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The impact of the scope of technological search on path dependence in export specialisation: Evidence for European countries

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The impact of the scope of technological search on path dependence in export specialisation: Evidence for European countries*

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Abstract

This paper examines how product relatedness and the breadth of technological search affect the path-dependent development of export specialisations across countries documented in prior research. The results of the econometric analysis in this paper show that broader technological search in an industry has a positive impact on the development of comparative advantages in the product lines it exports. The interplay between product relatedness and the scope of technological search has a two-edged character. On the one hand, broader technological search supports adjustments and consolidations of the export baskets on the extensive margin. This contributes to weaken path-dependency. On the other hand, it fosters the competitiveness of products that are related to current export specialisations, and thereby promotes path-dependency on the intensive margin of trade. These results differ across countries with different levels of technological capabilities.

Keywords: trade diversification, path dependency, knowledge creation, knowledge diffusion, product space

JEL Codes: I25, O11, O14

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1 Introduction

1.1 Path dependence in export specialisation

The "technology gap" perspective on international trade (cf. Dosi et al., 1990, 2015) argues that patterns of trade are related to technological asymmetries across countries. As these tend to be persistent over time, comparative advantages in trade and industrial specialisations are typically very persistent as well. This literature points to untraded interdependencies in national production and innovation systems (cf. Dosi et al., 1990; Breschi and Lissoni, 2001) as an important cause for these persistencies.

Untraded interdependencies are conceived as a collective asset of companies in geographic space that are related to technological complementarities, untraded technological linkages, information flows, coordination externalities as well as knowledge spillovers across companies that are enforced and perpetuated through common infrastructures as well as economic, technical and educational institutions that have been developed to support the knowledge base underlying these interdependencies. Untraded interdependencies are therefore instrumental in generating common experiences, knowledge and skills embodied in organisations and people moving between them. They have also been identified as an important cause for the path dependent development of regional industrial specialisations and for the emergence of industrial clusters (cf. Storper, 1995; Porter, 2003).

Recent work on the so-called "product space" reaches similar conclusions. It has linked the observed path dependence of countries' comparative advantages in trade to the relatedness of the product lines they export (cf. Hidalgo et al., 2007). This literature specifies product relatedness as an outcome based measure based on the co-exporting patterns of products across countries meant to capture latent information on common capabilities and knowledge bases needed to produce and export them. The underlying idea is that producers of related products will benefit more extensively from information and coordination externalities and therefore be better able to draw on capabilities, knowledge bases and institutions already present in a geographically delimited production system. New trade specialisations will therefore develop out of existing capabilities.

Product relatedness and the notion of untraded interdependencies are closely linked. Product relatedness results from diversification processes that take place both at the company and industry levels. Bottazzi and Secchi (2006) have shown that companies diversify their product portfolio through stochastic branching processes. These are observed when they learn and explore the product space through the recombination of existing with new technical knowledge and knowledge about products and markets (cf. Arthur, 2009; Bresnahan, 2012). Hence, the product scope of companies and their cumulated capabilities and technological learning are intrinsically related and co-evolve (cf. Teece et al., 1994; Pavitt, 1998; Piscitello, 2000).

Similar stochastic branching processes rooted in the existing competence base of companies have been identified as a key characteristic of structural change at industry and regional levels as well (cf. Frenken et al., 2007; Neffke et al., 2011). Successful new companies in an industry are more often than not born out of established companies (cf. Klepper, 2010; Klepper and Buenstorf, 2010; Boschma et al., 2012), and these new companies typically recombine knowledge from the former parent companies with new knowledge from other sources (cf. Klepper, 2001; Boschma, 2015). Hence, learning processes associated with observed product relatedness are not only recombinant but also interactive in the sense that they require the interaction of different firms and institutions that deliver different chunks of knowledge.

For recombinant, interactive learning to work effectively, it is necessary that the different actors in a production and innovation system are capable of absorbing knowledge spillovers and that they coordinate their actions to develop mechanisms to transfer complementary pieces of knowledge between them (cf. Cohen and Levinthal, 1989; Nooteboom, 2000; Boschma, 2005). The solution of this coordination problem is facilitated through joint investment of companies in education, training and research as well as public investments for the establishment of supporting educational, technical or research institutions, which as a consequence co-evolve with the local knowledge industrial base and become endogenous to the process of industrial development (cf. Nelson, 1994).

The ensemble of knowledge sources, actors, endogenous institutions and formal as well as informal linkages that support and perpetuate recombinant, interactive learning are what the technology gap literature refers to as untraded interdependencies. The observable product relatedness resulting from the branching processes described earlier is therefore at the same time both a manifest outcome and a determinant of untraded interdependencies, which by their very nature are difficult to observe directly.

Untraded interdependencies convey competitive advantages, and through their positive feedback effects on the technological and cost competitiveness of firms they lead to path-dependencies in comparative advantages in trade and industrial specialisation patterns. The better firms are embedded in this flow of information and coordination externalities the better they will be able to translate them into lower cost or higher quality products and hence higher productivity that favours their competitiveness in international markets. However, they will also contribute to it through their own learning activities thereby strengthening the competitiveness of other companies active in related fields of economic activity. Well-embedded firms are both a sink and a source for external effects. Companies that are not so well embedded in turn are more likely to be sorted out in the international competition process if they have to engage with competitors that can draw on untraded interdependencies in their own production environment.

This perspective is distinct both from “new-new” trade theories (cf. Melitz, 2003; Melitz and Trefler, 2012) and the “self-discovery” literature in the theory of economic development (Hausmann and Rodrik, 2003; Hausmann et al., 2007). While the former emphasise the importance of firm heterogeneity in the context of monopolistic competition, they consider differential efficiencies in production in the presence of unobserved sunk costs as a key determinant of the participation of firms in international markets. They are silent on the sources of these fixed costs and efficiencies, and being rooted in an equilibrium approach they also ignore the path dependent, evolutionary nature of both the entry into export markets as well as in the development of comparative advantages. From a technology gap perspective self-selection into the export market is not just a matter of unspecified productivity differentials, but is seen as the outcome of the capability of firms to exploit untraded interdependencies of the production and innovation system in which they are embedded that promote their international competitiveness.

The self-discovery literature on the other hand, while recognising the importance of local information and coordination externalities, relates them largely to the tinkering of firms with knowledge drawn from international linkages and ignores the specifics of path dependent local learning as outlined earlier. The focus on international linkages of this literature is also in contrast to the results by Laursen and Meliciani (2002) showing that only domestic up- and downstream technology spillovers have an impact on export shares, whereas international linkages do not significantly affect trade balances at the industry level. Hence, this literature overstates the importance of technology diffusion from abroad.

1.2 The breadth of technological search and the development of comparative advantages and diversification in trade

While comparative advantages in trade and industrial specialisations are very persistent, an increasing number of contributions has identified changes in the variety of industrial activities as an important regularity of long-term industrial development (cf. Imbs and Wacziarg, 2003; Cadot et al., 2013). Other authors have presented evidence that both the vertical and horizontal diversification of exports is important to increasing income levels and promote economic growth (Hausmann et al., 2007; Hausmann and Hidalgo, 2011; Sutton and Trefler, 2016). However, it has also been argued that dynamically increasing returns to technological learning and local technological search are likely to limit the variety in an economy in terms of produced and exported products, and that this constrains economic growth (cf. Grossman and Helpman, 1995; Rodrik, 2004).

Saviotti and Frenken (2008), finally, have pointed to the trade-off that exists between specialisation and diversification with regard to economic performance of a country. They have shown that export specialisation in related industries drives economic performance in the short-run, whereas the diversification of the export portfolio into weakly related industries is an important determinant of economic performance in the long-run. This leads to the question how exporters are able to overcome path dependencies and diversify into new, *weakly* related product lines and develop new comparative advantages over time.

Stochastic branching and recombinant, interactive learning as described earlier can lead to various outcomes. This depends on the breadth of companies' technological search activities defined in terms of the variety of the technological fields they use or explore in their technological or inventive activities. Research examining the relationship between the relatedness of the products companies produce and the breadth of their technological competencies remains somewhat inconclusive. Some authors have argued that companies produce and diversify into related products whereas their technological competencies are broader than would be needed to produce them (cf. Patel and Pavitt, 1997; Brusoni et al., 2001; Piscitello, 2000).

Recent work by Dosi et al. (2017) qualifies these findings. Using detailed product information from customs data as well as patent data for Italian companies these authors find that firms appear to be on average more specialised in terms of technological knowledge than products, i.e. companies are more diversified across products than across technologies. Firms that "know more than they produce" are rare. However, the authors also find that technological and product diversification both increase as firms grow, and that indeed the evolution of technological and production knowledge at the firm level are path dependent in the sense that new knowledge develops out of the existing competence base through recombination. This suggests that an increasing stock of production and technological knowledge allow broadening both the product and technological portfolios. The depth of the knowledge base and its breadth are therefore intrinsically related, as recent contributions to the management literature as well as the technological search literature indicate (cf. Yang et al., 2017; Boh et al., 2014).

This paper contributes to this literature by examining the interaction effect of product relatedness and changes in the breadth of technological search on the intensive and extensive margin in trade at the industry level across countries. Methodologically, it relies on the product space approach (Hidalgo et al., 2007) using granular trade data and on recent work examining how the relatedness of technological knowledge changes as countries, regions and cities develop over time using patent data (cf. Kogler et al., 2013; Boschma et al., 2015; Petralia et al., 2017).

The analysis in this paper focuses on European countries for which data with a sufficient level of detail and data quality especially for the control variables are available. It is limited to industrial commodities, as exports in natural resources and agricultural goods are more strongly bound to existing factor endowments and knowledge generation and transfer are likely to have only a limited impact on export specialisations. It considers the level of economic development, as the interaction between product relatedness and the breadth of technological search may play out very differently, if the companies in a country have on average relatively low levels of technological capabilities, but can draw on factor cost advantages to obtain comparative advantages.

As technological search is just one of several knowledge generation and transmission channels affecting this relationship, we also control for a number of other factors, such as schooling and college or university education, inward FDI or knowledge spillovers embodied in imported capital goods. Especially, the cognitive capabilities of the workforce have been shown to have an important impact on the path-dependence in trade specialisations (cf. Mehta and Felipe, 2014).

