of our sample. The classification can be downloaded at this link: https://datacatalogfiles.worldbank.org/ddh-published/0037712/DR0090754/OGHIST.xlsx. In the robustness analysis, we also experiment with two alternative classifications. First, we use all possible income groups categories. We prefer the two-group approach for expositional purposes and because it is consistent with our empirical results. Second, we define "South" differently by only including the low income countries in this category.

[20]We also obtained group-specific estimates, i.e., for the impact of diffusion on the countries in the North vs. South. The results are consistent with but less informative than our main estimates (since they do not distinguish between the direction of the patent flows).

Table 1: Gravity Estimates for Patent Flows

	(1) 1995	(2) 1995	(3) 2006	(4) 2018
LN_DIST	-0.350	-0.418	-0.314	-0.218
	(0.072)**	(0.075)**	(0.071)**	(0.071)**
CNTG	-0.186	-0.370	-0.458	-0.682
	(0.223)	(0.231)	(0.268)$^{+}$	(0.333)*
LANG.	1.403	1.313	1.315	1.363
	(0.202)**	(0.187)**	(0.198)**	(0.161)**
CLNY	0.025	-0.120	-0.430	-0.359
	(0.270)	(0.282)	(0.246)$^{+}$	(0.234)
BRDR.	-2.404			
	(0.366)**			
BRDR_N_N		-1.939	-1.736	-2.023
		(0.391)**	(0.356)**	(0.360)**
BRDR_N_S		-3.050	-2.851	-2.893
		(0.497)**	(0.661)**	(0.843)**
BRDR_S_S		-4.440	-4.724	-4.401
		(0.553)**	(0.570)**	(0.334)**
BRDR_S_N		-5.740	-3.741	-3.253
		(0.667)**	(0.790)**	(0.814)**
N	2326	2326	2782	2488

This table reports estimates of the effects of the 'standard' gravity variables on cross-border patent flows. The estimates are obtained from specification (21). The dependent variable in each specification is the number of patent applications and the estimator is PPML. The results in column (1) are for 1995. The estimates in column (2) allow for the effects of international borders to vary across four bilateral groups (including "North to South", "South to South", "North to North", and "South to North", which are based on the income classification of the World Bank for 2000. Finally, the results in columns (3) and (4) replicate the estimates from column (2) but for the years 2006 and 2018, respectively. Standard errors in parentheses are clustered by country pair. $^{+}$ $p < 0.10$, * $p < .05$, ** $p < .01$. See text for further details.

effects of the borders are very large regardless of the direction of cross-border patent flows. Second, the border effects are heterogeneous across the four groups in our specification. Perhaps not surprisingly, the smallest border estimates are for flows from "North to North". The combination of strong institutions and closer economic ties among the developed countries is a natural explanation for this result. The largest estimates are for patent flows from "South to North", followed by the estimate on flows from "South to South". The main conclusion that we draw based on these results is that the single border effects from column (1) has masked significant heterogeneity, which may have strong implications for development and inequality. Finally, we note that the rest of the gravity estimates in column (2) are not statistically significantly different from those in column (1).

The results in columns (3) and (4) of Table 1 replicate the results from column (2) but for the mid-year (2006) and for the last year in our sample (2018), respectively. The idea is to offer some preliminary evidence for the evolution of the gravity estimates during the period of investigation. Most estimates remain stable, e.g., for common language, colonial ties, borders between 'North to North', 'North to South', and 'South to South'. However, we also observe three interesting patterns. First, we see that the estimates on distance have fallen over time. This is consistent with the latest trade estimates and the notion that the world has become flatter. Second, we note that the effects of contiguity remain negative but increase in absolute value and become statistically significant. Comparative advantage in the development of patents is the natural explanation for this result. Finally, we see that the estimates of the border effects for cross-border patent flows from 'South to North' have fallen over time in absolute value. This is an interesting pattern, which should be interpreted with caution due to the possible omission of potentially important control variables in our specification. We take a step to address this concern by estimating the following econometric model:

$$\begin{aligned} \mathrm{Pat}_{ni,t} \quad = \quad & \exp[\chi_{i,t} + \pi_{n,t} + \overrightarrow{\mu}_{ni} + \sum_{t=1996}^{2018} \beta_t^{N,N} \times BRDR\_N\_N_{ni,t} + \sum_{t=1996}^{2018} \beta_t^{N,S} \times BRDR\_N\_S_{ni,t}] \times \\ & \exp[\sum_{t=1996}^{2018} \beta_t^{S,N} \times BRDR\_S\_N_{ni,t} + \sum_{t=1996}^{2018} \beta_t^{S,S} \times BRDR\_S\_S_{ni,t}] \times \epsilon_{ni,t}, \quad \forall\, i,n. \end{aligned} \tag{22}$$

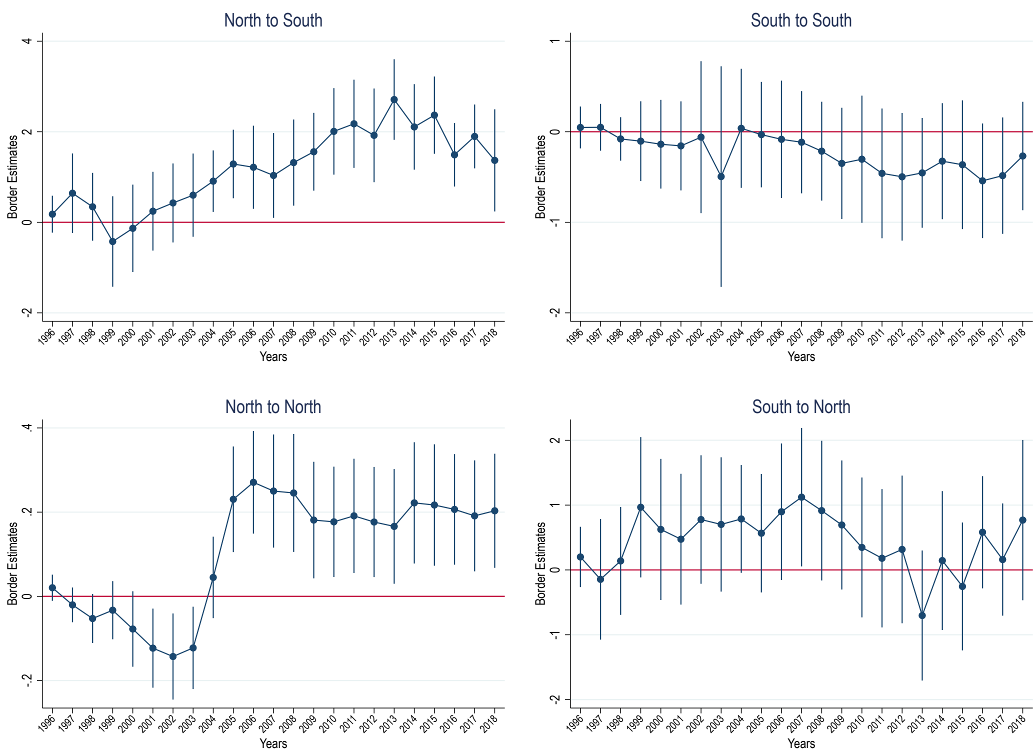
Specification (22) is a panel-data model, where we have replaced the standard time-invariant bilateral gravity variables with directional country-pair fixed effects ($\overrightarrow{\mu}_{ni}$). In addition, we allow for time-varying border effects, which will capture the impact of diffusion forces on cross border patent flows over time for each of the four groups of countries in our sample.[21] Due to perfect collinearity with the country-pair fixed effects in our

[21] The four sets of 'globalization' dummy variables (equivalent to the diffusion forces mentioned in the previous section) in specification (22) are essentially time-varying border variables for each year and each group of countries in our sample. The country-pair fixed effects in our setting will fully control for all time-invariant bilateral characteristics that impact cross-border patent flows. Thus, our diffusion estimates will be all-inclusive measures of the effects of time-varying bilateral factors that drive a wedge

model, we cannot estimate all border/diffusion effects for each group of countries and need to drop one of them for each group. Our choice is to drop, for each group, the border dummy for the first year in our sample, 1995. Thus, each of the diffusion effects that we obtain would be relative to the corresponding effect for the same group in 1995.

For expositional purposes (e.g., due to the large number of border estimates that we obtain), instead of using a tabular format, we report our findings in Figure 2. The figure reveals several interesting patterns across and within the four groups of estimates. First, the impact of diffusion has been the strongest for patent flows from 'North to South'. In terms of magnitude, our estimates suggest that diffusion forces have led to an increase of about 300 percent in the patent flows from 'North to South' during the period of investigation.[22] This result justifies our main focus on the cross-border patent flows from 'North to South'. We also see a de-globalization trend for this group post-2013.

Figure 2: Globalization and North-South Cross-border Patenting



Note: This figure reports estimates of the impact of diffusion on cross-border patent flows for four bilateral groups of countries, including "North to South" (top left panel), "South to South" (top right panel), "North to North" (bottom left panel), and "South to North" (bottom right panel). The country groups are based on the income classification of the World Bank, and all estimates are obtained from a single regression, which is based on specification (21) after allowing for heterogeneous effects for each of the four bilateral groups. See text for further details.

between domestic and cross-border patent flows. In a subsequent specification, we will isolate the effects of bilateral policies.

[22]Calculated as $[exp(1.368) - 1] * 100 = 292.69$, where the 1.368 is the estimate on $BRDR\_N\_S_{ni,t}$ that we obtain in 2018, which, by construction, captures the total diffusion effects for this group during the period of investigation.

The second largest impact of diffusion on cross-border patent flows is for the group 'North to North'. The impact of diffusion for this group follows an interesting pattern, where the overall increase in patent flows is exclusively driven by a very large increase during the period between 2002 and 2006. Further investigation of the drivers of the large increase in the early 2000s reveals that most of the 'jump' is due to the large cross-border patent flows from and to Korea and toward Germany and the United States.[23] Finally, we see from the two right panels of Figure 2 that diffusion has not benefited cross-border patents originating from the South, neither toward other 'South' countries nor toward the 'North'. These results are in sharp contrast to our findings from the top left panel of the figure, but they are consistent with our findings from the data.

Our main estimation results are obtained from specification (22), where, in addition to allowing the impact of diffusion to be heterogeneous across the four bilateral income groups, we also introduce the policy variables, which we expect may also affect cross-border patents differently by income group. Specifically, we estimate the effects of RTAs, which may or may not include technology provisions, the effects of the TRIPS agreement, and the effects of PCTs. Similar to the analysis of the effects of diffusion, we also allow for heterogeneous effects of each of the policy variables across the four bilateral income groups in our sample. To detect possible correlations between the different policies and to decompose their effects, we introduce them sequentially in the four columns of Table 2. The estimates in each column are obtained with the full set of heterogeneous border variables and the full set of fixed effects from specification (22). The dependent variable is always the number of patent applications, the estimator is PPML, and the standard errors are clustered by country pair.

The estimates in column (1) of Table 2 reveal that, overall, RTAs have been effective in promoting cross-border patent flows. We also note that the RTA effects have been quite heterogeneous across the four bilateral income groups in our sample.[24] The estimates of the RTA effects that we obtain are positive for each of the four groups, and they are statistically significant for flows from 'North to North', which is the largest estimate, and from 'South to North', which is a bit smaller but still sizable.

The results in column (2), where we distinguish between the effects of RTAs with and without technology provisions, reveal further heterogeneity. The estimates of the effects of RTAs with technology provisions that we obtain are also positive for all groups but, once again, these agreements have benefited patent flows from 'North to North' and from 'South to North'. According to our estimates, the patent flows from "North to North"

[23]We prove this in the Supplementary Appendix, where we reproduce the bottom-left panel of Figure 2 after dropping the observations for cross-border patent flows from and to Korea and toward Germany and the United States.

[24]The heterogeneous estimates that we obtain suggest that imposing common policy effects may lead to misleading policy implications. We offer such estimates in the robustness analysis in the Supplementary Appendix, where we also investigate the impact on the policy estimates from the use of domestic patent flows and from accounting for diffusion forces.

Table 2: Preferential Agreements and Cross-border Patents

	(1) RTA	(2) TECH	(3) TRIPS	(4) PCT
RTA_S_N	0.175			
	(0.064)**			
RTA_S_S	0.132			
	(0.315)			
RTA_N_N	0.239			
	(0.044)**			
RTA_N_S	0.074			
	(0.056)			
RTA_TECH_S_N		0.196	0.201	0.196
		(0.053)**	(0.052)**	(0.053)**
RTA_TECH_S_S		0.098	0.188	-0.212
		(0.344)	(0.376)	(0.278)
RTA_TECH_N_N		0.221	0.209	0.208
		(0.043)**	(0.041)**	(0.042)**
RTA_TECH_N_S		0.081	0.078	0.078
		(0.055)	(0.055)	(0.055)
RTA_NO_TECH_S_N		-0.675	-0.666	-0.690
		(0.932)	(0.910)	(0.881)
RTA_NO_TECH_S_S		0.080	0.104	-0.193
		(0.358)	(0.364)	(0.321)
RTA_NO_TECH_N_N		1.178	1.159	1.157
		(0.159)**	(0.155)**	(0.155)**
RTA_NO_TECH_N_S		-0.147	-0.147	-0.139
		(0.159)	(0.156)	(0.157)
TRIPS_S_N			0.211	0.219
			(0.178)	(0.178)
TRIPS_S_S			0.502	0.514
			(0.228)*	(0.207)*
TRIPS_N_N			0.209	0.210
			(0.126)+	(0.126)+
TRIPS_N_S			0.051	0.032
			(0.157)	(0.157)
PCT_S_N				0.637
				(0.444)
PCT_S_S				1.271
				(0.319)**
PCT_N_N				0.177
				(0.083)*
PCT_N_S				-0.041
				(0.221)
N	63846	63846	63846	63846

This table reports estimates of the effects of preferential agreements on cross-border patent flows. The estimates are obtained from specification (20), after allowing for the effects of diffusion to vary across four bilateral groups (including "North to South", "South to South", "North to North", and "South to North", which are based on the income classification of the World Bank. In addition, each column of the table introduces a new policy variable, whose effects are also allowed to vary across the four bilateral income groups. Specifically, column (1) accounts for RTAs. Column (2) distinguishes between the effects of RTAs with and without technology provisions. In column (3) we add the TRIPS variables. Finally, in column (4), we also introduce the effects of the PCT. The dependent variable in each specification is the number of patents and the estimator is PPML. Standard errors in parentheses are clustered by country pair. $^{+}$ $p < 0.10$, * $p < .05$, ** $p < .01$. See text for further details.

have benefited tremendously from the RTAs without technology provisions, while the effects of this type of agreements have not been significant for the other three groups in our sample.

In columns (3) and (4) of Table 2, we sequentially introduce the effects of the TRIPS agreement (in column (3)) and, in addition, the effects of the PCT (in column (4)). Since the introduction of the additional policy variables in each column does not significantly affect the estimates of the variables that were already included in our specification, we focus our discussion on the results from column (4), which presents our main and most comprehensive findings.

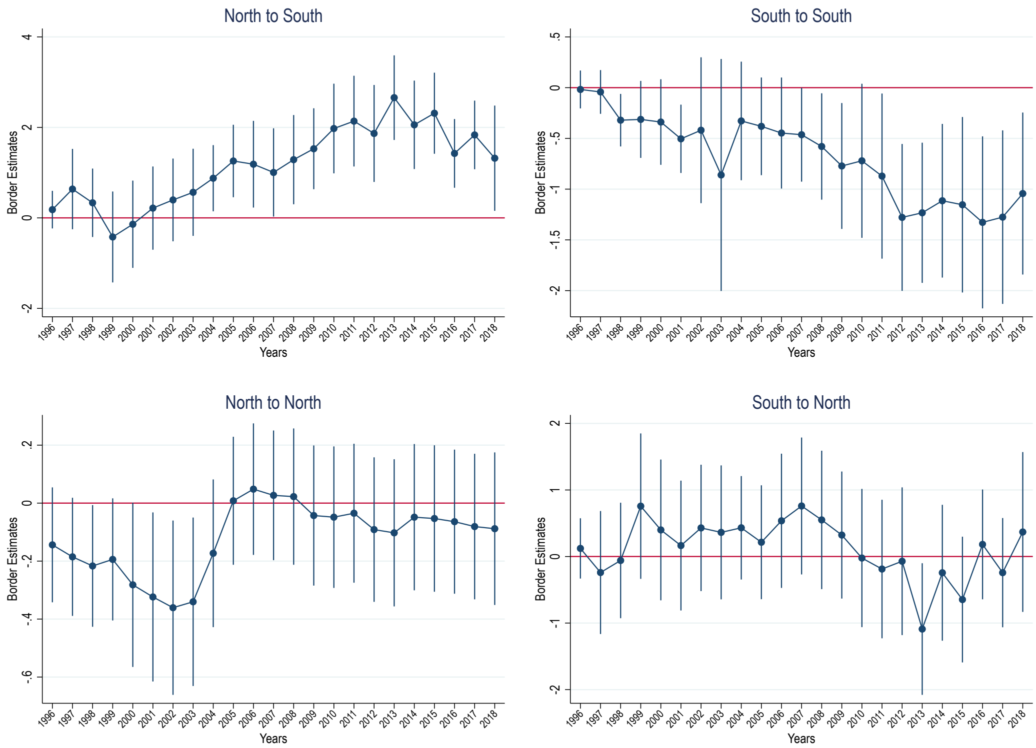
The estimates of the effects of RTAs with and without technology provisions are almost unchanged. According to our estimates, TRIPS has led to more patent flows from 'South to South' and, to a lesser degree, from 'North to North', while the effects for the other two groups are not statistically significant. Similarly, the PCT has been very effective in promoting patent flows from 'South to South', followed by 'North to North'. The estimate for flows from 'South to North' is also positive, but it is not statistically significant. Finally, the PCT has not been effective in promoting flows from 'North to South'.

