Offshoring, Product Scope and Patent Quality

Sasan Bakhtiari
Australian National U.

Antonio Minniti
U. of Bologna

Alireza Naghavi
U. of Bologna

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Abstract

This research sheds light on how offshoring affects the quality of patents by firms and how their product scope influences this relationship. Using a matched firm-patent dataset, we apply the generality measure of patent citation to investigate the effect of offshoring on the extent to which patents registered by firms are applicable to diverse technology fields, i.e. of higher quality. We find that offshoring is generally associated with patents of lower quality. However, engaging in more international activities while operating a more diversified portfolio of products is conducive to patents that open the way for follow-up research and inventions. The finding is robust to various specifications and sampling tests.

Keywords: Offshoring, Product scope, Patent quality, Technological spillovers, Fundamental innovation

JEL Code: F12, F14, F23, O32.

1 Introduction

It is well known that geographically dispersed operation by firms through offshore activities is in general accompanied by different forms of cost savings that arise from specialization gains or lower production and transport costs. The evaluation of long-term benefits from this strategy is however not trivial. Literature has highlighted both positive and negative effects of offshoring on the creation of new knowledge by firms while geographically segmented. The search for crucial elements that govern the impact of the geography of firms' activities on technological spillovers that follow within and across firms is at its early stages.

An element crucial for productivity growth often neglected in literature is the characteristic of patents produced by firms. Patents applicable to diverse technology fields are considered to be of higher quality because they open the way for follow-up research and inventions. Forming a matched firm-patent dataset, we explore the quality of patents by measuring the extent to which the application of patents registered by firms can be spread across different product lines. To this end, we use patent citation data from the U.S. Patent and Trademark Office (USPTO) to determine the quality of firms' patenting activities by applying the generality index of patent citations introduced in Trajtenberg *et al.* (1997). COMPUSTAT segmented data is then used to identify the extent to which multiproduct and multinational operations affect the quality of patents by firms.

Our empirical findings suggest that a larger share of offshoring activities negatively impacts the quality of patenting activities by a firm. However, combining the share of multinational production with the number of product lines reveals a contrasting picture in which an increase in international operations by firms with a wider product scope has an offsetting effect and induces them to produce patents that are more general than those generated by firms with fewer product lines. In other words, our estimations show a positive and highly significant interaction effect between the number of product lines and offshoring. These findings are robust to the choice of variables, methodology and sampling issues. We carry out a few exercises to investigate the impact of possible endogeneity on our results and again find much robustness there.

The results highlight the interplay between multinational and multiproduct operations on the applicability of firms' patents across diverse technology sectors. This can be associated to basic research or fundamental innovation, which is in turn closely related to large spillover effects within and across industries and therefore productivity growth (Akcigit *et al.*, 2013).[1] Patents deliver monopoly profits, but their citability may not seem important for achieving short-run gains. However, the quality of patents ends up impacting many parameters vital for continued progression of innovation dynamics that produce new technological and economic paradigms. Decisions to offshore based on immediate cost pressures may get in the way of such critical innovations necessary, for example, for the development of the large-scale optoelectronic integrated circuits that insure continual advancement of microprocessor speed (Naghavi and Ottaviano, 2009). At the same time, the existence of technological spillovers through multinational activities that increase firms' incentives and capability to undertake fundamental innovation is an undeniable phenomenon with a large body of evidence in the business and economic literature, see e.g. Branstetter (2006), Castellani *et al.* (2006), and Keller (2010). The idea is to bring the diversity hypothesis put forth by Nelson (1959) in a multinational context: offshoring leads firms with more diverse operations to engage in more fundamental innovation that originates from basic science. To this end, we aim to unify two branches of international trade literature, namely multiproduct firms and innovation (Dhingra, 2013) and multiproduct firms and offshoring (Eckel and Irlacher, 2015), to investigate how a firm's geographic and product scope interact to determine its innovation scope.[2]

Three underlying assumptions based on empirical evidence build our conceptual

[1]Fundamental innovation is defined as a creative idea that leads to follow up research and development (Gupta, 2007) or a basic research that opens the way for many other inventions (Elwell, 2013).

[2]For seminal work on trade and multiproduct firms see Eckel and Neary (2010), Bernard *et al.* (2011), Mayer *et al.* (2014), and Qiu and Zhou (2013).

framework. First, a substantial part of the core research and development by multinational firms is carried out in their home country. OECD (2007) reports that only 11.5% of R&D by US multinationals in 1994, and 13.3% in 2002 were being conducted abroad; moreover, those R&D were adaptive in nature to serve local markets (see also Picci, 2010). The home country bias pertains more to fundamental innovation also because it is higher for firms with diversified technology portfolios that are well positioned to realize knowledge spillovers between different technology fields (Belderbos *et al.* 2013). Second, knowledge spillovers are geographically localized by nature (Jaffe *et al.* 1993; Audretsch and Feldman 1996, 2004; Agrawal *et al.* 2008; Murata *et al.* 2014) and limited in international scope (Branstetter 2001; Keller 2002; Bottazzi and Peri 2003), for example due to their tacitness and the necessity for face-to-face interactions (Arrow 1962; Polanyi 1966). Third, globally-engaged firms are more productive than domestic firms as they can exploit channels of learning from the foreign markets (Bernard and Jensen, 1999), accessible external R&D in other regions (Peri, 2005), collaborative R&D and joint ventures with foreign firms (MacGarvie, 2006), learning by doing across international affiliates (Brambilla, 2009), or feedback from their intra-firm worldwide pool of knowledge or from suppliers, customers, and universities (Criscuolo *et al.*, 2010).

In this environment, offshoring is faced with two opposing forces that can affect the quality of patents: learning spillovers from foreign markets stimulate basic research, whereas the localized nature of fundamental innovation reduces its effectiveness in foreign plants. Given that no convincing test of these hypotheses have been conducted so far, in what follows we explore the role of product scope in determining the intensity of the two effects. Our findings evince that offshoring may block internal spillovers within the firm, particularly for more sophisticated innovations; however, there are external spillovers associated with learning from international markets that are reinforced through a larger product scope. Subsequently, multinationals active in more product lines are better posed to exploit such spillovers as diversified knowledge within a firm can influence the span of learning possibilities from international markets. As a result, increasing international operation by firms with more products gives them more opportunities and incentives to produce high quality patents.

The rest of the paper is as follows. Section 2 provides a description of the data and the respective measures used to characterize innovation. Section 3 delivers our empirical results, while Section 4 concludes.

2 Data

To lead our empirical study, we form a matched firm–patent dataset from two main sources: Standard & Poor's COMPUSTAT and the U.S. Patent and Trademark Office (USPTO) database of granted patents. We source our firm-level data from COMPUSTAT annual fundamentals, which report a rich set of economic and financial information on the publicly traded firms in the U.S. over the years 1964 to (currently) 2010.[3] For our exercises, we especially make use of the following set of information:

- annual sales ($SALE$),
- annual R&D expenditures (XRD),
- and annual advertising expenditures (XAD).

To focus on products and innovation in the conventional sense, we restrict ourselves to those firms in COMPUSTAT that report their main activity as manufacturing (SIC 2xxx and 3xxx). To make the direction of trade clear, we also restrict ourselves to firms that are headquartered in the U.S. (FIC="USA").

