Trade Agreements and Cross-Border Patenting: How Much and When?

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Abstract

Do regional trade agreements (RTAs) promote cross-border patenting, and does the inclusion of legally enforceable intellectual property provisions (IPAs) strengthen this effect? We examine these questions using bilateral patent application data for 213 origin countries and 91 patent application authorities over the period 1980–2019. We embed an extended two-way fixed effects estimator for staggered difference-in-differences within a structural gravity framework, allowing RTA effects to vary across treatment cohorts and years since entry into force. We find that RTAs increase bilateral patent application flows between member countries by about 33 percent. Conventional two-way fixed effects estimates are substantially larger, indicating that ignoring treatment-effect heterogeneity can overstate the effects of RTAs. The average effect also masks important dynamics: the increase in patenting builds gradually for around fourteen years after an RTA enters into force and differs substantially across treatment cohorts. In contrast, effect of legally enforceable IP provisions on patent flows emerge only after a considerable lag. By applying heterogeneity-robust staggered difference-in-differences methods to a structural gravity model, the paper provides new evidence on how RTAs affect cross-border technology diffusion and shows why conventional gravity estimates can be misleading when treatment effects vary across cohorts and over time.

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1 Introduction

Regional trade agreements (RTAs) have become a central part of the global trading system. With multilateral tariff liberalization reducing the scope for further cuts in tariffs, countries have increasingly turned to agreements that cover a wider range of behind-the-border policy areas. These include intellectual property rights (IPRs), investment, domestic regulation etc., reflecting a shift towards deeper economic integration. The effects of trade agreements may therefore extend beyond trade in goods and services. One such effect is the international diffusion of technology through cross-border patenting. To safeguard the returns from their innovations against imitation in foreign markets, firms file patent applications across multiple jurisdictions. Trade agreements can affect these decisions by changing the costs and risks of doing business across borders. Yet we know relatively little about whether RTAs promote cross-border patenting, or whether provisions that strengthen intellectual property protection add to this effect.

This paper examines two related questions. First, does membership in an RTAs increase bilateral patent application flows between member countries? Second, does the inclusion of legally enforceable intellectual property provisions strengthen this effect? We also ask whether the effects of RTAs depend on when an agreement entered into force and on how long it has been in force. These questions matter because the effects of trade agreements need not be confined to the reduction of trade barriers. They may also shape firms' decisions to protect and transfer technology across borders. Moreover, the growing coverage of modern trade agreements does not necessarily imply that agreements with more provisions generate larger gains. The effects depend on how firms respond to the commitments made by member countries as well as on the costs of complying with them.

There are several reasons why RTAs may increase cross-border patenting. By reducing trade barriers and uncertainty about future trade policy (Handley 2014; Limão and Maggi 2015; Handley and Limão 2015; Carballo et al. 2022), they can make foreign markets more attractive to firms. Firms may then have stronger incentives to protect their inventions in these markets before exporting or investing there. RTAs may also reduce the costs of cross-border economic activity and support the diffusion of knowledge between member countries.

Moreover, concerns over the scope of IPR protection under the 1994 Agreement on Trade Related Aspects of Intellectual Property Rights (TRIPS) have led high-income countries to push for stronger IPR

rules in RTAs with developing countries, often refereed as "TRIPS-plus" provisions. As a result, most modern RTAs include a variety of IP provisions, hereafter referred to as intellectual property agreement (IPAs). Whether these IPAs raise the flow of patented technology between members is however not known. On one hand, IP provisions and hence stronger protection can help reduce the risk of imitation thereby encouraging firms to seek patents abroad. On the other hand, compliance with complex legal and administrative requirements can also raise the cost of doing so. The net effect depends on whether the benefits of stronger protection outweigh these costs. The same tension applies to deep trade agreements (DTAs), which extend beyond tariff liberalization to cover a wider range of domestic policies.

We examine these questions using bilateral patent application data for 213 origin countries and 91 patent application authorities spanning 1980–2019. We use the 'Mario Larch's Regional Trade Agreements Database', which covers all bilateral and multilateral RTAs notified to the World Trade Organization (WTO) over the period 1950–2025 (Egger and Larch 2008). Our empirical framework is based on a structural gravity model of bilateral patent application flows. Following Nagengast and Yotov (2025), we nest an extended two-way fixed effects (ETWFE) estimator for staggered difference-in-difference within the structural gravity model. This approach allows the effects of RTAs to vary across treatment cohorts and also with the number of years since an agreement takes effect. We also use the World Bank's Deep Trade Agreements database from Hofmann et al. (2017, 2019) and Mattoo et al. (2020) to examine the effects of legally enforceable intellectual property provisions (IPAs). Finally, we use the same database to analyse the differential effects of deep versus shallow agreements, the depth of an agreement measured by the number of provisions contained in the corresponding agreement, and also whether the agreement includes at least one provision related to intellectual property rights.

The effects of RTAs on cross-border patenting are particularly important to understand for at least four reasons. First, cross-border patenting is a key mechanism through which innovation is protected, commercialized, and diffused internationally, and therefore plays an important role in fostering economic development. Second, firms are more likely to enter and export to foreign markets where their innovations are adequately protected; consequently, cross-border patenting can influence firms' market-entry and export decisions (Palangkaraya et al. 2017; Brunel and Zylkin 2022; De Rassenfosse et al. 2022; Gong et al. 2025). Third, patenting process facilitates the international diffusion of technology and knowledge. By securing

patent protection across multiple jurisdictions, innovators are required to disclose detailed information about their inventions while retaining legal protection against imitation and infringement. Such disclosures can serve as an important source of learning for domestic firms in recipient countries (Lanjouw et al. 1998). Fourth, patenting decisions often precede firms' decisions to engage in international trade. We depart from the existing literature by examining the first-order effects of RTAs and IPAs on bilateral patent application flows. To reduce the risk of imitation and maintain their competitive edge, firms typically seek intellectual property protection before exporting to foreign markets (Martínez-Zarzoso and Santacreu 2025).

Our paper contributes to two main strands of literature. The first examines the effects of RTAs or specific provisions within them, such as those related to investment and IPRs, on international trade in merchandise and foreign direct investment (FDI) (Baier et al. 2014, 2018, 2019; Campi and Dueñas 2019; Larch and Yotov 2024a, 2025; Sheikh and Kanwar 2024; Nagengast and Yotov 2025). Beyond the effects on trade and FDI, a small but growing empirical literature examines how RTAs and IPAs affect cross-border patent flows and technology diffusion, predominantly using gravity-type models estimated with conventional two-way fixed effects (TWFE) regressions (Coleman 2022; Howard et al. 2025; Martínez-Zarzoso and Arregui Coka 2025). These studies find that while RTAs can increase cross-border patenting, the evidence on the role of intellectual property provisions is less clear.

The closest to our study is Howard et al. (2025), which examines the impact of IPAs on bilateral patent applications. They find that WTO-ratified, legally enforceable IPAs do not have a significant impact on bilateral patent applications between agreement members. Similarly, Coleman (2022) report that free-trade agreements (FTAs) increase cross-border patent flows by around 20% on average, but find no statistically significant effect for FTAs that contain intellectual property provisions. In a related study, Martínez-Zarzoso and Arregui Coka (2025) examine the effects of FTAs with and without technology-related provisions on technology internationalization, measured using cross-country patent applications. They find that FTAs with and without technology-related provisions increase technology internationalization, with the magnitude of the estimated effects being larger for FTAs without such provisions. On the other hand, Santacreu (2025) develops a quantitative theory of bilateral trade agreements with intellectual property provisions and finds that signing a trade agreement that strengthens IPR protection increases international technology transfer between member countries, as measured by royalty payments.

The second strand of literature studies the relationship between patent protection, international technology transfer, and firms' trade decisions. Patents can help firms protect their inventions in foreign markets and reduce the risk of imitation. They may therefore influence firms' export decisions, both by encouraging the introduction of new products into foreign markets (the extensive margin) and also by increasing market shares in existing products (the intensive margin) (Palangkaraya et al. 2017; Brunel and Zylkin 2022; De Rassenfosse et al. 2022; Gong et al. 2025).

We add to this literature by examining bilateral patent applications as an outcome in their own right. This allows us to investigate cross-border patenting as an additional channel through which trade agreements may influence technology diffusion, alongside trade and FDI flows that have been studied in the existing literature.

A major limitation of existing studies of RTAs and cross-border patenting is that they use conventional two-way fixed effects (TWFE) gravity models. The TWFE estimator has recently come under considerable scrutiny in settings with staggered treatment adoption, such as when country pairs enter RTAs at different points in time. The TWFE estimator imposes a common/average impact of RTAs on cross-border patenting, which may yield biased estimates when treatment effects are heterogeneous. As we demonstrate later in the paper, this is indeed the case. The estimates of the effects of RTAs could vary across both cohort and event-time dimensions.

First, the effects of RTAs on cross-border patenting may differ across treatment cohorts, with country pairs that enter RTAs earlier experiencing larger effects than those that enter such agreements later, or vice versa. Second, the average effects of RTAs could also vary based on different lengths of exposure to the treatment. In other words, the average treatment effects could increase/decrease with the number of years since the inception of RTA. This implies that the existing TWFE RTA estimates from the gravity literature are possibly biased in the presence of treatment effect heterogeneity (Nagengast and Yotov 2025), for example, due to so-called "forbidden comparisons", which (mis)use country pairs that have already entered an RTA as a comparison group for country pairs that enter the agreement in later periods (De Chaisemartin and d'Haultfoeuille 2020; Goodman-Bacon 2021; Sun and Abraham 2021; Callaway and Sant'Anna 2021; Wooldridge 2023, 2025; Borusyak et al. 2024). This remains an important shortcoming in Howard et al. (2025), Martínez-Zarzoso and Arregui Coka (2025), and other related studies that rely

on the standard TWFE gravity-type models. We address this problem by incorporating an extended two-way fixed effects (ETWFE) estimator into the structural gravity framework. This allows us to estimate cohort-specific and event-time-specific effects of RTAs and to aggregate them without imposing a common treatment effect across all agreements. It also allows us to assess whether the estimates from conventional gravity models overstate the effects of RTAs on patenting.

Our results show that RTAs increase bilateral patent application flows between member countries by about 33 percent. This estimate is smaller than the corresponding estimate from the conventional TWFE model, which suggests that ignoring treatment-effect heterogeneity can overstate the effects of RTAs. The average effect also masks substantial variation across agreements and over time. For instance, we find that the increase in cross-border patenting builds gradually for around fourteen years after an RTA takes effect. The effects also differ across treatment cohorts. Agreements that took effect during 1994–2003 are associated with larger increases in patenting than those that took effect during 1982–1993 or 2004–2016. These findings suggest that the effects of RTAs depend both on the timing of entry into an agreement and on the time firms have had to adjust to its provisions. These results are consistent with Nagengast and Yotov (2025), who find similar heterogeneity in the RTA effects on trade flows across cohorts.

Notably, we do not find any statistically significant average effect of legally enforceable intellectual property provisions (IPAs) on cross-border patenting in line with the findings reported in Howard et al. (2025). The event-study estimates, however, suggest that any positive effects may emerge with a lag.[1] One plausible explanation is that, compared with tariff liberalization, policy commitments pertaining to behind-the-border measures, such as laws and regulations governing intellectual property rights, are inherently more complex and may therefore take longer time to negotiate and implement.

Our analysis of deep trade agreements points to a further distinction. Deep agreements have a negative effect on cross-border patenting, while the number of provisions in an agreement has no economically meaningful effect. These findings suggest that expanding the scope of an agreement does not necessarily increase cross-border patenting. The costs of complying with provisions that extend beyond tariff liberalization may offset the gains from stronger policy commitments. Taken together, these results show that the

[1] Larch and Yotov (2025) find that the positive effects of deep trade agreements with investment provisions on FDI materialize with a delay, with statistically significant effects emerging roughly 15 years after the agreements enter into force.

effects of trade agreements depend on the nature of their provisions, not only on whether countries sign an agreement.

Our paper makes three contributions to the extant literature. First, while the growing literature has examined the effects of RTAs on trade and FDI, often interpreted as the second-order effects, relatively less attention has been paid to their impact on alternative channels of technology diffusion, such as cross-border patent flows. To address this gap, we examine the effects of RTAs and IPAs on bilateral patent applications, providing new evidence on the relationship between RTAs and cross-border patenting. Second, we show that the effects of RTAs on cross-border patenting vary across treatment cohorts and over time, and that conventional TWFE estimates can overstate their magnitude. Understanding this sort of heterogeneity is particularly important, as countries that liberalized their trade relationships earlier through RTAs may experience larger increases in trade than those that liberalized later (Egger et al. 2024). A similar form of heterogeneity may also characterize the response of cross-border patenting across treatment-timing cohorts. Moreover, the gradual elimination of trade and patenting frictions, as well as the time required for firms to adapt to the new rules following the inception of an RTA (Egger et al. 2022; Sheikh and Kanwar 2024), suggests that the effects of an RTA on cross-border patenting may materialize only with a lag.

