Exporting Ideas: Knowledge Flows from Expanding Trade in Goods*

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April 2021

PRELIMINARY - PLEASE DO NOT CIRCULATE

Abstract

Combining French firm-level administrative, customs and patent data over 1995-2012, and using a difference-in-differences identification strategy with a staggered treatment design, we show that entry by a French firm into a new export market increases its patents' citations received from that destination. Moreover this technological spillover is stronger for French firms with higher average quality patents and in destination countries at intermediate levels of development.

JEL classification: O33, O34, O40, F10, F14

Keywords: International Trade, Spillover, Innovation, Patent, Competition

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1 Introduction

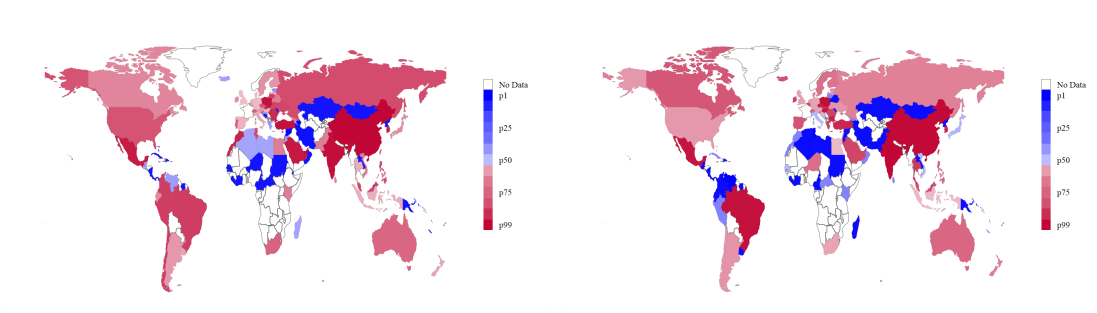
Modern growth theory predicts that international trade should enhance productivity growth for several reasons. First, trade allows potential innovators to sell to a larger market; and by *increasing market size*, trade increases the size of ex post rents that accrue to successful innovators, thereby encouraging R&D investments. Second, trade *raises competition* in product markets, which in turn encourages innovation aimed at escaping competition by more advanced firms while discouraging innovation by laggard firms in the domestic economy. Besides these within-firm impacts on productivity, trade induces general equilibrium effects, through the selection of firms able to compete on a given market. Trade also *induces knowledge spillovers* which allows producers in recipient countries to catch up with the technological frontier. Using detailed trade and patent data, we focus on this channel and show that firms export more than goods, they also export the ideas and technologies embedded in these goods, which the destination country can then capitalize on.

To motivate our analysis, we document that the countries where France exports to are closely related to the countries of origin of the citations to French patents. In Figure 1a, we plot the long difference between the number of French exporters from 1995 to 2012 (i.e. the difference between the number of French exporters in 2012 and the number in 1995) for the various geographical regions of the world. Each color corresponds to a decile in the long difference distribution across regions. Dark red (dark blue) corresponds to regions with the largest (resp. smallest) increase in the number of exporters from 1995 to 2012. In Figure 1b, we plot the long difference between the number of citations to French patents from 1995 to 2012 for different regions worldwide; again the dark red (dark blue) color refers to regions lying in the highest (resp. lowest) decile in terms of long difference increases in citations. We see that those destinations experiencing the largest increase in the number of French exporters also experience the largest increase in patent citations to French innovations over the same time period. The covariance between the two long differences is equal to 1.62

(s.e.=0.22).[1]

Figure 1: Evolution of Trade and Innovation Linkages

(a) Number of French Exporters (b) Citations



Notes: Evolution in the number of French exporters in each country (left-hand side panel) and the number of citations received from each country (right-hand side panel) between 1995 and 2012. Colors correspond to different deciles in the corresponding quantity.

We exploit comprehensive patent information about French exporters over the 1995-2012 period. For every year and potential export destination, we construct a citation count for each exporters' patents. These citations come from new patents introduced in that year by firms or inventors operating in the destination country. We then investigate how a French firm's citation count in a destination changes whenever that firm starts exporting to that destination. Increases in a new exporter's citations represent new patents recorded in that destination subsequent to the exporter's entry into the destination. Those patents citing the French exporter represent a measure of its technological influence in that destination. We use the timing of the exporter's entry into a market and its citations in that market to infer a causal relationship between the two.

More specifically, we use a difference-in-differences (DiD) strategy to analyze the response of patent citations to a French firm's export market entry in a particular year. We rely on a staggered treatment adoption design that exploits the fact that firms enter their export markets at different times. The identifying assumption is the existence of a common trend between entrants and non-entrants: inventors in a foreign country would have cited French entrants at the same rate as non entrants had the French firms not entered the

[1]That is: $\texttt{LDLnCitations}_j = 1.62(s.e. = 0.22) \times \texttt{LDLnExporters}_j + \upsilon_j$

country[2]. We use the de Chaisemartin and d'Haultfoeuille (2020) DiD estimator to account for potential weighting issues raised by standard estimators. We introduce both firm-year and destination-sector-year fixed effects to account for common shocks to treated and non treated observations. Identification results from comparing citations to a firm across all of its current and future export destinations after absorbing time-varying destination market factors.

We conduct our analysis, first at the firm level and then at the patent level, i.e. at the level of a particular patent issued by a French exporting firm.

Our first main finding is that exporting to a new foreign market increases the flow of triadic citations received by the exporter from firms in that market. The underlying idea is that entry into that new market raises the visibility of the exporter's technology to domestic firms in the market. Those domestic firms can then more easily generate further innovations that build on that technology, conditional on the host country's degree of absorptive capacity (Cohen and Levinthal, 1989). We find that the impact of entry on citations (and hence knowledge flows in the destination) is positive and significant starting 3 years after export market entry.

Our second finding is that entering a new foreign market increases more the probability of obtaining at least one or a few triadic citations - the extensive margin - than the probability of obtaining many citations - the intensive margin.

Our findings are robust to the choice of the functional form in the left-hand side variable, to dropping from the sample the citations added during the initial search process by the patent office or by the patent examiner, and to restricting our sample to foreign destinations where the firm never created an affiliate, i.e. to controlling for citations generated by

[2]Our identification strategy is inspired from Watzinger et al. (2017, 2018), who study the knowledge spillovers induced by professor transfers across universities. We use a similar approach to build a control group of French firms with an *ex-ante* similar probability of entry into a given market, but who did not enter in that particular year.

affiliates which would cite the French parent company.

The firm-level analysis does not account for patent specific characteristics (within-firm patent heterogeneity), such as age, technological fields, quality ... This leads us to disaggregate our data further and to conduct the analysis at the patent-destination level. Our analysis at the patent level suggests that inventors in destination countries conduct research that builds on the technologies embodied in the exported product.

We then analyze the extent to which the magnitude of the knowledge spillovers from French exporting firms to firms in the destination countries depends upon the average quality of the French firm's patents and the level of development of the destination country (which we use as a proxy for the country's degree of absorptive capacity). We find that French firms with higher average "patent quality", which also tend to be firms with higher productivity, generate a larger increase in citations in destination countries post-entry; these citations also happen to be of better quality.

Next, we find that the characteristics of destination countries also matter: namely, the level of development of destination countries - as measured by their GDP per capita - strongly influences the magnitude of the knowledge spillovers generated by French firms that start exporting to those countries. We find that the spillover intensity is hump-shaped with a peak around the 55-60 percentile of the GDP per capita distribution across destinations. The spillover intensity steadily decreases with development for richer countries beyond that peak – but remains positive. We also find a negative and significant spillover for the poorest set of destinations. This is consistent with the view that firms in those destinations have much lower "absorptive capacity" to use the knowledge spillover from the new French exporters, and mainly suffer from the increased competition generated by those French firms. Development then enhances a destination's ability to absorb - and build upon - the technology of the French exporters. At the other end, highly developed destinations may have already discovered the technologies that would allow them to make use of

the French firm's technology. Overall, our results vindicate Cohen and Levinthal (1989)'s view stated in the following quote: "*Economists conventionally think of R&D as generating one product: new information. We suggest that R&D not only generates new information, but also enhances the firm's ability to assimilate and exploit existing information. [...] we show that, contrary to the traditional result, intra-industry spillovers may encourage equilibrium industry R&D investment*." (Cohen and Levinthal, 1989, p.569).

Our analysis relates to several other strands of literature. There is first the literature on spillovers and trade, starting with Coe and Helpman (1995a), who show that a country's TFP is positively correlated not only with domestic R&D but also with foreign R&D and to an extent which increases with the country's degree of openness to foreign trade.[3] We contribute to this literature by using firm-level data and patent citation data to identify a causal effect of export on the innovative activity in the destination country.

Second, our paper relates to the recent literature on trade and innovation, including papers on both, imports and innovation (see Bloom et al., 2016; Autor et al., 2016; Bombardini et al., 2017) and on exports and innovation (see Lileeva and Trefler, 2010; Aghion et al., 2018). Overall, this literature concentrates on the competition and market size effects of trade. We contribute to that literature by looking at the technological spillover effects of trade, and more precisely at how exporting to a destination country affects the exporting firm's patent citations by firms in that destination country.

