Do Cross-border Patents Promote Trade?

Brunel, Claire and Zylkin, Thomas

American University, University of Richmond

3 March 2019

Do Cross-border Patents Promote Trade?*

Claire Brunel[†]
American University

Thomas Zylkin[‡]
University of Richmond

March 3, 2019

Abstract

While we would expect that cross-border patents are used to protect a technology that is made available in another country, that technology could either be produced locally or imported. International patent filings could therefore be either complements or substitutes to international trade. This study combines data on patenting and trade for 149 countries and 249 industries between 1974 and 2006 with a "three-way" PPML panel data model that addresses several biases emphasized in the trade literature in order to provide a systematic analysis of how bilateral trade responds to cross-border patent filings. We find that cross-border patents have a positive (complementary) overall effect on the patent-filing country's exports to the patent-granting country and no effect overall on imports flowing in the opposite direction. These effects vary substantially across industries and destination markets. Patents promote significantly more bilateral export growth—and significantly less bilateral import growth—in less-differentiated industries and are found to have stronger effects on exports to more distant destinations. These findings support the interpretation that cross-border patents are mainly used to protect cost and/or quality innovations from being adopted by producers of competing products in the patent-granting country.

JEL Classification Codes: F10; F13; F14; O34; K33

Keywords: Globalization; Intellectual Property Rights; Innovation.

*Thomas Zylkin is grateful for research support from the NUS Strategic Research Grant (WBS: R-109-000-183-646) awarded to the Global Production Networks Centre (GPN@NUS) for the project titled "Global Production Networks, Global Value Chains, and East Asian Development". Other acknowledgments will be added later.

[†]Email: brunel@american.edu

[‡]E-mail: tzylkin@richmond.edu

1 Introduction

As technological advancements have been a driving force behind economic growth and globalization, flows of international trade and international patents have mirrored one another in ways that hardly seem coincidental. Both have grown at rapid paces relative to world GDP since the 1970s (Fig. 1). And non-OECD countries have become substantially more involved both as recipients and originators of new patents over the last several decades (Fig. 2), just as they have also become more involved in trade in high tech manufactured goods over this same time frame. In policy circles, the lack of patenting rights is widely cited as an important barrier to trade and provisions on patent protections have become increasingly central to international agreements intended to promote and regulate trade (Maskus and Penubarti, 1995; McCalman, 2001; Limão, 2007; Saggi, 2016).

And yet, despite these suggestive anecdotes, much still remains unknown about how and to what extent patent protections influence trade. In theory, trade and patenting could be either complements or substitutes to one another. To the extent that patent protection incentivizes technology diffusion, for example, we might expect an increase in patenting activity to coincide with reduced trade, as firms file patents in a destination market with the intent of producing there directly, by-passing trade. On the other hand, an innovating firm in one country also may file for patent protection in another in order to protect innovations embedded in goods it intends to export, in which case we would expect the filing of bilateral patents to go hand-in-hand with the expansion of bilateral trade.[1]

Moreover, though a vibrant empirical literature has investigated how trade responds to national patent systems (a country-level indicator), only a few studies have examined how trade is affected by actual cross-border patents (which vary by origin, destination, and the specific technology they represent). Notably, none of these studies has investigated the trends in patenting and trade mentioned above in a panel setting with a large number of countries and for a large number of disaggregated industries. This is a conspicuous gap in the literature given the possibility that patents may be important for explaining the evolution of industry-level trade patterns over time. In general, whether or not cross-border patenting has historically promoted trade or impeded it is a largely open question with implications for both theory and policy.

To deliver answers, we assemble an extensive database of industry-level trade flows and patent filings for 249 disaggregated industries and 149 countries over the 32 year period 1974-2006. We

[1] Other reasons why the relationship and trade might be theoretically ambiguous are discussed in the following section.

then implement a rigorous industry-level gravity estimation methodology that specifically asseses whether increases in bilateral patenting in a given industry is followed by increases in trade in that same industry. By pooling across the 249 industries in our study, we are able to construct econometric averages of the overall effects that patents have had on each direction of trade as well as investigate whether patents have had heterogeneous effects across different types of industries and/or across different types of markets. We are also able to exploit the panel structure of our data to demonstrate the robustness of each of our findings to natural concerns about reverse causality between trade and patenting.

By bringing together patent and trade data in this way, we are able to unpack several new empirical facts about how patents are used in conjunction with trade. For our full, unconditional sample, we find an overall complementary relationship between patents and trade: increased bilateral patenting on average tends to stimulate increased bilateral exports flowing in the same direction, with no significant effect seen for imports flowing in the opposite direction. The effect is economically significant: the difference between a "high value" flow of patent and a "low-value" flow of patent—lying respectively one log-deviation above and below the log-mean of the distribution—is an average increase in exports of 8.87%, which is more than half of the average effect we find for a free trade agreement (FTA) on industry-level trade.[2]

Digging deeper, we also investigate whether patents have stronger effects on trade in more-differentiated industries where monopoly rights over a product's distinguishing characteristics should be more valuable. While this may seem like a natural hypothesis, we actually find overwhelming evidence for the opposite: patents have larger effects in less-differentiated industries where patents are relatively less valuable for protecting monopoly rights but instead serve to protect cost and quality advantages over producers of competing products. In fact, for these less-differentiated industries in particular, patents are not only associated with increased exports from from the patent-filing country to the patent-granting country, but also affect the opposite direction of trade as well, reducing import growth from the patent-granting country to the filing country. Notably, these effects are very robust, showing up across numerous different industry subgroupings and different ways of specifying the estimation. We also investigate other sources of heterogeneity, finding some evidence that patents generally promote exports more strongly to more geographically distant import markets. This latter result is consistent with the findings of Chalioti et al (2017) for the effects of patenting on Greek firm-level exports and lends further support to the interpretation that the patented technologies we observe reflect quality innovations specifically.

[2] These results, explained in section 5, are evaluated at the peak of a patent's life. We calculate patent stocks based on value-weighted patent flows, weighted by family size.

Studying the co-evolution of patents and trade over time presents a number of challenges. This is in large part because patents are complex objects to work with empirically: they are at once "lumpy" (occurring at irregular points in time, but intended to have effects for long durations) as well as highly specific to the technology they derive from and destination market they are filed in. Furthermore, as is well-documented in the trade literature, accounting for the many different dimensions of heterogeneity that naturally arise in a multilateral trade context quickly becomes computationally difficult even for estimations with aggregate trade flows (c.f., Glick and Rose, 2016; Larch, Wanner, Yotov, and Zylkin, 2018.)

To resolve these various challenges, we draw on several recent methodological innovations that naturally complement our focus on cross-border patents. First, because of the natural lumpiness of patent flows, we construct bilateral, industry-specific stock values reflecting the gradual obsolescence of old patents filed in that market in addition to the lag in diffusion for new flows (Popp, 2002, 2003). Our analysis therefore accounts for the lasting effects of previously-filed patents. Second, our econometric specification accounts for the industry-specificity of patents by effectively pooling across 249 disaggregated industry-level gravity estimations, each with its own set of exporter-industry-time, importer-industry-time, and country pair-industry fixed effects. This "three-way" fixed effects structure accounts for numerous sources of bias that have been shown to be important in the literature on trade agreements (and that we similarly show to be important for assessing the effects of patents).[3] Finally, we capitalize on some recent innovations by Correia, Guimarães, and Zylkin (2019a,b) to estimate our preferred model using Poisson Psuedo-maximum Likelihood (PPML). The use of PPML not only ensures our estimates are consistent, but also ensures they are not subject to any aggregation bias from pooling across disaggregated industries (see French, 2019.)

As mentioned above, the prior literature examining the empirical relationship between patenting and trade is limited in number and in scope. Most papers in this area have been constrained by data to examining a single flow (either imports or exports), a single bilateral relationship, a single country's trade relationships, and/or a single industry (Anderton, 1999; Greenhalgh, 1990; Antimiani and Costantini, 2013; Brunel, 2017; Chen, 2013; Chalioti, Drivas, and Katsimi, 2017) The one exception is Palangkaraya, Jensen, and Webster (2017), who also use a PPML gravity specification to examine the effects of successful patent applications on bilateral trade. They find, as we do, that patents seem to play a role in promoting bilateral exports (that is, that patents

[3] The "three way" gravity model for panel data was first used by Baier and Bergstrand (2007) in their study of the effects of free trade agreements on trade. Pooled gravity estimators are relatively new to the literature. French (2019) describes in detail the advantages of pooled estimators such as the one described in this paper. In other recent work, Schmidt and Steingress (2018) and Kinzius, Sandkamp, and Yalcin (2018) use similar specifications to study the effects of product standard harmonization and non-tariff barriers, respectively.

generally complement bilateral exports) using a data set with 13 host markets, 28 industries, and a large number of exporting countries.[4]

Our investigation goes beyond that of Palangkaraya, Jensen, and Webster (2017) in several ways. First, we investigate a wider range of effects, allowing patents to affect both directions of trade as well as allowing for heterogeneity across different industries and across different markets. Second, another key difference is that Palangkaraya, Jensen, and Webster (2017) focus on cross-sectional variation in patent application outcomes for the same invention across different patent offices with similar application processes, whereas we focus on longitudinal changes in trade within the same pair of markets as a result of successful patent filings. Our panel approach has the advantage of explicitly controlling for any omitted cross-sectional heterogeneity that might cause the propensity to file a patent in particular country to be correlated with the propensity to trade with that country. Third, our approach also facillitates our use of more expansive and varied data, with more years, more disaggregated industries, and (especially) a wider variety of OECD as well as non-OECD patent destinations.

In sum, we contribute to the literature by greatly expanding the geographical and industry-level scope of existing analyses and by using a large panel dataset which matches bilateral trade flows to bilateral patent flows at a highly detailed level of disaggregation. We notably exploit the panel dimension of this data to control for a large set of unobservable characteristics across both country-pairs and industries and simultaneously address numerous well-known sources of bias that have been articulated in the empirical trade literature and that generally cannot be addressed using firm-level data. Because we are able to surmount these many complex data and estimation challenges, our work is the first to pursue a comprehensive longitudinal analysis of the effects of cross-border patents on trade as well as the first to isolate some key sources of heterogeneity in this relationship.

2 Related Literatures

While only a limited amount of analysis has been devoted to the empirical relationship between patents and trade, an active related literature has looked at the "gravity"-like relationships that determine the geographical distribution of knowledge capital and patent flows. These include Keller and Yeaple (2013)'s influential work on the "gravity of knowledge" as well as Figueiredo, Guimarães, and Woodward (2015)'s study of the industry- and location-specific clustering of patent citations. Earlier contributions in this literature also include Robbins (2006) and Scherngell and Hu (2011).

[4]To be more precise, Palangkaraya, Jensen, and Webster (2017) find that the presence of either an apparent bias in the patent application process or a "blocking prior art" in the importing country deters exports.

Keller (2004) reviews the earlier literature on technology diffusion across countries, with trade being one of the channels.

The theoretical literature on patenting and trade, meanwhile, is very rich. As also observed in Palangkaraya, Jensen, and Webster (2017), this literature does not offer a consensus view on whether patents and trade should be complements or substitutes. For example, in Lai and Qiu (2003) and Grossman and Lai (2002), stronger patenting rights in the global South could decrease trade by stimulating innovation-intensive production in the South and thereby reducing North-South comparative advantage. Yang and Maskus (2009) show that, in a model where innovating North firms can serve the South market via exports, FDI, or licensing, stronger patent rights in the South can have ambiguous effects on both directions of trade, depending on the North firms' optimal mode of foreign sales and on their strategic incentives to transfer know-how to the South.[5] And Bond and Saggi (2014) show that patent regimes that include threat of compulsory licensing can induce an innovating foreign firm to serve a market directly rather than voluntarily license its patented product.[6]

In addition, it is likely that patent flows and trade flows we capture in our disaggregated study in many cases reflect concurrent decisions made by the same firms (or, at least, by related firms). As Saggi (2016) notes, "in a typical year", over 80% of international patent royalty payments are made between parent firms and their subsidiaries. Our work thus also broadly relates to a recent literature that studies the role that property rights play in determining how trade in intermediate inputs within a firm's supply chain is organized among related entities in different countries. Representative works in this area include Nunn and Trefler (2013), Antràs and Chor (2013), and Alfaro, Antràs, Chor, and Conconi (2015). Also related, is Blonigen (2001), who finds that FDI flows and trade flows are substitutes for one another in final goods industries, but complement one another in intermediate goods industries. intermediate and final goods in industries facing varying levels of competition. For our part, we find that cross-border patents strongly complement exports in intermediate goods associated with a high demand elasticity; for final goods (especially capital goods), patents can actually reduce (i.e., "substitute for") imports returning from the patentee country to the filing country, but only in high elasticity industries.

