Multinational Production and the Scope of Innovation*

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Abstract

This research sheds light on the role of multinational production on the type of innovation performed by firms. We construct matched firm-patent data to measure the scope of innovation, that is the extent to which the output of R&D can be spread across different product lines. We focus on two features of multinational production: (i) core knowledge is geographically more difficult to transfer abroad to foreign production sites, (ii) learning spillovers can occur from international operations. The results reveal that the second effect is more likely to dominate when a firm is active in more product lines. We argue that a more diversified portfolio of products increases a firm's span of learning from international operations, thereby enhancing its ability to engage in more fundamental research. In contrast, firms with fewer product lines that geographically separate production from innovation focus on more specialized types of R&D.

Keywords: Multinational production, Fundamental innovation, Multiproduct firms, Knowledge spillovers.

JEL Code: F12, F23, O31, O32.

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1 Introduction

The global fragmentation of production is by now a well-known concept in international trade and is increasingly seen as a necessity to maintain competitiveness in the world market. While geographically dispersed operation by firms, hereafter referred to as multinational production (MP), 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 in terms of innovation is not trivial. Literature has revealed both positive and negative effects of MP on knowledge spillovers that in turn determine the innovation capacity of firms. The search for crucial elements that govern the impact of the geography of firms' activities on knowledge flow and R&D spillovers within and across firms, however, remains an ongoing quest.

This research sheds light on the determinants of innovation across *multinational multi-product firms*, a concept first introduced in Baldwin and Ottaviano (2001).[1] Our analysis in particular explores the scope of innovation activities in terms of how inclusive firms' R&D is for their overall performance. We call this fundamental innovation, an important phenomenon for productivity growth because of its large spillover effects within and across industries (Akcigit *et al.* 2013). We show empirical evidence that although limited international spillovers through MP activities or diseconomies of scope through a larger product range, *per se*, may confine the scope of innovation, being active in more product lines while operating overseas compensates for this effect because it increases the span of learning from international markets. The results confirm the Nelson (1959) hypothesis in the context of multinational production: firms with more diverse operations tend to engage in more fundamental innovation that originates from basic science.

Evidence regarding the effect of MP on the diffusion of knowledge is at best mixed. For instance, Jaffe *et al.* (1993) use patent citation data to provide comprehensive evidence that knowledge spillovers can be geographically localized. Audretsch and Feldman (1996) use US data to argue that the local nature of spillovers could be due to the spacial distribution of production and innovation. This can be caused by imperfect international spillovers

[1] Yeaple (2013) has recently expanded the argument to study the proximity-concentration tradeoff in the simultaneous decisions of firms on the number of products to manage and the mode of serving the foreign market (exports versus MP).

that originate from limited feedback from R&D labs to production sites. Follow up work by Branstetter (2001), Keller (2002) and Bottazzi and Peri (2003) confirm the limitations on the scope of international knowledge diffusion. At the same time, it is well-documented by now that globally engaged firms are more productive than domestic firms, see for instance Melitz (2003) for exports and Helpman *et al.* (2004) for FDI. This can originate from 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). These channels all boil down to the question of whether engagement in multinational operations can foster innovation or increase the *scope* of innovation by firms.

The present study is a first step to weigh the positive and negative effects of MP on the scope of innovation and observe how this balance varies with the number of product lines handled by a firm. We examine the "fundamental" nature of innovation by measuring R&D that can be spread across different product lines as opposed to more specialized R&D aimed for example at reducing incremental costs of new varieties, adapting products to new international markets, or improving the organization of firm activities. To this end, we use patent citation data from the U.S. patent and trademark office (USPTO) to determine the fundamental share of firms' innovation activities by applying the generality and originality indexes introduced in Trajtenberg *et al.* (1997) (and later applied in Liu and Rosell, 2013). COMPUSTAT segmented data is then used to identify the extent to which multiproduct and international operations are conducive to fundamental patenting and innovation. Forming a matched firm-patent dataset for the years 1985 to 1999 allows us to simultaneously study the effect of multinational and multi-sectoral production on the scope (as opposed to scale) of innovation.

To pin down the idea, the empirical investigation is preceded by a simple theory that shows potential mechanisms at play. This is done by combining two existing channels through which MP interacts with innovation: (i) the mechanism from Naghavi and Ottaviano (2009) on how offshoring production reduces fundamental innovation due to imperfect international R&D

spillovers between labs and production sites; (ii) the notion from Peri (2005) that learning externalities from research in other regions also affect R&D productivity in generating innovation. The model explores the role of product scope in the balance between these two forces. The outcome is that precisely the localized nature of knowledge makes MP a tool to absorb new essential information abroad, more so the more diverse is a firm's portfolio of products.

The empirical section tests the above implications, finding that a wider scope of product lines and a larger share of multinational production both negatively impact the degree to which patenting activities by a firm are fundamental in nature. However, a larger product range tends to shift innovation activities of firms with larger international operation towards fundamental innovation. In other words, our estimations show a positive and highly significant interaction effect between the number of product lines and MP. Our results are robust to the inclusion of several instrumental variables to account for potential endogeneity concerns that arise due to reverse causality and omitted variable bias. In particular, one could argue that firms that engage in more specialized (adaptive) innovation can subsequently be more fit to operate abroad. We use exports (and imports) in an industry as instrument to determine the level to which a sector depends on international markets, since the flow of trade is correlated with MP but not directly related with the type of innovation by each firm.

The paper contributes to a recent but growing literature on multiproduct firms and innovation. Dhingra (2013) looks at the interaction between process and product innovation by multiproduct firms. She argues that access to a larger market through trade does not necessarily translate into innovation oriented towards the introduction of new products, but shifts focus towards process R&D to improve productivity on a limited range of products. Akcigit and Kerr (2012) likewise distinguish between explorative (product) and exploitative (process) innovation and show that the former does not scale with the number of product lines, resulting in less major innovations by larger firms. Liu *et al.* (2013) instead study the organization of firms exploiting the trade-off between a larger scope of inputs within a product in terms of functionality and higher quality. Eckel *et al.* (2011) further introduce firms' endogenous choice to compete on the basis of either quality or cost by investing to improve the quality of an individual variety or that of their overall brand respectively. Finally, in a closely related work to ours Liu and Rosell (2013) study how trade reduces the basicness of innovation undertaken by firms. The authors show evidence that this negative relationship arises because increased import competition leads domestic multiproduct firms to narrow the scope of their product lines reducing the payoff to basic research. We contribute to this literature by studying the role of multinational production on innovation by multiproduct firms. In addition, we single out the *quality* of firms' innovation (rather than product) in terms of the scope of its pertinence across product lines.