We also construct from COMPUSTAT a set of controls that will accompany our econometric specifications. The first one is a firm's stock of R&D as proxy for the firm's

[3]Made available by Wharton Research Data Services at `http://wrds-web.wharton.upenn.edu/wrds/`.

knowledge capital at the time of innovation. Following Hall (1990), we construct the R&D stock in a firm using the perpetual inventory model

$$R_{t+1} = (1 - \delta)R_t + XRD_{t+1},$$

in which $\delta = 0.15$. For the first year of a firm, we compose the R&D stock using the proposition by Hall (1990) and write $R_0 = XRD_0/(\delta + 0.08)$.[4] We also pursue the stock of a firm's commercial advertisement as a possible signal that the firm intends to engage in more specialized and commercial innovations. In view of the findings by Clarke (1976), which suggest that the effective lifespan of advertising expenditures is less than a year (a 100% annual depreciation rate), we set the stock equal to XAD. The values of XRD and XAD are turned into real terms using annual deflators from the NBER manufacturing database. Finally we use the deflated value of annual sales as a measure of size.

We source information about the granted patents from the USPTO patent database. These data include a diverse range of information about patents including the year of application filing and the year patent was issued, the patent classification code, plus information about the assignee and the citations made. The data covers all granted patents from 1901 to 2010. We convert the patent classification code provided with the data into the technology classification introduced by Hall *et al.* (2001) for a benchmark study of technological diversity among citations (leading to 37 technology fields). We only use the utility patents and match them to firm level data by the firms' identification code ($GVKEY$) using the dynamic links provided by the NBER Patent Citation Data (specifically the data file `dynass.dta`). For our analysis, we believe that the application year of a patent has stronger correlation with the actual time of innovation, therefore we utilize this year variable in our matching process instead of the granting year. In fact,

[4]Firms appear in COMPUSTAT once they go public, which leaves open the possibility that the firm was operational before its first appearance in the data.

Hall *et al.* (2001) find an average lag of two to three years between the year a patent is applied for and the year the patent is granted, which justifies our choice.

Our main explanatory variables of interest are, of course, the number of products and the share of offshore operations. To construct these two measures, we make use of COMPUSTAT segmented data. These data in part provide information on a firm's business segments, defined as a firm's operation in distinct 4-digit SIC areas. The segmented data coverage is more limited than the annual file and only spans 1976 to (currently) 2010. Additionally, from 2000 onwards, Standard & Poor requested that firms report operation segments instead of business segments. These operation segments pertain to state-by-state report of a firm's operation in the U.S. and do not reflect products. Hence, we take care not to use those years.

Focusing on the segmented data, we are inclined to treat each four-digit business segment in a firm as a product, a definition which is broader than what is traditionally used in the literature. But, we believe that such broad description of products, as opposed to the narrower 7-digit SIC, is advantageous to our investigations. Our main focus is the applicability of patents (or innovations) to various different fields; therefore, we need to make a certain degree of distinction between products to see the real diversity of applications. For instance, in the manufacturing of glass containers (SIC 3221), a patent can be easily applied to the subgroups of glass bottles, carboys, fruit jars, etc. with minor adaptations. It takes innovations of more fundamental nature to apply the same patent to both glass bottles (SIC 3221) and pressed and blown glassware (SIC 3229), the latter pertaining to a range of products including (but not limited to) glass artworks, dishes, lanterns, and trays.

Using the basis above, our first measure for the number of products is simply the count of 4-digit business segments for each firm in a certain year (N). This count could still be crude for our purpose and does not especially take into account how distant and diverse products in a firm are. For example, we would want to make a distinction between a two-product firm that produces glass bottles (SIC 3221) and glassware (SIC 3229) and another two-product company that produces glass bottles (SIC 3221) and plastic bottles (SIC 2821). We are hypothesizing that the latter firm would require a larger investment in basic research to reduce the costs of its both products. Therefore, our adjusted measure counts 3-digit business segments but weights them by the abundance of 4-digit segments within each 3-digit group, so that the measure better reflects the diversity of products. Let the following Herfindahl index be a measure of product diversity:

$$H = 1 - \sum_{n=1}^{N3} \left(\frac{\#(\text{Same 3-digit SIC})_n}{N} \right)^2,$$

in which $N3$ is the simple count of 3-digit segments. Then, the adjusted number of products is

$$N^H = N \times H + 1.$$

Let us look at the two extreme cases: when $H = 0$ (no diversity at 3-digit level), then $N^H = 1$, that is, the firm is producing products that are more or less the same. With perfectly even distribution of products among different 3-digit product lines, $H = 1 - 1/N$ and $N^H = N$; products are so diverse that each one counts as a distinct line in this definition.

In addition to business segments, the segmented data also reports sales by geographic segments. Each geographic segment describes the operation of the firm in a distinct geographic location (country is the minimum level of separation). One obvious geographic segment is the U.S. division, especially since we are only focusing on U.S. headquartered firms. Firms do not report the details of their overseas operation in a consistent manner, therefore, we aggregate all foreign operations and only focus on the domestic versus international operation of firms.[5] Specifically, our definition of international presence is

[5] In the segmented data, some firms only report their total overseas activities, some others report it by the continent of operation, and a few firms segment activities by each foreign country.

the share of total sales by the affiliates overseas, or more formally:

$$S = 1 - \frac{\text{Annual Sales originating from the U.S. Segment}}{\text{Total Annual Sales}}.$$

Table 1 lists the composition of our analysis sample by year. As mentioned earlier there are quality issues with the segmented data of year 2000 and afterwards, therefore, we restrict ourselves to the unbalanced panel of firms belonging to the years 1985 to 1999.[6] There are more than 2,000 firms per year in the panel, and these firms generated more than 17,000 patents a year, with the number of patents increasing over the years. Almost one-third of the firms in each year are multiproduct ($N > 1$), and the proportion increases to about half the firms in the ending years of our sample. The proportion of firms with international operation ($S > 0$) varies through the years but is still a substantial proportion of the total.

The simple counts of firms in Table 1, however, do not convey the full picture. The distribution of firms by the number of products and also by their share of international operation is highly skewed. Figure 1 shows the distributions by pooling all firm–years in the sample. Almost 98% of firm–years in our data have four products or fewer, while only 0.4% of firm-years have at least seven. Similarly, for more than 96% of firm–years at least half their production is in the US, while only 0.6% of firm–years are fully operating overseas with only headquarters in the U.S.

2.1 Measuring the Quality of Patents

The mainstream literature on innovation has not yet offered one standard definition of patent quality or its scope of applicability. We use two measures introduced by Trajtenberg *et al.* (1997) which we believe have a good degree of correlation with our notion of patent quality, and we use them to robustly test our hypothesis. What follows

[6]We also repeat our regressions with a more balanced panel of firms that appear for at least 10 years in our sample and our results remain robust.

Year	#Firms	#Patents	#Multi-product	#Multi-national
1985	2,759	17,153	783	981
1986	2,865	18,104	823	932
1987	2,889	19,364	845	887
1988	2,793	19,766	832	839
1989	2,726	19,581	815	777
1990	2,724	20,331	836	750
1991	2,806	21,303	888	727
1992	2,920	23,065	944	742
1993	3,052	28,660	1,000	727
1994	3,183	27,933	1,086	731
1995	3,439	33,145	1,180	716
1996	3,500	30,797	1,235	697
1997	3,383	31,047	1,229	702
1998	3,223	34,198	1,375	1,107
1999	2,622	33,694	1,501	1,195

Table 1: The count of firms and patents in the data by year. Multiproduct firms are those with more than one 4-digit product line ($N > 1$). Offshoring firms are those with non-zero share of international operation ($S > 0$).

is a brief description of each measure we use.

