Division of Labor and the Transmission of Growth*

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Abstract

This paper studies how an independent upstream capital good sector in a technology based industry can act as a mechanism for the transmission of growth across countries. Technologies, once developed, can be 'transferred' to other countries at low incremental cost. If there are upstream firms which specialize in providing technology and engineering services to downstream buyer firms, then the greater the number of such specialists, the greater the net surplus that buyers get. Since the number of specialists is determined by the size of the downstream sector, the growth of the downstream sector in leading countries (first world) has beneficial effects for the growth of the downstream sector in follower countries (less developed countries). We empirically test this proposition using a comprehensive data set of investments in chemical plants in the developing countries during the 1980s. We find that one additional specialized supplier in a given process technology would have increased the expected investment in LDCs by $100 million to $200 million, with the increases greater in more mature technologies, and for larger LDCs.

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1 Introduction

It is almost an article of faith for economists that specialization -- division of labor among firms -- promotes economic welfare. For instance, if the optimal scale of production for an input is larger than the optimal size of the firm itself, a specialized producer can produce the input more efficiently because it can spread the fixed cost over a larger volume of output. Hence, division of labor is thought to be more extensive in larger markets (Smith, 1776; Stigler, 1951). In turn, the more efficient production of the upstream input induces the downstream industry to grow more rapidly (e.g., Young, 1929).

But although plausible, there exists little systematic evidence on the effect of division of labor. In this paper we study how a division of labor in one country has beneficial spillovers for other countries. We show that an increase in the number of upstream technology suppliers in the chemical processing sector (in developed countries) substantially increases the investments in chemical plants in developing countries. The increased investment arises from a combination of an increase in the number of chemical plants and an increase in the average investment per plant.

As is well known, the small size of the domestic market of less developed countries (henceforth, 'LDCs') can be an important constraint on their growth. A typical constraint is that a small downstream sector limits the size of the upstream sector that supplies capital goods or technology. A small upstream sector in turn prevents the downstream sector from reaching its full potential. (See for instance Rosenberg, 1976.) The 'big push' theories, which suggest that countries need to coordinate investments on a broad front, are motivated by similar concerns (e.g. Nurkse 1953; Murphy, Shleifer and Vishny, 1989).

However, if the key upstream input can be transported cheaply, trade can relax the constraint of market size. Technology is such an input *par excellence*. Once developed, it can be applied at low incremental cost, and unlike many material inputs, technology can be transported at low cost. Thus, a specialized upstream sector producing technology can be an important means through which economic growth is transmitted across countries.

The paper is organized as follows. Section 2 provides the conceptual underpinnings of our approach and its links to the literature on international trade and endogenous growth. Section 3 presents a brief historical description of the chemical industry and the rise of the SEFs. This provides the basis for our model in section 4. Section 5 presents our empirical results. Section 6 extends the empirical analysis using dollar values of investment in chemical plants. Section 7 concludes the paper. An appendix describes in detail our data set along with some of its limitations.

2 Division of labor in a historical context

In this paper, we focus on investment in chemical plants in LDCs during 1980-89, and the role of firms that specialize in providing process technology and engineering services in developed countries (henceforth 'first world'). During the 1950s and the 1960s the chemical industry in the first world grew at a very fast rate. This growth stimulated the growth of firms that specialized in the design and engineering of the chemical processes. These specialized engineering firms, SEFs, were important reservoirs of expertise in chemical plant technologies, which they provided in the form of engineering services to the chemical firms. In the 1970s, and especially in the 1980s, as a modern chemical industry emerged in LDCs, it benefited from the presence of the process engineering sector that existed in the first world. Since then, SEFs from the first world are important suppliers of process technologies and related services to the domestic chemical industries in LDCs. In short, the growth of the chemical industry in the first world created an upstream sector, which later spurred the growth of the chemical industry in the third world during the 1980s.

Before discussing its details, we wish to highlight two important ingredients of our story. The first is that the cost of developing technical expertise are assumed to be much greater than the cost of 'transporting' it over space. Our emphasis on the lower cost of using technological capabilities compared with the cost of developing them is similar in spirit to the literature on endogenous growth (e.g. Romer, 1986, 1996). Clearly, applying what one has learnt in one place in another is not always easy, and the literature has shown that technology transfer is not costless (e.g., Teece, 1988). But what is important for our argument is that the transfer cost be substantially smaller than the cost of developing technology, an assumption that fits especially well in the context of technology and engineering services.

Second, we study the effects that arise when the creation of new markets follows a historical sequence. Our perspective differs somewhat from the way division of labor has typically been examined. Traditionally, the literature has focused on how revolutions in transportation or trade liberalization, by integrating hitherto distinct markets, give rise to more extended division of labor and growth. For instance, Rivera-Batiz and Romer (1991) argue that international economic integration increases growth because, with integration, the fixed cost of producing 'ideas' can be spread over a larger market. Instead, in our model the number of SEFs in the first world does not increase when the first world and LDC markets are integrated. Although analytically convenient, the primary reason for our assumption is that it is more faithful to history. We believe that most SEFs arose to serve the first world market and their investments were not motivated by the hope of serving LDC markets that did not as yet exist.

Further, while the analysis of the effects of economic integration is important, new markets typically do not arise in a timeless fashion. Indeed, the point is that the rise of new markets can be induced by the growth of existing markets. SEFs arose at a time when chemical production in LDCs was very modest, especially compared to the first world. Thus the bulk of the fixed costs of technology development were incurred by the SEFs were amortized over the first world markets. Once incurred, these costs were sunk.[1]

Is not this simply a story about international trade? The answer is yes, but with one important qualification. While the standard Heckscher-Ohlin trade model locates comparative advantage in natural resources or factor endowments, we locate it in the fact that chemical engineering services are based on cumulative learning and experience, and that the (fixed) costs of acquiring this expertise are already sunk when new markets arise.

Put differently, the distinction between our story and standard trade theory is that history is central to ours. If all countries started *tabula rasa*, the conventional trade argument predicts that the first world would develop an upstream chemical engineering sector if it has a comparative advantage in this sector and LDCs would specialize elsewhere. We remain agnostic on this point; we argue instead that the first world has a comparative advantage in engineering services simply because first world engineering firms were founded 40 to 50 (and in some cases, more than a 100) years ago in response to the growth of the oil and chemical sectors in their own countries. Having incurred the sunk costs of developing the required technological capability, the first world engineering firms now compete to supply the developing country markets. The crucial part the transmission mechanism whose effects we study in this paper is that the first world chemical firms, not LDC firms, ultimately paid for the investments of SEFs in technology development and learning.

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[1] If all industries arise at the same time, a division of labor is still beneficial in the sense that the fixed cost can be split over a larger volume of output. Each user sector then provides a beneficial externality to others, with larger users bestowing a greater externality.

Our paper is also related to the literature on the product life cycle (e.g. Vernon, 1979). The simplest product life cycle theory says that new products (industries) arise in the first world, and as they mature, the products are produced in LDCs as well. But the literature has focused on one mechanism through which this transfer of products and technologies occurs – multinational enterprises operating in final product markets (e.g. Nadiri, 1993). Sometimes the focus on multinationals has been justified by the argument that the upstream inputs are non-tradable, while the downstream products are (e.g. Rodriguez-Clare, 1996). In fact, in the chemical industry as in other high-tech industries, a key upstream input -- intangible knowledge and expertise -- is easier to move across locations, while the final products (chemicals such as ammonia and ethylene) are costly to transport.

We do not dispute that multinational enterprises are an important vehicle for technology transfer and for the growth of the host countries. However, contrary to conventional wisdom, we submit that when technologies are based on systematic body of knowledge (in this case, chemical engineering), multinationals are not the only, or even the most efficient, way of transferring technology. Instead, as in the chemical industry, specialized technology suppliers competing amongst themselves are the predominant means of technology transfer.[2]

As a guide to understanding our empirical results, we develop a simple model. We assume that the surplus from investing in a plant differs across LDC firms and also depends on the source of the process technology. A larger number of suppliers enables the buyers to choose from a larger pool, and this reduces the cost of acquiring the engineering services. It follows that an increase in the number of

[2] This also points to the importance of independent suppliers that do not produce the downstream product. Downstream producers are less likely to sell technology or other key inputs to other producers. Unlike upstream specialists (like SEFs), downstream producers (chemical firms) have to offset the gains from selling technology against the loss in actual or potential revenues from selling the downstream product. Thus, in addition to the classical gains from division of labor, specialization can have important pecuniary externalities that are sometimes overlooked.

SEFs increases the expected surplus that a buyer obtains. Our specification is consistent with a variety of ways in which buyers benefit from an increase in the number of SEFs including a lower prices, better contractual terms, lower search costs and availability of more advanced or more appropriate technology.

The model predicts that a larger number of SEFs in the first world implies greater investment in LDCs. From the point of view of LDCs, the number of potential suppliers (SEFs) is 'exogenous' – it is determined by the extent of division of labor in the first world. Thus, the organization of the industry in the first world, or to be precise, the extent of division of labor in the first world, influences the growth of the LDC chemical markets. A second implication is that an increase in the number of first world SEFs is associated with an increase in the number of plants in LDCs whose engineering services are 'bought' from an SEF, and negatively related to the number of plants whose engineering services are 'made' in-house by the chemical firm. The final implication of the model is that the beneficial effects of an increase in the supply of SEFs are more pronounced for companies that have higher cost of 'making' the technology in-house. Hence, SEFs can be more beneficial for local third world companies than for the multinational enterprises that locate in these markets. The model is tested using a comprehensive data set of more than 20000 chemical plants constructed during the 1980s worldwide.