Third, our paper distinguishes between the effects of RTAs as a whole and those of intellectual property provisions and deeper agreements. The results show that trade agreements can promote cross-border patenting, but that stronger commitments do not necessarily reinforce this effect. The findings therefore qualify the view that deeper trade integration always leads to greater economic integration.

The rest of the paper is organized as follows. Section 2 presents the theoretical framework for bilateral patent application flows. Section 3 develops the empirical specification and describes the ETWFE estimator. Section 4 discusses the data and treatment definition. Section 5 presents the baseline results and examines heterogeneity across cohorts and event time. Section 6 reports a series of robustness checks. Section 7 examines the effects of intellectual property agreements, and Section 8 uses the World Bank's Deep Trade Agreements database to assess the effects of agreement depth and specific provisions. Finally, Section 9 concludes.

2 Motivating Model

The theoretical model of bilateral patenting flows, as in trade, migration, and FDI flows, obeys the law of gravity: the "closer" and the "larger" two countries are, the more cross-border patents they would exchange. Our estimation framework relies on LaBelle et al. (2024), who derive a modified version of structural gravity equation for bilateral patent flows as follows:

$$PAT_{ij,t} = \frac{H_{it}P_{it}}{\eta V_{it}} \left(\frac{\Pi_{jt}}{P_{jt}T_{jt}} \right)^{\frac{1}{\xi-1}} \left[\tau_{ij}^{\frac{-1}{\xi-1}} \phi_{ij,t}^{\frac{1}{\xi-1}} \kappa_{ij,t}^{\frac{\xi}{\xi-1}} \right] \tag{1}$$

where $PAT_{ij,t}$ refers to source i patents filed in destination j at time t. Consistent with theory, $PAT_{ij,t}$ includes both international and domestic patent flows. According to Equation (1), cross-border patenting depends on several factors. First, it depends on the characteristics of the source (origin) country, $\frac{H_{it}P_{it}}{\eta V_{it}}$, which reflects the number of technologies being developed in the origin country, determined by the efficiency of innovation and investment in R&D. Second, it depends on the characteristics of the destination country where patent applications are filed, $\left(\frac{\Pi_{jt}}{P_{jt}T_{jt}} \right)^{\frac{1}{\xi-1}}$, which determines the attractiveness of the destination country. Firms typically prioritize patent filings in regions that promise higher expected returns on innovation, largely driven by the size of the destination market. Finally, as in trade, international patenting activity depends on time-invariant bilateral patenting frictions, $\tau_{ij}^{\frac{1}{\xi-1}}$, (e.g., distance, language, colonial relationships); policy variables that impact the probability of imitation in the destination country, $\phi_{ij,t}^{\frac{1}{\xi-1}}$, (e.g., strength of IPR enforcement, joint membership in RTAs/IPAs, membership in international IP conventions and treaties); and $\kappa_{ij,t}^{\frac{\xi}{\xi-1}}$, which represents the diffusion of ideas from source i to destination j, and alternatively captures the impact of globalization over time. The underlying mechanism is that globalization forces have led to a reduction in the costs of patenting internationally over time, making it increasingly easier for firms to protect their inventions across borders and thereby facilitating the diffusion of ideas. The parameter ξ denotes the increasing marginal costs associated with patenting additional technologies, arising from greater legal and administrative requirements, increased technological complexity, and higher R&D demands, particularly when overseeing an extensive patent portfolio (LaBelle et al. 2024).

3 From Theory to Empirics

The conventional approach to estimating the effects of RTAs on trade, patenting, and FDI is to specify a two-way fixed-effects (TWFE) gravity model and estimate it using the Poisson pseudo-maximum likelihood (PPML) estimator, which accounts for heteroskedasticity and the information contained in zero patenting flows (Silva and Tenreyro 2006; Yotov et al. 2016).

$$PAT_{ij,t} = exp\left\{\delta^{TWFE} RTA_{ij,t} + \chi_{i,t} + \psi_{j,t} + \mu_{ij} + \sum_{t} \beta_t \, BRDR_{ij,t}\right\} \times \epsilon_{ij,t} \tag{2}$$

where $RTA_{ij,t}$ is the dummy that takes the value of 1 if country i and country j are both members of RTA at time t and 0 otherwise; $\chi_{i,t}$ are *source-time* and $\psi_{j,t}$ are *destination-time* fixed effects, which account for the multilateral resistance terms of Anderson and Van Wincoop (2003), as well as any other observable and unobservable country-specific, time-variant determinants of bilateral patent flows, including the theoretical terms $\frac{H_{it}P_{it}}{\eta V_{it}}$ and $\frac{\Pi_{jt}}{P_{jt}T_{jt}}$, respectively; and μ_{ij} denote the *source-destination (country-pair)* fixed effects, which mitigate the endogeneity concerns with respect to our key policy variable, $RTA_{ij,t}$ (Baier and Bergstrand 2007) and additionally control for time-invariant bilateral determinants of patenting (τ_{ij}) like, distance, language, colonial relationship etc. Finally, following Bergstrand et al. (2015), we include a set of time-varying border dummy variables, $BRDR_{ij,t}$, to account for the common effects of globalization ($\kappa_{ij,t}$) [2], and $\epsilon_{ij,t}$ is a multiplicative error term.

The coefficient δ^{TWFE} in Equation (2) is the TWFE estimate of the effect of RTAs on cross-border patents. However, it captures the common/average effects of RTAs on bilateral patent flows and may led to erroneous conclusions when treatment effects are heterogeneous. In the specific context we are considering, the average impact of RTAs could vary across different dimensions. The treatment effects may differ across cohorts depending on the timing of agreements entry into force, as country pairs that entered into RTA earlier may exhibit systematically different effect compared to those that joined later, often referred as cohort-time heterogeneity.[3] Additionally, the impact of RTAs may vary with respect

[2] We obtain these dummy variable by interacting the binary indicator for each year t (D_t) with a time-invariant dummy variable ($BRDR_{ij}$) that takes the value 1 for cross-border patent flows ($i \neq j$) and 0 for domestic flows ($i = j$).

[3] For example, Egger et al. (2024), examined a scenario with sequential trade liberalization and solve for the gravity equation to explicitly account for the incumbency effects. They found that, ceteris paribus, countries trade more if they liberalized trade earlier, and less if they liberalize later. A similar pattern may also arise in cross-border patent flows.

to the length of exposure to the treatment (i.e., years since the inception of agreement). In other words, the average treatment effects may increase/decrease with elapsed treatment time, referred to as event-time heterogeneity.

The existing literature on RTAs and cross-border patent flows have relied exclusively on traditional "gravity-type" models, estimated using a two-way fixed effects (TWFE) estimator (Coleman 2022; LaBelle et al. 2024; Howard et al. 2025; and Martínez-Zarzoso and Arregui Coka 2025). However, the RTA estimates from these studies are possibly biased in presence of treatment effect heterogeneity, that is, if the effect of intervention varies between groups or over time, which is exactly the case with many of the policies that are evaluated with the gravity model, including RTAs (Nagengast and Yotov 2025). The source of bias in the TWFE estimator is due to so-called *"forbidden-comparisons"* that (mis)use already-treated units in the comparison group for units treated in later periods (De Chaisemartin and d'Haultfoeuille 2020; Goodman-Bacon 2021; Sun and Abraham 2021; Callaway and Sant'Anna 2021; Wooldridge 2023, 2025; Borusyak et al. 2024).

3.1 Staggered DiD Using the ETWFE Estimator

The empirical analysis is carried using the current best practice recommendation from structural gravity model and staggered DiD literature, as recently summarized by Nagengast and Yotov (2025). Specifically, we replace the single indicator variable for RTA membership between country i and country j at at time t ($RTA_{ij,t}$) from Equation (2) with the following term.

$$\sum_{g=q}^{T}\sum_{s=g}^{T}\delta_{gs}D_{gs}$$

where country pair ij belongs to treatment cohort g if the RTA onset was in year g, q is the first year of the treatment of cohort g, T is the last year of the sample period, D_{gs} is a time-varying dummy variable equal to 1 for cohort g for $s = t$ in post-treatment years and 0 otherwise. Accordingly, our main estimating equation becomes:

$$PAT_{ij,t} = exp\left\{\sum_{g=q}^{T}\sum_{s=g}^{T}\delta_{gs}D_{gs} + \chi_{i,t} + \psi_{j,t} + \mu_{ij} + \sum_{t}\beta_t\, BRDR_{ij,t}\right\} \times \epsilon_{ij,t} \tag{3}$$

Unlike the conventional TWFE estimator, Equation (3) implements the extended two-way fixed effects (ETWFE) estimator à la Wooldridge (2023) within a staggered difference-in-differences (DiD) framework for the estimation of nonlinear models. A key advantage of the ETWFE model is that it accommodates treatment-effect heterogeneity by estimating cohort-year-specific treatment effects, δ_{gs}, while avoiding the problem of "forbidden comparisons".[4]

However, as the number of cohorts and time periods increase, so too does the number of δ_{gs} parameters to be estimated, and interpreting all the cohort-year-specific treatment effects may become increasingly challenging. The ETWFE considers several partial aggregation schemes to combine δ_{gs} into a more manageable set of causal parameters. In line with the previous literature, our first estimation target is to obtain the average impact of RTA membership on bilateral patent flows, which is calculated as the weighted sum of the estimated cohort-year-specific treatment effects:

$$\bar{\hat{\delta}} = \sum_{g=q}^{T} \sum_{s=g}^{T} \frac{N_{gs}}{N_D} \hat{\delta}_{gs} \tag{4}$$

where N_{gs} corresponds to the number of observations of cohort g in period s and N_D is the total number of treated observations.

The average response of bilateral patent flows to the initiation of RTAs may vary with the length of exposure to the treatment, making the dynamic effects of particular interest. The ETWFE estimator computes the event-study estimand by averaging over cohort dimension as follows:

$$\overline{\hat{\delta}_{.s}} = \sum_{g=q}^{s} \frac{N_{gs}}{N_{.s}} \hat{\delta}_{gs} \tag{5}$$

where $N_{.s} = \sum_{g=q}^{s} N_{gs}$ is the total number of treated observations in period s.

Further, as noted above, country pairs that enter RTAs at different points in time may exhibit systematically different treatment effects. Thus, cross-border patent flows may be influenced not only by RTA membership itself but also by the timing of entry into these agreements, which we refer to as cohort

[4]For example, $\delta_{1990,1990}$ captures the instantaneous treatment effect of RTAs on cross-border patent flows for country-pairs that first became the members of RTA in the year 1990 and therefore belong to 1990 cohort ($g = 1990$) in the calendar year 1990 ($s = 1990$); $\delta_{1990,1991}$ captures the treatment effect for the same cohort ($g = 1990$) one year after the agreement entry into force, and so on.

heterogeneity. The cohort-specific estimand is obtained by averaging over the time dimension as follows:

$$\overline{\widehat{\delta}_{g.}} = \sum_{s=g}^{t} \frac{N_{gs}}{N_{g.}} \, \hat{\delta}_{gs} \tag{6}$$

where $N_{g.} = \sum_{s=g}^{t} N_{gs}$ is the total number of post-treatment observations of cohort g.

4 Data

We rely on several standard data sources for this study. The data on cross-border patent flows comes from the "International Patent and Citations across Sectors (INPACT-S)" database of LaBelle et al. (2024), which provides consistent data on both international and domestic patent flows for 213 countries of origin and 91 patent application authorities, covering 31 two-digit ISIC (Rev. 4) industries over the period 1980–2019. The inclusion of domestic patent flows is consistent with the theory, as their omission can bias the estimated effect of RTAs on cross-border patenting and render the resulting estimates inconsistent (Yotov 2022; Larch et al. 2025).

The data on regional trade agreements (RTAs) is drawn from the "Mario Larch's Regional Trade Agreements Database" (Egger and Larch 2008), which provides information on all bilateral and multilateral RTAs as notified to the World Trade Organization (WTO) over the period 1950-2025. The database contains 605 agreements classified into seven categories: Customs Union, Free Trade Agreement, Partial Scope Agreement, Economic Integration Agreement, Customs Union & Economic Integration Agreement, Free Trade Agreement & Economic Integration Agreement, Partial Scope & Economic Integration Agreement. Accordingly, the treatment variable, ($RTA_{ij,t}$), takes the value of 1 if country pair ij are members of an agreement belonging to any of the seven RTA categories in year t, and 0 otherwise.