– **Generality**

Our main indicator of patent quality is the generality index introduced by Trajtenberg *et al.* (1997). In effect, this index is driven by the diversity of citations made to a patent in their technological fields. Formally,

$$GENERAL = \frac{XG}{XG-1}\left(1-\sum_k\left(\frac{XG_k}{XG}\right)^2\right),$$

in which XG is the total number of citations to a patent, and XG_k is the number of citations to the patent in technology class k. The term $XG/(XG-1)$ adjusts for the estimation bias (Hall *et al.*, 2001, Appendix 12). The index is essentially a Herfindahl

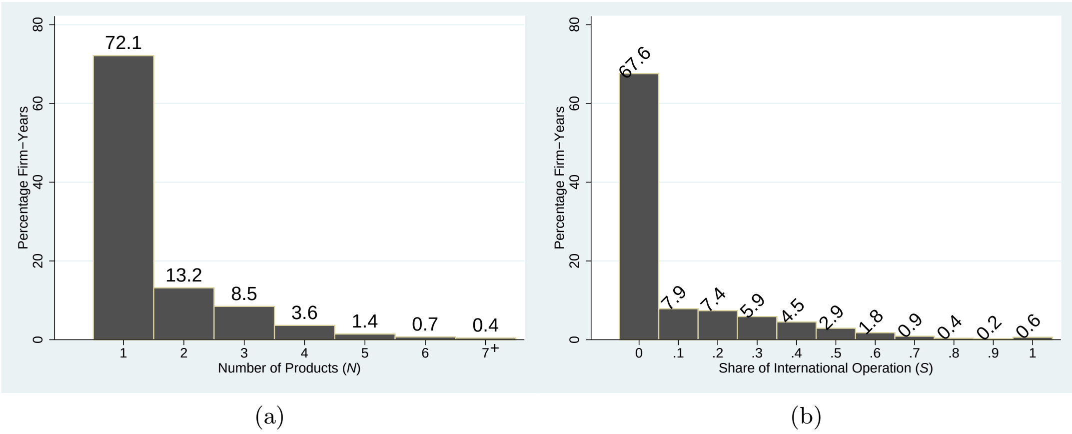


Figure 1: The distribution of firms by the number of products and international share of operation.

one which returns values closer to one when citations are received from a wide array of different technology fields, leading to the notion that the patent is applicable to very diverse fields. In this regard, there is a tight correspondence between this index and our idea of patent applicability. We classify patents using the first two digits of the USPTO patent classification codes to form the index, but we also rely on the technology classes defined by Trajtenberg *et al.* (1997) (from now on referred to as HJT) for comparison and robustness check.[7]

The shortcoming of the generality index is that it is forward looking. Due to the truncation of our patent information in 2010, we are bound to miss some future citations. The problem escalates for patents granted in later years. Given that patents can receive citations up to 20 years since their inception (Hall *et al.*, 2001), we anticipate some under-estimation in our generality measure. To check robustness, we also resort to a backward looking measure of patent quality described below.

– Originality

Along with the generality of a patent, Trajtenberg *et al.* (1997) also define the origi-

[7]We further experiment with classifying patents using the first digit of USPTO classification system but do not report the results. These results are weaker but still in the same direction as with the other indexes.

nality of a patent by the diversity of technological fields that the cited patent embodies. It is true that diversity in citations made does not guarantee diversity in future use, but it is quite possible for patents drawing on a diverse range of fields to get applied to the same diverse fields. The measure is defined as

$$ORIGINAL = \frac{XO}{XO-1}\left(1-\sum_k \left(\frac{XO_k}{XO}\right)^2\right),$$

which, similar to the forward measure, is basically a Herfindahl index. XO is the total number of patents cited, and XO_k is the number of cited patents in technology field k. The term $XO/(XO-1)$ is similarly used to adjust for the biases.[8] The benefit of using the originality index is that it is backward looking and we observe all patent information as early as 1901, so that the truncation issue does not show up here.

Table 2 reports the descriptive statistics for our key variables. Foremost, the results of the table show that the generality and originality indexes have by and large similar distributions. Regarding the number of products, our firm–years have anything between one to 11 products. The median values for the number of products and the share of international operation again confirm the skewed nature of the distribution and put most of the firm–years in our sample in the class of single-product firms and those firms with very small international presence. Given that the firms in the data are public firms, we are not surprised to see that most firms in sample exhibit quite large turnovers. We also notice that many firm–years in our sample do not spend anything on R&D or advertisement during a year, though, there is much variation in research and advertising activities amongst the sample firm–years.

Table 3 looks at cross-correlations between the key variables. The correlation co-

[8]The original adjustment proposed by Hall *et al.* (2001) also subtracts $1/(XO-1)$ from $ORIGINAL$. However, when the Herfindahl index is zero (which is a very likely event) this latter adjustment returns negative values for originality causing infeasibility in our estimation processes, so we dropped the last term. We also experiment by subtracting this last term from every patent except from those with zero originality, and the results we get are qualitatively the same but somewhat weaker.

Variable	#Obs	Mean	Std.Dev.	Min.	Median	Max.
GENERAL	321,767					
USPTO		0.465	0.322	0	0.524	1
HJT		0.398	0.320	0	0.426	1
ORIGINAL	332,672					
USPTO		0.431	0.335	0	0.5	1
HJT		0.373	0.328	0	0.4	1
N	44,884	1.532	1.058	1	1	11
N^H	44,884	1.490	0.968	1	1	10.1
S	44,884	0.101	0.185	0	0	1
$SALES$ ($mil)	44,884	1,090.8	27,844.5	0	448.6	3,504,234
R($000)	44,884	93.3	773.9	0	2.238	36,590.1
A($000)	44,884	15.6	481.7	0	0	43,939.8

Table 2: Descriptive statistics for the measures of patent quality and other firm characteristics. Statistics for patent quality are at patent level (for those patents that could be matched to a firm), and statistics for the other variables are at firm–year level.

efficient between the different indexes of generality and originality is about 0.2 to 0.3, which points to a positive yet non-overlapping relationship between the two indexes. At the same time, the generality index shows a positive correlation with the number of products but a negative correlation with the share of international operation. These preliminary findings do not account for the possibility of interaction between the two factors.

The last point to take from the table of correlations is that the relationship between N and S is not an obvious one. To explore the relationship in greater details, we compute the distribution of firms by their number of products and share of international operation which is shown in Figure 2. It seems that the proportion of multi-product firms increases initially with more of operation moving to overseas. However, as S grows beyond 0.3 the porportion begins to fall. The full pattern fails to suggest a strong and monotonic relationship between the two variables.

	USPTO *GENERAL*	HJT *GENERAL*	USPTO *ORIGINAL*	HJT *ORIGINAL*	N	N^H
GENERAL						
HJT	0.814					
ORIGINAL						
USPTO	0.248	0.205				
HJT	0.210	0.279	0.826			
N	0.015	0.013	0.001	-0.007		
N^H	0.017	0.020	-0.003	-0.005	0.943	
S	-0.039	-0.030	-0.007	-0.002	0.099	0.040

Table 3: The table of correlations between the key variables. Observations are at patent level (for those patents that are matched to firms).

3 Empirical Results

3.1 Econometric Strategy

With the necessary variables in place, we are now able to test these implications for our panel of firms with various levels of multinational operation and different number of business segments. In particular, we are investigating the impact of product range, as measured by N or N^H, and the impact of multinational operation, as measured by S, on the quality of patents. Exploiting the interaction between the two effects, we also determine the impact of operating in a larger range of product lines on the learning capability of firms engaged in offshoring, and therefore the overall effect of the latter on the patent quality.

We estimate those effects using the following linear model[9]

$$PAT_{ij,t+2} = \alpha_0 + \alpha_1 NP_{jt} + \alpha_2 S_{jt} + \alpha_3 NP_{jt} \times S_{jt} + X_{jt}\beta + \mu_i + \tau_t + \iota_j + \xi_{ijt}, \quad (1)$$

[9]Since our indexes are bounded between zero and one (with non-trivial mass of zeros), a more appropriate method of estimation would be the fractional response model of Papke and Wooldridge (1996), in which a probit transformation of the linear model is estimated instead using maximum likelihood. However, we find that the estimates of marginal effects from the linear and probit estimations are almost identical, while the linear model is much less computationally intensive (Appendix A.3). This last issue becomes especially important when we delve into the treatment of endogeneity.