3 Division of labor in the chemical processing industry

The chemical sector is one of the most important sectors of modern economies. In the US, it is the largest manufacturing sector, accounting for over 10% of the value added in manufacturing, and about 2% of the GDP. The chemical industry is also a leading 'high tech' sector. It is the fifth largest in the US in terms of total R&D spending, accounting for over 15% of total industrial R&D, and the largest in terms of privately financed R&D. In addition to the chemical industry proper (SIC 28), which includes organic and inorganic chemicals, plastics and synthetic fibers, chemical processing technology is used in a number of related sectors including rubber, oil refining, metallurgy and food processing.

Although the industry was quite large on the eve of world war II, its growth the in the developed countries accelerated sharply in the two decades after the war. Major product innovations in synthetic fibers and plastics contributed to growth rates that were about two or three times those of GDP (Freeman, 1968). This period also witnessed the development of major process innovations, which were followed by incremental process improvements. Very often these incremental efforts aimed at increasing the size of chemical plants to benefit from economies of scale in chemical production (Enos, 1962; Spitz, 1988; Stobaugh, 1988).

Before the war chemical and oil firms typically designed, engineered and built their own plants. But over time, minimum efficient scales expanded and, as process technology became more complex and sophisticated, the value of acquiring expertise in the design and engineering of plants increased. The rapid growth of demand after the second world war provided the opportunity of firms to specialize in the design, engineering, and construction of chemical plants. With increasing competition among chemical firms, even a small reduction in manufacturing costs was important for profitability. Chemical producers were therefore willing to employ specialist firms which would provide improved processes and cost efficient plants.

In addition to increases in the size of the market, there are some distinctive features of the chemical industry that encouraged specialization in process technology. First, the development of the discipline of chemical engineering provided a scientific and formal basis for the development of chemical processes. (See for instance Rosenberg, 1997.) Second, for a number of standardized chemical products, there was a separation between product and process innovation. This separation, in which chemical engineering also played an important role, lowered transaction costs for process specialists because their innovations were not idiosyncratic to particular downstream producers. Finally, oil companies played a critical role by taking the lead in "outsourcing" the engineering and design of oil refineries.[3]

The advantages of SEFs were the typical advantages of specialization. By working for many clients, they benefited from learning by doing. Thus, by the 1960s, SEFs had come to occupy an important place in the industry. Freeman (1968, pp. 30) notes that for the period 1960-66, "... nearly three quarters of the major new plants were 'engineered', procured and constructed by specialist plant contractors". These figures are confirmed by more recent data. (See Arora and Gambardella, 1997.) Table 1 shows the percentage of plants in different sectors of the chemical and related industries that are engineered in-house by the chemical firms. The table covers all the plants completed or constructed in the world during 1980-1990, and shows separately the percentage of 'makes' for plants located in the first world and in LDCs.[4] The table shows that in most sectors the bulk of the plants are engineered by SEFs, and it is indicative of the extent of division of labor in the chemical processing industries today. Moreover, the importance of SEFs is even more pronounced for plants located in LDCs than in the first world.

Most of the SEFs were founded very early after the war, although some are over a century old. They had varied backgrounds. Some of them where civil engineering constructors (e.g. Bechtel), while others (e.g. Lurgi or Lummus) were equipment makers for the chemical industry. As these firms grew in their ability to handle more sophisticated tasks, process design and engineering too came to be a

[3] See Arora and Gambardella (1997) for a more detailed discussion of the factors that encouraged the growth of process specialists in the chemical and oil refining industry.

part of their activities. SEFs originated as an American phenomenon. Soon, however, Europe and Japan developed their own SEFs. Till the 1970s, the market for chemical engineering services was largely confined to these three regions (e.g., Linder, 1994.) But when the developing countries sought to develop domestic chemical industries, SEFs from the advanced regions represented an important source of technology and process know-how. Many SEFs from Europe, Japan, and the US competed for new contracts in these countries. By the end of the 1980s, there was a large number of first world SEFs competing in LDC markets.[5]

Before proceeding further, we wish to clarify our terminology. In what follows, we analyze the market for engineering services of SEFs. This is not the market for the ultimate chemical product, even though the demand for plant design and engineering services is clearly derived from the demand for the final products. However, many markets in our sample do not map neatly to well defined products like polypropylene or ABS resins. Some of the markets are strictly processes, such as desulphurization and hydrogen recovery, that are applicable across a variety of products. Thus, by market we mean the market for the design and engineering services of a given type of process plant. The process plant may correspond to a well defined product like urea and polyvinyl chloride (PVC), or be a more generic process like hydrogen recovery or nitrogen separation.

4 The Theoretical framework

4. 1 Description of the model

Figure 1 summarizes the two critical effects that we want to highlight in our model.

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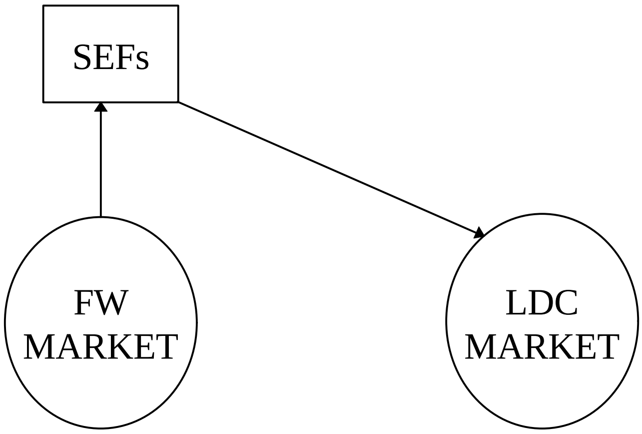
[4] The data are from Chemical Age Profile. This is the source of data that we use in our empirical analysis in section 4 below. This data set is described in section 4 and in the Appendix.

[5] In some of the more advanced LDCs in Asia or Latin America, domestic SEFs also entered their national markets. Typically, these SEFs were the outcome of attempts at self reliance that guided economic policies in many third world countries. First world SEFs however remain the main source of technology and engineering expertise.

Figure 1: *The transmission of growth*



First, the growth of the first world market for a given chemical process encourages the rise of engineering firms specialized in the design of chemical plants for that process. This result, which we do not formally prove here, is completely intuitive. It only requires that entry as an SEF have a fixed cost (corresponding to the cost of acquiring technical expertise), and that the price-cost margins (profits per unit of output) that SEFs earn, decline with the number of SEFs in that sector.

The second effect is from the SEFs in the first world to the size of the LDC market. To understand this effect suppose that for some reason first world SEFs could not move to LDCs. Then the number of potential suppliers of engineering services for that process in LDCs would be determined entirely by the size of the LDC market. But when the chemical markets first develop they are likely to be much smaller than in the first world. Hence, fewer SEFs would enter. In turn, fewer SEFs would imply that the expected surplus of setting up a plant would be lower. As suggested in the introduction, this could be due to a number of reasons. Having fewer SEFs to choose from increases search costs, reduces the likelihood of getting a plant design that ‘fits’ the buyer’s local raw material and output market needs, and lowers the bargaining power of the buyer. But if SEFs from the first world can ‘costlessly’ move to LDCs, then the number of potential SEFs for any chemical process in LDCs would be the same as the number of existing SEFs in that process market in the first world.

This simple stylized story rests on one obvious assumption, namely that the critical input is easily ‘tradable’ across countries. It is important to understand why is this input tradable, and what makes it tradable. To illustrate this point we borrow an example from the history of another industry. In his study of the US machine tool sector in the XIX century, Rosenberg (1976) noted that the various downstream industries using machine tools for their operations did not emerge contemporaneously. Firearm manufacturing emerged earlier than sewing machines, typewriters or bicycles. The growth of the firearm industry then spurred the growth of a machine tool sector specialized in the production of machines to cut metals into precise shapes. As Rosenberg points out, when the bicycle or other mechanical industries arose a few decades later, they had to perform metal cutting operations that were very similar to those of the firearm industry (e. g., boring, drilling, milling, planing, grinding, and polishing), and these were performed using very similar machines. This meant that what was learnt in the firearm industry to produce the metal cutting machines did not have to learnt again in bicycles. Hence, the machine tool producers could move across sectors even though these sectors were quite distant from the point of view of their final products. The ‘commonality’ in the learning processes, or what Rosenberg called ‘technological convergence’, was critical for the transmission of growth through the intermediation of an upstream sector.

If we look at this issue across countries rather than across sectors, the same logic applies. The technical expertise to produce ammonia plants in the US need not be acquired again to produce ammonia plants in India. Clearly chemical plants have to be adapted and modified to suit local conditions. But what remains unchanged are the basic principles and technologies of how an ammonia plant should be designed and engineered. The suppliers of the technology, and of the related technical expertise, have to bear the additional costs of adapting their knowledge to the specific conditions of the new plant but they do not have to incur again the cost of 'discovering' how an ammonia plant works or how to design it.

It is in this sense that the fixed cost of developing or inventing the technology is paid by the industries that emerge earlier (firearms or US fertilizer producers), while the industries that come later (bicycles or Indian fertilizer manufacturers) pay only the marginal cost. If for any reason the technology had to be invented again in the new country, there would be no transmission mechanism: Technological convergence is then the enabling factor for the transmission of growth mediated by division of labor. Division of labor is important because if the convergent technology remains in the hands of producers, they are less likely to develop it as rapidly and to apply it as broadly as specialized suppliers. Specialized suppliers competing amongst themselves have the incentives to disseminate technology as broadly as possible.