Finally, while the empirical literature on patents and trade is sparse, there is a rather extensive body of work relating the strength of national patent institutions to trade. See, for example, Maskus and Penubarti (1995), Briggs and Park (2014), Boring (2015), and Ivus (2010). Saggi (2002) also

[5] This type of theoretical ambiguity is also discussed in McCalman (2001).

[6] Of course, the recent debates surrounding TRIPS and other similar international issues have stimulated a much wider literature studying these and other related topics; for some recent surveys, see Saggi (2016) and Maskus (2018).

provides a survey of the earlier work in this area. As also emphasized in Palangkaraya, Jensen, and Webster (2017), an empirical design based on individual patents rather than on national institutions is a natural complement to this line of research. Interestingly, we generally do not find that the relationship between patents and trade varies significantly with the strength of the host country's intellectual property rights regime.

3 Estimating the Effects of Patents on Trade

As noted in our introduction, analyzing the relationship between bilateral patents and bilateral trade requires an ambitious empirical framework. We observe a many-country world where cross-border patents and trade flows each vary by origin, destination, industry, and time—to be denoted in the analysis by i, j, k, and t, respectively. We aim to identify the effects of patents on trade by exploiting within origin-destination-industry (or "pair-industry") variation in both patents and trade. Part of what makes this task complex is the inter-connected nature of global trade. As has been well-known at least since Anderson and van Wincoop (2003), correctly assessing the determinants of bilateral trade between any two countries requires first recognizing the potentially confounding role played by multilateral factors such as market size and geography with respect to third countries.[7] A further challenge is that patents are by their nature specific to the technologies they derive from. It is not necessarily the case, for example, that a patent filed for the production of aerospace equipment will affect trade in cosmetics products. We therefore require an empirical model that simultaneously accounts for both the multilateral complexity of trade and the industry-level specificity of a patent, as well as the many further dimensions of complexity that arise when our object of interest simultaneously varies by industry, origin, destination, and time.

Taking all of the above concerns onboard, our proposed estimation strategy takes the form of a "three way" panel gravity model, similar to the models currently used in the structural gravity literature to study the effects of trade agreements and other bilateral policy arrangements (c.f., Baier and Bergstrand, 2007; Glick and Rose, 2016; Larch, Wanner, Yotov, and Zylkin, 2018).[8] We then interact the standard set of origin-time, destination-time, and country-pair fixed effects that

[7] In Anderson and van Wincoop (2003) (and much of the literature following Anderson and van Wincoop 2003), each country's trade is shown to be function of the "multilateral resistance" it faces in the world trade network, such that standard controls such as GDP and other observables used in the traditional gravity literature are wholly inadequate for correctly isolating the determinants of bilateral trade linkages. Furthermore, because bilateral trade relationships and market sizes change over time, changes in multilateral resistance are themselves an important source of changes in trade over time which should be accounted for in any panel study (Baldwin and Taglioni, 2007).

[8] For more on gravity estimation, see Head and Mayer (2014) and Yotov, Piermartini, Monteiro, and Larch (2016). Yotov, Piermartini, Monteiro, and Larch (2016) provide in-depth discussion of econometric best practices related to three-way gravity models in particular.

have become standard in this literature with the industry dimension. That is to say, (a log-linear version of) our preferred empirical model can be expressed as follows:

$$\ln X_{ijkt} = \delta_{ikt} + \psi_{jkt} + \eta_{ijk} + \beta\mathbf{PATENT}_{ijkt} + \delta\mathbf{Z}_{ijkt} + \varepsilon_{ijkt}, \tag{1}$$

where $\ln X_{ijkt}$ denotes log trade flows and $\mathbf{PATENT}_{ijkt}$ are our industry-level bilateral patent variables (to be described shortly). The fixed effects used are exporter-industry-time (δ_{ikt}), importer-industry-time (ψ_{jkt}), and exporter-importer-industry or "pair-industry" (η_{ijk}). $\mathbf{Z}_{ijkt}$ is a set of other time-varying controls not absorbed by η_{ijk} (such as the presence of a free trade agreement), and ε_{ijkt} is our estimation error.

With this rich set of fixed effects in place, estimation via (1) addresses many of the leading biases commonly cited in the literature on gravity estimation, such as the need to account for multilateral inter-dependencies (*industry-level* inter-dependencies in our case, addressed by δ_{ikt} and ψ_{jkt}) as well as unobservable pair characteristics that coincide with the propensity to trade (captured by η_{ijk}).[9] More generally, we also note an appealing logic to the identification based on these fixed effects that speaks to our objectives. Our question concerns how *bilateral* patenting directly affects *bilateral* trade between a given pair of countries in a given industry. By completely stripping away industry-country-specific fluctuations in trade, the country-industry-time fixed effects δ_{ikt} and ψ_{jkt} allow us to specifically isolate the pair-industry dimension of the data. The pair-industry fixed effect η_{ijk} then ensures that identification of β and δ is driven solely through observed time-variation within pairs, as in standard panel data analysis.[10] In as much as a patent is valuable in multiple markets, these fixed effects guarantee that β picks up the effect of a strategic decision on where to protect an invention, rather than the effect of the innovation associated with that patent. To be sure, some patents could protect inventions aimed very specifically at a single market, in which case the innovation effect of the patent would not be controlled for by the fixed effects. However, in that case, we would expect that patents should have larger effects on trade in more differentiated industries where other varieties are perceived as less substitutable. As we will see in the next section, our findings do not support that hypothesis, indicating that country-specific inventions are not driving our results.

[9] The observation that estimates of time-varying gravity variables tend to be biased in the absence of pair fixed effects is generally credited to Baier and Bergstrand (2007).

[10] In another recent study that uses a similar methodology, Schmidt and Steingress (2018) observe that it is also possible to include a fourth fixed effect indexed by ijt that accounts for common changes in trade across all industries within each pair. We prefer to stick with the three-way model since it conforms to the intuition of pooling our results across 249 individual industry-level gravity estimations. As we document in Section 5.3, our results are not materially affected by adding this other fixed effect; in general, we find the ikt, jkt, and ijk fixed effects are much more important for inference by comparison.

As famously pointed out by Santos Silva and Tenreyro (2006), the log-transformation of the dependent variable to construct (1) is not innocuous, since the log-OLS moment condition $E[\ln \widehat{X}_{ijkt}|\cdot] = \ln X_{ijkt}$ does not also imply that $E[\widehat{X}_{ijkt}|\cdot] = X_{ijkt}$. Estimates of (1) should therefore be regarded as generally being inconsistent.[11] Accordingly, capitalizing on recent computational innovations by Correia, Guimarães, and Zylkin (2019a,b) that allow for all the necessary dimensions of the fixed effects in a PPML estimation, our fully-specified empirical design involves estimating the above log-linear model for trade flows in levels using Poisson Pseudo-maximum Likelihood (PPML) as the underlying estimator. That is, we estimate

$$X_{ijkt} = \exp\left[\delta_{ikt} + \psi_{jkt} + \eta_{ijk} + \beta \mathbf{PATENT}_{ijkt} + \delta \mathbf{Z}_{ijkt}\right] + \nu_{ijkt}. \tag{2}$$

It can be shown that the above PPML estimator will provide consistent estimates of β and δ under standard assumptions about the unobserved heterogeneity contained in ν_{ijkt}.[12] Because it is a pooled estimator that pools across disaggregated industries, it also benefits from the aggregation bias-minimizing properties of PPML described in French (2019).[13]

The above specification notably allows for the possibility that patents filed in a country could affect either direction of trade—i.e., exports as well as imports returning from that country. This is done by allowing $\mathbf{PATENT}_{ijkt}$ to depend on two distinct stocks of patents. The first stock follows the same direction as the flow of trade—patents filed in country j by inventors residing country i—and represents the effect of patents on exports. The second stock runs in the opposite direction of the trade flow—patents filed in country i by inventors residing country j—and represents the effect of patents on imports. The latter stock is useful for a number of reasons. For example, patents could be used within supply chain relationships to exert control over foreign suppliers, in which case we might observe patents facilitating imports of certain types of goods, such as parts and components. Alternatively, imports could be affected by patents filed in another country if the filing of the patent indirectly affects the foreign competitor's ability to compete in the patent-holder's

[11] For these types of estimations, the data generating process for X_{ijt} is typically assumed to be a constant-elasticity (exponential) model as shown in (2). Under this assumption, estimating a log-linearized specification only leads to consistent estimates under the very special case where the error term ε_{ijkt} is homoscedastic (a requirement that our data strongly rejects).

[12] Weidner and Zylkin (2018) show that the three-way FE-PPML gravity estimator is consistent so long as the conditional mean is correctly specified and the regressors of interest are exogenous after conditioning on the fixed effects. The latter requirement is an important consideration in any panel study with a potentially endogenous regressor. To deal with this concern, we follow the advice of Wooldridge (2002) and Baier and Bergstrand (2007) in introducing "lead" variables that serve as a placebo test against the possibility that changes in patents are responding to changes in trade. This placebo approach is described further below.

[13] French (2019) shows that pooled PPML estimation of common gravity variables such as log distance can be rationalized as aggregating the information from industry-by-industry estimates in a way that preserves the same aggregate trade volume in expectation. Pooled log-OLS does not have this property and is subject to aggregation bias. A similar result can be shown for industry-specific regressors such as patents.

own domestic market—perhaps by altering its ability to obtain credit or by generally preventing it from using better technologies.[14]

As discussed above, theory suggests numerous reasons why the effect of patenting and trade could be ambiguous. However, to fix ideas, a reasonable prior to start with is Palangkaraya, Jensen, and Webster (2017)'s supposition that patents have a role to play in protecting the cost and/or quality advantages that exporters enjoy in foreign markets. Importantly, this view not only suggests a baseline hypothesis—that patents promote bilateral exports—but also guides our more expansive investigation of the possibly heterogeneous effects of patents on trade in two main ways. First, the value of protecting a superior technology should be greater in less-differentiated industries with a higher elasticity of substitution between products. In these industries, the value of protecting a cost and/or quality advantage is greater because the replication of the patent-holder's technology represents a more direct threat to its profitability and (similarly) because the assertion of exclusive patent rights over a disputed technology by a foreign firm should have a relatively larger impact on trade. By either of these rationales, patents should be more strongly complementary to exports in high elasticity industries than in low elasticity industries.[15]

Second, to the extent that the protected technologies enhance the quality of the product specifically, another natural hypothesis to test is whether patents promote exports to markets with higher per-unit shipping costs. This is a version of the "Washington Apples" effect of Alchian and Allen (1972) and has also recently been explored in the context of patents and trade by Chalioti, Drivas, and Katsimi (2017).[16] Stimulated by Chalioti, Drivas, and Katsimi (2017)'s earlier results for Greek patent-owning firms, we will similarly examine whether patents have stronger effects on exports to markets that are more distant geographically.[17]

Of course, aside from protecting a technology embedded in one's exports, patents could also

[14] To be clear, a patent filed in a foreign country should only directly affect the ability of non-patent-owners to sell a product that uses the patented technology in that country without a license. Thus, it is not obvious that patent-owners file patents in other markets with the intention of reducing imports from that market (a patent filed domestically would typically suffice.) Nonetheless, we observe robust evidence that patents lead to relatively less import growth in less-differentiated industries where patents are more likely to be used to protect superior production technologies.

[15] As noted above, we are taking the view that the patented technologies we observe are inputs that either lower the cost of producing a product or enhance its quality. A competing view would be that the patents we observe protect the distinguishing characteristics that differentiate the product in the eyes of end-users. In that case, we might expect patents to have more pronounced effects in less-differentiated industries. This is not what we find.

[16] For empirical evidence of the "Washington Apples" effect, see Borcherding and Silberberg (1978) and more recently Hummels and Skiba (2004). Chalioti, Drivas, and Katsimi (2017) find that patent-holding Greek exporters gain more market shares in more distant markets and in industries that have a larger number of firms. They show this finding is consistent with a theory where patents are used to protect the innovations embedded in higher quality exports.

[17] We will also consider interactions between our patent variables and other indicators commonly associated with trade costs (namely, the sharing of a common legal system or common language), though these variables are arguably more likely to reflect the costs of obtaining and/or enforcing a patent than per-unit shipping costs.

be used in conjunction with other modes of serving a foreign market that substitute for exports, such as licensing or FDI. We do not observe the latter two modes of foreign sales directly, but as shown by Blonigen (2001), FDI generally serves as a complement to exporting in intermediate goods industries and a substitute to exporting in final goods industries. We therefore also allow for the possibility that patents have systematically different implications for trade in intermediate goods industries versus in final goods industries.