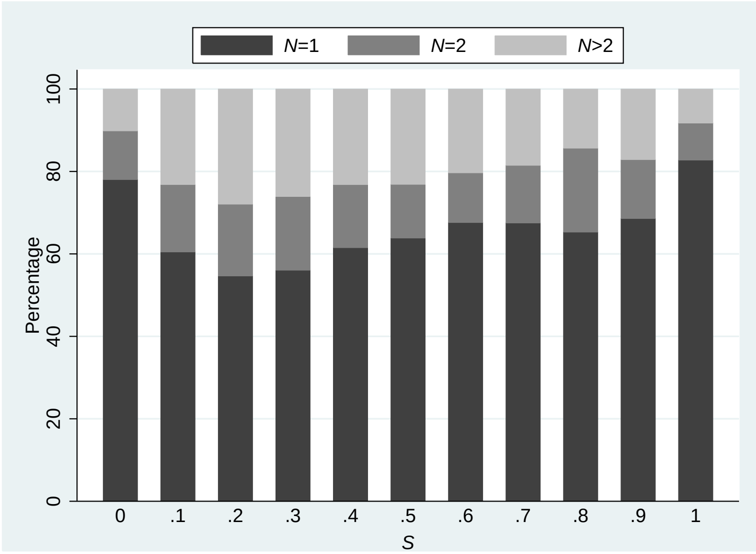
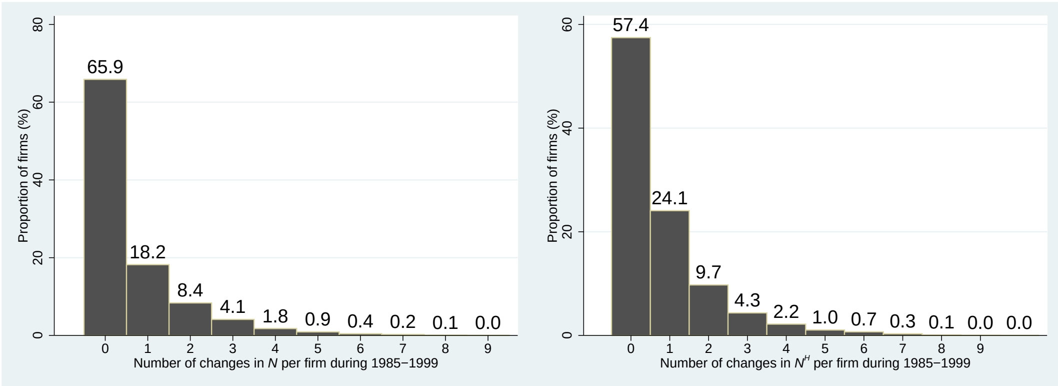


Figure 2: The distribution of firms by their number of products and share of international operation.

where PAT_{ijt} is one of the indexes of quality for patent i by firm j in year t. In our specification, NP_{jt} represents the number of products and will be replaced by either N or N^H in our estimations. Vector X_{jt} is a set of covariates that would also influence the patent quality. We primarily use log of real sales, R&D stock and advertising expenditures. Since there is a considerable number of observations in our sample with either zero R&D or zero advertising (see Table 2), we transform R&D stock and advertising expenditure not by taking logs, but by applying the following inverse hyperbolic sine transformation proposed by Burbidge *et al.* (1988):

$$r_{jt} = \log\left(R_{jt} + \sqrt{R_{jt}^2 + 1}\right), \quad a_{jt} = \log\left(A_{jt} + \sqrt{A_{jt}^2 + 1}\right).$$

There are a number of dummies that we use in our specification. In case patenting in certain fields inherently requires a higher degree of generality for instance, the effect is absorbed by the technology class dummies, μ_i. We are careful that the technology classes used for the generation of dummies and the index on the left-hand side always match. We also control for the effect of business cycles by including year dummies, τ_t.



(a) (b)

Figure 3: The count of times the number of products changes in a firm during 1985–1999 and the distribution of firms over these changes.

Finally, industry-dependent variations are absorbed by industry dummies, ι_j.

In specifying our econometric model, we especially allow for a two year lag between the patents and the firm characteristics. In doing so, we notice that current evidence points to an average gap of one to two years from research to innovation (see Pakes and Shankerman, 1984, for instance). By implementing the two year lag, we endeavor to make a closer connection between patents and the circumstances that gave rise to them.

In model 1, we intentionally refrain from using firm fixed effects. Our definition of product lines based on 4-digit SIC is rather broad, and we do not observe many firms altering their number of products. In fact, close to 70% of the firms in our panel do not change their number of products during the observed sample at all (Figure 3). More than 90% of the firms in our panel change their number of products fewer than three times during the observed sample. Estimating firm fixed effects with this low level of variations would effectively absorb all the contribution associated with the number of products and drive the relevant coefficient to near zero. By the same token, we can also treat the number of products as exogenous.

3.2 Estimation Results

We use OLS with noise clustering to estimate the coefficients and their standard errors in model 1. Given the existing background about the individual impacts of product range and offshoring on the quality of patents, we see fit to build up our evidence by first trying to replicate the existing findings elsewhere before presenting the full model.

In column (1) of the table, we only include S and observe that a higher level of offshoring is conducive to lower generality in patents. Such pattern was predicted by Naghavi and Ottaviano (2009) where they argue that the segmentation of firm activities across geographic boundaries impedes fundamental innovation by reducing internal technological spillovers. In columns (2) and (3) we look at the relationship between product range and patent generality. We find very small and statistically insignificant effects. Our results are similar to those found by Liu and Rosell (2013) where they also find near zero and mostly insignificant coefficients. Combining both aspects in column (4) and (5) does not change the picture, and the previous findings still apply.

In columns (6) and (7), we estimate the full specification by also adding the interaction terms. Inspecting this last set of results reveals an interesting pattern: the coefficient on the number of products is now negative and statistically significant. This result is combined with the fact that we estimate a positive and significant effect for the interaction term. The first implication of this pattern is that the reason we initially estimated a close to zero coefficient for product range in columns (2) to (5) was that the negative effect of this variable was actually being offset by the positive effect of the interaction term. In other words, ignoring the interplay of multinational and multi-product operation would have led to an imperfect conclusion.

The second implication is related to external technological spillovers. The learning possibilities multiply as firms operating in more product lines increase their international presence, eventually masking the negative effects of the geographic segmentation of firm activities on fundamental innovation. The interaction term in our specification tests for

	USPTO Generality							HJT Generality	
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
S_t	-0.025***			-0.025***	-0.026***	-0.061***	-0.062***	-0.029**	-0.034***
	(0.009)			(0.009)	(0.009)	(0.013)	(0.013)	(0.012)	(0.012)
N_t (SIC 4-digit)		-0.001		-0.001		-0.006***		-0.004***	
		(0.001)		(0.001)		(0.002)		(0.001)	
N_t^H (Herfindahl)			-0.000		-0.001		-0.007***		-0.004***
			(0.001)		(0.001)		(0.002)		(0.002)
$N_t \times S_t$						0.015***		0.007**	
						(0.004)		(0.004)	
$N_t^H \times S_t$							0.017***		0.010**
							(0.005)		(0.004)
$\log(SALE_t)$	-0.001	-0.001**	-0.001**	-0.001	-0.001	-0.000	-0.000	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
r_t	0.001***	0.001**	0.001**	0.002***	0.002***	0.001**	0.001**	0.001**	0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
a_t	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.001**	-0.001*
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Adj. R^2	0.049	0.049	0.049	0.049	0.049	0.050	0.050	0.061	0.061
F	74.8	73.8	73.9	73.9	73.9	74.8	74.9	105.2	104.8
Log Likelihood	-83,979.6	-84,007.1	-84,007.7	-83,977.9	-83,978.2	-83,935.8	-83,937.3	-79,120.5	-79,121.9
#Obs	320,628	320,628	320,628	320,628	320,628	320,628	320,628	320,628	320,628

Table 4: The OLS estimates for the indexes of generality as dependent. The numbers in parentheses are standard errors, clustered by firm–year. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively. A set of dummies for year, industry and patent class are also included, but not reported. The sample is at firm–year–patent level.

this prediction and obtains a positive effect in columns (6) and (7) of the table. This is in accordance with Nelson (1959) in an international context in that firms with a more heterogeneous portfolio of products engage in more fundamental innovation because they can better exploit technological spillovers from international markets. Calculating the total effect of S on patent generality shows that a higher share of offshoring increases the latter if a firm is active in more than 4 product lines when using N, and 3 product lines when using N^H to measure the number of products.