4. 2 The model

We focus our analysis on the investment decision of chemical firms in LDCs. We posit that the first world market for any given process technology has already emerged and a division of labor has been achieved in a previous stage. In other words, we take as given the number of SEFs, *k*, which have entered the market for engineering services in the first world[6]. We assume that first world SEFs can

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[6] In an earlier working paper (Arora, Fosfuri and Gambardella, 1996) we treat *k*, the number of first world SEFs, as endogenous. By modeling the upstream sector as competing on price, with a

costlessly move to LDCs, with technology-specific costs already sunk and 'paid for'[7]. Therefore, the number of SEFs which can potentially serve a LDC market is equal to *k* (i. e. the number of SEFs in the first world), and note that *k* is independent of the LDC market size[8]. We also assume that SEFs are ex-ante symmetric.

Let us now turn to the LDC market. We do not explicitly model downstream competition (i.e., competition in the chemical product market). Final demand generates a potential demand of inputs -- chemical plants -- that we take as given. We denote by *N* the exogenous potential demand for chemical processes and assume that the investment decision of a given chemical company in a given plant is independent of the investment decision in any other plant, even by the same user. When considering whether to invest in a new plant, each downstream firm has three choices. It can either not invest (and hence earn zero), or it can 'buy' engineering services from SEFs, or it can 'make' (engineer) the plant by itself.

We denote by $\Omega = \{B, M, f\}$ the set of possible alternatives where *B* stands for a plant bought from the upstream technological sector, *M* for in-house engineering and f for no investment. Also, let $S = B \bigcup M$ where *S* denotes the observed size of the LDC market.

Let p_n be the net surplus to a given buyer (chemical firm) from a plant supplied by the n^{th} SEF. We assume that p_n is ex-post idiosyncratic to the buyer-seller

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fixed entry cost and stochastic variable cost of engineering a plant, we show that *k* increases with the size of the market for engineering services in the first world.

[7] This could be easily generalized by allowing for the possibility that technology transfer is not costless and SEFs have to bear two types of fixed costs: product-specific, which are already sunk, and country-specific, which have to be incurred for each country in which SEFs want to penetrate. See Arora, Fosfuri and Gambardella (1996) for further details.

[8] Strictly speaking, this is true only if the size of the LDC market is too small to induce further entry. Also, we are assuming that first world SEFs are not fully forward looking. Else they would anticipate that a given LDC market would arise in the future and they would adjust their optimal investment (entry) decision. As noted earlier, neither assumption is formally necessary for LDCs to benefit from first world SEFs.

match. Therefore, p_n is an *i i d*. random variable with distribution function *G(.)*. Also, let $z = \underset{n}{Max}\, p_n$. Then, $\Pr(z \le t) = G^k(t)$, is the probability that the net surplus from running a plant bought from the upstream sector is less or equal than *t*. Finally, for any chemical firm let *a* be the net surplus from an in-house technology and let *a* be distributed according to the cumulative function *F(.)*.

We now analyze the investment decision of chemical firms in LDCs. By using the notation introduced so far, if $Max\{z, a\} \ge 0$, the firm will invest in the plant. Moreover, if $z \ge a$ the firm will buy the engineering services; and if $z < a$ it will supply them in-house. The expected number of plants, *E(size),* in a given LDC market is:

$$E(size) = N\left[\Pr(\Omega = S)\right] \tag{1}$$

where $$\Pr(\Omega = S) = 1 - F(0)G^k(0) \tag{2}$$

Result 1: *The total investment in a given LDC market, E(size), increases with the number of (potential) technology suppliers, k.*

<u>*Proof*</u>. By taking first differences with respect to *k* in expression (2) we get:

$$E(size|k+1) - E(size|k) = N\left\{F(0)G^k(0)\left[1 - G(0)\right]\right\} > 0 \tag{3}$$

which suffices to show Result 1.■[9]

Analogously we can write the expected number of plants that are bought from the upstream technological sector, *E(buy),* and the expected number of plants that are made in house by the chemical firms, *E(make)*:

$$E(buy) = N\left[\Pr(\Omega = B)\right] \tag{4}$$

$$E(make) = N\left[\Pr(\Omega = M)\right] \tag{5}$$

[9] It is also easy to see from (3) that E(*size*) is concave in *k*, so that the marginal increase in investment diminishes with *k*.

where $$\Pr(\Omega = B) = 1 - F(0)G^k(0) - \int_0^\infty G^k(t)dF(t) \tag{6}$$

$$\Pr(\Omega = M) = \int_0^\infty G^k(t)dF(t) \tag{7}$$

Now, by writing $\frac{\Delta E(buy)}{\Delta k} \equiv E(buy|k+1) - E(buy|k)$ and similarly for $\frac{\Delta E(size)}{\Delta k}$ and $\frac{\Delta E(make)}{\Delta k}$ we can state our second result:

Result 2: $\frac{\Delta E(buy)}{\Delta k} > \frac{\Delta E(size)}{\Delta k} > 0 > \frac{\Delta E(make)}{\Delta k}$

Proof. First note that $\frac{\Delta E(buy)}{\Delta k} = \frac{\Delta E(size)}{\Delta k} + \frac{\Delta E(make)}{\Delta k}$. Then, by taking first differences in expression (4) with respect to *k* one obtains:

$$\frac{\Delta\left[E(buy)\right]}{\Delta k} = \frac{\Delta\left[E(size)\right]}{\Delta k} - \int_0^\infty [G(t)-1]G^k(t)dF(t) > \frac{\Delta\left[E(size)\right]}{\Delta k} \tag{8}$$

which completes the proof.■

Finally, consider any variable *x* which increases the net surplus from running a in-house engineered plant (i.e. increases the profitability of the 'make' strategy). One could think of *x* as some characteristics of the process or as the level of in-house technological capability of the chemical firm. (We shall interpret it as the latter in this paper.) Formally, we assume that $x_1 \geq x_2$ implies $F(t;x_1) \leq F(t;x_2)$ for any *t*. We can then state our third result.

Result 3: $\left.\frac{\Delta\left[E(size)\right]}{\Delta k}\right|_{x=x_1} \leq \left.\frac{\Delta\left[E(size)\right]}{\Delta k}\right|_{x=x_2}$ *for all* $x_1 \geq x_2$.

Proof. One can rewrite $\left.\frac{\Delta\left[E(size)\right]}{\Delta k}\right|_{x=x_1} - \left.\frac{\Delta\left[E(size)\right]}{\Delta k}\right|_{x=x_2}$ as

$G^k(0)[1-G(0)][F(0;x_1)-F(0;x_2)]$ which is unambiguously non-positive. ■

Thus, other things being equal, the marginal effect on *E(size)* is lower when firms are characterized by a larger value of the parameter *x* (i.e., following our interpretation, when firms are multinational enterprises). The rest of the paper is devoted to empirically testing the three results derived in this section.

5 Empirical analysis

5. 1 Plant data and their limitations

Our source of plant-level data is Chemical Age Project File (CAPF), a data base compiled by Pergamon Financial Data Services, London (1990). This data base is described in more detail in the Appendix. The CAPF database contains information on 20581 plants all over the world in the broadly defined chemical sector for 1980-1989. For a given plant CAPF reports the name of the company that ordered the plant (the chemical company), the company that provided the engineering services (SEF), the name of the chemical process (e.g. ammonia, ethylene, coal gassification) and the location of the plant (country and city). CAPF plants are classified into one of 21 sectors. The complete list of these sectors is given in the Appendix.[10] In addition, CAPF provides the date on which the plant was first reported in the press (which provides an approximate date of the investment), and the status of the plant around the end of the 1980s. Most of the

[10] Along with core chemical sectors like inorganic chemicals, organic chemicals, petrochemicals and plastics, CAPF includes in sectors like oil refining, pharmaceuticals, food processing, pulp & paper and textile & fibers. Plants in these sectors are in essence chemical processing plants. In this paper we use only 9 sector dummies, obtained by aggregating the 21 CAPF sectors in larger groups of sectors with homogeneous characteristics. See the Appendix for further details.

plants in the data base were either 'completed' or 'under construction'. Some of them were 'planned', and a few were 'delayed', 'abandoned', 'canceled', or 'under study'. These records are not directly used in the empirical analysis, except for the calculations of some sector specific averages.

The CAPF is both comprehensive and enables us to identify whether for each plant the engineering services are 'bought' or 'made' because in the latter case the record for the plant reports 'staff' instead of the name of an outside contractor[11]. A serious limitation of this data base is that for about 45% of the 20581 plants the field of the engineering company is blank. Conversations with data providers in the industry suggested that these blanks could arise for a number of reasons. Companies may still be looking for suitable engineers (including possibly doing the engineering in-house), or they do not want to disclose the name, or simply the information is missing. However, as we shall see in the next section, our empirical analysis focuses only on the plants located in LDCs that are either completed or under construction. Within this sample, the percentage of blanks reduces to 21%.

