# International Technology Diffusion
# A Gravity Approach

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**Abstract**

This paper investigates, empirically, the determinants of international technology diffusion. To do that, I set up a multi-country model of innovation and diffusion with perfect enforcement of intellectual property rights (IPR). The model yields a gravity equation for bilateral royalty payments that is estimated using methods from empirical trade. I investigate discrepancies between model's predictions and observed royalty payments to identify the role of fundamentals vs. other factors such as imperfect IPR protection. Fundamentals account for most of the variation in royalty payments, whereas imperfect IPR protection and other factors are important in accounting for discrepancies between model and data.

Keywords: Technology Diffusion; Royalty payments; Intellectual Property Rights

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# 1 Introduction

Technological change is an important source of economic growth, both in developing and in developed countries. Developing countries grow mainly by adopting foreign technologies, which is less costly than investing domestic resources into innovation. Developed countries, instead, grow by conducting domestic innovation and advancing the technological frontier. They also benefit from transferring their innovations abroad if markets for technology work, as these transfers generate payments by foreign firms for the right to use the innovators' technology.

However, markets for technology are subject to failure. For instance, imperfect enforcement of IPR may deter developed countries from transferring technology to profitable markets if the threat of imitation in those markets could negatively affect the innovator's profits (see Maskus, 2004). Moreover, a country's taxation and legal system may drive technology transfer from high-taxation countries to low-taxation countries for profit-shifting motives (Guvenen et al., 2017; Bruner, Rassier, and Ruhl, 2018).[1] Understanding the economic fundamentals behind international technology diffusion as well as identifying potential market failures is important to promote technological change and, eventually, economic growth. Yet, existing empirical studies advancing on the understanding of international technology diffusion have either focused on indirect forms of diffusion, such as international trade (Coe, Helpman, and Hoffmaister, 2009; Keller, 1998, 2002, 2004), or are limited to one country (see Branstetter, Fisman, and Foley, 2006; Guadalupe, Kuzmina, and Thomas, 2012).

In this paper, I adapt gravity methods from empirical trade to address, empirically, two questions: (i) What are the economic fundamentals behind international technology diffusion? and (ii) What factors may impact international technology diffusion beyond those fundamentals? I restrict the analysis to market channels of technology diffusion which, from now on, I refer to as technology transfer. In particular, I focus on technology transfer that takes place through licensing of intellectual property (IP). Technology licensing captures a more direct form of diffusion (see Yang and Maskus, 2001; Branstetter, Fisman, and Foley,

[1] An important market distortion that has been discussed in the literature is that of quid-pro-quo practices, by which multinational firms have to transfer technology in return for market access. This used to be a widespread practice among developing countries in the 1970's, but it was slowly abandoned. China, however, still follows the policy. Holmes, McGrattan, and Prescott (2015) show, though the lens of a quantitative general equilibrium model, that this policy has had an important impact on global innovation and welfare (see also McGrattan et al., 2015).

2006; Mandelman and Waddle, 2019), which can be measured using data on cross-country payments for the use of foreign intellectual property (IP) from the Organization for Economic Co-operation and Development (OECD). These data are available for a large number of countries and time-period, include both intra-firm and third-party payments for the use of foreign IP, and are recorded in the balance of payments of a country as a trade in services.[2] For instance, consider a U.S.-based chips manufacturer that wants to expand to the Chinese market with a license. The U.S manufacturer could enter an agreement with a Chinese firm to use the patent in return for a payment. The Chinese firm could then manufacture and sell the chips in China. This transaction would be recorded as an export of services from the United States' perspective and an import of services from China's perspective.

To investigate the main economic fundamentals of international technology transfer, I set up a multi-country one-sector endogenous growth model of innovation and knowledge diffusion in which there is perfect enforcement of IPR. The trade part of the model follows Eaton and Kortum (2002), whereas the innovation and technology diffusion part follows Eaton and Kortum (1996) and Eaton and Kortum (1999).[3] Innovators choose their research efforts to create new ideas, and these ideas diffuse across countries, increasing the stock of knowledge around the world. Diffused ideas can be adopted to produce an intermediate good more efficiently. In that case, the adopter pays to the innovator a royalty fee for the right to use the innovator's technology, which is determined by the adopter's profits. There is perfect enforcement of IPR in that the innovator can enforce the royalty payments for the adopted ideas. Bilateral royalty payments are thus determined by the following economic fundamentals: the innovator's research and development (R&D) spending and productivity, the adopter's profits, and the probability that the adopter can use the foreign idea to produce the intermediate good more efficiently. Throughout the paper, the terms idea and technology are used interchangeably.

The model delivers an expression for bilateral royalty payments that resembles a gravity equation in which technology transfer depends on an exporter-time, importer-time, and country-pair fixed effects.[4] According to the model's fundamentals, the exporter-time fixed

[2]The data are reported in EBOPS 2012: Balanced International Trade in Services (1995-2012). It provides annual bilateral data on trade in services statistics covering 191 economies and their partners.

[3]The model is a one-sector version of Cai, Li, and Santacreu (2019) extended to allow for international royalty payments. This allows me to use royalty data as a measure of international technology diffusion.

[4]This equation resembles the gravity equation derived by Eaton and Kortum (2002) for the case of international trade flows.

effects are related to the exporter's innovative capacity and its productivity, whereas the importer-time fixed effects are related to the profitability of the importer, which depends on its size and how remotely it is from potential markets. The country-pair fixed effect reflect the importer's ability to use the exporter's technology, and depend on exogenous parameters in the model (i.e., the strength of knowledge diffusion between the countries).

The model is set-up to discipline the empirical analysis, which is the main contribution of the paper. I start by estimating the theory-based gravity equation using data on bilateral royalty payments from the OECD for a sample of 53 countries during the period 1995-2012. I deploy the Poisson Pseudo Maximum Likelihood (PPML) estimation approach developed by Silva and Tenreyro (2006) and regress bilateral royalty payments on exporter-time, importer-time, and country-pair fixed effects.[5] From this gravity regression, we can then recover and analyze the estimated fixed effects. The United States, Japan, the Netherlands, the United Kingdom, and Switzerland are, on average, the main senders of IP abroad (i.e, have the highest exporter fixed effects); the United States, Japan, Ireland, and Singapore are, on average, the main recipients of IP from abroad (i.e., have the highest importer fixed effects). Countries that are geographically and culturally closer to each other, such as Canada and the United States, the United Kingdom and Ireland, Belgium and Luxembourg, or Spain and Portugal have higher country-pair fixed effects.

I then use the model's structure to evaluate, empirically, the explanatory power of economic fundamentals on the fixed effects estimated from the gravity regression. Specifically, I regress the exporter-time fixed effects on R&D spending and GDP per capita, and find that these variables help explain 57 percent of the exporter's fixed effects. I then regress the importer-time fixed effects on GDP and a remoteness index, and find that these variables help explain 77 percent of the importer's fixed effects. Finally, although the country-pair fixed effects depend on exogenous parameters in the model, I regress them on two geographic variables used in the trade literature: distance and common language. I find that distance has a negative impact, whereas sharing a language has a positive impact. Both variables help explain over 10 percent of the variation of the country-pair fixed effects.[6] These results indicate that, while fundamentals account for a significant fraction of the observed variability of the estimated fixed effects, and hence of bilateral royalty payments, much remains unex-

[5]See Yotov et al. (2016) for the advantages of using this estimation method.

[6]In Cai, Li, and Santacreu (2019) we take a different route and estimate it using patent citation data.

plained. Thus, I then ask: To what extent may distortions impact international technology transfers beyond the model's economic fundamentals?

I proceed in three steps. First, I use PPML estimation methods to regress royalty payments *directly* on economic fundamentals. That is, instead of regressing royalty payments on fixed effects, and then the estimated fixed effects on fundamentals, I regress royalty payments directly on the exporter's R&D spending and productivity, the importer's GDP and remoteness index, and on distance and a dummy for sharing a common language between the exporter and importer.[7] A comparison between the predicted value from such a regression and the data reveals that the model can predict the observed evolution of royalty payments quite well (the correlation between the data and the model's predictions is around 45 percent). However, there are some exceptions. For instance, China's, Russia's and India's payments for the use of foreign IP are consistently lower than those predicted by the model; Ireland's, Switzerland's and Singapore's payments exceed those predicted by the model. Second, based on these results, I investigate whether the deviations between the model and data in such cases are mainly driven by characteristics of either the importer, or the exporter, or both that are not captured by the model. By adding importer and exporter fixed effects to the previous PPML regression on economic fundamentals, I find that missing characteristics of the importer account for most of the deviations. Third, I explore the role of two factors that could be driving the discrepancies: the importer's IPR protection, and the importer's taxation and the legal system.[8] Controlling for these channels significantly improves the fit of the model. Accounting for imperfect IPR protection is especially relevant for developing economies, whereas accounting for the taxation and legal system is important for tax havens.[9]

[7] By doing this, I avoid two potential econometric challenges: (i) the estimated fixed effects are measured with error, so the standard errors of estimated coefficients from regressing them on fundamentals might be wrong, and (ii) the model's fundamentals could be correlated with each other, so that adding them together in the regression will capture that possibility.

[8] In addition to these two channels, in a robustness exercise, I explore the role of the structure of production of the destination country, another channel not captured by the one-sector model. For instance, if a technology-importing country specializes in low-technology sectors, it may not be very profitable for a very innovative country to transfer technology to that destination.

[9] I also explore discrepancies between the model and the data in tax havens further by decomposing bilateral royalty payments into intra-firm and unaffiliated transactions. These data are only available for the United States either sending technology to or receiving technology from the other countries in the sample. I find that countries with a lower share of unaffiliated transactions, such as Ireland, Singapore or Switzerland, tend to pay more royalties (i.e., receive more technology) than predicted by the model. A large share of intra-firm royalty payments in those cases could be an indicator of transfers driven by profit-shifting motives.

Motivated by the current trade disputes between the United States and China, and U.S. accusations of IP theft from China, I conduct the following back-of-the-envelope exercise. I quantify how much technology the United States would have transferred to China if China's IPR protection had been identical to that of the United States. The results show that technology transfer would have been, on average during 1995-2012, 57 percent higher.

Finally, one challenge of the baseline PPML estimation is that some of the regressors could be endogenous and affected by royalty payments. More specifically, the exporter's R&D spending and its productivity could be impacted by the amount of royalty payments received. If the exporting-technology country transfers technology abroad because it expects to receive many royalty payments, that may increase the exporter's incentive to do more R&D spending and, in turn, its productivity. To address potential endogeneity and reverse causality, I conduct an instrumental variable (IV) analysis in which the two endogenous regressors—R&D spending and productivity—are instrumented with the number of patent applications and the trade-weighted R&D of the country's main trading partners. Current patent applications are correlated with R&D spending and productivity but not necessarily with licensing of technology (the dependent variable) directly. In general, IP licensing is made once the patent has been granted and this process takes time. Hence, a large number of patent applications today will not necessarily translate into more royalty payments today. The trade-weighted R&D stock of a country's main trading partners correlates with R&D spending and productivity, but not with royalty payments directly. A country's productivity is a function of both domestic and foreign R&D that has diffused to that country. Since an important channel of diffusion is international trade (see, for instance Santacreu, 2015; Keller, 2004), the trade-weighted R&D stock of a country's main trading partners will correlate with productivity. The empirical results from the baseline PPML estimation are robust to the use of IVs. In particular, the economic fundamentals identified in the model still have the expected sign and statistical significance.