It is important to clarify that we use the number of business segments to represent product lines in this paper. The advantage of using this measure is that it does not vary much over time, so it is arguably fairly predetermined. We believe a general measure as such is most suitable for our purpose as it can be treated as an exogenous variable allowing us to focus on its interaction with MP in determining the scope of innovation. The question on how firms alter their product mix according to changes in economic conditions in the international market has been addressed by Eckel and Neary (2010), who show that globalization increases firm productivity but decreases the scope of multiproduct firms by shifting their focus towards their core competence. Other influential papers such as Bernard *et al.* (2011) and Mayer *et al.* (2014) also provide evidence that tougher international competition leads firms to concentrate on exporting their key products, which in turn enhances their productivity. Qiu and Zhou (2013) is the latest contribution to this branch and shows that globalization can result in scope expansion by the most productive firms if the fixed cost of introducing new varieties is steeply rising in the product scope. Using the same concept, our analysis adds to the literature by studying how being active in several product lines may influence the impact of internationalization on the innovation decision and performance of firms.[2]

The rest of the paper is as follows. Section 2 sets up the underlying theoretical framework. Section 3 provides a description of the data and the respective measures used to characterize innovation. Section 4 delivers our empirical results, while Section 5 concludes by placing the features of our claim in the context of previous conceptual frameworks.

[2]The question of the relationship between innovation, international trade and MP have been elegantly modeled in Atkeson and Burstein (2010) and Arkolakis *et al.* (2013) respectively. Although the latter does incorporate the geographical separation of innovation and production in the light of Helpman (1984), they do not deal with the role of multiproduct firms or learning spillovers arising from the global disintegration of firms' activities.

2 A Simple Theory

We consider a very simple setting in which each active firm has access to a continuum of symmetric varieties. We denote by $N_j \subseteq R_+$ the set of varieties produced by a representative firm j. Due to symmetry, N_j also represents the size of the product range. Since according to our data the number of business segments does not change much over time, we treat N_j as an exogenous variable. The unit cost of production of each variety presents two components: a *core cost* c_{j0} common to all product varieties of firm j and an incremental cost $\gamma(N_j)$ directly associated to the number of varieties produced by firm j. The core cost can be reduced through fundamental innovation denoted as $\zeta_j \in [0, 1]$, which enables firm j to reduce the cost of production for all varieties within its product range through intra-firm spillovers. Incremental costs can be reduced through specialized (less broadly applicable) innovation $\omega_{ji} \in [0, 1]$. By investing ω_{ji}, firm j is able to reduce the cost of production of the i-th variety only.[3]

Suppose firms produce a fraction S of their output overseas. As described in the introduction, evidence points towards the localized nature of firms' fundamental R&D. Using this argument, we presume that fundamental R&D is more likely to remain in firms' headquarters, while specialized R&D can more easily follow a specific product to the location of its production. We therefore take from Naghavi and Ottaviano (2009) that a proportion ϕ of fundamental innovation is lost when applied in the international sites of a multinational. Consequently, a firm can only realize a reduction in its core cost equivalent to a fraction $1 - \phi S$ of the fundamental innovation it undertakes. In the following analysis, we denote by ϕS the total loss from limited international spillovers.

Operation in international markets can also be associated with learning spillovers, whereas diversified knowledge within a firm can influence the span of learning from other firms (or markets). In our model, this is captured by multinationals active in more diverse product lines being better posed to exploit such learning spillovers. We model learning externalities of operating in international markets as the functional relationship $\theta \equiv \theta(N, S)$, where

[3]The incremental component aims to capture the idea in Qiu and Zhou (2013) that new varieties are increasingly costly to produce. Using a similar concept in Nocke and Yeaple (2014), the function $\gamma(N_j)$ can hence be thought of as the average incremental cost spread across all varieties with $\gamma'(N_j) > 0$. Moreover, we abstract from cost heterogeneity within the firm as in Eckel and Neary (2010) and between firms as in Qiu and Zhou (2013) to introduce a single cost function that encompasses the output of different types of innovation.

$\theta'_S(N,S) > 0$ and $\theta'_N(N,S) > 0$ hold. The first property captures the notion of the propagation of accessible knowledge in other regions developed in Peri (2005) and the second takes from Nelson's diversity hypothesis that firms with a more heterogeneous portfolio of products are best able to internalize the benefits of basic research. Consequently, a firm can enhance the impact of its fundamental innovation by engaging in MP with a factor of $1 + \theta(N,S)$.

Summing the two cost components, the unit cost of production of firm j's variety i writes as:[4]

$$c_{ji}(\omega_{ji}, \zeta_j) = c_{j0}\left[1 - \left(1 + \theta(N_j, S)\right)\frac{\zeta_j^{1/2}(1-\phi S)}{\psi(N_j)}\right] + \gamma(N_j)\left(1 - \omega_{ji}^{1/2}\right). \tag{1}$$

Eq. (1) highlights that trade-off brought about by MP between imperfect international spillovers of fundamental R&D to foreign production sites and learning spillovers through access to new fundamental knowledge in foreign markets. In addition, the function $\psi(N_j)$ with $\psi'(N_j) > 0$ captures the concept of diseconomies of scope in R&D introduced in Akcigit and Kerr (2012): as the number of varieties N_j increases, R&D becomes less effective at reducing the core cost as its effect is diluted among a larger set of products.

Firm j decides on its investment in fundamental innovation, ζ_j, and in specialized innovation, ω_{ji}, for each product i along with the output of each variety, Q_{ji}, to maximize the following profit function:

$$\max_{Q_{ji},\omega_{ji},\zeta_j} \Pi_j = \int_0^{N_j} \left[\left(p_{ji} - c_{ji}\right)Q_{ji} - r_s\omega_{ji}\right] di - r_f\zeta_j, \tag{2}$$

where r_s and r_f are respectively the rates at which firms invest in specialized and fundamental innovation. With symmetric costs within firms, firm j chooses the same investment in specialized innovation and output for each variety produced, so that we can suppress the firm-product subscripts. Consequently, the profit function (2) can be written as $\Pi = N\pi - r_f\zeta$ where π is profit per product, that is $\pi = [p - c(\omega,\zeta)]\,Q - r_s\omega$.