Figure 3 reproduces the results from Figure 2 for the impact of diffusion on cross-border patent flows for the four bilateral income groups of countries in our sample. However, the new diffusion estimates are obtained from the econometric specification from column (4) of Table 2, which also includes the full set of our policy variables. Thus, the new diffusion effects that we visualize in Figure 2 are stripped from the policy effects that we just discussed.

We draw two conclusions based on the estimates from Figure 3. First, and most important for our purposes, the estimates of the impact of diffusion on the patent flows from 'North to South' (in the top-left panel of Figure 3) remain strong. Comparison between the corresponding results for this group between Figures 3 and 2 reveals that the agreements we account for have contributed very little to explain the diffusion effects in Figure 2. Thus, most of these diffusion effects, as well as their evolution over time, remain almost unchanged in Figure 3 and, therefore, cannot be attributed to the policy variables in our model. This reinforces our decision to allow for and retain the flexible border variables in our main specification.

Second, we see that the diffusion effects are significantly different for the other three groups in our analysis. The overall gains for the "North to North" group from Figure 2 have disappeared in Figure 3. However, in the early 2000s, we still see the strong impact of diffusion forces that are not captured explicitly in our model. The main conclusion from the top-right panel of Figure 3 is that without the policies from Table 2 in place the cross-border patent flows from "South to South" would have decreased over time. Thus, even though the net diffusion effects that we captured in Figure 2 were not significant, policy

Figure 3: Diffusion, Policy, and North-South Cross-border Patenting



Note: This figure reproduces the results from Figure 2 for the impact of diffusion on cross-border patent flows for the four bilateral income groups of countries in our sample. However, the new diffusion estimates are obtained from the econometric specification from column (4) of Table 2, which also includes the full set of our policy variables. See text for further details.

has indeed been effective to counter the decreasing trend in patent flows for this group. Finally, most estimates for the "South to North" group (bottom right panel) remain not statistically significant, reinforcing our conclusion that the policies in our model have not been effective to stimulate patent flows from "South to North". Our study applies the empirical methodology traditionally used to estimate border effects in international trade to analyze technology diffusion and cross-border patents, an area where this approach has not been previously employed. By extending the trade framework to patent flows, we are able to draw comparisons between our findings and those from the trade literature. This comparative analysis reveals both similarities and differences. For example, similar to manufacturing and services trade, we find that the effects of diffusion on cross-border patents have been strong. Moreover, as demonstrated below and similar to services trade (Anderson, Larch, and Yotov, 2018), we find that the effects of diffusion for cross-border patents have been quite heterogeneous depending on development. However, we observe different patterns in the evolution of the diffusion effects for cross-border patents vs. trade. Specifically, while the boom in the diffusion effects for manufacturing trade was in the 1990s (Kwon, Syropoulos, and Yotov, 2022), the strongest impact of diffusion on cross-border patent flows took place in the early 2000s. In addition, we note that the effects of global recessions are not as pronounced for cross-border patents as they are for trade. Finally, we see that the effects of diffusion for both trade and cross-border patents have been stable since 2010.

We conclude this section with a brief discussion of the results from the robustness experiments that we perform to test the sensitivity of our main findings and to highlight some additional dimensions of our new database. The corresponding estimates, along with a more detailed discussion, appear in the Supplementary Appendix. We reproduce our results: (i) Applying the OLS estimator. (ii) Using three-way clustering. (iii) Not controlling for the impact of diffusion explicitly. (iv) Excluding domestic patents. Importantly, in this setting we cannot estimate the effects of diffusion. (v) Leaving out China from our estimating sample. (vi) Using an alternative definition for "North" vs. "South". Specifically, we defined "South" as including only the "low" income countries and "North" for all other countries. (vii) Using patent citations to construct a new, quality adjusted measure of cross-border patents, which is used as our dependent variable. (viii) Imposing common effects across the different income groups for each of the policy variables in our model. (ix) Not using pair fixed effects in order to be able to identify the effects of "standard" gravity variables in the panel specification. (x) We also reproduced our main results at the sectoral level too. Overall, our main conclusions are reinforced by the additional experiments that we performed, but we also observed some intuitive heterogeneity.

Finally, we present results controlling for trade flows in our main gravity specification. It is worth noting that our model's country-time fixed effects may already implicitly control for trade flows through their effect on profits, potentially mitigating omitted variable bias concerns. However, recent studies have established a relationship between trade, innovation, and diffusion (Buera and Oberfield, 2019; Brunel and Zylkin, 2022; Lind and Ramondo, 2024). Diffusion likely influences both trade and cross-border patenting, with trade potentially mediating this relationship. Therefore, to address potential omitted variable bias in our analysis of cross-border patenting and border effects more directly, we explicitly added trade flows in our main gravity specification. Our analysis revealed several key findings. First, trade positively affects patenting. Second, policy estimates remain stable when controlling for trade flows. Third, RTA coefficients slightly decrease in magnitude for all country-groups but maintain the same sign and significance level. Fourth, estimated border effects are very similar to our main results. These findings suggest that the impact of diffusion on cross-border patenting is largely direct and not primarily mediated through trade. Moreover, they indicate that trade and cross-border patenting may be parallel outcomes of diffusion rather than sequential. In a final robustness exercise, we find that when we run the main gravity specification without border effects, the coefficients on the policy variables remain stable. This is in contrast with findings from the trade literature where, for example, (Bergstrand, Larch, and Yotov,

2015) demonstrate that not accounting for the effects of diffusion leads to upward biased estimates of the effects of Economic Integration Agreements.

4.2 Cross-border Patenting and Development

Our empirical results indicate that diffusion forces have been important drivers of cross-border patenting, especially from North to South. Cross-border patenting can serve as a proxy for technology transfer, as it often signals intentions to do business abroad, requires disclosure of technical details, and may precede licensing, trade, or FDI. In that case, these trends could be increasing income per capita in the South and impacting global inequality patterns. In this section, we study, through the lens of our model, the influence of diffusion on cross-border patenting, innovation, and development. Building upon the main estimates presented earlier, we conduct a numerical exercise to address the following questions: What would have been the trajectory of cross-border patenting from North to South between 1995 and 2018 if diffusion trends had remained at their 1995 levels?, and What are the implications for global income inequality? The model is solved period by period.

Calibration. To answer these questions, we employ our comprehensive dataset on patenting, geographical factors, and R&D intensity to calibrate our model. We use data for 42 countries for the period 1995 to 2018, due to data availability on R&D spending. We partition the countries into two groups belonging to North and South.[25]

Several parameters are calibrated from previous studies or taken directly from the data. The parameter of the Armington elasticity takes a value of 5, which implies a trade elasticity of 4, as is standard in the trade literature. The parameter for the elasticity of innovation is set to 0.5, which is consistent with previous studies in the literature (see Cai, Li, and Santacreu, 2022). Population is taken from the CEPII database. The iceberg transport costs and productivity parameters are calibrated using data on trade flows, geography measures, Gross Domestic Product (GDP) and population from CEPII, and deploying gravity methods using PPML. The elasticity of patenting costs is set to $\xi = 2$, so there are increasing marginal costs of patenting. We calibrate $\varepsilon_{in,1995}$ using the estimates from the cross-section gravity equation of cross-border patents in Table 1. We set $\phi_{in} = 0.25$, which implies that innovators receive 25 percent of profits from

[25]The countries that belong to the North are: Australia (AUS), Austria (AUT), Belgium (BEL), Canada (CAN), Switzerland (CHE), Germany (DEU), Denmark (DNK), Spain (ESP), Finland (FIN), France (FRA), United Kingdom (GBR), Greece (GRC), India (IND), Ireland (IRL), Israel (ISR), Italy (ITA), Japan (JPN), Netherlands (NLD), Norway (NOR), New Zealand (NZL), Portugal (PRT), Singapore (SGP), Sweden (SWE), United States (USA); the countries that belong to South are: South are: Argentina (ARG), Brazil (BRA), Chile (CHL), China (CHN), Colombia (COL), Ecuador (ECU), Hong Kong (HKG), South Korea (KOR), Lithuania (LTU), Mexico (MEX), Malaysia (MYS), Peru (PER), Philippines (PHL), Poland (POL), Slovakia (SVK), Thailand (THA), Turkey (TUR), Uruguay (URY).

foreign adopters (Santacreu, 2023) (except for the South, which only pays one-tenth of that amount to the North). We set $\phi_{ii} = 0.5$ so that domestic innovators and domestic adopters split the surplus equally. Table 3 reports the parameter values.

Table 3: Parameter Values

Parameter	Value	Description
σ	5	Armington elasticity
d_{NS}	6.6024	Iceberg trade costs from S to N
d_{SN}	6.1284	Iceberg trade costs from N to S
η	0.5	Elasticity of innovation
L_N	0.71	Population N
L_S	1	Population S
ξ	2	Elasticity in the cost of patenting
ϕ_{SN}	0.25	Santacreu (2024)
ϕ_{NS}	0.025	Santacreu (2024)
ϕ_{NN}	0.5	Santacreu (2024)
ϕ_{SS}	0.5	Santacreu (2024)
ε_{NS}	0.48	Gravity 1995
ε_{SN}	0.52	Gravity 1995
ε_{NN}	1	Gravity 1995
ε_{SS}	1	Gravity 1995

The remaining parameters, namely, the innovation efficiency, γ_{nt}, and the diffusion forces, reflected in $\varepsilon_{SN,t}$ in equation (12), are calibrated to match data on R&D intensity and the border effect obtained from our main specification in column (4) of Table 2 and Figure 3. We then feed the sequence of border effects into $\varepsilon_{SN,t}$, which captures diffusion effects in equation (12), and leave the others constant throughout the period, since diffusion forces for the other pairs of regions have remained stable over the period of analysis.

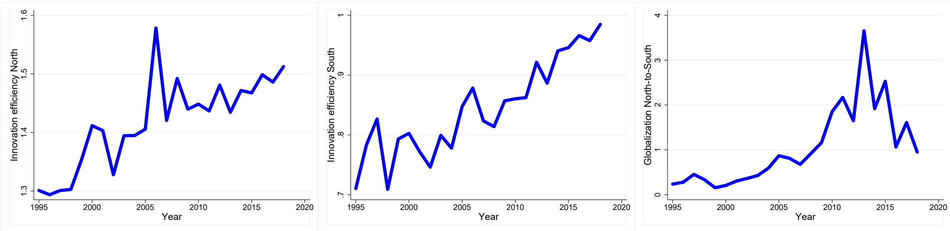
We calibrate γ_{nt} to match data for R&D intensity. The calibrated parameters are reported in Figure 4. Throughout the analyzed period, there has been an increase in innovation efficiency in the South relative to North corresponding with a rise in R&D investment in South relative to North.

External Validation. While our model is not explicitly calibrated using data on royalty payments, it can replicate the evolution of royalty flows from developing (South) to developed (North) countries over the period from 1995 to 2018. Figure 5 plots the royalty payments from South to North as predicted by the model alongside empirical data on these flows.[26] The model closely tracks the substantial rise in royalty payments

[26] Data are from from the OECD-WTO Balanced Trade in Services (BaTIS) dataset for 1995-2012 and combined with that for 2005-2021.

Figure 4: Calibrated Parameters

(a) γ_{Nt} (b) γ_{St} (c) $\varepsilon_{SN,t}$



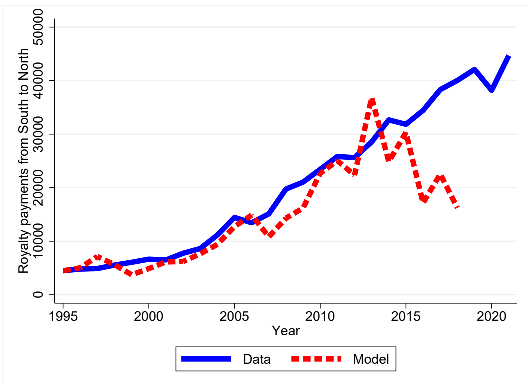
Notes: The figure plots the parameters γ_{nt} which we calibrate to match the data from R&D intensity, and $\varepsilon_{SN,t}$, which we have reported in Figure 2.

to developing countries that occurred over this period.

Importantly, the model is able to reproduce not just the overall growth trend, but also key fluctuations seen in the data, such as the noticeable dip and recovery between 2000 and 2005. It is worth noting that while the model successfully captures the overall trend and key fluctuations in royalty payments up to the late 2010s, there is some divergence between the predicted and actual values in the final few years of the analysis period. Specifically, the model appears to underestimate the royalty flows observed in the empirical data for 2020.

The close match between the model's predictions and the data royalty payment evolution serves as external validation.

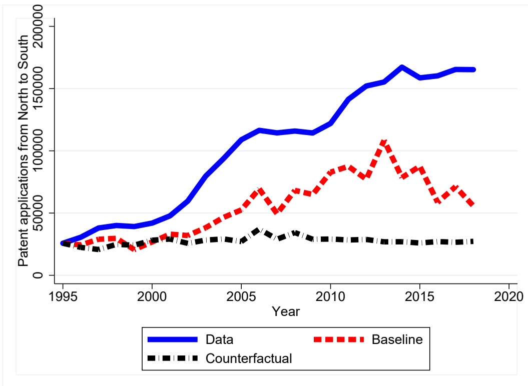
Figure 5: Royalty payments from South to North, 1995-2018 (million USD)



The figure shows royalty payments from South to North between 1995-2028 as predicted by the model and in the data. Data from the OECD-WTO Balanced Trade in Services (BaTIS) dataset.

Numerical Analysis: Cross-border Patenting and Income per Capita Differences. We proceed with our main numerical analysis, relying on the estimates of diffusion effects on patent flows from "North to South." We simulate a scenario without diffusion forces by using the estimated vector of diffusion trends from 1995 to 2018 as our baseline and setting all border estimates to their corresponding 1995 values. Our findings, summarized in Table 4, suggest that in the absence of diffusion trends, cross-border patenting would have been significantly lower. On average, cross-border patenting would have been 38 percent lower between 1995 and 2018 in the absence of the observed diffusion trends. This effect is particularly pronounced after 2000, with cross-border patenting from North to South being 46 percent lower in the absence of diffusion forces (see Figure 6).

Figure 6: Cross-border Patenting from North to South



Notes: The figure shows the evolution of cross-border patenting between 1995 and 2018 in the data (solid line), the baseline model incorporating diffusion forces (dashed line), and the counterfactual without diffusion forces (dotted-dash line).

Diffusion We complete the analysis by examining changes in income per capita differences between South and North, computed as the ratio of income per capita in South relative to that of North, between our baseline and our counterfactual where diffusion forces remain at 1995 levels. In the absence of diffusion effects, income inequality would have been 12.6 percent higher.

First, an increase in $\varepsilon_{SN,t}$ directly facilitates more technology transfer from the North to South by increasing the diffusion of ideas. Second, it indirectly promotes more technology transfer by encouraging more R&D investment and patenting in the North (higher Z_{Nt}), as innovators seek to take advantage of the increased value of patenting in South. South benefits from more technology diffusion, while North benefits from increased royalty payments from more patents, which spurs further innovation and technology transfer to South.

Policy Our findings suggest that the impact of cross-border patenting on income inequality operates through changes in idea diffusion ($\varepsilon_{SN,t}$) and IPR protection strength ($\phi_{SN,t}$). While stronger IPR protection could potentially increase inequality by raising technology costs for the South, our results indicate that the inequality-decreasing effect of increased technology diffusion has dominated.

Table 4: Numerical Analysis: Cross-border Patenting, Diffusion, and Income Inequality

	1995-2018	**2000-2018**
Cross-border patenting	38%	46%
Income pc differences	-12.6%	-15.6%

Notes: The table shows changes in cross-border patenting from North to South and relative income per capita in South (relative to North) between a world with no diffusion effects and one with diffusion effects.

Policy changes between 1995-2018 significantly impacted cross-border patenting and income inequality. Accounting for these changes alongside diffusion forces, we estimate a 10-13% decrease in income inequality between North and South during this period. Policies like RTAs, TRIPS, and PCT membership have been particularly effective in boosting North-North patent flows, with limited impact on North-South flows.

This asymmetric policy impact has nuanced implications for inequality. While South-South and South-North patenting increases income for the South, and North-North patenting benefits the North, the higher innovation intensity in the North means they benefit more from these policy changes. Consequently, income inequality between North and South decreases, but not as much as it would have under diffusion forces alone.

5 Final Remarks

We analyze the drivers of cross-border patenting in the context of diffusion and its consequences for economic development. Using data on international patent flows and developing a theoretical framework with a structural gravity model, we disentangle the effects of diffusion trends from policy-driven changes in IPR regimes.