The results show that broader technological search promotes adjustments on the extensive margin of trade by supporting the exploration of new export opportunities in weakly related products and by promoting the consolidation of the export basket. In this way, it helps overcoming path dependency in the development of export specialisations. This holds in particular for technologically advanced countries. On the other hand, broader technological search is an important means to exploit untraded interdependencies in an economy across sectors and foster the competitiveness of related products. In this case, broader technological search supports the hardening of path dependency in the development of export specialisations.

The paper is organised as follows: Section 2 presents the data and indicators used in the quantitative analysis along with a review of the literature justifying their choice. Section 3 discusses the econometric approach and related identification issues. Section 4 presents the econometric results. Section 5, finally, summarises the paper and offers a discussion of the results.

2 Data and indicators

2.1 Dataset description

The empirical analysis in the paper relies on a number of data sources. The principal source for trade data is the *Base pour l'Analyse du Commerce International* (BACI) data of the Centre d'Études Prospectives et d'Informations Internationales (CEPII). It contains data for 5,109 product categories classified using the *Harmonized System* at the 6-digit level (HS6). This study uses data based on HS-codes from the 1992 revision covering the years 1995 till 2016. A detailed description of the data is given by Guillaume and Zignago (2010). Next to the BACI data the PATSTAT database (release fall 2017) from European Patent Office (EPO) has been used to construct patent indicators. In addition, the paper relies on Eurostat and Worldbank data for country level indicators on inward FDI, human resources in science and technology and tertiary educated persons in the labour force. There are 26 European countries for which these indicators are available with a similar geographical and time coverage. While the BACI data extend beyond 2012 some of the Worldbank indicators we use as controls are only incompletely available after 2012 which determines the upper bound of time span covered in the present analysis.

The joint effects of relatedness in product space and the breadth of technological search on comparative advantages may differ qualitatively with the level of economic development of the countries in which companies operate, depending on whether comparative advantages are driven either by technology or simple cost or endowment effects. As the countries in the sample are relatively heterogeneous in terms of their level of economic development (cf. Radosevic and Kaderabkova, 2011), we will present results also for subgroups of countries. In line with the European Innovation Scoreboard (EIS) of the European Commission theses countries have been split up into a group consisting of twelve countries classified in the terminology of the EIS as “Innovation Leaders” or “Strong Innovators” (INNO) and a group of fourteen countries consisting of “Moderate” and “Modest Innovators” (NON-INNO).[1] Table 1 shows that the GDP per capita at purchasing power parities in the countries of the NON-INNO group was on average only 60% of countries in the INNO group, but they were growing at higher pace, active in fewer export lines, and showing more dynamics on the extensive

[1] See `http://ec.europa.eu/growth/industry/innovation/facts-figures/scoreboards_en`; last accessed May 2018.

margin of trade (product entries and exits).

Table 1: General Characteristics Inno Type

	INNO	NON-INNO
Avg. share of exp. products	94.66 %	86.31 %
Avg. GDP at PPP p.c. in 2012	43,134 $	25,858 $
Avg. nom. GDP Growth	6.3 %	8.46
Product Line Entries	408	3197
Product Line Exits	1420	2337

2.2 Indicators

Comparative advantages The paper focuses on the factors influencing export specialisation both in terms of the intensive and the extensive margin in trade. We measure the intensive margin in terms of the revealed comparative advantage (RCA) a country shows in a specific product line. Following Balassa (1965) the RCA is defined as:

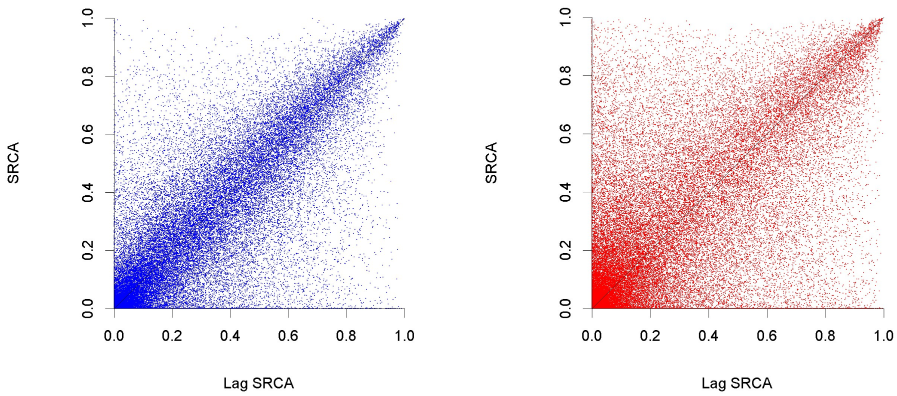
$$RCA_j^i = \frac{X_j^i / \sum_i X_j^i}{\sum_j X_j^i / \sum_{i,j} X_j^i},$$

where X_j^i are denoting the exports of product j of country i. Time indices have been omitted for better readability. It is the export share of a product in a country divided by the export share of this product in world exports. We use a transformed and standardised version of this index (cf. Laursen, 1998):

$$\mathrm{SRCA}_j^i = \frac{RCA_j^i}{RCA_j^i + 1}.$$

With this transformation we obtain $SRCA \in [0, 1[$. The threshold for having a comparative advantage is then 0.5.

To examine the joint impact of "untraded interdependencies" and the breadth of technological search on changes in the export basket at the extensive margin, we also analyse the likelihood that a country starts or stops



(a) INNO ($\rho = 0.78$) (b) NON-INNO ($\rho = 0.64$)

Figure 1: SRCA and Lagged SRCA (L=11)

to export a product line. The dependent variables in this case have been defined as follows: An entry in a product line occurs if the product has not been exported in the initial period of observation (2002) of our sample or before but is exported in the last period of observation (2012). In the case of exit, vice versa, the product has been exported in the initial period of observation, but has not been exported in the final year of your sample and in the consecutive years.

Figure 1 provides evidence for the persistency of RCAs. It plots the value for the SRCA calculated at the level of single product lines for the year 2002 against the value realised in 2012 for our sample of countries, split into the group of technological innovation leaders (left) and the group of more countries with more moderate technological innovation capabilities (right). If observations cluster close to the 45 degree line persistency is high. For the group of innovation leaders (INNO) export specialisations at the product level have been relatively stable over a decade. Changes were more accentuated for countries in the group of moderate and modest innovators

(NON-INNO). However, give the observed time span export specialisations have been very stable over time for both country groups as indicated by the correlation coefficients ρ.

Product relatedness One of the principal independent variables in our analysis is the indicator of product relatedness proposed by Hausmann and Klinger (2006). As discussed earlier it may be interpreted as a valid approximation to "untraded interdependencies" in domestic production, which are a latent factor. It exploits information on the clustering of comparative advantages of product lines across countries. The proximity measure, ϕ_{jk}, between two products j and k is defined as the pairwise conditional probability of a country exporting one good with comparative advantage given that it exports the other also with comparative advantage:

$$\phi_{jk} = \min\Big(Pr(IRCA^i_j|IRCA^i_k), Pr(IRCA^i_k|IRCA^i_j)\Big),$$

where

$$IRCA^i_j = \begin{cases} 1 & \text{if } SRCA^i_j \geq 0.5 \\ 0 & \text{else} \end{cases}.$$

Measure ϕ_{jk} corresponds to the edges of the product space network with the product lines constituting its nodes. This indicator is used to construct a country specific indicator that measures how closely related a product line k is to all other product lines j country i exports with comparative advantage:

$$\text{prod. relatedness}^i_k = \frac{\sum_{j,j\neq k} IRCA^i_j \cdot \phi_{jk}}{\sum_{j,j\neq k} \phi_{jk}}$$

The range of the indicator for product relatedness is the interval $[0,1]$.

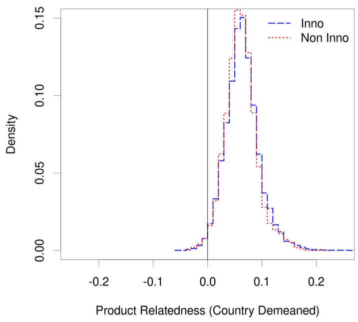
Hausmann and Klinger (2006) argue that the proximity in product space reflects shared knowledge bases needed to successfully export products j and k jointly or factor substitutability across products in a country.[2]

Figure 2 shows how the observed changes in comparative advantage across countries are linked to product relatedness. It presents the distribution of product relatedness (demeaned by country averages for direct comparability) by RCA and export status. Products with persistent RCAs and products that have developed an RCA in the observed decade are more strongly embedded in "untraded interdependencies" in their respective economies (Panels (a) and (c)) than products that either have not developed or lost comparative advantage (Panels (a) and (c)). The product relatedness values of the former two subgroups are systematically larger (and above their respective country averages) than for the latter two subgroups. This suggests that strong local external effects are indeed closely related to persistent comparative advantages.

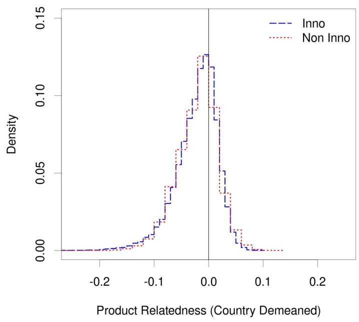
The lower right quadrant in Figure 2 illustrates that the development of new comparative advantages happens at intermediate levels of product relatedness. This suggests that the exporters of these products can draw on the stock of local capabilities and "untraded linkages" in an economy, but that their own capabilities lie somewhat outside the country specific core.

For changes on the extensive margin the two panels on the bottom of Figure 2 show that while products that product relatedness tends to be below the country average for both entries and exits. However, the modus and the right tail of the distribution of the product in which countries have

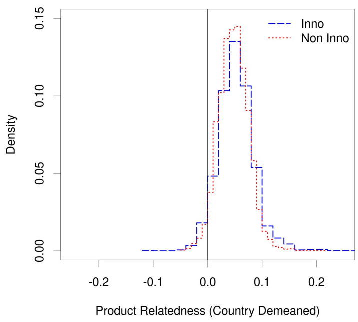
[2]The indicator used in this paper deviates from the original version, insofar, as the sum runs over all products j and excludes changes in export status by product k. Hence, the proximity of a product to all others is exclusively determined by changes in specialisation status of neighbouring products but not by own status changes. This has been applied to avoid potential endogeneity issues in the econometric analysis.