One remaining empirical challenge lies in the potential endogeneity of patents and trade. In general, estimates of the elasticity with respect to trade will be biased if changes in export demand or import supply affect the number of inventions that are subsequently patented in the partner country. Import competition, for example, has been shown by some recent papers to stifle innovation in the home country in some cases (Autor, Dorn, Hanson, Pisano, and Shu, 2016; Batrakova and Dechezleprêtre, 2013) and boost it in others (Bloom, Draca, and Reenen, 2011). Alternatively, a high level of trade in technology-intensive goods could point to a market that is highly active and innovative, or, on the contrary, to one where existing technologies are sufficient and patenting has plateaued. Moreover, multinational corporations could be influenced by strong existing trade relationships in their decisions about where to locate production. A strong bilateral trade relationship could thus be a precursor for a multinational corporation filing a patent to setup production capacity abroad.

To address these concerns, we would ideally want an instrument for bilateral patenting that is time-varying, industry- and pair-specific, and is strongly correlated with patent growth, but exogenous to changes in bilateral trade. A good instrument meeting these criteria is hard to find in this context, especially given the number of interactions we would ultimately need to instrument for. Consequently, our strategy for assessing the direction of causality is to perform a set of standard placebo tests to determine whether the changes in trade identifying our results occur on or after the observed change in the patent stock (c.f., Wooldridge, 2002; Baier and Bergstrand, 2007.) By constructing appropriate "lead" terms for our stock variables and their associated interactions (corresponding to the values these variables will take in 4 years time) we can effectively test whether our results may actually be picking up causality flowing from changes in trade to changes in bilateral patenting decisions. As we will see, our results are generally robust to this type of placebo test.

4 Data Construction

4.1 Trade Flows and Other Gravity Variables

The trade dataset consists of bilateral trade flows between 149 developing and developed countries for 249 industries at 3-digit level based on the Standard International Trade Classification (SITC) revision 2. We construct this data by combining the standard 1962-2000 NBER-UN World Trade Flows dataset of Feenstra, Lipsey, Deng, Ma, and Mo (2005) with additional data for 2000-2006 obtained from UN COMTRADE. We obtain a panel dataset covering both exports and imports between these countries from 1974-2006, using every 4 years. Both the start and the end of the time period are dictated by the patent data detailed in the next section. The use of every 4 years is following the recommendations of Cheng and Wall (2005) and also helps with facilitating computation.[18]

In order to investigate which types of industries drive which results, we find it useful to examine industry subgroups with similar factor intensities or usage patterns. Industry-level indicators for skill intensity, R&D intensity, and different measures of capital intensity are taken from Nunn and Trefler (2013). These data are originally provided at the Harmonized System (HS) 6 digit level, which we map to our own SITC-based industry codes using a concordance from the World Integrated Trade Systems. For data on the usage of each industry, we obtain UN Broad Economic Category (BEC) codes at the HS6 level from UN COMTRADE and concord them to SITC using the same concordance. Multiple HS codes can map to the same SITC-based industry; thus, we assign shares based on world exports of each HS category to construct usage shares for each SITC industry.

In addition, a particularly appealing variable for our analysis is the demand elasticity for each industry, which reflects the degree of price competition and product differentiation. We would naturally expect patent protections to play an important role in industries characterized by a high demand elasticity (indicating a relatively low degree of product differentiation), since it is in these industries that rival innovation and/or imitation most directly threatens the market share of an innovating firm. To construct our elasticity variables, we first obtain detailed estimates of import demand elasticities at the 3 digit SITC level from Broda and Weinstein (2006). Then, to acknowledge that the point estimates of these industry-specific elasticities are measured with error, we construct an indicator which is equal to 1 if the estimated elasticity is above the median estimate across all

[18] Specifically, Cheng and Wall (2005) note that “fixed-effects estimations are sometimes criticized when applied to data pooled over consecutive years on the grounds that dependent and independent variables cannot fully adjust in a single year’s time.” In our context, the use of intervals that span multiple years allows us to more cleanly observe the response of trade to changes in the patent stock. Our assumption that the effects of patents do not have their peak impact until several years after filing also assists in warding against this critique.

249 3-digit industries in our data.[19] We then focus on the results for patents in “high” versus “low” elasticity industries to test our hypotheses with respect to demand elasticity.

Finally, for data on free trade agreements, we consult the NSF-Kellogg database on Economic Integration Agreements created by Scott Baier and Jeff Bergstrand.[20]

4.2 Bilateral Patent Flows and Stocks

The patent data are drawn from the 2013 version of the PATSTAT database which includes all patent applications published at the national patent offices of the 149 countries in our sample as well as the European Patent Office (EPO), from which we pull out patents filed through 2006.[21] The extraction includes all patents filed into one of our 149 countries in all industries, regardless of the origin of the inventor, and all patents filed anywhere in the world by an inventor residing in one of the 149 countries in our sample.

Since a patent grants protection for a technology only in the country where it is filed, inventors have to file in all countries in which they desire protection. In our data, there is one exception: patents filed at the European Patent Office (EPO), which covers a number of European countries. A patent filed at the EPO would only be applicable in countries designated on the patent application but the designation data is not available in PATSTAT. Since each additional country designation incurred a fee, inventors have an incentive to be selective in the countries they designate. However, designation data collected for a subset of patents in Brunel (2017) shows that the list of designated countries often covered more than half of the EPO members and often all the largest EPO member economies. Therefore, throughout our time period, we assign an EPO patent to all EPO member countries in that year.[22] Since this is not exact, we also provide robustness checks without EPO patents.

Patents are classified by the end-use of the technology based on the International Patent Classification (IPC), which can be matched to trade data classification using concordances developed in

[19]The median elasticity in our data is about 2.53. Broda and Weinstein (2006) also provide their own indicators for “high”, “medium”, and “low” elasticities. Our results are very similar if we use these indicators instead, though we generally find the latter two categories have statistically similar effects to one another.

[20]This database is available for download on Jeff Bergstrand’s website: https://www3.nd.edu/~jbergstr/.

[21]The PATSTAT 2013 database contains patents through 2012 but we truncate the data to 2006 for two reasons. First, there can be delays between the date of patent filing and the date of publication —up to 18 month for patents filed at the EPO (**?**). Since we only observe published patents, counts in the years running up to 2012 suffer from missing observations (**?**). Second, more recent patents have not had as much time to be transferred to other countries, meaning that they will have lower family sizes. As explained in this section, we weight patents by family size to account for value so patent counts in the few years preceding 2012 would appear to have low values. For both both of these reasons, we do not include the year 2010 in our analysis, though the results are qualitatively similar if we include 2010.

[22]The list of EPO members and date of accession can be found at https://www.epo.org/about-us/foundation/member-states/date.html

Lybbert and Zolas (2014).[23] We match the IPC data to SITC rev. 2 at the 3-digit level.[24]

Patents have the advantage of being widely available and classified in a way that is linkable to trade data. However, several drawbacks of the data are worth discussing. First, given that filing a patent implies disclosing information on the technology, some inventors might chose to refrain from patenting their products. However, research shows that few inventors opt to protect the secrecy of their inventions, especially when the invention is more valuable (Dernis and Khan, 2004).

Second, different patents can have widely different values. A patent grants the inventor the exclusive right to use the technology. Some patents are used extensively by either protecting large amounts of production, being licensed to a wide number of users, or being filed in many different countries. On the other hand, some published patents are not granted or not enforced. In accordance with the literature, we account for the value of a patent weighing each patent by its family size, i.e. the number of countries in which that invention is patented. The logic behind this weighting system is that an invention that is not very valuable will most likely not seek wide geographical coverage. It is especially important to keep track of the value since our analysis covers a wide range of different sectors, and value is likely to differ across industries.[25]

We construct two measures of patents using this data. The first is a count of patents filed in each year weighted by family size, which represents the flow of new patents in any given year. However, trade flows between two countries are not only affected by the new flows of patents, but could also be influenced by existing patents. Therefore, we also create a stock of patents in each year. In aggregating patents, we account for a diffusion time, since a brand new patent might not be known and used immediately, and a decay rate as technologies lose relevance over time. The use of the patent should thus theoretically increase and then decrease as the technology eventually becomes outdated. Therefore, as in Popp (2002), we aggregate bilateral patent stocks in the following way:

$$\widehat{K}_{ijkt} = \sum_{s=0}^{\infty} e^{-\omega_1 s}(1 - e^{-\omega_2 (1+s)}) \times PAT_{ijk(t-s)} \tag{3}$$

where ω_1 is the decay rate set to 0.1, and ω_2 corresponds to the rate of diffusion and set at 0.25, following Popp (2003).[26] In line with the literature, which finds that R&D capital peaks between 3

[23] The concordances are available from Professor Lybbert's website: https://are.ucdavis.edu/people/faculty/travis-lybbert/research/concordances-patents-and-trademarks/

[24] Some IPC codes match to multiple SITC categories, so the flows can be non-integer values.

[25] To be sure, there are other ways of accounting for the value of patents, notably through citations data. Both have been proven to be significantly correlated with patent value and with each other. However, as discussed in De Rassenfosse (2013), the average family size is the "most internationally comparable indicator" since citation practices and the availability of citations data differ significantly across different patenting jurisdictions.

[26] Other papers which use these same parameters include Popp, Hascic, and Medhi (2011), Lovely and Popp (2011), and Brunel (2017).

and 5 years (Griliches, 1995), these two parameters imply the impact of a patent on trade should peak at about 4 years on average,[27] which should help us to decouple the timing of the decision to patent from the timing of trade, even before we consider any placebos.[28] We use the subscript $ijkt$ to denote the value of the patent stock in industry k owned by filing country i in destination j at time t. Therefore, we may consider "two-way" effects of bilateral patenting on trade: sticking with the same notation as above, "$\widehat{K}_{ijkt}$" will denote the exporter (i)'s patent stock in the importing country (j) in industry k at time t. However, we also consider the effect of "$\widehat{K}_{jikt}$", which will be used to assess how patents affect the flow of trade in the other direction (i.e., how j's filing a patent in country i affects its imports from i).

Table 1 presents the summary statistics for the raw patent counts (unweighted), patent counts weighted by family size, as well as for stocks. On average across all industries, time, and country pairs, there are 7 new patents filed, 56 on a value-weighted basis, and the stock mean is 221. For both measures, the standard deviation indicates a large amount of variation in patenting across our dataset. Stocks and flows country pair-industry-year observations can often be 0 (the median is zero or small for all rows) but can also reach weighted-values of over 500,000. Unsurprisingly, both stocks and flows are larger for OECD countries than for the group of non-OECD countries by an order of magnitude. Since the distribution of stock values is severely skewed, we use a log transformation of these stock in our analysis, which means we can only identify the effect of a stock after at least one patent has been filed. Focusing on non-zero stocks, typical values remain small: the median values of bilateral industry-specific patent stocks range from 2 for non-OECD countries to 19 for the OECD group.

5 Results

Having described our methods and data, we now turn to our main analysis, in which we investigate the effects of cross-border patenting on trade. We start with a broad analysis, deriving at first a set of overall, pooled estimates of how patents affect each direction of trade across all markets and industry types. Subsequent specifications then dig deeper into the heterogeneous patterns underlying these overall relationships, allowing for heterogeneity across industries, across markets, and within industry subgroups. A battery of sensitivity checksthen follows.

[27]We do not have information on the length of validity for each patent and that length varies across patent offices. However, given our stock formula the bulk of a patent's contribution to the stock occurs in the first 15 years, which is less than the 20 year patent term in the United States for example.

[28]In our sensitivity analysis, we also experiment with alternative values for ω_1 and ω_2 that allow for faster and slower rates of diffusion and decay.

5.1 Do Cross-border Patents Promote Trade?

Our empirical investigation begins in Table 2. Columns 1-7 of this table report PPML estimates of the effects of changes in the bilateral patent stock on both directions of bilateral trade (exports and imports), along with the estimated effect of an FTA (a standard time-varying control from the gravity literature). In addition to answering our main question of interest—do cross-border patents promote trade?—Table 2 also serves to highlight the validity and meaningfulness of our preferred fixed effects specification from (2). Column 1 starts with a relatively simple specification, with country-pair and time fixed effects only. Subsequent columns introduce industry fixed effects (column 2), standard exporter-time and importer-time "gravity" fixed effects (column 3), and go on to demonstrate how interacting the country-pair and country-time fixed effects with the industry dimension matters for inference (columns 4-7). All reported standard errors are clustered by country-pair. Since patents are observed at the industry-country-pair level, this should lead to conservative inferences that allow for correlated changes across different industries within the same pair.