The paper is related to several strands of the literature on international technology diffusion. First, it is related to studies on market channels of technology transfers. The channel of diffusion studied in the paper is IP licensing to either affiliates (intra-firm) or to third parties in a foreign country. Yang and Maskus (2001) develop a theoretical model in which firms in industrial countries innovate products of higher quality levels and decide whether to transfer production rights to developing countries through licensing. Different from their paper, I do not model explicitly the decisions to transfer the technology. My model is set-up to identify economic fundamentals of technology transfer with the purpose of disciplining the empirical analysis. Branstetter, Fisman, and Foley (2006) analyze, empirically, the response of technology transfer through licensing within U. S. multinational firms after IPR reforms in 16 countries receiving such transfers. In contrast to their paper, I analyze not only intra-firm IP licensing, but also licensing to unaffiliated parties, which is an important form of technology transfers in many countries. Moreover, instead of focusing on the United States, I evaluate bilateral royalty payments for 53 countries and the period 1995-2012. In a related paper, Lin and Lincoln (2017) use a gravity equation to show that multinationals export relatively more varieties to those countries that have improved their IPR protection. The paper also relates to studies on alternative market channels of technology transfers. One such channel is international trade, by which the developer of a new technology uses it to produce a good domestically and then exports it abroad. There is a large empirical literature evaluating the role of international trade as the vehicle of diffusion. These studies assume that technology is embodied in the good and then diffused around the world whenever the good is traded internationally (Grossman and Helpman, 1991; Coe, Helpman, and Hoffmaister, 2009; Keller, 1998, 2002, 2004; Nishioka and Ripoll, 2012). I use the approach in those papers to construct an instrument for productivity. More recently, several papers have modelled trade as the vehicle of diffusion in the context of general equilibrium models of international trade (see Santacreu, 2015; Buera and Oberfield, 2019). Another channel is through foreign direct investment (FDI), by which a domestic firm can open a foreign affiliate in a country of interest and transfer the ownership of the technology to produce the good there. Guadalupe, Kuzmina, and Thomas (2012) study, for the case of Spanish multinationals, how they transfer superior technologies and organizational practices to their foreign subsidiaries. Keller and Yeaple (2009) analyze international technology spillovers to U.S. manufacturing firms via both imports and FDI, and find that the latter leads to substantial productivity gains for domestic firms. FDI could be a substitute for IP licensing when the parent prefers to transfer the IP ownership to the foreign affiliate. I also explore this possibility when evaluating the role of the technology importer's legal system.

The paper also relates to the literature on non-market channels of technology diffusion (see Maskus, 2004, for a survey on studies analyzing non-market channels such as imitation, learning by doing, and immigration). Similarly to Arque-Castells and Spulber (2019), who disentangle market channels of technology diffusion from knowledge spillovers, my paper lies at the intersection of technology diffusion through market and non-market channels. In the model I set up, technology is both non-rival and partially excludable. It is non-rival in that ideas can diffuse freely through non-market channels to increase the stock of knowledge abroad. It is partially excludable in that the innovator receives royalty payments for those ideas that have been adopted to produce an intermediate good by a foreign firm. Excludable technologies are transferred internationally through market channels.

Finally, the paper is related to studies on the role of distortions on technology transfers. First, it relates to papers analyzing the impact of the quality of IPR enforcement (Yang and Maskus, 2001; Maskus, 2004; Branstetter, Fisman, and Foley, 2006). In a very recent paper, Mandelman and Waddle (2019) study the strategic interaction of trade policy and the enforcement of IPR in the context of the current U.S-China trade war. In their model, technology transfers happen at arms-length relationships. Second, it relates to studies on the role of taxation and the legal system of the country receiving the technology (Guvenen et al., 2017; Bruner, Rassier, and Ruhl, 2018).

# 2 The Model

I build a multi-country one-sector endogenous growth model in which productivity evolves endogenously through innovation and knowledge diffusion. There are $M$ countries indexed by $i$ and $n$, and time is continuous and indexed by $t$. In each country, there is a continuum of traded intermediate goods, which are heterogeneous in their productivity. The endogenous evolution of productivity is modelled as in the closed economy model in Eaton and Kortum (1999). Technology is both non-rival, as there is free technology diffusion that increases the world stock of knowledge, and partially excludable, as technology can be adopted to produce an intermediate good more efficiently in exchange for a royalty payment. I assume perfect enforcement of IPR. The model yields a structural gravity equation of bilateral royalty payments as a function of economic fundamentals, which disciplines the empirical analysis.

## 2.1 Households

In each country $i$ there is a representative household with lifetime utility

$$\int_{t=0}^{\infty} e^{\rho t} \log(C_{it}) dt, \tag{1}$$

where $\rho \in (0,1)$ is the discount factor and $C_{it}$ represents consumption of country $i$ at time $t$.

The household consumes, finances R&D activities of entrepreneurs, and owns all the firms. In return, the household receives labor income and the profits generated by entrepreneurs. The household's budget constraint is given by

$$P_{it}C_{it} + \dot{a}_{it} = r_{it}a_{it} + \Pi_{it} + W_{it}L_{it} + \text{TD}_{it}.$$

where $P_{it}$ is the price of the final good (to be defined later), $a_{it}$ is the household's holding of firms' shares, $r_{it}$ is the return on assets, $\Pi_{it}$ is the profit of firms that the household receives from financing firms' R&D activities, $W_{it}L_{it}$ is labor income, and $\text{TD}_{it}$ is the trade deficit.

## 2.2 Production

In each country $i$, a domestic final producer uses traded intermediate goods $\omega$ to produce a nontraded good, $Y_{it}$, according to the constant elasticity of substitution technology

$$Y_{it} = \left( \int_{t=0}^{\infty} x_{it}(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right)^{\frac{\sigma}{\sigma-1}}. \tag{2}$$

In this expression, $\sigma > 1$ is the elasticity of substitution across intermediate goods and $x_{it}(\omega)$ is the demand of intermediate goods.

In each country $i$, there is a continuum of intermediate producers indexed by $\omega \in [0,1]$ that use labor $l_{it}(\omega)$ to produce a traded intermediate good according to the following constant-returns-to-scale technology

$$x_{it}(\omega) = z_{it}(\omega) l_{it}(\omega). \tag{3}$$

Firms are heterogeneous in their productivity $z_{it}(\omega)$. The cost of producing each intermediate good $\omega$ is

$$c_{it}(\omega) = \frac{W_{it}}{z_{it}(\omega)}, \tag{4}$$

where $c_{it}(\omega)$ is the cost of production and $W_{it}$ the nominal wage rate. Intermediate producers operate under Bertrand competition and their equilibrium prices are characterized next.

## 2.3 International Trade

Trade in goods is costly. In particular, there are iceberg transport costs so that shipping a good from country $i$ to country $n$ requires producing $d_{ni} > 1$ units of the good in country $i$. The "triangular" inequality holds; thus $d_{ih}d_{hn} > d_{in}$. Bertrand competition is modelled as in Bernard et al. (2003). Final producers buy from the lowest-cost supplier, who charges a price that is a function of the production cost of the second lowest-cost supplier.

Trade is Ricardian, since productivity is allowed to vary by country (as in Eaton and Kortum, 2002). The productivity of producing a variety $\omega$ in country $i$ is a random variable drawn from a Fréchet distribution, which is characterized by $T_{it}$ and by the shape parameter $\theta > 1$: $F(z_i) = \exp\{-T_{it}z^{-\theta}\}$. A higher $T_{it}$ reflects higher fundamental productivity, whereas a lower $\theta$ reflects higher dispersion of productivity within the country.

Given these distributional assumptions, it can be shown that[10]

$$P_{it} = B\left(\Phi_{it}\right)^{-1/\theta}, \tag{5}$$

where $B = \left[\frac{1+\theta-\sigma+(\sigma-1)(\bar{m})^{-\theta}}{1+\theta-\sigma}\Gamma\left(\frac{2\theta+1-\sigma}{\theta}\right)\right]^{1/(1-\sigma)}$, $\bar{m} = \frac{1}{1-\sigma}$ is the markup, and $\Gamma[.]$ is the gamma function. Also,

$$\Phi_{it} = \sum_{n=1}^{M} T_{it}\left(W_{it}d_{in}\right)^{-\theta}. \tag{6}$$

Given the distributional assumptions on productivity, the probability that country $n$ is the lowest-cost supplier to country $i$ is

$$\pi_{in,t} = \frac{T_{nt}\left(W_{nt}d_{in}\right)^{-\theta}}{\Phi_{it}}. \tag{7}$$

Since there is a continuum of intermediate goods, it follows that $\pi_{in,t}$ is also the fraction of goods that country $n$ sells to country $i$. Formally, the share that country $i$ spends on goods

[10] See Bernard et al. (2003) for details on the derivation

from country $n$ is

$$\pi_{in,t} = \frac{X_{in,t}}{X_{it}}. \tag{8}$$

Here $X_{it} = P_{it}Y_{it}$ represents country $i$'s total expenditure on goods and $X_{in,t}$ denotes the value of intermediate products that country $i$ buys from country $n$.

In the model, $T_{nt}$ is endogenous, and it represents the stock of knowledge available in country $n$ at time $t$. I next describe the determinants of the evolution of $T_{nt}$.

## 2.4 Innovation and Knowledge Spillovers

Here I describe the main drivers of the evolution of the stock of knowledge in a country: innovation and knowledge spillovers. In each country $n$ there is a continuum of entrepreneurs who invest final output $Y^r_{nt}$ to come up with a new idea. Ideas arrive at a Poisson rate, which is given by

$$\lambda_n T_{nt} \left(Y^r_{nt}\right)^{\beta_r}. \tag{9}$$

Here $\lambda_n T_{nt}$ represents the efficiency of innovation, which depends on $\lambda_n > 0$ and the stock of knowledge already accumulated in country $n$ at time $t$, $T_{nt}$. The parameter $\beta_r \in (0, 1)$ represents diminishing returns to R&D.

Ideas are blueprints to produce an intermediate good more efficiently. New ideas are characterized by two random variables: the good to which they apply, which is drawn from a uniform distribution $[0, 1]$, and the quality of the idea, which is assumed to be distributed Pareto. Research efforts are targeted at any good in the continuum.

Ideas can diffuse exogenously across countries. The time lag for an idea developed in country $i$ to diffuse to country $n$ is exponentially distributed with parameter $\varepsilon_{ni}$. Diffused ideas, both domestic and foreign, increase the stock of knowledge of country $n$. In this sense, they are "non-rival". The evolution of the stock of knowledge is characterized by the following expression:

$$\dot{T}_{nt} = \sum_{i=1}^{M} \varepsilon_{ni} \int_{-\infty}^{t} e^{-\varepsilon_{ni}(t-s)} \lambda_i T_i \left(Y^r_{it}\right)^{\beta_r} ds. \tag{10}$$

From equation (10), the evolution of the stock of knowledge in country $n$ at time $t$ depends on the past research outcomes in each country $i$ at time $s < t$ that have diffused to $n$ at time

$t$ at the rate $\varepsilon_{ni}$.

Diffused ideas can be adopted by an intermediate producer to produce a good more efficiently. Adoption does not occur instantaneously and only a sub-set of diffused ideas is able to be adopted. An idea developed in country $i$ is adopted by country $n$ if its quality surpasses the productivity of the best idea in that country, which given the distributional assumptions assumed in the paper, occurs with probability $1/T_{nt}$ (see Eaton and Kortum, 1996, 1999, for more details). If the idea is adopted, the foreign producer in country $n$ pays the innovator in country $i$ a royalty fee for the right to use such an idea. In that sense, adopted ideas are said to be excludable, and this is the way technology transfer is modelled in the paper.[11]

The value of an innovator in country $i$ is

$$V_{it} = \sum_{n=1}^{M} \int_t^{\infty} e^{-\int_t^s r_{iu} du} \left(1 - e^{-\varepsilon_{in}(s-t)}\right) \frac{\Pi_{ns}}{T_{ns}} ds, \tag{11}$$

where $\Pi_{ns}$ are profits given by

$$\Pi_{ns} = \frac{\sum_{i=1}^{M} \pi_{in} X_{is}}{1+\theta}. \tag{12}$$

The value of an innovation in equation (11) is thus the present discounted value of profits, both domestic and foreign, that intermediate producers expect to make with a foreign technology. It incorporates the possibility that the technology is surpassed by a better technology in the future, through $T_{ns}$, in which case the intermediate producer leaves the market.[12]

## 2.5 Market Clearing Conditions

The labor market clearing condition is

$$W_{it} L_{it} = \sum_{n=1}^{M} \pi_{ni,t} X_{nt}. \tag{13}$$

[11] As noted by Correa (2003), technology transfer through licensing cannot be learned instantaneously; successful transfers typically require some capacity to introduce technologies into a production process.

[12] Chaney (2008) also introduces an international market of ideas in which there are international royalty payments.

Total income is composed of labor income and profits

$$P_{it}Y_{it} = W_{it}L_{it} + \Pi_{it}. \tag{14}$$

Trade is not balanced in each country, because there are royalty payments across countries. The balance of payments equation is

$$P_{it}Y_{it} - P_{it}C_{it} = \sum_{n=1}^{M} RP_{ni,t}, \tag{15}$$

where $RP_{ni,t}$ is the amount of royalty payments country $i$ receives from ideas that have been adopted by country $n$, which is given by

$$RP_{ni,t} = \omega_{ni,t}\xi_{nt}\Pi_{nt}, \tag{16}$$

with $\omega_{ni,t}$ the fraction of ideas that have been developed in $i$ and adopted by $n$. Equation (16) implies that, if there is perfect enforcement of IPR (i.e., $\xi_{nt} = 1$), adopters pay all their profits generated with the foreign ideas to the innovators, and innovators can enforce those payments perfectly. I provide an expression for $\omega_{ni,t}$ in the next section.