We also performed a systematic diagnostic check of the blanks using information about these plants from another data base. The details of this check are discussed in the Appendix. The check suggested that the blanks may in fact be predominately 'buys'. To test the robustness of the results, we performed all our empirical analyses in the next sections under a variety of assumptions about the blanks – viz., all the blanks are 'buys'; all the blanks are 'makes'; the blanks are 50% 'buys' and 50% 'makes'; the blanks are distributed between 'buys' and 'makes' in the same proportion as in the case in which the name of the engineering

[11] In addition, we counted as 'makes' all the plants in which the engineering company was a subsidiary of the chemical company that operated the plant. Subsidiaries were determined using Predicasts (1991) and other company thesauruses. In some cases, plants were not engineered by independent SEFs, but by the engineering subsidiary of a chemical company unaffiliated with the buyer. These cases are rare and the vast majority of engineering services is provided by independent SEFs.

company (or 'staff') is observed. Here we present only the results in which we treat all the blanks as 'buys'. We note that all the other assumptions produced results that were even more favorable to our theory. Thus, we present here only the results which correspond to the least favorable assumption for our case.

5. 2 Variations across markets – a first cut at the data

Our goal in this empirical section is to estimate an equation linking the number of plants for a given chemical process in LDCs to the number of SEFs that operate in that chemical process market in the first world. Our first world countries consist of all the Western European countries, USA, Canada, Japan, Australia and New Zealand. (See the Appendix.)

We focused only on the 14893 plants that were either completed or under construction. These corresponded to 2081 processes. We constructed three main variables: $SIZEFW_i$ and $SIZELDC_i$ are the total number of plants in each of our 2081 processes in the first world and in LDCs, respectively, and KFW_i is the number of SEFs operating in each of these processes in the first world, where i is an index of the chemical processes.[12] Table 2 shows the distributions of $SIZELDC_i$, $SIZEFW_i$ and KFW_i by size classes. These distributions are very skewed, and most of the processes in our data base are 'small markets' with 0 or 1 plants.

The first column of table 3 presents a simple OLS regression of the number of plants in the third world ($SIZELDC_i$)on the size classes of number of first world SEFs (KFW_i). The table shows that the mean value of $SIZELDC_i$ increases as one

[12] Note that this is not the number of plants engineered by an outside contractor, but the number of different contractors operating in the i^{th} process market in the first world. Moreover, because we want to measure the number of potential suppliers, in counting KFW_i we did not restrict our attention to the plants that were completed or constructed. Even if a plant is planned or under study, but the name of the SEF is given, that SEF is presumably a potential supplier for the

moves to classes with a larger number of potential SEFs. Clearly, this result may be influenced by process-specific characteristics. To control for these effects, the second column of table 3 presents the same regression where we control for the size of the process in the first world and include sector dummies among the regressors. Although there is a decline in the effect of KFW_i for the largest class, there is a positive effect of KFW_i on $SIZELDC_i$ even after controlling for market size (SIZEFW) and sector specific effects.[13] The decline in the effect of KFW_i as we move to larger classes is suggestive of diminishing returns implied by our model.

These results could still reflect unobserved differences across processes. For instance, it could well be that processes that have greater potential application in the third world are also those where a larger number of SEFs exist. Even though we control for the size of the first world market, and for the sub-sector fixed effects, this may be inadequate. We try to get at this issue in several ways.

First, one implication of our model is that while KFW_i has a positive effect on the number of 'buys', it has a negative effect on the number of 'makes'. Note that in terms of the implications for economic development there is little difference between 'buys' and 'makes'; what matters is how much production capacity is created. But we test this implication of our theory to check whether our empirical measure of the potential supply of SEFs, KFW_i, actually captures the effect produced by a larger number of SEFs rather than simply reflect unobserved heterogeneity across the different processes. Thus, in the next section we estimate the conditional probability of 'makes' for a sample of 38 LDCs test whether it decreases with the number of SEFs in the first world.

process. In practice, it made very little difference whether in counting KFW_i one considered only the plants that were completed or under construction, or all the plants.

[13] The choice of the classes for KFW_i, $SIZELDC_i$, and $SIZEFW_i$ was somewhat arbitrary. We experimented with different classes but with little change in the results.

Second, we collected additional data on characteristics for a sub-sample of the processes, and re-estimate, in sections 5.4 and 5.5 below, the relationship between the number of SEFs and the investments in chemical plants using a panel data set composed of this sub-sample of processes and the 38 LDCs above. We also test the two implications of the model, namely that an increase in the number of SEFs should increase the investments in plants whose engineering services are ‘bought’, and decrease the investments whose engineering services are ‘made’. Section 5.6 also examines the implication that investment by LDC firms are more sensitive to the number of first world SEFs than investment by multinational enterprises investing in LDCs.

5. 3 Share of ‘makes’ – logit regression

As discussed earlier, if the observed relationship in table 3 is due to unobserved scale effects, then the conditional probability of ‘makes’ should also be positively related to the number of SEFs. On the other hand, our model in section 3 suggests that this conditional probability decreases with the number of potential SEFs.[14] Accordingly, we estimate a logit regression using observations at the plant level, where the dependent variable takes the value 0 if the plant is a ‘buy’, and 1 if the plant is a ‘make’.

Since the plants are located in different countries, we also need to control for country-specific effects. These data were obtained from two main sources. We obtained data on energy consumption and other measures of industrialization from UN Statistical Yearbooks, and macroeconomic data for countries from Barro-Lee (1994) – a standard source of consistent country-level data. We obtained reasonably complete data for 38 countries which account for about 80% of the

[14] Using the notation of our model, the size parameter N cancels out in the expression for this probability. Hence, the conditional probability of makes does not depend on market size, unless,

plants located outside the OECD area in our data base. The complete list of the countries is given in the Appendix. Table 4 lists the country-specific variables that we constructed.

Our logit regression is based on the 5006 observations corresponding to all the plants in the data base that are located in these 38 countries. The dependent variable is the dummy for 'makes' defined earlier. The independent variables include: a) country characteristics given in table 4 (indexed by *j*);[15] b) process market characteristics (indexed by *i*) -- the number of SEFs and sector dummies; c) plant characteristics — whether the plant is an expansion ($DEXPANSION_j$) or a revamp ($DREVAMP_{ij}$) of an existing plant.[16]

The results of our logit estimation are in table 5. The table shows that the conditional probability of makes is negatively related to the log of the number of first world SEFs. The estimates imply that a market with 5 SEFs in the first world would have a conditional probability of 'makes' that is smaller by 0.035 units than a market with only 1 first world SEF. This difference is not large, but this is only to be expected since the percentage of 'makes' in the sample is small. However, the estimated t-statistic of the coefficient of KFW_i suggests that this effect is statistically significant. We also estimated a multinomial logit in which we allowed for three possible choices, 'buys', 'makes', and 'blanks', where the latter accounted for the cases in which CAPF reported no information about the engineer. In this case the negative effect of KFW_i on the probability of 'makes' was even more pronounced. Thus our results may understate the true relationship.

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contrary to our assumptions, market size enters non-linearly into the probabilities of buy and make.

[15] We experimented with other characteristics such as steel production and the number of automobiles per capita, but found that population, GDP and total energy consumption jointly appear to capture the bulk of the measurable country specific features.

[16] CAPF provides this information for each plant. Also, we used $\log(1+KFW_i)$ because KFW_i can be equal to zero.

5. 4 Variations across markets and countries

Our logit regressions imply that the observed relationship between SEFs and investments in LDCs is unlikely to be simply due to unmeasured scale effects. But in order to directly estimate the impact of SEFs we need better ways of controlling for differences across processes, especially in potential demand for chemical plants. This poses some serious difficulties. For example, measures of the size of the downstream markets of these processes are possible measures of the size of the process markets. Yet, to identify appropriate measures of downstream demand for our 2081 markets can be prohibitively difficult because such disaggregated data are not available. Moreover, many of our processes serve similar downstream markets. For instance, all the processes to produce fertilizers in our sample would need measures of demand like the agricultural production in LDCs. The problem could be even more severe for processes which typically serve a variety of downstream sectors, such as air separation and oil refining.

The alternative approach we pursued was to re-design our sample so as to make it better suited to address these problems. We constructed a data set composed of the 38 countries defined in the previous section, and the 139 process technologies in the data base with 20 or more plants worldwide that are either completed or under construction. This gave us a balanced "panel" of 5282 observations, where the unit of observation is a process-country pair.

The obvious drawback of restricting to the 139 processes with 20 or more plants is that we are selecting on the dependent variable. However, as noted earlier, gathering information about processes with only a few plants is very difficult, and often, prohibitively so. For instance, as we shall see below, we constructed detailed measures of technological novelty and complexity using the number of patents in each of these processes, to use as controls for process heterogeneity. To develop such measures for all our 2081 processes is very costly. One could also use alternative selection criteria (i.e. random selection of markets, or stratified sample thereof), but one would still select too many 'small markets' for which developing reliable technological measures is very difficult, both as a conceptual and a practical matter. Moreover, restricting to the top 139 processes is probably not so serious a problem in practice. After all, the criterion we used enabled us to select a comprehensive sample of all the important and widely diffused chemical technologies in the world. We have also experimented with different cutoffs such as all markets with at least 10 or 40 plants in the entire data base. The qualitative results are very similar. Finally, even using the entire sample, albeit without such extensive controls, we obtained similar results, as reported in our earlier working paper (Arora, Fosfuri and Gambardella, 1996).

In addition, one advantage of using panel data is that we can use country specific factors to control for variations across markets. Using the notation of our model, the problem is that we want to find controls for *N*. In section 5.2 we used $SIZEFW_i$ as a control for N_i, i.e. the number of plants in market *i*. By contrast, we have now defined a market to be the combination of a process technology and a country, and we look at N_{ij}, where *j* is the index for countries.