The main messages from Table 2 are two-fold. First, the varying of the fixed effects across columns reveals that using a more relaxed fixed effects specification introduces large biases in our estimates. When exporter-industry-time and importer-industry-time fixed effects are not used (in columns 1-3 and 5-6), both the export-side and import-side coefficients are always statistically significant at the $p < 0.05$ level and the export-side effect is always larger than 0.1. When these fixed effects are added, the import effect always becomes statistically and economically near-zero while the estimated export effect falls by an order of magnitude. As discussed in French (2016, 2019), these ikt- and jkt-specific fixed effects can be thought of as respectively capturing the exporter's industry-level comparative advantages and the importer's pattern of relative demands. Our results therefore indicate that these industry-country-specific supply and demand shifters change substantially over the sample and should generally be regarded as an important source of bias in panel data gravity settings, consistent with the arguments of French (2016, 2019).[29] Introducing exporter-importer-pair effects also dramatically reduces the magnitude of the export effect (compare columns 1 & 5, 3 & 6, or 4 & 7.) This is evidently because the propensity to trade is heterogeneous across industries within exporter-importer pairs and this heterogeneity is correlated with the propensity to file a patent in the importing country.

Second, while moving to our preferred fixed effects specification in column 7 is seen to reduce

[29] Notice it is these fixed effects, not the ijk pair-industry fixed effect, that has the largest effect on the FTA coefficient, which is not industry-specific.

each estimate substantially, the effect of patenting on exports remains positive and statistically significant. The estimated coefficient for the export effect of 0.018 can be interpreted in a variety of ways (depending on whether one considers the filing of a single patent, multiple patent filings, or more simply a change in the stock value). But to establish a baseline for comparison, we note that the family-weighted flow of patents filed in a particular industry and country in a particular year is well-approximated by a log-normal distribution. If we define a "high value" patent flow PAT^{high} as having a value lying one log-standard deviation above the distribution's log-mean, and a "low value" patent as having a value one log-standard deviation below the log-mean, we obtain values of $PAT^{high} = 155.774$ and $PAT^{low} = 1.125$. Applying our estimated coefficient of 0.018 to these values along with the formula we use for the stock value in (3) suggests high value patent flows increase industry-level exports at their peak by 8.87% relative to low value patent flows.[30] For comparison, this effect represents about half of our estimated boost to industry-level trade from participating in an FTA. No overall effect is found for bilateral imports returning in the opposite direction.

Our next task is to determine whether we can reasonably say these estimates reflect causality flowing from patents to trade, rather than the reverse. In the last column of Table 2, we use "lead" stock values to test whether changes in the patent stock in a prior year anticipate changes in trade. These lead variables are economically and statistically near-zero while the original estimates are scarcely changed. This simple test lends significant credibility to the results shown in column 7.[31]

5.2 Exploring the Heterogeneous Effects of Patents on Trade

While our overall results shown in Table 2 are informative, patents can be used for very different purposes (c.f., Griliches, 1998; De Rassenfosse, Palangkaraya, and Webster, 2016.) The effects of patents on trade flows are therefore likely to depend in a heterogeneous way on the industry-level and market-level contexts in which patents are used. Investigating this heterogeneity is important for informing new theory as well as for understanding how the international patent data may be mapped onto existing ways of thinking about trade and innovation.

Once we go beyond the broad empirical question of whether patents affect trade, the next

[30] We obtain this number using $0.018 \times [\log(e^{-0.1\times5}(1-e^{-0.25\times6}) \times PAT^{high}) - \log(e^{-0.1\times5}(1-e^{-0.25\times6}) \times PAT^{low})]$. Alternatively, if we consider "very high" and "very low" value patent flows that respectively lie at the 95th percentile and 5th percentiles of the distribution, we obtain a difference in peak effects of 14.6%.

[31] What's more, recall that our stock variables assume patents only reach their peak value 5 years after the date of filing. If anything, this assumption should lend more conservatism to this type of test by making it more likely that we observe significant lead coefficients in column 8. Also notice that the lead value for "FTA" in Table 2 is actually marginally significant, which generally goes to show that it is by no means unlikely that we should find evidence of anticipation effects and/or pre-trends in the data.

source of potential ambiguity in this relationship we wish to speak to is what types of innovations the patents we observe generally represent. To fix ideas, consider a monopolistically competitive environment of a kind often used to study trade and patent protection where firms produce imperfectly substitutable varieties.[32] In this type of environment, if patents are used to patent the "variety" itself, the value of owning exclusive rights over that "variety" is larger when varieties are more differentiated from one another. However, if patents instead are used to protect innovations that generate cost and/or quality advantages for the producer of a particular variety over other producers, we should observe the opposite: patents should have larger effects for less differentiated industries where cost and quality differences weigh more heavily on market share.

Column 2 of Table 3 interacts both of our patent stock variables with a "high elasticity" indicator equal to 1 for industries with an above-median demand elasticity, 0 otherwise. The results overwhelmingly support the interpretation that patents have larger effects on trade in less differentiated (i.e., high elasticity) industries.[33] In fact, not only do we find that our earlier positive and significant estimates for the effects of the exporter's patent stock on trade are entirely driven by high elasticity industries, we also find that the interaction between the *importer*'s stock of patents in the exporting country is significant and negative. To interpret, patents in high elasticity industries appear to induce anti-competitive effects affecting both directions of trade: the patent filing country's exports grow and the patent granting country's exports to the filing country fall relative to exports in other sectors. Note that we cannot definitively say whether this latter interaction is significant because patents increase low elasticity imports or because they significantly decrease high-elasticity imports. Neither the main import effect nor the sum of the main effect and its interaction with "high elasticity" are statistically significant.[34]

What we can say is that the effects of patents on exports in high elasticity industries specifically is highly significant economically in addition to being statistically significant. The sum of the coefficients on "log $\widehat{K}_{ijkt}$" and "log $\widehat{K}_{ijkt}$ $\times$ high elasticity" is 0.038 and is itself statistically significant ($p < 0.01$). Using our earlier calculations, this combined coefficient equates to a difference in peak effects on exporting of 18.7% for high versus low value patent flows in these industries, comparable to the average effect of an FTA on industry-level trade. Furthermore, the leads associated with all

[32] For a canonical example, see Grossman and Lai (2004).

[33] Interestingly, the distributions of patents are very similar in high- and low-elasticity industries, implying no important difference between the two industry groups in terms of the value of patents.

[34] One explanation for this ambiguity is demonstrated in column 3, which suggests a slight negative pre-trend for imports in low elasticity industries versus high elasticity industries and (as a consequence) shows a significant and positive contemporaneous effect for imports in low elasticity industries. Another explanation, which we will document momentarily, involves the narrow concentration of these negative effects on imports in "capital goods" categories in particular.

patent variables from column 2 of Table 3, added next in column 3, continue to show no evidence of significant pre-trends in trade in either direction of trade. Notably, they also show no evidence that pre-trends in high elasticity industries differ significantly either from zero or from pre-trends in other industries.

Next, we test for evidence whether the patents we observe represent innovations that affect the quality of the product specifically (as opposed to only affecting the production cost). Following the "Washington apples" literature, we include interactions between our patent stock variables and the log of bilateral distance, a natural proxy for the per-unit shipping costs that are needed to induce a "Washington apples"-type effect in this context. As column 4 of Table 3 shows, the interaction between log $\widehat{K}_{ijkt}$ (the export-side patent stock) and the log of distance in column is positive and significant, indicating the effect of patents on exports is larger for more distant markets as expected.[35] Columns 5-7 shows this effect remains steady when we add leads (column 5), interactions with "high elasticity" (column 6), or both (column 7). Our earlier results for "high elasticity" are also unaffected. Consistent with our earlier results, the import effect remains insignificant. When we add leads in column 5 and 7, the lead effect for the import-side patent stock-distance interaction ("log $\widehat{K}_{jikt+4}$ $\times$ ln DIST") is negative and statistically significant, which may suggest a pre-trend on the import effect for more distant markets but does not take away from the other results. Moreover, as we add more interactions between the two patent stocks and other variables in this way, this type of test should be expected to become more demanding.

The last column of Table 3 then interacts both stock variables with several further controls that could affect trade costs and/or patenting costs. These include the sharing of a common language or legal system as well as indicators for whether the patent-granting countries has a "medium" or "high" level of intellectual property rights protections. These latter dummies use the Park (2008) index for the quality of patent protections, a standard measure in the literature. Specifically, the index scores countries between 0 and 5. "Low", "medium", and "high" IPR correspond to scores less than 2, between 2 and 4, and above 4 respectively. The inclusion of IPR rights is important because high levels of patenting could simply hide strong IPR regulation. Interestingly, the interactions between patent stocks and the IPR indicators are not significant. A possible explanation is that higher IPR protections may attract both trade and other channels for foreign sales that substitute for trade in roughly equal measure. Our earlier results are not materially affected by the addition

[35]Since log distance is a continuous variable, we use the difference between log distance and the mean log distance for these interactions. This means all other point estimates can be interpreted as occurring at the mean log distance between countries. If we do not do this, the main effect captures the mean log distance effect and changes in the mean effect across specifications become harder to interpret.

of these controls.[36]

High and medium tech versus low tech industries. Having established these results for all 249 industries in our data, a natural way of further demonstrating their validity is to separate out the industries where we would expect to observe patents playing an important role. Following Palangkaraya, Jensen, and Webster (2017), we therefore show in Table 4 how our results vary across "high and medium tech" industries versus "low tech" industries. To make this distinction, we use industries whose R&D intensities lie above the 33rd percentile as the "high- and medium-tech" group of industries. All other industries are considered "low-tech". As Table 4 shows, our earlier results are driven entirely by high- and medium-tech industries.[37,38]

Heterogeneous effects by end-usage. Given that the cross-border patenting may be important for the spreading and deepening of global supply chains, another interesting way of splitting up industries is by end-usage (e.g., as intermediate input versus final goods). Columns 3-6 of Table 5 thus examine how our earlier results vary for intermediate goods, final goods, and two different final goods subcategories ("Consumption Goods" and "Capital Goods"). All results repeat the same specification from the last column of Table 3 with a full set of controls. Surprisingly, results do not vary much across these very different product categories. All of these industry subgroupings aside from Capital Goods exhibit positive and significant effects for exports in high elasticity industries within that category. Even for Capital Goods, results are not especially dissimilar: while we do not observe significant effects for capital goods exports for either high or low elasticity industries, the negative and highly significant coefficient for "log $\widehat{K}_{jikt}$ × high elasticity" of -0.045 ($p < 0.01$) for Capital Goods indicates that, even though Capital Goods exports do not increase following the filing of new patents, competition in the patent-holder's own *domestic* market may still be affected. Results for distance do not change much in magnitude either across these subgroupings, though statistical significance appears mainly driven by the "intermediate goods" category in this case.

We also show results for "homogeneous" industries versus "differentiated" industries, using the

[36] While we document statistically significant interactions for some of these controls that could invite various interpretations (perhaps sharing common legal substitutes substitutes for stronger patenting, for example.), we have generally found these results disappear when we examine pre-trends for these interactions. Thus, we have chosen not to devote much exposition to interpreting these coefficients, preferring instead to view them mainly as controls worth taking into account.

[37] The inclusion of lead variables for high- and medium- tech industry groupings does not indicate the presence of pre-trends. This is the case also for all remaining tables: the results remain even with the inclusion of lead variables, which are consistently not significant.

[38] We can also break out results for high versus medium tech. As one might expect, results are similar across both categories. The main differences turn out to be that the coefficient for the import-side interaction with "high elasticity" is only significant for high tech industries and that IPR institutions seem to be important for promoting high tech exports but not medium tech exports.

Rauch (1999) measure of product differentiation. These experiments, shown in columns 1 and 2 of Table 5, are motivated based on our preference for the elasticity estimates from Broda and Weinstein (2006) as our measure of differentiation. Notably, our results for industries we classify as "differentiated" based on Rauch (1999)'s coding in column 1 continue to demonstrate similar coefficients for the two interactions between our patent stock variables and our index based on Broda and Weinstein (2006)'s estimates as we have seen throughout the preceding experiments. The coefficient for the export-side distance effect is also similar as before. The results for "homogeneous" industries are slightly different, showing no significant effect of patents on exports, but a large and significant negative coefficient for log $\widehat{K}_{jikt}$ × high elasticity. The takeaway here again seems to be that the degree of differentiation appears to matter within either broad category.