Third is the literature on academia, scientists and citations. Thus Azoulay et al. (2010) and more recently Jaravel et al. (2018) analyze the impact of an inventor's death on the subsequent innovation and income patterns of the inventor's surviving coauthors. Waldinger (2011) analyzes the impact of the dismissal of Jewish scientists's by the Nazi government in Germany in the '30s. And Watzinger et al. (2017, 2018) analyze the impact of the mobility of scientists across German universities on local citations to their work. We contribute to

[3] See also Keller and Yeaple, 2009, Coe et al., 2009, and Keller and Yeaple, 2009.

this and the broader literature on knowledge spillovers and absorptive capacity by looking at how trade interacts with knowledge spillovers and absorptive capacity.[4]

The remaining part of the paper is organized as follows. Section 2 presents the data and details our empirical strategy. Section 3 outlays our main results. Section 4 shows how the magnitude of the knowledge spillovers generated by new French exporters, varies with both, the quality of French firm's patents and the level of development of destination countries. Section 5 concludes.

2 Data and Methodology

2.1 Data

We build a database that covers all French firms and links export, production and innovation/citation data from 1994 to 2012. Our database builds upon three separate sources. First, detailed customs data provide information on French exports by product and country of destination for each French firm over 1993-2012. Every firm must report its exports by destination country and by very detailed product (with a classification of 10,000 different products consistent with 8-digit CN codes).[5] From this database, we extract the date of first entry into a foreign market for each firm.

Our second data source is the INSEE-DGFiP administrative fiscal dataset (FICUS-FARE), which provides extensive production and financial information for all firms operating in France. This data is drawn from compulsory reporting to fiscal authorities in France, supplemented by further census data collected by INSEE.

Our third data source is the Spring 2016 PATSTAT dataset from the European Patent Office. This dataset contains detailed information on all patent applications from most patent

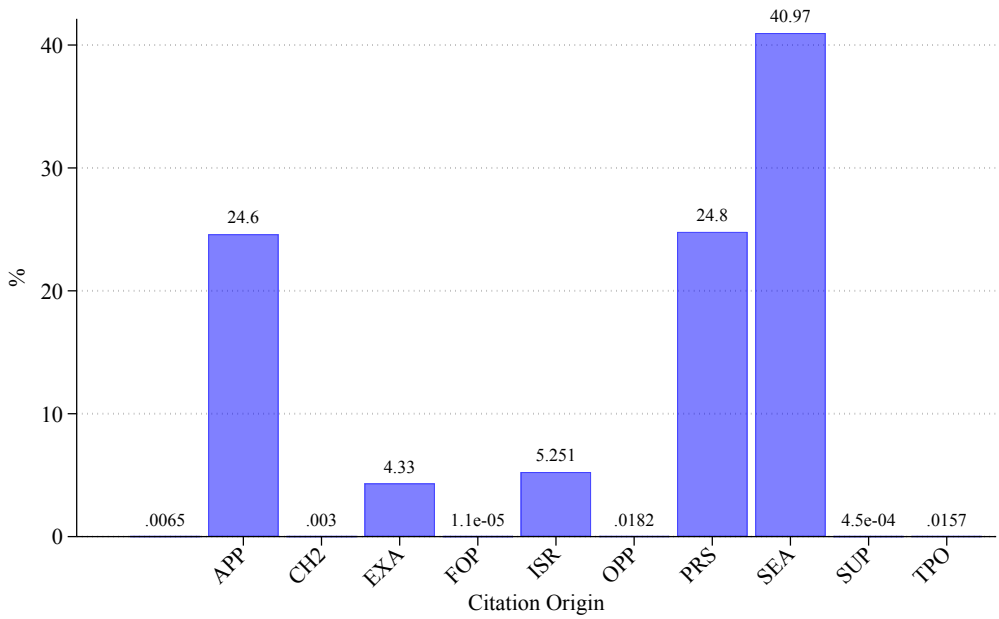
[4] See Aghion and Jaravel (2015) for more detailed references to that literature.
[5] i.e. one extra level of desaggregation compared to HS6 UN Comtrade harmonized data.

offices worldwide, including information on the network of patent linkages via citations. We use it to measure French firms' patent stocks and the citations from foreign inventors to French firms' patents. Although each French firm has a unique identifying number (Siren) across all French databases, patent offices identify firms using only their name. The recording of the name is sometimes inconsistent from one patent to another, and may also contain typos. Various algorithms have been developed to harmonize assignees' names (for example this is the case of the OECD's Harmonized Assignee Name database) but none of those have been applied specifically to French firms. One notable exception is the matching algorithm developed by Lequien et al. (2019) to link each patent application with the Siren numbers of the corresponding French firms; for all firms with more than ten employees. Based on supervised learning, this new method provides significant performance improvements relative to previous methods used in the empirical patent literature: the algorithm's recall rate (i.e. the share of all the true matches that are accurate) is 86.1% and its precision rate (i.e. the share of the identified matches that are accurate) is 97.0%. This is the matching procedure we use for our empirical analysis in this paper. We restrict citations, i.e. new foreign patents citing a French patent, to "triadic citations". Those are patents that were filed in the European Patent Office (EPO), the Japan Patent Office (JPO) and the United States Patent and Trademark Office (USPTO). Filing applications in all three major patent offices represents a significant cost for the patenting firm. Those patents represent innovations that were deemed valuable enough to warrant the additional protection coverage (Lanjouw (1998), Harhoff et al. (2003), Squicciarini et al. (2013)). They are therefore unlikely to be purely defensive or "troll" patents.

There is some concerns that citations may not capture properly between-firms (foreign and domestic) knowledge spillovers. It may instead capture the patent examiner's knowledge about the foreign technical literature (Alcacer and Gittelman, 2006). The patent database PATSTAT references three main types of citations (Figure 2): (i) citations added

by the applicant before the application was filled (c. 25%), (ii) citations added during the initial search process by the patent office (c. 70%); (iii) citations added by the examiner (c. 5%). Based on USPTO and EPO documentation, a possible case is that an applicant does not cite the "inspiring" patent but does transmit to the patent office "The trade names and providers of any goods or services in competition with the goods" which inspired the invention. The patent office will then find the relevant patent and add the citation. In this case, the patent added by the patent office during the search may still reflect knowledge spillovers between firms. In any case, we check the robustness of our main result by estimating our baseline model on a sub-sample restricted to citations added by the applicant. We find similar effects that follows the same dynamic pattern with the same order of magnitude.

Figure 2: Citation Origin



Notes: This figure shows who added the citation (applicant, patent office during the search process, patent examiner, etc.)

We seek to measure the knowledge spillovers from new French exporters-innovators who enter an export destination during our 1995-2012 sample years, to firms/inventors in that destination. There are 6,753 such French exporters-innovators (with at least one patent that can potentially be cited) who enter one of 156 destinations during our sam-

ple years. Those firms account for 125,700 patents that have generated 614,847 citations (new patents) in foreign destinations. Those entries represent 139,954 potential knowledge spillover links between a foreign patent and a French firm. All those numbers are reported in Table 1 below.

Table 1: Sample Description

Level	N
Year	19 (1993-2012)
Countries	156
Firms	6,753
Patents	125,700
Citations	614,847
Links (firms * destination)	139,954

NOTE: This table describes the composition of the main estimation sample

2.2 Identification strategy

We want to estimate how a French firm's entry into a new export market affects its flow of new citations from this destination to the firm's patents. The most natural approach is to aggregate our data at the firm-destination level. More specifically, we want to estimate how a firm's entry into a new export market j affects subsequent citations Y to its stock of existing patents received from firms located in that destination j. Therefore we aim at implementing regressions in the spirit of Equation (1):

$$Y_{f,j,t} = \sum_k \beta_k \times 1_{E_{f,j}=t-k} + \chi(f, j, t) + \epsilon_{f,j,t} \tag{1}$$

Citations to firm f's patents coming from country j at date t, $Y_{f,j,t}$, depend on characteristics of the firm, the destination market and the date, that are captured with the generic $\chi(f, j, t)$ function. In practice we will use a set of firm-year and destination-sector-year fixed effects. The coefficients β_k capture the additional citations that can be linked to firm f

starting exporting to j k years before the citation date t (so $E_{f,j}$, the date at which f enters j for the first time, is equal to $t-k$).

We rely on a Difference-in-Differences strategy with a staggered treatment adoption design and we exploit the fact that firms enter their export markets at different times. The identifying assumption is the existence of a common trend between entrants and non-entrants: inventors in a foreign country j would have cited French entrants at the same rate as non entrants had the French firms not entered country j.

This assumption likely holds for two reasons. First, we restrict the sample to exporting firms - i.e. firms with non zero exports over the sample period - that are also innovating firms - i.e. firms with a strictly positive patent stock - and to firms-destinations pairs that are eventually "treated" by entry. The sample is therefore relatively homogeneous and we only exploit differences in the *timing* of entry. Second, we check the correlation between the entry decision and future citations and do not detect any pre-trends.