## 2.6 A Structural Gravity Equation

I use the model to derive a gravity-type equation for bilateral royalty payments between country $i$ and country $n$ ($RP_{ni}$ in equation 16) along the balanced growth path (BGP). On the BGP, the stock of knowledge, $T$, grows at a constant rate, $g$, which is common for all countries. Variables are stationarized so that they are constant on the BGP; for notational simplicity, I drop all time subindexes.

I begin by deriving an expression for $\omega_{ni}$, which is defined as the stock of ideas that country $n$ has adopted from country $i$ as a fraction of the total stock of ideas in country $n$; that is

$$\omega_{ni} \equiv \frac{T_{ni}}{T_n}. \tag{17}$$

Using equation (10) on the BGP

$$T_n = \sum_{i=1}^{M} T_{ni} = \sum_{i=1}^{M} \frac{\varepsilon_{ni}}{\varepsilon_{ni}+g} \lambda_i T_i \left(L_i^R\right)^{\beta_r}, \tag{18}$$

we obtain an expression for equation (17) as

$$\omega_{ni} = \frac{\varepsilon_{ni}}{\varepsilon_{ni}+g} \lambda_i \frac{T_i}{T_n} \left(L_i^R\right)^{\beta_r}. \tag{19}$$

Hence, substituting into equation (16)

$$RP_{ni} = \frac{\varepsilon_{ni}}{\varepsilon_{ni}+g} \lambda_i T_i \left(Y_i^r\right)^{\beta_r} \Pi_n. \tag{20}$$

Equation (20) resembles a gravity equation in which bilateral royalty payments between country $i$ and country $n$ can be written as a function of the characteristics of the exporter $i$, $\lambda_i T_i \left(L_i^R\right)^{\beta_r}$; the characteristics of the importer $n$, $\Pi_n = \omega_n^{-\theta} \frac{\sum_k d_{kn}^{-\theta} X_k}{\Phi_k}$; and the probability that, conditionally on being diffused, an idea developed in country $i$ can be adopted for production in country $n$, $\frac{\varepsilon_{ni}}{\varepsilon_{ni}+g}$.

We can express equation (20) as

$$\log(RP_{ni}) = S_i + F_n + d_{ni} \tag{21}$$

with $S_i = \log\left(\lambda_i T_i \left(L_i^R\right)^{\beta_r}\right)$, $F_n = \log\left(\Pi_n\right)$, and $d_{ni} = \log\left(\frac{\varepsilon_{ni}}{\varepsilon_{ni}+g}\right)$.

With perfect enforcement of IPR, the economic fundamentals of technology transfer in the one-sector model just described are: the source's innovation and productivity, the destination's profitability, and ability of the destination to adopt a technology from the source.

# 3 Empirical Analysis

This section evaluates how well the economic fundamentals documented in equation (20) can explain the different components in equation (21). Note that, despite of deriving the gravity regression on the BGP, I exploit the time dimension of the data in the empirical analysis, as I am interested in capturing the evolution of international technology transfer over time.

## 3.1 Gravity Regression

I start by estimating equation (21) using bilateral royalty payments data for 53 countries during the period 1995-2012.[13] The estimation approach uses a PPML methodology in which bilateral royalty payments are regressed on country-pair, exporter-time and importer-time fixed effects using a non-linear version of equation (21).[14] That is,

$$RP_{ni,t} = \exp\left[S_{it} + F_{nt} + d_{ni} + u_{ni,t}\right]$$

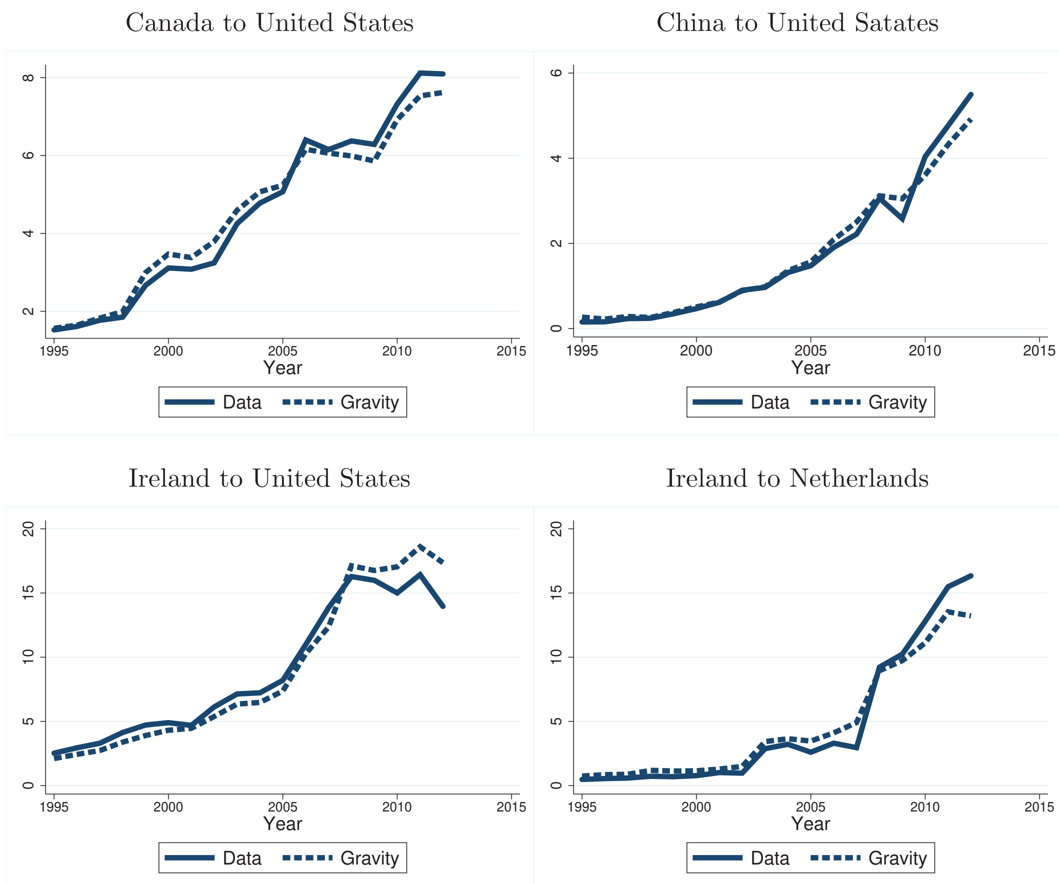
where $u_{ni,t}$ is a residual. Country-pair fixed effects are allowed to be asymmetric, so that the probability of a technology transferring successfully from China to the United States can be different than from the United States to China. The R-squared of the regression is 0.98. Figure 1 shows, for a sample of countries, that royalty payments predicted by the gravity equation (dashed line) fit the data (solid line) almost perfectly.

I then analyze how well the model's fundamentals can explain the estimated fixed effects. First, following the gravity trade literature, I regress the country-pair fixed effects on distance and a dummy for sharing a common language. Even though the country-pair fixed effects depend on exogenous parameters, our findings from the gravity regression suggest that pairs of countries that are geographically and culturally closer to each other tend to share more technology on average. Table 1 (first column) shows that distance has a negative and statistically significant effect, whereas common language has a positive and statistically significant effect. These variables explain just over 10 percent of the variation of the country-pair fixed effects. Controlling for bilateral trade flows, in addition to geography and cultural variables, the R-squared increases to 26 percent. As the second column of table 1 shows, trade has a positive and statistically significant effect. Indeed, a significant amount of technology transfers happen at arms-length relationships between a firm and its suppliers (Mandelman and Waddle, 2019). Distance and common language still have the expected signs and are statistically significant. The results suggest that there are components of trade beyond geography and culture that matter for explaining the probability of adoption. Finally, I also control for the structure of production by computing a measure of technology-intensive production of country $i$ receiving technology from country $n$, $p_{int}$, as

[13] The list of countries is reported in Appendix B.

[14] I use the Stata command developed by Zylkin (2018).

Figure 1: International technology diffusion (Data vs Gravity model)
The figure shows the evolution of bilateral royalty payments from the importing-technology country to the exporting-technology country, between 1995-2012, in the data (solid line) and in the gravity model (dashed line).




$$p_{int} = \sum_{j=1}^{J} \frac{VA_{it}^{j}}{\sum_{j=1}^{J} VA_{it}^{j}} \left[1 + \log(P_{nt}^{j})\right], \tag{22}$$

where $VA_{it}^{j}$ is the value added of country $i$ in sector $j$ at time $t$ and $P_{nt}^{j}$ is the number of patents of country $n$ in sector $j$ at time $t$. A higher value of technology-intensive production indicates that the importing-technology country specializes in sectors in which the exporting-technology country innovates more. Hence, we should expect to see more technology transfer between the countries in those cases.

Figure 2 plots the measure from equation (22) against the royalty payments between two countries, averaged for 1995-2012. Each dot in the figure represents a country-pair. We observe a clear positive correlation between the two variables.

Figure 2: Technology-intensive production and royalty payments
The figure shows relation between the measure of production structure in equation (22) and data on royalty payments, averaged for 1995-2012. Each dot represents a country-pair.

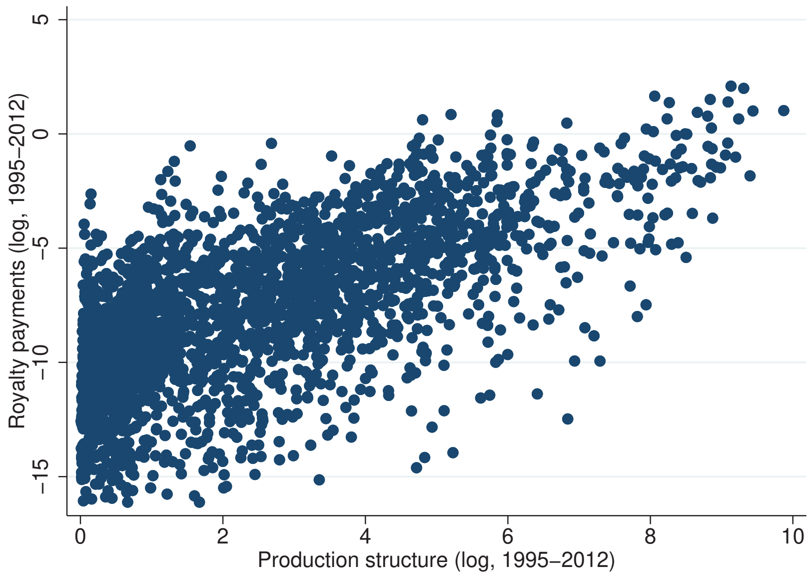



Table 1: Country-pair fixed effects and economic fundamentals
The table shows the effect of geography and cultural variables on country-pair fixed effects from the gravity regression (first column), controlling also for trade (second column) and the production structure (third column).

| | (1) | (2) | (3) |
|---|---|---|---|
| log(Distance) | -0.479*** | -0.427*** | -0.308*** |
| | (0.0338) | (0.0325) | (0.0353) |
| Common language | 1.432*** | 1.031*** | 0.812*** |
| | (0.144) | (0.136) | (0.140) |
| log(Trade) | | 0.323*** | 0.215*** |
| | | (0.0136) | (0.0173) |
| log(Prod. str.) | | | 0.219*** |
| | | | (0.0208) |
| $N$ | 2,723 | 2,422 | 2,324 |
| R-squared | 0.102 | 0.266 | 0.303 |

Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The third column of table 1 reports the results after controlling for the structure of production. Both trade and the production structure have a positive and statistical significant effect on royalty payments, while distance and common language maintain the previous sign, magnitude and statistically significance. The R-squared increases to 30 percent.

Next, I recover the exporter and importer fixed effects from the gravity regression and explore the predictive power of the main economic fundamentals from equation (20) on such fixed effects. Through the lens of the model, the exporter fixed effects are related to the exporter's R&D spending and productivity, and the importer fixed effects are related to the importer's profitability. Profitability depends on the importer's size and how remotely located it is relative to other markets. The remoteness index is computed, following Head and Mayer (2014), as

$$Rem_i = \sum_j \frac{d_{ij}}{Y_j/Y_w}. \tag{23}$$

with $d_{ij}$ the geographic distance between country $i$ and country $j$, $Y_j$ the GDP of country $j$, and $Y_w$ the GDP of the world, $Y_w = \sum_j Y_j$.