To study the impact of MP on the scope of innovation, we build an index using the share of innovation performed by firms aimed at reducing the core costs relative to product-specific incremental costs. We first derive the first order conditions (FOCs) for the firm problem and

[4] The choice of the exponent 1/2 ensures that the firm's problem is concave. This assumption is not restrictive as this value can be replaced with any positive number less than 1.

determine the optimal ω^* and ζ^*. Using these values, this index can be calculated as:

$$\Omega \equiv \frac{\zeta^*}{\zeta^* + N\omega^*} = \frac{\frac{c_0^2 N}{r_f^2 \psi(N)^2}(1+\theta(N,S))^2(1-\phi S)^2}{\frac{c_0^2 N}{r_f^2 \psi(N)^2}(1+\theta(N,S))^2(1-\phi S)^2 + \frac{\gamma(N)^2}{r_s^2}}. \tag{3}$$

Changing the share of output that is produced overseas by firms has two effects on Ω. The first effect is positive and arises from learning spillovers: increasing the share of operation in international markets S makes the scope of learning from other firms $\theta(N,S)$ larger. As a result, R&D becomes more effective at reducing the core cost. Because a larger S increases the investment in fundamental innovation ζ^*, it also increases the scope of innovation. The second effect is negative and is due to the localized nature of firms' fundamental R&D: increasing the share of output that is produced overseas S makes the loss from being multinational ϕS larger. Consequently, in this case, R&D becomes less effective at reducing the core cost. We conclude that a larger S decreases the investment in fundamental innovation ζ^* and therefore the scope of innovation. Assuming $\theta(N,S)$ to be multiplicative separable ($\theta(N,S) = \theta_1(N)\theta_2(S)$) and denoting by $\epsilon_{\theta S} = \frac{\theta'_S(N,S)}{\theta(N,S)}S$ the elasticity of $\theta(N,S)$ with respect to S, we state the following proposition:

Proposition 1. *For $\epsilon_{\theta S} > \frac{\phi S}{(1-\phi S)}$, there exists a threshold number of product lines above (below) which MP increases (decreases) the scope of innovation.*

Proof. The derivative of (3) with respect to S is:

$$\frac{d\Omega}{dS} = \frac{\frac{2c_0^2 N}{r_f^2 \psi(N)^2}\left[(1+\theta(N,S))(1-\phi S)^2\theta'_S(N,S) - (1+\theta(N,S))^2(1-\phi S)\phi\right]\frac{\gamma(N)^2}{r_s^2}}{\left[\frac{c_0^2 N}{r_f^2 \psi(N)^2}(1+\theta(N,S))^2(1-\phi S)^2 + \frac{\gamma(N)^2}{r_s^2}\right]^2}.$$

The sign of the above derivative is determined by the expression

$$(1-\phi S)\theta'_S(N,S) - (1+\theta(N,S))\phi \lesseqgtr 0.$$

Using $\theta(N,S) = \theta_1(N)\theta_2(S)$, the expression can be written as

$$\theta_1(N) \lesseqgtr \frac{\phi}{(1-\phi S)\theta'_2(S) - \phi\theta_2(S)}. \tag{4}$$

When the elasticity of learning spillovers with respect to S is large enough so that $\epsilon_{\theta S} > \frac{\phi S}{(1-\phi S)}$, the denominator in (4) is positive. Fixing S, and by the monotonicity of $\theta_1(N)$, there exists a threshold $N^*(S)$ such that for $N < N^*(S)$ the derivative is negative and for $N > N^*(S)$ the derivative turns positive. □

To elucidate the role of the product range in shaping the relationship between the scope of innovation and the share of MP activities, consider a simplified case when $\theta(N, S) = NS$. Plugging this function back into (4) generates a closed form condition:

Corollary 1. *When $\theta(N, S) = NS$, then*

$$N^*(S) = \frac{\phi}{1 - 2\phi S},$$

determines the threshold number of product lines that reverses the negative impact of MP operation on the scope of innovation.

Corollary 1 establishes that a higher loss from limited international spillovers, ϕS, makes it more likely for MP to cause a reduction in the scope of innovation. The condition $\phi S > 1/2$ in Corollary 1 specifically outlines the level of losses that makes this effect always prevail. Proposition 1 further establishes that the product range plays an important role in the relationship between the scope of innovation and the share of MP. The benefit from learning spillovers is increasing in the the number of business segments in which the firm operates. We thus expect the interaction term between MP and the number of business segments to take a positive sign. This also highlights the positive role that a larger product range plays in increasing fundamental innovation despite of the negative forces it creates through diseconomies of scope. We shed light on this issue in the Appendix by illustrating the relationship between MP and the quality of innovation through a numerical example.

3 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.[5] 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 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 $R_0 = XRD_0/(\delta + 0.08)$.[6] 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 GDP deflators for the US. Finally we use the annual sales deflated by CPI 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

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

[6] 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.

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 onfile 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, 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 internationalization of production. 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 ($N4$). 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 fundamental 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:

$$H = 1 - \sum_{n=1}^{N3} \left(\frac{\#(\text{Same 3-digit SIC})_n}{N4} \right)^2,$$

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

$$NH = N4 \times H + 1.$$

Let us look at the two extreme cases: when $H = 0$ (no diversity at 3-digit level), then $NH = 1$, 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, $H = 1 - 1/N4$ and $NH = N4$; 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.[7] Specifically, our definition of international presence is the share of total sales by

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

Year	#Firms	#Patents	#Multi-product	#Off-shoring
1985	2,761	17,164	782	982
1986	2,867	18,108	822	933
1987	2,891	19,366	845	887
1988	2,795	19,770	832	841
1989	2,728	19,586	814	780
1990	2,725	20,336	834	751
1991	2,809	21,314	887	728
1992	2,924	23,068	945	743
1993	3,055	28,668	1,002	729
1994	3,184	27,936	1,088	732
1995	3,438	33,157	1,180	716
1996	3,499	30,803	1,234	694
1997	3,306	26,690	1,198	640
1998	2,639	31,030	1,216	810
1999	2,181	30,951	1,326	904