We use the de Chaisemartin and d'Haultfoeuille (2020) Differences-in-Differences estimator. This estimator accounts for potential weighting issues raised by standard difference-in-differences estimator (see for instance Callaway and Sant'Anna (2019) and Goodman-Bacon (2018)). [6] Thus we estimate β_k in equation (1) using the following estimator:

$$DID_k = \sum_{t=0}^{T} \frac{N_t^k}{N_{DID_k}} DID_{t,k} \tag{2}$$

where

[6] In particular de Chaisemartin and d'Haultfoeuille (2020) show that the coefficients identified by the canonical two-way fixed effect (TWFE) model capture a combination of the actual treatment effects and of "weights" effects. In the case of a staggered design, the TWFE mechanically computes negative weights for some periods and groups. In some cases this may result in negative estimated coefficients when the treatment effects are in fact positive. This problem is more acute in the presence of treatment effect heterogeneity, either across groups or across periods. The de Chaisemartin and d'Haultfoeuille (2020) methodology which we follow here, is meant to avoid this problem.

$$DID_{t,k} = \underbrace{\sum_{f,j:E_{f,j}=t-k} \frac{1}{N_t^k}(\overbrace{\tilde{Y}_{f,j,t}}^{\text{Now}} - \overbrace{\tilde{Y}_{f,j,t-k-1}}^{\text{Before}})}_{\text{Treated}} - \underbrace{\sum_{f,j:E_{f,j}>t} \frac{1}{N_t^{nt}}(\overbrace{\tilde{Y}_{f,j,t}}^{\text{Now}} - \overbrace{\tilde{Y}_{f,j,t-k-1}}^{\text{Before}})}_{\text{Not yet Treated}} \tag{3}$$

N_t^k denotes the number of firm-destination links treated at date $t-k$ and $N_{DID_k} = \sum_t N_t^k$. $\tilde{Y}$ is the residualized outcome over a set of fixed effects. In our baseline regression, we include firm-year and destination-sector-year fixed effects. These are meant to capture global innovation shocks in a given market and firm innovation intensity. We compute a relatively large set of lags and leads in order to capture the full evolution of citations to firm f 's patents following its entry into country j. We cluster standard errors at the country-sector level. This allows for autocorrelations of the error term within an export market. It also allows for correlation across buyers within the same market.

As a baseline, we estimate DID_k with the outcome variables $\tilde{Y}$ being measured in levels, i.e. by the number of triadic citations. Thus ΔY is the average change in affected destination-firm pairs relative to unaffected pairs. It does not require the omission of observations taking the value zero as opposed to using the log of this outcome. We expect a lower frequency of zero citation flows from the affected destination in the aftermath of entry. Dropping those observations would bias $DID_{t,k}$ toward zero. We show that these results are robust to using various transformation of the left hand side variable ($log(1+Y)$, $asinh(Y)$, etc.) in Section 3.2 and to functional forms misspecifications in Section 3.3.

The above baseline specification does not distinguish between the various patents owned by a given firm f. In particular, it does not account for patent specific characteristics (within-firm patent heterogeneity), such as age, technological fields, quality ... This leads us to disaggregate our data further and to conduct the analysis at the patent-destination level. We thus also consider the estimator:

$$DID_{t,k} = \underbrace{\sum_{p(f),j:E_{p(f),j}=t-k} \frac{1}{N_t^k}(\overbrace{\bar{Y}_{p(f),j,t}}^{\text{Now}} - \overbrace{\bar{Y}_{p(f),j,t-k-1}}^{\text{Before}})}_{\text{Treated}} - \underbrace{\sum_{p(f),j:E_{p(f),j}>t} \frac{1}{N_t^{nt}}(\overbrace{\bar{Y}_{p(f),j,t}}^{\text{Now}} - \overbrace{\bar{Y}_{p(f),j,t-k-1}}^{\text{Before}})}_{\text{Not yet Treated}}, \quad (4)$$

where $E_{p(f),j}$ is the date at which French firm f that issued patent p enters destination j for the first time. This level of disaggregation allows us to control for the global lifecycle of each innovation by introducing a patent-year fixed effects. Once again we cluster the standard errors at the country-sector pair.

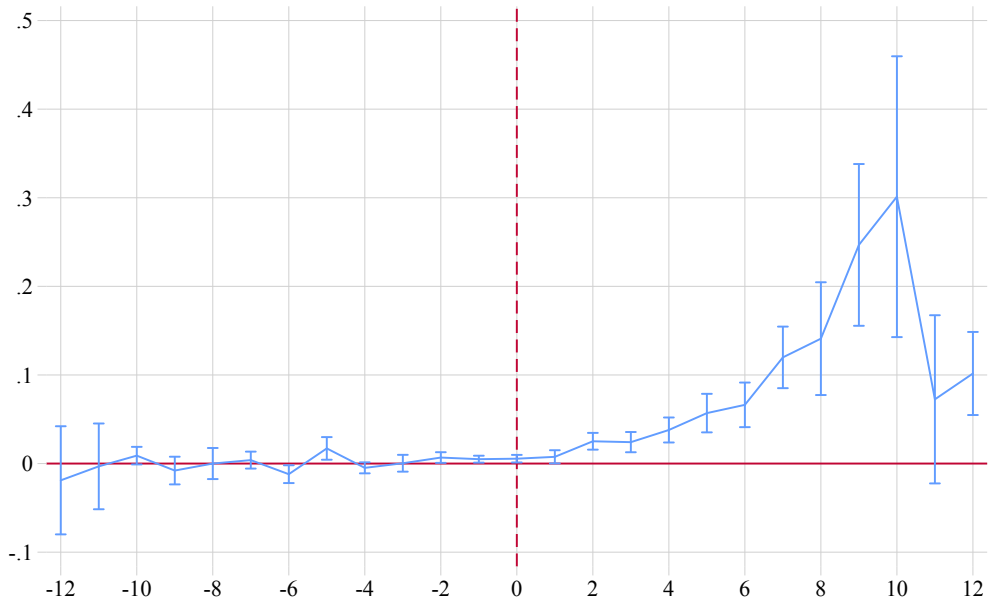
3 Results

3.1 Baseline firm-level results

We estimate parameters β_k from Equation (1) and report their values $\hat{\beta}_k$ and associated 99% confidence intervals in Figure 3. $k = 0$ marks the first year a firm exports to country j. The outcome variable is the count of triadic citations to the French firm's patents. In the regression we control for destination-sector-year and for firm-year fixed effects. Standard errors are clustered at the country-sector level.

As Figure 3 shows: (i) the estimates for the pre-entry coefficients are not significantly different from zero: in other words, there are no pre-trends; (ii) starting 2 years after entry, the estimates for the post-entry coefficients are significantly positive. This reflects the time it takes for foreign firms to build upon the French firm's knowledge; (iii) triadic citations steadily and sharply increase over time, until the effect eventually dies out after 11 years. This shows that the trade-induced technological spillovers lead to long-lasting bursts of innovation in the destination countries.

Figure 3: Baseline



Notes: This figure presents estimates of the coefficient DID_k from Equation (2). The x-axis represents the value of k, $k = 0$ being the first year the firm exports to country j. 99% error bands, computed with robust standard errors clustered at the destination-sector level, are displayed as blue brackets.

Magnitude: Quantitatively, firms entering into a destination receive an additional 0.024-0.056 citations for their patents from that destination 3 to 5 years after entry, compared to a destination that the firm has not yet entered at that time. This corresponds to a 32-72% increase from the mean citation rate in our sample (0.073).

In order to assess the magnitude of the full treatment effect, we compute the sum of coefficients between the 1st and 5th year after entry and find a total coefficient of 0.15. Over this 6 year time window after entry, a firm receives an average of 0.59 citations whereas a firm that does not export to that destination receives an average of 0.44 citations. This corresponds to a 74.5% increase in citations from the export destination country.

3.2 Different functional forms

We estimate Equation (2) replacing the triadic citation count Y by its inverse hyperbolic sinus $\mathcal{H}(C)$, by its cubic root, by $\log(1 + Y)$, and by a dummy equal to 1 if country j cites firm f's patents (Figure 4). The results remain qualitatively the same as in the baseline regression: flat pre-trends, a small initial increase in the outcome variable, and a sharp increase after 2 years, which fades away after a decade.

Table 2: Results Summary

Y =	C	$\mathcal{H}(C)$	$C^{(1/3)}$	$\log(1 + C)$	$1_{C>0}$
$k = 6$ Y	0.0662	0.0038	0.0041	0.0049	0.002
$k = 10$ Y	0.301	0.0151	0.0152	0.018	0.0057
$E(Y)$	0.073	0.022	0.019	0.017	0.014