Figure 3 plots correlations between the exporter and importer fixed effects from the gravity regression and the main economic fundamentals predicted by the model. Each dot of the figure represents a country-year. The top two panels show a clear positive relationship between the exporter fixed effect and both the exporter's R&D spending (left panel) and productivity (right panel). More innovative and productive countries are more likely to send technology abroad, and hence receive more royalty payments. The bottom two panels are also consistent with the model. The left panel shows that the more remote a technology importer is from its potential markets, the lower the importer fixed effect, hence the less likely it is to receive foreign technology. The right panel shows that larger countries are more likely to receive foreign technology.

Figure 3: Gravity fixed effects and economic fundamentals
The figure shows correlations between exporter-time fixed effects (Y-axes of top two subplots) and the exporter's R&D spending and productivity (X-axes of top two subplots); and between importer-time fixed effects (Y-axes of bottom two subplots) and the importer's remoteness index and size (X-axes of bottom two subplots). Each dot represents a country-year. The time period is 1995-2012.

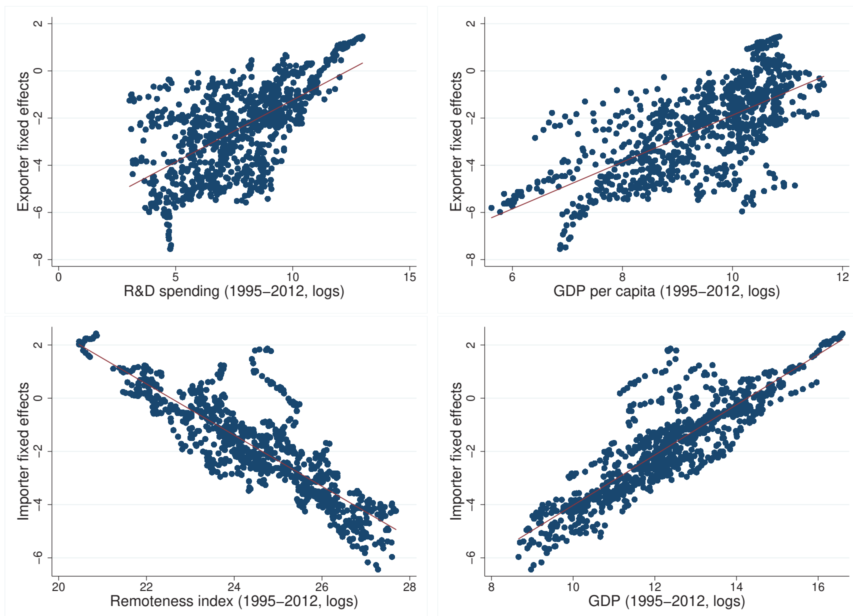



Figure 4 reproduces the graphs in figure 3, averaging across time for each country. The results are consistent with the model. For instance, the United States and Japan are the main technology exporters (i.e, have the largest average exporter fixed effects) and they also have the largest R&D spending and productivity. The United States, Japan and Ireland are the main technology importers (i.e, have the largest average importer fixed effects). The United States and Japan have the lowest remoteness index and the largest GDP. Ireland is an outlier in that, despite not being among the most profitable countries based on its remoteness index and GDP, is one of the main recipients of foreign technology. The next section explores this point further.

Figure 4: Gravity fixed effects and economic characteristics, averaged over 1995-2012
The figure shows correlations between exporter fixed effects (Y-axes of top two subplots) and the exporter's R&D spending and productivity (X-axes of top two subplots); and between importer fixed effects (Y-axes of bottom two subplots) and the importer's remoteness index and size (X-axes of bottom two subplots). Each dot represents a country, averaged across 1995-2012.


More formally, I conduct an OLS regression of the exporter-time and importer-time fixed effects from the gravity model, on the economic fundamentals predicted by the model—i.e., on the same variables presented in figure 3. The results are displayed in tables 2 and 3. Consistently with the model, table 2 shows that the exporter's R&D spending and productivity have a positive and statistically significant effect on the exporter-time fixed effects. The value of the estimated coefficient on the log of R&D spending is about 0.31. The estimated coefficient on the log of productivity is about 0.72. These two variables alone explain 57 percent of the variation of the exporter-time fixed effects.

Table 2: Exporter-time fixed effects and economic fundamentals
This table reports OLS results from regressing exporter-time fixed effects from the gravity regression on the exporter's log of R&D and log of productivity.

| | Exporter-time fixed effects (log) |
|---|---|
| log(R&D Spending) | 0.311$^{***}$ |
| | (0.0208) |
| log(GDP pc exporter) | 0.722$^{***}$ |
| | (0.0357) |
| $N$ | 953 |
| R-squared | 0.57 |

Standard errors in parentheses.

$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

The results in table 3 show that the importer's size has a positive and statistically significant effect on the importer-time fixed effects, and remoteness has a negative and statistically significant impact. The estimated coefficient on the log of the importer's GDP is about 0.8, whereas the coefficient on the log of the remoteness index—computed as in equation (23)—is about -0.16. Consistently with the model, larger countries are receiving, on average, more technology; remote countries are receiving less foreign technology, as they are less profitable because they are either close to small countries or far from large countries. These two variables together explain around 77 percent of the variation in the importer-time fixed effects.

The economic fundamentals identified by the model have a good predictive power of the fixed effects estimated from the gravity regression. That is, an important component of the variation of what the technology exporter sends abroad, and of what the technology importer receives, can be explained by those variables. However, some remains unexplained. The next section explores discrepancies between the model's predictions and the data.

Table 3: Gravity importer-time fixed effects and economic characteristics
This table reports OLS results from regressing importer-time fixed effects from the gravity regression on the importer's log of GDP and log of the remoteness index.

| | Importer-time fixed effects (log) |
|---|---|
| log(GDP importer) | 0.797*** |
| | (0.0667) |
| log(Remoteness) | -0.158* |
| | (0.0695) |
| $N$ | 953 |
| R-squared | 0.774 |

Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

# 4 Evaluating Deviations between Model and Data

In this section, I identify discrepancies between the model and the data, and explore the role of several channels in driving those discrepancies. To do that, royalty payments are regressed directly on the economic fundamentals predicted by equation (20) ("baseline" model). I compare predicted royalty payments from that regression to the data to identify discrepancies. Then, I explore whether deviations between the baseline model and the data are driven by characteristics of the importer, of the exporter, or of both that are not captured by the model's fundamentals. Finally, I study the role of two channels that could be driving the discrepancies: (i) the quality of IPR protection, and (ii) the tax and legal system. Controlling for those factors in the baseline model yields the "augmented" model.

**The Baseline Model** I start by conducting—for the sample of 53 countries and the period 1995-2012—a PPML estimation where bilateral royalty payments are regressed directly on the economic fundamentals from the non-linear version of equation (20).

$$RP_{ni,t} = \exp\left[\log\left(\frac{\varepsilon_{ni}}{\varepsilon_{ni}+g}\right) + \log\left(\lambda_i T_{it}\left(Y_{it}^{r}\right)^{\beta_r}\right) + \log\left(\Pi_{nt}\right) + \epsilon_{ni,t}\right]. \tag{24}$$

with $\epsilon_{ni,t}$ an error term.

This exercise addresses several econometric challenges that could arise in the previous section. There, royalty payments were first regressed on fixed effects and then, the estimated fixed effects were regressed on economic fundamentals. The standard errors from the second regression could be wrong as the estimated fixed effects are measured with error. Moreover, if some of the economic fundamentals are correlated with each other, adding them directly to the regression will yield different estimated coefficients, and hence a different impact of economic fundamentals on royalty payments. Yet, the previous analysis was informative, as a first step, to evaluate the predictive power of the model's economic fundamentals on the country characteristics identified from the gravity regression.

The results are reported in the first column of table 4. Distance has a negative and statistically significant effect on royalty payments, whereas sharing a common language has a positive and statistically significant effect. The exporter's R&D spending and productivity have a positive and statistically significant effect. Finally, the importer's remoteness has a negative and statistically significant effect, while its size, measured by GDP, has a positive and statistically significant effect. The estimated coefficients are also economically significant. The correlation between the data and the predicted value of this regression is around 44 percent.

While the economic fundamentals from the model seem to have a good predictive power of bilateral royalty payments, some remains unexplained. To explore discrepancies between the model and the data further, I then use the estimation results from the first column of table 4 and compare, for a sub-sample of countries, the evolution of royalty payments predicted by the model to those in the data. The results are shown in figures 5-7.

Figure 5 plots country pairs for which observed royalty payments conforms to the model. For instance, the observed evolution of royalty payments from Canada to Switzerland is very similar to what the model would predict, given the innovative capacity of Switzerland, the profitability of Canadian firms, and the ability of Canada to adopt technologies proceeding from Switzerland. The same result applies to royalty payments from China to the Netherlands, from Brazil to the United States, and from the United States to the United Kingdom.

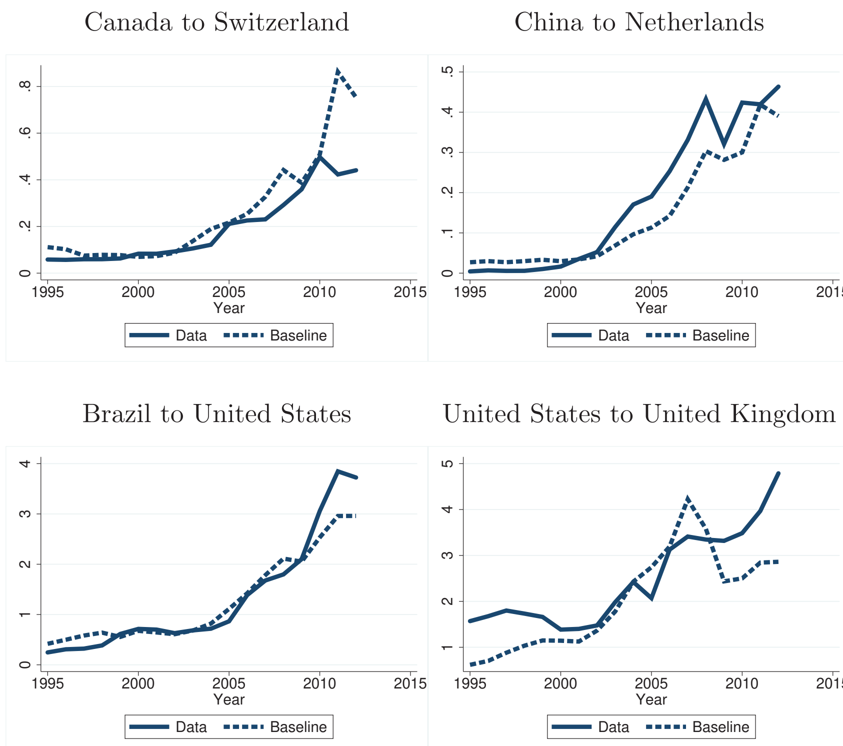
Table 4: Bilateral royalty payments and economic fundamentals
This table reports PPML estimation results of regressing bilateral royalty payments for 53 countries over the period 1995-2012 on economic fundamentals (first column). I control for importer fixed effects (second column), exporter fixed effects (third column), and importer and exporter fixed effects (fourth column).

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| log(Distance) | -0.232*** | -0.301*** | -0.287*** | -0.421*** |
| | (0.0194) | (0.0201) | (0.0226) | (0.0160) |
| Common language | 0.796*** | 0.336*** | 0.618*** | 0.0373 |
| | (0.0757) | (0.0655) | (0.0820) | (0.0537) |
| log(R&D exporter) | 0.875*** | 0.904*** | 0.526* | 0.514** |
| | (0.0188) | (0.0152) | (0.261) | (0.176) |
| log(GDP pc exporter) | 1.268*** | 1.537*** | 0.317 | 0.281 |
| | (0.0731) | (0.0731) | (0.330) | (0.233) |
| log(Remoteness importer) | -0.407*** | -0.887*** | 0.207* | 0.256 |
| | (0.131) | (0.131) | (0.0817) | (0.132) |
| log(GDP importer) | 0.307*** | -0.0502 | 0.937*** | 1.051*** |
| | (0.0606) | (0.0656) | (0.0889) | (0.0888) |
| Importer FE | No | Yes | No | Yes |
| Exporter FE | No | No | Yes | Yes |
| $N$ | 49,608 | 49,608 | 49,608 | 49,608 |
| R-squared | 0.440 | 0.728 | 0.468 | 0.838 |

Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 5: International technology transfer (data vs model)
The figure shows royalty payments from a technology-importing country to a technology-exporting country for the period 1995-2012 in the data (solid line) and in the baseline model (dashed line), which corresponds to the predicted value from the regression displayed in the first column of table 4.