We find that diffusion-driven patent flows from developed (North) to developing (South) countries have had an increasingly positive impact on the South, particularly after the 2000s. This trend has contributed to a reduction in global income inequality, highlighting the potential of knowledge diffusion as a force for economic convergence. While policies like TRIPS and the PCT appear to have influenced overall patenting patterns, our results suggest that North-South patent flows are primarily driven by technological diffusion rather than policy changes. Our numerical analysis underscores the importance of these diffusion forces: in their absence, the income per capita gap between North and South would have been more pronounced, particularly in the post-2000 period. This finding reinforces the notion that the international flow of ideas and innovations is a key factor in global economic development.

While our study focuses primarily on the interplay between diffusion, trade policy, and cross-border patenting, other factors may influence firms' decisions to seek international patent protection. These could include escape-competition motives or quality-signaling strategies. Future research could explore these additional channels and their interactions with trade agreements and IPR regimes.

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SUPPLEMENTARY APPENDIX: FOR ONLINE PUBLICATION

A Model equations

The endogenous variables are:

$$\{P_{it}, Y_{it}, W_{it}, p_{in,t}, x_{in,t}, \pi_{in,t}, H_{it}, Z_{it}, T_{it}, Z_{it}^{W}, \lambda_{in,t}, Pat_{in,t}, \Pi_{it}, \Pi_{it}^{all}, V_{in,t}^{pat}, V_{nt}\}$$

The parameters are:

$$\{\sigma, \gamma_n, \tau_{in}, \Omega_i, \xi, d_{in}, \eta\}$$

There us also a shock process: $\{\varepsilon_{in,t}\}$.

Resource constraint

$$Y_{nt} = C_{nt} + H_{nt}$$

Prices

$$P_{nt} = \left(\sum_{i=1}^{M} \Omega_i^{\sigma-1} T_{it} p_{ni,t}^{1-\sigma} \right)^{\frac{1}{1-\sigma}}$$

Price intermediate goods

$$p_{in,t} = \bar{m} W_{nt} d_{in}$$

where $\bar{m} = \frac{\sigma}{\sigma-1}$

Demand intermediate goods

$$p_{in,t} x_{in,t} = T_{nt} \Omega_n^{\sigma-1} \left(\frac{\bar{m} W_{nt} d_{in}}{P_{it}} \right)^{1-\sigma} P_{it} Y_{it}$$

Trade share

$$\pi_{in,t} = \frac{\Omega_n^{\sigma-1} T_{nt} \left(W_{nt} d_{in}\right)^{1-\sigma}}{\sum_{k=1}^{M} \Omega_k T_{kt} \left(W_{it} d_{ik}\right)^{1-\sigma}}$$

Profits intermediate producers

$$\Pi_{nt} = \frac{1}{\sigma - 1} W_{nt} L_n$$

Number of intermediate goods

$$T_{nt} = \sum_{i=1}^{M} \varepsilon_{ni,t} Z_{it}$$

Number of ideas

$$Z_{nt} = \gamma_{nt} \left(\frac{H_{nt}}{Y_{nt}} \right)^{\eta}$$

FOC R&D

$$H_{nt} = \eta Z_{nt} \frac{V_{nt}}{P_{nt}}$$

Value of innovation

$$V_{nt} = \sum_{i=1}^{M} V_{in,t}^{pat}$$

Number of patented ideas

$$Pat_{in,t} = \lambda_{in,t} \varepsilon_{in,t} Z_{nt}$$

Share of patented ideas

$$\lambda_{in,t} = \tau_{in}{}^{-1/(\xi-1)} \left(\frac{V_{in,t}^{pat}}{P_{nt}} \right)^{1/(\xi-1)}$$

Value of a patented technology

$$V_{in,t}^{pat} = \varepsilon_{in,t} \phi_{in,t} \frac{\Pi_{it}}{T_{it}}$$

Budget constraint

$$P_{nt} C_{nt} = W_{nt} L_{nt} + \Pi_{nt}^{all}$$

- Profits of all firms

$$\Pi_{it}^{all} = \Pi_{it} - \sum_{n=1}^{M} \varepsilon_{in,t} \lambda_{in,t} \phi_{in,t} \frac{\Pi_{it}}{T_{it}} Z_{nt} + \sum_{k=1}^{M} \varepsilon_{ki,t} \lambda_{ki,t} \phi_{ki,t} \frac{\Pi_{kt}}{T_{kt}} Z_{it} - P_{it} H_{it}$$

B Extended Model: Dynamic Innovation with Partial Depreciation

In this section, we present an extension of our baseline model where ideas depreciate at rate $\delta \in (0, 1)$ instead of fully depreciating. This modification affects both the innovation and adoption processes, requiring adjustments to the value functions and resulting in a gravity equation that only holds on the BGP.

B.1 Modified Innovation and Adoption Processes

The stock of ideas in country n at time t, denoted as Z_{nt}, evolves according to:

$$Z_{nt} = (1-\delta)Z_{n,t-1} + \gamma_{nt}\left(\frac{H_{nt}}{Y_{nt}}\right)^{\eta} \tag{B.1}$$

where δ is the depreciation rate of ideas. The adoption process for ideas from country n in country i is now given by:

$$A_{in,t} = (1-\delta)A_{in,t-1} + \varepsilon_{in,t}Z_{nt} \tag{B.2}$$

where $A_{in,t}$ represents the stock of ideas from country n that have been adopted in country i. The total number of intermediate goods produced in country n at time t is now:

$$T_{nt} = \sum_{i=1}^{M} A_{ni,t} \tag{B.3}$$

B.2 Modified Value Functions

The value of a patented technology must now account for its continued existence over time. The present value of a patented technology from country n in country i becomes:

$$V_{in,t}^{pat} = \sum_{s=t}^{\infty}[(1-\delta)(1-\phi_{in,s})]^{s-t}\varepsilon_{in,t}\phi_{in,t}\frac{\Pi_{it}}{T_{it}} \tag{B.4}$$

where the term $(1-\delta)(1-\phi_{in,s})$ captures both the survival probability of the idea and the probability it remains unimitated. As before, we assume $V_{in,t}^{nopat} = 0$.

The first-order condition for the share of patented technologies becomes:

$$C'(\lambda_{in,t})P_{it} = \sum_{s=t}^{\infty}[(1-\delta)(1-\phi_{in,s})]^{s-t}\varepsilon_{in,t}\phi_{in,t}\frac{\Pi_{it}}{T_{it}} \tag{B.5}$$

The value of innovation is now:

$$V_{nt} = \sum_{i=1}^{M}\sum_{s=t}^{\infty}[(1-\delta)(1-\phi_{in,s})]^{s-t}\varepsilon_{in,t}\lambda_{in,t}\phi_{in,t}\frac{\Pi_{it}}{T_{it}} \tag{B.6}$$

B.3 Balanced Growth Path Analysis

On the BGP, all variables grow at constant rates and bilateral diffusion rates $\varepsilon_{in,t}$ converge to constant values $\bar{\varepsilon}_{in}$. Let g_Z denote the growth rate of ideas and g_A the growth rate of adopted technologies. On the BGP:

$$(1+g_A)A_{in} = (1-\delta)A_{in} + \bar{\varepsilon}_{in}Z_n \tag{B.7}$$

$$(1+g_Z)Z_n = (1-\delta)Z_n + \gamma_n\left(\frac{H_n}{Y_n}\right)^{\eta} \tag{B.8}$$

The gravity equation for cross-border patents on the BGP becomes:

$$\text{Pat}_{in} = \tau_{in}^{-1/(\xi-1)} \bar{\varepsilon}_{in} (\bar{\varepsilon}_{in}\phi_{in})^{1/(\xi-1)} \left(\frac{\Pi_i}{T_i P_i}\right)^{1/(\xi-1)} \frac{(g_Z+\delta)Z_n}{1-(1-\delta)(1-\phi_{in})} \tag{B.9}$$

B.4 Comparison with Baseline Model

The key difference between this extension and our baseline model is that the gravity equation (B.9) only holds on the BGP, where diffusion rates are constant and both innovation and adoption processes incorporate partial depreciation. The presence of the term $\frac{1}{1-(1-\delta)(1-\phi_{in})}$ in the gravity equation reflects the expected present value of patent protection given partial depreciation. In contrast, the baseline model with full depreciation yields a gravity equation that holds in every period, allowing for time-varying diffusion rates $\varepsilon_{in,t}$.

Given our paper's focus on time-varying patent flows and the role of changing diffusion patterns, we opt for the full depreciation specification in the main text. This choice allows us to derive and estimate a gravity equation that captures the rich dynamics of international patent flows, including the effects of time-varying diffusion rates that are central to our empirical analysis, while avoiding the additional complexity introduced by tracking the stock of ideas over time.

B.5 Eaton and Kortum (1999)

Both our model and an Eaton and Kortum (1999) framework with trade and Bertrand competition generate isomorphic gravity equations for patent flows, but they achieve this through distinct microfoundations. The Eaton and Kortum (1999) (EK) model builds on a Bertrand competition structure where firms engage in dynamic innovation races, with stochastic quality improvements and explicit modeling of market leadership dynamics. In contrast, our framework employs an Armington structure where differentiated varieties from each origin country remain distinct, with innovation expanding the range of available varieties rather than improving their quality. The models also differ in their treatment of technology diffusion: EK emphasizes the role of quality ladders and creative destruction in determining market leadership, while our approach focuses on the extensive margin of technology adoption and the decision to patent adopted technologies. We derive the main equations of the EK framework and the resulting gravity equation next.

We consider a world economy with N countries where production and trade follow the Eaton-Kortum framework with endogenous innovation. Each country produces final output using a continuum of intermediate goods indexed by $j \in [0, 1]$, with research productivity endogenously determined by the accumulated stock of knowledge in that country. International trade in intermediate goods faces standard iceberg costs $\tau_{ni} \geq 1$, where delivering one unit from country i to country n requires shipping τ_{ni} units. The model features endogenous innovation protected by patents, which provide temporary protection against imitation, creating incentives for research and development. This environment combines the standard Eaton-Kortum structure of international trade with an endogenous innovation process shaped by knowledge accumulation and intellectual property rights.

Production and Trade Structure The model follows Eaton and Kortum (2002) with Bertrand competition. In each country n, final output at time t is produced using a continuum of intermediate inputs according to:

$$Y_{nt} = \exp\left(\int_0^1 \ln x_{nt}(j)dj\right) \tag{B.10}$$

where $x_{nt}(j)$ is the quantity of intermediate input j used in country n at time t. Under Bertrand competition, each variety j is purchased only from the lowest-cost supplier. The unit cost of delivering variety j from country i to country n is:

$$c_{nit}(j) = \frac{\tau_{ni} w_{it}}{z_{it}(j)} \tag{B.11}$$

where w_{it} is the wage in country i, $z_{it}(j)$ is productivity for variety j, and $\tau_{ni} \geq 1$ represents iceberg trade costs. Given Bertrand competition, buyers in country n source each input from the lowest-cost supplier:

$$p_{nt}(j) = \min_i \{c_{nit}(j)\} \tag{B.12}$$

Following Eaton and Kortum (2002), productivity draws $z_{it}(j)$ are distributed Fréchet with shape parameter θ and location parameter related to the stock of ideas μ_{it} in country i. This generates a gravity structure for trade flows, where the probability that country n sources a given variety from country i is:

$$\lambda_{nit} = \frac{\mu_{it}(\tau_{ni} w_{it})^{-\theta}}{\sum_{k=1}^{N} \mu_{kt}(\tau_{nk} w_{kt})^{-\theta}} \tag{B.13}$$

Price and First-Order Condition Derivations The final good producer in country n solves:

$$\max_{x_{nt}(j)} \left\{ \exp\left(\int_0^1 \ln x_{nt}(j)dj\right) - \int_0^1 p_{nt}(j) x_{nt}(j)dj \right\} \tag{B.14}$$

where $p_{nt}(j)$ is the price of variety j in country n at time t.

For each variety j, the FOC is:

$$\frac{\partial}{\partial x_{nt}(j)} : \frac{Y_{nt}}{x_{nt}(j)} = p_{nt}(j) \tag{B.15}$$

This implies:

$$x_{nt}(j) = \frac{Y_{nt}}{p_{nt}(j)} \tag{B.16}$$

Substituting back into the production function:

$$Y_{nt} = \exp\left(\int_0^1 \ln\left(\frac{Y_{nt}}{p_{nt}(j)}\right) dj\right) \tag{B.17}$$

$$= Y_{nt} \exp\left(-\int_0^1 \ln p_{nt}(j)dj\right) \tag{B.18}$$

Therefore, the price index is:

$$P_{nt} = \exp\left(\int_0^1 \ln p_{nt}(j)dj\right) = 1 \tag{B.19}$$

This unity price index is a well-known property of the Cobb-Douglas aggregator.

For each variety j, producers from different countries compete in prices. The cost of delivering from country i to country n is:

$$c_{nit}(j) = \frac{\tau_{ni} w_{it}}{z_{it}(j)} \tag{B.20}$$

Under Bertrand competition, the price equals the second-lowest cost:

$$p_{nt}(j) = \min_{i \neq i^*(j)} \{c_{nit}(j)\} \tag{B.21}$$

where $i^*(j)$ is the lowest-cost supplier.

Given Fréchet distributed productivity:

$$Pr[z_{it}(j) \leq z] = \exp(-\mu_{it} z^{-\theta}) \tag{B.22}$$

The probability that the price from source i is below p is:

$$Pr[c_{nit}(j) \leq p] = 1 - \exp(-\mu_{it}(\tau_{ni} w_{it})^{-\theta} p^{\theta}) \tag{B.23}$$

The probability that country i is the lowest-cost supplier to country n is:

$$\lambda_{nit} = Pr[c_{nit}(j) \leq \min_{k \neq i}\{c_{nkt}(j)\}] \tag{B.24}$$

$$= \int_0^{\infty} \frac{\partial}{\partial p} \left[1 - \exp(-\mu_{it}(\tau_{ni} w_{it})^{-\theta} p^{\theta})\right] \tag{B.25}$$

$$\times \prod_{k \neq i} \exp(-\mu_{kt}(\tau_{nk} w_{kt})^{-\theta} p^{\theta}) dp \tag{B.26}$$

$$= \frac{\mu_{it}(\tau_{ni} w_{it})^{-\theta}}{\sum_{k=1}^{N} \mu_{kt}(\tau_{nk} w_{kt})^{-\theta}} \tag{B.27}$$

The exact price index satisfies:

$$P_{nt} = \gamma \left[\sum_{i=1}^{N} \mu_{it}(\tau_{ni} w_{it})^{-\theta}\right]^{-1/\theta} \tag{B.28}$$

where $\gamma = \left[\Gamma\left(\frac{\theta+1-\sigma}{\theta}\right)\right]^{1/(1-\sigma)}$ and $\Gamma(\cdot)$ is the gamma function.

Total expenditure from n on goods from i is:

$$X_{nit} = \lambda_{nit} Y_{nt} \tag{B.29}$$

This yields the gravity equation for trade flows in levels:

$$X_{nit} = \frac{\mu_{it}(\tau_{ni} w_{it})^{-\theta}}{\sum_{k=1}^{N} \mu_{kt}(\tau_{nk} w_{kt})^{-\theta}} Y_{nt} \tag{B.30}$$

Or in logs:

$$\ln X_{nit} = \ln \mu_{it} - \theta \ln w_{it} + \ln Y_{nt} - \ln \sum_{k=1}^{N} \mu_{kt}(\tau_{nk} w_{kt})^{-\theta} - \theta \ln \tau_{ni} \quad \text{(B.31)}$$

Innovation and Research Process The model's innovation process combines three key stochastic elements: the arrival of new ideas, their quality distribution, and international diffusion. In each country i at time t, researchers generate new ideas according to a Poisson process, with the arrival rate determined by research productivity a_{it} and research intensity s_{it} raised to power β. The aggregate flow of new ideas in country i follows:

$$\dot{\mu}_{it} = a_{it} s_{it}^{\beta} \quad \text{(B.32)}$$

This specification captures the idea that innovation requires both underlying research capability and deliberate allocation of resources to research activities.

When a new idea arrives, its quality is drawn from a Pareto distribution with shape parameter θ and minimum quality level z_{min}. The probability that an idea's quality Z is below any given level z follows:

$$Pr[Z \leq z] = 1 - \left(\frac{z_{\min}}{z}\right)^{\theta} \quad \text{(B.33)}$$

The Pareto distribution is particularly suitable for modeling innovation quality because it captures the empirical regularity that breakthrough innovations are rare while incremental improvements are common. The parameter θ plays a crucial role in determining the dispersion of innovation quality—a higher θ implies less variation in quality across innovations.

Research productivity depends endogenously on the accumulated stock of knowledge through the relationship:

$$a_{it} = a_i \mu_{it} \quad \text{(B.34)}$$

where a_i represents country-specific baseline research capability and μ_{it} is the current stock of ideas. This linear specification embodies strong knowledge spillovers, suggesting that researchers become more productive as they build upon a larger foundation of existing knowledge.