The data on RTAs that include provisions related to intellectual property rights, which we refer to as intellectual property agreements (IPAs), is sourced from World Bank's database on Deep Trade Agreements (Hofmann et al. 2017, 2019; Mattoo et al. 2020). Specifically, we employ the "Horizontal Depth" measure of deep trade agreements (DTAs) that maps the coverage of 52 selected policy areas in 400 RTAs notified to the WTO over the period 1958-2023. The database ranks the legal enforceability (LE) of each policy area on a scale of 0, 1, 2, with 0 indicating that the provisions is not mentioned in the agreement or not

legally enforceable; 1 describes that the provision is mentioned and legally enforceable, but explicitly excluded from dispute settlement; and 2 indicates that the provision is articulated in strongly enforceable legal language and is subject to dispute settlement procedures. However, the mere coverage of a policy area in an RTA does not necessarily imply that the provision is legally enforceable, particularly when it is explicitly excluded from dispute settlement procedures (Hofmann et al. 2017, 2019; Mattoo et al. 2020). Therefore, to examine the impact of membership in the intellectual property agreements (IPAs) on cross-border patent flows, we follow Howard et al. (2025) and define the treatment variable ($IPA_{ij,t}$) that takes the value of 1 if country pair ij are members of an RTA containing intellectual property provisions that are legally enforceable and subject to dispute settlement ($LE = 2$), and 0 otherwise. Further, as a robustness exercise, we exploit the rich dimensionality of the World Bank's DTA database to examine the response of bilateral patent flows to (i) membership in preferential trade agreements ($PTA_{ij,t}$), also commonly referred to as regional trade agreements; (ii) the depth of trade agreements, measured by the number of policy provisions contained in an agreement in our sample ($Depth_{ij,t}$); (iii) the heterogeneous effects of deep and shallow agreements ($DTA_{ij,t}$)[5]; (iv) the effect of DTAs that include intellectual property related provision ($IPR_{ij,t}$); and (v) the depth of $IPR_{ij,t}$, which counts the total number of IP-related provisions in an agreement ($Depth - IPR_{ij,t}$) [6].

Finally, data on additional control variables, including standard gravity covariates (i.e., bilateral distance between country pairs ij) and indicators of common WTO and EU membership, are sourced from the CEPII "Gravity" database (Conte et al. 2022), while data on compliance with the Agreement on Trade-Related Aspects of Intellectual Property Rights (TRIPS) are obtained from Sheikh and Kanwar (2025). The final estimation sample consists of a panel of cross-border patent flows from 213 countries of origin to 91 patent application authorities across 31 two-digit ISIC (Rev. 4) industries over the period 1980–2019.

4.1 Treatment definition

The established methods on heterogeneity-robust staggered DiD assumes treatment to be in an absorbing state and therefore does not accommodate cases in which a country pair ij switches from being

[5]Following Larch and Yotov (2025), we define $DTA_{ij,t}$ as an indicator equal to 1 for deep trade agreements (i.e., when the $Depth_{ij,t}$ is greater than 0) and equal to 0 for shallow agreements (i.e., when the $Depth_{ij,t}$ equals 0).

[6]We refer the reader to Wu (2020) for detailed discussion on IPR related provisions in DTAs

treated to untreated (Goodman-Bacon 2021; Sun and Abraham 2021; Callaway and Sant'Anna 2021; Wooldridge 2023, 2025; Borusyak et al. 2024).[7] However, country pairs that join an agreement may subsequently withdraw from it. Thus, membership in RTAs or IPAs should be viewed as a treatment with both *entry* and *exit*, which, in turn, poses potentially important challenges for identifying their effects. To address this issue, we drop the country pairs that switch from being RTA members to non-members during the sample period. Moreover, for econometric reasons, we also exclude country pairs with an RTA onset prior to 1980, the so-called always-treated units. The treatment effects of membership in RTAs for $g = 1980$ cohort (always-treated) cannot be identified because these pairs have no pre-treatment observations and, in the presence of treatment-effect heterogeneity, they do not serve a valid comparison group (Nagengast and Yotov 2025).

The existing RTA dataset employed in this study records the effective date of entry into force as the initial date of the RTA. However, in practice, firms may begin adjusting in anticipation of an agreement, with some trade and patenting barriers potentially starting to decline even before the agreement formally enters into force (Moser and Rose 2012; Egger et al. 2022; Sheikh and Kanwar 2024). Accordingly, following Nagengast and Yotov (2025), we will assume an "onset" of RTAs three years before their entry into force. As a robustness test (see Subsection 6.2), following Wooldridge (2023, 2025), Nagengast and Yotov (2025), and Nagengast et al. (2026), we omit first three periods prior to the inception of an RTA to account for the potential anticipation effects. Alternatively, to test the sensitivity of baseline results, we shift the treatment forward by three years to their effective date of entry into force.

5 Baseline Findings

This section presents our main results. In Subsection 5.1, we test the identifying assumptions underlying the ETWFE estimator. We proceed to obtain our main findings of the average effect of RTA membership on bilateral patent application flows in Subsection 5.2. Finally, in Subsection 5.3, we present the event-study estimates that describe the evolution of RTA effects over time, as well as series of cohort-specific estimates in Subsection 5.4.

[7] The estimator proposed by De Chaisemartin and d'Haultfoeuille (2020) allows for non-absorbing treatment status in linear settings. However, in nonlinear settings, such as PPML, the literature on nonlinear DiD that accommodate staggered treatment adoption with entry and exit remains limited.

5.1 Parallel Trends Assumption

The ETWFE estimator requires the parallel trends assumption to hold, which states that, in the absence of RTA membership, cross-border patent flows for RTA members and non-members would have followed similar path. Note that when the distribution of covariates differs substantially between treated and never-treated country pairs, as is the case in our setting, the conditional parallel trends assumption is more appropriate (Heckman et al. 1997, 1998; Abadie 2005; Callaway and Sant'Anna 2021; Wooldridge 2023, 2025). To test the validity of the parallel trends and no-anticipation assumptions underlying the ETWFE estimator, we replace the treatment effects in Equation (3) with cohort-year-specific placebo effects for periods prior to treatment onset, conditional on the time-constant covariate, i.e., bilateral distance between country pairs.[8]

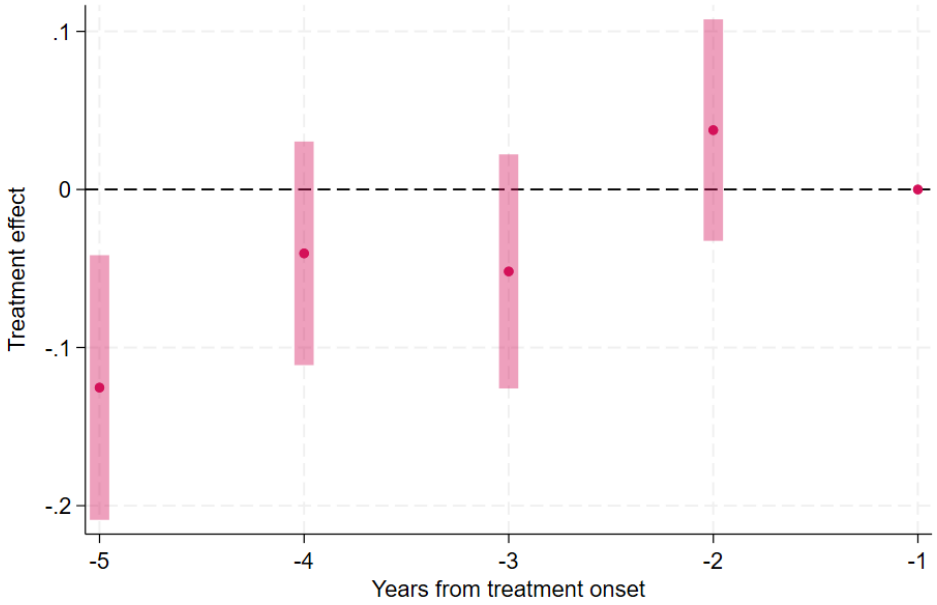
Figure 1 presents the resulting placebo effects, aggregated across cohorts by event-time using Equation (5). The average treatment effects in the years preceding RTA onset are statistically insignificant, providing evidence in favor of parallel trends assumption. Nevertheless, we observe a statistically significant difference in cross-border patenting between RTA members and non-members five periods prior to the agreement's entry into force. Note, however, that this lead is sufficiently distant from treatment onset that not all treated units are observed (Clarke and Tapia-Schythe 2021; Callaway and Sant'Anna 2021). As a result, the estimated decline is likely driven by compositional changes and does not necessarily imply a systematic violation of the parallel trends assumption. We therefore conclude that there is no evidence of significant pre-trends, suggesting that the parallel trends assumption and no anticipation assumption are tenable in our setting, and proceed to obtain our main results.

5.2 Estimates of the RTA Effects on Cross-Border Patenting

This section presents the average effects of membership in RTAs on bilateral patent application flows. The corresponding results are reported in Table 1. The TWFE RTA estimate in column (1) is obtained from Equation (2), estimated using the PPML estimator with desination-year, source-year, and destination-source fixed effects. The RTA estimate is positive and statistically significant, implying that RTAs have

[8]We condition on bilateral distance for two reasons. First, the ETWFE estimator accommodates only time-invariant covariates, thereby avoiding potential post-treatment bias that may arise when a covariate is itself affected by treatment (Zeldow and Hatfield 2021; Roth et al. 2023). Second, bilateral distance is the most widely used proxy for bilateral trade costs in structural gravity models (Anderson and Van Wincoop 2004; Disdier and Head 2008).

Figure 1 Placebo pre-treatment effects of RTAs



Notes: The figure reports the cohort-year-specific placebo effects in the five years prior to RTA onset, obtained from a PPML estimation of Equation (3). The regression is estimated using never-compliant units as a comparison (Borusyak et al. 2024). The pre-trend estimates were obtained by aggregating cohort-year-specific treatment effects using Equation (5). The cohort-time specific treatment effects are allowed to vary by time-constant covariate, i.e., the bilateral distance between country pairs ij. The 95% confidence intervals were obtained from standard errors clustered by country pair.

led to an increase of about 70 percent $\left((e^{0.534} - 1) \times 100 = 70.57\right)$ in cross-border patent flows between member countries relative to non-members. However, the relatively large TWFE RTA estimate in column (1) of Table 1 should be interpreted with caution, as it may be confounded by broader globalization forces that are not attributable to the RTA membership.

Therefore, to address this issue, we estimate the same TWFE specification in column (3), but additionally include cross-border-year fixed effects to effectively control for the common effects of globalization (Bergstrand et al. 2015). The TWFE RTA estimate is again positive and statistically significant, but with the magnitude that is smaller than the corresponding estimate based in column (1), implying that RTAs in our sample have led to an increase of about 46 percent $\left((e^{0.377} - 1) \times 100 = 45.7\right)$ in bilateral patent application flows.

Next, in columns (2) and (4) of Table 1, we present our preferred ETWFE RTA estimates from Equation (3), which implements the heterogeneity-robust staggered DiD method à la Wooldridge (2023). Note that the ETWFE estimator yields a set of 563 cohort-time-specific treatment effects (δ_{gs}), which are then aggregated using Equation (4) to obtain a single average effect of RTAs on patenting. The ETWFE

Table 1 Average RTA effects on cross-border patenting: TWFE vs. ETWFE estimates

	(1) TWFE	(2) ETWFE	(3) TWFE	(4) ETWFE
$RTA_{ij,t}$	0.534***	0.463***	0.377***	0.288***
	(0.073)	(0.057)	(0.055)	(0.067)
Observations	56,434	56,434	56,434	56,434
Destinations	91	91	91	91
Sources	207	207	207	207
Years	40	40	40	40
Coefficients	1	563	1	563
Destination × Year FE's	Yes	Yes	Yes	Yes
Source × Year FE's	Yes	Yes	Yes	Yes
Destination × Source FE's	Yes	Yes	Yes	Yes
Cross-border × Year FE's	No	No	Yes	Yes

Notes: The table presents the PPML estimates using both TWFE regression, which captures the common RTA effect and the ETWFE model, which implements the heterogeneity-robust staggered DiD method. The cohort-year-specific treatment effects in ETWFE model were aggregated using Equation (4) to obtain an aggregate treatment effect estimate. The dependent variable is the number of patent application filed by source country i in destination country j at time t in levels. The standard errors in parentheses are clustered by country pair ij. *, **, *** denotes $p < 0.10$, $p < 0.05$, $p < 0.01$, respectively.

RTA estimate in column (2) is positive and statistically significant, suggesting that RTA membership is associated with an approximately 59 percent $\left((e^{0.463} - 1) \times 100 = 58.8\right)$ increase in bilateral patent application flows. In column (4), we additionally include cross-border-year fixed effects (for reasons stated above). We find that, relative to the estimate reported in column (2), the ETWFE RTA estimate in column (4) is somewhat smaller but remains economically meaningful, corresponding to an increase of about 33 percent $\left((e^{0.288} - 1) \times 100 = 33.3\right)$ in cross-border patent flows among RTA members. For econometric and theoretical reasons, we prefer the results reported in column (4) of Table 1 as our main estimate of the impact of RTAs on cross-border patent flow.