Since our dependent variables are non-negative integers we used a negative binomial specification (see Hausman, Hall and Griliches, 1984). We used the following specification:

$$\log E(X_{ij}) = const + aY_j + bZ_i \tag{9}$$

where X_{ij} is either $SIZE_{ij}$, BUY_{ij}, or $MAKE_{ij}$, Y_j is a vector of country-specific characteristics, and Z_i a vector of process specific characteristics. We allow for factors like the size of country market (GDP_j, POP_j, $ENERGY_j$), or other country characteristics (human capital: $HKAP_j$; openness to imports of intermediate goods: $OPEN_j$, geographic area, presence of oil or gas reserves) to affect $SIZE_{ij}$, BUY_{ij}, and $MAKE_{ij}$.[17] We used the following process-specific characteristics as controls: sector dummies, log($SIZEFW_i$), log($COST\_FW_i$), log($PROCPAT_i$), and $NOVELTY_i$.[18]

The average plant cost for a certain process is likely to be correlated with the average size of the plants in that process. We control for this source of variation across processes through $COST\_FW_i$, which is the average reported cost of a plant in the first world in process *i*.[19] The variables $PROCPAT_i$ and $NOVELTY_i$ are two measures of the nature of the technology. PROCPAT is the total number of 1976-1997 US patents granted for the chemical process *i*. It covers only the patents relating to the process itself rather than to the use of the output produced by the process. In other words, for polyethylene, we only include patents dealing with the process for polyethylene production and exclude patents dealing with the extrusion of polyethylene resin or the use of polyethylene in the production of other articles. One plausible interpretation of PROCPAT is as a measure of the complexity of the process technology, and the potential for multiple inputs, pathways, and final product qualities.

PROCPAT was constructed as follows. We selected all relevant patents using a keyword search with the process as the keyword. From these, we selected and read the full abstracts of patents that exactly fit our criterion. The patent classes (and sub-classes) into which these patents were classified were examined to ensure that the invention was in fact a process invention. These subclasses of the US patent classification system were used along with the process name as the basis for the Boolean queries of the US patent database to generate the final set of patents,

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[17] We also estimated a specification using country dummies to control for country specific factors instead of the variables above, with no appreciable change in the results.
[18] Two of our 139 process had $KFW_i = 0$. For those products we set $KFW_i = 1$, and used log(KFW_i).
[19] $COST\_FW_i$ was obtained using all plants in the first world for that process for which the cost information was given.

one set for each process.[20] The titles (and some abstracts selected at random) of the patents in the final sample for each process were examined to ensure that the final sample did not contain irrelevant patents. Three of our 139 chemical processes were very broad categories (‘resins’, ‘specialty chemicals’, and ‘refinery’), and they turned out to have a significantly higher number of patents than the other processes. For these three processes we used a dummy, $DPROCPAT_i$.

$NOVELTY_i$ is based on the count of all US patents whose title contained of the process *i*. $NOVELTY_i$ is the growth rate of these patents between the two periods 1976-1985 and 1986-1995. Unlike PROCPAT, NOVELTY does not distinguish between process and product patents. Thus, for instance, this variable also includes the development of new uses of the product. NOVELTY is thus likely to be a measure of the rate of change of technology in that area. We do not wish to stress our interpretation of either NOVELTY or PROCPAT. Our ultimate objective is to control for possible sources of heterogeneity across processes, and we believe that together, these variables control for the maturity and complexity of the technology.[21] These variables are important because technologies with a larger number of SEFs may be those that are older and more standardized. By controlling for the changes in the technology it becomes less plausible that the estimated coefficient KFW_i simply reflects the effect that LDCs are more likely to invest in older and more mature processes.

5. 5 Empirical results and discussion

Table 7 presents the results of the negative binomial specification. It shows that the elasticity of SIZE with respect to KFW is about 0.34 and of BUY is about

[20] In some cases, the query excluded specific patent classes that were typically concerned with product (composition of matter) patents. The boolean queries used to generate PROCPAT are available from the authors upon request.

0.36, and both are statistically significant. As predicted, the point estimates for BUY are higher than those for size, although the differences is small. Similarly, the elasticity of MAKE with respect to KFW is negative, although not significantly different from zero. The control variables also have reasonable signs. For instance, measures of technological novelty and change are associated with lower third world investment in chemical plants.

Our empirical procedure raises two sets of issues that we need to address. The first one is that our measure of potential suppliers KFW_i implies that we ignore the possibility that a given SEF operating in a certain market could be a potential supplier for a related process. Specifically, we have assumed that unless an SEF operates in a process market in the first world, it is not a potential supplier of that process in the third world. This assumption is not entirely implausible. Many of our processes are quite distinct from one another. Further, SEFs are typically very specialized and focus on very specific process technologies. For instance, three different sets of SEFs supply the markets for three different types of polyethylene -- high-density, low-density, and linear low density polyethylene (LLDPE), with very little overlap.

Even if the assumption is not true, it implies that KFW is measured with error. If so, our estimates our likely to be downward biased towards zero. In turn, this implies that our estimates of the effects of SEFs are likely to understate the true impact. As a robustness check, we estimated a specification using the same panel of 38 countries and 21 sectors, using the number of SEF that operate in sector *i* in the first world as the measure of the number of suppliers.[22]. This amounts to

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[21] The qualitative results did not change when we only use either one of the two measures.

[22] These regressions were performed using all the 2081 processes in the data base grouped in the 21 sectors. We also used aggregate measures of PROCPAT and NOVELTY at the level of sectors, and used as an additional regressor the number of products in each sector to control for process differentiation. The results of these regressions, along with the details about how they were performed, are available from the authors upon request.

assuming that an SEF operating in a certain process in a given sector in the first world is a potential supplier of engineering services in any other process in that sector in LDCs. The estimated impacts of KFW_i on $SIZE_{ij}$, BUY_{ij}, and $MAKE_{ij}$ were qualitatively similar to those reported in table 7 (i.e., negative for $MAKE_{ij}$, and positive for the other two). Therefore, the assumption that SEFs only supply engineering services for those processes in LDCs that they supplied in the first world as well is unlikely to be key to our empirical results.

The second point concerns the way we are identifying the effect of SEFs. In principle, a more satisfactory way of identifying this effect is to look for variations in the potential supply of SEFs across countries. We tried to distinguish among countries according to the extent to which they were open to the inflow of foreign technologies. However, many countries which have protected downstream markets have in fact been open to imports of technology and engineering services. Aggregate measures of openness, such as the ratio of exports and imports to GDP, or even the measure we use here, $OPEN_j$, cannot capture this subtlety. More importantly, the rise of West European and Japanese SEFs has made the market for chemical processes a truly global market. Indeed, our data show that even in a country like Libya, which is clearly unfriendly to the US, is served by a large number of non US SEFs and European subsidiaries of US SEFs. Thus, although in principle the potential supply of SEFs in Libya is lower than in Mexico, this difference does not appear to be quantitatively very significant. In short, there seemed to be insufficient cross country variation in the effective supply of SEFs for this to be a useful way to identify the impact of SEFs.

Furthermore, there are important differences in the potential supply of SEFs across technologies that are economically meaningful for our purposes. Some of the processes in our data base are technologies that are based on well defined and codified scientific knowledge. This encourages specialization and, all else held constant, increases the number of SEFs for that process. Put differently, there are processes where specialization is more valuable relative to costs. In other cases, such as pharmaceuticals, the design of process is intertwined with the specific product. Separation between product and process is additionally difficult if there is product specific know-how of the buyer that would be disclosed if the process design and engineering were to be contracted out. In this case, there would be fewer SEFs. In short, we believe that differences in the nature of the knowledge-base across different processes is a very important source of variation in the number of SEFs, and it is this difference that we are exploiting.

5. 6 LDC investments by domestic firms and multinational enterprises

Given the results in the previous sections, we were encouraged to explore further. In particular, one implication of our story is that the benefits of SEFs are more pronounced for companies that have a lower ability to 'make' the engineering services in-house. The obvious reference is to third world chemical firms vis-à-vis multinational enterprises. It is plausible that the former are less able than the multinational corporations in engineering their own plants. Therefore, if our story is correct, an increase in the number of first world SEFs ought to matter more for LDC chemical firms than multinationals.

To test this, we constructed two additional variables from our data base, $DOMESTIC_{ij}$ and MNE_{ij}. The former is the total number of plants in country j and process i by chemical companies with LDC nationality, while MNE_{ij} is the total number of plants in by first world chemical companies[23]. The results are given in table 8. As table 8 shows, SEFs have a considerable impact on the investments of domestic chemical companies. The estimated elasticity of DOMESTIC with respect to KFW is 0.42. By contrast, SEFs have practically no impact on the LDC investments of multinational enterprises. Thus, while SEFs are an important vehicle for technology transfer to local chemical companies, the investments of multinational firms are not affected by them. Our model predicted that SEFs encourage investment by companies that would otherwise not invest. Our empirical results suggest that these companies are largely the domestic chemical companies in the developing countries. SEFs are therefore a means of creating greater competition in downstream product markets in these countries, for inducing the growth of production by local firms, and more generally for reducing barriers to entry.