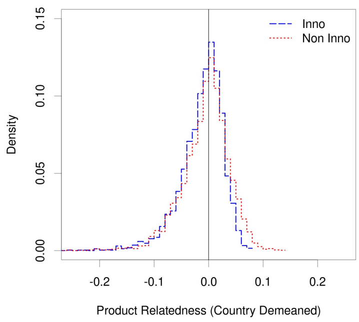
(a) RCA in both periods
$RCA_{2012} >= 1$, $RCA_{2002} >= 1$



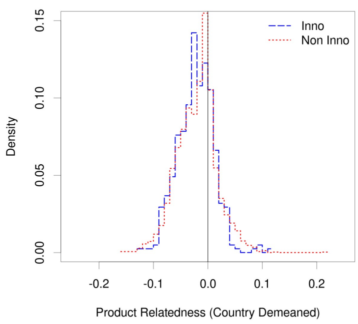
(b) No RCA in both periods
$RCA_{2012} < 1$, $RCA_{2002} < 1$



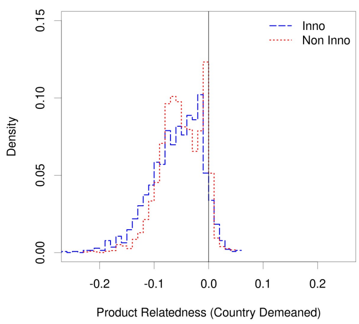
(c) Gaining RCA
$RCA_{2012} >= 1$, $RCA_{2002} < 1$



(d) Loosing RCA
$RCA_{2012} < 1$, $RCA_{2002} >= 1$



(e) Entries



(f) Exits

Figure 2: Histogram product relatedness distribution in the base year 2002 over RCA changes between 2002 and 2012

entered is more heavily skewed towards higher values of product relatedness, suggesting that also for the entry a certain degree of embeddedness of a product in domestic untraded interdependencies is important.

Technological capabilities and the breadth of technological search To examine how the breadth of the technological capabilities affects the impact of untraded interdependencies on the development of comparative advantages, we rely on 4-digit industry specific patent measures.

To capture the scope of technological search at the industry level, we calculate the breadth of technological search by exploiting information on the technological fields assigned to patents (IPC classes) and the four digit industry to which a patent filing is assigned in the data. PATSTAT maps IPC classes on to four digit industry codes following the NACE classification. These assignments are not unique most of the times. Therefore, if a technological class can be observed in two NACE four-digit sectors, there is an overlap in terms of the technological capabilities needed to develop new technologies in a sector. It is therefore possible to calculate a matrix capturing the technological relatedness or proximity of any pair of four digit industries (cf. Kogler et al., 2013):

$$\psi_{r,s} = \frac{P_{r,s}}{\sqrt{P_r P_s}},$$

where $P_{r,s}$ is the count of patents with overlapping technological fields which are assigned to sectors r and s, and P_r and P_s is the total count of patents in each sector r, s. The technological relatedness of two sectors $\psi_{r,s}$ therefore captures the (cognitive) overlap of technological search activities across 4-digit industries.

In the next step, we calculate the country-industry specific breadth of technological search, i.e. the measure on how broadly the technological search activity in a 4-digit industry in a country overlaps with the technological search activities of other 4-digit industries in the country. In a first step we calculated citation weighted patent stocks per capita ($PatStock_s^i$) for each sector. They have been calculated using the perpetual inventory method with geometric discounting (discount factor 0.9, implying that a given stock of patents at time t decreases to half its size after seven years). The resulting stocks have then been normalized over all countries to obtain a maximum of 1 in each sector (patent stock relative to the country leader in the sector). The indicator for technological breadth is then defined as follows:

$$\text{techn. breadth}_s^i = \frac{\sum_{r \in S, r \neq k} \frac{\text{PatStock}_r^i}{\max_i(\text{PatStock}_r^i)} \cdot \psi_{r,k}}{\sum_{r \in S, r \neq k} \psi_{r,k}}.$$

The technological search breadth of sector s in country i is the larger the closer the indicator is to its maximum of one.

The patent stocks proxy cumulated technological knowledge and closely correlate with cumulated past R&D expenditures. Citation weighted stocks capture especially the qualitative dimension of business R&D (cf. Hall et al., 1991). The data on patent filings at the EPO and inward citations have been drawn from the PATSTAT database. As a consequence of its construction, our indicator $techn.breadth_{s_j}^i$ is closely related to patent stocks and therefore captures both, the breadth of technological search, but also the cumulated capabilities in any specific sector as shown in Table 5 below.

Table 2 shows that the distributions of $techn.breadth_{s_j}^i$ are heavily skewed towards values close to zero indicating that most sectors in the present sam-

Table 2: Technological breadth: values at different quantiles

Quantile	All	INNO	NON-INNO
0.90	0.55	0.78	0.07
0.75	0.38	0.52	0.04
0.50	0.06	0.41	0.02
0.25	0.02	0.19	0.02
0.10	0.01	0.11	0.01

ple have a low technological search breadth. There are however considerable differences, if we distinguish between technologically advanced and less advanced countries in our sample. In the former (INNO) the technological search breadth across sectors is considerably larger ranging between 0.11 and 0.41 for the 50% of the observations lying between the 25% and 75% quantile. In the latter group of countries (NON-INNO) technological activities are considerably lower and as a consequence the resulting technological search breadth is also very low. Table A.1 in the appendix presents a further breakdown of this indicator by country.

2.2.1 Control variables for knowledge generation and diffusion

We use a number of indicators that capture technological capabilities at the country level to control for them impact different domains of knowledge generation and transfer in a country have on the relation between product relatedness and comparative advantages. Table 3 gives an overview on the sources, time and geographical coverage of these indicators.

Table 3: Source and coverage of control variables

Indicator	Source	Years	Countries
Tertiary education	World Bank - SL_TLF_TERT_ZS	1996 - 2014 (discontinued)	World
HRSTC	Eurostat - hrst_st_nsec(2)	1994 - 2016	EU
Inward FDI stock	Eurostat - tec00105	1994 - 2016	EU
Import complexity	BACI 92/own calculation	1995 - 2016	World
Trade openness	BACI 92/own calculation	1995 - 2016	World

With regard to technological capabilities related to domestic knowledge creation and transmission, we use two alternative human capital indicators related to the diffusion of concept based cognitive skills from higher education into the business sector and to domestic R&D activities. Tertiary graduates are the most important transmission channel of knowledge from academia into the business sector. This has been shown to affect the diversification of export baskets (Agosin et al., 2012), and path-dependence in trade specialisation (Mehta and Felipe, 2014). We use the country level indicator on the labour force with tertiary education which is available from the World Bank. It represents the share of total labour force with attained or completed tertiary education as highest level of education.

The share of persons active in R&D activities in the total work force in an economy, on the other hand, reflects the intensity of technological and scientific search and discovery processes in an economy relative to other economic activities, and is directly related to the development of comparative advantages in trade as discussed by the technology gap literature. It has also been shown to be an important determinant of international technology diffusion (Keller, 2004). We use the core concept of what is defined as "human resources in science and technology" (HRSTC) in established OECD statistics. It comprises the share of persons in the total workforce with a scientific or technical tertiary degree that are active in research and development activities.

To capture capabilities related to knowledge inflows from abroad we examine inward foreign direct investment, the technological sophistication of imports and general trade openness. Inward foreign direct investment is considered to be an important channel of international knowledge diffusion. Recent contributions find evidence for significant technology spillovers into receiving economies through the activity of multinational enterprises (cf. Keller, 2009). Inward FDI data on the value of the investment stocks held by multinational enterprises in the economy of the reporting country are available from Eurostat and cover all EU member states and several other industrialised countries. It is measures inward FDI as percentage of GDP of the reporting country. International knowledge diffusion takes also place through imports of capital goods.

More sophisticated capital goods support domestic producers to augment the quality and widen the scope of their production capabilities (Pack, 2001; Keller and Acharya, 2007). This is likely to impact on existing industrial specialisation patterns. We have used trade data to construct an indicator for the level of technological sophistication of capital goods imports as proposed by Hidalgo and Hausmann (2009). We have relied, however, on the method advanced by Klimek et al. (2012) which overcomes some conceptual and computational issues related to the work of the latter authors. After obtaining a product level complexity score which are considered to capture latent information on the knowledge intensity and complexity of any traded commodity, we have calculated a weighted average of this score over all imported capital goods using the Broad Economic Categories classification of the United Nations.[3]

Trade openness finally promotes also learning through exporting and importing (Keller, 2002). It may also contribute to the export specialisation by sorting out economic activities and related exports that are not competitive. This indicator has been calculated in a standard way as the coefficient between the total sum of exports and imports divided by the nominal GDP

[3] See `http://unstats.un.org/unsd/cr/registry/regcst.asp?Cl=10`, last accessed May 2018.

of a country. Exports and imports were drawn from the BACI/Comtrade data and nominal GDP was obtained from World Bank data.

2.3 Descriptive statistics

Table 4 provides summary statistics of the indicators used in the econometric analysis. Table 5 reports the correlations of these indicators. In both tables we include also information on the patent stock indicators that have been used to construct the indicator of technological breadth, but are not directly used in the econometric analysis.

Table 4: Descriptive Statistics

Statistic	N	Mean	St. Dev.	Min	Max
(1) SRCA	98,475	0.286	0.269	0.000	0.997
(2) Lag SRCA	98,475	0.291	0.269	0.000	0.997
(3) Lag Product Relatedness	98,475	0.255	0.117	0.036	0.817
(4) Lag Patent Stock	98,475	0.140	0.357	0.000	3.100
(5) Lag Technological breadth	98,475	0.183	0.235	0.001	0.986
(6) Lag Tertiary	98,475	21.480	6.613	9.900	31.700
(7) Lag HRSTC	98,475	9.052	3.010	5.700	16.300
(8) Lag Inward FDI Stock	98,475	36.180	24.404	9.300	133.400
(9) Lag Import Complexity	98,475	0.414	0.135	0.109	0.601
(10) Lag Trade Openness	98,475	0.568	0.272	0.203	1.410

Note: Variables refer to valued in the base year 2002 (‘Lag’) and the last period of observation, 2012.