The results presented in Table 1 have two main implications. First, the failure to account for time-varying border effects in structural gravity regressions may result in upward bias in the estimated effects of trade agreements on cross-border patenting, irrespective of the underlying model (TWFE or ETWFE) under consideration (Dai et al. 2014; Bergstrand et al. 2015; Baier et al. 2019; Campos et al. 2021; Larch and Yotov 2025). This remains an important shortcoming of prior studies that do not incorporate domestic patent flows and, consequently, do not account for time-varying border effects when estimating

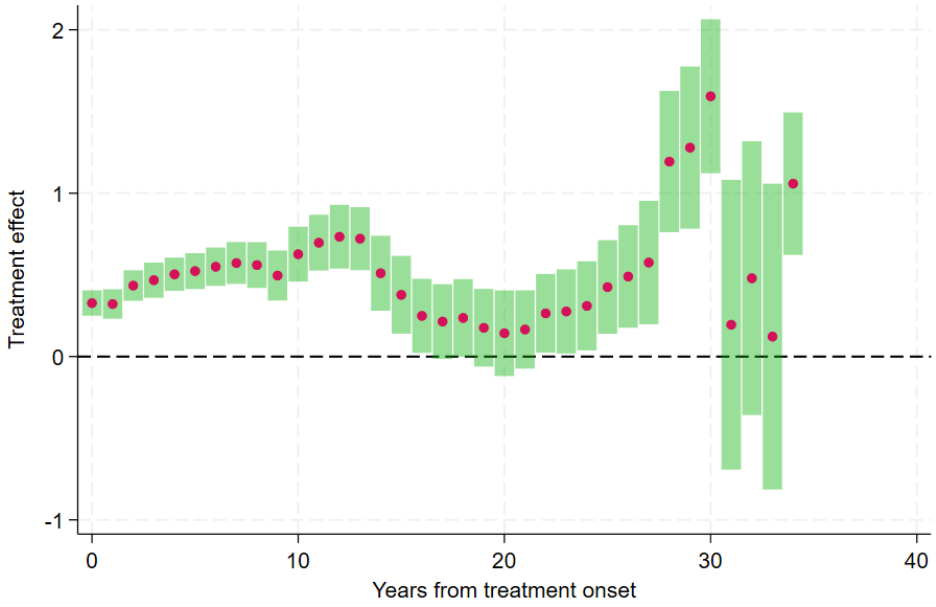
the effects of RTAs on patenting. Second, the estimates based on the heterogeneity-robust ETWFE estimator are substantially smaller than those obtained from the traditional TWFE estimator commonly employed in structural gravity estimation, implying that existing studies relying on the TWFE model may be overestimating the impact of RTAs on cross-border patent flows.

The RTA estimates reported in Table 1 are obtained by aggregating cross-border patent flows from the INPACT-S database across industries. However, the literature generally recommends using disaggregated data on bilateral patent application flows whenever available, as pooling observations across industries rather than aggregating them can improve efficiency (Yotov et al. 2016; Breinlich et al. 2024; Larch et al. 2025). Accordingly, in Section A.1 of the Supplementary Appendix, we use the INPACT-S data pooled across industries and re-estimate Equation (3) using both the TWFE and ETWFE estimators. We find that the resulting RTA estimates remain close to the baseline estimates reported in Table 1, suggesting that our main findings are robust to alternative levels of data aggregation.

5.3 Event-Study Estimates of RTAs

The aggregate RTA effects reported in Table 1 may mask significant heterogeneity, as treatment effects may vary with the duration of exposure to RTA membership. Moreover, failure to account for dynamic treatment effects may yield biased and inconsistent estimates (Bergstrand et al. 2015; Larch et al. 2025) and therefore remains an important caveat in the existing literature on RTAs and patenting. We complement the aggregated RTA estimates from Table 1 with a set of event-time-specific ETWFE RTA effects, which are visualized in Figure 2. We find that the effects of RTAs on bilateral patent application flows are positive and statistically significant, with treatment effects increasing slowly but monotonically for up to fourteen years following RTA onset. We offer two plausible explanations for the modest increase in RTA effects over time. Firms may take time to adjust to the new trade rules, while the associated trade and patenting barriers may decline gradually following the agreement's implementation. Further, we find that the positive effects of RTAs begin to attenuate fifteen years after the agreement's inception. This finding can be attributed to the fact that RTAs may have reached a "maturity phase", beyond which the response of cross-border patent flows to RTA entry into force may start to diminish. A similar pattern is documented by Egger et al. (2022) in the context of the effects of FTAs on trade. Finally, we observe discrete 'jumps' in RTA effects

Figure 2 Event-time specific RTA effects



Notes: The figure reports the event-time specific RTA effect on cross-border patenting. The cohort-year-specific treatment effects were aggregated across cohorts using Equation (5) to obtain the dynamic effects relative to the RTA onset. The dependent variable is the number of patent application filed by source country i in destination country j at time t in levels. The 95% confidence intervals were obtained from standard errors clustered by country pair.

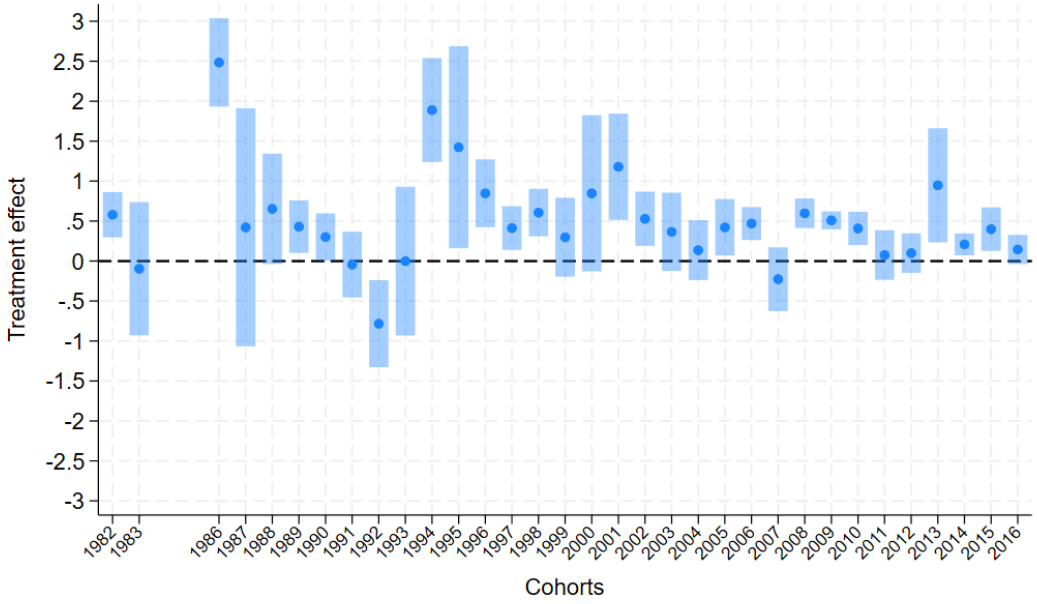
roughly twenty-five years after the agreement onset. A possible explanation of these results is that the composition of treatment cohorts contributing to the aggregate event-study estimates changes substantially across the event-times. At earlier event-times, the treatment effect estimates are obtained by aggregating the cohort-time-specific treatment effects (δ_{gs}) from a relatively large number of cohorts, including both early- and late-treated cohorts. By contrast, at later event-times, the aggregate event-study estimates are based on progressively fewer cohorts, as later-treated cohorts by construction do not have sufficiently long post-treatment histories. As a results, changes in the composition of the contributing cohorts across event-times may generate apparent shifts in the aggregate event-study estimates. This pattern of RTA effects over longer event horizons is consistent with the effects of EU integration on trade in Nagengast et al. (2026).

5.4 Cohort-Specific Effects of RTAs

Next, we examine the heterogeneity in RTA effects across different treatment-timing cohorts. This sort of heterogeneity is particularly relevant in gravity-type models, as it may help us understand the role of sequential trade trade liberalization and incumbency effects, whereby country pairs that entered into

RTAs earlier may exhibit systematically different treatment effects from those that became members of these agreements later (Egger et al. 2024). The cohort-specific RTA effects presented in Figure 3 reveal substantial heterogeneity across treatment-timing cohorts. We find that the earlier treatment-timing cohorts, i.e., those with RTA onset between 1982-1993 period, exhibit either economically smaller or statistically insignificant effects, whereas for cohorts treated during 1994-2003 period, RTAs are associated with a relatively larger effects on cross-border patent flows. The average treatment effects for cohorts entering RTAs between 2004-2016 period remain statistically significant but are economically smaller in magnitude[9].

Figure 3 Cohort-specific RTA effects



Notes: The figure reports the cohort-specific RTA effect on cross-border patenting. The cohort-year-specific treatment effects were aggregated over the time dimension using Equation (6). The dependent variable is the number of patent application filed by source country i in destination country j at time t in levels. The 95% confidence intervals were obtained from standard errors clustered by country pair.

We offer several intuitive explanations for the heterogeneity of our RTA estimates. The economically modest and statistically insignificant effects for the earlier treatment-timing cohorts are consistent with the view that agreements signed during the 1982-1993 period were generally characterized by weaker standards of commitments, thereby limiting the market integration. By contrast, RTAs that entered into force during the 1994–2003 period, widely regarded as the "golden age" of trade liberalization, were potentially associated with larger effects on cross-border patent flows, as explicit barriers to trade

[9]Note that the classification of cohorts into early (1982-1993), intermediate (1994-2003), and later period (2004-2016) is arbitrary and intended to reflect the apparent shift in treatment effects observed in Figure 3.

and patenting declined considerably during this period. Finally, the smaller effects for later treatment-timing cohorts, with RTA onset between 2004-2016 period, can be attributed to significant economic crises, including the dot-com bust, and the financial crisis, followed by Brexit and the Trump presidency, which may have heightened the trade policy uncertainty and weakened the momentum towards further liberalization. Moreover, as we show in the subsequent analysis, RTAs have become deeper and more comprehensive over time, which may have contributed to the relatively smaller effects observed for the later treatment-timing cohorts.

The detailed analysis of the underlying determinants of heterogeneous RTA effects across both event- and cohort-specific dimensions is beyond the scope of this paper. However, in the robustness experiment presented in Section 8, we perform a subgroup analysis to examine the differential effect of deep versus shallow agreements, depth of the agreements, agreements that include at least one intellectual property related provision and their corresponding depth, and the effects of globalization forces on cross-border patent flows relative to domestic filings over time. We find that deep trade agreements and agreements containing at least one intellectual property related provision significantly reduce cross border patenting, whereas globalization forces are associated with significant increase in bilateral patent application flows relative to domestic filings. However, neither the overall depth of agreements nor the depth of IPR-related provisions has an economically meaningful effect on cross-border patenting.

6 Robustness Analysis

This section presents a series of robustness checks. In Subsection 6.1, we assess the robustness of our baseline findings by imposing restrictions on treatment-effect heterogeneity and employing the OLS instead of the PPML estimator, while in Subsection 6.2, we examine the sensitivity of our results to the assumptions underlying the DiD and the ETWFE estimator.

6.1 Treatment Effects Heterogeneity and Alternative Estimators

This section presents the robustness of our main finding reported in Table 1 by allowing treatment effects to vary only along the event- or cohort-specific dimension; to alternative clustering of standard errors; and

employing OLS instead of the workhorse PPML estimator. The results from this section are reported in Table 2.

6.1.1 Restrictions on Heterogeneity

The ETWFE RTA estimate in column (1) of Table 2 is obtained by allowing the treatment effects to vary only at the event-year level, but are constrained to be constant across treatment-timing cohorts. It is akin to the dynamic event-study specification commonly applied in the DiD literature. We find that the resulting RTA estimate in column (1) of Table 2 is larger than the corresponding ETWFE estimate obtained in column (2) of Table 1. By contrast, the model in column (2) of Table 2, which allows treatment effects to vary only across treatment-timing cohorts, yields an estimate similar to our baseline ETWFE estimate reported in column (2) of Table 1. We therefore conclude that cohort heterogeneity is more important in our setting than treatment effect heterogeneity across event-time, consistent with the theoretical predictions of Egger et al. (2024).

6.1.2 Standard Error Clustering

The baseline ETWFE RTA estimate in column (2) of Table 1 is obtained by clustering standard errors at $destination \times source$ level, while allowing complete heterogeneity in treatment effects across both event-time and cohort-specific dimensions. In column (3) of Table 2, we employ the same specification but access the robustness of the baseline results by clustering standard errors at the $destination$, $source$, $year$ level. The standard errors become slightly larger, although the statistical significance of the estimated treatment effect remains unchanged. We therefore conclude that, while alternative clustering of standard errors may affect the magnitude of standard errors, the resulting changes are not large enough to alter the statistical significance of our main results.