In the last two columns, we conduct a robustness test by estimating the same model but using as the independent variable the generality index that we constructed from the HJT classifications. We do not find any change in the implications in this last set of results.

A few control variables are also part of the estimated model that are reported in the table. These variables also show some direction. A larger stock of R&D, on the other hand, leads to more general patents. We explain this last outcome as such that, being of a breakthrough nature, more general patents are more likely to require larger and costlier investments. We also hypothesized earlier that higher advertising is to be associated with lower generality by indicating that the firm is more market-oriented, and the figures from the table are in support of the hypothesis.

3.3 Endogeneity of International Operations

One issue casting doubt on the reliability of the results found in Table 4 is the possibility that the quality of patents is in fact influencing the decision by firms to operate overseas in the first place. We have reasons to believe that the endogeneity does not apply to the intensive margin but only acts in the extensive margin because only some firms self-select into offshoring, see for instance Helpman *et al.* (2004) and Alfaro and Chen (2012). This can be due to a fixed innovation cost a firm has to bear in order to become multinational (Guadalupe *et al.*, 2012). This type of endogeneity would be embodied by firms that switch from fully domestic operations to multinational operations (a move from $S = 0$ to $S > 0$). One would therefore generally think of the relationship between investing in basic research and becoming a multinational to be positive. In our case, we have shown that offshoring has a negative effect on the generality index. For reverse causality to be an issue we could think of firms that tend to focus on more specialized (adaptive or organizational, not fundamental) innovation being better fit to go abroad because they can more easily adjust to new markets and organize their value chain across countries. Moreover, these latter firms may be more open to moving operation to those foreign countries where contracts are weakly enforced, as the outward spillover of knowledge is effectively contained due to the specialized nature of innovations.

The possibility of this (negative) reverse channel for causality can act as a source of bias in the estimated results of the previous section and needs to be addressed by a few robustness checks. Before all, we have already taken steps to minimize the extent of this bias in model (1) by maintaining a two-year gap between the dependent and independent variables. We also observe that by increasing the time-gap the results actually improve.

Our main robustness check involves the exclusion of all firms that switch from being fully domestic ($S = 0$) to multinational ($S > 0$) during the sample period. Also recall that the majority of our firms hardly ever change their number of products.[10] Table 5 shows the distribution of firms by the number of changes in N and also by the behavior of firms in switching from domestic to multinational or maintaining their status throughout the sample. To make our point in more details, we conduct a series of exercises by re-estimating equation (1) while restricting ourselves to different samples listed in Table 5 and comparing the results. These results are shown in Table 6.

The estimation in column 1 is based on the sample of firms that do not switch status, that is, remain either fully domestic or multinational during all years. We find that all of our previous findings stay robust with this treatment. Using N^H instead of N as the

[10]Note that no change in product numbers does not rule out a simultaneous dropping and addition of a product during the same year.

Number of Changes in N	All firms	No switching		Switching to multinational
		Multinational	Domestic	
0	3810	937	2505	368
1	798	212	384	202
2	328	59	164	105
3	147	32	61	54
4	60	12	27	21
5	25	6	7	12
6	14	1	8	5
7	6	2	1	3
8	1	0	0	1
9	2	0	0	2
Total	5191	1261	3157	773

Table 5: The count of firms by the number of changes in product numbers for firms staying domestic or international constantly and for firms that switch from domestic to multinational at some point.

indicator of product number does not affect the implications.

In column 2 we further restrict the sample to firms that have been multinationals in all years, and we manage to obtain the same results. There is only some deterioration in the statistical significance which was expected as a result of sample reduction.

In column 3, we focus on firms that neither switch their geographical status nor their number of products (measured in N). This column by definition also deals with possible endogeneity bias in the interaction term of our baseline regression. Interestingly, we find that not only the prior implications do not change but also they become more nuanced.

Column 4 offers another view for our argument above. In this column, we restrict our sample to those firms that switch from being fully domestic to becoming multinational at some point within our window of years. We specifically note that the coefficients for the key variables are all smaller in their absolute values, compared to the other columns, despite having the same signs. The change suggests to us that our prior results could have been affected by some endogeneity bias, however, the bias is positive for S and negative for $N \times S$. The endogeneity is mainly captured by the act of switching from $S = 0$ to $S > 0$ and removing the bias only makes our results stronger.

We additionally conduct robustness tests by using instrumental variables to treat for endogeneity. A suitable instrument in this context would be one that affects a firm's incentive to increase its share of production overseas, but does not bear any connection with the generality of patents generated by the firm except through offshoring. We found the task of finding an appropriate instrument most challenging as most of the candidates at our disposal were in some way also related to how firms undertake innovation. Given this preliminary, our preferred instrument is the volume of annual exports (in logs and lagged by two years relative to the dependent variable) by US firms aggregated to 4-digit SIC. The volume of exports (or imports) in an industry determines the level to which a sector depends on global markets. A firm operating in a sector that is highly internationalized is also more likely to engage in offshoring. At the same time, it is unlikely that all patents registered in sectors that are more global by nature have similar characteristics independently from the pervasiveness of a firm's multinational operations.

Note that one can still suspect that aggregate exports in a sector can be correlated with the extent to which a firm's patents are general: as it is likely that the better and more productive sectors are the ones exporting, firms in those sectors should also be able to achieve higher quality patents. It is however very unlikely that firms' productivity responses to trade shocks are reflected contemporaneously in the firms' innovation choices as the latter take time to affect productivity (Mayer *et al.*, 2015). Analogously, one could argue that shocks to exports in a sector should not affect innovation outputs, at least in the short run. In fact, Mayer *et al.* (2015) establish how exporting directly results in an increase in the productivity of multiproduct firms through induced reallocation across firms and products, not through investments in technology or innovation.

The nominal values of exports and imports are fetched from the International Trade

Data of Bernard *et al.* (2006), and converted to real term using the annual CPI as deflator.[11] Despite being at industry level, the aggregate exports for a few industries are reported to be zero, therefore, we use $\log(1+EXP)$ as our main instrument – with EXP being the value of exports – in order not to lose firms in those industries. Since the share of international operations in our specification appears both as a standalone term and interacted with the number of products, we also construct one additional instrument by multiplying the log of exports by the number of products. This should deal with the possibility of a bias through a positive reverse causality, where a firm with more general patents may expand both the international and the product scope of its operations.