Our key variables of interest are product relatedness and technological breadth. Product relatedness varies between 0.036 and 0.817 with a mean value of 0.291. These values vary systematically across countries and are typically higher for countries with more specialised export portfolios. The inclusion of country dummies in the regressions discussed later will control for these level effects. The same holds true for the indicator of technological breadth. Despite the fact that all countries in our sample are industrialised countries the country level indicators vary widely reflecting the differences in economic development across countries in our sample.

Table 5: Correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1)	1	0.692	0.486	0.126	0.112	0	0.075	-0.141	0.171	-0.21
(2)		1	0.572	0.149	0.15	0.001	0.11	-0.126	0.214	-0.225
(3)			1	0.24	0.347	-0.072	0.314	-0.368	0.529	-0.548
(4)				1	0.541	0.163	0.233	-0.001	0.278	-0.141
(5)					1	0.297	0.379	-0.012	0.565	-0.271
(6)						1	0.027	0.251	0.043	-0.172
(7)							1	-0.145	0.535	-0.188
(8)								1	0.054	0.505
(9)									1	-0.417
(10)										1

Note: The numbers in the first row and column refer to the numbered variables in Table 4.

Table 5 shows that there is a high correlation between the SRCA indicators and product relatedness, as would be expected. Technological relatedness in turn is highly positively correlated with both citation weighted patent stocks and product relatedness, where the correlation between product relatedness and technological breadth is somewhat lower. As we have argued, the indicator for technological breadth by construction captures cumulated technological capabilities, which explains both positive correlations.

If both product relatedness and technological breadth are included in the same regression, product relatedness will reflect untraded interdependencies net of cumulated technological capabilities. These will be captured by the indicator for technological breadth. Product relatedness and technological breadth both correlated strongly with the country level indicators for domestic and imported knowledge transmission. So, by including all these indicators in the regressions there is the danger of inflated coefficients due to collinearity. While we will present a fully specified model that includes all these indicators, we will however opt for more parsimonious models when analysing the marginal effects and the joint impact of product relatedness and technological breadth on comparative advantages and on changes in the extensive margin of trade.

3 Econometric approach

Our analysis of how the breadth of technological search affects the impact of untraded interdependencies on export specialisation proceeds in three steps. In the first step, we analyse how the two factors jointly influence the development of comparative advantages at the country-product level. In the second step, we break the analysis down into impacts on the intensive and the extensive margins of trade. This allows distinguishing between effects on diversification and market shares in trade. Finally, we examine in detail the interaction effects between product relatedness and technological breadth relying on predictions of our econometric model.

The empirical estimation is in line with the following equation:

$$
\begin{aligned}
E(SRCA_{c,p,t_1}|x_{c,p,t_0}) = G\Big(&\alpha + \beta_0 SRCA_{c,p,t_0} \\
&+ \beta_1 \text{prod. relatedness}_{c,p,t_0} + \beta_2 \text{techn. breadth}_{c,s,t_0} \\
&+ \beta_3 (\text{prod. relatedness}_{c,p,t_0} \times \text{techn. breadth}_{c,s,t_0}) \\
&+ \sum_{CAP} \beta_{CAP} (\text{prod. relatedness}_{c,p,t_0} \times \text{CAP}_{c,t_0}) \\
&+ \sum_{c} \sum_{s} \delta_{c,s} d_c d_s \Big)
\end{aligned}
\tag{1}
$$

where α is the usual constant. As a maximum likelihood estimation is carried out error terms are not included. Variables prod. relatedness and techn. breadth correspond to the product relatedness indicator and the technological breadth. Our analysis focuses on the interaction term $\text{prod. relatedness}_{c,p,t_0} \times \text{techn. breadth}_{c,p,t_0}$ which will reveal to what extent the scope of technological search affects the impact of product relatedness on comparative advantages over time. In addition we present regression results where we control for the interaction between product relatedness and the indicators on the share of tertiary educated in the workforce in a country, share of persons active in R&D activities in the total work force in an economy following the HRSTC definition, the inward FDI stock, the complexity of imported capital goods and trade openness subsumed with variable CAP. The indices are for country c and time t. The term $\sum_c \sum_s \delta_{c,s} d_c d_s$ stands for the country-sector dummies. In some specifications country and sector dummies will enter the regressions separately.

We use a fractional logit model to estimate equation 1. The reason for this is that the principal dependent variable in our analysis, SRCA_{c,p,t_1}, is a fractional indicator with $0 \leq \text{SRCA}_{c,p,t_1} \leq 1$. This is by construction and not due to censoring, and as such estimators modelling censored variables between two strictly defined bounds, such as two limit Tobit models, will not produce consistent estimates of the conditional mean $E(SRCA_{c,p,t_1}|\cdot)$. For this type of dependent variables fractional logit models deliver consistent estimates (Papke and Wooldridge, 1996).[4]

To break the analysis down to the extensive and intensive margins of trade, we replace the dependent variable in equation 1 with variables $entry_{c,p,t_1}$, $exit_{c,p,t_1}$ and SRCA_{c,p,t_1}, with $0 < \text{SRCA}_{c,p,t_1} < 1$. As the former two are binary variables, we will use a binary fractional logit approach. For the estimation of the probability of entry we have to exclude the term $SRCA_{c,p,t_0}$ from the regressions, because this vector collapses to a zero vector. For the estimation of the probability of entry all possible entries, i.e. all product lines that have never been active in the data available to us, have been used as observations. In the estimations of the probability of exit the subset con-

[4]We have carried robustness checks with OLS estimations to ensure that the results do not depend on our choice of estimators.The qualitatively very similar results are reported in an appendix to this paper available from the authors.

sists of all observations, which have a positive $SRCA$ value in the initial period, but are zero at the end of the period of observation.

Finally, the paper examines the interaction effect between product relatedness and the technological breadth on changes in the intensive and extensive margins of trade in detail. Here, we follow the approach proposed by Greene (2010) which focuses on analysing interaction effects in non-linear models based on model predictions for economically significant scenarios.

The identification strategy is similar to the one proposed by Mehta and Felipe (2014). Even though the data used in this analysis are available as panel for the countries on which the analysis focuses, we have refrained from using them because both trade data and most of the indicators for knowledge creation and diffusion are very persistent. By controlling for the level of the dependent variable in the base year, it is however possible to examine how the product relatedness and technological breadth in some base year jointly affect the observed change in RCA values at the end of this observation period. This setting avoids problems of reverse causation or endogeneity between the dependent and our key explanatory variables which would be difficult to control for in a panel setting.

4 The impact of knowledge creation and diffusion on path dependence in export specialisation

4.1 Baseline results

To understand how product relatedness and the technological breadth jointly affect export specialisations at the country-product level, we first regress changes in SRCA values for $\mathrm{SRCA}_{c,p,t_1} \geq 0$ at the country-product level on product relatedness and technological breadth. In doing so, we proceed by introducing the two key indicators, their interaction term, and interaction terms with the control variables incrementally. This allows assessing both the stability of the results and more importantly different propositions emerging from the literature.

Table 6 reports the estimated coefficients of the regression with robust standard errors clustered at the country and sector levels to account for heteroskedasticity and Moulton bias. Marginal effects for the two key indicators are discussed at the end of this section, as these have to be derived analytically in non-linear models with interaction effects. The signs of the estimated coefficients indicate the impact the levels of the indicators for product relatedness and technological breadth at the beginning of the period of observation have had on the observed SRCA at the end of the period of observation, controlling for its initial level as well as other unobserved factors both at the country and sector level.

Model (1) shows that comparative advantages at the product level across countries are highly persistent and strongly depend on untraded interdependencies. Controlling for the initial levels of SRCA product relatedness in the base period has a statistically significant and positive effect on observed SRCAs ten years later. This mirrors findings of both the product space and the technology gap literature. Model (2) regresses technological breadth in the base period on product level SRCAs in the end period. While the literature is not entirely conclusive on the impact of technological breadth on the dynamics of market shares and comparative advantages, the results show that it is positive. As by construction the indicator of technological breadth and the cumulated stock of patents at the industry level are highly correlated this outcome is in line with a key proposition of the technology gap literature, namely that cumulated technological capabilities are an important determinant of comparative advantages.

The share of explained variation of these two models varies between 0.51 and 0.53. The coefficient for the SRCA in the initial period is higher in Model (2). In the absence of the indicator for product relatedness, the lagged SRCA value therefore captures an important part the variation product relatedness would explain. This indicates that technological breadth explains less variation than product relatedness. One reason for this is that unlike lagged SRCAs technological breadth is an industry and not a product level indicator and it cannot capture as much variation. In addition, it has to be kept in mind that technological, or more specifically patenting activities vary considerably across sectors and countries in our sample. The indicator for technological breadth has therefore more explanatory power for SRCAs in technologically more advanced countries. Finally, it is also important to consider that technological knowledge and technological search are only a subset of production knowledge that spreads across many more knowledge domains. As a consequence, when the two models are combined into Model (3) we can observe that the coefficients of all indicators remain stable, but the level of statistical significance of technological breadth decreases. A first conclusion, therefore is that product relatedness with its broader scope in the knowledge domain has a more pronounced effect on changes in comparative advantages than knowledge breadth in the technology domain.

In Models (4) and (5) we examine the interaction effect between product relatedness and technological breadth. With the introduction of an interaction term, the interpretation of the coefficients for product relatedness and technological breadth changes. Now, the coefficients capture the direct effect of one indicator under the assumption that the other one is zero. The overall effect follows from the combination of the direct and the inter-

Table 6: Fractional regressions, dependent variable SRCA.