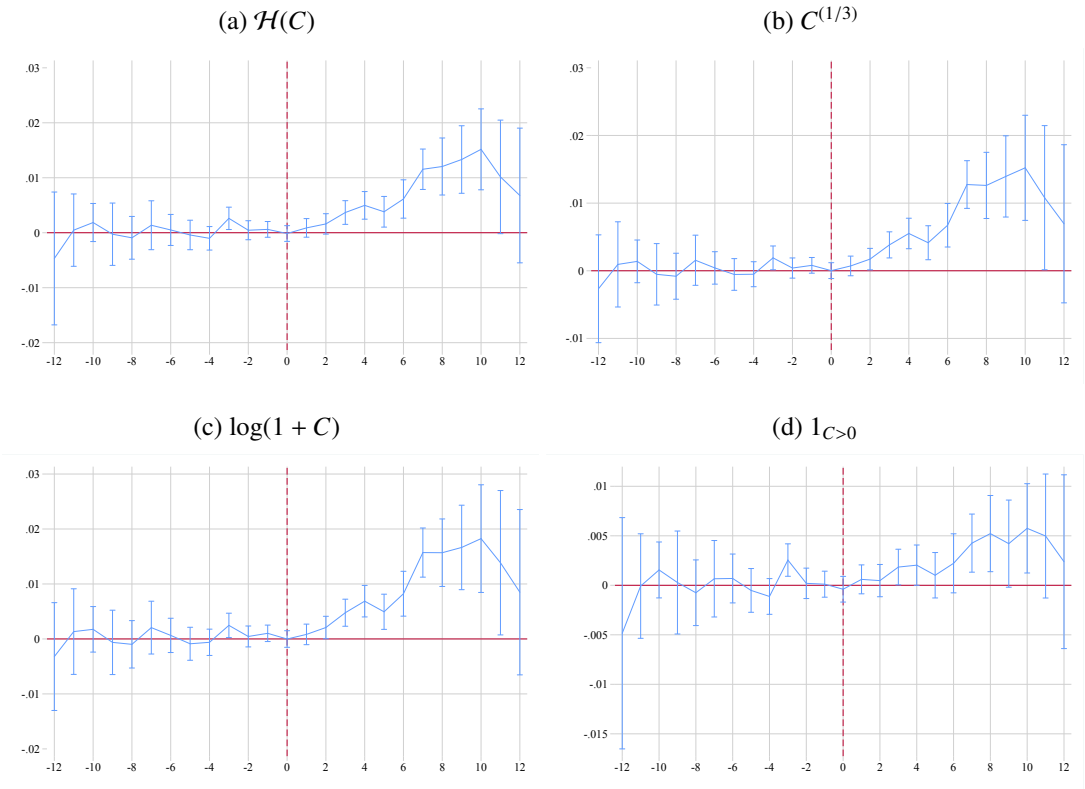
NOTE: This table presents estimates from the previous two sections.

3.3 Entry and the distribution of citation counts

The effect of entry on the number of citations to French firms' patents may be driven either by an "extensive margin" effect - entering the foreign market moves the French firm from being a "non-cited" firm to becoming a "cited" firm - or it may be driven by an "intensive margin" effect - the firm's patents were already cited by firms in the foreign country but they become increasingly more cited once the French firm enters the foreign market. To investigate this question, we use the "distribution regression" method developed in Chernozhukov et al. (2013) to estimate the entire conditional distribution of the citation count variable Y. Importantly, it does not require the outcome to have a smooth conditional density as in quantile regressions.

In the top panel (Figure 5a) each point is estimated using a linear probability model and corresponds to the effect on the probability of the French firm having accumulated more citations than the value indicated on the horizontal axis six years after entry into the

Figure 4: Other LHS functional forms

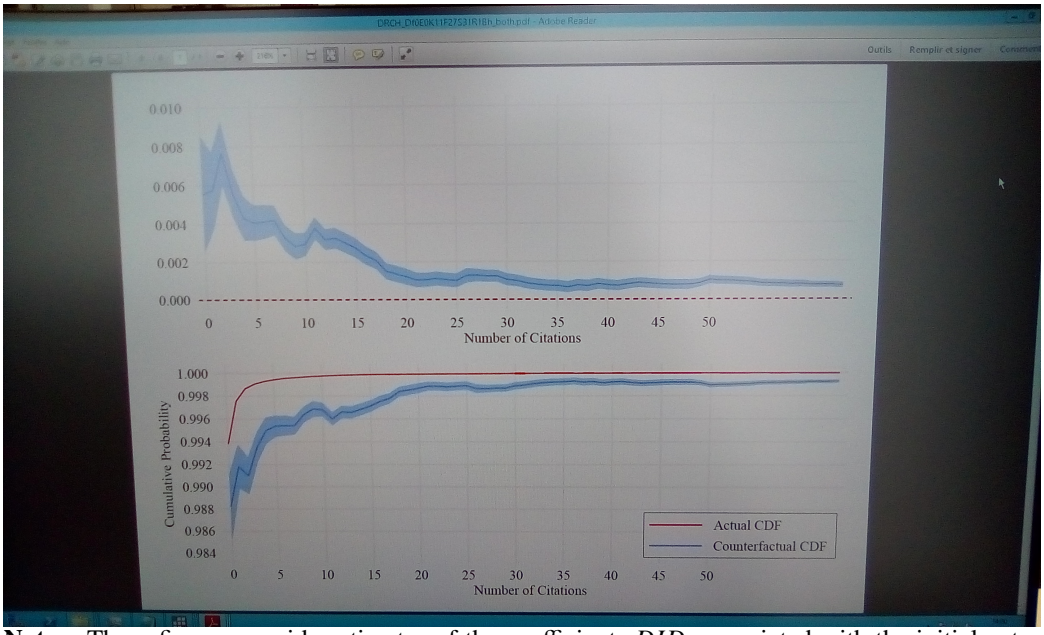


Notes: Panel 4a presents the results from estimating Equation (2) after transforming the outcome variable with the Inverse Hyperbolic Sine. In Panel 4b we use the cubic root of citations, in Panel 4c the log of 1+ the number of citations and in Panel 4d a dummy variable equals to 1 when the French firm is cited by the destination country that year. Everything else in unchanged.

foreign market. The fixed effects are the same as in the baseline regression (firm-year and destination-sector-year fixed effects) and we once again cluster the standard errors at sector-destination level (the blue bands show the 99% confidence intervals). The first coefficient is obtained from a regression where the outcome variable is a dummy that takes one if the citation rate is strictly greater than zero. It is therefore the effect on the extensive margin. We find that entry increases the probability of being cited by 0.6 percentage points. The effect is similar for low numbers of citations ($x < 5$) then it decreases for higher levels. It remains positive and statistically significant for the entire distribution. We see that entering a new foreign market increases more the probability of obtaining at least one or a few triadic citations - the extensive margin - than the probability of obtaining many citations -

the intensive margin.

Figure 5: Distribution Regression



Notes: These figures provide estimates of the coefficients DID_k associated with the initial entry into a foreign destination on the probability of having a citation rate greater than the amount on the x-axis. 99% error bands, computed with standard errors clustered at the destination-sector level, are displayed as a blue band. In Panel 5a, we plot the sequence of coefficients. In Panel 5b, we plot the sample CDF in red and the estimated counterfactual CDF in blue. For details on distribution regressions see Chernozhukov et al. (2013).

In the bottom panel (Figure 5b) we plot the sample cumulative distribution function in red and the counterfactual distribution in blue (ie the red curve translated with the coefficients from the top panel, thus adding the impact of entry). As the sample cumulative distribution function shows, triadic citations are rare events. They become less rare after entry. While this is especially true for firms receiving a small number of triadic citations, it is striking that virtually no firm receives a large number of triadic citations from a country where it has not exported to yet.

3.4 Citations added by the applicant

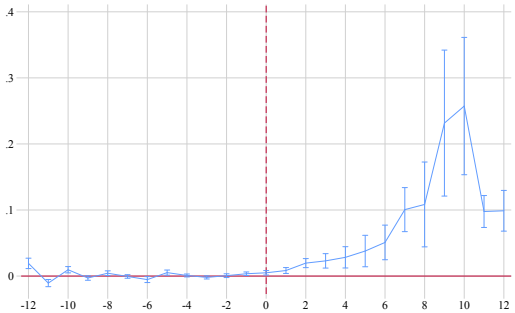
Here we estimate our baseline model, but we restrict our attention to citations added by the foreign patent applicant, thus we ignore the citations added during the initial search process by the patent office, and we also ignore the citations added by the patent examiner. Fixed effects and the clustering of standard errors remain the same as in the baseline regression. In Figure 6a the outcome variable is the raw count of triadic citations Y as in the baseline regression; in Figure 6b, the outcome variable is the Inverse Hyperbolic Sine of Y, $\mathcal{H}(C)$, and in Figure 6c the outcome variable is a dummy variable equal to one if the French firm receives any positive number of triadic citations in year t and equal to zero otherwise. For all these measures of citations, entry entails a similar impact as in the baseline regressions. We can therefore exclude that the knowledge spillover we uncover only touches the patent examiner.

3.5 Entry without affiliates

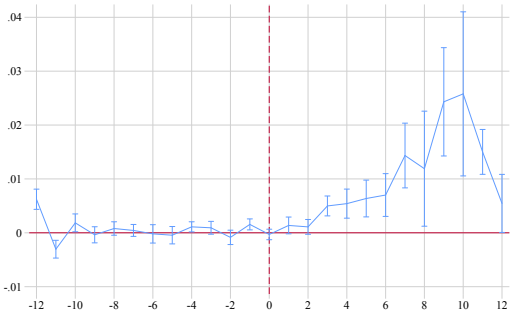
The affiliates of a French parent company may conduct R&D activity and would naturally be inclined to cite intellectual property developed and owned by their parent company. Furthermore with a foreign affiliate in a country, foreign firms in this country may cite the French firm's patents because they observe the production process or the products sold directly and locally by the affiliate rather than because they observe the exported product by the parent company. To account for these mechanisms, we reproduce our baseline results on a sample restricted to foreign destinations where the firm never opens an affiliate. As Figure 7 shows, the dynamic pattern of citations remains the same as in the baseline specification, even though the smaller coefficients indicate that part of the effect captured in the baseline estimates might be due to affiliates innovating in the destination country – which

Figure 6: Firm level regression - Applicant added Citations

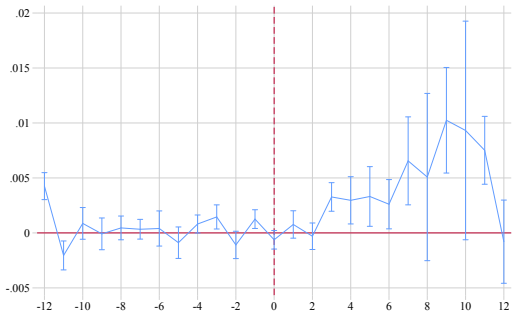
(a) Y



(b) $\mathcal{H}(C)$



(c) $1_{Y>0}$



Notes: Panel 6a presents the results from estimating Equation 2 after restricting citations to applicant added citations only. Panel 6b presents the results from estimating Equation 2 after transforming the outcome variable with the Inverse Hyperbolic Sine $\mathcal{H}(C)$. In Panel 6c we use a dummy variable equals to 1 when the french firm is cited by the destination country that year. Everything else in unchanged.