Figures 6 and 7 show pairs of countries for which there are discrepancies between the model and the data. Figure 6 plots countries that receive less technology transfers (i.e., pay less royalties) than predicted by the model. These are mainly developing countries, which as it is shown later, tend to present low IPR protection and a poor business climate. As a result, innovators in developed countries may be, everything else constant, more reluctant to market their technologies in those developing economies. That is the case of China and India receiving IP from the United States, and of Argentina receiving IP from Canada. Given the profitability of India, China and Argentina, and the innovative capacity and productivity of the United States and Canada, observed royalty payments among those countries are too low.

Figure 7 shows countries that receive more technology transfers (i.e., pay more royalties) than predicted by the model. This tends to be the case of tax havens such as Ireland, Luxembourg, and Singapore. As I show later, one reason for those discrepancies may be the existence of lower corporate income taxes in these countries, which may trigger technology transfers for reasons other than market profitability.

Figure 6: International technology transfer (data vs model)
The figure shows royalty payments from a technology-importing country to a technology-exporting country for the period 1995-2012 in the data (solid line) and in the baseline model (dashed line), which corresponds to the predicted value from the regression displayed in the first column of table 4.

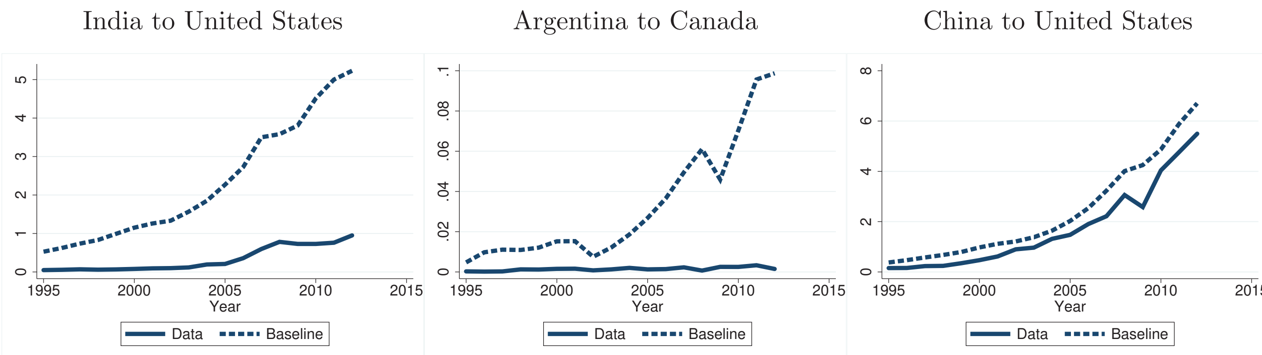
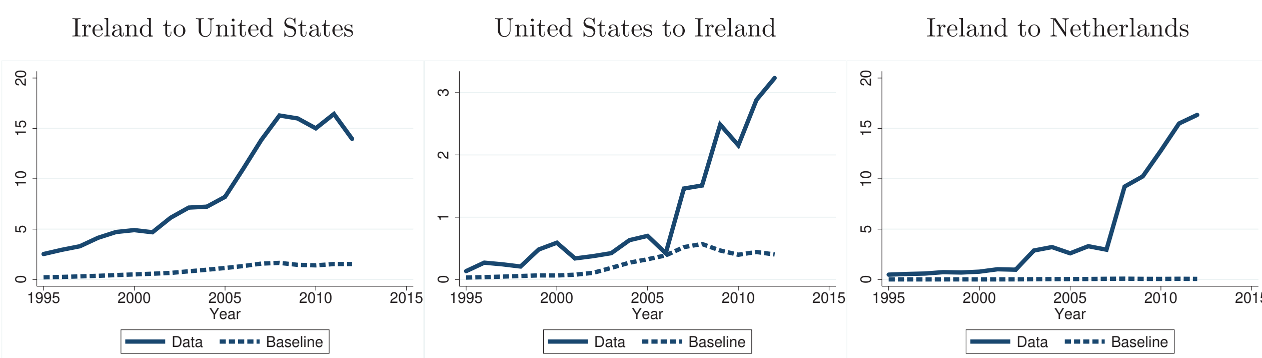



Figure 7: International technology transfer (data vs model)
The figure shows royalty payments from a technology-importing country to a technology-exporting country for the period 1995-2012 in the data (solid line) and in the model (dashed line), which corresponds to the predicted value from the regression displayed in the first column of table 4.



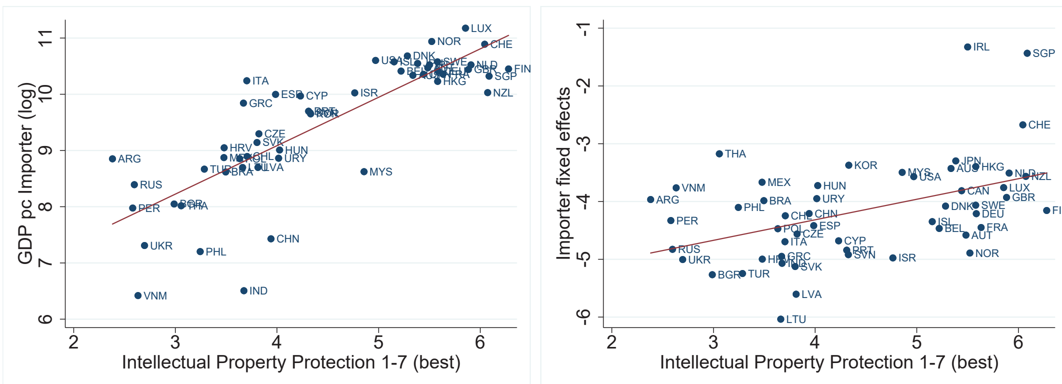

**Evaluating Discrepancies between Model and Data** The discrepancies between the model and the data that we just identified could be driven by characteristics of the importer, or of the exporter, or of both that have not been modelled explicitly. To explore this point further, I repeat the regression in the first column of table 4, controlling for importer fixed effects (second column), exporter fixed effects (third column), and both importer and exporter fixed effects (fourth column). Including only importer fixed effects improves significantly the fit of the model. The correlation between the data and the predicted value in this case is around 73 percent. Including only exporter fixed effects increases the correlation between the data and the model from 44 percent to just 47 percent. Including both importer and exporter fixed effects increases the correlation to 84 percent. Hence, deviations between the model and the data seem to be driven, mainly, by omitted characteristics of the technology importer. In other words, the residual from the regression displayed in the first column of table 4 is correlated with importer's characteristics that are missing from the baseline model.

Based on these results, I explore two potential channels, from the perspective of the importer, that could be explaining discrepancies between the model and the data: (i) The quality of IPR protection; and (ii) the level of taxation and the legal system.

First, weak IPR protection could yield less than optimal technology transfer from abroad. As Maskus (2004) mentions, many developing countries have complained that the amount of technology transfer received through market channels is below optimal. For an innovator to have an incentive to license a technology in a foreign market, she must be confident that firms licensing the technology will not copy it or leak it to other competitors. In this case, the investment climate of the technology importer is important to attract foreign IP through licensing. To explore the role of IPR protection, I use data from the Global Competitiveness Index (GCI) historical dataset published by the World Economic Forum. The dataset provides rankings of countries according to their competitiveness based on various indicators. I focus on the index of IPR protection, which ranges from 1-7, as a measure of the quality of IPR enforcement. Figure 8a plots this index against the log of GDP per capita for the sample of 53 countries, averaged over 1995-2012. There is a clear positive correlation between the two variables, suggesting that developed countries have better enforcement of IPR than developing ones. Finland, Singapore, Switzerland, and New Zealand have the highest index of IPR protection, whereas Belarus, Argentina, Peru and Ukraine have the lowest index. Figure 8b shows a positive relation between the quality of IPR protection and the importer fixed effects estimated in the second column of table 4. Countries with low importer fixed effects tend to have low quality of IPR enforcement (in the regression, low importer fixed effects are associated to lower observed royalty payments than predicted by the model).

Figure 8: IPR Protection index
These figures plot the correlation between the IPR protection index from the GCI dataset and: (i) the level of development measured by GDP per capita (left panel), and (ii) the importer fixed effect from the regression in the second column of table 4 (right panel).

(a) IPR Protection and Development (b) IPR Protection and Importer FE

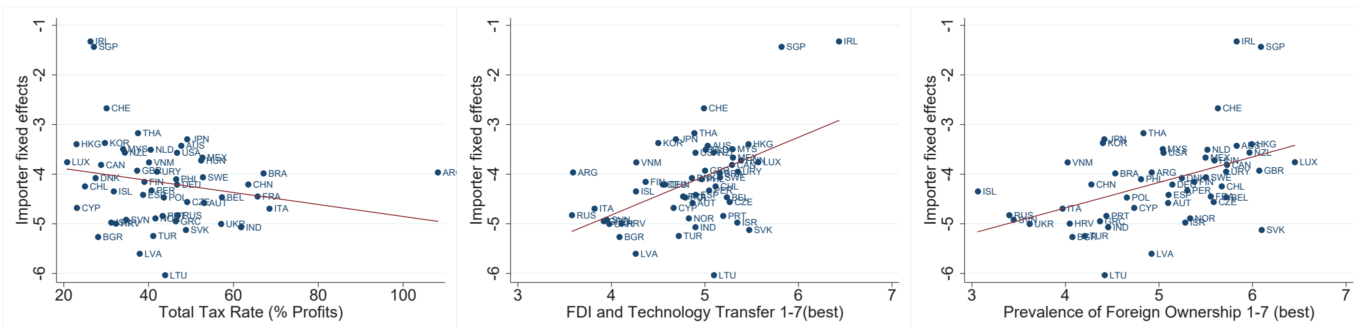



Second, I use data from the GCI historical dataset for various indicators about taxation and the legal system that could have an impact on royalty payments beyond size and remotenes: (i) the tax rate (as a percentage of profits), as countries with high corporate income taxes may be tempted to transfer their technology to countries with low tax rates because of profit-shifting motives (see Guvenen et al., 2017; Bruner, Rassier, and Ruhl, 2018); (ii) the amount of FDI and technology transfers, which measures the extent to which FDI brings new technology in another country; and (iii) the degree of foreign ownership. A large amount of FDI and foreign ownership could either increase or decrease royalty payments, since a parent company that opens a foreign affiliate could transfer its IP abroad in two ways: licensing it in exchange of a royalty payment, or transferring the IP's ownership, in which case profits would remain abroad and would be taxed according to foreign corporate income taxes. Licensing the technology abroad will increase royalty payments whereas transferring the ownership will imply less royalty payments.

Figure 9 plots the correlation between the importer fixed effects from the regression displayed in the second column of table 4 and the three aforementioned indicators that capture the effect of taxation and the legal system. There is a clear negative correlation between taxation and the importer fixed effects, suggesting that, once we control for economic fundamentals, lower tax countries pay, on average, more royalties. There is a strong positive correlation between the importer fixed effect and the amount of FDI that brings new technology into the country, and between the importer fixed effect and the presence of foreign ownership. Note that Ireland, Singapore and Switzerland are outliers in the three plots of figure 9. They pay royalties above what their size and remoteness would suggest; they also have lower corporate income taxation and higher FDI.

Figure 9: Differences in taxation and regulation
These figures plot the correlation between the three variables from the GCI dataset capturing taxation and the legal system, and the importer fixed effect from the regression displayed in the second column of table 4.

(a) Taxes and Importer FE (b) FDI and Importer FE (c) Foreign Ownership and Importer FE




**The Augmented Model** I explore the impact of the channels identified previously by controlling in the regression on the baseline model, for indicators of IPR protection and taxation and the legal system. I refer to this specification as the augmented model. The results are reported in the second column of table 5. The additional variables all have a statistically significant coefficient and the signs are as expected. Better quality of IPR protection has a positive effect. Countries with a higher corporate income tax receive less technology on average, whereas countries with more FDI, receive more technology on average. Foreign ownership has a negative effect, suggesting that once we control for FDI aimed at transferring technology, the remaining FDI is driven by profit-shifting motives, and firms prefer to transfer their IP's ownership abroad, rather than licensing it. The estimated coefficients on the economic fundamentals remain similar in magnitude and statistical significance. Controlling for the additional variables increases the correlation between the model and the data from 44 percent to 66 percent, improving significantly the fit of the model.