Heterogeneous effects by factor-intensity. Continuing in a similar vein as Table 5, Table 6 shows further results for industry subgroupings broken out by factor intensity. Thanks to the rich data provided by Nunn and Trefler (2013), we are able to consider a very wide range of factor intensities, including not only capital intensity, skill intensity, and labor intensity, but also several different subcategories of capital intensity (building intensity, machine intensity, automobile intensity, computer intensity, and "other capital" intensity") as well as the value added share. For each of these factor intensity measures, we take any industry with a factor intensity above the median across all industries to be intensive in that factor. The one exception is for labor intensive industries, which we take to be any industry that is neither skill-intensive nor capital-intensive.

The different columns of Table 6 show results for the sets of industries that are especially intensive in each of these factors (including the share of value added in the value of output). The results are once again strikingly similar across all the different industry types we consider.[39] Taken together with our earlier results, we can conclude the sources of heterogeneity we are identifying in our full data set are very common across many different types of industries, especially our results for industries associated with a higher elasticity of substitution.

5.3 Additional Sensitivity Checks

Because the empirical framework we have constructed requires a complex set of choices on our part, Table 7 examines the sensitivity of our analysis to various reasonable alternatives. We consider first whether our results are affected by dropping all EPO countries from our sample. Noting that our PATSTAT data does not indicate the country (or countries) where EPO patents are designated

[39]We also experimented with removing the pharmaceutical industry, which is highly reliant on intellectual property and could behave differently from the rest, but we do not find any significant difference.

to be applied, this is an important check that ensures our results are not driven by how we have treated these patents. Though removing the EPO is very costly in terms of how it affects the sample (removing 80% of the original number of observations), we actually find that our results for patenting in high elasticity industries are, if anything, even stronger than before. On the other hand, the distance effect we observed for exports in the full sample declines in magnitude substantially without the EPO (from 0.011 to 0.002) and also loses its statistical significance.

Next, Column 2 of Table 7 experiments with dropping only a single country, the U.S. The motivation behind this check is the concern that our results could be driven by "non-practicing entities" (often referred to as "patent trolls"), which are known for asserting patent rights inventions without actually producing products associated with those innovations.[40] Anecdotally, patent trolls are known to be predominantly active in the U.S. (Fusco, 2013). Dropping the U.S. entirely is thus a conservative way of dealing with this concern. Patents continue to have a statistically significant effect on exports in high elasticity industries when the U.S. is removed, though our results for imports in high elasticity industries and for the interaction with distance weaken and become statistically insignificant. An interesting observation based on this experiment is that the inclusion of the U.S. as an exporter is necessary for us to observe differences between high and low elasticity industries on the import side.

Column 3 of Table 7 drops any importer with a "low" level of intellectual property rights protection (i.e., a Park index below 2). Intuitively, we might expect low IPR countries to be less relevant as patent destinations. However, compared with earlier results, the main difference that sticks out here is that patents become more effective for promoting exports over longer distances. One possible interpretation is that higher IPR protections may be relatively more conducive for protecting quality innovations versus other innovations.

Columns 4-5 experiment with varying the fixed effects used. Column 4 adopts an even more rigorous fixed effects specification with an added ijt fixed effect that accounts for common trends in trade within pairs across all industries. Column 5 moves in the other direction by relaxing our ikt and jkt fixed effects in favor of it, jt, and kt fixed effects. Neither change substantially affects our prior results for the role of the elasticity of substitution, but the results without ikt and jkt fixed effects lead to a large and significant coefficient for the main import effect of 0.074, consistent with the upward bias found earlier in Table 7.[41]

[40] This is related also to 'strategic patenting", where a patent is filed in a country to ensure that no production occurs in that country, rather than to sell in said country. If this type of patenting was driving our results, we should see no effect of patents filed by country i in country j on trade between that ij pair. Our results clearly show this is not the case.

[41] An alternative interpretation might be that patents are stimulating spillovers in productivity that induce increased

Finally, columns 6-8 employ various alternative ways of constructing our patent stock variables. Column 6 uses alternate stock values calculated using $\omega_1 = 0.35$ and $\omega_2 = 0.05$, which correspond to faster diffusion and slower decay relative to our baseline. The stocks used in column 7 assume $\omega_1 = \omega_2 = 0.15$, or slower diffusion and faster decay. Interestingly, these two sets of results are more similar to one another than they are to our original results, though they are not radically different either. A simple goodness of fit test indicates our preferred values for ω_1 and ω_2 give us stock values that fit the data better than either of these alternatives. The last column uses $\log(1 + \widehat{K})$ instead of $\log \widehat{K}$ for the two patent variables. This change in functional form has the advantage of enabling us to include additional observations where $\widehat{K}$ is 0 (tripling the sample), but has the disadvantages of imposing strong assumptions about how observations with zero stock values should be treated and altering the assumed life span of a patent. At any rate, the general result that patents promote exports in more elastic sectors is overwhelmingly supported here as well. We do not observe any significant results for distance or for imports in more elastic sectors, however. It is plausible these latter results emanate from the gradual accumulation of existing patent stocks over time, rather than from the initiation of new patent stocks.

6 Conclusion

Cross-border patenting is regarded anecdotally and theoretically as an important marker of globalization and the spread of knowledge across borders. But what the decision to file a patent in a particular trade partner can tell us about the motivations behind cross-border patents and their implications for trade remains an open question. To provide answers, we assemble a highly disaggregated data set of industry-level trade flows and cross-border patents, which we subject to a rich set of fixed effects that allow us to specifically isolate the bilateral dimension of the data for a given industry. Notably, ours is the first study to systematically investigate what the implications of bilateral patenting are for international trade using a large and highly disaggregated data set.

Our main finding is that bilateral patents in a given industry on average promote bilateral exports in that same industry, with no significant effect seen for imports returning in the opposite direction. However, we find these overall results mask substantial sources of heterogeneity across industries and across markets. Namely, we find very strong evidence that the pro-exporting effects

exports from the patent-granting country to all destinations (i.e., not just to the country where the patent originated from). In our preferred specification, this type of spillover is absorbed by the *ikt* fixed effect. In general, it is hard to determine whether patents flow to sectors with fast productivity growth or whether foreign patents flowing to a particular sector independently contributes to changes in sectoral comparative advantage. This alone could be the subject of a future study building on the methods put forward in this paper.

of patents are concentrated in less-differentiated industries and slightly weaker (though still on the whole robust) evidence that import growth in less-differentiated industries is concurrently negatively affected. We also find some evidence the patents promote exports more strongly to more distant markets. Taken together, these results support the interpretation that patents are used to preserve advantages in production costs and/or product quality versus foreign competitors. Given that technology diffusion is a significant determinant of economic growth (c.f., Comin and Hobijn, 2010), we hope these findings can inform policies intended to stimulate innovation and promote the diffusion of knowledge.

A further intended contribution of this paper is our attempt to provide a methodology that can be used to analyze bilateral patent flows in conjunction with bilateral trade flows in a panel setting. By allowing patents to have effects that grow and decay over time and by pursuing a rigorous fixed effects specification that allows us to specifically isolate the within-industry and within-pair dimension of the data, we are able to obtain estimates that we would argue are surprisingly well-identified in the face of natural concerns about reverse causality. For future work, an attractive extension would be to adopt a more structural approach in order to disentangle whether foreign patents contribute to the transmission of technological comparative advantage in a manner consistent with theories of trade and growth.

References

ALCHIAN, A. A., AND W. R. ALLEN (1972): *University Economics: Elements of Inquiry.* Wadsworth.

ALFARO, L., P. ANTRÀS, D. CHOR, AND P. CONCONI (2015): "Internalizing Global Value Chains: A Firm-Level Analysis," Working Paper 21582, National Bureau of Economic Research.

ANDERSON, J. E., AND E. VAN WINCOOP (2003): "Gravity with Gravitas: A Solution to the Border Puzzle," *American Economic Review*, 93(1), 170–192.

ANDERTON, B. (1999): "Innovation, Product Quality, Variety, and Trade Performance: An Empirical Analysis of Germany and the UK," *Oxford Economic Papers*, 51(1), 152–167.

ANTIMIANI, A., AND V. COSTANTINI (2013): "Trade Performances and Technology in the Enlarged European Union," *Journal of Economic Studies*, 40(3), 355–389.

ANTRÀS, P., AND D. CHOR (2013): "Organizing the Global Value Chain," *Econometrica*, 81(6), 2127–2204.

AUTOR, D., D. DORN, G. H. HANSON, G. PISANO, AND P. SHU (2016): "Foreign Competition and Domestic Innovation: Evidence from U.S. Patents," Working Paper 22879, National Bureau of Economic Research, DOI: 10.3386/w22879.

BAIER, S. L., AND J. H. BERGSTRAND (2007): "Do Free Trade Agreements Actually Increase Members' International Trade?," *Journal of International Economics*, 71(1), 72–95.

BALDWIN, R., AND D. TAGLIONI (2007): "Trade Effects of the Euro: A Comparison of Estimators," *Journal of Economic Integration*, 22(4), 780–818.

BATRAKOVA, S., AND A. DECHEZLEPRÊTRE (2013): "Is there a Trade-off between 'Dirty' Imports and 'Clean' Innovation?," Discussion paper, Mimeo.

BLONIGEN, B. A. (2001): "In Search of Substitution between Foreign Production and Exports," *Journal of International Economics*, 53(1), 81–104.

BLOOM, N., M. DRACA, AND J. V. REENEN (2011): "Trade Induced Technical Change? The Impact of Chinese Imports on Innovation, IT and Productivity," Working Paper 16717, National Bureau of Economic Research, DOI: 10.3386/w16717.

BOND, E. W., AND K. SAGGI (2014): "Compulsory Licensing, Price Controls, and Access to Patented Foreign Products," *Journal of Development Economics*, 109, 217–228.

BORCHERDING, T. E., AND E. SILBERBERG (1978): "Shipping the Good Apples Out: the Alchian and Allen Theorem Reconsidered," *Journal of Political Economy*, 86(1), 131–138.

BORING, A. (2015): "The Impact of Patent Protection on US Pharmaceutical Exports to Developing

Countries," *Applied Economics*, 47(13), 1314–1330.

Briggs, K., and W. G. Park (2014): "There will be Exports and Licensing: The Effects of Patent Rights and Innovation on Firm Sales," *The Journal of International Trade & Economic Development*, 23(8), 1112–1144.

Broda, C., and D. E. Weinstein (2006): "Globalization and the Gains from Variety," *Quarterly Journal of Economics*, 121(2), 541–585.

Brunel, C. (2017): "Green Innovation and Green Manufacturing: Links between Environmental Policies, Innovation, and Production," *unpublished manuscript*.

Chalioti, E., S. Drivas, Kyriakos Kalyvitas, and M. Katsimi (2017): "Innovation, Patents and Trade: A Firm-level Analysis," Discussion paper, mimeo.

Chen, W.-C. (2013): "The Extensive and Intensive Margins of Exports: The Role of Innovation," *The World Economy*, 36(5), 607–635.

Cheng, I.-h., and H. J. Wall (2005): "Controlling for Heterogeneity in Gravity Models of Trade and Integration," *Federal Reserve Bank of St. Louis Review*, 87(1), 49–64.

Comin, D., and B. Hobijn (2010): "An Exploration of Technology Diffusion," *The American Economic Review*, 100(5), 2031–2059.

Correia, S. (2015): "Singletons, Cluster-robust Standard Errors and Fixed Effects: A Bad Mix," *Unpublished paper*.

Correia, S., P. Guimarães, and T. Zylkin (2019a): "PPMLHDFE: Fast Poisson Estimation with High-dimensional Data," *Unpublished manuscript*.

——— (2019b): "Verifying the Existence of Maximum Likelihood Estimates for Generalized Linear Models," *Unpublished manuscript*.

De Rassenfosse, G. (2013): "Do Firms Face a Trade-off between the Quantity and the Quality of their Inventions?," *Research Policy*, 42(5), 1072–1079.

De Rassenfosse, G., A. Palangkaraya, and E. Webster (2016): "Why do Patents Facilitate Trade in Technology? Testing the Disclosure and Appropriation Effects," *Research Policy*, 45(7), 1326–1336.

Dernis, H., and M. Khan (2004): "Triadic Patent Families Methodology," .

Feenstra, R. C., R. E. Lipsey, H. Deng, A. C. Ma, and H. Mo (2005): "World Trade Flows: 1962-2000," Working Paper 11040, National Bureau of Economic Research.