International technology diffusion occurs through a separate stochastic process. Ideas originating in country i diffuse to country n according to a Poisson process with rate parameter ϵ_{ni}. The probability that an idea has diffused by time t is given by:

$$Pr[\text{diffusion from } i \text{ to } n \text{ by } t] = 1 - e^{-\epsilon_{ni} t} \quad \text{(B.35)}$$

This specification implies exponentially distributed waiting times for diffusion and constant hazard rates, capturing the notion that knowledge flows face persistent international barriers but gradually overcome them over time.

The interaction of these three stochastic processes—Poisson arrivals, Pareto qualities, and independent diffusion—generates a Fréchet distribution for the frontier technology available in each country. The highest quality available in country n for variety j at time

t follows:

$$Pr[Z_{nt}(j) \leq z] = \exp\left(-\sum_{i=1}^{N} \mu_{it}(1 - e^{-\epsilon_{ni}t})z^{-\theta}\right) \tag{B.36}$$

This result emerges because the maximum of independent Pareto random variables, thinned by a Poisson process, follows a Fréchet distribution. This property proves crucial for deriving tractable expressions for trade flows and patent decisions.

The value of an idea to its inventor depends on the profits it can generate across all potential markets, accounting for diffusion probabilities and dynamic obsolescence. For an idea of quality z, the present value under patent protection is:

$$V_{it}^{pat}(z) = \int_t^{\infty} \sum_{n=1}^{N} \pi_{nit}(z)e^{-r(s-t)}(1 - e^{-\epsilon_{ni}(s-t)}) \times e^{-\sum_n (M_{ns}-M_{nt})z^{-\theta}} ds \tag{B.37}$$

Here, $\pi_{nit}(z)$ represents the instantaneous profit flow from market n, discounted by interest rate r and weighted by the probability of successful diffusion. The term $e^{-\sum_n (M_{ns}-M_{nt})z^{-\theta}}$ captures the probability of maintaining market leadership against future innovations.

The instantaneous profit function is given by:

$$\pi_{nit}(z) = \frac{Y_{nt}}{J}(1 - \frac{1}{\sigma})\left(\frac{\tau_{ni}w_{it}}{z}\right)^{1-\sigma} P_{nt}^{\sigma-1} \tag{B.38}$$

This expression reflects several key economic mechanisms: market size (Y_{nt}/J), markup ($1 - 1/\sigma$), cost advantage $(\tau_{ni}w_{it}/z)^{1-\sigma}$, and market competition ($P_{nt}^{\sigma-1}$). Together, these components determine the incentives for innovation and patent protection across markets with different characteristics.

This rich structure generates a model where innovation rates, diffusion patterns, and patenting decisions respond endogenously to economic fundamentals. Research intensity influences innovation through both direct effects on idea arrival rates and indirect effects through knowledge accumulation. Trade costs affect technology diffusion both directly through their impact on market access and indirectly through their effect on the value of innovations. Competition operates through multiple channels, affecting both the immediate profitability of innovations and their long-run survival prospects against future improvements.

Balanced Growth Path Analysis On the balanced growth path (BGP) in this economy, all variables must grow at constant rates to maintain consistency with the model's structure. The core growth relationships can be expressed as exponential paths for output, wages, and the mass of ideas:

$$Y_{nt} = Y_{n0}e^{g_Y t} \tag{B.39}$$
$$w_{it} = w_{i0}e^{g_w t} \tag{B.40}$$
$$M_{nt} = M_{n0}e^{g_M t} \tag{B.41}$$

These growth rates are fundamentally interconnected through the economy's production and innovation structure. Starting from the Eaton-Kortum trade framework, we can derive the relationship between output growth and idea growth. The productivity distribution in country n follows a Fréchet with scale parameter depending on the mass of ideas:

$$Pr[Z_{nt}(j) \leq z] = \exp\left(-\sum_{i=1}^{N} \mu_{it}(1 - e^{-\epsilon_{ni}t})z^{-\theta}\right) \tag{B.42}$$

Taking logs of the output equation and differentiating with respect to time yields the fundamental relationship:

$$g_Y = \frac{1}{\theta} g_M \tag{B.43}$$

This relationship reflects how improvements in productivity drive output growth, with the Fréchet shape parameter θ governing the translation of new ideas into productivity gains.

The growth rate of ideas is determined by the endogenous innovation process. From the flow equation for new ideas:

$$\dot{\mu}_{it} = a_{it} s_{it}^{\beta} \tag{B.44}$$

On the BGP, the growth rate of ideas must be constant:

$$g_M = \frac{\dot{\mu}_{it}}{\mu_{it}} = \frac{a_{it} s_{it}^{\beta}}{\mu_{it}} = a_i s_{it}^{\beta} \tag{B.45}$$

where the last equality uses $a_{it} = a_i \mu_{it}$. This implies research intensity s_{it} must be constant on the BGP.

The value function for patented ideas takes a particularly tractable form on the BGP. For an idea of quality z:

$$\begin{aligned} V_{it}^{pat}(z) = \sum_{n=1}^{N} \frac{Y_{nt}}{J}(1 - \frac{1}{\sigma})\lambda_{nit} \\ \times \int_t^{\infty} e^{-(r-g_Y)(s-t)}(1 - e^{-\epsilon_{ni}(s-t)})e^{-g_M(s-t)} ds \end{aligned} \tag{B.46}$$

To solve this integral, we can break it into parts:

$$\int_t^{\infty} e^{-(r-g_Y)(s-t)}(1 - e^{-\epsilon_{ni}(s-t)})e^{-g_M(s-t)} ds \tag{B.47}$$

$$= \int_t^{\infty} e^{-(r-g_Y+g_M)(s-t)} ds - \int_t^{\infty} e^{-(r-g_Y+g_M+\epsilon_{ni})(s-t)} ds \tag{B.48}$$

$$= \frac{1}{r - g_Y + g_M} - \frac{1}{r - g_Y + g_M + \epsilon_{ni}} \tag{B.49}$$

$$= \frac{\epsilon_{ni}}{(r - g_Y + g_M)(\epsilon_{ni} + r - g_Y + g_M)} \tag{B.50}$$

For the BGP to exist, several conditions must be satisfied. First, the effective discount rate must exceed growth:

$$r > g_Y + g_M \tag{B.51}$$

This ensures finite firm values. Second, wage growth must match output growth:

$$g_w = g_Y \tag{B.52}$$

Third, research intensity must be constant:

$$\dot{s}_{it} = 0 \tag{B.53}$$

These conditions, combined with the fundamental growth relationships, create a linked system. Using $g_Y = g_M/\theta$, we can express all growth rates in terms of g_M:

$$g_Y = \frac{1}{\theta} g_M \tag{B.54}$$

$$g_w = \frac{1}{\theta} g_M \tag{B.55}$$

$$g_M = a_i s_i^\beta \tag{B.56}$$

The implications for patent flows can be derived from the patent flow equation:

$$P_{nit} = \epsilon_{ni} a_i \mu_{it} s_{it}^\beta q_{nit}^{-\theta} \tag{B.57}$$

Taking logs and time derivatives yields the patent flow growth rate:

$$g_P = g_M + g_Y = (1 + \frac{1}{\theta}) g_M \tag{B.58}$$

This reflects both idea creation (g_M) and market size growth (g_Y). The threshold quality for patenting adjusts to maintain this balanced growth:

$$q_{nit} = \left[\frac{f_{nit} J(r - g_Y + g_M)(\epsilon_{ni} + r - g_Y + g_M)}{Y_{nt} \epsilon_{ni} (1 - \frac{1}{\sigma}) \lambda_{nit}} \right]^{\frac{1}{\theta}} \tag{B.59}$$

On the BGP, this threshold grows at rate $g_q = g_Y$ to maintain constant patent flows to output ratios across countries.

Patent Decisions and Gravity Structure The patent decision in our model is characterized by a threshold rule where inventors choose to patent an idea when the value gain from patent protection exceeds the filing costs. Formally, an innovator patents when:

$$V_{it}^{pat}(q_{nit}) - V_{it}^{not}(q_{nit}) = f_{nit} \tag{B.60}$$

where f_{nit} represents the cost of patenting in market n. This condition determines a quality threshold for patenting:

$$q_{nit} = \left[\frac{f_{nit} J(r - g_Y + g_M)(\epsilon_{ni} + r - g_Y + g_M)}{Y_{nt} \epsilon_{ni} (1 - \frac{1}{\sigma}) \lambda_{nit}} \right]^{\frac{1}{\theta}} \tag{B.61}$$

The costs of patent filing play a crucial role in shaping patenting decisions. We assume the cost of filing a patent from country i in country n at time t takes a specific functional form that captures several key economic mechanisms:

$$f_{nit} = f_{it} \cdot f_{nt} \cdot \exp(-\gamma \ln(1 - e^{-\epsilon_{ni,t}}) + \beta(\iota^{pat} - \iota^{not})) \tag{B.62}$$

This cost structure embodies several important economic forces. The term f_{it} represents origin-specific costs such as the initial preparation of patent documentation, while f_{nt} captures destination-specific costs like local filing fees. The component $\exp(-\gamma \ln(1 - e^{-\epsilon_{ni,t}}))$ reflects how patenting costs vary with the ease of technology diffusion—when diffusion is easier (higher ϵ_{ni}), costs tend to be lower due to reduced translation and adaptation requirements. The final term $\exp(\beta(\iota^{pat} - \iota^{not}))$ accounts for how costs depend on the strength of patent protection.

The structure of patent costs is motivated by several key economic considerations. First, the multiplicative separability between origin and destination components reflects the fact that patent preparation is largely independent of the filing location, while local fees are typically uniform across origins. This separability also proves valuable for empirical work as it allows for multiplicative fixed effects in estimation. Second, the diffusion-related component captures how information flows and network effects in patent attorney services can reduce costs when technologies diffuse more easily. Third, the protection adjustment term reflects the higher administrative burden and monitoring costs associated with stronger patent protection.

Given this structure, we can derive a gravity equation for patent flows. The flow of patents from country i to country n is given by:

$$P_{nit} = \epsilon_{ni} a_i \mu_{it} s_{it}^{\beta} Pr[z > q_{nit}] \tag{B.63}$$

Under the Fréchet distribution of qualities, the probability of exceeding the threshold is:

$$Pr[z > q_{nit}] = q_{nit}^{-\theta} \tag{B.64}$$

Substituting the threshold condition and cost function, then taking logs, yields our gravity equation for patent flows:

$$\begin{aligned} \ln P_{nit} = [\ln a_i + \ln \mu_{it} + \beta \ln s_{it} - \theta \ln f_{it} + \ln \sum_n \lambda_{nit} Y_{nt}] \\ + [-\theta \ln f_{nt} - \ln J] + \ln \epsilon_{ni} + \theta\gamma \ln(1 - e^{-\epsilon_{ni}}) \\ + [\ln(\iota^{not} - \iota^{pat}) - \theta\beta(\iota^{pat} - \iota^{not})] \end{aligned} \tag{B.65}$$

This gravity equation provides a rich decomposition of the forces driving international patent flows. The first bracketed term represents an origin fixed effect capturing research capacity, local costs, and market potential. The second bracketed term represents a destination fixed effect absorbing market size and local filing fees. The remaining terms capture bilateral resistance through diffusion and protection effects. This structure reveals how patent flows are shaped by the interaction of origin research capabilities, destination market conditions, and bilateral factors affecting both technology diffusion and patent-related policies, including strengthened patent protection (i.e., RTAs with IP provisions) and streamlined application procedures (i.e., PCT).

The distributional consequences of increased cross-border patenting differ depending on whether they come from improved technology diffusion (ϵ) or strengthened patent protection (ι). When driven by higher diffusion rates (ϵ), both North and South tend to benefit since technologies spread more naturally—the North gains from easier market access while the South benefits from faster technology absorption, even without patents. In contrast, stronger patent protection (higher ι) creates more asymmetric effects: the North captures greater profits from its innovations through enhanced market power, while the South faces more restricted and costly access to technologies. This protection-driven increase primarily benefits Northern innovators at the expense of Southern adopters, at least in the short run, though long-term effects depend on whether stronger protection eventually stimulates domestic innovation in the South.

C Construction of INPACT-S

We proceed in several steps. From the raw PATSTAT data, we use Structured Query Language (SQL) to pull appln_id, person_id, earliest_pat_publn_id, appln_auth, person_ctry_code, appln_filing_year, publn_nr, publn_nr_original, publn_auth, publn_kind, ipc_class_symbol from tables tls201_appln (table containing the bibliographical data elements of the application), tls207_pers_appln (table linking the applicants/inventors of the most recent publication to an application), tls206_person (table with identifying information on the applicants/inventors), tls209_appln_ipc (table containing the IPC classifications of an application), and tls211_pat_publn (table containing information about patent publications). These variables give us a raw dataset that reports, for each patent, the jurisdiction where the application was filed, the country of the applicant(s)/inventor(s), the year of application, and the full, disaggregated IPC class associated with each patent.

Importantly, we restrict our data to application type "A," which in PATSTAT represents basic patents, and we do two separate pulls, one to get all persons who are inventors and another to get all persons/entities who are applicants. Moreover, rather than restricting the sample to the first patent in a family, we consider every patent from the same family. There is merit to analyzing only the first patent in the family, as one can get a better sense of breakthrough innovation, since all further patents in that family are a variation of that initial invention. However, our goal is to create a more comprehensive dataset that captures all innovation flows across the world because we seek to understand why patents are filed where they are. To this end, where the last patent in a family is filed holds just as much importance to us as where the first patent was filed.[27]

A few remarks are in order regarding how we treat patents filed by multinational companies. Patents are attributed to the country of the filing entity, which may not necessarily coincide with the location of the multinational's headquarters. For instance, if a subsidiary of a multinational company based in Ireland files a patent application in China, it is recorded as a patent flow from Ireland to China, despite the parent company being headquartered in another country. This approach is primarily dictated by the available data, as patent applications typically provide information on the filing entity and its location, but may not always identify the ultimate owner or the location of the headquarters. This can lead to potential drawbacks in accurately representing the true geographical distribution of patent ownership and innovation activities. However, for the

[27]The EPO defines a patent family as "A patent family is a collection of patent applications covering the same or similar technical content."

purposes of our analysis, this may not be too problematic, as the primary focus is on the flow and interaction of patent activities between countries rather than pinpointing the exact origin of multinational innovation.

We make several adjustments to the raw data, which we explain next. First, we aggregate the IPC classifications to the 4-digit level. Second, in many instances, one application may feature multiple applicants/inventors from different countries. Similarly, for a majority of applications, a single patent belongs to multiple IPC technology classifications. To avoid counting the same applications multiple times for different origins/classifications, we employ a fractional counting method for both technology class and origin country. For example, if an application has four inventors, one from the US and three from Canada, then this will be counted as 0.25 patents from the US and 0.75 from Canada, as opposed to four different applications. To ensure consistency, we implement built-in checks and crosscheck with the OECD, which also relies on a fractional method.

We use the same idea to avoid counting one patent that falls into multiple IPC classification as multiple different applications. If, as in our example above, the IPC classifications of the patent are G06F 1/04, G06F 1/16, and G08B 1/02, then 0.67 of the application is assigned to G06F and 0.33 is assigned to G08B. This means that in the case of the four inventors described above, the Canadian inventors receive credit for 0.75 of the patent, and 0.67 of that is assigned to the G06F classification. This results in a total of 0.5 patents assigned to the Canadian G06F class.

Third, in several cases, applications are filed to regional patent authorities covering two or more countries rather than a single country. This is a decision made at the individual level. In some cases, applicants may opt for the cheaper upfront cost of applying to just one or two European countries, and others may decide to go the more expensive route and apply to the European Patent Office (EPO) as a whole, which is cheaper than applying to many countries individually. As recognized by WIPO, the major regional authorities are African Regional Intellectual Property Organization (ARIPO), EPO, Eurasian Patent Organization (EAPO), Gulf Cooperation Council (GCC) Patent Office, and Organisation Africaine de la Propriété Intellectuelle (OAPI).[28] Under these jurisdictions, applicants can send one application to these authorities for a singular granting process and receive the possibility of protection in all fully ascended member states.

We attempt to take the regional patent authority application totals and disperse them in favor of individual member country applications. To this end, we make the reasonable assumption that not all member states of an authority are attracting patent applications equally. For example, it is likely that far more applications filed with the EPO are intended to be used to protect IP in a large, traditionally innovative country, such as Germany, than in a smaller member, such as Slovenia or Liechtenstein. Therefore, when measuring the main destinations of cross-border patents, equating all patents to the EPO to count as one for each and every member state would paint a skewed image of technology transfer. This approach could make small countries that are part of a large regional authority seem like more of a technology destination than they are in reality.

To address this issue, we employ a weighted-dispersion method in which we allocate patent applications, from an origin to a regional authority, across the individual member states of that regional authority. We base this dispersion probability on the share of direct patent applications from each origin country to each individual member state in that same year and technology class. To visualize this point, imagine a hypothetical regional patent authority, UKESPDEU, which consists of only the United Kingdom, Spain, and Germany.

[28] https://www.wipo.int/patents/en/topics/worksharing/regional-patentoffices.html

Suppose that applicants from Australia filed 100 patents in the textiles industry with UKESPDEU in 2022. Suppose that, also in 2022, Australian applicants filed 25 textile patents directly in Germany, 10 textile patents directly in Spain, and 5 textile patents directly in the United Kingdom. Out of these 40 directly filed patents, Germany received 62.5%, Spain received 25%, and the United Kingdom received 12.5%. These shares serve as the probabilities of the intended final destination of patents filed to the regional authority. We use these probabilities as our weights to disperse out the patents filed to UKESPDEU. Following this method, dispersing the 100 Australian textile patents filed to UKESPDEU and adding them to the direct totals would result in 87.5 patents to Germany, 35 patents to Spain, and 17.5 patents to the United Kingdom.