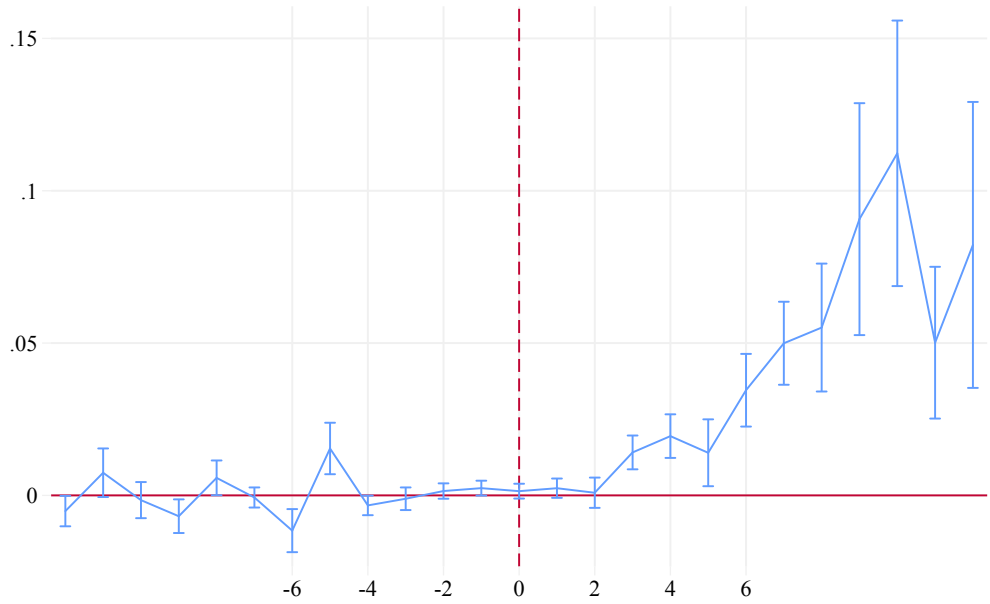
also constitutes a technological transfer.[7]

3.6 Patent-level results

The above specifications does not distinguish between the various patents owned by a same firm f. In particular, it does not allow us to separate citations made to new patents from those made to older patents, in particular to patents issued prior to the firm's entry into foreign market j. This in turn leads us to disaggregate our data further and to conduct the

[7]Excluding countries with affiliates, 0.11 extra citations are recorded in the 10th year after entry, which corresponds to an increase of 239% over the sample average of 0.046 citations. The corresponding increase in the baseline regression is 410%.

Figure 7: Excluding countries with affiliates



Notes: This figure presents estimates of the coefficient DID_k from Equation (2). The sample excludes the destination-firm pairs for destinations where the firm owns an affiliate. The x-axis represents the value of k, $k = 0$ being the first year the firm exports to country j. 99% error bands, computed with robust standard errors clustered at the destination-sector level, are displayed as blue brackets.

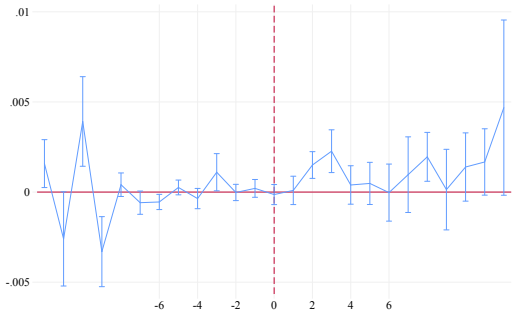
analysis at the patent-destination level. This level of disaggregation allows us to look more precisely at how entry into a foreign market affects the standard lifecycle of the citations received by a given French firm's patent and to control more precisely for the observable characteristics of this patent (technological class, quality, age etc...).

The outcome variable is the raw count of triadic citations by inventors in the foreign destination to a particular patent generated by a French firm. The fixed effects follows the same logic as in the baseline: in addition to the destination-sector-year fixed effects, we include patent-year fixed effects. We continue to cluster the standard errors at the sector-destination level. Figure 8a shows the same flat pre-trend and clear break post-entry, but the flow of extra triadic citations to a French firm's patent first increases sharply in years 2 and 3 but then declines in year 4.

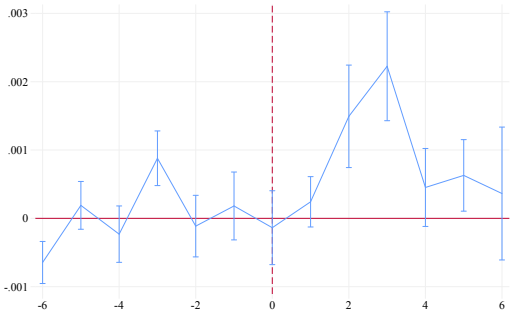
In Figure 8b we repeat the same exercise, but we restrict our sample to French patents

Figure 8: Patent level regression

(a) All patents



(b) Pre-entry patents



Notes: Panel 8a presents the results from estimating Equation 2 at the patent level. Panel 8b presents the results from restricting the sample to patents that are filed no later than 2 years after the entry date.

that were issued no later than 2 years after the entry[8]. The products exported by the French firm at the time of entry most probably incorporate the technologies already patented at that time. The dynamic pattern of the raw triadic citation counts to the French patent is similar to that in Figure 8a. This confirms that local inventors conduct research that relies on the technologies embodied in the exported product.

4 Heterogeneity

In this section, we investigate how the impact of entry on citations varies with: (i) the average quality of the French firm's patents; (ii) the level of development of the destination country (which we use as a proxy for the country's degree of absorptive capacity).

[8]The lengthy application process means that many patents start receiving citations in the two years preceding the application date recorded in PATSTAT

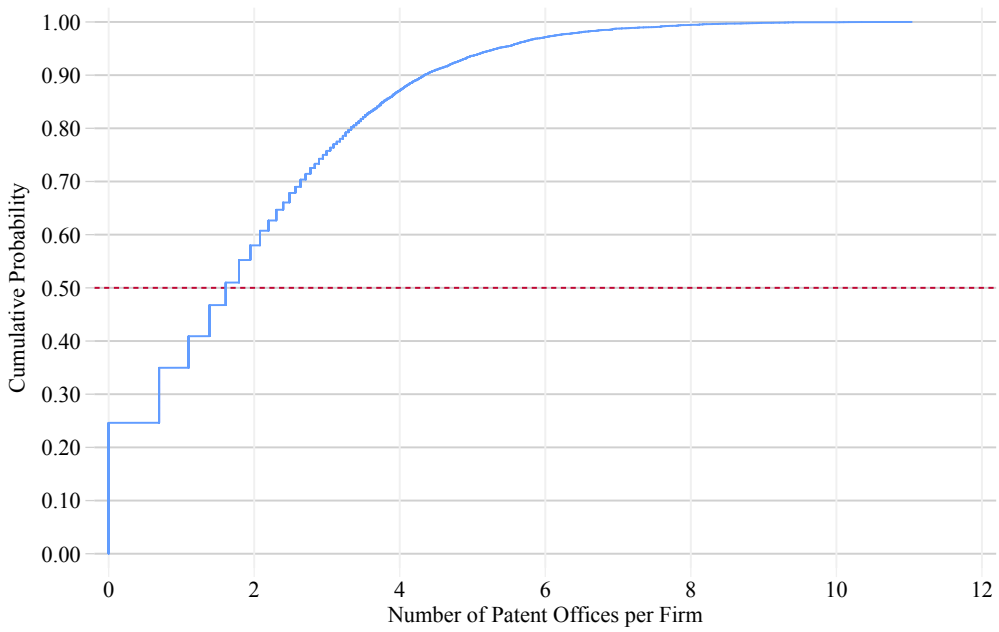
4.1 Impact of the exporting firm's patent quality

Measuring patent quality

We follow the OECD patent data manual to construct a measure of patent quality for the French exporting firm, based on the number of patent offices the patent was submitted to by the firm. Submitting a patent to a higher number of patent offices amounts to extending the geographical coverage of intellectual property protection for the patent. Doing so is costly for the firm, hence the firm will decide to incur the additional cost of applying to more patent offices only if it anticipates the patent to be sufficiently successful, which we take as reflecting the patent's quality.

Figure 9 shows the distribution of the number of patent office submissions (over all patents of the firm and in log) for the French exporting firms. We see that 25% of firms submit to only one patent office, 50% of firms submit to less than 6 patent offices. Only 10% of firms submit to more than 66 offices.