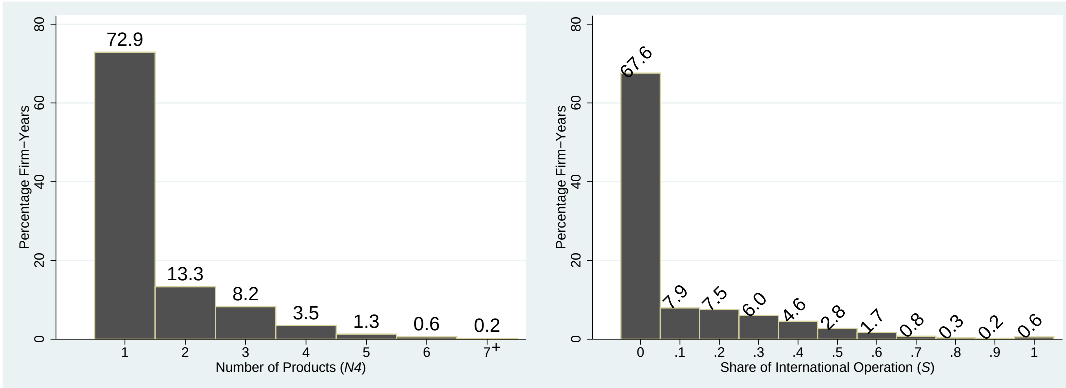
Table 1: The count of firms and patents in the data by year. Multiproduct firms are those with more than one 4-digit product line ($N4 > 1$). Offshoring firms are those with non-zero share of international operation ($S > 0$).

affiliates overseas, or more formally:

$$S = 1 - \frac{\text{Annual Sales of the U.S. segment}}{\text{Total Annual Sales}}.$$

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.[8] 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 ($N4 > 1$), 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.

[8] 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.



(a) (b)

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

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 0.2% 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.

3.1 Measuring Fundamental Innovation

The mainstream literature on innovation has not yet offered one standard definition that classifies a patent as fundamental or determines the scope of a patent. We use two measures introduced by Trajtenberg *et al.* (1997) which we believe have a good degree of correlation with our notion of fundamental innovation, and we use them to robustly test our hypothesis. What follows 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 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 our definition of fundamental innovation and generality. We rely on the technology classes defined by Trajtenberg *et al.* (1997) (from now on referred to as HJT) to form the index, but we also classify patents using the first two digits of the USPTO patent classification codes for comparison and robustness check.[9]

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 originality 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

[9] 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.

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.[10] 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 10 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 coefficient 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 fraction of single and MP firms by their share of international operation and plot the fractions in Figure 2. The figure misses a clear direction and does not support a strong confounding between the two quantities.

[10] 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	313,671					
USPTO		0.466	0.322	0	0.524	1
HJT		0.399	0.319	0	0.429	1
ORIGINAL	323,560					
USPTO		0.430	0.336	0	0.5	1
HJT		0.373	0.328	0	0.4	0.999
$N4$	43,802	1.497	0.988	1	1	10
NH	43,802	1.476	0.928	1	1	10
S	43,802	0.099	0.182	0	0	1
$SALES$ ($mil)	43,802	824.0	4,769.5	0	56.6	174,694
R($000)	43,802	134.1	1,059.0	0	4.4	49,161.5
A($000)	43,802	16.8	140.0	0	0	4,602.3

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.

4 Empirical Results

4.1 Econometric Strategy

In the theoretical section, we build an environment in which multinationalization of production has two opposing effects on fundamental innovation. Learning spillovers from foreign markets stimulates fundamental innovation, whereas the localized nature of such innovation reduces its effectiveness in foreign plants. Finally, having more product lines increases the learning span of firms in international markets.

Now that the necessary variables are in place, we are able to test these implications for our panel of firms with various levels of multinational operation and different number of business segments. In particular, our empirical estimations should reveal the sign of the direct effect of (i) MP and (ii) product range on the fundamental nature of innovations. Exploiting the interaction between the two effects, we also determine the impact of (iii) operating in a larger range of product lines on the learning capability of firms engaged in MP, and therefore the overall effect of the latter on the scope of innovation.

	USPTO *GENERAL*	HJT *GENERAL*	USPTO *ORIGINAL*	HJT *ORIGINAL*	$N4$	NH
GENERAL						
HJT	0.815					
ORIGINAL						
USPTO	0.249	0.206				
HJT	0.211	0.280	0.828			
$N4$	0.030	0.032	-0.011	-0.013		
NH	0.024	0.029	-0.012	-0.012	0.948	
S	-0.026	-0.014	-0.011	-0.005	0.063	0.008

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

We estimate those effects using the following linear model[11]

$$F_{ij,t+2} = \alpha_0 + \alpha_1 N_{jt} + \alpha_2 S_{jt} + \alpha_3 N_{jt} \times S_{jt} + X_{jt}\beta + \mu_i + \tau_t + \iota_j + \xi_{ijt}, \tag{5}$$

where F_{ijt} is one of the indexes of fundamental innovation for patent i by firm j in year t. In our specification, N_{jt} represents the number of products, and we use the variety of measures we defined in the previous section to replace N_{jt}. Vector X_{jt} is a set of covariates that would also influence the fundamental nature of patents. 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 fundamental innovation, the effect is absorbed

[11] 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.4). This last issue becomes especially important when we delve into the treatment of endogeneity.

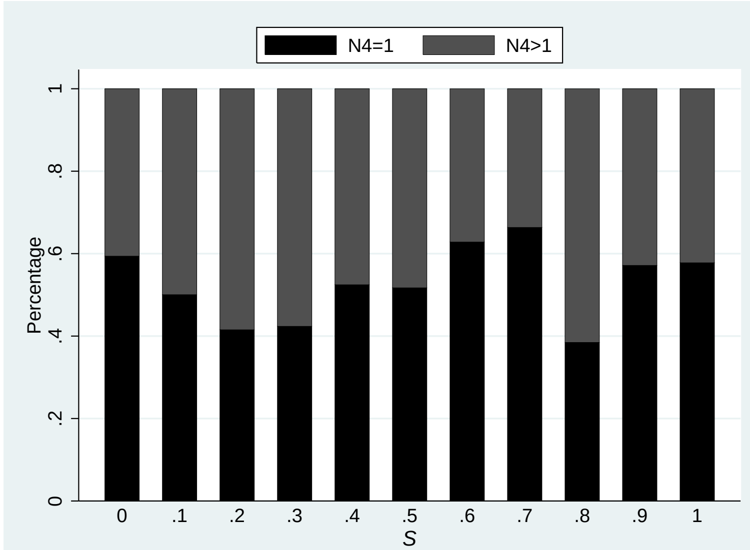
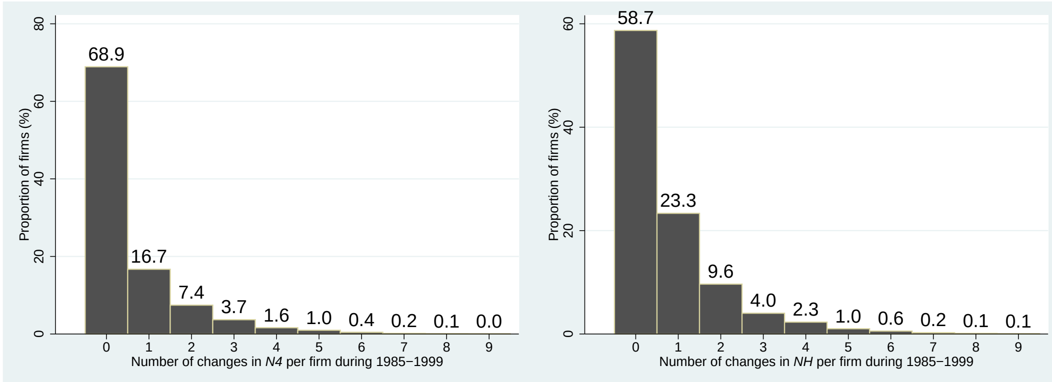