	Dependent variable:						
	Standardized RCA						
	fractional	fractional	fractional	fractional	fractional	fractional	fractional
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
prod. relatedness$_{c,p,t_0}$	2.956***		2.947***	2.770***	3.155***	3.397***	3.849***
	(0.100)		(0.100)	(0.135)	(0.168)	(0.566)	(0.755)
SRCA$_{c,p,t_0}$	2.873***	3.257***	2.873***	2.879***	2.801***	2.866***	2.797***
	(0.022)	(0.016)	(0.022)	(0.023)	(0.023)	(0.023)	(0.024)
tech. breadth$_{c,s,t_0}$		0.338***	0.156*	−0.046		−0.255*	
		(0.083)	(0.084)	(0.121)		(0.144)	
prod. relatedness$_{c,p,t_0}$ × tech. breadth$_{c,s,t_0}$				0.623**	1.303***	1.144***	1.897***
				(0.264)	(0.338)	(0.350)	(0.449)
prod. relatedness$_{c,p,t_0}$ × Tertiary educ.$_{c,t_0}$						−0.065***	−0.041**
						(0.014)	(0.018)
prod. relatedness$_{c,p,t_0}$ × HRSTC$_{c,t_0}$						−0.145***	−0.168***
						(0.028)	(0.035)
prod. relatedness$_{c,p,t_0}$ × FDI$_{c,t_0}$						−0.010	−0.019**
						(0.007)	(0.009)
prod. relatedness$_{c,p,t_0}$ × Imp. complexity$_{c,t_0}$						3.788***	3.811***
						(1.046)	(1.332)
prod. relatedness$_{c,p,t_0}$ × Openness$_{c,t_0}$						1.573***	1.193
						(0.602)	(0.771)
Country dummies	Yes	Yes	Yes	Yes	No	Yes	No
Sector dummies	Yes	Yes	Yes	Yes	No	Yes	No
Country Sector dummies	No	No	No	No	Yes	No	Yes
R2	0.51	0.51	0.51	0.51	0.53	0.51	0.53
Observations	98,475	98,475	98,475	98,475	98,475	98,475	98,475
Group	ALL	ALL	ALL	ALL	ALL	ALL	ALL
Note:							*p<0.1; **p<0.05; ***p<0.01

action effect. The two models differ insofar as the former includes sector and country dummies, whereas the latter includes country-sector dummies to better control for potential unobserved heterogeneity at the sector level across countries.

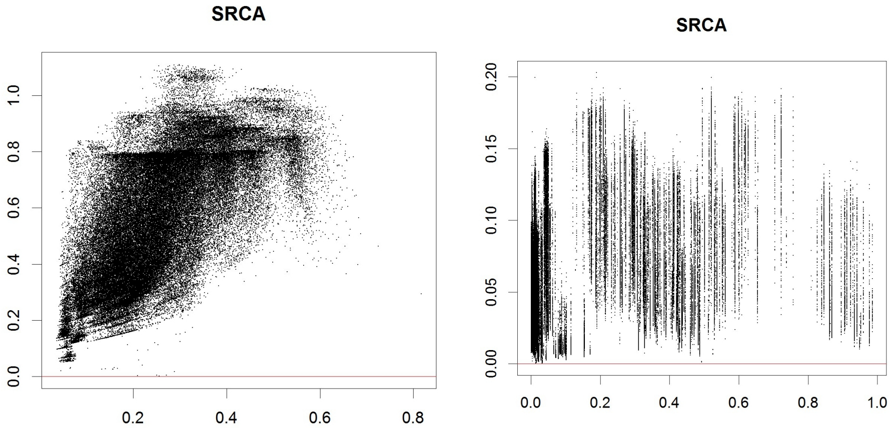
In line with previous work we should expect that the interaction effect between product relatedness and technological breadth is positive and significant. Previous work has shown that technological and product diversification are contingent one upon the other pointing therefore at a complementarity between untraded interdependencies and the scope of technological search.

The expected impact of product relatedness when techological breadth is zero, should be positive as it captures a wide variety of local external effects beyond pure technology spillovers and cumulated technological capabilities that favour the development of comparative advantages. The expected impact of technological breadth when product relatedness is zero on the other hand is more ambiguous. Some contributions have argued that when product relatedness is low, technological breadth should have no or even negative effects on changes in comparative advantages due to a lack of knowledge coherence which is important to fully exploit existing stocks of production knowledge. We should therefore expect either a statistically insignificant or negative coefficient for technological breadth.

The results are in line with these expectations. In the model with country and sector dummies the coefficient for technological breadth is not significantly different from zero. However, the interaction term between product relatedness and technological breadth is positive. An implication of this result is that local production capabilities and broader technological search show a statistically significant and robust complementary relationship. Only if product lines are minimally embedded in the local production system, broadening the scope of technological search at the industry level unfolds a positive effect on global market shares and comparative advantages. This is confirmed by Model (5) which controls better for industry specific unobserved heterogeneity. This comes however at the cost that technological breadth drops out of the estimation, as its variation is now captured by the country-sector dummy. The estimated coefficient for the interaction term is here statistically significant and positive and about twice as high as in Model (4). In both models the estimated coefficients for product relatedness are positive and statistically highly significant.

These results are confirmed and strengthened, if we control for other characteristics of the national system of innovation and production that have an influence on untraded interdependencies in an industry. In Models (6) and (7) the estimated coefficient for technological breadth now turns significant and negative (when product relatedness is zero). The interaction effect between product relatedness and technological breadth remains positive and statistically highly significant with the value of the coefficient increasing relative to the simpler models. The difference between the two models is again that the former controls for unobserved heterogeneity through country and sector dummies, whereas in the latter we have used country-sector dummies.

The interaction effects of these controls with product relatedness are in most cases statistically significant. The interaction effects of product relatedness with the share of tertiary educated persons and the share of human resources in science and technology (HRSTC) in the total workforce are negative, suggesting that a substitutive relationship exists and that HRSTC contribute to relax existing path-dependencies in the production system.



(a) product relatedness

(b) technological breadth

Figure 3: Marginal Effects for SRCA in fractional regressions

The coefficient for the interaction of inward FDI and product relatedness is weakly significant only in Model (7) an insignificant in Model (6). The moderating effect of FDI therefore seems to be weak and to point into the same direction as that for HRSTC. The coefficient of the interaction terms of product relatedness with both the complexity of imported capital goods and the openness of the economy are either positive or not significant indicating that they tend to strengthen domestic untraded interdependencies through different channels. The former through the diffusion of more sophisticated capital goods in established industries, the latter through a selection effect, sorting out poorly embedded product lines.

In order to establish, how the impact of product relatedness and technological breadth on comparative advantages in trade differ, Figure 3 shows now the analytically derived marginal effects taking account of the interaction effect for product relatedness and technological breadth (see the appendix of this paper for details on their derivation).

Panel (a) of Figure 3 plots the predicted change of SRCA for a marginal change of product relatedness for any value of technological breadth observed in the sample using the estimation results for Model (5). As would be expected from the literature there is a strong positive relationship. Marginal effects tend to increase with increasing product relatedness and are strictly positive for all observations in the sample.

Panel (b) shows the predicted change of SRCA for a marginal change of technological breadth for any observed value of product relatedness in the sample using the estimation results for Model (4). The marginal effect of this indicator is positive over its entire support for any given level of product relatedness, but the effect is considerably smaller than for product relatedness. The magnitude of the marginal effect of technological breadth never exceeds 0.2, whereas the magnitude of the marginal effects for product relatedness for most observations lies above this value.

The marginal effects of technological breadth seem also to follow a somewhat discontinuous patterns with marginal effects having a tendency to fall for technological breadth values between 0.1 and 0.5, increase again for values up to 0.8 and then fall again. As can be seen from Table 2 this is on the one hand due to the circumstance that technological breadth values are particularly low in countries that are part of the NON-INNO group. These observations are largely condensed in the interval [0, 0.1], whereas more than 90% of the observations for the countries in the INNO group are larger than 0.1. The discontinuities seem therefore largely due to systematic differences in the (generally positive) impact of changes in technological breadth on SRCA.

The analysis of the marginal effects in Figure 3 corroborates the conclusions drawn in the discussion of Models (1) through (3). When we control for the level of product relatedness, the magnitude of the impact of changes in technological breadth on SRCAs is considerably smaller than that of product relatedness. This would suggest that at any given level of product relatedness broader technological search contribute less to observed comparative advantages and specialisation patterns than untraded interdependencies, but both have a clear positive impact on comparative advantages.

4.2 Intensive and extensive margins

To obtain a comprehensive picture on how product relatedness and technological breadth affect the observed persistence of specialisation patterns in trade across countries, we now explicitly distinguish between their joint impact on the probability of a country starting or stopping to export a particular product line, i.e. changes in the extensive margin of trade, and changes in world market shares or intensive margin, i.e. for $\text{SRCA}_{c,p,t_0} > 0$ and $\text{SRCA}_{c,p,t_1} > 0$. Product relatedness or technological breadth will contribute to this persistence if they act as a barrier to diversification, while at the same time enforcing competitive advantages in exported product lines through positive feedbacks.

Table 7 reports the impact of product relatedness and technological breadth on the probability that a country starts exporting in a previously inactive product line (column 'entry'), on changes in SRCA values (column 'fractional'), and on the probability that a country stops exporting in a previously inactive product line (column 'exit'). The specifications correspond to Models (4) and (5) in Table 6.[5]

The results for the intensive margin are largely identical to those pre-

[5]We report results corresponding to Models (6) an (7) in Table 6 in the appendix (see Table A.2). The inclusion of additional control variables does not qualitatively affect the reported outcomes.

Table 7: Regressions for entry, exit and intensive margin.

	Dependent variable:					
	entry binary	intensive margin fractional	exit binary	entry binary	intensive margin fractional	exit binary
	(1)	(2)	(3)	(4)	(5)	(6)
prod. relatedness$_{c,p,t_0}$	6.481^{***}	1.945^{***}	-7.338^{***}	5.133^{**}	2.199^{***}	-9.037^{***}
	(1.942)	(0.129)	(0.651)	(2.203)	(0.160)	(0.783)
SRCA$_{c,p,t_0}$		2.902^{***}	0.062		2.829^{***}	0.117
		(0.022)	(0.093)		(0.023)	(0.097)
tech. breadth$_{c,s,t_0}$	-5.158	-0.522^{***}	-0.570			
	(5.231)	(0.116)	(0.677)			
prod. relatedness$_{c,p,t_0}$ × tech. breadth$_{c,s,t_0}$	39.645	2.007^{***}	2.102	117.231^{**}	2.928^{***}	4.788^{**}
	(28.027)	(0.253)	(1.726)	(47.988)	(0.326)	(2.108)
Country dummies	Yes	Yes	Yes	No	No	No
Sector dummies	Yes	Yes	Yes	No	No	No
Country Sector dummies	No	No	No	Yes	Yes	Yes
R2	0.1	0.52	0.04	0.16	0.53	0.04
Observations	3,669	85,010	90,498	3,669	85,010	90,498
Group	ALL	ALL	ALL	ALL	ALL	ALL

Note: *p<0.1; **p<0.05; ***p<0.01

sented earlier in Table 6. The coefficients vary slightly in magnitude, but all signs remain consistent with the previous results. We will therefore focus on the probabilities of entry and exit.