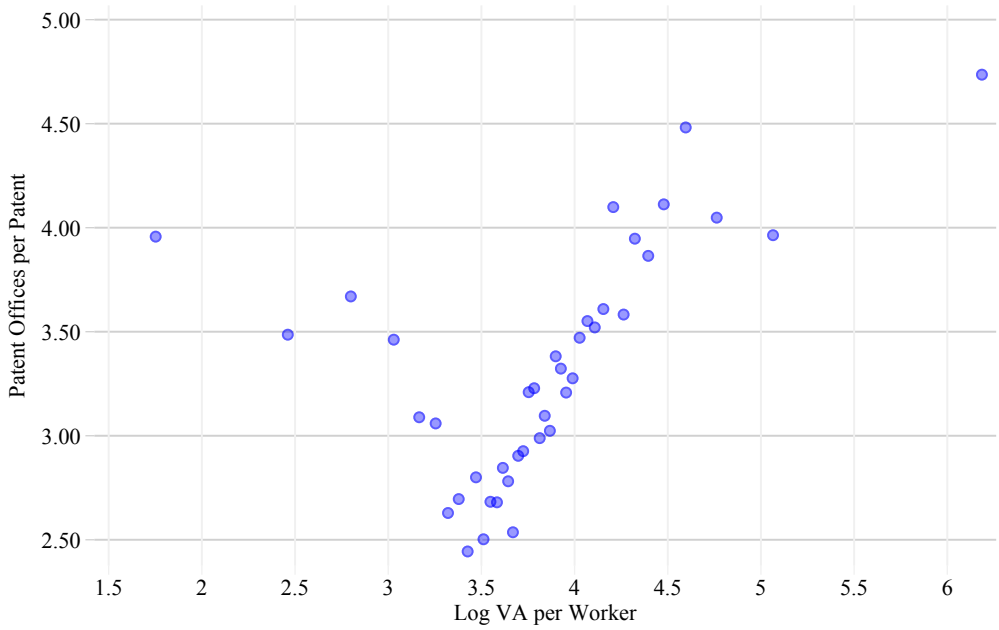
Figure 9: Distribution of the number of patent offices used by firms



Notes: This figure presents the cumulative distribution of the log of the number of patent offices where firms apply for protection (summed over all patents).

We test whether the number of patent office submissions is truly related to more common measures of firm quality. We first describe the relationship between the number of patent office submissions and firm level productivity measured by the value added divided by the number of employees. Figure 10 depicts a binscatter of the log of the number of patent offices against the log of the firm's value added per worker. Each dot corresponds to a bin that contains 2.5 percent of the overall distribution of firm productivities. The figure shows that beyond the 15th percentile of firm-level productivities, patent quality measured by the number of patent offices is clearly positively correlated with labor productivity.

Figure 10: Relationship between labor productivity and the firm-level average number of patent offices per patent

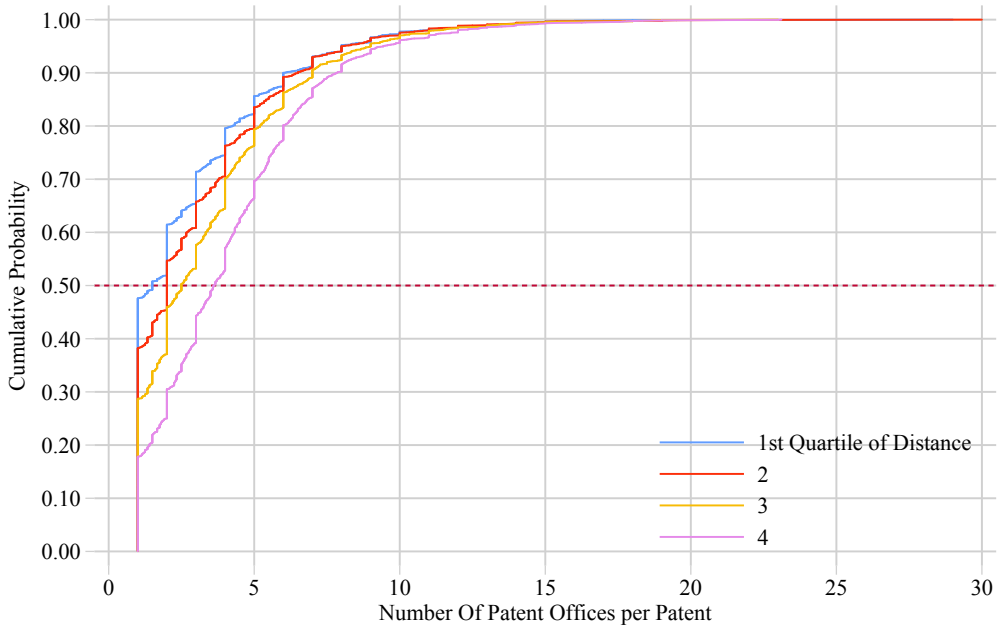


Notes: This figure presents a binscatter of the relationship between labor productivity and the average number of patent offices per patent used by firms. Bin size is set at 2.5 percentiles.

Next, one can look at the extent to which our measure of patent quality relates to the firm's ability and/or propensity to export to destinations that are further away from France. In Figure 11 we group firms according to the average distance between France and the firms' export markets. Each color represents a different quartile on the scale of export distances. The figure shows a positive correlation between our measure of patent quality

and the average export distance of a firm, which is consistent with the view that French firms with higher quality patents are willing to pay a higher trade cost to reach more remote export markets.

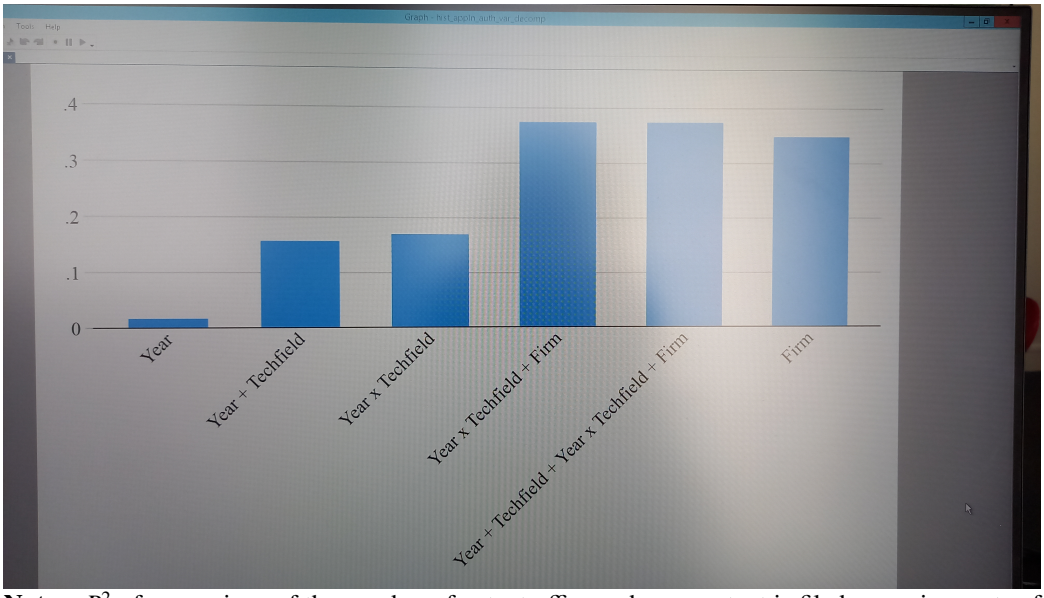
Figure 11: Relationship between the average distance to their export market and the firm average patent offices per patent



Notes: cumulative distribution of the number of patent offices per patent where firms apply for protection after grouping firms according to the average distance of their export market.

To address the concern that our measure of patent quality could reflect firm level characteristics other than patent quality per se, in Figure 12 we regress the number of patent offices on a set of fixed effects. The figure shows that around 60% of the variance in the number of patent offices is unexplained by aggregate and firm level factors. Aggregate factors such as the year of application, technological fields and the interaction between the two, only explains about 17% of the variance in the number of patent offices. A firm fixed effect only explains about 35% of the variance. The residual (60%), after controlling for all possible combinations of fixed effects, is by construction related to differences across patents within firms.

Figure 12: Variance decomposition of patent quality



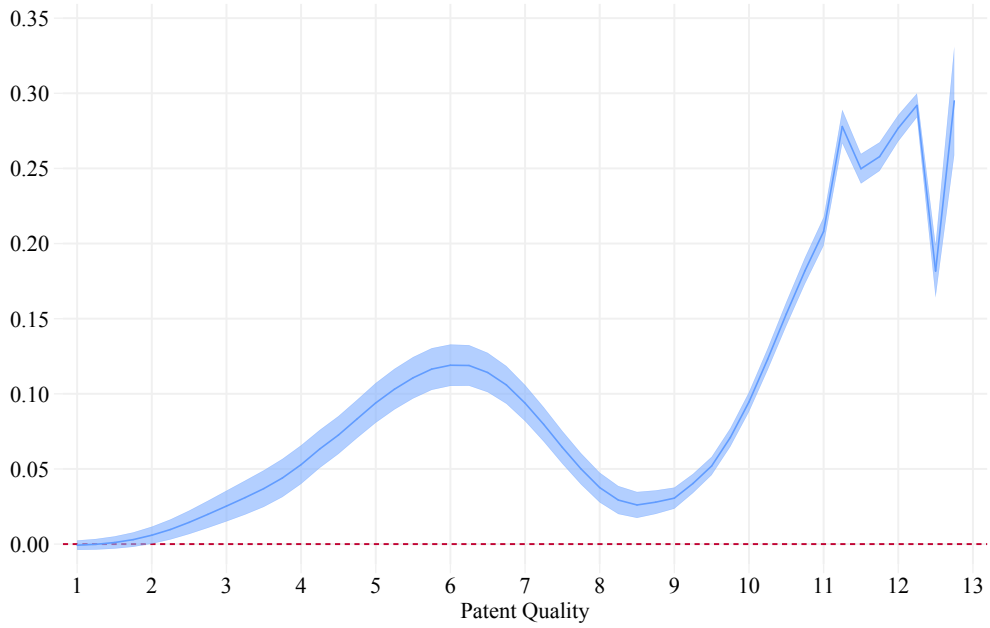
Notes: R^2 of regressions of the number of patent offices where a patent is filed on various sets of fixed effects.