Figure 2: The distribution of single- versus multiproduct firms by their share of international operation.

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. 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 5, 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, about 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.



(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.

4.2 Estimation Results

The coefficients for model (5) are estimated using OLS and reported in Table 4. Columns (1) and (2) use $N4$ to count the number of products. The difference is that in column (1) the index of generality (and the patent class dummies) is based on 2-digit USPTO classification. In column (2), the HJT classification is used instead for robustness check. The same holds for columns (3) and (4), except that the number of products in those columns is measured in NH.

Regardless of the combination of the measures used for the number of products and for generality, all models in Table 4 build the consensus that an increasing share of international operation negatively influences the generality of patents. This finding is in line with our theoretical argument that the segmentation of production across geographic boundaries is detrimental to the fundamental elements of innovations. Similarly, we observe across all specifications presented in Table 4 that more product lines, *per se*, reduce the generality of a firm's patents.[12]

Turning to the key message of our paper, we recall that learning possibilities multiply as firms operating in more product lines increase their international presence, masking the effects of the geographic segmentation of production and leading to a positive effect on fundamental

[12] Interestingly, regressing generality on the number of product lines only results in a coefficient very close to zero. This shows that the negative and the positive effects of a larger product scope on incentives to engage in fundamental innovation present in our model cancel each other out.

Variable	Dependent: Generality USPTO (1)	Generality HJT (2)	Generality USPTO (3)	Generality HJT (4)
S_t	-0.066***	-0.037***	-0.069***	-0.043***
	(0.013)	(0.012)	(0.013)	(0.012)
$N4_t$ (SIC 4-digit)	-0.007***	-0.003**		
	(0.002)	(0.001)		
$N4_t \times S_t$	0.018***	0.008**		
	(0.004)	(0.004)		
NH_t (Herfindahl)			-0.008***	-0.003**
			(0.002)	(0.001)
$NH_t \times S_t$			0.021***	0.011***
			(0.005)	(0.004)
$\log(SALE_t)$	-0.004***	-0.010***	-0.004***	-0.010***
	(0.001)	(0.001)	(0.001)	(0.001)
r_t	0.006***	0.009***	0.006***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)
a_t	-0.003***	-0.001**	-0.003***	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
R^2	0.051	0.062	0.051	0.062
Adj. R^2	0.051	0.062	0.051	0.062
F	72.9	108.6	73.1	108.9
#Obs	312,558	312,558	312,558	312,558

Table 4: The OLS estimates for the index of generality as dependent. 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.

innovation. The interaction term in our specification tests for this prediction and obtains a positive effect across all the columns in the table. Moreover, these effects are all statistically significant.

A few control variables are also part of the estimated model that are reported in the table. These variables also show some direction. In particular, larger firms, in terms of annual turnover, seem to be patenting less general innovations. 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, fundamental innovations 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.

4.3 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.

4.4 Endogeneity of International Operation

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. For instance, firms that tend to focus on more specialized (adaptive or organizational) innovation may be better fit to go abroad because they can adjust more easily to new markets and organize their value chain across countries. Moreover, these latter firms are 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. This reverse causality between one of the key variable and the dependent could potentially introduce enough bias into the coefficients estimated by OLS to generate the wrong impression about the direction of effects.

We have already tried to minimize the reverse causality in model (5) 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. However, for a more thorough treatment of any residual endogeneity that might persist despite the time lags, we resolve to introduce instrumental variables into our estimation. A suitable instrument in this context would be the one that affects a firm's incentive to transfer part of its production to a foreign country or increase the share of production overseas but does not bear any connection with the generality of patents generated by the firm except through MP. 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. We finally settle on using as instrument 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 international markets. A firm operating in a sector that is highly internationalized is also more likely to engage in multinational production. At the same time, the characteristics of innovation by one firm cannot influence the internationality of an entire industry even if it can affect MP by that firm. The nominal values are fetched from the International Trade Data of Bernard *et al.* (2006), and we turn the values into real term using the annual CPI as deflator.[13]

Since the share of international production 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. 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.

As a preliminary test of our instruments, the level of correlations between the trade variables and our key variables are listed in Table 5. The log of exports, in particular, exhibits a positive correlation with S, that is, industries that export larger volumes also have larger outputs 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

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

Variable	S	$N4$	NH	$\log(1+EXP)$
$N4$	0.071			
NH	0.015	0.947		
$\log(1+EXP)$	0.089	-0.210	-0.192	
$\log(1+IMP)$	0.093	-0.191	-0.186	0.880

Table 5: The table of correlations between the key variables and the instruments at firm–year level. All correlations are significant at 1% level.

intensely feeding into the foreign markets through both exporting and offshore production.

Using the instruments described above, we repeat our exercise by conducting a two-stage least squares (2SLS) estimation of model (5). These results are reported in Table 6. Columns (1) to (4) in this table are identical in specification to those in Table 4.

We observe that the key results in Table 6 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 affect the generality of patents. The interaction, however, leads to a positive effect and helps to increase generality.

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.4.[14]

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 interdependence, we use model (1) from Table 6 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

[14] 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.