As a preliminary test of our instruments, the level of correlations between the trade variables and our key variables are listed in Table 7. The log of exports, in particular, exhibits a positive correlation with S, that is, industries that export larger volumes also have a larger share of operations overseas. There are multiple ways to interpret this finding. If the overseas subsidiaries are used for the production of inputs to be shipped back to the US, then higher export demands higher inputs leading to a positive correlation. However, given the level of the correlation, which is not that strong, we also wonder whether the foreign subsidiaries are mainly export platforms the way often emphasized as *horizontal offshoring* (Markusen, 2002). Under this interpretation, industries actively participating in foreign markets are more intensely feeding into the foreign markets through both exporting and offshoring.

Using the instruments described above, we repeat our exercise by conducting a two-stage least squares (2SLS) estimation of model (1). These results are reported in Table 8. Columns (1) to (4) in this table are identical in specification to those in Table 4. We observe that the key results in Table 8 have not been affected by the the treatment of endogeneity and the exact same inferences can be made as before. Specifically, a larger share of international production and a larger number of products, *per se*, adversely

[11]The data are HS-level US import and export data available from `http://faculty.som.yale.edu/peterschott/sub_international.htm`.

affect the generality of patents. The interaction term still leads to a positive effect and helps to increase generality. Note that when we use instrumental variables we find an increase in the magnitude of both the negative coefficient of offshoring and the positive coefficient of the interaction term. This reinforces our key findings as it implies that our OLS estimation undermined our results due to a positive bias on the effect of offshoring on general patenting and a negative bias on the interaction term. Putting these together with the results obtained in Table 6 reveals that the bias may originate from the inclusion of firms that switch from being domestic to multinational players reaffirming the validity of our instrumental variable.

To test the strength of our instruments, we report Cragg–Donald statistics for the case of two endogenous variables and two instruments (Cragg and Donald, 1993). The critical value to reject at 5% significance the hypothesis that bias in the 2SLS estimates is larger than 10% is 7.03 (Stock and Yogo, 2002). We find that our Cragg–Donald statistics strongly reject the hypothesis in all cases. We also investigate the joint significance of the estimated coefficients of endogenous variables by reporting the F statistic of Anderson and Rubin (1949) and find that in all cases the coefficients are very significant statistically. More details regarding the corresponding first-stage estimates are presented in Appendix A.3. An interesting observation in the first-stage estimates is the negative and highly significant relationship between exports in a business segment and the share of offshoring by firms. This can be due to substitutability between exporting and offshoring as a mode of serving a foreign market. Given the positive bias on the effect of offshoring on the generality index found above, this further diminishes the likelihood of a positive link between productivity in a sector and generality of patenting by firms.[12]

The discussion so far concentrated on the effects of N, S and $N \times S$ separately, as if these variables are independent of each other. To see a picture that accounts for the

[12] One may here argue that some other external factor could be simultaneously affecting both the instrument (export) and the dependent variable (generality) without going through the endogenous variable (S). To further assure the exogeneity of our IV, we estimated a separate model with time trend instead of time dummies and our results remain unchanged.

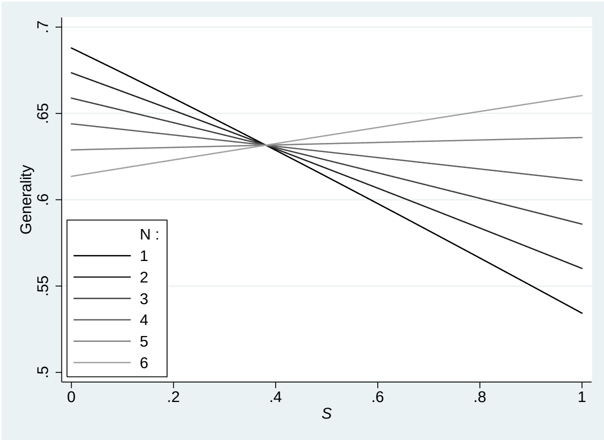


Figure 4: The index of patent generality as a function of N and S, keeping other variables fixed at their means.

interdependence, we use model (1) from Table 8 to predict the changes in the generality index as a function of N and S, keeping all other variables fixed at their means. Figure 4 illustrates the prediction results when the number of products ranges from one to six and the share of international operations varies between zero and one.

It is evident from the picture that single product firms are the ones with the most general patents when operation is restricted to be fully domestic. Multiproduct firms with domestic operations tend to be generating patents with lower levels of generality as their number of products becomes larger. However, once international operation is allowed, the lead by single product firms quickly erodes. When more than 40% of firms' activities go overseas, the rank begins to reverse, and multiproduct firms are the ones to introduce the more general patents, whereas the same index plunges for the single product firms with an increase in the share. In the limit when all of a firm's activities take place overseas ($S = 1$), single product firms are generating the least general patents.

Besides exports, the international trade data of Bernard *et al.* (2006) also reports imports at 4-digit SIC, which we also deflate using the annual CPI. We find in Table 7 that the correlation between imports and exports is quite strong at industry level. Consequently, we also try our IV regression estimation using as instrument $\log(1 + IMP)$

– with IMP representing imports at industry level – and its interaction with the number of products and compare our results. Again, the instrument is contemporaneous with the right-hand side variables and lagged by two period relative to the dependent variable. These estimated coefficients for the key variables can be found in Table 9.

The coefficients in Table 9 do not show any qualitative difference to those in Tables 4 and 8. The share of multinational operations and the number of products are still showing negative effects and the interaction between the two has a positive effect. The only difference is that the results in this table are slightly weaker statistically than the results we found in Table 8 when using the USPTO generality index. The Cragg–Donald statistics in these cases also reject the hypothesis that the bias in 2SLS estimates is larger than 10% at 5% significance level (Stock and Yogo, 2002).

3.4 Self-citation Affecting the Results?

We also contemplate that self-cited patents might be irrelevant to our study as they could be attempts to increase the patent count or mainly intended for litigation, hence, of very low innovation value. To investigate whether the results obtained in the previous sections might be driven by this quality issue, we did a robustness check by excluding all self-cited patents. We define a self-cited patent in the strictest sense: as the one that has at least one citation to another patent with the same assignee. Even with this definition, we find that fewer than 5% of all the patents matched to our firm data can be classified as self-cited. Moreover, only one percent of the citations by these patents are made to self-patents on average. Unsurprisingly, excluding the self-cited patents and re-estimating the models did not have any conspicuous impact on the results.

3.5 Originality of Patents

We also investigate the robustness of our results by considering the index of originality as the measure of patent quality. As we already explained in Section 2, compared to generality, the index of originality has the advantage that it does not suffer from year truncation that affected the computation of generality index. Nonetheless, it has a weaker correlation with our notion of patent applicability across multiple distinct fields. We estimate model (1) through a 2SLS estimation using the indexes of originality as dependent and the log exports and its interaction as instruments. Table 10 reports these results.

The overall picture offers the same insight as the results in previous tables. The share of multinational operations and the number of products are still negatively affecting the originality in the same way as they affected generality. The interaction of the two factors, however, increases the originality of patents. Most of these effects enjoy a solid level of statistical significance.

4 Conclusion

In this paper, we analyze the effect of offshoring and product scope on the quality of patents of firms by measuring the applicability of patents, i.e. their citation, across different technology fields. Given the spillover nature of high-quality patents, to interpret our results we relate the quality of patents to fundamental innovation as an output of basic research that can be utilized across different product lines. To this end, we build evidence on previous findings regarding the localized nature of knowledge spillovers, but we additionally show that multinationalization of firm activities increases fundamental innovation by firms engaged in a diversified portfolio of products. Three underlying features define this prediction. First, fundamental innovation continues to take place in the headquarter home location of firms. Second, fundamental innovation can be applied to several product lines but is geographically more difficult to transfer abroad to foreign sites. Third, operating in international markets nurture learning spillovers, which can increase in magnitude when a firm is active in a broad range of activities.