Heterogeneous effect of entry with respect to patent quality

Overall, Figures 10, 11 and 12 provide support to using the number of patent offices per patent as a proxy for patent quality. We now look at the impact of a firm's average patent quality on how entry by firm affects subsequent citations to its patents by firms in destination countries. Presumably, firms with higher quality patents are more likely to induce follow-up innovations by firms in the destination countries, and therefore to generate more citations to their patents. To see this, we adapt the baseline regression to allow for varying coefficients with respect to the quality of the exporting firm's patents. More specifically, in Figure 13 we combine the de Chaisemartin and d'Haultfoeuille (2020)'s estimator with a local linear estimation and use a kernel re-weighting scheme across percentiles of average patent quality. This kernel approach allows us to flexibly estimate the functional form of the marginal effect of entry on subsequent patent citations by firms in the destination countries, across percentiles in average firm-level patent quality. The kernel is estimated with a bandwidth of 1.

Each dot in Figure 13 corresponds to the effect of entry on subsequent citations estimated at a given level of firm's average patent quality. We see that the higher the average quality of a French firm's patents, the stronger the effect of entry by that firm on subsequent citations by firms in the destination countries.

Figure 13: Relationship between patent quality and the effect of entry on citations



Notes: This figure presents estimates of the coefficient DID_k from Equation (2). The x-axis represents the value of k, $k = 0$ being the first year the firm exports to country j. The coefficients are estimated locally along the support of the distribution of the firm level proxy for patent quality. 99% error bands, computed with robust standard errors clustered at the destination-sector level, are displayed as blue brackets.

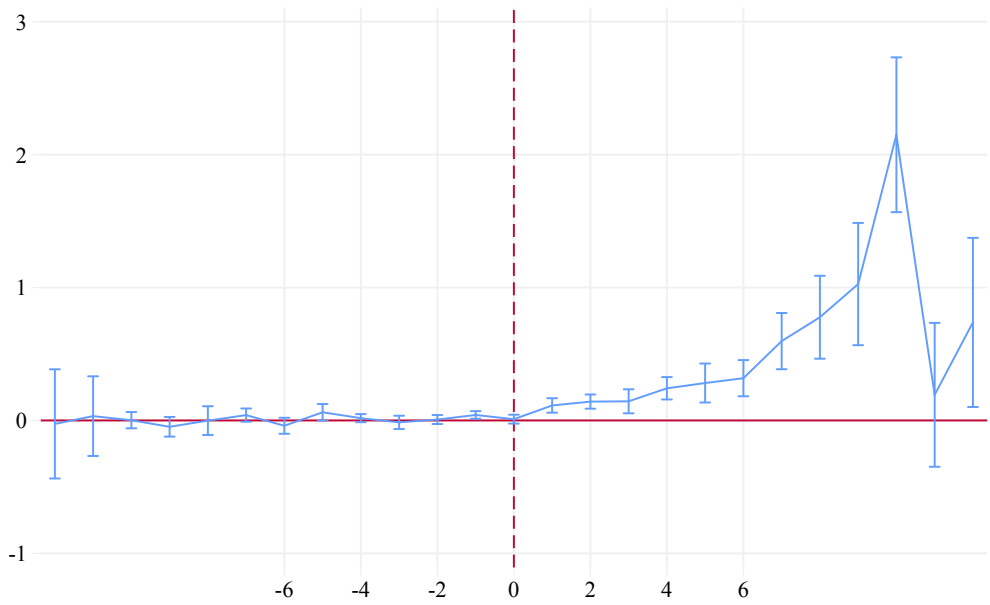
Effect of entry on patent quality

Next, we look at the effect of the French firm's average patent quality on the quality of subsequent citations to the firm's patents by firms in the destination countries. For that purpose, we build a sample of all citations by firms in destination countries, not just the triadic citations used in our analysis so far. To measure the quality of a citing patent, we again use the number of patent offices the patent is submitted to: for example a citing patent submitted to one patent office counts for 1, whereas a citing patent submitted to three patent

offices counts for 3. This gives us a quality weighted measure of citations.

We first estimate our baseline model with firm-year and destination-sector-year fixed effects, but with quality-weighted citing patents as left-hand side variable. Figure 14 shows that this quality-adjusted measure of subsequent citations evolves over time pretty much as the raw triadic citations to a French firm's patent in our baseline regression, namely: (i) the pre-trends are flat and precisely estimated close to zero; (ii) the increase in quality-weighted citations is moderate during the first few years after entry by the French firm into the new foreign market; (iii) the quality-adjusted citations then increase sharply until year 10 after entry.

Figure 14: Effect of Entry on quality weighted citations



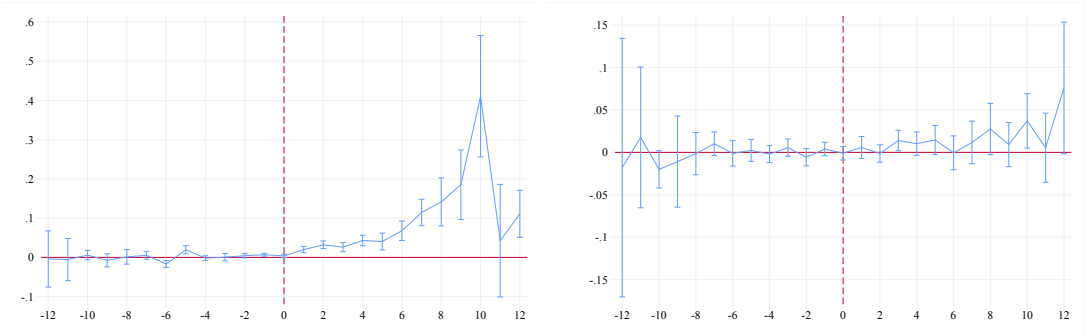
Notes: This figure presents estimates of the coefficient DID_k from Equation (2). The x-axis represents the value of k, $k = 0$ being the first year the firm exports to country j. 99% error bands, computed with robust standard errors clustered at the destination-sector level, are displayed as blue brackets.

We further decompose the impact of the French firm entry on the quality-adjusted citations received from the destination countries into a "quantity component", the number of citations by firms in destination countries, and a "quality component", the average number of patent offices per citation in destination countries (Figure 15). Most of the increase in

quality-adjusted citations after en entry comes from the quantity of citations. The quality contribution is positive but barely significant. The magnitudes of the effects uncovered are very large: after ten years, the citation rate is multiplied by 5.7, and given an increase in quality of 4.3 %, the quality weighted citations are multiplied by 5.8.

Figure 15: Quantity versus Quality

(a) Quantity (b) Quality



Notes: Panel 15a presents the results from estimating Equation 2 with the count of citations as outcome variable. Panel 15b presents the results from the same estimation but with the citation quality proxy as outcome variable.

Overall, the analysis in this subsection has several interesting implications. First it helps rule out that subsequent innovations post-entry would be purely defensive or marginal improvements with low potential: if anything the quality of the citations increase with entry. Second, the higher effect of entry on citations for firms with higher quality technology has important implication in terms of "gains from trade": not only do higher quality firms export to more destinations, but they also generate higher spillovers on inventors in destination countries. Additionally, such spillovers translate into both a higher number of citing patents and a higher quality of citing patents by firms in destination countries.