6 SEFs and the value of investment in chemical plant

A shortcoming of the results in our previous section is that they are in terms of counts of chemical plants. Plants for different types of chemical processes imply different levels of investment, and the dollar cost of investments is a natural weighting system. Moreover, estimating the effect of SEFs on the value of investment in chemical plants is additionally valuable because the results have a more direct and natural interpretation.

But estimating the impact on the value of investment raises two related set of issues. One econometric issue relates to the treatment of zero values. As noted earlier, a large fraction of the markets have no investment. This pattern is consistent with the idea that efficient investment in chemical plant has to exceed a minimum threshold. However, this threshold is not observed and is likely to vary with across processes.

Further, only a little more than a third of the plants in our sample report a dollar figure for investment. This raises difficulties because the observations with the

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[23] In computing $DOMESTIC_{ij}$ and MNE_{ij} we adjusted for investments by subsidiaries of multinationals by including them in MNE_{ij}. See Appendix for details.

missing dollar figures may not be random. The definition of investment costs for individual plants often depends on arbitrary cost imputation.[24] The reported dollar figures are also likely to contain biases. For instance, countries may systematically differ in what costs are counted in the investment cost of plants and these differences could be correlated with the extent of investment. As a result, the use of the average dollar cost of investment of plants in process *i* as the weighting factor appeared to be the only prudent choice.

In this respect, an increase in the number of SEFs has two kinds of effects for a given process. First, it may increase the probability of investment. Second, given the number of plants, it can increase the average investment per plant. The latter is an effect that the count specification of section 5 does not capture. The increase in average investment may arise because SEFs make more recent vintage technology available to LDC firms. Plants embodying more recent technology are likely to be more expensive than plants based on older technologies.

A variety of empirical specifications can be used to model this process. Specifically, we model the process generating the number of plants, S_{ij}, in process *i* and country *j* as

$$\log(S_{ij}) = const + aY_j + bZ_i + e_{ij} \tag{10}$$

where Y_j is a vector of country-specific characteristics, and Z_i a vector of process specific characteristics. We assume that the average value of investment, AVG_INVEST_{ij} is affected by process specific factors plus a market specific error so that

$$\log(AVG\_INVEST_{ij}) = const + cZ_i + u_{ij} \tag{11}$$

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[24] For instance, plants can be located within larger plant complexes. This complicates how the fixed costs of shared facilities are allocated to individual plants. In the opinion of industry experts, publicly reported cost measures for individual plants are very noisy measures of the true investment cost. This argued for using average cost figures based on as large sample sizes as possible.

$$\log(\text{INVEST}_{ij}) = \log(\text{AVG\_INVEST}_{ij} \times S_{ij}) =$$
$$const + aY_j + (b+c)Z_i + w_{ij} \qquad (12)$$

We observe the total investment, INVEST_{ij}, in the given market only when S_{ij} is positive. If w_{ij} and e_{ij} are normally distributed with mean 0 and variance-covariance matrix Σ, we obtain a type II generalized tobit likelihood function (see Amemiya, 1985, p.385-7). This is the procedure we use to estimate the vector of coefficients *a*, *b* and *c*. Note that the identifying assumption is that the average value of investment in the ij^{th} market depends only on the characteristics of the process *i* and not on the observed country characteristics. Given our measure of the average value of investment-- the average value across all countries in *i* – this identifying assumption is natural. The generalized tobit is not the only empirical model that can be used in this situation. However, when we tried to estimate less restrictive models they presented severe convergence problems.

Table 9 presents the results of this maximum likelihood estimation. The first point to note is that the coefficient estimates are consistent (where comparable) with the estimates from the negative binomial regressions. Specifically, the estimated elasticity of the number of plants with respect to the number of SEFs is 0.33 which is very close to the earlier estimate of 0.34 (see table 7). Further, the results imply that conditional upon at least one plant being constructed, a 10% increase in the number of SEFs would increase the average dollar value of investment per plant by 1.6%. If one assumes that the vintage of technology is unchanged, this implies that a 10% increase in SEFs increase the average size of plants in an LDC by about 2.5%.[25]

Other estimates are similarly in line with our priors and with the estimates reported earlier in table 7. For instance, technological novelty and complexity reduce the expected number of plants, and have a negative, albeit statistically insignificant, effect on the average dollar value of investment per plant. Similarly, a greater number of first world plants increase the expected number of plants in a third world country, but not the average dollar value of investment per plant. By contrast, an increase in the cost of chemical plants in the first world reduces the expected number of plants, but conditional upon investment, increases the average dollar value of investment per plant.

The quantitative impact of an increase in the number of SEFs is not easy to discern from the regression coefficients. In particular, it would interesting to compute the increase (unconditional) expected total dollar value of investment in LDCs due to one additional SEF in each process. Figure 2 presents the results for selected countries. As figure 2 shows, the average increase is about $5.4 million over the ten year period, with the increases being larger in larger countries like China and India, and smaller in smaller countries. For the third world as a whole, the increase in investment would be more than $205 million.[26]

To get some further perspective, note that there are on average 12 SEFs per product. (See Table 6.1.) Therefore, an additional SEF implies an increase of a little less than 8.5%. The average investment per process in LDCs over the ten year period of the study is about $3 billion. Thus $205 million implies an increase

[25] This is an application of the so called “two thirds” law, a rule of thumb that the capital cost of a chemical plant increases only 66% when the capacity of the plant is increased by 100%. See for instance Landau (1966).

[26] Even this is likely to be an underestimate because our sample does not include all third world countries. It does include all the major third world countries, and therefore our results are likely to be close.

of more than 6.5%. Using the estimated elasticity from the negative binomial estimates in table 7, an 8% increase in the number of SEFs would result in additional investment of nearly \$93.5 million. As discussed earlier, this figure of \$93.5 million does not take into account the effect of SEFs in the form of an increase in the average investment per plant. In other words, even a conservative estimate of the impact of an additional SEF would be at least a \$100 million. For the 139 processes taken together, this implies an increase in investment of \$139 - \$278 million *per year*. By comparison, from our dataset, the estimated total investment in LDCs is about \$15.5 billion per year, of which about \$5 billion is foreign direct investment.[27]

Further, this effect varies by size and nature of the process. For instance, figure 3 shows that the effect diminishes with size. Processes where there are a large number of third world plants are likely to be less affected than others. There are two forces at work here. On the one hand, a given percentage increase in investment implies a larger dollar increase if the base level investment is high. On the other hand, as noted earlier, an additional SEF in the market is more important when the number of SEFs is small than when the number is large. Our results suggests that the "diminishing returns to the number of SEFs" effect dominates when there are a large number of plants. Similarly, given that technological maturity increases both the expected number of plants, and the average investment per plant, our estimates imply that the benefit of an additional SEF is likely to be greater in more mature processes. This is borne out by figure 4, which shows that

[27] These figures are broadly consistent with other sources. For 1993, foreign direct investment (FDI), by US chemical firms in selected developing countries was as follows: \$2.3 billion (Mexico), \$2.1 billion (Brazil), \$0.1 billion (India), 0.24 billions (S. Korea), 0.1 billion (China) and \$0.36 billion (Philippines). Although we do not have the aggregate direct investment in developing countries as a whole by US chemical firms, it is unlikely to have been more than \$8 billion. Since FDI by US chemical firms in 1985 was only a third of its 1993 level, this implies that FDI directed to LDCs in 1985 was about \$2.6 billion (See Lenz, 1996, pp 16, 90.)

processes where the technological frontier is moving rapidly are likely to benefit less than more mature processes.

7 Conclusions

Technological spillovers play an important role in the process of economic growth. (See for instance Griliches (1979) or Jaffe (1986).) But the typical description of the mechanism of these spillovers is, in Alfred Marshall's often used phrase, one where “the secrets ... are in the air”. Important as this ethereal mechanism may be, there are other mechanisms which are more material and amenable to economic analysis. In this paper, we argued that an important institutional form through which these spillovers take place is the division of labor, and the development of an upstream sector (typically a capital good sector). Moreover, these spillovers need not involve real externalities, the focus of much of the literature on spillovers. Instead, the benefits may be through a reduction in search costs and a reduction in the market power of upstream firms.

The economics of the spillovers is very simple. As Romer (1990) has emphasized, the development of technological capability is a fixed cost activity, while the productive application of the technological capability is a (low) marginal cost activity. In our story, firms in the upstream sector invest in learning about the production process. If the upstream sector is competitive these costs are ultimately paid by customers downstream. The expertise and the technologies that they supply are process -- and not location -- specific, and thus, can be made available to downstream firms in other countries. Competition between these profit seeking firms implies that the benefits of the acquired expertise will be made available to users in other countries, or in other sectors of the economy, at prices close to marginal cost because the development costs have already been sunk.

The historical sequence of development plays an interesting role. Such a sequencing is not logically necessary for our argument. If all industries arise at the same time, a division of labor is still beneficial because the fixed costs can be spread over a larger volume of output. Each user sector then provides a beneficial externality to the others. As a historical matter, however, some sectors and countries have tended to lead. Thus, the division of labor can act as the transmission mechanism for beneficial externalities that leaders create for followers.

What our results are saying in practice is not that the observed rates of investment in chemical plants in LDCs could never be achieved without the international movement of engineering expertise. But the rise in investment is probably taking place much earlier than if LDCs had to ‘re-invent the wheel’ -- that is, the growth of the chemical industry in the LDCs would have been considerably delayed if the latter had had to incur the fixed cost of developing process technologies and the broader engineering expertise required to design and construct chemical plants. In short, the organization of the industry in the first world ‘matters’, and in our story it matters for the growth of investments in the developing countries. Put differently, the intermediation of an upstream sector has been critical for the transmission, to other countries, of the benefits associated with the quintessential immobile factor, to wit, a large market, and with it, of the implied opportunities for growth led by division of labor.