Figueiredo, O., P. Guimarães, and D. Woodward (2015): "Industry Localization, Distance Decay, and Knowledge Spillovers: Following the Patent Paper Trail," *Journal of Urban Economics*, 89(C), 21–31.

French, S. (2016): "The Composition of Trade Flows and the Aggregate Effects of Trade Barriers," *Journal of International Economics*, 98, 114–137.

——— (2019): "Comparative Advantage and Biased Gravity," *Unpublished manuscript.*

Fusco, S. (2013): "Markets and Patent Enforcement: A Comparative Investigation of Non-Practicing Entities in the United States and Europe," *Mich. Telecomm. & Tech. L. Rev.*, 20, 439.

Glick, R., and A. K. Rose (2016): "Currency Unions and Trade: A Post-EMU Reassessment," *European Economic Review*, 87, 78–91.

Greenhalgh, C. (1990): "Innovation and Trade Performance in the United Kingdom," *The Economic Journal*, 100(400), 105–118.

Griliches, Z. (1995): "R&D and Productivity: Econometric Results and Measurement Issues," in *Handbook of the Economics of Innovation and Technological Change*, pp. 52–89. Blackwell Publishers.

——— (1998): "Patent Statistics as Economic Indicators: a Survey," in *R&D and Productivity: the Econometric Evidence*, pp. 287–343. University of Chicago Press.

Grossman, G. M., and E. L.-C. Lai (2002): "International Protection of Intellectual Property," *NBER Working Paper*, 8704.

——— (2004): "International Protection of Intellectual Property," *American Economic Review*, 94(5), 1635–1653.

Head, K., and T. Mayer (2014): "Gravity Equations: Workhorse, Toolkit, and Cookbook," in *Handbook of International Economics*, ed. by G. Gopinath, E. Helpman, and K. Rogoff, vol. 4, pp. 131–195. North Holland, 4 edn.

Hummels, D., and A. Skiba (2004): "Shipping the Good Apples Out? An Empirical Confirmation of the Alchian-Allen Conjecture," *Journal of Political Economy*, 112(6), 1384–1402.

Ivus, O. (2010): "Do Stronger Patent Rights Raise High-tech Exports to the Developing World?," *Journal of International Economics*, 81(1), 38–47.

Keller, W. (2004): "International Technology Diffusion," *Journal of Economic Literature*, 42(3), 752–782.

Keller, W., and S. R. Yeaple (2013): "The Gravity of Knowledge," *The American Economic Review*, 103(4), 1414–1444.

Kinzius, L., A. Sandkamp, and E. Yalcin (2018): "Trade Protection and the Role of Non-tariff Barriers," Discussion paper.

Lai, E. L.-C., and L. D. Qiu (2003): "The North's Intellectual Property Rights Standard for the

South?," *Journal of International Economics*, 59(1), 183–209.

Larch, M., J. Wanner, Y. V. Yotov, and T. Zylkin (2018): "Currency Unions and Trade: A PPML Re-assessment with High-dimensional Fixed Effects," *Oxford Bulletin of Economics and Statistics*.

Limão, N. (2007): "Are Preferential Trade Agreements with Non-trade Objectives a Stumbling Block for Multilateral Liberalization?," *The Review of Economic Studies*, 74(3), 821–855.

Lovely, M., and D. Popp (2011): "Trade, Technology, and the Environment: Does Access to Technology Promote Environmental Regulation?," *Journal of Environmental Economics and Management*, 61(1), 16–35.

Lybbert, T. J., and N. J. Zolas (2014): "Getting Patents and Economic Data to Speak to each Other: An 'Algorithmic Links with Probabilities' Approach for Joint Analyses of Patenting and Economic Activity," *Research Policy*, 43(3), 530–542.

Maskus, K. E. (2018): "International Agreements on Intellectual Property Rights: TRIPS and Beyond," in *Handbook of International Trade Agreements*, pp. 59–70. Routledge.

Maskus, K. E., and M. Penubarti (1995): "How Trade-related are Intellectual Property Rights?," *Journal of International Economics*, 39(3), 227–248.

McCalman, P. (2001): "Reaping What you Sow: An Empirical Analysis of International Patent Harmonization," *Journal of International Economics*, 55(1), 161–186.

Nunn, N., and D. Trefler (2013): "Incomplete Contracts and the Boundaries of the Multinational Firm," *Journal of Economic Behavior & Organization*, 94(Supplement C), 330–344.

Palangkaraya, A., P. H. Jensen, and E. Webster (2017): "The Effect of Patents on Trade," *Journal of International Economics*, 105, 1–9.

Park, W. G. (2008): "International Patent Protection: 1960–2005," *Research Policy*, 37(4), 761–766.

Popp, D. (2002): "Induced innovation and energy prices," *American economic review*, 92(1), 160–180.

——— (2003): "Pollution control innovations and the Clean Air Act of 1990," *Journal of Policy Analysis and Management*, 22(4), 641–660.

Popp, D., I. Hascic, and N. Medhi (2011): "Technology and the Diffusion of Renewable Energy," *Energy Economics*, 33(4), 648–662.

Rauch, J. E. (1999): "Networks versus Markets in International Trade," *Journal of International Economics*, 48(1), 7–35.

Robbins, C. A. (2006): "The Impact of Gravity-weighted Knowledge Spillovers on Productivity in Manufacturing," *The Journal of Technology Transfer*, 31(1), 45–60.

Saggi, K. (2002): "Trade, Foreign Direct Investment, and International Technology Transfer: A Survey," *The World Bank Research Observer*, 17(2), 191–235.

——— (2016): "Trade, Intellectual Property Rights, and the World Trade Organization," in *Handbook of Commercial Policy*, vol. 1, pp. 433–512. Elsevier.

Santos Silva, J. M. C., and S. Tenreyro (2006): "The Log of Gravity," *Review of Economics and Statistics*, 88(4), 641–658.

Scherngell, T., and Y. Hu (2011): "Collaborative Knowledge Production in China: Regional Evidence from a Gravity Model Approach," *Regional Studies*, 45(6), 755–772.

Schmidt, J., and W. Steingress (2018): "No Double Standards: Quantifying the Impact of Standard Harmonization on Trade," Discussion paper, mimeo.

Weidner, M., and T. Zylkin (2018): "Bias and Consistency in Three-Way Gravity Models," *unpublished manuscript*.

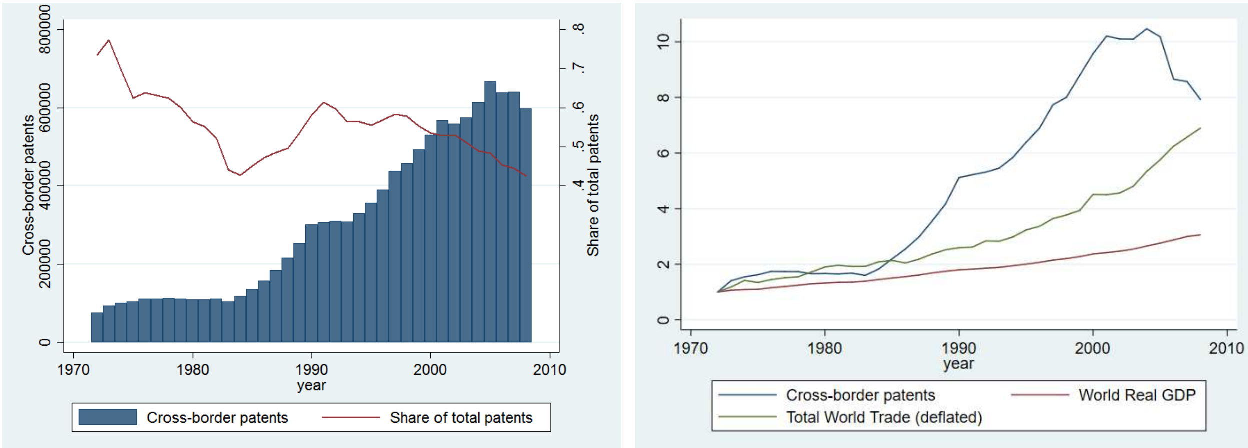
Wooldridge, J. M. (2002): *Econometric Analysis of Cross Section and Panel Data*. MIT Press, Cambridge, MA.

Yang, L., and K. E. Maskus (2009): "Intellectual Property Rights, Technology Transfer and Exports in Developing Countries," *Journal of Development Economics*, 90(2), 231–236.

Yotov, Y. V., R. Piermartini, J.-A. Monteiro, and M. Larch (2016): *An Advanced Guide to Trade Policy Analysis: The Structural Gravity Model*. World Trade Organization, Geneva.

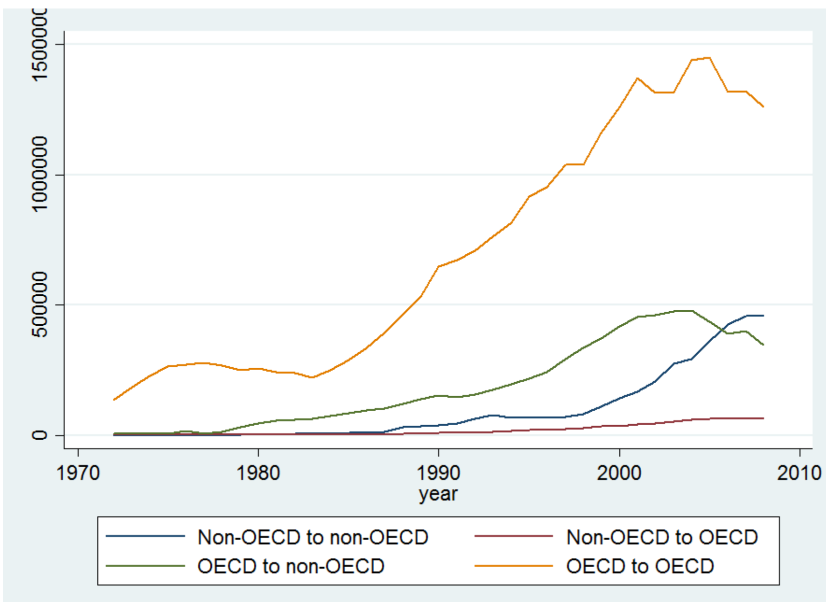
7 Figures

Figure 1: Growth in Cross-border Patenting Flows,1972-2008



Note: the left graph shows total world cross-border patents as share of total world patents. The right graph shows growth in cross-border patenting between 1972-2008 versus growth in world trade and world real GDP. All values in the right graph are normalized to 1 in 1972. World trade values are deflated using the US GDP deflator. Patent counts are the raw number of patents filed in a given year. Sources: PATSTAT, WDI.

Figure 2: Counts of patents by origin type and destination type, 1972-2008



Note: Patent counts are the raw number of patents filed in a given year. We include cross-border patents only. Source: PATSTAT.

8 Tables

Table 1: Summary statistics of patent data

Variable	Mean	Median	Std. Dev.	Min.	Max.
Patent flow (unweighted)	7	0	89	0	$30,532$
OECD	11	0	110	0	$30,532$
Other	1	0	31	0	$21,438$
Patent flow (weighted)	33	0	529	0	$131,408$
OECD	59	0	718	0	$131,408$
Other	2	0	48	0	$27,274$
Patent stock	179	0	2914	0	$593,947$
OECD	322	0	3729	0	$593,947$
Other	10	0	185	0	$34,179$
Patent stock (non-zero only)	689	10	5683	0.0001	$593,947$
OECD	958	19	6771	0.0002	$593,497$
Other	61	2	446	0.0001	$34,179$

Unweighted patent flows are simple counts of the number of patents filed. Weighted patents flows account for value by weighting each patent by its family size. Stocks are created using the value-weighted patent flows. Due to the concordance between the patent and trade datasets, flows can be non-integer values below 1.

Table 2: Do Cross-Border Patent Promote Trade?