Next, to evaluate further how much the additional channels improve the predictive power of the model, I compute the evolution of royalty payments predicted by the augmented model and compare it to the predicted by the baseline model and to the data. Figures 10-13 plot the results, for the same group of countries as in figures 5-7. Figure 10 does not show substantial differences in the evolution of royalty payments between the baseline and augmented models. In these countries the model tracked the data quite closely.

Figure 10: International technology transfer (data vs model)
The figure shows royalty payments from a technology-importing country to a technology-exporting country for the period 1995-2012 in the data (solid line), in the baseline model (dashed line), and in the augmented model (dotted-dashed line).

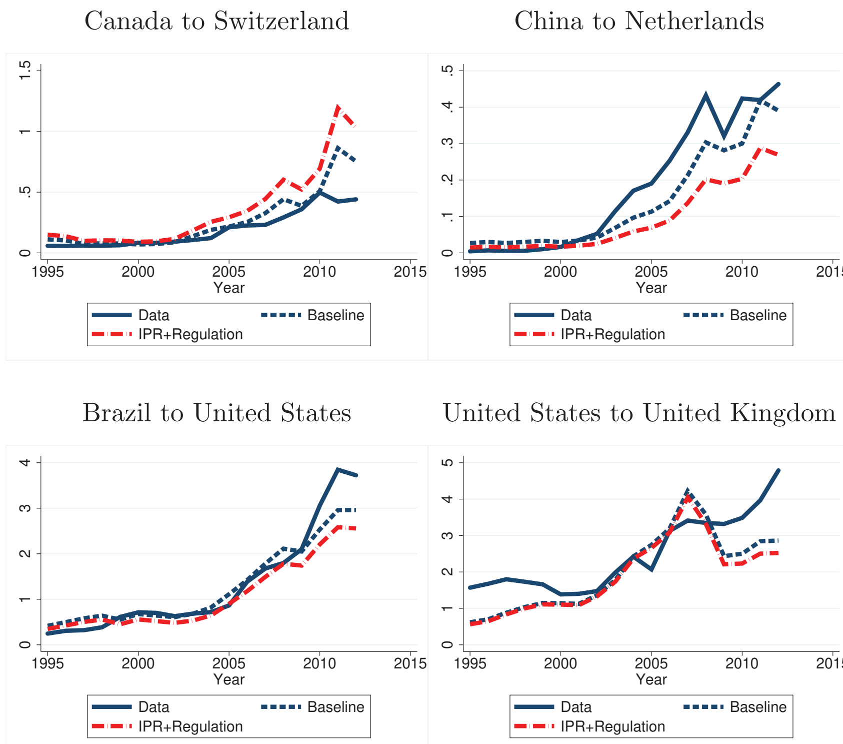
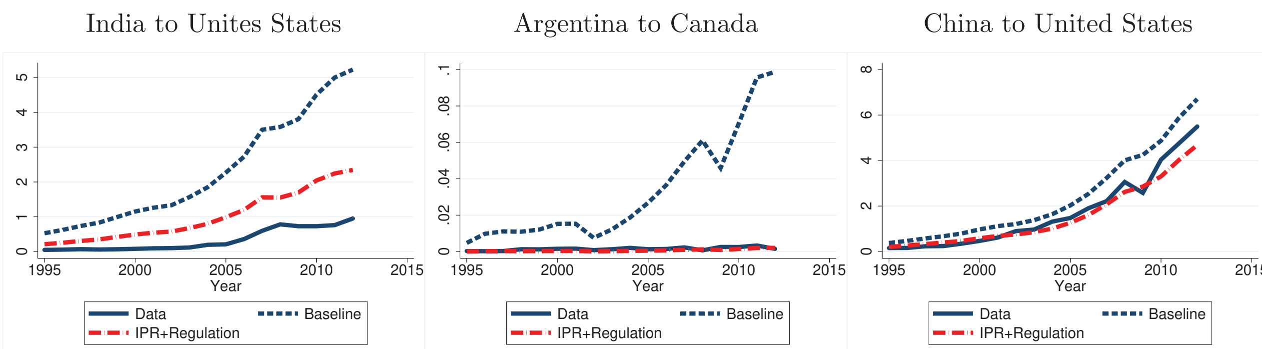



Figure 11 shows countries for which the baseline model predicted larger royalty payments than those observed in the data (i.e., the solid line is below the dashed line). This was the case of developing countries—India, China and Argentina—that imported technologies from innovative countries—the United States and Canada. Controlling for the additional variables improves the fit of the model and developing countries start receiving technology transfers more accordingly to the data (the dotted-dashed line is closer to the solid line). Further analysis suggests that deviations between the model and the data in these cases are mainly driven by differences in the quality of IPR protection.[15] That is, once we control

[15] These results are not reported in the text. I find them by not including the indicators on taxation and the legal system in the regression, and controlling just for IPR enforcement.

for the fact that IPR enforcement in India, Argentina, and China is lower than for the average country, the predictions of the augmented model conform with the data. Take the case of Argentina, for instance. According to the baseline model (dashed line), Argentina should be paying more royalties for the use of Canadian IP than what it is currently paying. One way to interpret this result through the lens of the model is that, given the size and remoteness of Argentina, and given the innovative capacity and productivity of Canada, Argentina should be receiving more technology transfers from Canada. However, as shown in Figure 8, Argentina is one of the countries with lowest IPR protection, so that Canadian firms might fear that Argentinian firms will not honor the contract or that they will leak protected information. Once we control for this possibility, the augmented model predicts less technology transfer to Argentina, and hence royalty payments that are closer to what we observe in the data. Similar arguments apply for China and India. In China, however, the discrepancies between the model and the data were not that large to start with, implying that the Chinese market is very profitable and attracts a lot of foreign technology, despite having low IPR protection.

Figure 11: International technology transfer (data vs model)
The figure shows royalty payments from a technology-importing country to a technology-exporting country for the period 1995-2012 in the data (solid line), in the baseline model (dashed line), and in the augmented model (dotted-dashed line).




In the case of India, there are still some remaining discrepancies between the model and the data, even after including additional variables in the regression. I address this issue by controlling also for India's structure of production, which is another channel missing from the one-sector baseline model. The idea is that countries specialized in high R&D intensive industries may not want to send their technology to countries that specialize in low R&D intensive industries, as the latter countries may not be able to use that technology to generate profits. To control for this possibility, I add the measure of production structure computed in equation (22) to the augmented model's regression. The results are displayed in the third column of table 5. Production structure has a positive and statistically significant effect on royalty payments. Countries with a structure of production more similar to the technology-exporting country receive, on average, more technology. The estimated coefficients of the other variables remain very similar in magnitude and are statistically significant. One exception is the coefficient on the log of R&D spending, which becomes non-significant. The measure of production structure included in the regression uses the number of patents of the exporter, which is correlated with R&D spending. Figure 12 plots the evolution of royalty payments from India to the United States, once we control for India's production structure (long-dashed line). In that case, technology transfer from the United States follows the data more closely.

Figure 12: The structure of production
The figure shows royalty payments from India to the United States for 1995-2012 in (i) the data (solid), (ii) the baseline model (dashed), (iii) the augmented model (dotted-dashed), and (iv) the augmented model controlling for the structure of production (long-dashed).

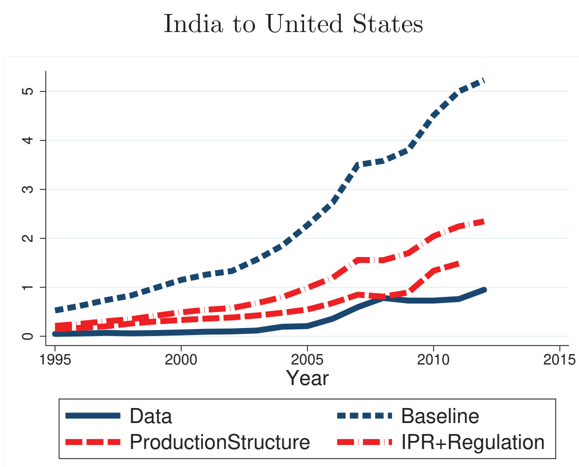



Figure 13 plots countries for which the baseline model predicts lower technology flows than what we observe in the data. This tends to be the case of tax havens, where taxation and the legal system have been found to drive technology transfer for reasons other than size or remoteness. Controlling for the additional variables improves the fit of the model in the case of Ireland importing technology from the United States (left panel of figure 13). However, there are still substantial discrepancies between the model's predictions and observed royalty

Table 5: Bilateral royalty payments and economic fundamentals: This table reports PPML estimation results of the regression of bilateral royalty payments for 53 countries over the period 1995-2012 on economic fundamentals and additional controls.

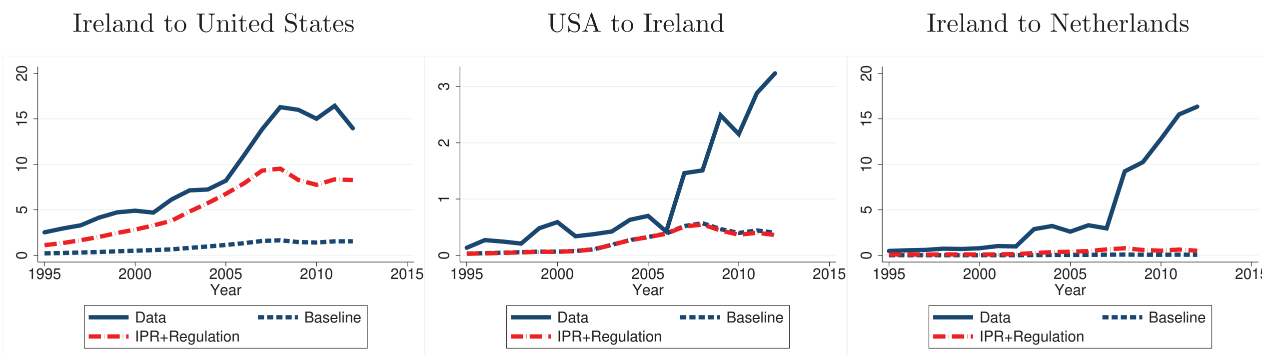
| | (1) | (2) | (3) |
|---|---|---|---|
| log(Distance) | -0.232*** | -0.230*** | -0.289*** |
| | (0.0194) | (0.0200) | (0.0205) |
| Common language | 0.796*** | 0.306*** | 0.284*** |
| | (0.0757) | (0.0634) | (0.0625) |
| log(R&D exporter) | 0.875*** | 0.877*** | 0.0660 |
| | (0.0188) | (0.0161) | (0.0495) |
| log(GDP pc exporter) | 1.268*** | 1.424*** | 1.556*** |
| | (0.0657) | (0.0676) | (0.0932) |
| log(Remoteness importer) | -0.407*** | -0.695*** | -0.318*** |
| | (0.0616) | (0.0563) | (0.0621) |
| log(GDP importer) | 0.307*** | 0.184*** | 0.542*** |
| | (0.0606) | (0.0540) | (0.0606) |
| IP protection index | | 0.441*** | 0.172*** |
| | | (0.0325) | (0.0320) |
| Tax rate (% profits) | | -0.834*** | -0.747*** |
| | | (0.0722) | (0.0614) |
| FDI and technology transfer | | 1.460*** | 1.180*** |
| | | (0.0989) | (0.0933) |
| Foreign ownership | | -0.713*** | -0.390*** |
| | | (0.0541) | (0.0530) |
| log(Prod. str.) | | | 0.657*** |
| | | | (0.0374) |
| $N$ | 49,608 | 48,672 | 40,425 |
| R-squared | 0.440 | 0.660 | 0.725 |

Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

payments from the United States to Ireland and from Ireland to the Netherlands. This could reflect technology transfers being driven by profit-shifting motives. For instance, if a U.S corporation transfers its IP's ownership to an affiliate in Ireland to avoid paying high corporate income taxes in the United States, we would observe more royalty payments from the United States to Ireland than predicted by the model (middle panel of figure 13). The case of the Netherlands may reflect the so-called double Irish "Dutch sandwich", a profit-shifting practice by which a firm in a high corporate income tax country, say the United States, sets up two Irish affiliates and a Dutch affiliate. The U.S firm sends profits through the first Irish company, which then receives royalties from sales sold to U.S. consumers. Since

Irish taxes on royalties are very low, the U.S. profits, and hence paid corporate taxes, are lowered. This scheme could help explain the middle of figure 13. Those profits are then be paid to a Dutch company, showing up as royalty payments from Ireland to the Netherlands (this could explain the right panel of figure 13). Finally, the profits are move to a second Irish company that has its headquarters in a tax haven such as Bermuda or the Cayman Islands. These practices could explain why the augmented model cannot capture the large amount of royalty payments in such cases. Moreover, countries with low corporate income taxes tend to have a large share of intra-firm royalty payments, making them more prone to profit-shifting practices.