6.1.3 Ordinary Least Squares Estimator

Finally, we report results from the standard TWFE specification estimated using OLS instead of the PPML estimator. The estimated TWFE OLS estimate reported in column (4) is substantially smaller than the corresponding TWFE estimate obtained using the PPML estimator in columns (1) of Table 1. We conclude

Table 2 Degree of heterogeneity of the ETWFE and alternative estimators

	(1)	(2)	(3)	(4)
$RTA_{ij,t}$	0.629***	0.463***	0.463***	0.109***
	(0.087)	(0.059)	(0.079)	(0.035)
PPML/OLS	PPML	PPML	PPML	OLS
Estimator	ETWFE	ETWFE	ETWFE	TWFE
Unit heterogeneity		Cohort	Cohort	Cohort
Time heterogeneity	Event		Event	Event
Standard error clustering	Dst × Src	Dst × Src	Dst, Src, Year	Dst × Src
Observations	56,434	56,434	56,434	56,434
Destinations	91	91	91	91
Source	207	207	207	207
Years	40	40	40	40
Coefficients	35	33	563	1
Destination × Year FE's	Yes	Yes	Yes	Yes
Source × Year FE's	Yes	Yes	Yes	Yes
Destination × Source FE's	Yes	Yes	Yes	Yes

Notes: The table presents the PPML estimates of Equation (3) using variants of the ETWFE model, except for columns (4), which are based on OLS. The ETWFE estimates are obtained by aggregating cohort-time-specific treatment effects using Equation (4) to derive the overall impact of the RTA. Column (1) imposes complete homogeneity in treatment effects across cohorts while allowing heterogeneity along the event-year dimension. Column (2) allows treatment effects to vary across cohorts but imposes complete homogeneity along the event-year dimension. Column (3) allows treatment effects to vary across both cohort-year and event-year dimensions as in column (2) of Table 1, with standard errors clustered at the destination, source, year level. Columns (4) report the TWFE estimates obtained using OLS estimator, where the dependent variable is the logarithm of patent flows. Across all specifications, standard errors clustered at the destination-source level are reported in parentheses (except for column 3). *, **, *** denotes $p < 0.10$, $p < 0.05$, $p < 0.01$, respectively.

that, relative to PPML, the OLS estimator yields downward-biased estimates of the effects of RTAs on bilateral patent application flows.

6.2 DiD- and ETWFE-Specific Assumptions

Next, we examines the robustness of the baseline results to alternative definitions of treatment onset; the potential effects of other treatments; a variant of the ETWFE model that relaxes the parallel-trends assumption while accounting for other major trade policy changes, such as WTO and EU membership;

and alternative weighting schemes for obtaining the aggregate treatment-effect coefficient. Our finding are reported in Table 3.

6.2.1 Treatment Onset

The analysis presented in the previous sections assumed that RTA onset occurred three years before the agreement's entry into force to account for potential anticipation effects on cross-border patent flows. Here, we consider two alternative strategies. First, following Wooldridge (2023, 2025), Nagengast and Yotov (2025), and Nagengast et al. (2026), we exclude periods that may be affected by anticipation effects, i.e., the first three periods immediately preceding RTA inception. The resulting estimate reported in column (1) of Table 3 is slightly larger than the our baseline estimate from column (2) of Table 1. This is as expected, given that the RTA effects in the three years immediately preceding agreement inception were smaller than the remaining treatment effects. Second, we use the effective date of RTAs entry into force as the treatment onset by shifting the treatment onset forward by three years. Note that the anticipation effects then become the part of pre-treatment periods. We find that the corresponding ETWFE RTA estimate reported in column (2) of Table 3 remains positive and statistically significant, albeit smaller than the baseline estimate. We therefore conclude that our main results are robust to alternative definitions of treatment onset that account for potential anticipation effects.

6.2.2 Exclusion of Other Treatments

A potential concern with estimating treatment effects over a long time period is that other policy interventions may be implemented in the meantime, making it difficult to disentangle their effects from those of the original treatment under consideration. In our case, the most salient event is the Agreement on Trade-Related Aspects of Intellectual Property Rights (TRIPS), adopted under the auspices of World Trade Organization (WTO) in 1995. The TRIPS agreement brought about notable changes in the international legal framework governing the ownership and flow of knowledge, technology, and other intellectual assets, and may therefore have independently affected cross-border patent flows. As a result, changes in bilateral patent application flows following RTAs could partly reflect the effects of TRIPS rather than the effects of RTAs themselves. To rule out any contamination from the TRIPS, we omit all post-treatment periods

of cross-border patenting between TRIPS members from the estimation sample, taking into account the staggered entry dates of individual countries into the TRIPS agreement.[10] The resulting ETWFE RTA estimate in column (3) of Table 3 remains positive and statistically significant but is smaller than the baseline estimate reported in column (2) of Table 1, suggesting that part of the baseline RTA effect may be attributed to TRIPS.

Table 3 Robustness with regard to DiD- and ETWFE-specific assumptions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$RTA_{ij,t}$	0.502***	0.351***	0.317***	0.280***	0.413***	0.501***	0.431***	0.557***	0.451***
	(0.067)	(0.060)	(0.061)	(0.057)	(0.062)	(0.058)	(0.051)	(0.080)	(0.057)
Sample/Treatment									
Omit anticipation	Yes								
Shift treatment by 3 years		Yes							
Exclude TRIPS			Yes						
Covariate interactions									
ln Distance				Yes					
WTO and EU controls					Yes				
Weights	Obs.	Obs.	Obs.	Obs.	Obs.	Cohort	Event	Cohort × Year	Patent
Observations	54,177	63,545	34,799	56,434	56,434	56,434	56,434	56,434	56,434
Destinations	91	91	91	91	91	91	91	91	91
Sources	207	207	207	207	207	207	207	207	207
Years	40	40	40	40	40	40	40	40	40
Coefficients	468	601	436	1121	567	563	563	563	563
Destination × Year FE's	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Source × Year FE's	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Destination × Source FE's	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The table reports the PPML estimates of Equation (3) corresponding to DiD-and the ETWFE-specific assumptions. The ETWFE estimates are obtained by aggregating cohort-time-specific treatment effects using Equation (4) to obtain an aggregate treatment effects estimate. The dependent variable is the number of patent application filed by source country i in destination country j at time t in levels. Column (1) omits the years immediately preceding RTA onset in each cohort to exclude periods with anticipation effects, following Wooldridge (2023, 2025). Column (2) shifts RTA onset forward by three years. Column (3) omits all post-treatment periods of cross-border patenting between TRIPS members. Column (4) includes interactions between *ln* Distance and cohort-year-specific treatment effects thereby relaxing the parallel trends assumption (Callaway and Sant'Anna 2021; Wooldridge 2023). Column (5) includes WTO and EU dummies as exogenous control variables. Columns (6)–(9) report results from alternative weighting schemes for the cohort-year-specific treatment effects to obtain the aggregate treatment effect estimates. The standard errors in parentheses are clustered by country pair. *, **, *** denotes $p < 0.10$, $p < 0.05$, $p < 0.01$, respectively.

[10]The data on countries compliance with the TRIPS agreement is taken from Sheikh and Kanwar (2025).

6.2.3 Time-Constant Covariates

The difference in observed covariates may create a non-parallel outcome dynamics between treatment and comparison groups. In this case, the conditional parallel trend assumption underlying difference-in-differences may be more plausible to recover sensible causal parameters of interest (Heckman et al. 1997, 1998; Abadie 2005; Callaway and Sant'Anna 2021; Wooldridge 2023, 2025). Therefore, we next extend the ETWFE model to allow cohort-time-specific treatment effects (δ_{gs}) to vary with time-invariant covariates, specifically the bilateral distance between country pairs (see Subsection 5.1 for more details). Note that this specification comes at the cost of estimating a considerably larger number of coefficients. The aggregate ETWFE RTA estimate in column (4) of Table 3 remain positive, albeit smaller than the baseline estimate. This finding is consistent with evidence from related studies, which finds that bilateral distance has a negative and statistically significant effect on cross-border patent flows (LaBelle et al. 2024). Therefore, the effect of RTAs on bilateral patent application flows may be relatively smaller after controlling for distance.

6.2.4 WTO and EU Controls

The membership in RTAs during our sample period coincided with the establishment of the World Trade Organization (WTO) and the European Union (EU). To control for these major trade policy changes, we augment our ETWFE specification in column (5) of Table 3 by including dummy variables for membership in the WTO and the EU. We find that the resulting ETWFE RTA estimate is closer to the baseline estimate, indicating that our estimated RTA effect is robust to controlling for these major trade policy changes.

6.2.5 Alternative Weighting Schemes

Finally, in columns (6)–(9) of Table 3, we employ alternative weighting schemes for the cohort-year-specific treatment effects to obtain the aggregate treatment effect estimates. Note that the baseline ETWFE RTA estimates are obtained by assigning equal weight to each post-treatment observation. In this experiment, we give every cohort (column 6), every event-year (column 7), and every cohort-year cell (column 8) the same weight. In addition, we also consider a variant of ETWFE model that uses patent-share weights (column 9). We find that aggregate RTA estimates in columns (6) and (8) are relatively larger than the baseline estimates, since they place larger weights on cohort-year cells with larger treatment effects, whereas the

ETWFE RTA estimates in columns (7) and (9) are closer to the baseline estimate. Therefore, we conclude that our results are robust to using alternative weighting schemes.

7 Intellectual Property Agreements and Patent Flows

This section presents the average response of cross-border patent flows to membership in RTAs containing legally enforceable intellectual property provisions (IPAs) notified to the WTO. Accordingly, the treatment variable, $IPA_{ij,t}$, takes the value of 1 if both i and j share common membership in an RTA containing intellectual property provisions that are legally enforceable and subject to dispute settlement ($LE = 2$), and 0 otherwise (Howard et al. 2025).

While the structural gravity estimation can be performed at any level of aggregation. The literature recommends using disaggregated data whenever available (Yotov et al. 2016; Breinlich et al. 2024; Larch et al. 2025). Therefore, to obtain average effects of IPAs on bilateral patent application flows, we use INPACT-S data pooled across industries and re-estimate Equation (2) and (3) using the TWFE and ETWFE estimator, respectively. Unlike the RTA estimates obtained in Sections 5 and 6, the dependent variable used to obtain the IPA estimates, $PAT_{ijk,t}$, is measured at the industry level and refers to patents filed from source i to destination j in industry k at time t. The baseline specifications remain unchanged, except that we replace the treatment variable, $RTA_{ij,t}$, in TWFE specification with $IPA_{ij,t}$. As a result, the indicator variable, D_{gs}, in the ETWFE specification is defined based on IPA membership, with cohort g corresponding to the time period in which both countries i and j first became members of an IPA. Finally, we include *destination-industry-year* and *source-industry-year* fixed effects to control for industry-specific inward and outward multilateral resistances, respectively (Anderson and Van Wincoop 2003), and *destination-source-industry* fixed effects to account for unobservable time-invariant bilateral characteristics specific to a given industry (Yotov et al. 2016; Brunel and Zylkin 2022).

The IPA estimate based on the TWFE estimator, reported in column (1) of Table 4, is positive and statistically significant, suggesting that legally enforceable intellectual property provisions in RTAs increase cross-border patent flows by approximately 41 percent $\left((e^{0.342}-1)\times 100 = 40.77\right)$. The TWFE IPA estimate is consistent with the findings of Martínez-Zarzoso and Arregui Coka (2025), who estimate the structural gravity equation within a standard TWFE specification to examine the impact of FTAs with- and without-

technology-related provisions on technology internalization, measured using bilateral patent application flows and co-patenting as alternative proxies. They find that both types of FTAs have a significant positive impact on cross-country patenting. However, the corresponding estimate obtained using the heterogeneity-robust ETWFE estimator, reported in column (2) of Table 4, does not indicate a statistically significant effect of IPAs on bilateral patent application flows, confirming the findings in Coleman (2022) and Howard et al. (2025).

Table 4 Average IPA effects on cross-border patenting

	(1) TWFE	(2) ETWFE
$IPA_{ij,t}$	0.342***	0.004
	(0.030)	(0.028)
Observations	571,483	571,483
Destinations	90	90
Sources	170	170
Industries	31	31
Years	40	40
Coefficients	1	411
Destination × Industry × Year FE's	Yes	Yes
Source × Industry × Year FE's	Yes	Yes
Destination × Source × Industry FE's	Yes	Yes

Notes: The table presents the PPML estimates using both TWFE regression, which captures the common IPA effect and the ETWFE model, which implements the heterogeneity-robust staggered DiD method. The cohort-year-specific treatment effects in ETWFE model were aggregated using Equation (4) to obtain an aggregate treatment effect estimate. The dependent variable is the number of patent application filed from source country i to destination country j in industry k at time t. The standard errors in parentheses are clustered at Destination × Source × Industry level. *, **, *** denotes $p < 0.10$, $p < 0.05$, $p < 0.01$, respectively.