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FTA	0.376***	0.386***	0.270***	0.167***	0.404***	0.241***	0.155***	0.128***
	(0.140)	(0.142)	(0.055)	(0.037)	(0.122)	(0.049)	(0.029)	(0.029)
log $\widehat{K}_{ijkt}$ (*export effect*)	0.307***	0.296***	0.404***	0.059***	0.116***	0.109***	0.018**	0.016**
	(0.020)	(0.021)	(0.024)	(0.009)	(0.018)	(0.011)	(0.007)	(0.007)
log $\widehat{K}_{jikt}$ (*import effect*)	0.031**	0.057***	0.038**	-0.001	0.069***	0.032***	0.000	0.001
	(0.014)	(0.014)	(0.016)	(0.004)	(0.013)	(0.007)	(0.003)	(0.003)
FTA$_{t+4}$ (*lead FTA effect*)								0.049*
								(0.025)
log $\widehat{K}_{ijt+4}$ (*export effect, lead*)								0.003
								(0.011)
log $\widehat{K}_{jit+4}$ (*import effect, lead*)								-0.002
								(0.003)
Fixed effects:								
Country pair	x	x	x	x				
Industry		x	x					
Time	x	x		x	x			
Exporter-time			x			x		
Importer-time			x			x		
Exporter-industry-time				x			x	x
Importer-industry-time				x			x	x
Industry-country pair					x	x	x	x
N	1,102,503	1,102,503	1,102,404	1,080,301	1,022,501	1,022,388	1,000,617	904,131

The dependent variable is industry-level (3 digit SITC rev 2) trade flows between 149 countries covering 1974-2006, using every 4 years. All estimations use PPML. Standard errors, shown in parentheses, are clustered by country-pair. log $\widehat{K}_{jikt}$ refers to (the log of) the stock of patents filed by the importer j in the exporting country i in industry k. log $\widehat{K}_{ijt}$ refers to (the log of) the stock of patents filed by the exporting country i in the importing country j in industry k. The construction of these stocks is described in Section 4.2. Observation counts vary because we first use the algorithm of Correia (2015) to reduce the sample by removing perfectly predicted observations.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Concentration of Effects in More Competitive Industries & More Distant Export Markets

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FTA	0.155***	0.154***	0.128***	0.166***	0.158***	0.166***	0.140***	0.171***
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
log $\widehat{K}_{ijkt}$ (*export effect*)	0.018**	0.001	0.001	0.013*	0.013*	-0.004	-0.003	-0.002
	(0.007)	(0.009)	(0.009)	(0.007)	(0.007)	(0.009)	(0.009)	(0.009)
log $\widehat{K}_{jikt}$ (*import effect*)	0.000	0.005	0.007**	0.001	0.000	0.006	0.007*	0.006
	(0.003)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.005)
log $\widehat{K}_{ijkt}$ × high elasticity		0.037***	0.034***			0.038***	0.035***	0.037***
		(0.011)	(0.012)			(0.011)	(0.012)	(0.011)
log $\widehat{K}_{jikt}$ × high elasticity		-0.011**	-0.013**			-0.011**	-0.014***	-0.012**
		(0.005)	(0.005)			(0.005)	(0.005)	(0.005)
log $\widehat{K}_{ijkt}$ × ln DIST				0.011***	0.010**	0.011***	0.010**	0.009**
				(0.004)	(0.005)	(0.004)	(0.005)	(0.004)
log $\widehat{K}_{jikt}$ × ln DIST				-0.003	0.001	-0.003	0.001	-0.005
				(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
FTA$_{t+4}$ (*lead FTA effect*)			0.050**		0.047*		0.048*	
			(0.025)		(0.025)		(0.025)	
log $\widehat{K}_{ijt+4}$ (*export effect, lead*)			-0.002		0.002		-0.003	
			(0.014)		(0.010)		(0.014)	
log $\widehat{K}_{jit+4}$ (*import effect, lead*)			-0.006		0.001		-0.002	
			(0.004)		(0.004)		(0.005)	
log $\widehat{K}_{ijkt+4}$ × high elasticity			0.012				0.011	
			(0.015)				(0.015)	
log $\widehat{K}_{jikt+4}$ × high elasticity			0.008				0.008	
			(0.006)				(0.006)	
log $\widehat{K}_{ijkt+4}$ × ln DIST					0.005		0.005	
					(0.005)		(0.005)	
log $\widehat{K}_{jikt+4}$ × ln DIST					-0.008**		-0.008**	
					(0.004)		(0.004)	
log $\widehat{K}_{ijkt}$ × LANG								-0.022**
								(0.010)
log $\widehat{K}_{jikt}$ × LANG								-0.019**
								(0.009)
log $\widehat{K}_{ijkt}$ × LEGAL								0.018***
								(0.007)
log $\widehat{K}_{jikt}$ × LEGAL								0.003
								(0.006)
log $\widehat{K}_{ijkt}$ × MED IPR								0.014
								(0.025)
log $\widehat{K}_{jikt}$ × MED IPR								-0.010
								(0.022)
log $\widehat{K}_{ijkt}$ × HIGH IPR								0.002
								(0.023)
log $\widehat{K}_{jikt}$ × HIGH IPR								0.011
								(0.023)
N	1,000,617	999,600	903,481	1,000,617	904,131	999,600	903,481	999,600

The dependent variable is industry-level (3 digit SITC rev 2) trade flows between 149 countries covering 1974-2006, using every 4 years. Standard errors, shown in parentheses, are clustered by country-pair. All estimations use PPML with exporter-industry-time (ikt), importer-industry-time (jkt), and exporter-importer-industry (ijk) fixed effects. log $\widehat{K}_{jikt}$ refers to (the log of) the stock of patents filed by the importer j in the exporting country i in industry k. log $\widehat{K}_{ijkt}$ refers to (the log of) the stock of patents filed by the exporting country i in the importing country j in industry k. The construction of these stocks is described in Section 4.2. Observation counts vary because we first use the algorithm of Correia (2015) to reduce the sample by removing perfectly predicted observations.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: High- & Medium-Tech vs. Low-Tech Industries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	High & med tech				Low-tech			
FTA	0.143***	0.156***	0.133***	0.160***	0.262***	0.243***	0.166***	0.242***
	(0.031)	(0.030)	(0.031)	(0.030)	(0.062)	(0.067)	(0.059)	(0.065)
log $\widehat{K}_{ijkt}$ (*export effect*)	0.019**	-0.004	-0.008	-0.001	0.010	0.010	0.040**	0.000
	(0.008)	(0.009)	(0.010)	(0.010)	(0.011)	(0.018)	(0.018)	(0.016)
log $\widehat{K}_{jikt}$ (*import effect*)	0.001	0.006	0.007*	0.005	-0.005	0.001	0.001	0.009
	(0.003)	(0.004)	(0.004)	(0.005)	(0.006)	(0.011)	(0.012)	(0.010)
log $\widehat{K}_{ijkt}$ × high elasticity		0.044***	0.046***	0.043***		0.003	-0.030	0.008
		(0.012)	(0.013)	(0.012)		(0.023)	(0.022)	(0.022)
log $\widehat{K}_{jikt}$ × high elasticity		-0.012**	-0.014**	-0.012**		-0.003	-0.007	-0.005
		(0.006)	(0.006)	(0.006)		(0.011)	(0.011)	(0.011)
log $\widehat{K}_{ijkt}$ × ln DIST		0.011***	0.011**	0.009**		0.003	-0.001	0.003
		(0.004)	(0.005)	(0.004)		(0.007)	(0.007)	(0.007)
log $\widehat{K}_{jikt}$ × ln DIST		-0.002	0.002	-0.004		-0.011***	-0.008**	-0.012***
		(0.003)	(0.003)	(0.003)		(0.004)	(0.004)	(0.004)
FTA_{t+4} (*lead FTA effect*)			0.039				0.137***	
			(0.026)				(0.048)	
log $\widehat{K}_{ijt+4}$ (*export effect, lead*)			0.006				-0.088***	
			(0.015)				(0.031)	
log $\widehat{K}_{jit+4}$ (*import effect, lead*)			-0.003				0.004	
			(0.006)				(0.010)	
log $\widehat{K}_{ijkt+4}$ × high elasticity			0.000				0.100***	
			(0.017)				(0.035)	
log $\widehat{K}_{jikt+4}$ × high elasticity			0.009				-0.004	
			(0.007)				(0.011)	
log $\widehat{K}_{ijkt+4}$ × ln DIST			0.004				0.014	
			(0.006)				(0.009)	
log $\widehat{K}_{jikt+4}$ × ln DIST			-0.008*				-0.011**	
			(0.004)				(0.005)	
log $\widehat{K}_{ijkt}$ × LANG				-0.029***				0.027
				(0.011)				(0.019)
log $\widehat{K}_{jikt}$ × LANG				-0.016*				-0.048***
				(0.010)				(0.014)
log $\widehat{K}_{ijkt}$ × LEGAL				0.019***				0.004
				(0.007)				(0.011)
log $\widehat{K}_{jikt}$ × LEGAL				0.002				0.013
				(0.006)				(0.009)
log $\widehat{K}_{ijkt}$ × MED IPR				0.045*				-0.184***
				(0.026)				(0.063)
log $\widehat{K}_{jikt}$ × MED IPR				-0.012				0.024
				(0.024)				(0.036)
log $\widehat{K}_{ijkt}$ × HIGH IPR				0.021				-0.118**
				(0.024)				(0.048)
log $\widehat{K}_{jikt}$ × HIGH IPR				0.018				-0.024
				(0.026)				(0.038)
N	832,122	831,105	753,566	831,105	168,495	168,495	149,915	168,495

The dependent variable is industry-level (3 digit SITC rev 2) trade flows between 149 countries covering 1974-2006, using every 4 years. Standard errors, shown in parentheses, are clustered by country-pair. All estimations use PPML with exporter-industry-time (ikt), importer-industry-time (jkt), and exporter-importer-industry (ijk) fixed effects. log $\widehat{K}_{jikt}$ refers to (the log of) the stock of patents filed by the importer j in the exporting country i in industry k. log $\widehat{K}_{ijkt}$ refers to (the log of) the stock of patents filed by the exporting country i in the importing country j in industry k. The construction of these stocks is described in Section 4.2. High- and medium-tech industries are distinguished from low-tech industries using R&D intensities (R&D/Sales ratios) from Nunn and Trefler (2013). Observation counts vary because we first use the algorithm of Correia (2015) to reduce the sample by removing perfectly predicted observations.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Industry-level Breakdown (by end-use)

	(1) Differentiated	(2) Homogeneous	(3) Intermediate Goods	(4) Final Goods	(5) Consumption Goods	(6) Capital Goods
FTA	0.163***	0.236***	0.211***	0.061	0.108**	0.070
	(0.030)	(0.072)	(0.029)	(0.046)	(0.052)	(0.048)
log $\widehat{K}_{ijkt}$ (*export effect*)	-0.001	-0.020	-0.005	0.004	-0.010	0.023
	(0.009)	(0.054)	(0.012)	(0.012)	(0.015)	(0.015)
log $\widehat{K}_{jikt}$ (*import effect*)	0.004	0.045**	0.004	0.005	0.000	0.011
	(0.005)	(0.020)	(0.006)	(0.006)	(0.009)	(0.008)
log $\widehat{K}_{ijkt}$ × high elasticity	0.042***	0.029	0.041***	0.032*	0.051**	0.012
	(0.011)	(0.059)	(0.014)	(0.019)	(0.022)	(0.027)
log $\widehat{K}_{jikt}$ × high elasticity	-0.010*	-0.051**	-0.005	-0.025***	0.002	-0.045***
	(0.006)	(0.021)	(0.007)	(0.008)	(0.011)	(0.011)
log $\widehat{K}_{ijkt}$ × ln DIST	0.010**	-0.000	0.010**	0.007	0.008	0.009
	(0.004)	(0.010)	(0.005)	(0.005)	(0.007)	(0.006)
log $\widehat{K}_{jikt}$ × ln DIST	-0.005	-0.005	-0.007**	0.001	0.005	-0.004
	(0.003)	(0.007)	(0.003)	(0.004)	(0.005)	(0.005)
log $\widehat{K}_{ijkt}$ × LANG	-0.027**	0.042	-0.021*	-0.023	-0.005	-0.034*
	(0.011)	(0.028)	(0.012)	(0.016)	(0.019)	(0.020)
log $\widehat{K}_{jikt}$ × LANG	-0.023**	-0.009	-0.016	-0.025*	-0.045***	-0.013
	(0.009)	(0.020)	(0.010)	(0.014)	(0.016)	(0.016)
log $\widehat{K}_{ijkt}$ × LEGAL	0.020***	-0.001	0.017**	0.020**	-0.002	0.019
	(0.007)	(0.017)	(0.008)	(0.010)	(0.012)	(0.013)
log $\widehat{K}_{jikt}$ × LEGAL	0.001	0.029**	-0.002	0.012	0.010	0.002
	(0.006)	(0.014)	(0.007)	(0.008)	(0.010)	(0.010)
log $\widehat{K}_{ijkt}$ × MED IPR	0.039	-0.177**	0.019	-0.000	0.014	0.065
	(0.025)	(0.079)	(0.030)	(0.032)	(0.040)	(0.044)
log $\widehat{K}_{jikt}$ × MED IPR	-0.017	0.053	-0.013	-0.002	-0.001	0.005
	(0.023)	(0.058)	(0.026)	(0.033)	(0.040)	(0.048)
log $\widehat{K}_{ijkt}$ × HIGH IPR	0.016	-0.084	-0.007	0.016	0.083**	-0.003
	(0.024)	(0.061)	(0.026)	(0.028)	(0.037)	(0.036)
log $\widehat{K}_{jikt}$ × HIGH IPR	0.011	-0.001	0.014	0.004	0.005	0.024
	(0.024)	(0.058)	(0.027)	(0.034)	(0.036)	(0.049)
N	887,334	112,266	674,484	325,116	206,841	173,942