The results reveal that firms' product scope plays a decisive role in determining how the geographical fragmentation of firm activities impacts their incentives to engage in basic research. We first confirm that the negative internal technological spillover effect of offshoring within a firm is present and actively reduces fundamental innovation. We then show that the positive external learning spillover effect of using various production locations kicks in when firms engage in more product lines.

We conclude that firms with a larger share of multinational operations active in a larger range of product lines tend to better exploit learning due to the heterogeneous nature of their knowledge and conduct more fundamental innovation. In contrast, firms with less product lines that geographically separate their operations focus on less basic research or patents that produce less spillovers across industries. The findings suggest the hypothesis of Nelson (1959) going global in the sense that firms operating in diverse industries are able to do more research of a fundamental nature because they can better internalize the benefits of technological spillovers arising from multinational activities.

A natural direction for future research would be to link the spillovers brought about by fundamental innovation to productivity growth. Upon the availability of geographically segmented data, a next step would be to study the impact of the characteristics of the destination (production location) of multinational firms. More detailed research on the location of R&D that gives rise to innovations of different scopes is another attractive path to pursue.

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A Appendix

A.1 COMPUSTAT Data

Our firm-level data originates from Standard & Poor's COMPUSTAT which is actually a collection of various data. We particularly make use of two sources in COMPUSTAT: fundamental annuals and historic segmented files.

To focus on manufacturing, we use the firms' report of their Standard Industry Classification (SIC) associated with their main activity. We only keep those firms whose SIC falls in the range 2000 to 3999. We form a list of firms headquartered in the US from COMPUSTAT annual fundamentals (FIC="USA") and match it by the firm identifier $GVKEY$ to our segmented firms, then drop all firms in our segmented file that cannot be found in the other list.

Each segment (business or geographic) for a firm is reported with a segment ID (SID) which is unique within firm and the segment type. Some segments are reported with $SID = 99$. We find that most of these segments do not report any sales and pertain either to administrative and corporate activities or to discontinued and non-operational segments. We use the segment names ($SNMS$), that in most cases provides a description of the segment operation, to filter those that are not productive. The keywords we use to flush these segments are:

ADJUSTMENT, CORPORATE, DISCONTINUED, DIVESTED, ELIMINATED, FOREIGN, HEADQUARTER, INTERNATIONAL, INVESTMENT, (RE)CONSOLIDATED

Some firms in the data submit more than one report per year for the same segment, updating the previous reports. We are only using the most recent report in these cases. At this point, it is straightforward to count the number of business segments ($STYPE$="BUSSEG") as the number of products, N. We use the sales ($SALES$) reported for the US segment ($STYPE$="GEOSEG" and $GEOTP = 2$) over the total sum of sales to construct our measure of internationalization, S.

We later add R&D (XRD) and advertising (XAD) expenditures from COMPUSTAT annual fundamentals. Annual GDP deflators obtained from the Federal Reserve Economic Data (FRED) are used to turn both expenditures into 2000 dollar values. At this point we have the key variables and the controls needed as explanatory variables.

A.2 Patent Data

We obtain the source file provided by the US Patent and Trademark Office reporting more than four million granted patents from 1901 to 2010. The data is administrative, hence, requires some processing and cleaning before being used in the econometric applications. In what follows, we describe the steps we take to get the data ready for our use.

We fetch the following information from the main body of data:

- patent number,
- assignee code,
- date of filing application,
- patent class and subclass.

The data also provides the date patent was issued, but as we explained in the text, the issuing date is not an accurate indication for the time of innovation.

For benchmarking with other similar works, we only keep utility patents. These patents often relate to the invention of a new method or device. The selection excludes all design patents (number or class starting with the letter 'D') that register the ornamental design of a functional item and plant patents (number starting with the letter 'P' or class starting with letters 'PLT') that register a whole plant. We also drop patents with numbers starting with the letter 'H'. The USPTO explains that these patents are not real inventions but statutory ones, claiming an invention as prior art and preventing others from patenting it. However, we keep patents whose numbers start with letters 'RE'. These are reissued patents that fix omissions and errors in the original filing of an earlier patent.

The classifications for the utility patents are then standardized into technology codes according to the conversion table in Hall *et al.* (2001, Appendix 1). The list of citing and cited patents are, in turn, matched with the patent numbers and the corresponding technology codes. Computing the generality and originality indexes is straightforward as per instructed by Hall *et al.* (2001).

The final stage is matching the patents to firms. Firms in COMPUSTAT are identified by unique GVKEY codes. We first use the file pat76_06_ipc.dta from the NBER Citation Data project (Hall *et al.*, 2001) to bridge assignee codes to another identifier, PDPASS. Then using dynass.dta from the same project, we are able to link PDPASS to the GVKEY of the assignee. In the process, we use the first GVKEY (GVKEY1) in the list as it is the first assignee in the chronological order and most likely associated with the inventor. Once the link between a patent and its GVKEY is established, linking patents to firm characteristics is just a matter of merging by GVKEY.

A.3 Extension to Empirical Results

A peculiarity of the dependent variables, namely, the indexes of generality and originality, is that both are bounded between zero and one (inclusive). Such variables are termed as fractional response variables. Estimating a linear model ignores these constraints and might generate a flatter curvature by under-estimating the coefficients. Papke and Wooldridge (1996) propose to estimate a probit transformation of (1) in a bid to effectively enforce these constraints. The estimation then proceeds by applying a maximum likelihood estimation. We estimate a fractional response version of our main model in the simplest case where there are no instruments to see whether the replacement of our linear model with a nonlinear one justifies the increased computational intensity. The estimated coefficients are listed in Table 11. Comparing these result to those in Table 4, we find them to be almost identical, that is, our linear model is already doing a job at least as good as the fractional response model.

To test the robustness of the results to the endogneity problem, we ran a few IV regressions with the main results reported in Tables 8 and 9. The Cragg–Donald statistics in those tables are strongly in favor of the instruments we used. For a better insight into the performance of our instruments of choice, we report the first stage results of those regressions in this section. Table 12 reports the first stage results for Table 8, where exports are used as the key instrument.

Apart from the coefficients, the table also reports Kleibergen–Paap statistic (Kleibergen and Paap, 2006). Overall, the first stage results still paint a favorable picture of the instruments. The same procedure is followed for Table 9, and the first-stage results are listed in Table 13 with similar interpretation.

Sample	No switching			Switching to Multinational
		multi-nationals	Unchanging product number	
Variable	(1)	(2)	(3)	(4)
S_t	-0.138***	-0.131***	-0.154***	-0.040***
	(0.022)	(0.029)	(0.023)	(0.015)
N_t (SIC 4-digit)	-0.005**	-0.005	-0.007*	-0.005***
	(0.003)	(0.004)	(0.004)	(0.002)
$N_t \times S_t$	0.037***	0.041***	0.048***	0.012***
	(0.009)	(0.012)	(0.010)	(0.005)
Adj. R^2	0.055	0.053	0.055	0.052
#Obs	52,373	29,313	45,698	268,255

Variable	(1)	(2)	(3)	(4)
S_t	-0.151***	-0.143***	-0.169***	-0.040***
	(0.023)	(0.031)	(0.024)	(0.016)
N_t^H (Herfindahl)	-0.006**	-0.005	-0.007*	-0.006***
	(0.003)	(0.005)	(0.004)	(0.002)
$N_t^H \times S_t$	0.047***	0.049***	0.059***	0.013***
	(0.010)	(0.013)	(0.011)	(0.005)
Adj. R^2	0.055	0.053	0.056	0.051
#Obs	52,373	29,313	45,698	268,255

Table 6: The OLS estimates for the USPTO generality index using different restricted samples to minimize the endogneneity effect. The numbers in parentheses are standard errors, clustered by firm–year. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively. A set of controls are also included, but not reported. The sample is at firm–year–patent level.