We offer several explanations for these findings. The standard TWFE specification may yield biased and inconsistent in the presence of treatment effect heterogeneity, whereas ETWFE estimator remains robust to such heterogeneity. The average ETWFE IPA estimate, although statistically insignificant, may mask significant heterogeneity across both event-time and cohort-specific dimensions. Moreover, the null average estimate from the ETWFE model may reflect the fact that deep trade agreements containing IPR provisions are inherently complex and difficult to comply with, such that their effects on cross-border patenting take time to materialize (Larch and Yotov 2024b, 2025). In subsequent analyses, we demonstrate that this is indeed the case.

7.1 Disaggregated IPA Effects on Cross-Border Patenting

This section explores several dimensions of underlying heterogeneity in the effects of IPAs on bilateral patent application flows. First, we examine how treatment effects vary with the duration of exposure to IPA membership, commonly referred to as event-study estimates. To obtain the dynamic effects relative to the IPA onset, we aggregate cohort-year-specific treatment effects across cohorts using Equation (5). Second, we examine IPA effects across different treatment-timing cohorts, which are computed from the cohort-year-specific treatment effects by averaging over the time dimension, as specified in Equation (6). Our findings are presented in Figure 4.

7.1.1 Dynamic Effects of IPAs on Patenting

The event-time-specific ETWFE IPA effects appear in panel (a) of Figure 4. Several patterns stand out from the evolution of IPA effects over time. First, consistent with our aggregate estimate, the estimated phasing-in effects of IPAs on cross-border patent flows remain statistically insignificant for up to seven years following IPA onset. As previously discussed, one possible explanation for this finding may be the gradual removal of tariff and non-tariff barriers, together with the slow adjustment of firms to the new trade rules since the inception of IPAs, such that the effects of IPAs on cross-border patent flows take time to materialize. Second, eight years after the agreement's inception, IPAs are associated with a statistically significant decline in patent flows. A possible explanation for the significant negative effects of IPAs on patent application flows in our setting is that strongly enforceable IPAs that are subject to dispute settlement procedures are inherently more complex and difficult to comply with. As a result, highly complex agreements may introduce new frictions and, in some cases, become protectionist (Krueger 1999; Ghodsi 2020; Egger et al. 2022; Herman 2024; Larch and Yotov 2024b, 2025; Nagengast and Yotov 2025), thereby inhibiting rather than facilitating cross-border patent flows. Third, the estimated effects of IPAs becomes positive and statistically significant only sixteen years after the agreement's entry into force, suggesting that potential benefits of IPAs on cross-border patenting emerge with a lag, which is also consistent with Larch and Yotov (2025), who find that the positive effects of DTAs with investment provisions on FDI manifest themselves fifteen years after the implementation of an agreement.

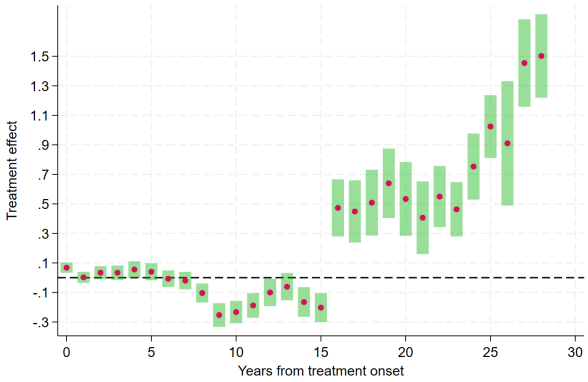
We see several possible explanations for the delayed effects of IPAs on bilateral patent application flows. The first reason pertains to the sluggish adjustment of firms to new trade rules and the gradual removal of trade and patenting frictions. The duration of response adjustment may take altogether about ten to fifteen years on average (Egger et al. 2022). The second reason may be attributed to the fact that, over a longer event horizon, the initial negative effects associated with the complexity and depth of IPAs may be dampened by broader globalization forces and the implementation of other policy areas within deep trade agreements, resulting in an increase in cross-border patenting over time. As we demonstrate in Section 8, this is indeed the case. Alternatively, changes in the composition of contributing cohorts over longer event-time horizons may generate apparent shifts in the aggregate event-study estimates, as discussed in Subsection 5.3. We therefore conclude that the direct patenting response to IPAs is highly non-linear, consistent with the estimated effects of FTAs on trade reported in Egger et al. (2022).

7.1.2 Heterogeneous Effects of IPAs Across Cohorts

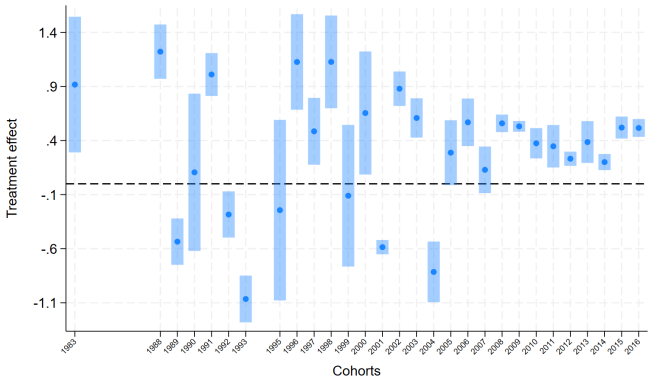
The cohort-specific ETWFE IPA estimates are presented in panel (b) of Figure 4. Two main findings stand out. Although the average estimate reported in column (2) of Table 4 does not indicate a statistically significant effect of IPAs on patent flows, the treatment effects exhibit significant heterogeneity across cohorts. Specifically, earlier treatment-timing cohorts with an IPA onset between 1988-2003 exhibit significantly larger effect, whereas the treatment effects for cohorts entering into IPAs during 2005-2016 are positive but relatively small in magnitude. A possible explanation may be that, ceteris paribus, countries that liberalized their trade relations earlier by entering into DTAs containing legally enforceable IPR provisions may have experienced greater increases in patenting relative to countries that entered into these agreements later. These findings are consistent with the theoretical predictions in Egger et al. (2024) on the role of sequential trade liberalization and incumbency effects in international trade (see Section 3 for more details). Alternatively, the economically modest effects in later cohorts could be due to the fact that IPAs have become deeper, cumbersome, and more complicated over time, thereby dampening their effects on cross-border patenting.

Figure 4 Event-time and cohort specific effects of IPAs on cross-border patenting

(a) Event-time



(b) Cohort



Notes: The figure presents the event-time and cohort-specific effects of IPAs on cross-border patenting in panel (a) and panel (b), respectively. The dependent variable is the number of patent applications filed from source country i to destination country j in industry k at time t. The 95% confidence intervals were obtained from standard errors clustered at the $Destination \times Source \times Industry$ level.

8 Additional Experiments

This section presents additional robustness experiments. The ETWFE estimates related to the depth of RTAs are presented in Subsection 8.1. Further, in Subsection 8.2, we employ the standard TWFE structural gravity framework to examine the effects of preferential trade agreements ($PTA_{ij,t}$), their depth ($Depth_{ij,t}$), the differential effects of deep versus shallow agreements ($DTA_{ij,t}$), agreements containing at least one IPR related provisions ($IPR_{ij,t}$), and memberships in Agreement on Trade-Related Aspects of Intellectual Property Rights ($TRIPS_{ij,t}$), among other factors [11]. Finally, in Subsection 8.3, we evaluate the effects of globalization forces on cross-border patenting.

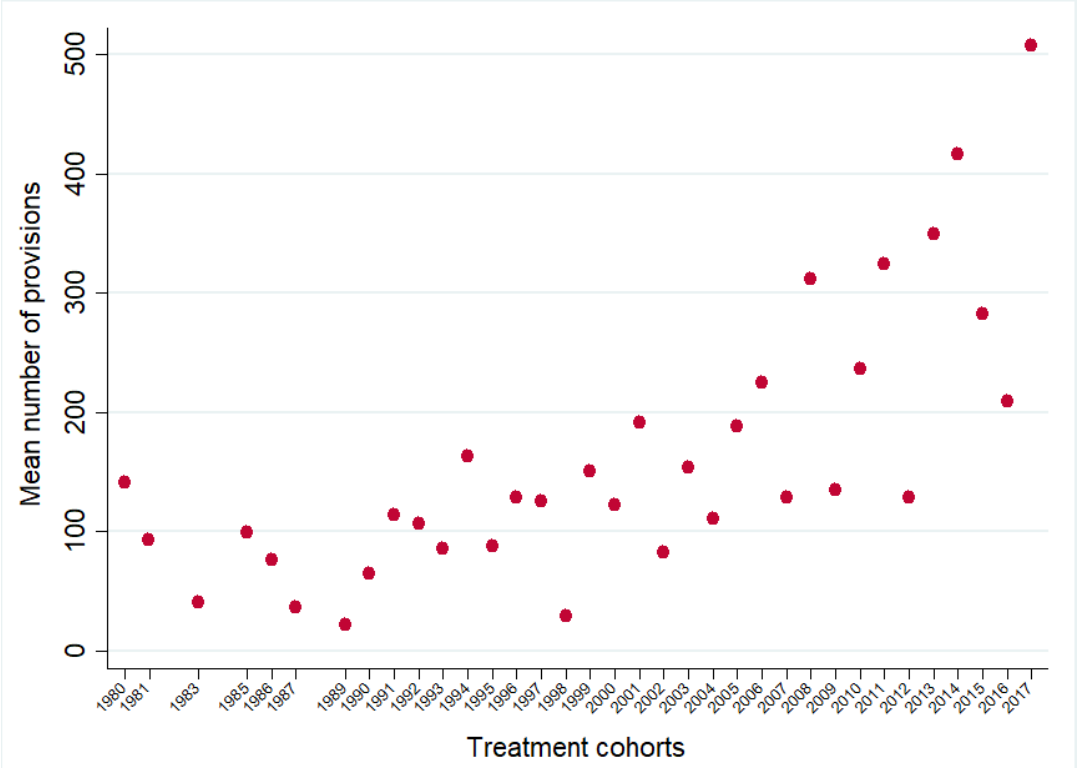
8.1 The Depth of RTAs

The effects of RTAs on cross-border patenting may vary by the type of agreement. Moreover, Hofmann et al. (2017, 2019) and Mattoo et al. (2020) demonstrate that the number of policy areas covered in RTAs has increased over the last two decades, both in the *intensive margin* (specific commitments within a policy area) and the *extensive margin* (number of policy areas covered). This is confirmed in Figure 5, where we plots the number of provisions in the agreements in our sample by cohort. The earlier treatment

[11] The heterogeneity-robust ETWFE estimator for staggered difference-in-differences does not accommodate time-varying covariates, such as $Depth_{ij,t}$, $DTA_{ij,t}$, $TRIPS_{ij,t}$ etc., making the TWFE estimator a natural choice in this case.

timing cohorts predominantly comprise members of RTAs with fewer than 90 provisions, whereas the later treatment-timing cohorts are associated with RTAs containing between 250 and 500 provisions.

Figure 5 Mean number of provisions by cohort



Notes: This figure shows the mean number of provisions per agreement by cohort. The data on the number of provisions comes from the World Bank's Database on the Deep Trade Agreements (Hofmann et al. 2017, 2019; Mattoo et al. 2020).

Against this backdrop, we split the agreements in our sample into two groups depending on whether the number of provisions that they include is above or below the median for the sample.[12] The motivation for this experiment is to examine whether differences in agreement depth can reconcile our baseline findings of declining RTA effects across more recent cohorts, reported in Figure 3. The ETWFE estimates from this exercise are reported in Table 5. The result in columns (1) correspond to RTA effects for agreements with a number of provisions below the median ($Depth_{ij,t} < P50$), while column (2) report the effects of RTAs with the number of provisions at or above the sample median ($Depth_{ij,t} \geq P50$). We find that RTAs in both sub-samples have significant positive effects on bilateral patent application flows.[13] However, the effect is substantially smaller for deeper RTAs, defined as agreements with a number of provisions above the sample

[12]Following Nagengast and Yotov (2025), we use the maximum in case the number of provisions changed over time for a given agreement.

[13]Note that the sub-sample of RTAs with $Depth_{ij,t} < P50$ contains a relatively small number of observations, and most group-time average treatment effects (δ_{gs}) are dropped due to collinearity with the fixed effects. Therefore, the ETWFE RTA estimate in column (1) should be interpreted with caution.

median, than for relatively shallower agreements.[14] Therefore, the significant positive but economically modest effects of RTAs observed for later treatment-timing cohorts in Figure 3 may partly reflect the greater depth of the RTAs associated with these cohorts, given that deeper RTAs, which are inherently more complex to comply with, generate relatively smaller increases in bilateral patent application flows.