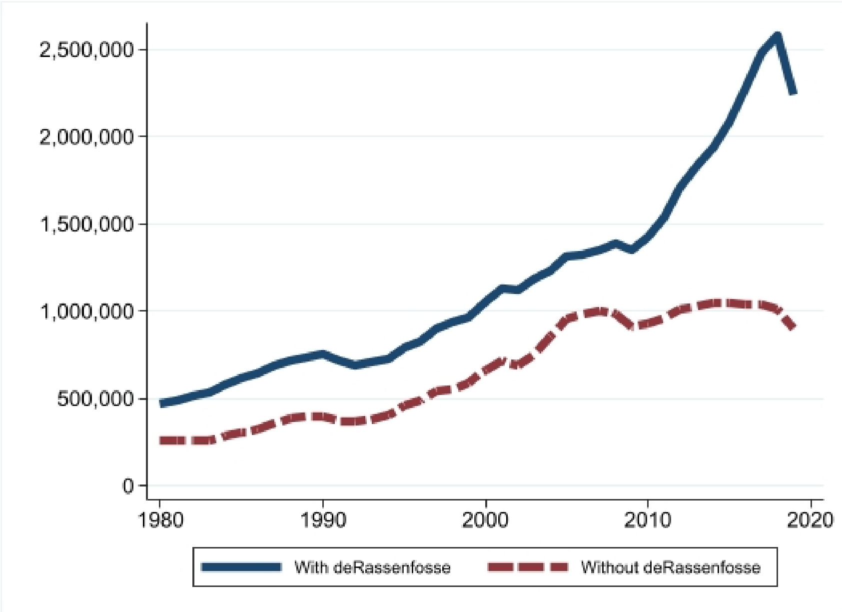
Fourth, we address a commonly discussed problem of PATSTAT database. Since PATSTAT is maintained by the EPO, they are unable to edit the data voluntarily provided to them by other authorities that are sometimes lacking in detail. This results in a prevalence of missing data in a number of categories, including in the country of the applications' applicant(s)/inventor(s), as documented by De Rassenfosse, Kozak, and Seliger (2021). We follow two steps for imputing blank origin countries. In the first step, we use the SQL code provided by De Rassenfosse, Kozak, and Seliger (2021) to impute missing values in the raw PATSTAT data. Before imputation, there are over 26 million applicants with a known origin from 1980-2019 and nearly 24 million inventors in our dataset; after applying their method, we have over 46 million applicants and 44 million inventors.

Figure A1 showcases the differences in known origins before and after imputation for each year in our sample. They use familial linkages between worldwide applications to impute the origin that is missing, based on data found in related patents filed elsewhere. Patents for the same technology are often filed in more than one jurisdiction (or even in the same jurisdiction for a slightly different but related technology). One authority may report incomplete information on the origin of a patent, but another authority may report more complete information for the same (or similar) technology in the same family. PATSTAT provides data that can be used to link priority filings with subsequent filings across the globe, making it possible to take information from related patent applications to impute the missing information, which is precisely what their provided code does. In brief, their method can be summarized as the following: If the information is not available on the patent application, search for the information from direct equivalent patents in the same family. If the information cannot be found on those direct equivalents, search for the information in subsequent filings in the same patent family. This continues on until all possibilities are exhausted.

The De Rassenfosse, Kozak, and Seliger (2021) method, although impressively comprehensive, is unable to account for all missing origins. In the second step, instead of simply dropping the remaining blank origin data, we use the aggregate bilateral data from WIPO to disperse the remaining "origin missing" applications. At the current stage, after applying all the edits stated above, our dataset contains authority, IPC 4-digit class, year, and origin. However, for every authority, in each year, in each ISIC industry there exists a blank country of origin with some patents attributed to it. Our goal is to assign all these remaining patents to origin countries rather than simply lose that data.

One possibility would be to follow a method similar to the one described above for the dispersion of regional authorities' applications. That is, dispersing applications based on shares of the applications, which are already assigned. However, this method might be a biased way of dispersing the "missing origin" applications. Some origins have more robust

Figure A1: Imputing missing values with De Rassenfosse, Kozak, and Seliger (2021)



Note: This figure shows, for each year, the difference between the applicants we have with known origins before and after using the De Rassenfosse, Kozak, and Seliger (2021) imputation method.

patent families for the De Rassenfosse, Kozak, and Seliger (2021) method to pull from. In addition, some authorities report better data than others, and these authorities receive applications from different origins at different rates. For example, Japan reports Japanese origins very well but is less reliable on reporting cross-border patents. Additionally, in recent years, China rarely reports origin countries at all to the EPO. As a result, using shares derived from our existing dataset would be reinforcing established biases in the data.

To account for this problem, we instead use the WIPO aggregate bilateral data as a proxy. We take the authorities from WIPO and compute the share of total patents for each authority that originate from each origin country for a given year. We then, as with the regional authorities described above, apply those probabilities to the "missing origin" data, and distribute them based on these WIPO weights. A key assumption with this approach is that the probabilities are assumed to be constant across all technology classes for each origin/authority/year relationship. Roughly 9% of our observations by applicant are dispersed with this method and 11% of our patents by inventor.

Finally, the 4-digit IPC technology classes are converted into ISIC rev. 3 2-digit industries using a crosswalk that can be found in Goldschlag, Lybbert, and Zolas (2016).[29] Our patent numbers for each technology class are multiplied by the probability weights provided and then summed by industries to give us a bilateral patenting dataset by country and industry rather than technology class.

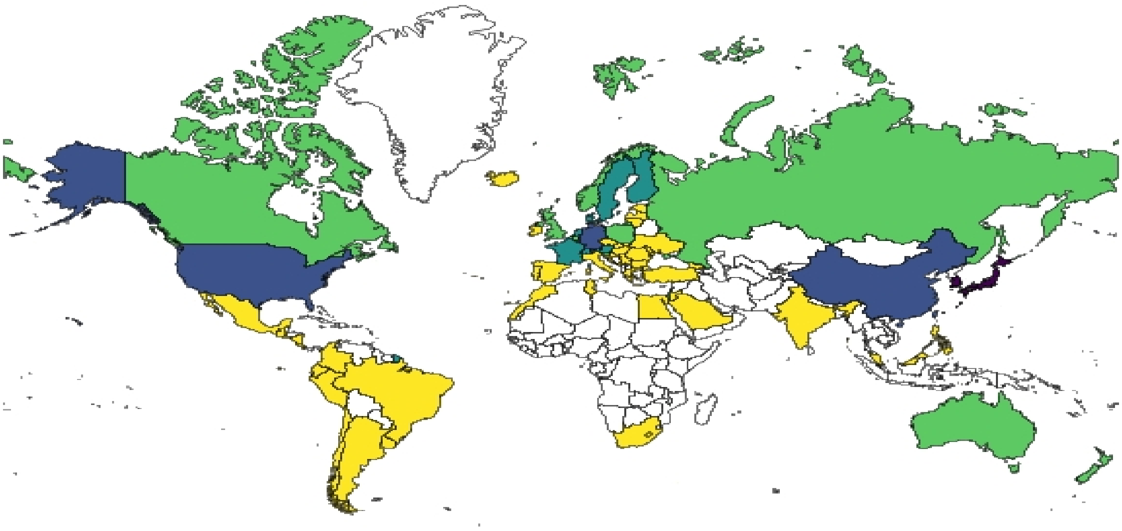
The origins of innovation. Figure A2 shows the worldwide distribution of patent applications per million people filed by (i) domestic inventors inside the country—domestic

[29] https://sites.google.com/site/nikolaszolas/PatentCrosswalk.

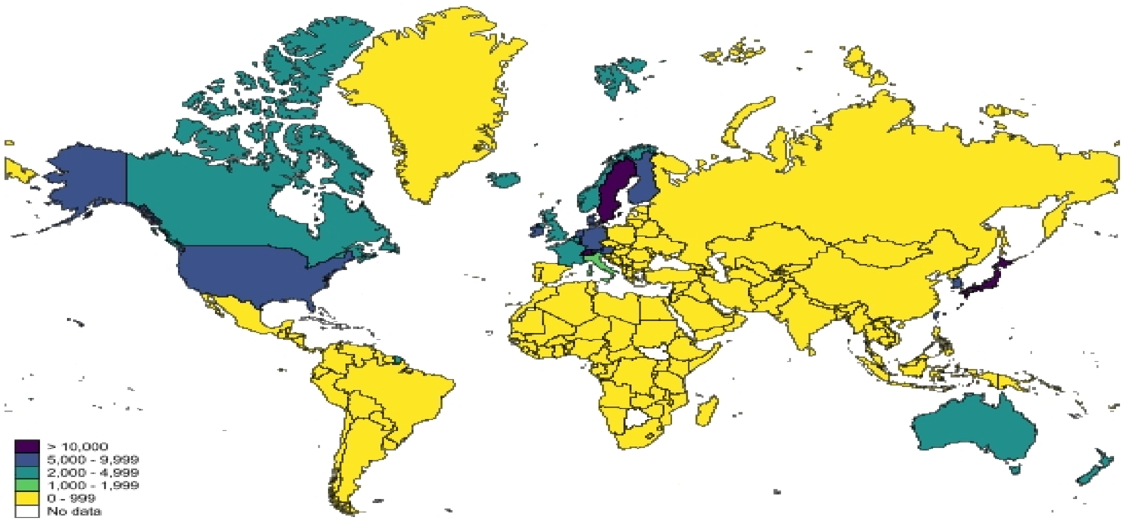
applications—in the upper panel, and (ii) domestic inventors to the world—cross-border applications—in the bottom panel, throughout the decade of the 2010s.[30]

Figure A2: Origins of Innovation

(a) Domestic patent applications



(b) Cross-border patent applications



Note: The upper panel (a) shows the number of domestic patent applications per million people in the 2010s; the bottom panel (b) shows cross-border patent applications per million people in the 2010s. Blank countries do not have data available as authorities.

The figure shows that innovation is concentrated in a few countries, mainly in Europe, the United States, and Eastern Asia. While Europe and North America have traditionally been innovation hubs, our data show the rise of Eastern Asian countries as new innovators. In terms of domestic patent applications, China stands out as the main innovator. Indeed, 37% of all patent applications being filed around the world in the 2010s can be attributed

[30]Population is calculated by taking the average across the decade.

to Chinese domestic applications. The other leaders of total domestic applications were Japan, the United States, South Korea, and Germany in that order.

The rise of Eastern Asian countries on the world innovation stage centers around four countries: Japan, South Korea, China, and Taiwan.[31] Japan and South Korea are more traditionally innovative countries, with their technology sectors dating back decades, while China and Taiwan have become new powerhouses of innovation, with a growth in the number of domestic patent applications between 1995 and 2018 by a factor of 13 in Taiwan and by a factor of 162 in China. China's explosion in terms of domestic patenting is unprecedented. In fact, there is reason to believe that this remarkable growth can be attributed to China's generous patent subsidy programs. However, on January 27, 2021, the China National Intellectual Property Administration (CNIPA) announced that these subsidies are to be phased out by 2025.

Aside from the domestic market, these 4 countries have also become important sources of cross-border patent applications. Japan, likely due to the age of its technology sector, dominates the other Eastern Asian countries in the number of patent applications filed abroad. However, South Korea has become more prominent in the international patent market beginning in the 90s, followed by Taiwan and China in the 2000s. Interestingly, China's unprecedented domestic patent growth has not been replicated on the international level in terms of the total number of cross-border patent applications filed, but the growth rate has. Though their cross-border patent applications are dwarfed by their domestic applications, China has still seen an increase by a factor of 230 in terms of cross-border applications filed from 1995 to 2018. These trends indicate an increase in these countries' presence in terms of innovative activity.

If we isolate the analysis to cross-border patent applications, applications filed by each origin country to the world excluding domestic applications, the picture looks slightly different. The main discrepancy lies in China, where Chinese innovators seek protection mainly domestically. Indeed, out of all patent applications to the world during the 2010s, only 1.5% are accounted for by Chinese cross-border patents. Again, this discrepancy is an indication of the market intervention introduced by the Chinese government in the late 2000s that sought to incentivize patent applications through a subsidy.[32] During the decade, the main innovators seeking protection abroad are Japan, the United States, Germany, and South Korea. From the 1990s to the 2010s, we find that Japan, South Korea, and Taiwan are the countries that have experienced the largest increase in the number of cross-border patent applications per million residents filed.[33]

To better illustrate the emergence of new regions as origins of patent applications, we partition the countries in our dataset into regions.[34] Figure A3 shows the evolution of patenting across the different regions. In the upper panel, we show the total number of cross-border patents filed by the countries in each world region, whereas in the bottom panel we show the same but for the countries that make up Eastern Asia.[35]

[31] Eastern Asia also includes Hong Kong and Mongolia but their overall values are small and inconsequential so we focus on the four mentioned.

[32] `https://www.stlouisfed.org/on-the-economy/2018/february/china-overtaken-us-terms-innovation`.

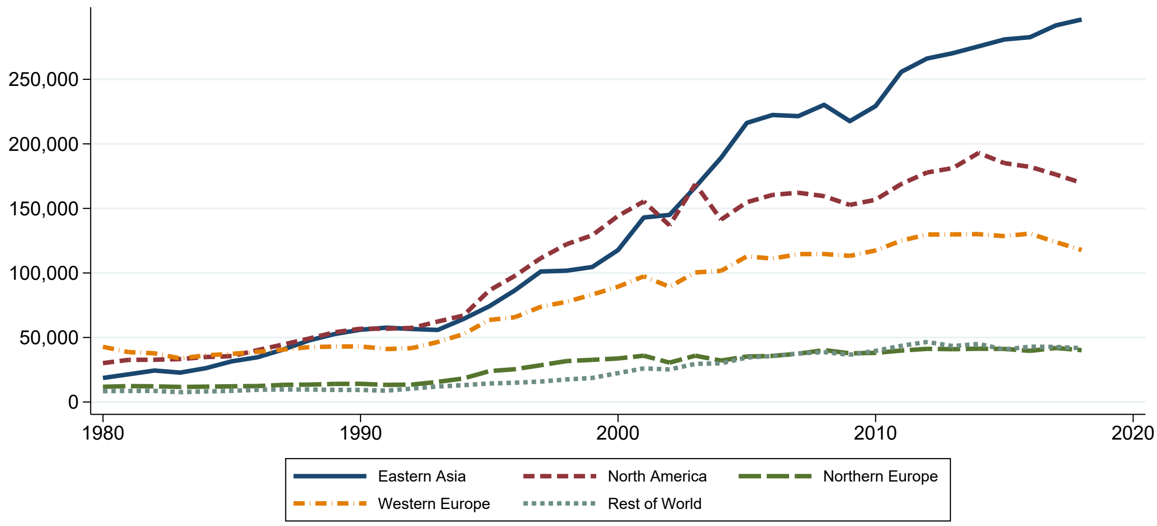
[33] This is excluding countries that are commonly labeled as "Tax Havens", which typically saw incredible patent growth over this period.

[34] We use regions as defined by the UN `https://unstats.un.org/unsd/methodology/m49/`: Australia and New Zealand, Central Asia, Eastern Asia, Eastern Europe, Latin America, Melanesia, Micronesia, Northern Africa, Northern America, Northern Europe, Polynesia, South-eastern Asia, Southern Asia, Southern Europe, Sub-Saharan Africa, Western Asia, Western Europe.