Looking at the probability of entry first, the coefficients for product relatedness are positive in both models. As they explain the impact of product relatedness on the probability of entry when technological breadth is zero, this indicates that the probability of entry increases in product relatedness irrespective of the level of technological breadth observed in an industry. However, technological search activities contribute to exploit the benefits of untraded interdependencies as technological breadth increases. This follows from the positive and statistically highly significant coefficient for the interaction effect. This echoes the results for the intensive margin.

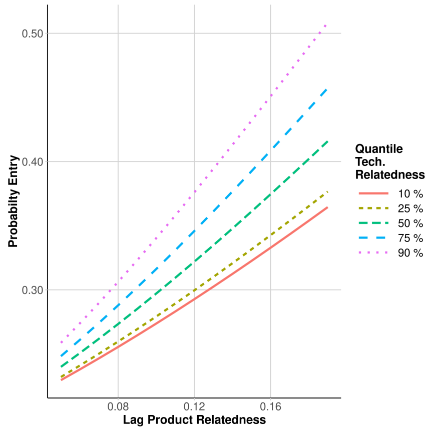
The exit equations reveal that product relatedness acts as a barrier to exit and therefore is a factor hardening path dependence in trade specialisation. It leads to a predicted decrease of the probability of exit. Increases in the breadth of technological search in turn tend to offset this effect, as suggested by the positive and significant coefficient of the interaction effect. For entry on the other hand, broader technological search seems to contribute to better exploit domestic untraded interdependencies, and thereby favours the uptake of exports in new product lines.

These results indicate that product relatedness favours path dependence in the export specialisation of an industry across countries. Technological breadth on the other hand, does not have a statistically significant impact neither on entry nor on exit. However, once we control for all possible factors influencing the variation at the industry-country level, we observe that it increases the effect of product relatedness on the probability of entry, while it reduces its negative effect on the probability of exit. This indicates that technological breadth may help to lower the barriers to exit for highly embedded product lines, whereas it helps lowering barriers to entry for poorly embedded ones. On the other hand, it augments the effect of product relatedness on both the probability of entry and market shares in well embedded product lines. We will explore this evidence further with an in-depth analysis of the interaction effects in the next section.

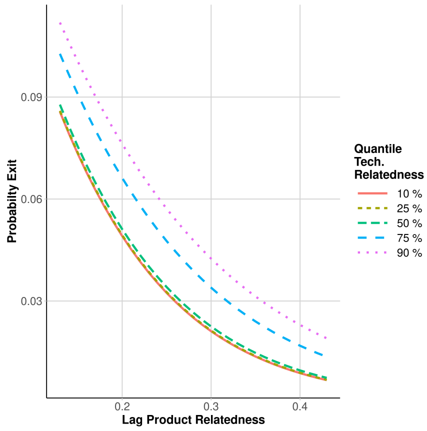
4.3 Analysis of the interaction effects between untraded interdependencies and the scope of technological search

The interaction between product relatedness and technological breadth either increase or decrease the direct effect of these two variables on outcomes. These second order effects are however difficult to interpret economically in non-linear models as the ones used in our analysis (Ai and Norton, 2003). Greene (2010) has therefore proposed to use graphical representations of model predictions as differences in the slope of the predicted outcome at a specific value of the indicator of interest unveil the interaction effect. In our case, we are interested to explore how changes in the scope of technological search affect the impact of product relatedness on the probabilities of entry or exit as well as comparative advantages. We therefore predict the impact of product relatedness on the outcome variables by keeping technological breadth constant at a certain empirically meaningful level. If we repeat this exercise for different levels of technological breadth, the observed differences in the slope of the predicted effect for a specific value of product relatedness will then unveil the interaction effect between the two indicators at this value. This is shown in Figures 4 and 5.

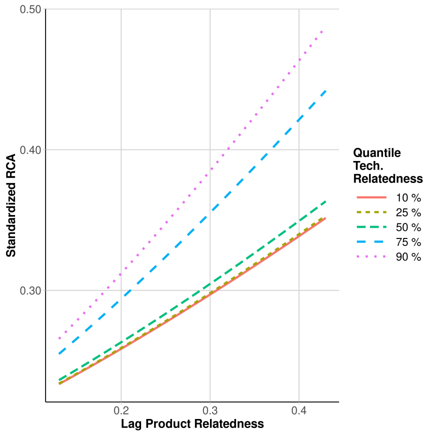
Figure 4 displays the predictions for the probability of (a) entry, (b)



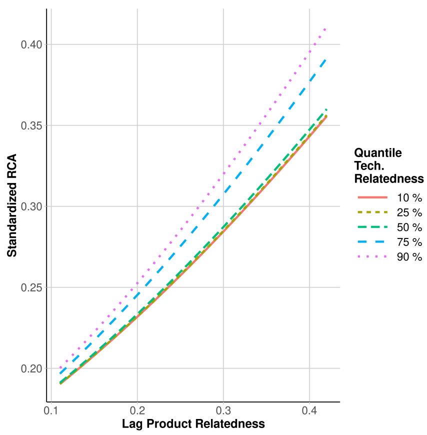
(a) Entry



(b) Exit



(c) Intensive margin



(d) All observations

Figure 4: The effect of product relatedness on the probability of entry, exit and the predicted SRCA for different values of technological breadth

exit, (c) the intensive margin and (d) for the overall sample. These have been obtained from the models presented in Table 7, and Model (5) in Table 6. The levels of technological breadth indicated in the figures refer to the empirically observed values at different quantiles as shown in Table 2.

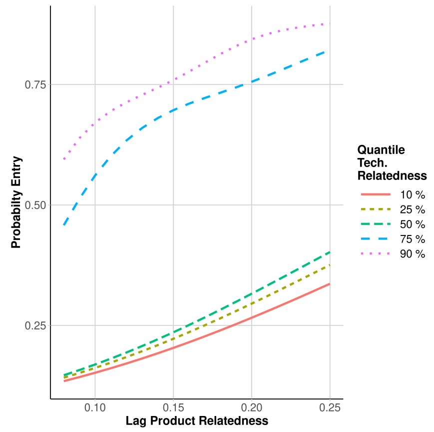
The probability of entry into a new product line across countries increases with increasing product relatedness. However, this effect is stronger the higher the level of technological breadth of a sector as shown in Panel (a). The predicted probabilities of entry increases as product relatedness and technological breadth increase, pointing to an interaction effect reinforcing existing specialisation patterns rooted in current capabilities. At the same time, product relatedness acts also as a barrier to exit (Panel b). The probability of a product line leaving a country's product portfolio falls with higher product relatedness. Paradoxically, however, the probability of exit is higher in industries with higher levels of technological search breadth. This echoes the results presented in the previous section. As will be shown later, this is largely due to specific differences in the dynamics between the technologically advanced and less advanced countries. The predicted intensive margin in trade for any product, finally, also increases in the product relatedness and its impact is amplified by higher levels of technological breadth (Panel c). This mirrors the evidence for the predictions of the probability of entry. The results are also confirmed if we examine the entire sample without explicit distinction between intensive and extensive margins (Panel d).

As technological activities in terms of patenting differ considerably across countries in the sample, the results reported for Figure 4 may differ as the technological capabilities of the observed countries change. For this reason, in Figure 5 we present results for two subsamples of countries introduced earlier in this paper. The predictions have again been obtained using the empirically observed values of technological breadth for these subsamples reported in Table 2.

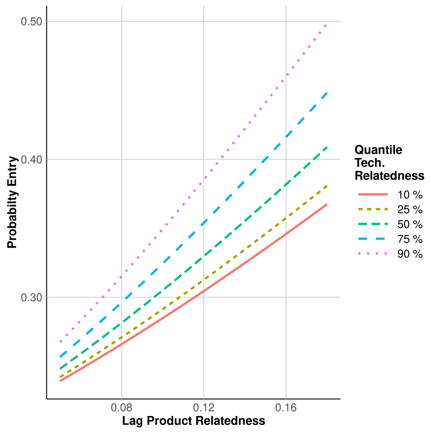
Panels (a) and (b) in Figure 5 reveal an important qualitative difference in the interaction effect between technological breath and product relatedness across country groups. In the countries with high technological capabilities higher levels of technological search breadth strongly increase the probability of entry for export lines with low product relatedness. This effect flattens out at higher levels of product relatedness, but it continues to increase with higher product relatedness. It is highest for the highest observed levels of product relatedness and technological breadth. At lower levels of technological breadth, the probability of entry increases in both technological breadth and product relatedness at an increasing rate. The same can be observed for the countries with low technological capabilities at all levels of technological breadth.

Panels (c) and (d) show other differences in the joint impact of technological breadth and product relatedness on the probability of exit for countries with different levels of technological development. Across country groups higher product relatedness acts as a barrier to exit: The probability of leaving the export portfolio of a country drops with increasing product relatedness. However, while in the technologically less advanced countries we do not observe a significant interaction effect between technological breadth and product relatedness, in the technologically advanced countries such interaction effect can be observed. The probability of exit falls with increasing product relatedness but increases with higher technological breadth.