Table 5 Robustness with regard to depth of agreements

	$Depth_{ij,t} < P50$	$Depth_{ij,t} \geq P50$
	(1)	(2)
$RTA_{ij,t}$	0.992***	0.673***
	(0.260)	(0.062)
Observations	2,912	19,630
Destinations	86	89
Sources	121	136
Years	40	40
Coefficients	49	472
Destination × Year FE's	Yes	Yes
Source × Year FE's	Yes	Yes
Destination × Source FE's	Yes	Yes

Notes: The table presents PPML regression results using the ETWFE estimator (Equation 3), for which the cohort-times-specific treatment effects were aggregated using Equation (4) to obtain an aggregate treatment effect estimate. The dependent variable is bilateral patent application flows which vary over the destination-source-year dimension. The results in columns (1) report RTA effects for agreements where the number of provisions is below the median ($Depth_{ij,t} < P50$), whereas those in column (2) correspond to agreements for which the number of provisions is above the sample median ($Depth_{ij,t} \geq P50$). The standard errors in parentheses are clustered by country pair. *, **, *** denotes $p < 0.10$, $p < 0.05$, $p < 0.01$, respectively.

8.2 A Gravity Detour

Next, we leverage the "Vertical Depth" measure of the World Bank's database on deep trade agreements (DTAs) that provides detailed information on the content of policy areas covered in the corresponding agreements (Hofmann et al. 2017, 2019; Mattoo et al. 2020). Employing the standard TWFE estimator, we examine the effect of membership in preferential trade agreements, the effects of DTAs containing intellectual property-related provisions, as well as the differential effects of *deep* versus *shallow* agreements on patent flows. Additionally, we will allow for the effects of DTAs to vary depending on their depth,

[14] The corresponding cohort- and event-time specific results are available upon request.

which is measured by counting the total number of provisions included in the corresponding agreement.[15] We follow the current best practice recommendation from the structural gravity literature to estimate the effects of DTAs on patent flows. Therefore, our estimating equation for bilateral patent application flows becomes:

$$PAT_{ijk,t} = exp\left\{\alpha \mathbf{DTA}_{ij,t} + \gamma \mathbf{GRAVITY}_{ij,t} + \chi_{ik,t} + \psi_{jk,t} + \mu_{ijk} + \sum_{t} \beta_t \, BRDR_{ij,t}\right\} \times \epsilon_{ijk,t} \qquad (7)$$

The vector $\mathbf{DTA}_{ij,t}$ includes set of variables whose estimates would be of central interest to us. Specifically, it included an indicator, $PTA_{ij,t} = 1$, if i and j are members of preferential trade agreements in year t, and $= 0$ otherwise; an indicator, $DTA_{ij,t} = 1$, if i and j are members of deep trade agreements (DTAs), and $= 0$ otherwise.[16] Moreover, the World Bank's database on deep trade agreements contains information on 120 intellectual property related provisions (Wu 2020). Based on this information, we define an indicator, $IPR_{ij,t}$, which takes a value of 1 if the corresponding DTA includes at least one IPR-related provision, and 0 otherwise. Note that the definition of the treatment variable in the benchmark case (Section 7) is based on membership in an RTA containing legally enforceable intellectual property provisions that are subject to dispute settlement. By contrast, in this setting, the variable, $IPR_{ij,t}$, captures whether the corresponding DTA contains at least one IPR-related provision, regardless of whether the provision is legally enforceable and subject to dispute settlement.[17] Moreover, we includes two continuous measures of trade agreement depth, namely, $Depth_{ij,t}$, which is a count measure of the total number of provisions in the PTA, and $Depth - IPR_{ij,t}$, which counts the number of IPR-related provisions in an agreement. Finally, we include an indicator for common membership in the Agreement on Trade-Related Aspects of Intellectual Property Rights ($TRIPS_{ij,t}$), which brought about notable changes in the international legal framework governing intellectual assets. We expect that the TRIPS may exert a direct positive effect on bilateral patent application flows. The vector $\mathbf{GRAVITY}_{ij,t}$ includes a set of time-varying bilateral

[15] The actual data file on the number of provisions that we used in this case is "All_provisions_bilateral_Jan_2021.csv" under the label "Deep Trade Agreements database 2.0 (Vertical depth)-Bilateral observations". In related work, Anderson et al. (2019) and Larch and Yotov (2025) utilized the same source for their analysis of FDI.

[16] For our $DTA_{ij,t}$ variable, we use the variable, pta_mapped, from Hofmann et al. (2017, 2019) and Mattoo et al. (2020), which is 1 whenever the depth variable is greater than 0, and 0 otherwise.

[17] The "Vertical Depth" measure of the Deep Trade Agreements database does not provide a ranking of the legal enforceability of IPR provisions on a scale of 0 to 2.

variables that control for membership in the World Trade Organization ($WTO_{ij,t}$) and the European Union ($EU_{ij,t}$).

We estimate Equation (7) using the data pooled across industries and employ the Poisson pseudo-maximum-likelihood (PPML) estimator to account for potential heteroskedasticity in the bilateral patent application flows and to take advantage of the information in the zero patent flows (Silva and Tenreyro 2006; Larch et al. 2025). In addition, we employ a rich set of *source-industry-year* ($\chi_{ik,t}$), *destination-industry-year* ($\psi_{jk,t}$), and *destination-source-industry* (μ_{ijk}) fixed effects (see Section 7 for more details), as well as a full set of time-varying border dummies ($\sum_t \beta_t \, BRDR_{ij,t}$) to account for common globalization trends.

8.2.1 Estimates of Deep Trade Agreements on Cross-Border Patenting

The PPML estimates of deep trade agreements from Equation (7) are reported in Table 6. The specification in column (1) includes a single indicator variable, $PTA_{ij,t}$, that reflects the presence of a preferential trade agreement between i and j at time t, regardless of their type (deep or shallow) or depth. Unsurprisingly, the TWFE estimate of $PTA_{ij,t}$ effects remain positive and statistically significant, although they are larger than the corresponding estimate in column (3) of Table 1. A possible explanation for this difference is that the estimates in Table 1 are obtained using aggregate data, whereas those in Table 6 are based on disaggregated data pooled across industries. This difference in the level of aggregation may suggest that the TWFE estimate based on aggregate data could be downward biased (Larch et al. 2025).

In column (2), we additionally include an indicator for deep trade agreement, $DTA_{ij,t}$, to allow for heterogeneous effects between deep and shallow trade agreements. We find that DTAs that extend beyond simple tariff liberalization to encompass behind-the-border measures have a statistically significant negative effect on bilateral patent application flows. One possible explanation could be that DTAs may impose substantial administrative and regulatory burden on firms, potentially outweighing any market-expansion incentives for cross-border patenting.

Next, in column (3) we include a continuous measure of the number of provisions specified in an agreement, $Depth_{ij,t}$. The total number of provisions across the DTAs in our sample varies between 12 to 640. The estimate in column (3) is economically small, suggesting that an increase in the number

Table 6 Estimates of the effects of deep trade agreements on cross-border patent flows

	(1)	(2)	(3)	(4)	(5)	(6)
$PTA_{ij,t}$	0.514***	0.642***	0.604***	0.617***	0.594***	0.582***
	(0.027)	(0.044)	(0.045)	(0.043)	(0.044)	(0.044)
$DTA_{ij,t}$		-0.141***	-0.334***	-0.346***	-0.349***	-0.273***
		(0.039)	(0.059)	(0.056)	(0.059)	(0.067)
$Depth_{ij,t}$			0.0007***	0.0006***	0.0007***	0.0004***
			(0.0001)	(0.0001)	(0.0001)	(0.0001)
$TRIPS_{ij,t}$				0.598***	0.596***	0.591***
				(0.026)	(0.026)	(0.026)
$IPR_{ij,t}$					-0.075***	-0.146***
					(0.022)	(0.024)
$Depth - IPR_{ij,t}$						0.003***
						(0.0009)
$WTO_{ij,t}$	-0.067	-0.070	-0.009	-0.408***	-0.389***	-0.413***
	(0.067)	(0.067)	(0.068)	(0.064)	(0.065)	(0.066)
$EU_{ij,t}$	-1.190***	-1.096***	-1.032***	-1.043***	-1.052***	-1.080***
	(0.047)	(0.048)	(0.052)	(0.051)	(0.052)	(0.053)
Destination × Industry × Year FE's	Yes	Yes	Yes	Yes	Yes	Yes
Source × Industry × Year FE's	Yes	Yes	Yes	Yes	Yes	Yes
Destination × Source × Industry FE's	Yes	Yes	Yes	Yes	Yes	Yes
Cross-border × Year FE's	Yes	Yes	Yes	Yes	Yes	Yes
Observations	511,943	511,943	511,943	511,943	511,943	511,943

Notes: The table reports the estimates of DTAs on cross-border patent flows from Equation (7) using the data pooled at industry level. The results are obtained using a three-way gravity specification with *destination-industry-time*, *source-industry-time*, *destination-source-industry* fixed effects, and time-varying border dummies. The estimates of these fixed effects are omitted for brevity. Standard errors clustered at $Destination \times Source \times Industry$ level are reported in parentheses. *, **, *** denotes $p < 0.10$, $p < 0.05$, $p < 0.01$, respectively.

of provisions in an agreement does not lead to an economically meaningful effect on bilateral patent application flows. This may indicate that adding more provisions primarily makes agreements more difficult for firms to comply with, rather than generating additional incentives for cross-border patenting.

The TRIPS agreement harmonized the international legal framework governing intellectual property rights and, therefore, is expected to facilitate technological diffusion through patenting. The main finding from column (4) is that we obtain positive, sizable, and statistically significant estimate on $TRIPS_{ij,t}$, which suggests that, on average, the TRIPS agreement in our sample have led to a 82 percent $\left((e^{0.598} - 1) \times 100 = 81.8\right)$ increase in cross-border patent flows between their members.

In column (5), we isolate the effect of deep trade agreements that include at least one intellectual property related provision ($IPR_{ij,t}$). The estimated effect of $IPR_{ij,t}$ on bilateral patent application flows is

negative and statistically significant, indicating that, on average, intellectual property related provisions in the corresponding DTAs are associated with 7.2 percent reduction in patent flows.

The difference in the estimated effects of $TRIPS_{ij,t}$ and $IPR_{ij,t}$ is noteworthy and warrants further explanation. The intellectual property provisions in DTAs aim to achieve tighter and strict standards of commitment related to IPRs, exceeding those mandated by the TRIPS agreement, often referred to as *'TRIPS-plus'* provisions (Hofmann et al. 2017, 2019; Mattoo et al. 2020; Wu 2020). By contrast, TRIPS agreement mandated minimum and flexible standards of IPR protection, involving relatively less stringent regulatory and compliance requirements. As a result, bilateral patent application flows may respond positively to the TRIPS agreement and negatively to the IPR provisions in DTAs, possibly because the latter may impose substantial administrative and regulatory burden on firms.

Finally, in column (6), we include $Depth - IPR_{ij,t}$, a continuous measure counting the number of IPR-related provisions in each DTA, which ranges from 1 to 110 in our sample. The estimate in column (6) indicate an economically modest effect of the increase in the depth (number of IPR-related provisions) on cross-border patenting, for the reasons discussed above.

The estimates for the control variables capturing common membership in $WTO_{ij,t}$ and $EU_{ij,t}$ are negative and statistically significant. These findings should be interpreted with caution, as the INPACT-S data on cross-border patent flows cover 213 countries of origin but only 91 patent application authorities, potentially resulting in mismeasurement of these variables in our sample.