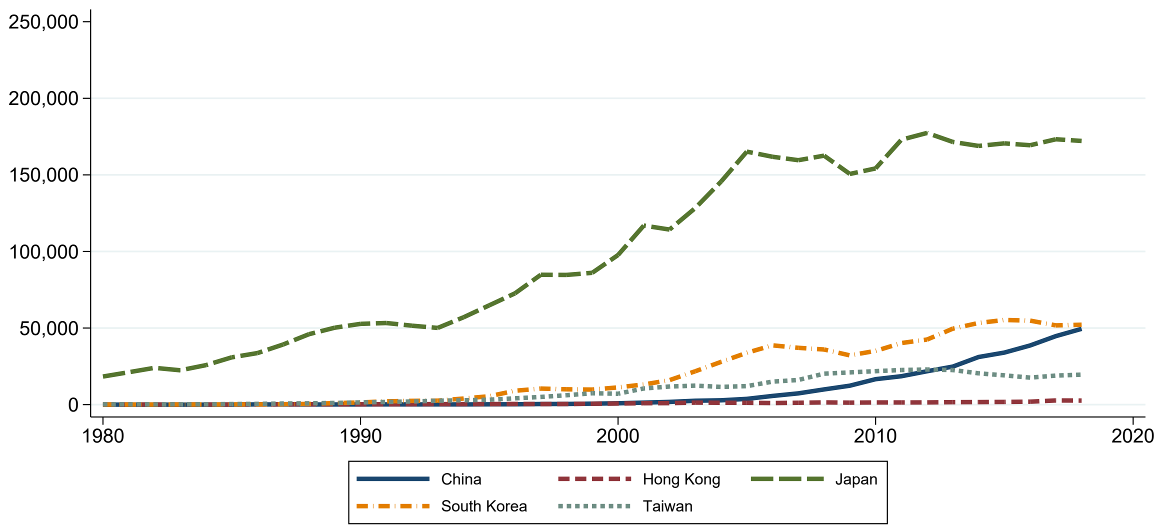
[35] Cross-border patents are determined at the jurisdiction level rather than the regional level. A patent

Figure A3: Patent Evolution by Region of Origin

(a) World Regions



(b) Eastern Asia

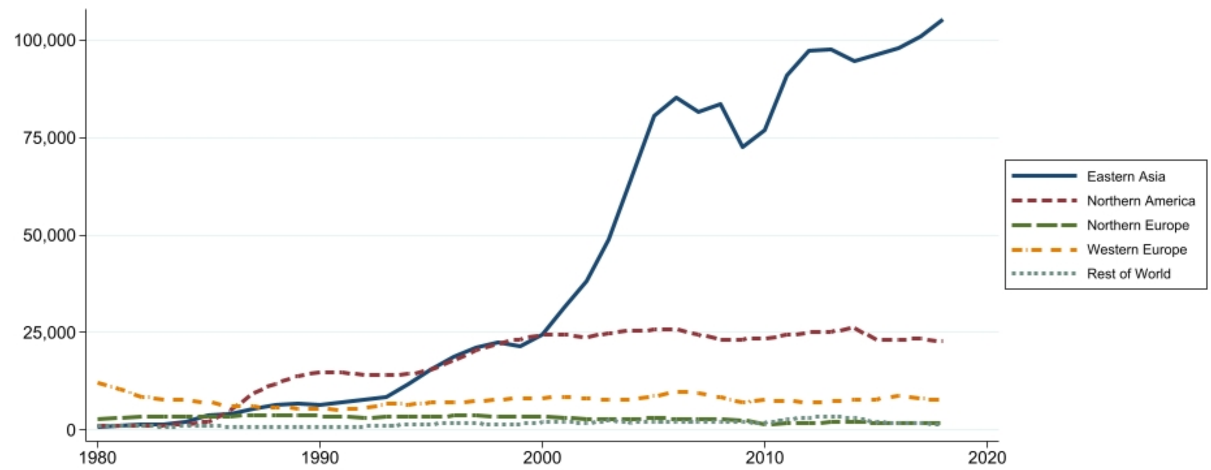


Note: The upper panel (a) shows cross-border patent applications filed by the countries of different regions of the world; the bottom panel (b) plots patent applications filed by each country in Eastern Asia.

What stands out in the upper panel is Eastern Asia catching up to North America in terms of foreign applications filed in the mid-2000s and maintaining the lead since. Also notable is the speed at which Eastern Asia caught up to North America, closing the gap with the United States very quickly after the turn of the century. No other region comes close to matching Eastern Asia's growth over this time frame. From the bottom panel, we can see that this growth was largely due to Japan and, to a lesser extent, South Korea. However, while Japan, South Korea and Taiwan have plateaued in recent years, China has begun their own rapid growth as inventors of cross-border patents.

If we focus on patent applications to other countries within the region, we observe a strong bias of Eastern Asian countries to file cross-border patents that remain within the region (Figure A4). Beginning in 1990s, Eastern Asian countries began rapidly filing patents to other countries in the region, and after 2000, around the time of China's ascension to the WTO, this grew even faster while most other regions either stayed steady or increased just moderately over this span. This is consistent with an overall trend towards Eastern Asia in the global patent market.

Figure A4: Regional Bias in Patenting Applications



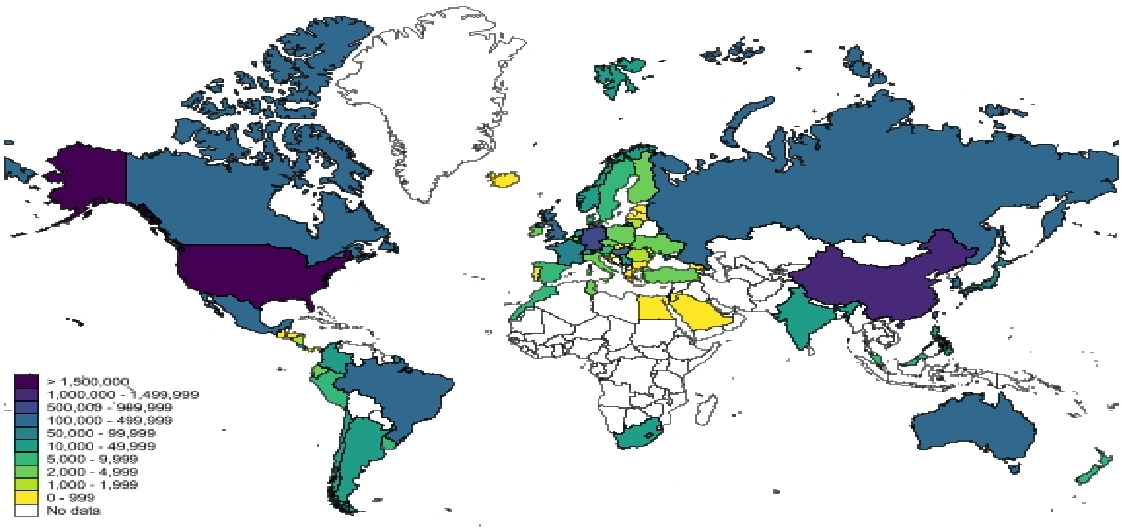
Note: This figure shows the number of cross-border patents filed by countries of a region which were filed elsewhere in that same region. The Rest of the World is an aggregate where we first compute this intra-region number for each region individually and aggregate them together.

The Destinations of Innovation. So far, we have documented the rise of Asia as an innovation hub. In this section, we investigate the following question: Where are innovators seeking protection for their ideas? Figure A5 shows that Eastern Asia has risen as a destination of cross-border patent applications in addition to being an innovator. This suggests that the region may be seen as a competitor destination to traditionally innovative countries, such as the US. By the 2010s, the US and China have dominated as destinations where inventors seek protection of their IP, being the only countries to attract more than a million cross-border patent applications in the decade.

Additionally, South Korea attracted the 4th most cross-border patents, while Taiwan attracted the 7th most. There are two possible reasons for this: either these countries are

from South Korea to Japan occurs in the same region but is a cross-border application.

Figure A5: Main Destinations of Cross-border patents in the 2010s



Note: This figure shows the number of cross-border patent applications received in the2010s. Blank countries do not have data available as authorities.

becoming more innovative and competing with western innovation such that innovators want to ensure their technology is protected from imitation here, or typically innovative countries are doing more business in these countries, leading to an increased need for ensuring business assets are protected.

International Patenting Across Industries. Next, we leverage the industry dimension of the data and ask the following question: In what industries are innovators seeking international protection? Taking the United States as the world innovation leader, we find that patent applications from the United States to the world are concentrated in a few industries: Chemicals, Computers and electronics, and Medical and optical equipment. These are also R&D-intensive industries in that they account for most of the R&D spending and number of patents being created around the world. Second, we find that nine countries account for more than 80% of cross-border patent applications filed by United States applicants to the world: China, Canada, Great Britain, Australia, Germany, South Korea, Taiwan, Brazil, and Mexico. In Table A1, we report the share of patent applications from the US to each of these countries across five of the most R&D-intensive industries.

The table shows that about one-third of the patents filed by the US in Mexico, one-fourth of the patents filed in Canada and South Korea, and one-fifth of those filed in China, UK, and Taiwan are in the chemical industry. However, in the case of Germany, US inventors seek protection mainly in the medical and optical equipment industry. Also notable is Taiwan, where 19% of US patents in Taiwan after the turn of the century were in the radio, television, and communication equipment industry, far higher than shares to other countries. This is notable because of Taiwan's importance in the semiconductors industry and the fact that this industry comprised just 7% of US patents to the rest of the world over this same period. Additionally, 14% of patents filed in Germany were in machinery, which is more than double its share of US patents filed in the rest of the world. Differences in patent applications across industries and countries could be

Table A1: Industries of Patents filed by the US, Post 2000

Destination	Chemical Mfg	Computing	Machinery n.e.c.	Medical /Optical Equip	Radio/TV/ Comms Equip
Australia	27%	12%	5%	14%	3%
Brazil	30%	9%	7%	11%	3%
Canada	25%	10%	7%	13%	3%
China	16%	13%	9%	15%	10%
Germany	9%	13%	14%	18%	7%
UK	16%	21%	5%	18%	6%
Korea	23%	17%	4%	15%	11%
Mexico	32%	7%	6%	9%	3%
Taiwan	19%	17%	3%	15%	19%
ROW	17%	21%	6%	16%	7%

Notes: The table reports the share of patent applications from the US to each of the countries across five of the most R&D-intensive industries. R&D intensity is computed as the proportion of patents generated by each industry in relation to the overall number of patents across all industries.

explained by supply chain linkages requiring countries to seek protection in a particular industry, depending on the particular position in the supply chain.

The empirical findings suggest that innovators from developed countries are increasingly seeking patent protection in Asia primarily to facilitate market entry and operations. The data reveals a significant share of U.S. patents filed in countries like China, South Korea, and Taiwan are in high-tech sectors such as chemicals, computers, electronics, and communication equipment, aligning with the growing technological capabilities and market opportunities in these Asian economies. This concentration of cross-border patents in industries closely tied to the strengths and demands of Asian markets points to a strategic, market-seeking approach to patenting by innovators from rich countries. In other words, innovators may strategically be seeking patent protection in Asia to capitalize on market opportunities and align with the region's technological strengths.

C.1 Comparison with Alternative Datasets

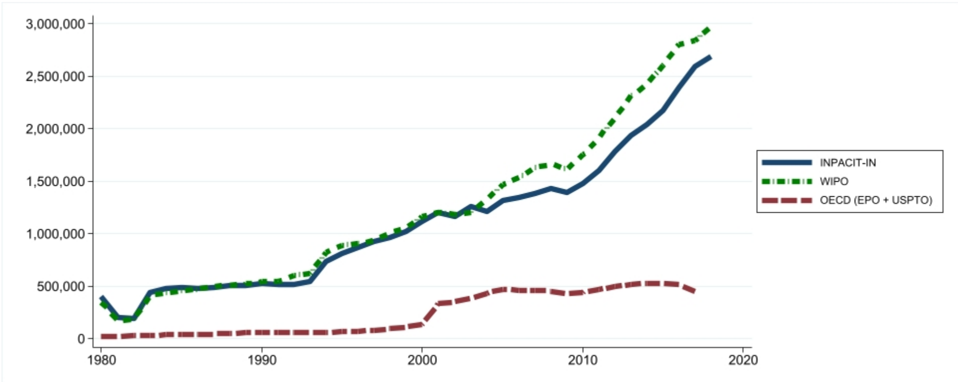
Our novel INPACT-S dataset complements and improves on existing patent data publicly available from the United States Patent and Trademark Office (USPTO), the Organisation for Economic Co-operation and Development (OECD), and the World Intellectual Property Organization (WIPO), along several dimensions.

While the USPTO only accounts for patents filed in the United States, the OECD database is slightly more comprehensive, including patents that have been filed in the United States (USPTO), in the European Union (EPO), and under the PCT. In contrast, our dataset covers 91 patent offices around the world. This extension is important in capturing the innovation trends observed in the past four decades, in addition to the rise of new players in the knowledge sector.

The WIPO dataset is closer to ours, as it includes patent applications filed in all patent offices for which data are available, but it does not report the data at the industry level and differs in the way it imputes some data points, as we elaborate on later. Hence, our dataset is more comprehensive than other existing publicly available datasets on international patenting flows. Beyond just these improvements, we provide data on citations across country-sector pairs, which allows us to compute a measure of quality-adjusted patent applications used in the robustness tests.

Figure A1 shows the comparison of our dataset with the OECD and WIPO. For this comparison, we use the patent applications by applicant counts.[36] One important difference between the WIPO and our dataset is that the WIPO dataset does not have an industry dimension. Therefore, for comparison we must aggregate across our industries by bilateral relationships and year in our final dataset. We also aggregate OECD patents filed to USPTO and EPO.

Figure A1: Comparisons with similar datasets



Note: The green line represents the aggregate WIPO world patent totals by year while the blue line represents INPACT-S totals after using the methods described above. The red line represents OECD, EPO, and USPTO patents. OECD has a group of applications filed under the PCT, but since they do not provide indicators as to where those applications are going we leave them out. Including those just increases their total slightly each year.

Aside from a slight divergence in the early 2000s, our method matches the aggregate trends in the WIPO data extremely closely. However, there are a few important differences between the methods used to derive our data and the WIPO data. First, as described above, we find it unrealistic to assume each country in a regional authority is equally attracting patents to that authority. WIPO instead chooses to count the patents for these authorities by assigning one patent to each jurisdiction in the region. Furthermore, rather than fractionally dispersing out the patent equally amongst the applicant(s)/inventor(s), WIPO chooses to assign the patent to the country of the first applicant, under-counting the number of patent applications originating in some jurisdictions. Since we are focused on understanding where innovators from different countries seek protection for their inventions, we see value in recording the origin of every applicant/inventor rather than just one.[37]

The discrepancies between our dataset and the OECD dataset reflect the additional patent offices we capture with ours, while the OECD restricts the sample to patent

[36]By definition, fractional counting creates identical totals in aggregate whether summed by applicant or inventor despite the fact individual bilateral relationships may differ.

[37]https://www.wipo.int/ipstats/en/help/

applications filed to just the EPO and USPTO patent offices.[38] Note that these differences are increasing over time, as new countries begin attracting more patent applications and are becoming new innovation powerhouses.

Having identified some of the main differences between our data and the OECD and WIPO datasets, we want to make sure that the choices and assumptions made in the construction of our dataset are reasonable and do not yield aggregate numbers that differ significantly from those reported by these more established datasets.

We begin by computing the correlation between INPACT-S and publicly available OECD and WIPO datasets. For comparison to the OECD, we take the raw PATSTAT data and employ our fractional method to patent applications filed to the EPO and the USPTO, the only jurisdictions available in the OECD dataset. Moreover, we do not impute any missing country codes. Here, we are only attempting to measure the accuracy of our fractional counting of the raw patent data.

For the full sample period, 1980-2019, our data are consistent with the OECD data, with a correlation of around 90% for international patenting by both applicants and inventors. When we restrict the sample to just 2010-2018 the correlation is nearly 100% for both. The reason is twofold: (i) Patent data have a lag in reporting and are only reliable after a few years, so dropping 2019 helps clean some of the noise, and (ii) the data provided by the OECD that cover patents filed to the USPTO are exceptionally poor prior to 2010.

Figure A2 shows the evolution of patent applications to the EPO and USPTO over the period of analysis using our data and those provided by the OECD dataset. In the upper panel, we observe that, overall, our dataset perfectly tracks world applications to the EPO from 1980 until very recently, when the OECD reports a sharp decline not found in our data. In contrast, our dataset captures a steady rise in patent applications to the EPO even in the most recent years. In the bottom panel, we restrict to patent applications to the USPTO as reported by the OECD dataset. The data provided by the OECD are poor prior to 2000 and follow an unrealistic growth trend afterward, while our dataset provides a more realistic growth pattern.

D Estimation Results

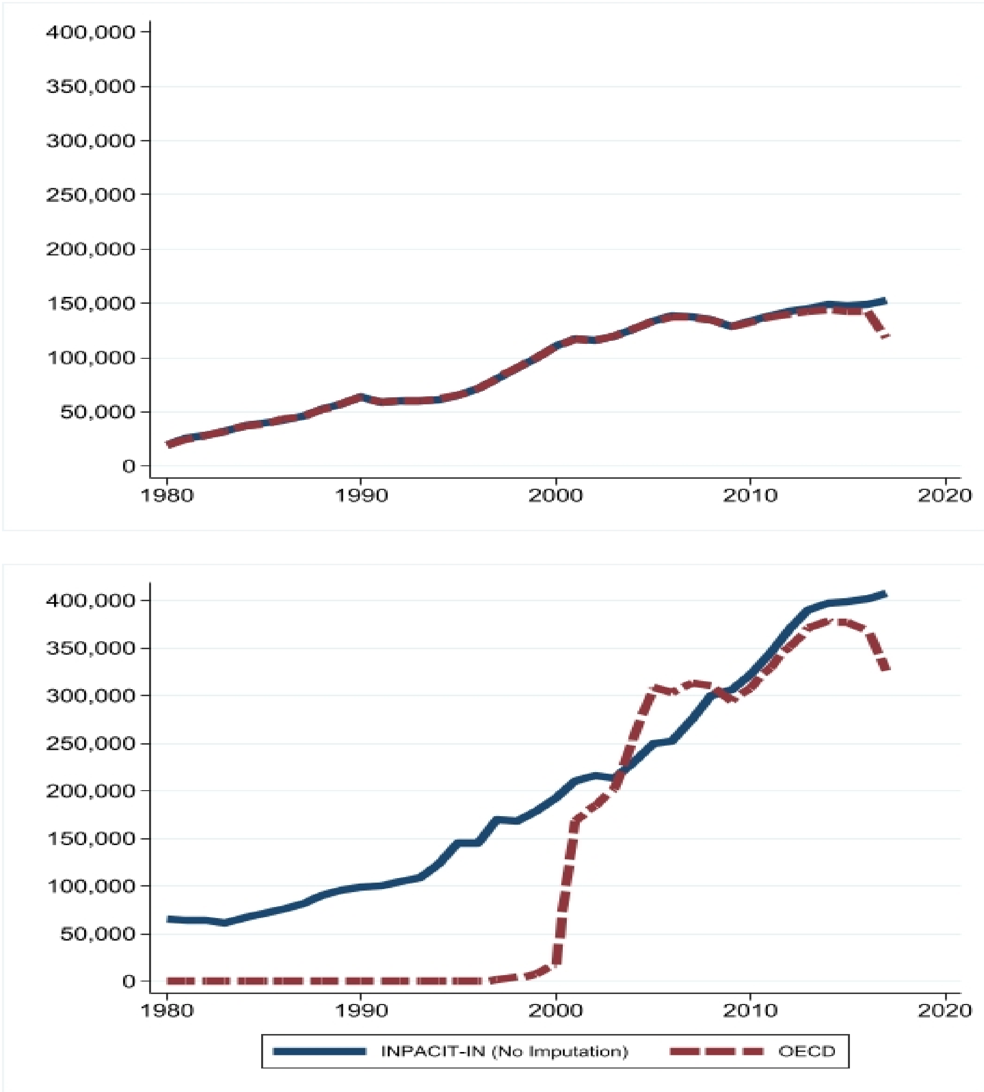
This appendix reports and discusses the results from a series of experiments we performed to test the robustness of our main findings and to highlight the dimensions of our new data. The experiments appear in the order in which they were mentioned in the main text. The first two experiments we perform are related to the heterogeneous estimates of the effects of diffusion.