The dependent variable is industry-level (3 digit SITC rev 2) trade flows between 149 countries covering 1974-2006, using every 4 years. Standard errors, shown in parentheses, are clustered by country-pair. All estimations use PPML with exporter-industry-time (ikt), importer-industry-time (jkt), and exporter-importer-industry (ijk) fixed effects. log $\widehat{K}_{jikt}$ refers to (the log of) the stock of patents filed by the importer j in the exporting country i in industry k. log $\widehat{K}_{ijkt}$ refers to (the log of) the stock of patents filed by the exporting country i in the importing country j in industry k. The construction of these stocks is described in Section 4.2. Homogeneous versus differentiated industries are distinguished using the classification from Rauch (1999). "Parts & accessories", "Processed", "Capital Goods", and "Consumption Goods" are determined using BEC classifications for these categories at the HS 6 digit level. More precisely, any 3 digit SITC industry in which more than one-half of world trade meets the BEC definition for one of these categories is coded as belonging to that category. Observation counts vary because we first use the algorithm of Correia (2015) to reduce the sample by removing perfectly predicted observations.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Industry-level Heterogeneity (by factor-intensity)

	(1) High-value added	(2) Skill-intensive	(3) Capital-intensive	(4) Building-intensive	(5) Machine-intensive	(6) Automobile-intensive	(7) Computer-intensive	(8) "Other capital"-intensive	(9) Labor-intensive
FTA	0.178***	0.147***	0.177***	0.123***	0.188***	0.160***	0.192***	0.172***	0.238***
	(0.035)	(0.034)	(0.031)	(0.034)	(0.032)	(0.033)	(0.033)	(0.032)	(0.042)
log $\widehat{K}_{ijkt}$ (*export effect*)	-0.006	-0.007	0.001	-0.017	-0.003	-0.001	-0.006	0.002	-0.019
	(0.011)	(0.011)	(0.013)	(0.012)	(0.013)	(0.012)	(0.011)	(0.013)	(0.013)
log $\widehat{K}_{jikt}$ (*import effect*)	0.009	0.006	0.004	0.004	0.004	0.004	0.008	0.005	0.012
	(0.006)	(0.006)	(0.007)	(0.006)	(0.007)	(0.006)	(0.006)	(0.007)	(0.007)
log $\widehat{K}_{ijkt}$ × high elasticity	0.042***	0.041**	0.038**	0.049***	0.047***	0.049***	0.053***	0.045***	0.054***
	(0.016)	(0.017)	(0.016)	(0.016)	(0.016)	(0.015)	(0.015)	(0.016)	(0.017)
log $\widehat{K}_{jikt}$ × high elasticity	-0.024***	-0.020***	-0.006	-0.023***	-0.006	-0.014*	-0.012*	-0.009	-0.018*
	(0.008)	(0.007)	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.011)
log $\widehat{K}_{ijkt}$ × ln DIST	0.014***	0.013***	0.009**	0.013***	0.010**	0.009**	0.009**	0.009**	0.006
	(0.005)	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)
log $\widehat{K}_{jikt}$ × ln DIST	-0.005	-0.005	-0.005	-0.006	-0.005	-0.004	-0.005	-0.005	-0.003
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)
log $\widehat{K}_{ijkt}$ × LANG	-0.029**	-0.018	-0.027**	-0.014	-0.020*	-0.029**	-0.028**	-0.026**	0.004
	(0.013)	(0.013)	(0.012)	(0.013)	(0.012)	(0.011)	(0.011)	(0.011)	(0.016)
log $\widehat{K}_{jikt}$ × LANG	-0.012	-0.015	-0.017	-0.010	-0.021*	-0.014	-0.020*	-0.018*	-0.019
	(0.012)	(0.012)	(0.011)	(0.011)	(0.011)	(0.010)	(0.011)	(0.010)	(0.012)
log $\widehat{K}_{ijkt}$ × LEGAL	0.027***	0.027***	0.015*	0.028***	0.016**	0.019**	0.019**	0.019**	0.017*
	(0.009)	(0.009)	(0.008)	(0.009)	(0.008)	(0.008)	(0.007)	(0.008)	(0.010)
log $\widehat{K}_{jikt}$ × LEGAL	-0.005	-0.001	0.000	-0.002	-0.001	0.005	0.002	0.001	0.004
	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.009)
log $\widehat{K}_{ijkt}$ × MED IPR	0.007	0.041	0.039	0.062*	0.032	0.063**	0.038	0.046	-0.001
	(0.034)	(0.036)	(0.030)	(0.032)	(0.030)	(0.029)	(0.033)	(0.029)	(0.029)
log $\widehat{K}_{jikt}$ × MED IPR	-0.008	0.008	-0.051*	-0.029	-0.030	-0.026	-0.012	-0.043	0.041
	(0.028)	(0.028)	(0.028)	(0.025)	(0.027)	(0.025)	(0.027)	(0.026)	(0.034)
log $\widehat{K}_{ijkt}$ × HIGH IPR	0.001	0.014	0.016	0.039	0.014	0.038	0.021	0.018	0.028
	(0.030)	(0.031)	(0.029)	(0.030)	(0.028)	(0.028)	(0.029)	(0.027)	(0.027)
log $\widehat{K}_{jikt}$ × HIGH IPR	0.001	0.014	-0.015	-0.025	0.004	-0.007	-0.001	-0.025	0.045
	(0.029)	(0.030)	(0.029)	(0.026)	(0.028)	(0.027)	(0.029)	(0.028)	(0.033)
N	513,994	516,679	511,049	516,126	520,931	571779	566,655	562,974	225,282

The dependent variable is industry-level (3 digit SITC rev 2) trade flows between 149 countries covering 1974-2006, using every 4 years. Standard errors, shown in parentheses, are clustered by country-pair. All estimations use PPML with exporter-industry-time (ikt), importer-industry-time (jkt), and exporter-importer-industry (ijk) fixed effects. log $\widehat{K}_{ijkt}$ refers to (the log of) the stock of patents filed by the importer j in the exporting country i in industry k. log $\widehat{K}_{ijkt}$ refers to (the log of) the stock of patents filed by the exporting country i in the importing country j in industry k. The construction of these stocks is described in Section 4.2. Homogeneous versus differentiated industries are distinguished using the classification from Rauch (1999). Parts & accessories shares are obtained using the BEC classification. Industry-level value added shares, skill intensities, and all capital intensities (including Building-, Machine-, Automobile-, Computer-, and "Other capital"-intensities) are constructed using data from Nunn and Trefler (2013). For each of these factor intensity measures, we take any industry with an intensity higher than the median intensity across all industries to be intensive in that factor. Labor-intensive industries are industries which are neither capital-intensive nor skill-intensive. Observation counts vary because we first use the algorithm of Correia (2015) to reduce the sample by removing perfectly predicted observations.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Additional Sensitivity Checks

	(1) Drop EPO Countries	(2) Drop USA	(3) Drop Low-IPR Importers	(4) Add ijt FE	(5) Relax ikt, jkt FEs	(6) Slower Patent Decay	(7) Faster Patent Decay	(8) Use log $(1+\widehat{K})$
FTA	0.155***	0.175***	0.182***		0.177***	0.161***	0.160***	0.149***
	(0.039)	(0.032)	(0.032)		(0.040)	(0.029)	(0.029)	(0.022)
log $\widehat{K}_{ijkt}$ (*export effect*)	-0.047	0.025	-0.145***	0.009	0.082*	0.005	0.005	-0.002
	(0.064)	(0.038)	(0.036)	(0.008)	(0.044)	(0.011)	(0.010)	(0.010)
log $\widehat{K}_{jikt}$ (*import effect*)	0.065	0.030	0.036	0.035	0.074**	0.012	0.011	0.008
	(0.073)	(0.026)	(0.027)	(0.025)	(0.035)	(0.007)	(0.007)	(0.008)
log $\widehat{K}_{ijkt}$ × high elasticity	0.094***	0.023**	0.041***	0.022**	0.031***	0.024**	0.019***	0.028***
	(0.025)	(0.011)	(0.012)	(0.010)	(0.008)	(0.009)	(0.007)	(0.008)
log $\widehat{K}_{jikt}$ × high elasticity	-0.042***	-0.005	-0.010*	-0.012**	-0.011	-0.008	-0.005	-0.002
	(0.013)	(0.005)	(0.006)	(0.005)	(0.007)	(0.005)	(0.005)	(0.005)
log $\widehat{K}_{ijkt}$ × ln DIST	0.004	-0.003	0.017***	0.014***	-0.008	0.006	0.008**	-0.000
	(0.008)	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
log $\widehat{K}_{jikt}$ × ln DIST	-0.006	-0.003	-0.004	-0.004	-0.007*	-0.003	-0.003	-0.003
	(0.008)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
log $\widehat{K}_{ijkt}$ × LANG	-0.037*	-0.020	-0.019*	-0.024	-0.052***	0.023***	0.020***	-0.023*
	(0.021)	(0.012)	(0.011)	(0.016)	(0.017)	(0.008)	(0.007)	(0.013)
log $\widehat{K}_{jikt}$ × LANG	0.002	-0.020*	-0.019**	-0.022**	0.005	0.013*	0.013*	-0.024**
	(0.020)	(0.011)	(0.009)	(0.011)	(0.018)	(0.007)	(0.007)	(0.011)
log $\widehat{K}_{ijkt}$ × LEGAL	0.042***	0.006	0.015*	-0.008	0.007	-0.029***	-0.022**	0.010
	(0.014)	(0.007)	(0.008)	(0.011)	(0.011)	(0.011)	(0.010)	(0.008)
log $\widehat{K}_{jikt}$ × LEGAL	0.025	-0.002	0.007	-0.005	0.004	-0.022*	-0.021**	0.005
	(0.016)	(0.006)	(0.006)	(0.006)	(0.011)	(0.011)	(0.010)	(0.007)
log $\widehat{K}_{ijkt}$ × MED IPR	0.123***	0.016		-0.036*	-0.011	-0.013	-0.013	-0.014*
	(0.048)	(0.025)		(0.021)	(0.033)	(0.009)	(0.009)	(0.008)
log $\widehat{K}_{jikt}$ × MED IPR	0.049	0.009		-0.001	0.065**	-0.014	-0.015	0.000
	(0.047)	(0.021)		(0.017)	(0.025)	(0.010)	(0.010)	(0.008)
log $\widehat{K}_{ijkt}$ × HIGH IPR	0.052	0.007	0.005	-0.018	0.005	-0.002	-0.002	-0.018*
	(0.053)	(0.022)	(0.017)	(0.017)	(0.031)	(0.006)	(0.006)	(0.009)
log $\widehat{K}_{jikt}$ × HIGH IPR	0.058	0.021	0.016	0.005	0.035	-0.016**	-0.015**	-0.008
	(0.046)	(0.020)	(0.015)	(0.013)	(0.022)	(0.008)	(0.007)	(0.008)
N	158,665	895,845	914,833	996,734	1,016,742	999,600	999,600	3,544,739

The dependent variable is industry-level (3 digit SITC rev 2) trade flows between 149 countries covering 1974-2006, using every 4 years. Standard errors, shown in parentheses, are clustered by country-pair. Columns 1-3 and 6-8 use PPML with exporter-industry-time (ikt), importer-industry-time (jkt), and exporter-importer-industry (ijk) fixed effects. Column 4 adds an ijt fixed effect and column 5 uses it, jt, and kt fixed effects in place of the ikt and jkt fixed effects. log $\widehat{K}_{jikt}$ refers to (the log of) the stock of patents filed by the importer j in the exporting country i in industry k. log $\widehat{K}_{ikjt}$ refers to (the log of) the stock of patents filed by the exporting country i in the importing country j in industry k. The construction of these stocks is described in Section 4.2. Observation counts vary because we first use the algorithm of Correia (2015) to reduce the sample by removing perfectly predicted observations.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.