8.2.2 Effects of DTAs with IPR Provisions Over Time

The dynamic effects of DTAs containing IPR provisions over time are estimated using the following leads and lags specification (Egger et al. 2022):

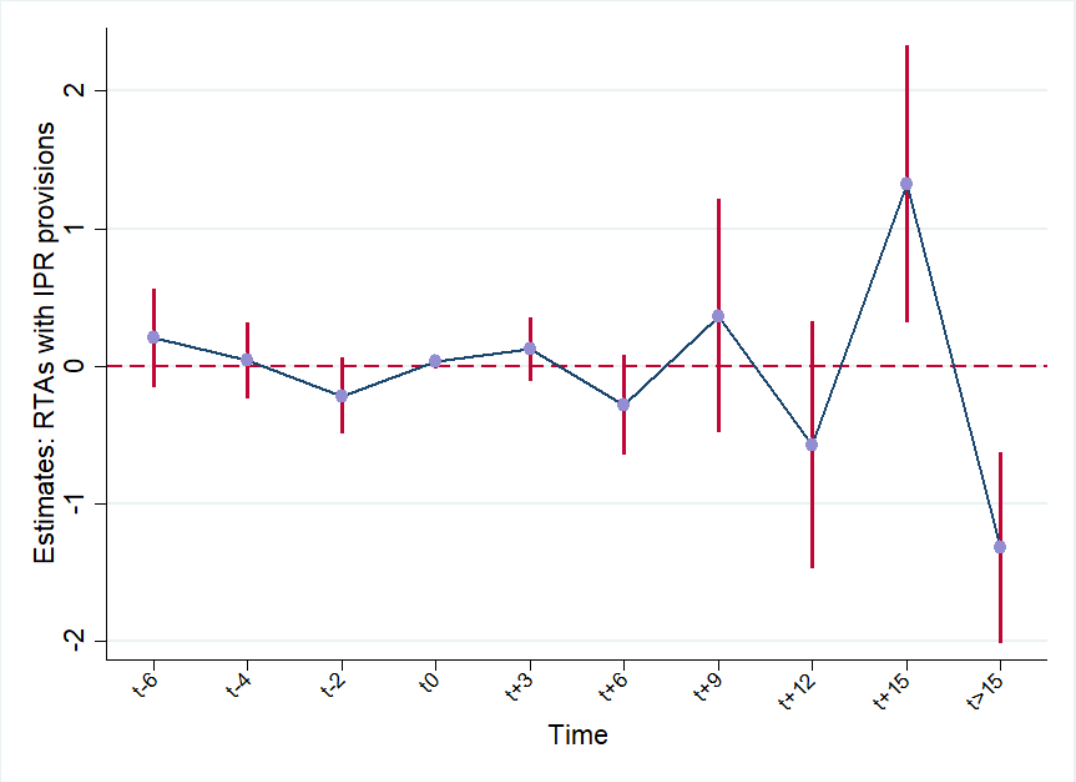
$$\begin{aligned} PAT_{ijk,t} = exp\left\{\alpha\, IPR_{ij,t} + \sum_{s} \gamma_s\, IPR_{ij,(t+s)} + \sum_{k} \delta_k\, IPR_{ij,(t-k)}\right\} \\ \times exp\left\{\chi_{ik,t} + \psi_{jk,t} + \mu_{ijk} + \sum_{t} \beta_t\, BRDR_{ij,t}\right\} \times \epsilon_{ijk,t} \quad \forall \quad i,j,t \end{aligned} \tag{8}$$

Here, the parameter 'α' captures the contemporaneous effect of IPR provisions on bilateral patent application flows. We include $s = 6$ IPR lead, such that, parameter γ_s captures the potential impact of $IPR_{ij,t}$ prior

to their inception, and $k = 15$ lags to capture possible phasing-in effects of $IPR_{ij,t}$ following the entry into force, given by parameter δ_k. We estimate Equation (8) using the PPML estimator on data pooled across industries, including *source-industry-year*, *destination-industry-year*, and *destination-source-industry* fixed effects, as well as a full set of time-varying border dummies, for the reasons discussed in Section 7.

The dynamic effects of DTAs with IPR provisions are presented in Figure 6. Two main findings stand out: (i) we do not find evidence of IPR anticipation effects; and (ii) the effects of DTAs with IPR provisions on cross-border patenting take almost fifteen years to materialize, consistent with the event-study estimates in the previous section that we obtained using the heterogeneity-robust ETWFE estimator (see Figure 4). Moreover, our findings of a lagged response of cross-border patent flows to the inception of DTAs with IPR provisions are also consistent with Larch and Yotov (2025), who document a similar evolution in the impact of DTAs with investment provisions on FDI. A possible explanation may be that, compared to trade, intellectual property-related relationships between the parties to an agreement may take longer to develop.

Figure 6 Evolution of the effects of DTAs with IPR provisions on cross-border patenting



Notes: This figure plots the evolution of the effects of DTAs with IPR provisions ($IPR_{ij,t}$) on cross-border patent flows from Equation (8). The designation t_0 denotes the year of entry into force of the DTA. The 95% CI's are obtained from standard errors clustered at $Destination \times Source \times Industry$ level. See text for further details.

8.3 Globalization and Cross-border Patenting

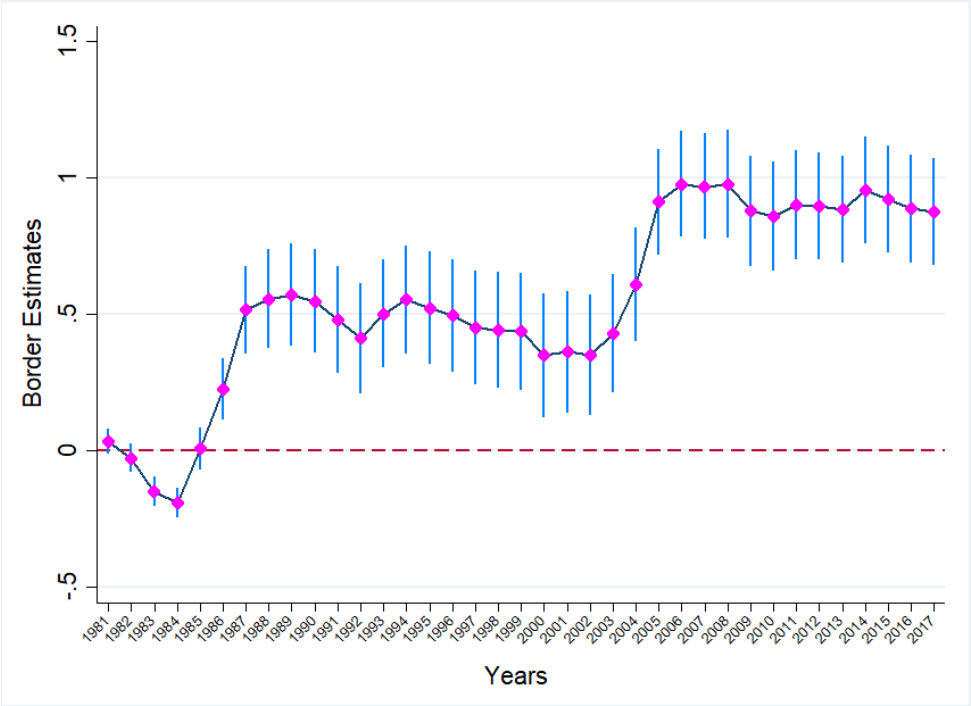
Finally, we examine whether international patent filings over time have increased relative to domestic filings. To this end, we follow Bergstrand et al. (2015) by defining a variable, $BRDR_{ij}$, that takes the value 1 for international filings ($i \neq j$) and 0 for domestic filings ($i = j$), which we interact with a set of year dummies in our sample, creating $BRDR_{ij,t}$, $BRDR_{ij,t+1}$,.....etc., such that, $t = 1980, \ldots, 2017$. Therefore, using the state-of-art gravity equation with both international and domestic patent flows, we estimate the following specification on data pooled across industries:

$$PAT_{ijk,t} = exp\left\{\chi_{ik,t} + \psi_{jk,t} + \mu_{ijk} + \sum_{t=1980}^{2017} \beta_t \, BRDR_{ij,t}\right\} \times \epsilon_{ij,t}$$

The parameter β_t will capture the evolution over time of the effects of any forces that are driving a wedge between international and domestic filings. Alternatively, it can also be interpreted as capturing declining trends in unobservable bilateral fixed and variable costs that may have increased international patent filings relative to domestic filings, commonly referred to as globalization forces (Anderson and Van Wincoop 2003; Bergstrand et al. 2015). Note, however, that due to perfect collinearity with the *destination-source-industry* (μ_{ijk}) fixed effects in our model, we cannot estimate all border-time effects. To address this issue, we omit the border dummy for the first year in the sample, i.e., $BRDR_{ij,1980}$, which serves as our reference category. Thus, all other border-time effects are interpreted relative to the reference category.

The PPML estimates of the effects of globalization forces on bilateral patent application flows are reported in Figure 7. The figure reveals several noteworthy pattern. First, we find that, relative to the reference year, international patent filings were significantly lower than domestic filings during the period 1981–1986. A possible explanation may be that bilateral trade and patenting frictions were relatively more pronounced during this period, while IPR protection remained less stringent in most low- and middle-income countries, which may have constrained firms' incentives to file patents in foreign markets. Moreover, these findings may help explain the relatively modest increase in the effects of RTAs and IPAs over time, as shown in Figures 2 and 4, respectively. Second, globalization forces have strengthened over time, leading to an increasing share of patents being filed internationally relative to domestically. Several factors may explain this trend, including the establishment of the WTO, the entry into force of TRIPS,

Figure 7 Estimates of the effects of globalization forces on cross-border patenting



Notes: This figure plots the estimates of time-varying border effects, which capture the impact of diffusion and globalization forces on cross border patent flows over time. 95% CI's are obtained from standard errors clustered at $Destination \times Source \times Industry$ level. See text for further details.

and the proliferation of RTAs, which may have substantially reduced barriers to international trade and cross-border patenting. Alternatively, the increase in the magnitude of the effects of RTAs and IPAs at later event-times in Figures 2 and 4, respectively, may partly be explained by the strengthening of globalization forces over time.

9 Conclusion

The conventional approach to estimating the effects of RTAs on trade, patenting, and FDI flows is to employ a TWFE specification estimated using PPML estimator. However, the TWFE estimator imposes a common treatment effects across units, and in presence of treatment effect heterogeneity, it may yield biased and inconsistent estimates due to 'forbidden comparisons'. This paper contributes to the emerging empirical literature on the relationship between RTAs and bilateral patent application flows across several dimensions. First, we incorporate the ETWFE estimator for staggered difference-in-differences into the structural gravity model, allowing treatment effects to vary across both cohorts and event times. Unlike

the conventional TWFE estimator, the ETWFE estimator remains robust to treatment effects heterogeneity. Second, effects of RTAs on bilateral patent application flows may vary with the length of exposure to treatment, as firms may require time to adjust with new trade rules. Moreover, country pairs that liberalized their trade relationship earlier by entering into RTAs may experience different effects than those that joined these agreements later. The preferred ETWFE estimator allows us to examine heterogeneity in treatment effects across both cohorts and event time. Third, intellectual property provisions in RTAs often extend IPR protection beyond the minimum standards mandated by TRIPS agreement. We therefore additionally examine the effects of legally enforceable intellectual property agreements (IPAs), which are subject to dispute settlement, on cross-border patent flows.

We find that RTAs have a significant positive effect on bilateral patent application flows. The conventional TWFE estimates are larger than the ETWFE estimates, suggesting that ignoring treatment effect heterogeneity may overstate the impact of RTAs. Moreover, average treatment effects exhibit substantial heterogeneity across different treatment-timing cohorts, with relatively larger effects observed for the early cohorts. The event-study estimates further indicate that treatment effects increase slowly but monotonically for up to fourteen years following RTA onset. Furthermore, legally enforceable IPAs have no significant effect on patent flows, although their effects emerge only after a considerable lag. A battery of robustness check confirm the validity of our baseline findings.

This paper nests an ETWFE estimator for staggered difference-in-differences within a structural gravity model to provide new evidence on the role of RTAs and IPAs in fostering technology diffusion, measured using bilateral patent application flows. It also shows why conventional gravity estimates can be misleading when treatment effects vary across cohorts and over time.

Heterogeneous Effects of Regional Trade Agreements on Cross-Border Patenting

Ridwan Ah Sheikh Rajeswari Sengupta

Supplementary Appendix

A.1 Additional results

This section examines the robustness of the main results reported in Table 1 using data on bilateral patent application flows pooled across industries. We include *destination-industry-year* and *source-industry-year* fixed effects to control for industry-specific inward and outward multilateral resistance, respectively (Anderson and Van Wincoop 2003), as well as *destination-source-industry* fixed effects to account for unobservable time-invariant bilateral characteristics specific to a given industry (Yotov et al. 2016; Brunel and Zylkin 2022). The resulting TWFE and ETWFE RTA estimates reported in column (1) and (2), respectively, of Table A1 remain positive and statistically significant are close to the baseline estimates reported in Table 1. Therefore, we conclude that our main findings on the effects of RTAs are robust to alternative levels of data aggregation.

Table A1 Average RTA effects with industry level pooled data

	(1) TWFE	(2) ETWFE
$RTA_{ij,t}$	0.542***	0.418***
	(0.026)	(0.028)
Observations	753,689	753,689
Destinations	91	91
Sources	212	212
Industries	31	31
Years	40	40
Coefficients	1	562
Destination × Industry × Year FE's	Yes	Yes
Source × Industry × Year FE's	Yes	Yes
Destination × Source × Industry FE's	Yes	Yes

Notes: The table presents the PPML estimates with data pooled across industries using both TWFE regression, which captures the common RTA effect, and the ETWFE model, which implements the heterogeneity-robust staggered DiD method. Standard errors clustered at $Destination \times Source \times Industry$ level are reported in parentheses. *, **, *** denotes $p < 0.10$, $p < 0.05$, $p < 0.01$, respectively.

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