- In our first experiment we obtain directional diffusion estimates based on all four income categories of the World Bank, including, “high income”, “upper-middle income”, “lower-middle income”, and “low income”. Figure A1 reports our estimates, which are intuitive and as expected. Most importantly, the strongest effects of diffusion are from rich to poor countries. The relationship between these estimates and our main results is that the latter are essentially weighted averages of the results in Figure 2.

- In Figure A2 we reproduce our main results from Figure 2, but without allowing

[38] The OECD also has PCT patents, but those provide no value in discerning bilateral patent trends.

Figure A2: INPACT-S (without imputation) vs OECD



Note: The upper panel shows patents filed to the EPO from the world according to our data (blue line) and the OECD data (red line); the bottom panel plots patents filed to the USPTO filed by the world according to our data (blue line) and the OECD data (red line).

for directional effects, i.e., just for 'North' vs. 'South'. The results are expected and are consistent with our main findings.

Table A1 shows the results for a number of robustness checks, obtained by estimating variations of the main empirical model form column (4) of Table 2. For clarity and expositional simplicity, we report only the diffusion effects for "North" to "South" and the estimates from all specifications are included in a single Figure A3.

- The first variation consists of estimating a linear model using the natural log of patent counts as a dependent variable. As can be seen in column (1), the estimated coefficients for RTA present higher standard errors than for the PPML model with the dependent variable in levels. Nevertheless, the few coefficients that are accurately estimated present the same sign and similar magnitudes.

- The second column of Table A1 presents the results when standard errors are clustered by three dimensions: origin, destination, and time (instead of by pair). The statistical significance of the coefficients decreases slightly, but most interpretations remain valid.
- Column (3) shows the results when the model is estimated excluding the terms that proxy for diffusion. In this case, the coefficients slightly change in magnitude compared with column (2) but remain within similar confidence bands.
- Column (4) excludes domestic patents, which results in lower coefficients for the RTA variables in the "North" to "South" group and slightly higher TRIPS coefficients, but the significance for the PTC vanishes. Importantly, this specification does not allow us to obtain estimates of any of the diffusion effects that have been of central interest to us.
- Finally, column (5) shows the results excluding China, showing that this affects the significance for the SN policy variables, whereas coefficients for the North to North, and South to South pairs remain similar.

In Table A2 five additional robustness checks are presented.

- In column (1) a different classification of North and South is used, placing in South exclusively low-income countries, whereas North contains the other WB categories: upper- and lower-middle- and high-income. While the RTA coefficients remain basically the same, a noticeable change in the TRIPS coefficients is that the SN group has a much higher coefficient than in the baseline classification that is now significant at the 1 percent level. The PCT coefficients loose significance with respect to the main specification.
- A common concern when analyzing patents trend is controlling for the quality of patents. There are some cases when patents might be filed en masse for reasons other than increasing innovation. For example, if a country improves its IPR quickly and significantly, it may cause a surge in patenting, as innovators rush to take advantage of this new IP protection. This could lead to a situation where the patenting activity of a country increases by much more than their innovation level would indicate. Another notable example would be the case of government subsidies for filed patents. This would incentivize the filing of many patents regardless of if they are actually of any merit. These factors make it important to consider the notion of "quality patents"; in other words, patents that are actually the result of innovation and result in a new useful knowledge base being created. This motivates our next experiment, in which we construct a quality-adjusted patent count.

  There are many ways to adjust for quality, but we follow one of the methods developed by Coelli, Moxnes, and Ulltveit-Moe (2022) in which they look at the number of citations created as a share of the number of patents filed. We calculate this relative quality of patent flows as follows: Let c_p denote the number of citations that occur within the first three years after patent p was filed. Let μ_f be the average number of citations within the first three years after filing across that DOCDB family such that:

$$\mu_f = \frac{\sum_{p \in \Xi_{pf}} c_p}{\sum_{p \in \Xi_{pf}} p},$$

where Ξ_{pf} is the number of patents, p, in that DOCDB family, f. The sum of citations for each origin is then:

$$Q_{it} = \sum_{p \in \Xi_{pf}} \mu_f,$$

where Ξ_{ft} is the set of country i's families filed in year t. The full average quality for origin i in year t is given by:

$$\hat{Q_{it}} = \frac{Q_{it}}{P_{it}},$$

where P_it is the total patents filed by country i in year t.

Our new estimates with the quality-adjusted dependent variable appear in column (2) of Table A2, and they show an increase in the statistical significance of the RTA coefficients for agreements between SS. The corresponding diffusion effects for the group North to South are shown in the bottom-left panel in Figure A3, showing positive and significant effects for 2002 onward.

- Next, in column (3) the averaged result for each policy variable are shown, without considering the level of development of the pair or countries. The results indicate that, on average, the effect of having an RTA with or without technology provisions is positive, higher in magnitude for the second and more accurately estimated. However, an important message from these results, in combination with our main findings, is that the average agreement estimates are masking significant heterogeneity in the impact of policy on cross-border patent flows.
- Finally, in column (4) we replace the pair fixed effects with a set of "standard" gravity variables, including the logged distance between countries (weighted by population), which is allowed to have heterogeneous effects for domestic vs. international patents, and dummy variables for sharing a common border, having the same official language and a past or present or past colonial relationship. Consistent with the trade gravity literature, our estimates for cross-border patents reveal that cross-border patenting decreases with distance and increases when countries share an official language. In fact, the estimate on common official language is significantly larger in magnitude than the standard estimate from the trade literature. We find this result intuitive, as language is potentially a more important factor for patent sharing.

  We also obtain some results that are different from those for trade. For example, we obtain negative and significant estimates for the effects of common borders and colonial ties, while the corresponding estimates from the trade literature are mostly positive and statistically significant. The estimate for having ever had a colonial link is in accordance with the results obtained in the cross-sectional estimations in the main text. In addition, unlike the trade literature, we obtain a larger negative impact of domestic distance as compared to international distance. We are not aware of existing estimates of domestic distance for cross-border patents against which we can benchmark our findings. Although these results are not important for our main purposes, we find them interesting and possibly worth further investigation.

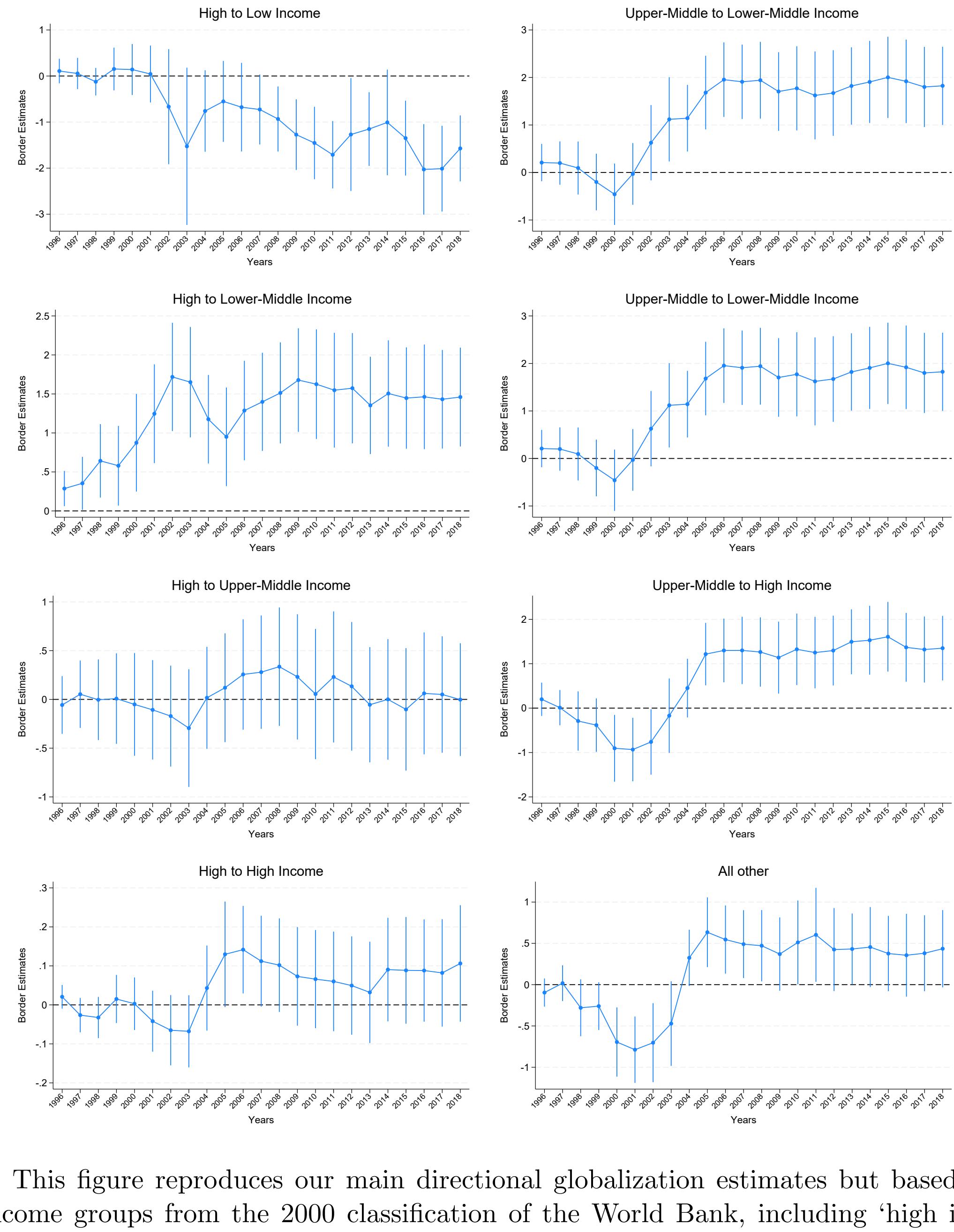
Finally, to highlight the sectoral dimension of our new dataset, we also obtain disaggregated estimates. Table A3 reports estimates at the sectoral level. Estimations are presented for all sectors in column (1) and for specific groups of manufacturing sectors, according to the Standard Industrial Classification Revision 3, in columns (2)-(5). The results shown in column (1) permit us to discard the existence of aggregation bias in our main results. In addition, results for specific groups of sectors are presented according to their level of sophistication. S1, S2 and S3 denote respectively sectors 15-19, 20-29 and 30-37, respectively. S1 includes food and beverages, tobacco, textile and apparel, leather and footwear; S2 includes paper and printing, chemicals and metals, among others; and S3 are office and computing machinery, communication equipment, vehicles and medical, precision and optical instruments, for example. The effect of RTA with technology provisions has a significantly higher magnitude for flows of patents going from North to North or to South in S3, whereas those without technology provision show a negative and weakly significant effect only for innovators in South patenting in North offices and for S3. The effect of other policy variables, TRIPS and PCT, do not vary much across sectors. Two main policy implications stand out from this analysis. First, the heterogeneity that we document across the broad sectors implies that serious policy analysis should be performed at the disaggregated level, potentially even more disaggregated than presented here (for which our data allow). Second, for RTA to facilitate/promote cross-patenting between rich and poor countries, the agreements must contain specific chapters on IPR and innovation.

D.1 Cross-border Patenting and Trade Flows

We present results from estimating our main gravity specification after controlling for trade flows (in logs) are reported on Table D.4.

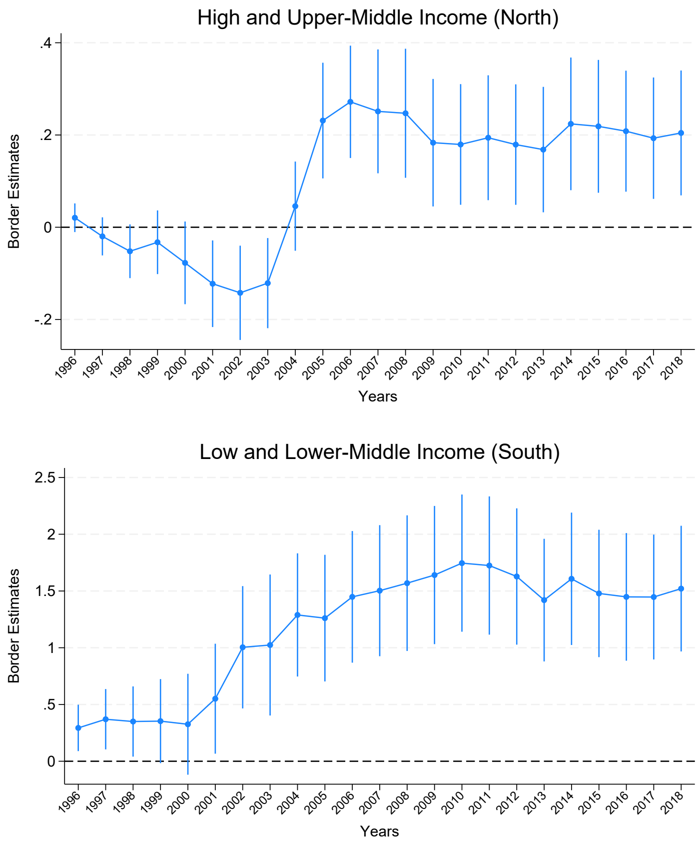
The globalization effects that we obtain after controlling for trade flows are reported in Figure D.1.1. We find that the estimated globalization effects after controlling for trade flows remain stable.

Figure A1: Globalization and Cross-border Patenting, Directional



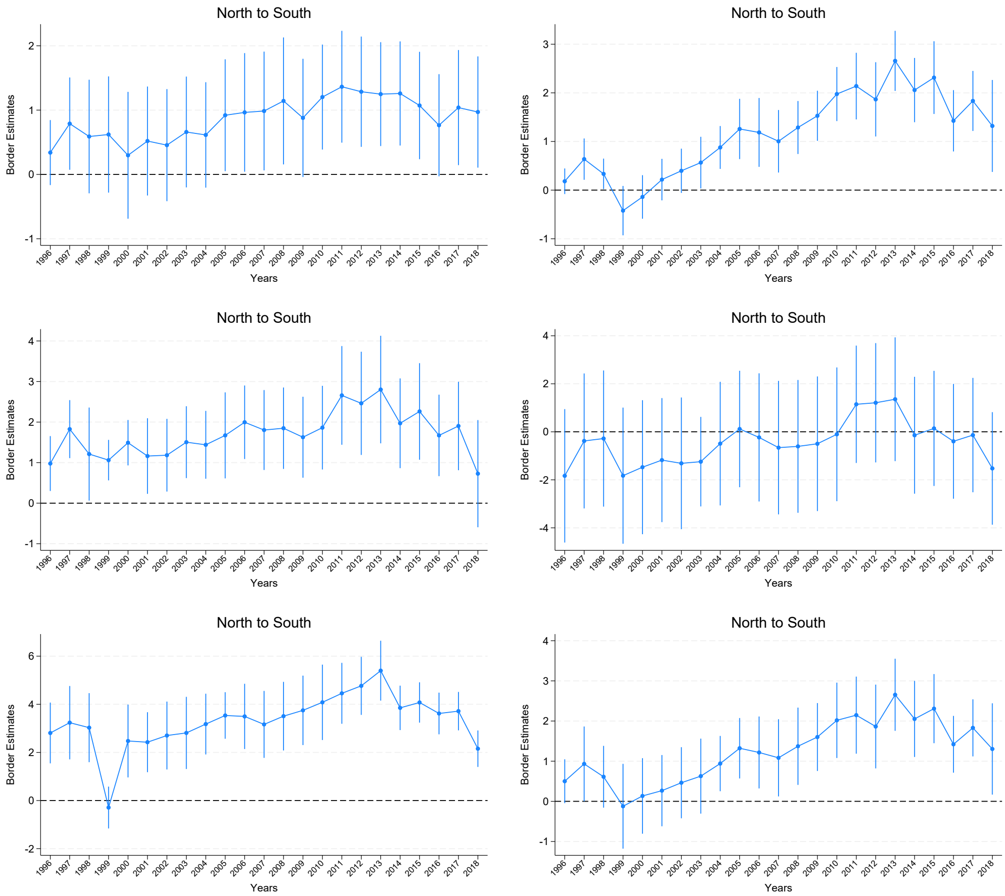
Note: This figure reproduces our main directional globalization estimates but based on the four income groups from the 2000 classification of the World Bank, including ‘high income’, ‘upper-middle income’, ‘lower-middle income’, and ‘low income’. All estimates are obtained from a single regression, which is based on specification (21) after allowing for heterogeneous effects for each of the four bilateral groups. See text for further details.