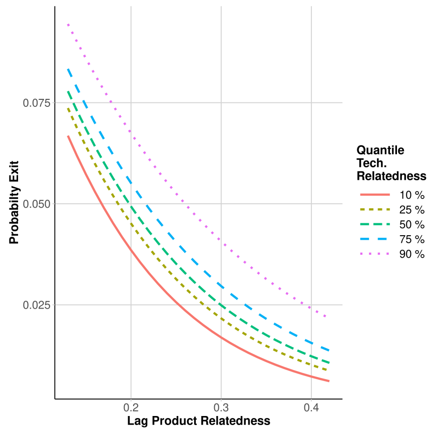
Panels (e) and (f), finally, show the joint impact of technological breadth and product relatedness on the intensive margin in trade across country



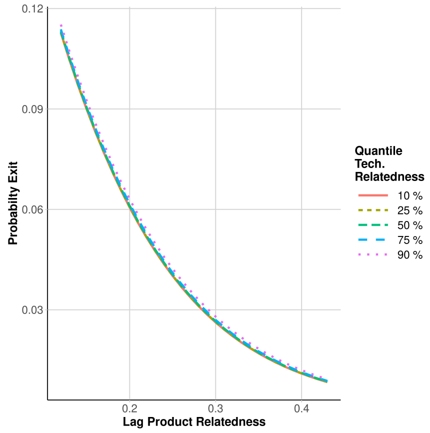
(a) Entry - INNO



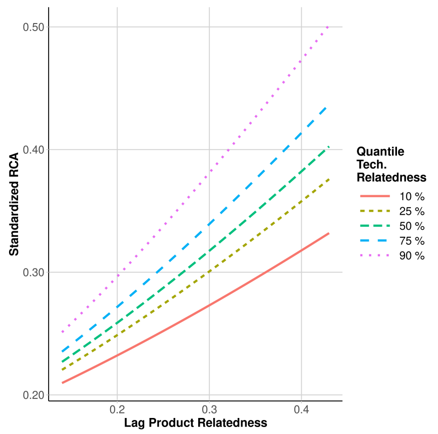
(b) Entry - NON-INNO



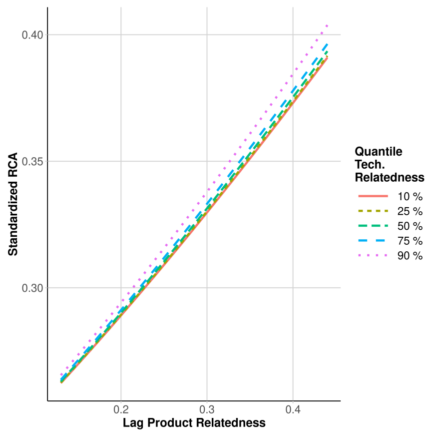
(c) Exit - INNO



(d) Exit - NON-INNO



(e) Intensive margin - INNO



(f) Intensive margin - NON-INNO

Figure 5: The effect of product relatedness on the probability of entry, exit and the predicted SRCA for different values of technological breadth by level of economic development of the countries (INNO - NON-INNO).

groups. We observe a mutual self-enforcing effect between product relatedness and technological breadth. Given the generally higher levels of technological breadth in the technologically advanced countries the effects are considerably more pronounced in this group.

While the difference between the results for the two subsamples shown in Figure 5 is most likely related to the low level of technological breadth in the NON-INNO group, it suggests that industries with a higher technological breadth are more likely to sort out highly related products, which may no longer be competitively produced and exported in the technologically more advanced countries. On the other hand, they adjust their product portfolios by using their broader competence base to start exporting products that are only weakly related to the current export specialisation. These sectors therefore seem able to overcome the mixed blessing of untraded interdependencies, while at the same time being able to better exploit them to the benefit of the competitiveness of related products. In the technologically less advanced countries in turn increasing technological breadth seems to predominantly favour the better exploitation of untraded interdependencies.

5 Summary and conclusions

Prior research has shown that long run growth across countries is associated with an increase in the variety of exports and industrial activities more in general. However, there is also robust evidence that export specialisations develop in a path dependent fashion which may constrain this process and limit the long run growth and economic development potential of countries.

Various feedback mechanisms associated with individual and collective learning processes contribute to this path dependent development. They are related to information and coordination externalities that build on knowledge bases and experiences shared by companies and other actors in a geographically delimited space. The technology gap literature refers to them as untraded interdependencies.

Recombinant learning in the context of these untraded interdependencies leads, on the one hand, to unique locally shared competencies that favour the development of comparative advantages relative to other geographical areas in specific domains of economic activity. On the other hand, it promotes an industrial development where new industries develop out of current ones, and where new products are related to existing ones. Technological search and learning fuel these processes by constantly injecting new knowledge.

A common conjecture in the literature is that broad technological search favours diversification and promotes structural change. This is justified on grounds that it favours the absorption of technological knowledge from other fields of economic and technological activity that may be complementary to the existing competence base and lead to new or technologically improved products. The interplay between the existing competence base in an industry and the breadth of technological search activities is therefore likely to have an impact on the development trajectories of industrial specialisation.

This paper has examined the joint impact of product relatedness and the breadth of technological search on export specialisations across countries over time. The analysis relies on measures for product relatedness developed in the context of the so-called product space literature to capture the impact of untraded interdependencies on comparative advantages. They indicate how close a product is to the current specialisation of a country and have been shown to be strongly associated with the development of comparative advantages and the observed persistency of export specialisations. Patent data have been used to construct an indicator capturing the scope of technological search process at the industry level. An econometric analysis has then analysed how the technological search scope and product relatedness jointly affect changes in the export basket across countries at both the intensive and extensive margins of trade.

The empirical results show that broader technological search in an industry has a positive impact on the development of comparative advantages in the product lines it exports. However, the magnitude of the impact is substantially smaller than that of product relatedness. This indicates that comparative advantages are driven by a broad spectrum of country specific capabilities and related knowledge spillovers that go well beyond technological competencies.

Looking at the interplay between product relatedness and the scope of technological search, the paper finds that broader technological search tends to reinforce the positive impact of product relatedness on both the intensity with which products are exported and the probability of entry into product lines a country has not exported earlier. The joint effect differs, however, for the probability of exit. In this case product relatedness acts as a barrier to exit, but broader technological search weakens this effect.

The paper shows some important differences in these results across countries, if one considers their level of technological development. In the technologically most advanced countries, industries with a high technological breadth seem to use their broader technological competence base to sort out highly related but potentially non-competitive products and to start exporting weakly related ones. At the same time they use their broad technological competence base to better exploit untraded interdependencies and foster the competitiveness of products that are related to the current specialisation. In the technologically less advanced countries, in turn, increases in the technological search breadth predominantly go along with the exploitation of untraded interdependencies to the benefit of the competitiveness of products close to the current specialisation. Given that the country sample analysed consists exclusively of industrialised countries, these differences are remarkable.

The paper therefore shows the two-edged character of the interaction of technological search breadth with product relatedness. Broader technological search promotes adjustments on the extensive margin of trade by supporting the exploration of new export opportunities in weakly related products and by promoting the consolidation of the export basket. In this way it helps overcoming path dependency in the development of export specialisations. This holds in particular for technologically advanced countries. On the other hand, broader technological search is an important means to exploit untraded interdependencies in an economy and foster the competitiveness of related products. In this way, it contributes to harden path dependencies in the development of export specialisations especially on the intensive margin. This holds at all levels of technological development across countries analysed in this paper.

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A Appendix

A.1 Descriptive statistics for technological breadth across countries in the sample

Table A.1: Technological breadth

Iso2	Inno	Mean	Variance	Coefficient of Variation
AT	X	0.49118	0.00720	0.17273
BG		0.00709	0.00000	0.11788
CH	X	0.87983	0.00208	0.05189
CY		0.01818	0.00001	0.19435
CZ		0.03656	0.00001	0.10372
DE	X	0.64112	0.00687	0.12929
DK	X	0.47843	0.00931	0.20163
EE		0.02630	0.00003	0.21765
ES		0.06553	0.00004	0.09115
FI	X	0.45233	0.00306	0.12237
FR	X	0.29325	0.00050	0.07600
GB	X	0.18127	0.00012	0.05927
GR		0.01953	0.00001	0.13138
HR		0.01533	0.00001	0.20939
HU		0.03154	0.00004	0.19306
IE	X	0.11080	0.00018	0.12191
IT		0.20453	0.00128	0.17512
LT		0.00977	0.00002	0.45994
LV		0.01719	0.00012	0.64513
MT		0.03344	0.00048	0.65694
NL	X	0.39267	0.00273	0.13301
PT		0.02703	0.00006	0.28585
SE	X	0.46535	0.00539	0.15774
SI	X	0.10230	0.00051	0.22016
SK		0.01892	0.00005	0.38272

A.2 Analytical derivation of the marginal effects for prod. relatedness$_{c,p,t_0}$ and tech. breadth$_{c,p,t_0}$

Keeping in mind that the link function is a logit model, the marginal effect for prod. relatedness$_{c,p,t_0}$ is given by:

$$\begin{aligned}\frac{\partial E(SRCA_{c,p,t_1}|x_{c,p,t_0})}{\partial \text{prod. relatedness}_{c,p,t_0}} &= \frac{\partial G(LP)}{\partial \text{prod. relatedness}_{c,p,t_0}} \\ &= \Big(\beta_1 + \beta_3 \text{tech.breadth}_{c,s,t_0}\Big)\frac{dG(LP)}{dLP}.\end{aligned} \tag{2}$$

Similarly, the marginal effect for tech. breadth$_{c,p,t_0}$ is

$$\begin{aligned}\frac{\partial E(SRCA_{c,p,t_1}|x_{c,p,t_0})}{\partial \text{tech. breadth}_{c,p,t_0}} &= \frac{\partial G(LP)}{\partial \text{tech. breadth}_{c,p,t_0}} \\ &= \Big(\beta_2 + \beta_3 \text{prod.relatedness}_{c,s,t_0}\Big)\frac{dG(LP)}{dLP},\end{aligned} \tag{3}$$

where in both equations LP is the linear predictor[6]. In our model, the term $\frac{dG(LP)}{dLP}$ corresponds to the density function of the logistic distribution function at point LP.

A.3 Regressions for entry, exit and intensive margin, full model with control variables

[6] $LP := \alpha + \beta_0 SRCA_{c,p,t_0} + \beta_1 \text{prod. relatedness}_{c,p,t_0} + \beta_3 \text{prod. relatedness}_{c,p,t_0} \times \text{techn. breadth}_{c,s,t_0} + \sum_c \sum_s \delta_{c,s} d_c d_s$

B Appendix - not for publication

B.1 Robustness checks - OLS regressions

Table A.2: Fractional logit regressions for entry, exit and intensive margin.