Appendix: Description of the data

The Chemical Age Project File (CAPF) (1989) data base provides information on 20581 plants announced or constructed all over the world in the broadly defined chemical sector during 1980-1989. The data base is organized by plants. It reports the name of the company that ordered the plant, the name of the engineering company (or 'staff' for in-house engineering), the location of the plant (city and country), the name of the chemical process or of the product being produced, the date in which the investment was first reported in the specialized trade press, along with other information. For about 40% of the plants in the data base, CAPF also reports the total cost of investment in the plant in US million dollars. Finally, the data base reports the status of the plant along with the date in which the information was last updated. In most of the cases the information was updated in 1988-1989, which suggests that we can reasonably assume that this was the status of the plant at the end of our sample period. There are 14893 plants in the data base which are either 'completed' or 'under construction'. The rest are 'planned', 'under study', 'abandoned', 'canceled', 'delayed', or other.

We focused our analysis on the plants that were either completed or under construction. This is because we did not want to include in our measures investments plants whose realization was not yet certain. For the same reason we did not include investments that were abandoned, canceled, etc.. Thus, all the following variables – $SIZEFW_i$, $SIZELDC_i$, $BUYLDC_i$, $MAKELDC_i$, $SIZE_{ij}$, BUY_{ij}, $MAKE_{ij}$ – are obtained by using only the 14893 plants that are completed or constructed. Only in the case of KFW_i, we used all the 20581 plants in the data base. As also suggested in the text, we thought that even plants that were planned, under study, abandoned, or other, provided useful information about whether a given SEF was a potential supplier for that technology. For similar reason, we used all the available information about plant costs to compute $COST\_FW_i$, and to determine the mean value of plant costs in LDCs, which we used to compute the dollar values of $SIZE_{ij}$, BUY_{ij}, and $MAKE_{ij}$.

CAPF classifies the plants in the following 21 sectors (in parenthesis the number of plants that are completed or under construction in each sector): Agricultural Chemicals (116), Air Separation (596), Coal Refining (32), Desalination (40), Engineering Materials (110), Environmental Technologies (75), Fertilizers (1000), Food Products (308), Gas Handling (1014), Inorganic Chemicals (1249), Industrial Gases (613), Minerals and Metallurgy (532), Miscellaneous (505), Organic Chemicals (1114), Oil Refining (2246), Petrochemicals (2155), Pharmaceuticals (745), Plastics and Rubber (1474), Pulp and Paper (396), Synthetic Fuels (135), Textiles and Fibers (438). The sector dummies that we actually used in all our regressions were obtained, however, after aggregating these 21 sectors in 9 classes of relatively homogeneous sectors. This is because for some of our regressions the complete set of 21 sector dummies created computational problems. In particular, this was the case in all our 'make' regressions. Since there are very few 'makes' in the data base, and especially in LDCs, some of the sector dummies completely predicted the dependent variable or the choice (in the logit regression). To be consistent, we then used the same 'aggregate' sector dummies in all the regressions, including those that did not show similar computational problems. The 9 aggregate sectors are: AGRICULTURE (Agricultural Chemicals and Fertilizers), GAS (Gas Handling, Air Separation, and Industrial Gases), ORGANIC CHEMICALS (Organic Chemicals, Explosives, Textile and Fibers, Food Products, and Pharmaceuticals); we then left OIL REFINING, PETROCHEMICALS, MINERALS & METALLURGY, PLASTICS & RUBBER, and INORGANIC CHEMICALS by themselves; the remaining CAPF sectors are aggregated in a general MISCELLANEOUS category.

We complemented our CAPF data with other information. We used Predicast's (1991) and other company thesauruses to group all the companies that were subsidiaries of other companies in the data base under the names of their mothers. From the same thesaurus sources, we attributed to each company the nationality of their mothers. This enabled us to determine the nationalities of the SEFs, and of the domestic or multinational chemical firms. Some engineering companies were subsidiaries of larger chemical groups (especially for European and Japanese SEFs). However, because they normally act as independent firms in the national and international markets, we treated them as independent firms. At any rate, whenever one of these SEFs was providing services for the company that owned that SEF we counted that case as a 'make' rather than a 'buy', while if that SEF was serving another chemical company we counted it as a 'buy'. In computing KFW_i the issue arose whether one had to count only SEFs operating in the first world whose nationality was also first world. In practice however there are no SEFs operating in the first world whose nationality is from an LDC. Thus, KFW_i is the number of SEFs in process *i* in the first world markets.

Although CAPF is a commercial data base, and it is constructed from various sources such as questionnaires and reports in the trade press, its vast coverage suggests that biases are unlikely. As noted in the text, its most serious limitation is that for about 45% of the plants no name of the engineering company is given. The most obvious reason is that the name of the contractor is unknown, and the data base provider was unable to identify whether the engineering services were provided in-house. We then performed a diagnostic check to assess which assumption was most appropriate for the blanks. The diagnostic check used information about these plants from another data base, Hydrocarbon Processing Information (HPI), compiled by Gulf Publishing, Texas. HPI supplies similar plant-level information for plants located all over the world in a subset of the CAPF technologies (mainly oil refining, petrochemicals, and plastics). We randomly picked, from our original CAPF data base, 500 plants located in the third world, in the sectors that were also covered by HPI, and in which the name of the engineering company was blank. We tried to identify each of these 500 plants in HPI using information about the plant that were common to both data bases, i.e. the name of chemical company, the name of the process, the city of the plant, the date of announcement. We then checked the name of the engineering company in the latter data set. We considered two plants to be the same if they had exactly the same names for the company, the process, and the city, and if they had approximately the same data of announcement.

Of the original 500 plants we identified about 200 plants that were also in HPI. For about 100 of these 200 plants the name of the engineering company was blank in HPI as well. For the remaining 100 plants we found that the engineering services were predominately ‘buys’ rather than ‘makes’ - i.e., HPI provided the name of an independent outside contractor. Only in 4 cases was the name of the engineering company the same as the one of the chemical company or a subsidiary thereof. Thus, the diagnostic check did not enable us to draw straightforward conclusions about our assumption for the blanks because a large number of the identified plants were still blanks. However, it ruled out the possibility that the blanks are predominately ‘makes’. At any rate, as also noted in the text, we performed all our empirical analyses under different assumptions about the blanks – i. e. all the blanks are ‘buys’, all the blanks are ‘makes’, the blanks are 50% ‘buys’ and 50% ‘makes’, the blanks are distributed between ‘buys’ and ‘makes’ in the same proportion as in the case in which the name of the engineering company (or ‘staff’) is observed. The results presented here are those where we assume that all the blanks are ‘buys’, which correspond to the least favorable assumption for our theory. The results of our estimation under the other assumptions about the blanks are available from the authors upon request.

Finally, in all our tables, and for all the variables that we constructed, we defined first world to be all the OECD countries, but Mexico, the Czech Republic, Hungary, Poland, South Korea, and Turkey. These countries joined the OECD only very recently, and in any case we thought that, for the purpose of our study, it was more appropriate to include them in the LDC category. Our first world countries are all the Western European countries, the USA and Canada, Japan, Australia and New Zealand. All other countries are LDCs.

The 38 countries in our sample are: Algeria, Argentina, Bangladesh, Brazil, Burma, Chile, China, Colombia, Ecuador, Egypt, Hong Kong, Hungary, India, Indonesia, Iran, Iraq, Kuwait, Malaysia, Mexico, Morocco, Nigeria, Pakistan, Peru, Philippines, Poland, Saudi Arabia, Singapore, South Africa, South Korea, Sri Lanka, Sudan, Syria, Taiwan, Thailand, Tunisia, Turkey, Venezuela, Yugoslavia.

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Table 1: *% of 'makes' by sector, in the first world (FW) and in LDCs.*

Sector	No. of plants in FW	No. of 'makes' in FW	No. of plants in LDCs	No. of 'makes' in LDCs	% of 'makes' in FW	% of 'makes' in LDCs
Agro-chem	65	8	51	0	12.31%	0.00%
Air Separat.	346	158	250	15	45.66%	6.00%
Coal Refining.	22	0	10	0	0.00%	0.00%
Desaliantion	2	0	38	1	0.00%	2.63%
Eng. Mat	88	10	22	2	11.36%	9.09%
Environ. Tech	57	1	18	3	1.75%	16.67%
Fertilizer	280	22	720	16	7.86%	2.22%
Food Products	167	3	141	6	1.80%	4.26%
Gas Handling	637	16	377	22	2.51%	5.84%
Inorg Chem.	714	73	535	23	10.22%	4.30%
Indust. Gas	374	73	239	10	19.52%	4.18%
Mineral & Metals	286	12	246	7	4.20%	2.85%
Miscl	297	21	208	4	7.07%	1.92%
Org. Chem	836	141	278	16	16.87%	5.76%
Oil Refining	1315	69	931	50	5.25%	5.37%
Petrochem	1126	146	1029	66	12.97%	6.41%
Pharmaceut	468	21	277	18	4.49%	6.50%
Plastics	1011	146	463	34	14.44%	7.34%
Pulp & Paper	291	5	105	0	1.72%	0.00%
Synth. Fuels	101	12	34	6	11.88%	17.65%
Textile Fiber	132	21	306	4	15.91%	1.31%

Note: FW and LDCs correspond to OECD and non-OECD countries. See section 4 and the Appendix.