Figure A2: Globalization and Cross-border Patenting, North vs South



Note: This figure reproduces our main globalization estimates for the 'North' vs. 'South' group of countries but without allowing for directional effects. All estimates are obtained from a single regression, which is based on specification (21) after allowing for heterogeneous effects for each of the four bilateral groups. See text for further details.

Figure A3: Globalization and Cross-border Patenting, Robustness



Note: This figure reproduces our main directional globalization estimates for the group 'North to South' but based on the robustness checks presented in tables (A1) and (A2), including in this order from top to bottom and left to right: 'OLS', 'CLUST', 'NOCHN', 'POOR', 'QALTY' and 'CMMN'. See the notes below tables (A1) and (A2) for further details. The graphs are obtained from from specification (20), after allowing for the effects of globalization to vary across four bilateral groups ('North to South', 'South to South', 'North to North', and 'South to North'. See text for further details. Notice that only results for the first group are presented, since there were the only group showing significant effects, after including in the empirical model the policy variables.

Table A1: Preferential Agreements and Cross-border Patents: Robustness I

	(1) OLS	(2) CLUST	(3) NOGLOB	(4) NODOM	(5) NOCHN
rta_tech_S_N	0.031	0.196	0.174	0.218	0.094
	(0.080)	(0.072)**	(0.058)**	(0.041)**	(0.087)
rta_tech_S_S	-0.104	-0.212	-0.515	-0.379	0.024
	(0.137)	(0.233)	(0.302)$^{+}$	(0.317)	(0.297)
rta_tech_N_N	0.005	0.208	0.236	0.076	0.224
	(0.039)	(0.071)**	(0.036)**	(0.036)*	(0.041)**
rta_tech_N_S	-0.034	0.078	0.084	0.004	0.032
	(0.067)	(0.064)	(0.058)	(0.042)	(0.121)
rta_notech_S_N	0.059	-0.690	-0.501	-0.703	0.582
	(0.155)	(0.919)	(0.589)	(0.801)	(0.230)*
rta_notech_S_S	-0.125	-0.193	-0.177	-0.179	-0.244
	(0.244)	(0.319)	(0.298)	(0.302)	(0.299)
rta_notech_N_N	0.785	1.157	1.183	0.814	1.190
	(0.087)**	(0.202)**	(0.157)**	(0.164)**	(0.154)**
rta_notech_N_S	0.178	-0.139	-0.150	-0.210	0.078
	(0.081)*	(0.258)	(0.152)	(0.141)	(0.113)
trips_S_N	0.283	0.219	1.004	1.388	0.325
	(0.100)**	(0.153)	(0.234)**	(0.208)**	(0.156)*
trips_S_S	0.320	0.514	-0.077	0.812	-0.018
	(0.102)**	(0.262)*	(0.186)	(0.229)**	(0.133)
trips_N_N	0.140	0.210	0.215	0.285	0.205
	(0.062)*	(0.219)	(0.081)**	(0.110)**	(0.125)
trips_N_S	0.215	0.032	0.130	0.838	-0.148
	(0.086)*	(0.172)	(0.179)	(0.220)**	(0.129)
pct_S_N	0.010	0.637	0.947	-0.196	0.799
	(0.114)	(0.591)	(0.413)*	(0.426)	(0.213)**
pct_S_S	-0.119	1.271	0.800	-0.256	1.786
	(0.143)	(0.575)*	(0.233)**	(0.305)	(0.355)**
pct_N_N	0.345	0.177	0.174	0.149	0.143
	(0.078)**	(0.078)*	(0.069)*	(0.126)	(0.081)$^{+}$
pct_N_S	0.024	-0.041	0.109	-0.452	0.230
	(0.087)	(0.384)	(0.230)	(0.157)**	(0.159)
N	54334	63846	63846	62176	61229
R2	0.931				

This table reports a number of robustness checks. The estimates are obtained from specification (20), after allowing for the effects of globalization to vary across four bilateral groups ('North to South', 'South to South', 'North to North', and 'South to North', which are based on the income classification of the World Bank. Each column of the table introduces a variation of the main model. Specifically, in column (1) uses a linear specification that is estimated by OLS with the dependent variable in natural logs. Column (2) clusters standard errors differently (multi-clustering). In column (3) the globalization effects are excluded from the specification. In column (4), estimates the model without domestic patents. Finally, column (5) excludes China from the sample. The dependent variable in each specification is the number of patents and the estimator is PPML in all but column (1). Standard errors in parentheses are clustered by country pair in all columns but . $^{+}$ $p < 0.10$, * $p < .05$, ** $p < .01$. See text for further details.

Table A2: Preferential Agreements and Cross-border Patents: Robustness II

	(1) POOR	(2) QALTY	(3) COMMN	(4) GRAV
rta_tech_S_N	0.188	0.206		-0.592
	(0.053)**	(0.077)**		(0.354)$^{+}$
rta_tech_S_S	-0.452	-0.507		1.281
	(0.305)	(0.193)**		(0.607)*
rta_tech_N_N	0.207	0.113		-0.535
	(0.041)**	(0.036)**		(0.203)**
rta_tech_N_S	0.083	0.005		-0.609
	(0.055)	(0.046)		(0.247)*
rta_notech_S_N	-0.540	0.269		-0.599
	(0.677)	(0.255)		(0.374)
rta_notech_S_S	-0.223	0.024		1.191
	(0.300)	(0.505)		(0.492)*
rta_notech_N_N	1.162	1.047		0.041
	(0.155)**	(0.204)**		(0.197)
rta_notech_N_S	-0.148	-0.364		-0.385
	(0.153)	(0.173)*		(0.233)$^{+}$
trips_S_N	0.897	-0.174		1.694
	(0.240)**	(0.254)		(0.416)**
trips_S_S	-0.234	0.786		-0.272
	(0.235)	(0.248)**		(0.312)
trips_N_N	0.191	0.112		0.366
	(0.122)	(0.150)		(0.221)$^{+}$
trips_N_S	0.054	0.426		0.728
	(0.182)	(0.252)$^{+}$		(0.360)*
pct_S_N	0.685	0.404		-2.153
	(0.455)	(0.164)*		(0.712)**
pct_S_S	0.551	1.150		-1.747
	(0.342)	(0.336)**		(1.238)
pct_N_N	0.167	0.314		-1.458
	(0.082)*	(0.106)**		(0.362)**
pct_N_S	-0.043	-0.371		-1.570
	(0.216)	(0.171)*		(0.714)*
rta_tech			0.171	
			(0.039)**	
rta_notech			0.739	
			(0.164)**	
trips			0.329	
			(0.185)$^{+}$	
pct			0.372	
			(0.120)**	
lndist_int				-0.563
				(0.077)**
lndist_dom				-1.045
				(0.127)**
contig				-0.632
				(0.215)**
comlang				1.191
				(0.159)**
comcolever				-0.606
				(0.218)**
N	63846	60357	63846	65439

This table reports a number of robustness checks. The estimates are obtained from specification (20), allowing for the effects of globalization to vary across four bilateral groups ('North to South', 'South to South', 'North to North', and 'South to North', which are based on the income classification of the World Bank, in columns (1), (2) and (5). Each column of the table introduces a variation of the main model. Specifically, column (1) uses a different classification of North and South countries, with South including only low income countries. Column (2) uses as dependent variable the number of patents weighted by the number of citations. In column (3) we present average common effects of the policy variables. In column (4), we introduce "gravity" variables: the natural log of distance weighted by population (distinguishing between international and domestic distance), common border, common language and past or present colonial link; instead of pair FE. Finally, column (5) introduces the same "gravity" variables in the model that allows for heterogeneous effects. The dependent variable in all specifications but (2) is the number of patents and the estimator is PPML in all columns. Standard errors in parentheses are clustered by country pair in all columns. $^{+}$ $p < 0.10$, * $p < .05$, ** $p < .01$. See text for further details.

Table A3: Preferential Agreements and Cross-border Patents: Sectors

	(1) ALL	(2) S1	(3) S2	(4) S3
rta_tech_S_N	0.208	0.266	0.174	0.236
	(0.049)**	(0.081)**	(0.054)**	(0.073)**
rta_tech_S_S	-0.071	0.265	-0.252	0.205
	(0.240)	(0.371)	(0.379)	(0.317)
rta_tech_N_N	0.214	0.156	0.174	0.250
	(0.030)**	(0.043)**	(0.040)**	(0.046)**
rta_tech_N_S	0.081	-0.037	0.069	0.145
	(0.041)+	(0.118)	(0.055)	(0.080)+
rta_notech_S_N	-0.791	-0.402	-0.463	-1.313
	(0.538)	(0.480)	(0.782)	(0.577)*
rta_notech_S_S	-0.210	-1.027	-0.212	0.434
	(0.273)	(0.677)	(0.339)	(0.535)
rta_notech_N_N	1.166	1.314	1.190	0.906
	(0.114)**	(0.182)**	(0.137)**	(0.223)**
rta_notech_N_S	-0.162	-0.055	-0.142	-0.259
	(0.105)	(0.154)	(0.121)	(0.284)
trips_S_N	0.177	0.321	0.243	0.306
	(0.138)	(0.158)*	(0.160)	(0.323)
trips_S_S	0.527	0.641	0.500	0.302
	(0.167)**	(0.322)*	(0.233)*	(0.264)
trips_N_N	0.198	0.116	0.258	0.126
	(0.088)*	(0.131)	(0.121)*	(0.099)
trips_N_S	-0.004	0.236	-0.028	-0.011
	(0.129)	(0.132)+	(0.142)	(0.268)
pct_S_N	0.587	0.389	0.885	0.526
	(0.296)*	(0.414)	(0.365)*	(0.838)
pct_S_S	1.374	1.578	1.439	1.069
	(0.247)**	(0.303)**	(0.312)**	(0.533)*
pct_N_N	0.167	0.300	0.178	0.135
	(0.061)**	(0.069)**	(0.072)*	(0.144)
pct_N_S	0.043	0.105	0.042	0.341
	(0.158)	(0.253)	(0.188)	(0.543)
N	157054	49271	60991	48510

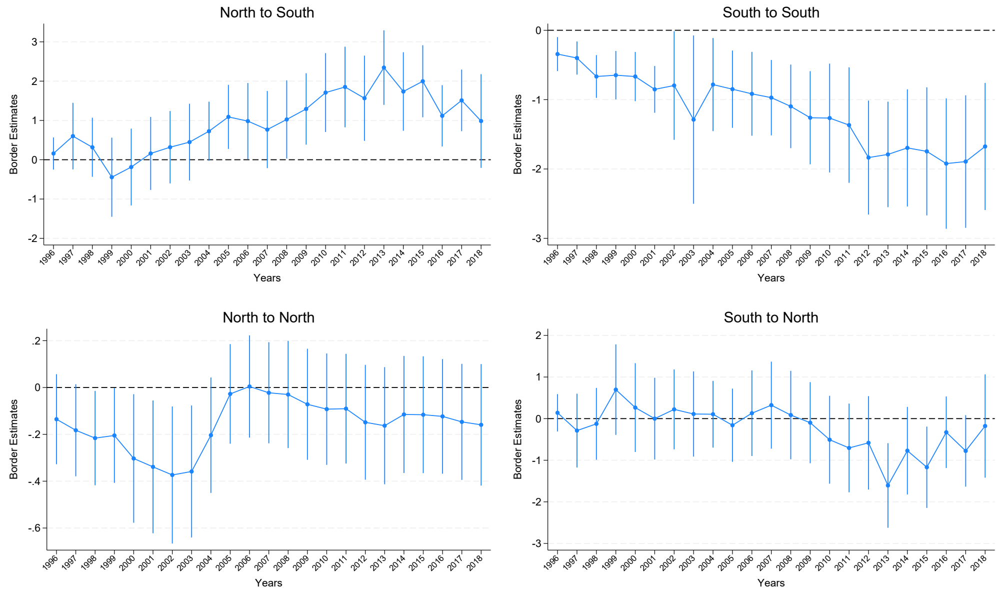
This table reports results for disaggregated data. The estimates are obtained from specification (20), after allowing for the effects of globalization to vary across four bilateral groups ('North to South', 'South to South', 'North to North', and 'South to North', which are based on the income classification of the World Bank. In column (1) results are presented for all manufacturing sectors at 2 digit-level of the International Standard Industrial Classification (ISIC). Column (2) presents the result for sectors 15-19. In column (3) for sectors 20 to 29. In column (4), sectors 30-37 are grouped. The dependent variable in each specification is the number of patents and the estimator is PPML. Standard errors in parentheses are clustered by country pair in all columns but . $^{+}$ $p < 0.10$, * $p < .05$, ** $p < .01$. See text for further details.

Table D.4: Preferential Agreements and Cross-border Patents: Trade in Logs

	(1) RTA	(2) TECH	(3) TRIPS	(4) PCT
rta_S_N	0.150			
	(0.067)*			
rta_S_S	0.068			
	(0.293)			
rta_N_N	0.230			
	(0.042)**			
rta_N_S	0.048			
	(0.065)			
lnTrade_S_N	0.214	0.212	0.217	0.215
	(0.048)**	(0.047)**	(0.047)**	(0.047)**
lnTrade_S_S	0.104	0.105	0.107	0.109
	(0.041)*	(0.041)*	(0.041)**	(0.037)**
lnTrade_N_N	0.089	0.093	0.090	0.091
	(0.022)**	(0.022)**	(0.021)**	(0.022)**
lnTrade_N_S	0.151	0.150	0.151	0.152
	(0.052)**	(0.052)**	(0.052)**	(0.052)**
rta_tech_S_N		0.170	0.176	0.170
		(0.055)**	(0.054)**	(0.055)**
rta_tech_S_S		0.027	0.119	-0.282
		(0.320)	(0.352)	(0.272)
rta_tech_N_N		0.211	0.199	0.200
		(0.041)**	(0.039)**	(0.039)**
rta_tech_N_S		0.054	0.051	0.052
		(0.064)	(0.064)	(0.064)
rta_notech_S_N		-0.648	-0.640	-0.666
		(0.879)	(0.857)	(0.832)
rta_notech_S_S		0.094	0.128	-0.168
		(0.348)	(0.361)	(0.323)
rta_notech_N_N		1.182	1.163	1.164
		(0.160)**	(0.156)**	(0.156)**
rta_notech_N_S		-0.127	-0.127	-0.119
		(0.142)	(0.139)	(0.140)
trips_S_N			0.276	0.286
			(0.172)	(0.171)$^{+}$
trips_S_S			0.509	0.520
			(0.223)*	(0.199)**
trips_N_N			0.204	0.204
			(0.123)$^{+}$	(0.123)$^{+}$
trips_N_S			0.042	0.021
			(0.152)	(0.152)
pct_S_N				0.579
				(0.481)
pct_S_S				1.271
				(0.324)**
pct_N_N				-0.019
				(0.129)
pct_N_S				-0.078
				(0.254)
N	63846	63846	63846	63846

Standard errors in parentheses
$^{+}$ $p < 0.10$, * $p < .05$, ** $p < .01$
This table reports estimates of the effects of preferential agreements on cross-border patent flows. The estimates are obtained from specification (20), after controlling for trade flows (in logs) and allowing for the effects of globalization to vary across four bilateral groups (including "North to South", "South to South", "North to North", and "South to North", which are based on the income classification of the World Bank. In addition, each column of the table introduces a new policy variable, whose effects are also allowed to vary across the four bilateral income groups. Specifically, column (1) accounts for RTAs. Column (2) distinguishes between the effects of RTAs with and without technology provisions. In column (3) we add the TRIPS variables. Finally, in column (4), we also introduce the effects of the PCT. The dependent variable in each specification is the number of patents and the estimator is PPML. Standard errors in parentheses are clustered by country pair. $^{+}$ $p < 0.10$, * $p < .05$, ** $p < .01$. See text for further details.

Figure D.1.1: Globalization and North-South Cross-border Patenting: Controlling for Trade



Note: This figure reports estimates of the impact of globalization on cross-border patent flows, after controlling for trade flows, for four bilateral groups of countries, including "North to South" (top left panel), "South to South" (top right panel), "North to North" (bottom left panel), and "South to North" (bottom right panel). The country groups are based on the income classification of the World Bank, and all estimates are obtained from a single regression, which is based on specification (21) after controlling for trade flows, and allowing for heterogeneous effects for each of the four bilateral groups. See text for further details.