Dependent: Variable	Generality USPTO (1)	Generality HJT (2)	Generality USPTO (3)	Generality HJT (4)
S_t	-0.663***	-0.454**	-0.565***	-0.373**
	(0.213)	(0.190)	(0.161)	(0.155)
$N4_t$ (SIC 4-digit)	-0.056***	-0.042***		
	(0.014)	(0.013)		
$N4_t \times S_t$	0.147***	0.114***		
	(0.033)	(0.031)		
NH_t (Herfindahl)			-0.052***	-0.039***
			(0.011)	(0.011)
$NH_t \times S_t$			0.135***	0.107***
			(0.027)	(0.027)
$\log(SALE_t)$	0.009	-0.001	0.007	-0.002
	(0.006)	(0.005)	(0.005)	(0.004)
r_t	0.012***	0.011***	0.011***	0.010***
	(0.004)	(0.004)	(0.003)	(0.003)
a_t	-0.004***	-0.002***	-0.004***	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
Adj. R^2	0.012	0.045	0.026	0.053
F	53.85	83.25	59.26	87.99
Cragg-Donald Test	924.7	783.2	1100.2	952.8
Anderson–Rubin F	18.830	12.043	18.550	12.908
p-value	[0.000]	[0.000]	[0.000]	[0.000]
#Obs	282,482	282,482	282,482	282,482

Table 6: 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.

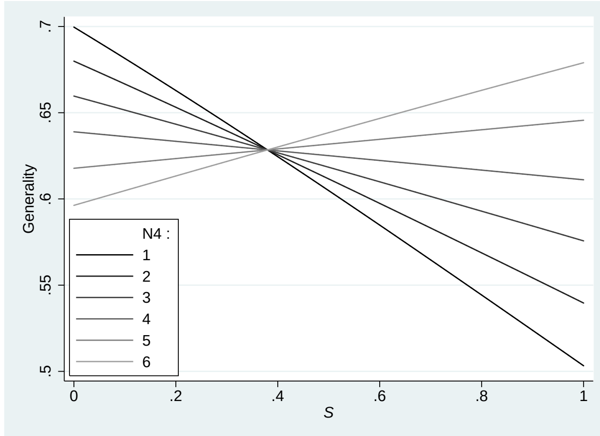


Figure 4: The index of patent generality as a function of N and S, keeping other variables fixed at their means.

illustrates the prediction results when the number of products ranges from one to six and the share of international production 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 appear to be choosing 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' productions 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 full production is happening 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 5 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 7.

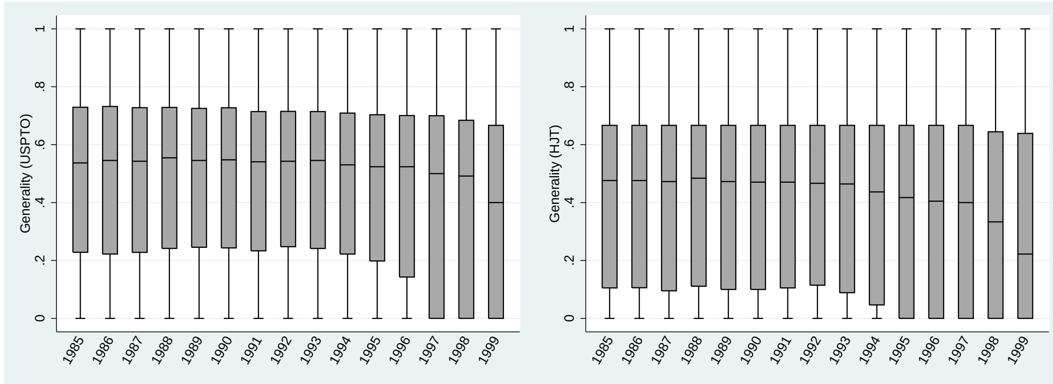
Dependent: Variable	Generality USPTO (1)	Generality HJT (2)	Generality USPTO (3)	Generality HJT (4)
S_t	-0.116	-0.107	-0.100	-0.069
	(0.096)	(0.102)	(0.103)	(0.111)
$N4_t$ (SIC 4-digit)	-0.018***	-0.014**		
	(0.007)	(0.007)		
$N4_t \times S_t$	0.051***	0.041**		
	(0.019)	(0.019)		
NH_t (Herfindahl)			-0.018**	-0.014**
			(0.007)	(0.007)
$NH_t \times S_t$			0.052***	0.046**
			(0.020)	(0.020)
Adj. R^2	0.051	0.063	0.051	0.062
F	67.65	98.74	67.93	97.96
Cragg-Donald Test	1239.2	1180.4	947.5	916.5
Anderson–Rubin F	3.759	2.624	3.773	3.430
p-value	[0.023]	[0.073]	[0.023]	[0.032]
#Obs	282,482	282,482	282,482	282,482

Table 7: 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.

The coefficients in Table 7 do not show any qualitative difference to those in Tables 4 and 6. The share of international production 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 statistically weaker than the results we found in Table 6. 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).

4.5 Is There a Structural Change?

So far, we have been able to establish that the number of products and the share of international operation jointly impact the generality of patents in a certain way. The panel used for the analysis spans 15 years, which could raise the legitimate question of whether the partic-



(a) (b)

Figure 5: The distribution of generality index by year.

ular relationship is time invariant or whether it is a new(old) phenomenon as international relationships evolve and the old order is replaced by a new one.

The period in question has indeed witnessed the commencement of several measures to liberalize international trade. Two notable agreements with direct impact on the US firms are NAFTA and WTO, coming into effect in 1994 and 1995 respectively. One channel through which these agreements could influence the generality of patents is the expected one and by encouraging firms to shift a larger share of their operations overseas.

The full picture, however, could be more complex. For instance, the introduction of WTO was accompanied by an agreement on the trade-related aspects of intellectual property rights that set the standards for the awarding and the protection of copyrighted material and innovations crossing borders. Besides, firms could have opted to switch trading partners in the new trade environment, perhaps from developed countries to developing countries. Each move can have implications for the underlying process of innovation. In a sign that innovation has been changing, there seems to have been a secular downward shift in the distribution of the generality of patents generated by the US firms which starts from 1994 (Figure 5). In view of the circumstances, it is instructive to observe whether our theorized mechanism is robust to the overhaul of trade relationships.