Figure 13: International technology transfer (data vs model)
The figure shows royalty payments from a technology-importing country to a technology-exporting country for the period 1995-2012 in the data (solid line), in the baseline model (dashed line), and in the augmented model (dotted-dashed line).




Next, I decompose royalty flows into intra-firm and unaffiliated transfers and control, in the previous regression, for the share of royalty payments between unaffiliated parties. I use data from the International Transactions, International Services, and International Investment Position tables reported by the Bureau of Economic Analysis (BEA) under the title "Charges for the use of intellectual property".[16] These data are disaggregated into affiliated and unaffiliated transactions, and are available between 2006 and 2012 for the United States—both as a sender and as a recipient of technology—with respect to the other countries in the sample.[17] In 2012, 35 percent of all royalty payments received by the

[16]See `https://apps.bea.gov/itable/itable.cfm?reqid=62&step=1`. Table 2.2 in that link contains information on trade in services by type of service and by country or affiliation between 2006 and 2012.

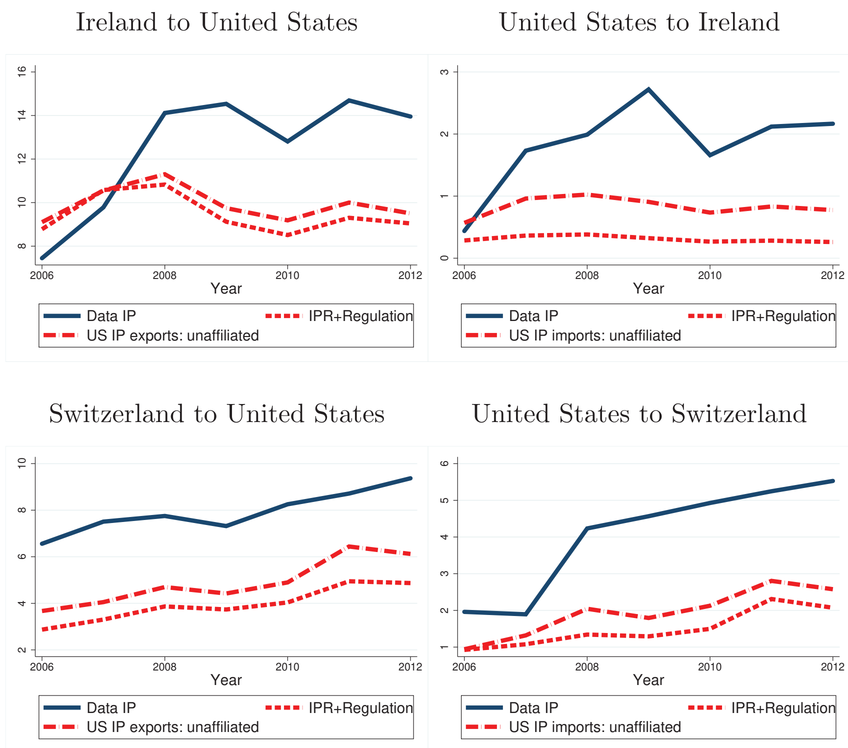
[17]To the best of my knowledge, data that decomposes royalty payments between affiliated and unaffiliated parties for all the country-pairs in the sample is not available.

United States proceeded from unaffiliated parties. These numbers vary substantially across technology-importing countries. In Ireland, for instance, only 10 percent of royalty payments to the United States proceeded from unaffiliated firms. In Switzerland, this ratio was also low, while in China it was about 75 percent. Ireland and Switzerland are also receiving large amounts of royalty payments from the United States. These numbers suggest that technology transfers to those countries may be driven by profit-shifting motives.

Controlling for the share of unaffiliated transactions in the previous regressions increases the amount of royalty payments predicted by the model in tax havens and takes them closer to what we observe in the data (see figure 14). However, there are still important discrepancies suggesting that the legal system in tax haven is quite complex, and controlling for the additional variables is not enough to close the gap. A model that addresses these issues explicitly could allow us to understand better the main determinants of technology transfers to and from these countries.[18]

[18]In Appendix C, I explore issue further. I use data on IP flows from the International Transactions, International Services, and International Investment Position, and redo the previous regression analysis on: (i) total IP flows, (ii) IP flows between affiliated parties, and (iii) IP flows between unaffiliated parties.

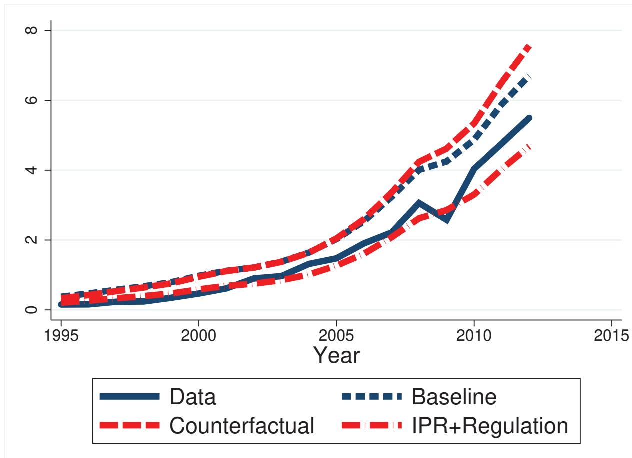
Figure 14: The share of unaffiliated transfers
The figure shows royalty payments from a technology-importing country to a technology-exporting country for the period 2006-2012 in the data (solid line), in the augmented model (dashed line), and controlling in the augmented model for the share of unaffiliated transfers (dotted-dashed line).




**Back-of-the-Envelope Counterfactual** Motivated by the current trade disputes between the United States and China, and the accusations from the U.S. administration of IP theft by China, I use the empirical results to infer how much technology transfer China would have received from the United States if its IPR protection index had been identical to that of the United States. Figure 15 plots the evolution of royalty payments from China to the United States in that case. If China had the same quality of IPR protection as the United States during 1995-20102, technology transfer from the United States would have been, on average during the period of analysis, 57 percent higher.

Figure 15: Back-of-the-envelope Counterfactual:
The figure shows royalty payments from China to the United States during 1995-2012 in (i) the data (solid), (ii) the baseline model (dashed), (iii) the augmented model (dotted-dashed), and (iv) the augmented model assuming an IPR index for China identical to the United States (dotted-dashed).

China to United States




# 5 Instrumental Variable Analysis

One challenge of the analysis performed so far is that some of the regressors in the PPML estimation could be endogenous. More specifically, there could be reverse causality if the exporter's R&D spending and its productivity were endogenous to the amount of royalty payments received. For instance, if an exporter receives many royalties from abroad because the recipient country is very profitable, that could increase the exporter's innovators incentives to do more R&D spending and, in turn, its productivity. To address potential endogeneity and reverse causality, I perform an IV analysis in which I instrument the two endogenous regressors—R&D spending and productivity—using (i) the country's number of patent applications, and (ii) the trade-weighted R&D stock of its main trading partners.

The number of patent applications is correlated with the endogenous regressors but not necessarily with licensing of technology (the dependent variable), satisfying the exclusion restriction. The reason is that, in general, IP licensing is made once the patent has been granted. Even in sectors in which, because of the long delays in the review process, a company decides to license patents that have not yet been granted, patent applications take time to diffuse and be adopted. In the model, only a technology that has diffused and been adopted can generate royalty income. I collect data for total patent applications for the sample of 53 countries during the period 1995-2012 from WIPO IP Statistics Data Cente.[19]

Similarly, the trade-weighted R&D stock of a country's main trading partners is correlated with the endogenous regressors but not with licensing of technology directly. In the model, a country's productivity is a function of both domestic and foreign R&D that has diffused to that country—regardless of whether or not it has yet been adopted and thus can generate royalty income. Therefore, foreign R&D that has diffused should correlate with domestic productivity. Because international trade has been found to be an important channel of diffusion in the literature, the trade-weighted R&D stock of a country's main trading partners is used as the instrument. I obtain trade data from the BACI—the world trade database developed by the CEPII, and keep, for each country, those trading partners that together account for at least 90 percent of imports. I then calculate a measure of R&D stock as the cumulative sum of R&D spending for those trading partners and construct the trade-weighted R&D stock.

I start by estimating equation (20) in logs using both OLS and a two-stage least-squares (2SLS) IV regression procedure. This method allows us to apply standard econometric techniques to test for weak instruments. Table 6 reports the estimation results. With both OLS and 2SLS, the right-hand-side variables have the expected signs, and the estimated coefficients have a similar magnitude.

[19]The data can be found in: https://www3.wipo.int/ipstats/

Table 6: Log-linear model: OLS vs IV
This table reports both OLS (second column) and 2SLS results of the log-linear version of the augmented model (third column). The endogenous regressors are the exporter's R&D spending and GDP per capita. The instruments are the exporter's number of patent applications and trade-weighted R&D stock of its main trading partners.

| | OLS | IV |
|---|---|---|
| log(distance) | -0.665*** | -0.638*** |
| | (0.00959) | (0.0181) |
| Common language | 1.147*** | 1.126*** |
| | (0.0370) | (0.0302) |
| log(R&D exporter) | 0.704*** | 0.749*** |
| | (0.00531) | (0.0185) |
| log(GDPpc exporter) | 0.675*** | 0.790*** |
| | (0.00924) | (0.0730) |
| log(Remoteness importer) | -0.123*** | -0.280*** |
| | (0.0276) | (0.0555) |
| log(GDP importer) | 0.988*** | 0.832*** |
| | (0.0263) | (0.0558) |
| IP protection index | 0.0235 | 0.0222 |
| | (0.0121) | (0.0125) |
| Tax rate (% profits) | -1.374*** | -1.386*** |
| | (0.0392) | (0.0400) |
| FDI and technology transfer | 0.0426 | 0.0388 |
| | (0.0278) | (0.0325) |
| Foreign ownership | 0.223*** | 0.227*** |
| | (0.0207) | (0.0231) |
| $N$ | 45,433 | 44,427 |
| adj. $R^2$ | 0.658 | 0.658 |

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7 reports weak identification test results from the first-stage regressions, which demonstrate the strength of the proposed instruments for each first-stage equation. The adjusted R-squared are 25 percent and 85 percent, which shows that the instruments can explain a sizable share of the variation in the endogenous variables. More importantly, the Cragg–Donald F-statistic exceeds the Stock–Yogo weak identification test critical values by substantial margins at all the conventional sizes; this, too, shows that the instruments are strong.

Table 7: Weak identification test: First-stage regression
This table reports the results from the first-stage IV regression: Adjusted R-squared for the OLS regression of each endogenous regressor on the instruments and exogenous regressors, the Cragg-Donald Wald F-statistic, and critical values for the Stock and Yogo test.

| Regressor | Instrument | $R^2$ | CD Wald F-stat. | Stock–Yogo |
|---|---|---|---|---|
| | | | | 10%, 7.03 |
| log(R&D), | log(Patents) and | 0.85 | | |
| | | | | 15%, 4.58 |
| | | | 410.03 | |
| | | | | 20%, 3.95 |
| log (GDPpc) | log(Trade-weighted R&D) | 0.26 | | |
| | | | | 25%, 3.63 |

Finally, after having shown that we can reject the null hypothesis of weak instruments in the log-linear version of the model, I conduct an IV regression of the nonlinear model using an IV Poisson estimation procedure, originally described in Windmeijer and Santos Silva (1997). This estimation procedure compares more directly with the analysis performed in the previous sections of the paper. The results are reported in table 8. The first column reports results from the PPML regression of the augmented model (already shown in the second column of table 5). The second column reports results from the IV Poisson estimation. All variables have the expected signs and are statistically significant, with the exception of the presence of foreign ownership that becomes non-significant when instruments are used. The main differences in the magnitude of the estimated coefficients with respect to the PPML regression are that, in the IV regression: (i) distance and common language have a stronger effect on royalty payments between countries, (ii) exporter's R&D and GDP per capita, i.e. the instrumented variables have a weaker effect, (iii) size matters more, and (iv) the additional controls become less important. The coefficients are still statistically significant.

In summary, the results are robust to the use of instrumental variables that address potential endogeneity of some of the regressors.