	Dependent variable:					
	entry	intensive margin	exit	entry	intensive margin	exit
		SRCA > 0			SRCA > 0	
	binary	fractional	binary	binary	fractional	binary
	(1)	(2)	(3)	(4)	(5)	(6)
prod. relatedness$_{c,p,t_0}$	23.057	2.834***	−6.159**	33.974*	2.698***	−7.707**
	(14.285)	(0.541)	(2.931)	(17.750)	(0.719)	(3.894)
SRCA$_{c,p,t_0}$		2.900***	0.091		2.837***	0.135
		(0.022)	(0.094)		(0.023)	(0.098)
tech. breadth$_{c,s,t_0}$	−11.337*	−0.594***	−0.205			
	(5.789)	(0.138)	(0.772)			
prod. relatedness$_{c,p,t_0}$ × tech. breadth$_{c,s,t_0}$	79.887**	2.045***	0.839	171.989***	2.659***	2.960
	(33.012)	(0.337)	(2.304)	(53.114)	(0.433)	(3.029)
prod. relatedness$_{c,p,t_0}$ × Tertiary educ.$_{c,t_0}$	−0.807**	−0.064***	0.036	−0.888*	−0.039**	0.041
	(0.377)	(0.013)	(0.077)	(0.459)	(0.017)	(0.101)
prod. relatedness$_{c,p,t_0}$ × HRSTC$_{c,t_0}$	1.261	−0.171***	0.084	1.004	−0.199***	0.259
	(0.917)	(0.026)	(0.168)	(1.139)	(0.033)	(0.215)
prod. relatedness$_{c,p,t_0}$ × FDI$_{c,t_0}$	−0.040	−0.003	0.024	−0.185	−0.011	0.061
	(0.191)	(0.007)	(0.034)	(0.260)	(0.008)	(0.042)
prod. relatedness$_{c,p,t_0}$ × Imp. complexity$_{c,t_0}$	−69.539***	5.675***	−0.877	−87.853***	6.859***	−4.374
	(24.247)	(1.002)	(4.720)	(30.725)	(1.268)	(6.081)
prod. relatedness$_{c,p,t_0}$ × Openness$_{c,t_0}$	18.184**	−0.639	−5.742**	18.895*	−1.012	−8.325**
	(8.419)	(0.580)	(2.577)	(10.438)	(0.737)	(3.315)
Country dummies	Yes	Yes	Yes	No	No	No
Sector dummies	Yes	Yes	Yes	No	No	No
Country Sector dummies	No	No	No	Yes	Yes	Yes
R2	0.1	0.52	0.04	0.16	0.54	0.04
Observations	3,669	85,010	90,498	3,669	85,010	90,498
Group	ALL	ALL	ALL	ALL	ALL	ALL
Note:						*p<0.1; **p<0.05; ***p<0.01

Table B.1: OLS regressions, dependent variable SRCA.

	Dependent variable: Standardized RCA						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
prod. relatedness$_{c,p,t_0}$	0.698***		0.696***	0.603***	0.676***	0.649***	0.590***
	(0.017)		(0.017)	(0.022)	(0.026)	(0.093)	(0.119)
SRCA$_{c,p,t_0}$	0.561***	0.650***	0.561***	0.564***	0.545***	0.562***	0.546***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
tech. breadth$_{c,s,t_0}$		0.077***	0.036**	−0.066***		−0.073***	
		(0.017)	(0.017)	(0.023)		(0.026)	
prod. relatedness$_{c,p,t_0}$ × tech. breadth$_{c,s,t_0}$				0.335***	0.567***	0.318***	0.419***
				(0.049)	(0.060)	(0.066)	(0.084)
prod. relatedness$_{c,p,t_0}$ × Tertiary educ.$_{c,t_0}$						−0.010***	−0.003
						(0.002)	(0.003)
prod. relatedness$_{c,p,t_0}$ × HRSTC$_{c,t_0}$						−0.046***	−0.050***
						(0.005)	(0.006)
prod. relatedness$_{c,p,t_0}$ × FDI$_{c,t_0}$						−0.005***	−0.006***
						(0.001)	(0.001)
prod. relatedness$_{c,p,t_0}$ × Imp. complexity$_{c,t_0}$						1.596***	1.891***
						(0.162)	(0.200)
prod. relatedness$_{c,p,t_0}$ × Openness$_{c,t_0}$						0.192**	0.048
						(0.093)	(0.114)
Country dummies	Yes	Yes	Yes	Yes	No	Yes	No
Sector dummies	Yes	Yes	Yes	Yes	No	Yes	No
Country Sector dummies	No	No	No	No	Yes	No	Yes
Observations	98,475	98,475	98,475	98,475	98,475	98,475	98,475
R^2	0.772	0.768	0.772	0.772	0.779	0.773	0.779

Note: *p<0.1; **p<0.05; ***p<0.01

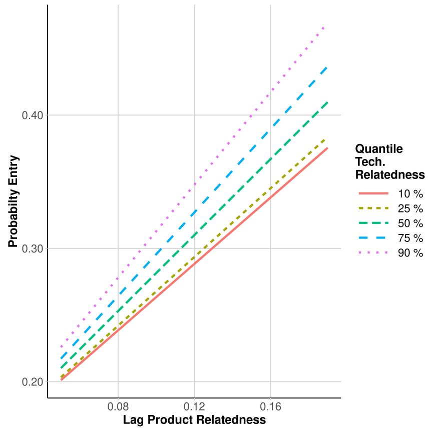
Table B.2: OLS Regressions for entry, exit and intensive margin.

	Dependent variable:		
	entry	srca	exit
	(1)	(2)	(3)
prod. relatedness$_{c,p,t_0}$	1.203***	0.544***	$-$0.302***
	(0.442)	(0.027)	(0.028)
SRCA$_{c,p,t_0}$		0.579***	0.002
		(0.004)	(0.004)
prod. relatedness$_{c,p,t_0}$ $\times$ tech. breadth$_{c,s,t_0}$	15.836**	0.668***	0.329***
	(6.580)	(0.061)	(0.065)
Country dummies	No	No	No
Sector dummies	No	No	No
Country Sector dummies	Yes	Yes	Yes
Observations	3,669	85,010	90,498
R^2	0.439	0.816	0.082
Note:	*p<0.1; **p<0.05; ***p<0.01		

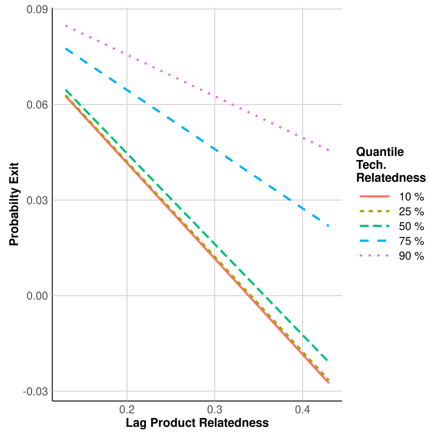
Table B.3: OLS Regressions for entry, exit and intensive margin.

	Dependent variable:					
	entry	srca	exit	entry	srca	exit
	(1)	(2)	(3)	(4)	(5)	(6)
prod. relatedness$_{c,p,t_0}$	4.338	0.625***	−0.294***	5.930*	0.527***	−0.267**
	(2.993)	(0.097)	(0.102)	(3.602)	(0.124)	(0.131)
SRCA$_{c,p,t_0}$		0.598***	0.001		0.581***	0.005
		(0.003)	(0.004)		(0.004)	(0.004)
tech. breadth$_{c,s,t_0}$	−2.003*	−0.099***	−0.001			
	(1.090)	(0.027)	(0.028)			
prod. relatedness$_{c,p,t_0}$ × tech. breadth$_{c,s,t_0}$	15.093**	0.385***	0.041	25.549***	0.507***	0.096
	(6.217)	(0.066)	(0.070)	(7.879)	(0.084)	(0.090)
prod. relatedness$_{c,p,t_0}$ × Tertiary educ.$_{c,t_0}$	−0.155**	−0.010***	0.001	−0.147	−0.003	−0.002
	(0.077)	(0.002)	(0.003)	(0.091)	(0.003)	(0.003)
prod. relatedness$_{c,p,t_0}$ × HRSTC$_{c,t_0}$	0.303	−0.041***	0.013**	0.262	−0.047***	0.014**
	(0.192)	(0.005)	(0.005)	(0.227)	(0.006)	(0.007)
prod. relatedness$_{c,p,t_0}$ × FDI$_{c,t_0}$	−0.009	−0.004***	0.002	−0.041	−0.005***	0.003**
	(0.041)	(0.001)	(0.001)	(0.052)	(0.001)	(0.002)
prod. relatedness$_{c,p,t_0}$ × Imp. complexity$_{c,t_0}$	−14.350***	1.486***	0.277	−16.795***	1.861***	0.217
	(5.039)	(0.173)	(0.179)	(6.165)	(0.213)	(0.222)
prod. relatedness$_{c,p,t_0}$ × Openness$_{c,t_0}$	3.584**	−0.162	−0.480***	3.416*	−0.269**	−0.616***
	(1.720)	(0.099)	(0.102)	(2.076)	(0.122)	(0.127)
Country dummies	Yes	Yes	Yes	No	No	No
Sector dummies	Yes	Yes	Yes	No	No	No
Country Sector dummies	No	No	No	Yes	Yes	Yes
Observations	3,669	85,010	90,498	3,669	85,010	90,498
R^2	0.401	0.810	0.073	0.441	0.816	0.082

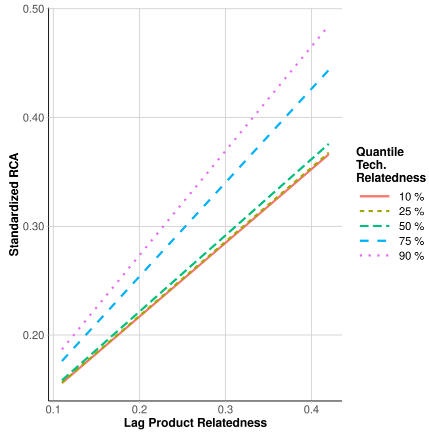
Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$



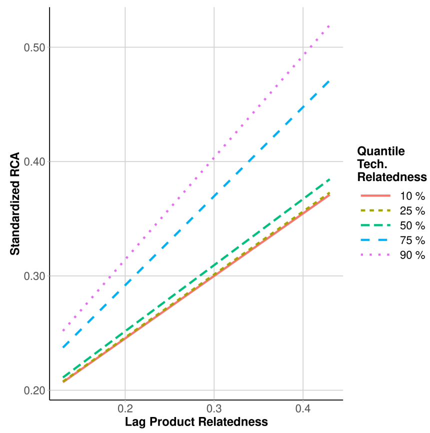
(a) Entry



(b) Exit



(c) Intensive margin



(d) All observations

Figure B.1: The effect of product relatedness on the probability of entry, exit and the predicted SRCA for different values of technological breadth, OLS