To investigate the issue, we split our sample into two subsamples, one spanning years 1985–1992 and the other spanning 1994–1999, with one-year gap in the middle, and re-estimate the model of generality separately for each subsample. The split leaves us with two

Variable	1985–1992 Generality USPTO (1)	1985–1992 Generality HJT (2)	1994–1999 Generality USPTO (3)	1994–1999 Generality HJT (4)
S_t	-1.100**	-0.786*	-0.501	-0.238
	(0.509)	(0.444)	(0.321)	(0.309)
$N4_t$ (SIC 4-digit)	-0.077**	-0.056**	-0.074***	-0.052*
	(0.031)	(0.028)	(0.025)	(0.027)
$N4_t \times S_t$	0.181***	0.136**	0.193***	0.134**
	(0.067)	(0.061)	(0.064)	(0.068)
Adj. R^2	-0.046	0.010	0.025	0.049
F	29.64	56.48	27.73	51.39
Cragg–Donald test	211.4	188.6	316.8	299.0
Anderson–Rubin F	11.084	5.871	8.363	4.977
p-value	[0.000]	[0.003]	[0.000]	[0.007]
N	119,574	119,574	140,087	140,087

Table 8: The 2SLS estimates of key variables for the index of generality as dependent within two time periods, using the log of exports and its interaction as instrument. The numbers in parentheses are standard errors, clustered by firm–year. ***, ** and * indicate significance at 1%, 5% and 10%, 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.

subsamples of almost comparable observation sizes. In addition, the second subsample is particularly focusing on the period of trade liberalization. We estimate the models for each subsample using 2SLS and using the log of export as the key instrument. The estimation results for each subsample is listed in Table 8.

The main conclusion from this table is that the key findings of the previous sections still hold, and the signs of the effects are unchanged regardless of which subsample one is looking at. The only time dependent effect seems to be that of S. The coefficients for this variable are much larger in absolute value during the earlier period and smaller in magnitude and statistically insignificant during the later period. The number of products and its interaction with international share do not show any time-variant features from one subsample to the other.

Dependent: Variable	Originality USPTO (1)	Originality HJT (2)	Originality USPTO (3)	Originality HJT (4)
S_t	-0.557***	-0.276	-0.510***	-0.267
	(0.174)	(0.175)	(0.148)	(0.162)
$N4_t$ (SIC 4-digit)	-0.049***	-0.030**		
	(0.012)	(0.013)		
$N4_t \times S_t$	0.128***	0.079**		
	(0.031)	(0.032)		
NH_t (Herfindahl)			-0.047***	-0.030**
			(0.011)	(0.012)
$NH_t \times S_t$			0.119***	0.080***
			(0.027)	(0.029)
Adj. R^2	0.035	0.047	0.040	0.048
F	68.48	76.37	70.00	75.58
Cragg–Donald	886.3	750.0	978.0	836.9
Anderson–Rubin F	8.405	5.074	8.417	5.407
p-value	[0.000]	[0.006]	[0.000]	[0.004]
#Obs	280,671	280,671	280,671	280,671

Table 9: The 2SLS estimates for the index of originality 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.

4.6 Originality of Patents

We also investigate the robustness of our results by considering the index of originality as the degree to which patents are fundamental. As we already explained in Section 3, 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 fundamental innovation as the one that applies to multiple distinct fields. We estimate model (5) through a 2SLS estimation using the indexes of originality as dependent and the log exports and its interaction as instruments. Table 9 reports these results.

The overall picture offers the same insight as the results in previous tables. The share of international production 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.

5 Conclusion

In this paper, we build on previous findings on the localized nature of knowledge spillovers, but we additionally show that multinationalization of production increases the scope of innovation when a firm engages in a diversified portfolio of products. Two features define this prediction. First, fundamental innovation can be applied to several product lines but is geographically more difficult to transfer abroad to foreign production sites. In contrast, specialized innovation is limited to one product line, but can be easily transferred and used (internationally) in multiple locations. This is in line with vast existing evidence among which are surveys on multinationals summarized in Mansfield *et al.* (1979), Kuemmerle (1999), Frost and Ensign (2002), and Naghavi and Comune (2012) for several industries and in different countries. These studies suggest that fundamental innovation continues to take place in the headquarter home location of firms, while the R&D in subsidiaries tends to focus on incremental or adaptation efforts and the application of existing scientific and technical knowledge. Second, we emphasize learning spillovers that occur from international operations and how these can increase in their magnitude when a firm is active in more product lines regardless of the diseconomies of scope. This is in line with the concept in Noteboom (2000) that the heterogeneity of knowledge is essential for learning and should be "sufficiently small to allow for understanding, but sufficiently large to yield non-redundant knowledge." Moreover, we add the concept of learning to the hypothesis by Nelson (1959) by stating that firms operating in diverse industries are able to do more research of a fundamental nature through the learning externalities that arise from multinational activities.

The results reveal that the product range of firms plays a decisive role in determining how the geographical fragmentation of production impacts firm incentives to engage in different types of innovation. Our findings are threefold. We first confirm that the negative international knowledge spillover effect of MP is present and actively reduces fundamental innovation. We then show that the positive learning effect of using various production locations kicks in as a firm engages in more product lines. We conclude that firms with a larger share of MP engaged in a larger range of product lines tend to better exploit learning due to the heterogeneous nature of their knowledge and increase their fundamental innovation. In contrast, firms with less product lines that geographically separate production from innovation focus on more specialized types of R&D.

Although our approach does not take into consideration cost heterogeneities among products of a firm, the notion of innovation in our model parallels that in Eckel *et al.* (2011), where the two kinds of investment are made on quality rather than process innovation. In their work, a more broad type of innovation could enhance the attractiveness of the firm's brand (i.e. all products), while a more specific innovation improves only the quality of an individual product. Interestingly, they show that a higher level of product differentiation induces firms to invest relatively more in the quality of individual varieties than in the quality of their overall brand. An interesting extension of the current framework would be to account for the distance of a variety from the core competence of a firm in order to distinguish between innovation aimed at the quality of its core competence as opposed to more generic attempts to improve the overall performance of firms. Doing so allows us to study yet another dimension of MP by looking at how multinationalization impacts the innovation decision of firms in their core and non-core sectors.