Variable	S	N	N^H	$\log(1+EXP)$
N	0.105			
N^H	0.050	0.942		
$\log(1+EXP)$	0.166	-0.169	-0.191	
$\log(1+IMP)$	0.168	-0.151	-0.184	0.856

Table 7: The table of correlations between the key variables and the instruments at firm–year level. All correlations are significant at 1% level.

	USPTO Generality		HJT Generality	
Variable	(1)	(2)	(3)	(4)
S_t	-0.510***	-0.488***	-0.499***	-0.480***
	(0.106)	(0.096)	(0.120)	(0.109)
N_t (SIC 4-digit)	-0.040***		-0.043***	
	(0.008)		(0.009)	
$N_t \times S_t$	0.106***		0.109***	
	(0.020)		(0.022)	
N_t^H (Herfindahl)		-0.039***		-0.042***
		(0.008)		(0.008)
$N_t^H \times S_t$		0.104***		0.112***
		(0.020)		(0.021)
Adj. R^2	0.028	0.031	0.039	0.042
F	59.88	59.39	80.65	81.67
Cragg–Donald test	2,142.2	2,384.9	1,817.3	2,025.6
Anderson–Rubin F	17.419	18.472	15.001	16.519
p-value	[0.000]	[0.000]	[0.000]	[0.000]
#Obs	290,684	290,684	290,684	290,684

Table 8: The 2SLS estimates for the index of generality as dependent and using the log of exports and its interaction as instruments. The numbers in parentheses are standard errors, clustered by firm–year. *** and ** indicate significance at 1% and 5%, respectively. A set of dummies for year, industry and patent class are also included, but not reported. The sample is at firm–year–patent level.

Variable	USPTO Generality (1)	(2)	HJT Generality (3)	(4)
S_t	-0.150**	-0.148**	-0.209***	-0.208***
	(0.066)	(0.064)	(0.072)	(0.070)
N_t (SIC 4-digit)	-0.014**		-0.019***	
	(0.006)		(0.006)	
$N_t \times S_t$	0.036**		0.047***	
	(0.015)		(0.016)	
N_t^H (Herfindahl)		-0.014**		-0.020***
		(0.006)		(0.006)
$N^H \times S$		0.037**		0.053***
		(0.016)		(0.017)
Adj. R^2	0.050	0.050	0.060	0.060
F	67.83	68.04	91.67	92.10
Cragg–Donald test	2,948.2	2,822.5	2,695.5	2,574.4
Anderson–Rubin F	2.764	2.925	4.529	5.225
p-value	[0.063]	[0.054]	[0.011]	[0.005]
#Obs	290,684	290,684	290,684	290,684

Table 9: The 2SLS estimates of key variables for the index of generality as dependent and using the log of imports and its interaction as instruments. The numbers in parentheses are standard errors, clustered by firm–year. *** and ** indicate significance at 1% and 5%, respectively. A set of controls plus dummies for year, industry and patent class are also included, but not reported. The sample is at firm–year–patent level.

Variable	USPTO Originality (1)	(2)	HJT Originality (3)	(4)
S_t	-0.075***	-0.078***	-0.052***	-0.059***
	(0.019)	(0.019)	(0.016)	(0.017)
N_t (SIC 4-digit)	-0.006***		-0.005**	
	(0.002)		(0.002)	
$N_t \times S_t$	0.014***		0.007*	
	(0.004)		(0.004)	
N_t^H (Herfindahl)		-0.006***		-0.005**
		(0.002)		(0.002)
$N_t^H \times S_t$		0.017***		0.011**
		(0.005)		(0.005)
Adj. R^2	0.056	0.056	0.050	0.050
F	88.01	87.89	89.33	88.78
#Obs	331,503	331,503	331,503	331,503

Table 10: The OLS estimates for the index of originality as dependent. The numbers in parentheses are standard errors, clustered by firm–year. ***, **, and * indicate significance at 1%, 5%, and 10%, respectively. A set of dummies for year, industry and patent class are also included, but not reported. The sample is at firm–year–patent level.

Variable	USPTO Generality (1)	USPTO Generality (2)	HJT Generality (3)	HJT Generality (4)
S_t	-0.061***	-0.062***	-0.030**	-0.034***
	(0.013)	(0.013)	(0.012)	(0.012)
N_t (SIC 4-digit)	-0.006***		-0.004***	
	(0.002)		(0.001)	
$N_t \times S_t$	0.015***		0.007**	
	(0.004)		(0.004)	
N_t^H (Herfindahl)		-0.006***		-0.004***
		(0.002)		(0.002)
$N_t^H \times S_t$		0.017***		0.010**
		(0.005)		(0.004)
$\log(SALE_t)$	-0.000	-0.000	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
r_t	0.001**	0.001**	0.001**	0.001*
	(0.001)	(0.001)	(0.001)	(0.001)
a_t	-0.002***	-0.002***	-0.001**	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)
Log Likelihood	-173,015.3	-173,016.0	-168,546.9	-168,547.3
χ^2	7,167.3	7,179.4	7,275.0	7,235.5
p-value	[0.000]	[0.000]	[0.000]	[0.000]
#Obs	320,628	320,628	320,628	320,628

Table 11: The average marginal effects from the estimation of a fractional response model of generality index. The numbers in parentheses are standard errors, clustered by firm–year. *** and ** indicate significance at 1% and 5%, respectively. A set of dummies for year, industry and patent class are also included, but not reported. The sample is at firm–year–patent level.

Variable	(1)	(2)	(3)	(4)
S equation				
$\log(1+EXP_t)$	-0.029***	-0.027***	-0.031***	-0.029***
	(0.006)	(0.005)	(0.006)	(0.005)
$\log(1+EXP_t)\times N_t$	0.010***	0.009***		
	(0.001)	(0.001)		
$\log(1+EXP_t)\times NH_t$			0.010***	0.010***
			(0.002)	(0.002)
1st Stage F-test	22.36	19.40	24.07	20.65
$\log(1+EXP_t)$	-0.060***	-0.056***	-0.059***	-0.055***
	(0.019)	(0.018)	(0.016)	(0.016)
$\log(1+EXP_t)\times N_t$	0.037***	0.037***		
	(0.006)	(0.006)		
$\log(1+EXP_t)\times NH_t$			0.037***	0.037***
			(0.006)	(0.006)
1st Stage F-test	21.52	25.13	22.28	25.82
#Obs	290,684	290,684	290,684	290,684

Table 12: First stage estimates for Table 8, where the value of exports is used as the key instrument. Numbers in the parentheses are standard errors.

Variable	(1)	(2)	(3)	(4)
S equation				
$\log(1+IMP_t)$	-0.028***	-0.027***	-0.028***	-0.027***
	(0.005)	(0.004)	(0.005)	(0.004)
$\log(1+IMP_t)\times N_t$	0.008***	0.008***		
	(0.001)	(0.001)		
$\log(1+IMP_t)\times NH_t$			0.008***	0.008***
			(0.001)	(0.001)
1st Stage F-test	22.21	18.85	24.33	20.39
$\log(1+IMP_t)$	-0.043**	-0.040**	-0.040***	-0.038**
	(0.017)	(0.017)	(0.015)	(0.015)
$\log(1+IMP_t)\times N_t$	0.026***	0.026***		
	(0.005)	(0.005)		
$\log(1+IMP_t)\times NH_t$			0.025***	0.025***
			(0.005)	(0.005)
1st Stage F-test	22.22	23.12	23.32	24.20
#Obs	290,684	290,684	290,684	290,684

Table 13: First stage estimates for Table 9, where the value of imports is used as the key instrument. Numbers in the parentheses are standard errors.