4.2 Impact of a destination's development level

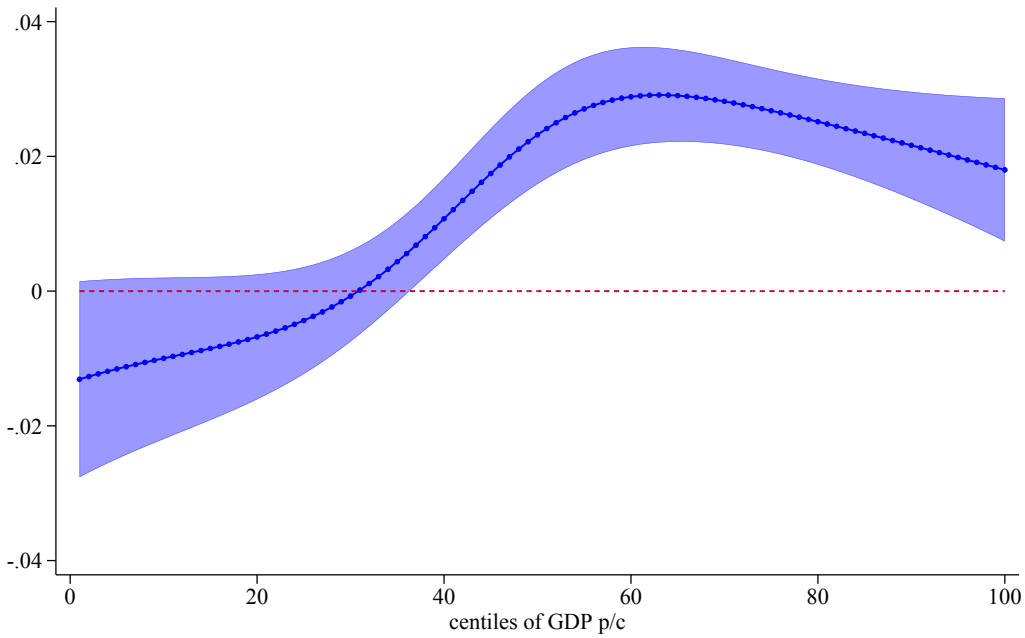
The transfer of knowledge from a French exporter to firms in the export destination is likely to depend upon the destination's technological development relative to the French exporter.

If firms in the destination country lag far behind the French firm, then presumably these firms are not adequately equipped to build on the French firm's innovation, and therefore the French firm's entry should have a limited impact on innovation in the destination country. The French firm might even deter such innovation in the destination country due to the increased competition it induces for potential innovators in that country (see Aghion et al., 2005): as a result, the impact of the French firm's entry on citations by firms in the destination country may even turn negative. On the other hand, if firms in the destination country are neck-and-neck with the French firm, then these firms can easily build upon the French firm's technology to generate new innovations: in that case entry by the French firm should increase citations by the destination country of the firm's innovations. Finally, if firms in the destination country are far ahead of the French firm's technology, then these firms will often not find it useful to develop further the French innovation as they already enjoy a better technology: entry by the French firm would then have little to no impact on its citations by firms in the destination country.[9]

To test for a differential impact of entry on citations varying with a destination's development level, we run a similar version of our static specification described above. But we now allow for our coefficient to vary across the percentiles of the destinations' GDP per capita. At low levels of GDP per capita (below the 30th percentile), entry decreases citations (Figure 16). At intermediate-high level of GDP per capita (between the 30th and the 60th percentile), entry increases citation. The effect is then decreasing in GDP per capita for the richest countries, though it remains significantly positive.

[9] All these developments should have different consequences for the destination firms' products as well, but the lack of data on those products prevents us from assessing such impacts. They also bring about different consequences for the French exporter's products, which we plan to investigate in future work.

Figure 16: Relationship between development and the effect of entry on citations



Notes: This figure plots the effect of the initial entry into a foreign destination estimated locally at a given percentile of the ex-ante distribution of country-level GDP per capita. The dependant variable is the number of citations. We use Gaussian weights with a bandwidth set to 20 centiles. 90% confidence interval are presented. Standard errors are clustered at the link (country-firm) level.

5 Conclusion

Using French firm-level fiscal, customs, and patent citation data over the period 1995-2012, we estimate the impact of export market entry on the citations of the exporter's patents in the destination country. We find a positive and significant effect of entry on those citations. There are more of them and they are of higher quality. Overall, our results validate the notion that trade induces technological spillovers (in line with Coe and Helpman, 1995b). And the results are also consistent with Cohen and Levinthal (1989)'s view that spillovers occur conditionally upon the recipient country exhibiting sufficient *absorptive capacity*.

Our findings have several implications. First, our main findings that trade induces knowledge spillovers is in line with the notion that trade is a source of cross-country convergence. Second, fostering development in the destination country increases the country's

ability to build upon the innovations brought by foreign exporters, thus inducing a snowball effect on its productivity. Third, more productive firms – in addition to being more likely to export – are also (slightly) more likely to induce technological spillovers.

Our analysis can be extended in several interesting directions. One avenue would be to explore other dimensions of heterogeneity, in particular the impact of the degree of "upstreamness" of the exporting firm in the production chain, building on Baqaee and Farhi (2019). Another avenue would be to look at the extent to which new patents in the destination country subsequently lead to an increase in productivity growth in sectors and destinations that are more highly exposed to entry by French innovative firms. It would also be interesting to look at the mirror of this *exporting of ideas*: how new products imported in France comes with *imported ideas* and brings about French patents citing the technologies embedded in these products. These and other extensions of our analysis in this paper are left for future research.

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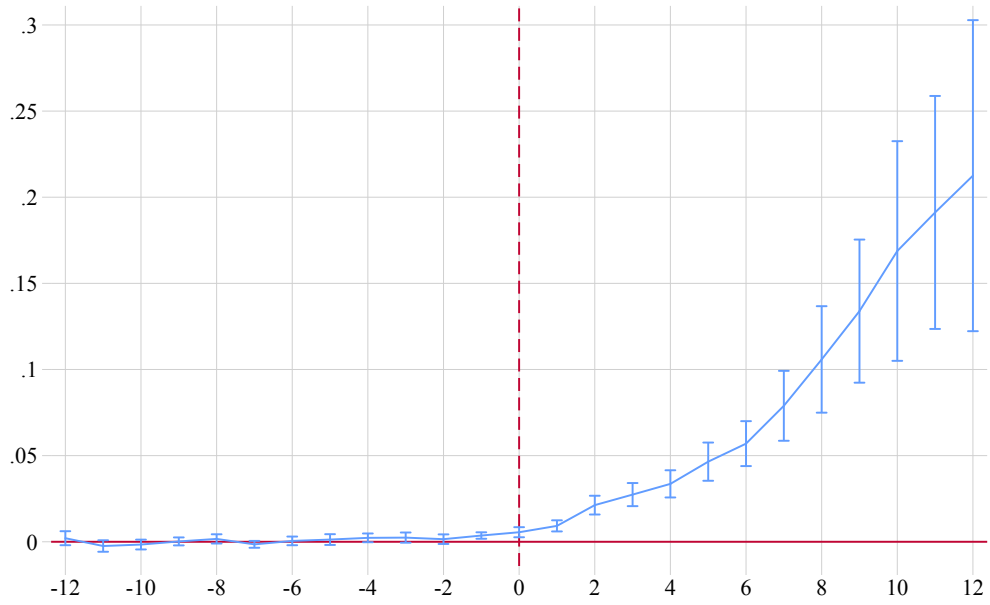
APPENDIX

A Robustness

A.1 Fixed Effects

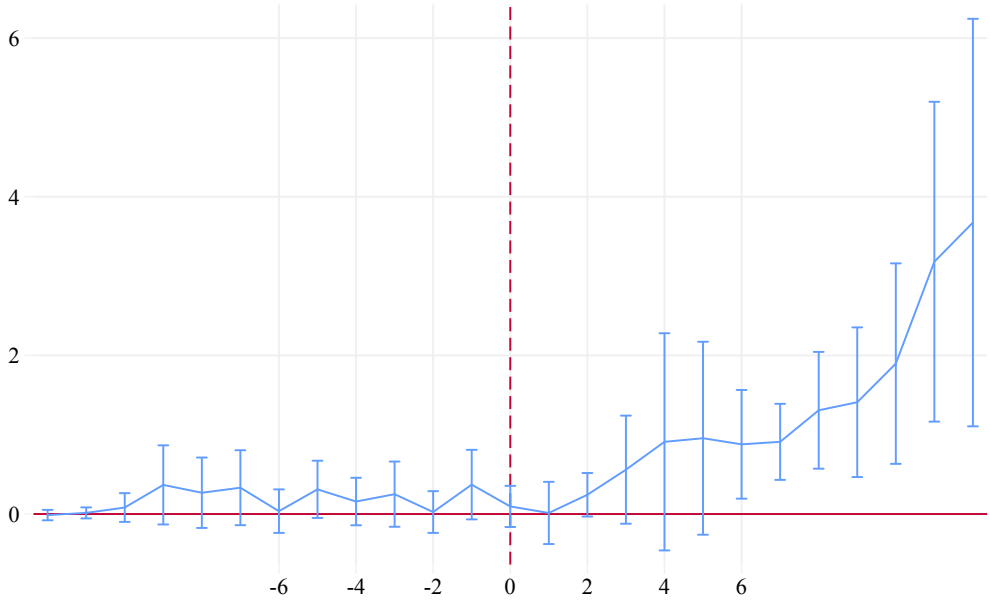
Figure 17: Firm-Region-Year Fixed Effects



Notes: This figure presents estimates of the coefficient DID_k from Equation (2). The x-axis represents the value of k, $k = 0$ being the first year the firm exports to country j. 99% error bands, computed with robust standard errors clustered at the destination-sector level, are displayed as blue brackets. This specification replaces the set of fixed effects with a Firm-Region-Year Fixed Effects. Regions correspond to North America, South America, Western Europe, etc.

A.2 Affiliate induced spillovers

Figure 18: Effect of opening an affiliate on citations



Notes: This figure presents estimates of the coefficient DID_k from Equation (2). The x-axis represents the value of k, $k = 0$ being the first year the firm declares owning an affiliate in country j. 99% error bands, computed with robust standard errors clustered at the destination-sector level, are displayed as blue brackets. This specification includes firm-year and destination-sector-year fixed effects as well as a control for the log(1+exports) to the destination country.