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A Appendix

A.1 A Numerical Example

Suppose that the diseconomies of scope take a specific functional form that is increasing in N:

$$\psi(N) = 1 + N.$$

Note that $\psi(0) = 1$ and is linearly increasing in N. This gives the positive diffusion effect of a larger set of products a concave shape. In other words, the benefits from fundamental innovation are decreasing in N as the function $\frac{N}{\psi(N)} = \frac{N}{1+N}$ is concave. Incremental costs of introducing new products are also increasing in N inducing more specialized innovation. This also works as a negative force towards the share of investments dedicated to fundamental innovation. To capture this, we give a simple functional form to $\gamma(N)$ that is linear in N (with $\gamma(0) = 0$) that is:

$$\gamma(N) = N.$$

Equation (3) hence turns to:

$$\Omega \equiv \frac{\zeta}{\zeta + N\omega} = \frac{\frac{c_0^2}{r_f^2}\frac{N}{(1+N)^2}(1+SN)^2(1-\phi S)^2}{\frac{c_0^2}{r_f^2}\frac{N}{(1+N)^2}(1+SN)^2(1-\phi S)^2 + \frac{N^2}{r_s^2}}. \tag{6}$$

We further give values $c_0 = 0.9$, $r_f = 0.2$, $r_s = 0.2$ and $\phi = 0.5$ without loss of generality. Figure 6 depicts the effect of MP on the quality of innovation for different levels of product range $N = 0.5$, $N = 1$ and $N = 2$. It is easy to see that when the product range is small, a higher fraction of MP reduces the scope of innovation. Increasing the number of product lines to $N = 1$, we see the positive learning spillovers taking effect for low values of S creating an inverted-U shaped relationship between Ω and S. Finally, for a sufficiently large product range such as $N = 2$, MP is always increasing Ω, except for very large values of S. As we saw in the empirical section, the maximum value of S in our data is low. The effect of MP on the scope of innovation hence turns out to be unambiguously positive.

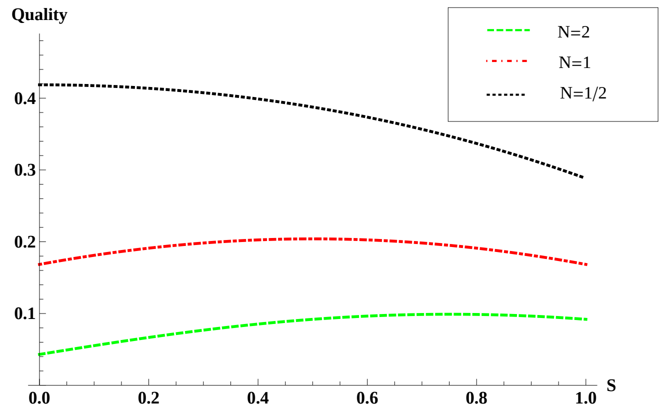

Figure 6: The relationship between the scope of innovation and MP

A.2 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.3 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.4 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 (5) 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 10. 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.

Dependent: Variable	Generality USPTO (1)	Generality HJT (2)	Generality USPTO (3)	Generality HJT (4)
S_t	-0.066***	-0.038***	-0.069***	-0.042***
	(0.013)	(0.012)	(0.013)	(0.012)
$N4_t$ (SIC 4-digit)	-0.007***	-0.003**		
	(0.002)	(0.001)		
$N4_t \times S_t$	0.018***	0.008**		
	(0.004)	(0.004)		
NH_t (Herfindahl)			-0.008***	-0.003**
			(0.002)	(0.001)
$NH_t \times S_t$			0.021***	0.011***
			(0.005)	(0.004)
$\log(SALE_t)$	-0.004***	-0.010***	-0.004***	-0.010***
	(0.001)	(0.001)	(0.001)	(0.001)
r_t	0.006***	0.008***	0.006***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)
a_t	-0.003***	-0.001**	-0.003***	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
Log Likelihood	-1.7e+05	-1.6e+05	-1.7e+05	-1.6e+05
χ^2	6,971.5	7,485.3	6,993.6	7,491.3
p-value	[0.000]	[0.000]	[0.000]	[0.000]
#Obs	312,558	312,558	312,558	312,558

Table 10: 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.

To test the robustness of the results to the endogneity problem, we ran a few IV regressions with the main results reported in Tables 6 and 7. 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 11 reports the first stage results for Table 6, 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 7, and the first-stage results are listed in

Variable	(1)	(2)	(3)	(4)
S equation				
$\log(1+EXP_t)$	-0.018***	-0.017***	-0.019***	-0.018***
	(0.007)	(0.006)	(0.007)	(0.006)
$\log(1+EXP_t) \times N4_t$	0.008***	0.008***		
	(0.002)	(0.002)		
$\log(1+EXP_t) \times NH_t$			0.008***	0.008***
			(0.002)	(0.002)
1st Stage F-test	11.63	12.52	11.53	12.78
$N \times S$ equation				
$\log(1+EXP_t)$	-0.028**	-0.026**	-0.022*	-0.022*
	(0.014)	(0.013)	(0.013)	(0.012)
$\log(1+EXP_t) \times N4_t$	0.033***	0.033***		
	(0.006)	(0.006)		
$\log(1+EXP_t) \times NH_t$			0.031***	0.031***
			(0.006)	(0.006)
Kleibergen–Paap test	3.321	3.363	4.095	4.285
N	282,482	282,482	282,482	282,482

Table 11: First stage estimates for Table 6, where the value of exports is used as the key instrument. Numbers in the parentheses are standard errors.

Table 12 with similar interpretation.

Variable	(1)	(2)	(3)	(4)
S equation				
$\log(1+IMP_t)$	-0.017***	-0.016***	-0.016***	-0.015***
	(0.005)	(0.005)	(0.006)	(0.005)
$\log(1+IMP_t)\times N4_t$	0.006***	0.006***		
	(0.002)	(0.001)		
$\log(1+IMP_t)\times NH_t$			0.005***	0.005***
			(0.002)	(0.001)
1st Stage F-test	6.85	7.47	5.35	6.14
$N\times S$ equation				
$\log(1+IMP_t)$	0.003	0.004	0.004	0.004
	(0.014)	(0.014)	(0.013)	(0.013)
$\log(1+IMP_t)\times N4_t$	0.017***	0.017***		
	(0.005)	(0.005)		
$\log(1+IMP_t)\times NH_t$			0.016***	0.016***
			(0.005)	(0.005)
Kleibergen–Paap test	6.312	6.876	5.092	5.736
N	282,482	282,482	282,482	282,482

Table 12: First stage estimates for Table 7, where the value of imports is used as the key instrument. Numbers in the parentheses are standard errors.