Table 8: Non-linear model: PPML vs IV Poisson:
This table reports both PPML (second column) and IV Poisson (third column) results of the non-linear augmented model. The endogenous regressors are the exporter's R&D spending and GDP per capita. The instruments are the exporter's number of patent applications and trade-weighted R&D stock of its main trading partners.

| | PPML | IV Poisson |
|---|---|---|
| log(distance) | -0.230*** | -0.453*** |
| | (0.0200) | (0.0230) |
| Common language | 0.306*** | 0.850*** |
| | (0.0634) | (0.0554) |
| log(R&D exporter) | 0.877*** | 0.509*** |
| | (0.0161) | (0.0181) |
| log(GDP pc exporter) | 1.424*** | 1.076*** |
| | (0.0676) | (0.0635) |
| log(Remoteness importer) | -0.695*** | -0.283*** |
| | (0.0563) | (0.0661) |
| log(GDP importer) | 0.184*** | 0.686*** |
| | (0.0540) | (0.0650) |
| IP protection index | 0.441*** | 0.0854*** |
| | (0.0325) | (0.0179) |
| Tax rate (% profits) | -0.834*** | -0.786*** |
| | (0.0722) | (0.0856) |
| FDI and technology transfer | 1.460*** | 0.258*** |
| | (0.0989) | (0.0680) |
| Foreign ownership | -0.713*** | 0.0502 |
| | (0.0541) | (0.0453) |
| $N$ | 48,672 | 47,652 |
| $R^2$ | 0.660 | |

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

# 6 Concluding Remarks

This paper has identified, through the lens of a multi-country general equilibrium model of innovation and international technology diffusion with perfect IPR protection, the main economic fundamentals of international technology transfer. Deviations between the data and the model's predictions have been explained with three channels, from the perspective of the technology-importing country, that are not captured by the model: (i) imperfect enforcement of IPR; (ii) taxation and the legal system; and (iii) the structure of production. Controlling for these channels significantly improves the fit of the model. A back-of-the-envelope counterfactual has shown that had the IPR protection in China been the same as in the United States, technology transfer from the United States to China would have been, on average during the period of analysis, 57 percent higher. These results are robust to the use of IV variables addressing potential endogeneity.

This analysis has identified several important channels that would be relevant to model explicitly in a quantitative framework analyzing international technology diffusion. First, the model could be extended to include patenting decisions of innovators when there is imperfect enforcement of IPR (i.e., when there is a positive probability of imitation or misappropriation of a foreign technology). Second, it could be extended to model the decision of a firm in a high corporate income tax country to transfer technology to an affiliate in a low corporate income tax country for profit-shifting motives. I leave these extensions, as well as a more formal quantitative analysis, for future research.

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# APPENDIX

# A Data

Table 9: **Raw Data and Sources**

| Variables | Sources | Time Period |
|---|---|---|
| Charges for IP services (imports and exports, millions U.S.$) | OECD.stat | 1995-2012 |
| GDP (Constant U.S.$), GDP per capita (Constant U.S.$) | World Bank WDI | 1995-2012 |
| R&D expenditure (millions U.S.$) | World Bank WDI | 1995-2012 |
| Bilateral distance (most pop cities, km), common language dummy | CEPII | 1995-2012 |

## A.1 Important Notes on Variables

- *Total trade in services, and IP services: OECD, Trade in Services Balanced Panel EBOPS 2012*
  - I use the OECD balanced panel EBOPS 2012, as opposed to 2010, to maintain a balanced dataset of trade flows with mirror trade flows.

- *R&D expenditure, World Bank WDI:*
  - Values for R&D expenditure are given as a percentage of GDP. Using GDP data from the World Bank, I convert these values to millions of USD. I interpolate missing values of R&D expenditure using GDP as the reference variable.

# B Country List

| Country | ISO | Country | ISO |
|---|---|---|---|
| Argentina | ARG | Italy | ITA |
| Australia | AUS | Japan | JPN |
| Austria | AUT | Korea | KOR |
| Belgium | BEL | Lithuania | LTU |
| Bulgaria | BGR | Luxembourg | LUX |
| Belarus | BLR | Latvia | LVA |
| Brazil | BRA | Mexico | MEX |
| Canada | CAN | Malaysia | MYS |
| Switzerland | CHE | Netherlands | NLD |
| Chile | CHL | Norway | NOR |
| China | CHN | New Zealand | NZL |
| Cyprus | CYP | Peru | PER |
| Czech Republic | CZE | Phillipines | PHL |
| Germany | DEU | Poland | POL |
| Denmark | DNK | Portugal | PRT |
| Spain | ESP | Russia | RUS |
| Finland | FIN | Singapore | SGP |
| France | FRA | Slovakia | SVK |
| United Kingdom | GBR | Slovenia | SVN |
| Greece | GRC | Sweden | SWE |
| Hong Kong | HKG | Thailand | THA |
| Croatia | HRV | Turkey | TUR |
| Hungary | HUN | Ukraine | UKR |
| India | IND | Uruguay | URY |
| Ireland | IRL | United States | USA |
| Iceland | ISL | Vietnam | VNM |
| Israel | ISR | | |

# C IP Flows: Total, Affiliated and Unaffiliated

In this section, I explore further whether the behavior of royalty payments differs depending on the type of transactions: intra-firm or unaffiliated. Using data from the International Transactions, International Services, and International Investment Position from the BEA, I conduct a PPML regression analysis on: (i) total IP flows, (ii) IP flows between affiliated parties, and (iii) IP flows between unaffiliated parties. As there is only available information on royalty payments between the United States and other countries in the sample, this is an unbalanced panel. The results are reported in table 10. Several interesting facts stand out. The coefficient on the importer's size is not significant when transfers happen between affiliated firms; however, it is positive, statistically significant and large in the case of unaffiliated transfers. The coefficient on the remoteness index changes its sign in the case of flows between unaffiliated parties. In this case, size becomes more important, suggesting that the United States pays more attention to size in the case of technology that is transferred to unaffiliated parties. IPR protection has the same effect regardless of the type of transactions, but the tax rate has a larger effect on affiliated transactions, as we would expect if intra-firm flows capture profit-shifting motives.

Using the results from table 10, figure 16 plots the evolution of royalty payments–total (top panel), affiliated (middle panel) and unaffiliated (bottom panel)—from Ireland to the United States and from China to the United States, both in the data and in the augmented model. Ireland is paying royalties above the predictions of the model in the case of intra-firm transfers. In contrast, the figure shows that Ireland should be paying more than what it is currently paying to the United States in the case of transactions with unaffiliated firms. Therefore, a large share of intra-firm technology transfer in tax havens may be associated with profit-shifting practices. Instead, China's royalty payments to the United States are closer to the data in the case of affiliated transactions, but it is paying less than predicted in the case of unaffiliated transactions. This result suggests that it may be more difficult to enforce payments from third parties than from intra-firm transactions.

Figure 16: Total, unaffiliated vs affiliated IP payments

The figure shows royalty payments from a technology-importing country to a technology-exporting country for the period 2006-2012 in the data (solid line), and in the augmented model (dashed line) for three cases: total payments (top panel), affiliated (middle panel), and unaffiliated (bottom panel)

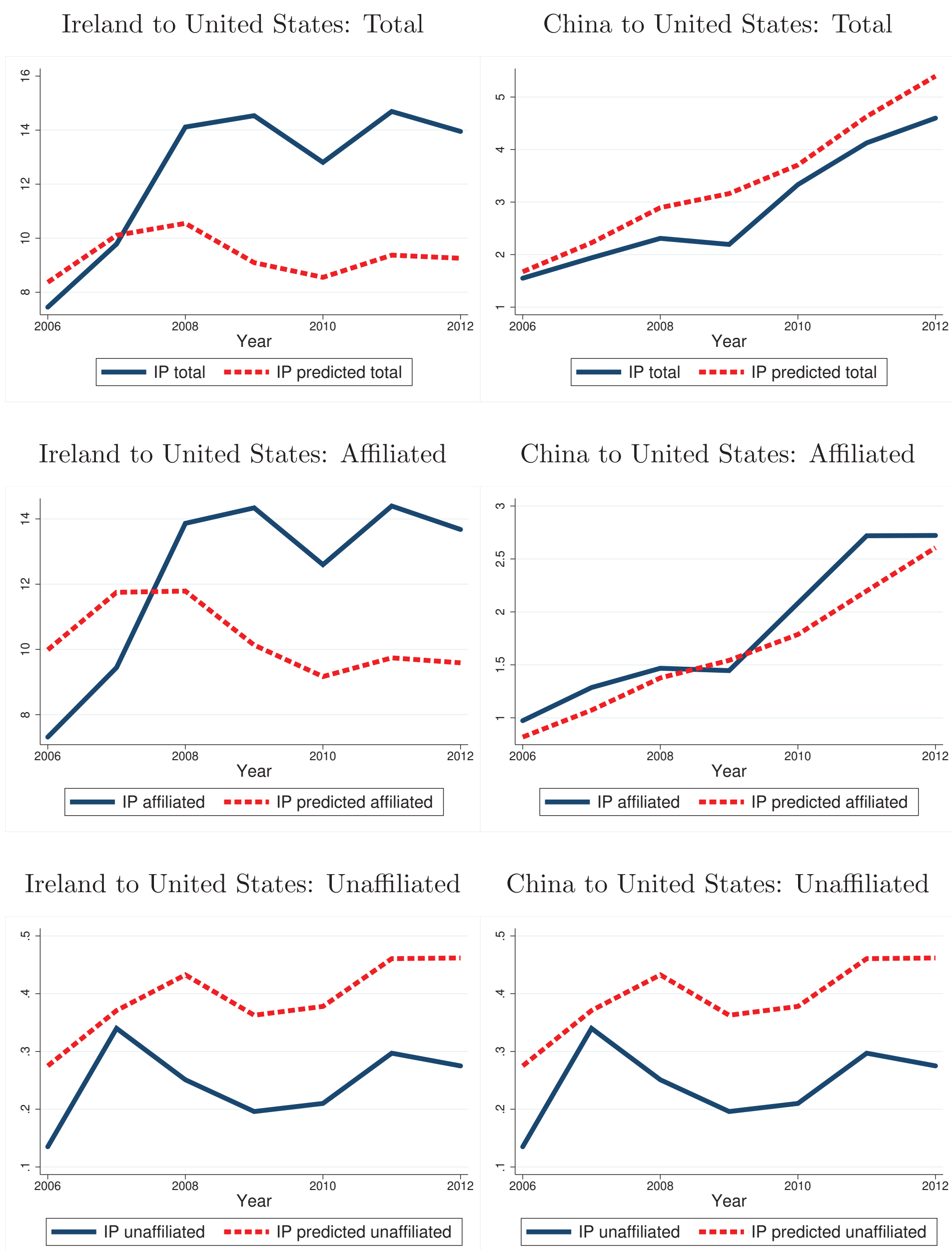

Table 10: Bilateral royalty payments between affiliated and unaffiliated parties: This table reports PPML estimation results of the regression of bilateral royalty payments from BEA data for the United States, both as receiver and sender of technology, with respect to the other 52 countries, for 2006-2012. The regressions are performed on all the firms (second column), unaffiliated (third column) and affiliated firms (fourth column).

| | All firms | Unaffiliated | Affiliated |
|---|---|---|---|
| log(Distance) | -0.0154 | -0.183*** | 0.0444 |
| | (0.0299) | (0.0444) | (0.0321) |
| Common language | 0.0344 | 0.304** | -0.229 |
| | (0.101) | (0.105) | (0.143) |
| log(R&D exporter) | 1.022*** | 1.059*** | 1.028*** |
| | (0.0447) | (0.0423) | (0.0572) |
| log(GDP pc exporter) | 1.275*** | 0.640*** | 1.685*** |
| | (0.186) | (0.121) | (0.286) |
| log(Remoteness importer) | -0.580*** | 0.679*** | -1.069*** |
| | (0.121) | (0.158) | (0.150) |
| log(GDP importer) | 0.339** | 1.466*** | -0.0376 |
| | (0.120) | (0.150) | (0.149) |
| IP protection index | 0.480*** | 0.447*** | 0.483*** |
| | (0.0523) | (0.0672) | (0.0624) |
| Tax rate (% profits) | -1.198*** | -1.023*** | -1.225*** |
| | (0.187) | (0.267) | (0.222) |
| FDI and technology transfer | 1.299*** | -0.221 | 1.810*** |
| | (0.122) | (0.138) | (0.124) |
| Foreign ownership | -0.384*** | -0.277* | -0.178 |
| | (0.0896) | (0.117) | (0.101) |
| $N$ | 606 | 576 | 578 |
| R-squared | 0.848 | 0.766 | 0.838 |

Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$