Table 2: *Distribution of KFW_i, $SIZEFW_i$, and $SIZELDC_i$ in 2081 chemical process markets by classes*.

Classes of KFW_i [range of KFW_i]	1 [0-1]	2 [2-4]	3 [5-8]	4 [9-12]	5 > 12
Number of markets per class	1801	155	50	27	48

Classes of $SIZEFW_i$ [range of $SIZEFW_i$]	1 [0-1]	2 [2-5]	3 [6-10]	4 [11-20]	5 [21-50]	6 [51-100]	7 > 100
Number of markets per class	1328	506	96	70	51	18	12

Classes of $SIZELDC_i$ [range of $SIZELDC_i$]	1 [0-1]	2 [2-5]	3 [6-10]	4 [11-20]	5 [21-50]	6 [51-100]	7 > 100
Number of markets per class	1665	240	60	48	42	16	10

Table 3: *OLS regressions of $SIZELDC_i$ on classes of KFW_i, $SIZEFW_i$, and sector dummies for 2081 chemical process markets*.

	Dependent variable	
Parameter	**$SIZELDC_i$**	**$SIZELDC_i$**
Constant	0.650	0.178
	(0.225)	(0.486)
KFW2	4.169	2.529
	(0.798)	(0.766)
KFW3	10.150	5.260
	(1.366)	(1.425)
KFW4	30.646	18.717
	(1.848)	(2.009)
KFW5	58.725	13.567
	(1.394)	(2.518)
SIZEFW2	-	0.261
	-	(0.422)
SIZEFW3	-	2.134
	-	(0.929)
SIZEFW4	-	3.488
	-	(1.192)
SIZEFW5	-	16.276
	-	(1.862)
SIZEFW6	-	43.131
	-	(2.931)
SIZEFW7	-	103.227
	-	(3.310)
Sector dummies	no	yes
R-squared	0.499	0.678
No. of obs.	2081	2081

Note: Standard errors in parenthesis.

Table 4: *List of country characteristics*.

GDP_j	Real GDP of country in 1985 in billions of US dollars. Obtained from per capita GDP of country (Barro-Lee) times population.
POP_j	Population of country in 1985 in thousands. (Barro-Lee)
$ENERGY_j$	Total energy consumption of country (1985-1987 average) in thousand metric tons of coal equivalent. (UN Statistical Yearbook)
$HKAP_j$	Human Capital. Average schooling years of population over 25 in the country. (Barro-Lee) Equal to zero if data is missing in Barro-Lee (missing data for: China, Egypt, Morocco, Nigeria, Saudi Arabia).
$DHKAP_j$	Dummy equal to 1 for countries for which $HKAP_j$ is missing in Barro-Lee.
$OPEN_j$	Own-import weighted tariff rates of the country on intermediate inputs and capital goods. (Barro-Lee) This is Barro-Lee's variable OWTI. Equal to zero if data is missing in Barro-Lee (missing data for: Burma, Hungary, Poland, South Africa).
$DOPEN_j$	Dummy equal to 1 for countries for which $OPEN_j$ is missing in Barro-Lee.
$DOIL_j$	Dummy equal to 1 for countries with oil reserves: Algeria, Argentina, Brazil, China, Colombia, Ecuador, Egypt, India, Indonesia, Iran, Iraq, Kuwait, Malaysia, Mexico, Nigeria, Saudi Arabia, Syria, Venezuela. (Main countries with oil reserves listed in *World Atlas*, 1990.)
$DGAS_j$	Dummy equal to 1 for countries with natural gas reserves: Algeria, Argentina, Indonesia, Mexico, Venezuela (Main countries with natural gas reserves listed in *World Atlas*, 1990.)
Geographical Area Dummies	Africa, Eastern Europe, Middle East, Central and South America, Far East.

Table 5: *Share of 'makes' - logit regression.*

Dependent variable: Dummy equal to 1 if plant is a 'make', 0 if 'buy'.

Parameter	Estimate	Standard Error
constant	-23.33	5.03
$DOIL_j$	-1.62	0.35
$DGAS_j$	0.12	0.25
$DHKAP_j$	0.39	0.49
$(1- DHKAP_j)*HKAP_j$	0.16	0.08
$\log(GDP_j)$	1.86	0.54
$\log(POP_j)$	-0.67	0.31
$\log(ENERGY_j)$	-0.64	0.30
$DOPEN_j$	0.27	0.63
$(1- DOPEN_j)*OPEN_j$	1.10	0.49
$\log(1 + KFW_i)$	-0.14	0.06
$DEXPANSION_{ij}$	0.21	0.19
$DREVAMP_{ij}$	0.16	0.36
Number of observations:		5006
Log of Likelihood Function:		-946.011
Fraction of Correct Predictions:		0.947
Number of 0 (percentage):		4739 (95.67%)
Number of 1 (percentage):		267 (5.33%)

Note: The regression includes sector dummies and dummies for geographical areas.

Table 6.1: *Descriptive statistics.*

Variable	No. Obs.	Mean	Std Dev	Min	Max
$SIZE_{ij}$	5282	0.72	2.14	0	48
BUY_{ij}	5282	0.69	2.06	0	44
$MAKE_{ij}$	5282	0.04	0.27	0	8
$DOMESTIC_{ij}$	5282	0.56	1.88	0	44
MNE_{ij}	5282	0.16	0.740	0	18
$INVEST_{ij}$ [1]	5282	78.09	431.40	0	17751
AVG_INVEST_i [1]	139	121.12	250.69	0.50	2218.96
KFW_i	139	11.94	11.77	0	60
$SIZEFW_i$	139	38.68	45.40	2	278
$COST\_FW_i$ [1]	139	76.47	145.49	0.8	1190
$NOVELTY_i$	139	0.17	0.65	-0.78	3.600
$PROCPAT_i$ [2]	136	61.19	60.65	1	345
GDP_j [3]	38	171.28	323.40	19.63	1918.79
POP_j [4]	38	84.90	204.40	1.70	1059.50
$ENERGY_j$ [5]	38	61.26	126.70	1.48	765.18
$OPEN_j$	34	0.237	0.23	0.00	1.32
$HKAP_j$	33	4.85	2.18	0.91	10.75

Notes:
1. In millions of US dollars.
2. Missing values for ‘specialty chemicals’, ‘resins’, and ‘refinery’.
3. In billions of US dollars.
4. In millions
5. Millions metric tons of coal equivalent

Table 6.2: *Distribution of 139 products by classes of KFW_i.*

Classes of KFW_i [Range of KFW_i]	Number of markets
KFW1 [0-1]	9
KFW2 [2-4]	37
KFW3 [5-8]	25
KFW4 [9-12]	21
KFW5 [>12]	47

Note: Same classes as in Table 2.

Table 7: *Negative Binomial Regressions – SIZE, BUY, MAKE*

Parameter	*DEPENDENT VARIABLE*		
	SIZE	**BUY**	**MAKE**
Constant	-10.45	-9.64	-31.74
	(1.55)	(1.58)	(6.13)
DOIL	0.08	0.09	-0.04
	(0.08)	(0.09)	(0.42)
DGAS	-0.23	-0.21	-0.62
	(0.09)	(0.09)	(0.32)
DHKAP	-0.45	-0.43	-1.49
	(0.14)	(0.14)	(0.78)
HKAP	0.01	0.01	0.28
	(0.03)	(0.03)	(0.12)
log(GDP)	0.10	0.03	1.26
	(0.17)	(0.17)	(0.62)
Log(POP)	-0.09	-0.06	-0.27
	(0.09)	(0.09)	(0.36)
log(ENERGY)	0.65	0.68	0.30
	(0.09)	(0.09)	(0.38)
DOPEN	-0.97	-0.98	-1.17
	(0.17)	(0.17)	(0.80)
(1-DOPEN)*OPEN	0.26	0.27	0.06
	(0.15)	(0.15)	(0.63)
log(SIZE_FW)	0.52	0.51	0.93
	(0.05)	(0.06)	(0.20)
log(COST_FW)	-0.08	-0.08	-0.13
	(0.03)	(0.04)	(0.10)
NOVELTY	-0.13	-0.12	-0.23
	(0.04)	(0.04)	(0.15)
(1-DPROCPAT)*log(PROCPAT)	-0.11	-0.12	-0.02
	(0.03)	(0.03)	(0.10)
DPROCPAT	-0.56	-0.61	-0.04
	(0.22)	(0.23)	(0.82)
log(KFW)	0.34	0.36	-0.06
	(0.06)	(0.06)	(0.19)
Delta	0.60	0.64	1.27
	(0.04)	(0.04)	(0.28)
Log Likelihood	-4780.99	-4666.21	-563.09
No of Observations	5282	5282	5282

Note: Standard errors are in parenthesis. DELTA is the negative binomial overdispersion parameter, so that the variance to mean ratio is (1 + DELTA)/DELTA. All regressions include sector dummies and dummies for geographical areas of country.

Table 8: *Investment by MNEs and Third World Firms (Negative Binomial Regressions – SIZE*

Parameter	*DEPENDENT VARIABLE*	
	Domestic	**MNE**
Constant	-7.04	-18.06
	(1.86)	(2.65)
DOIL	0.18	-0.27
	(0.10)	(0.17)
DGAS	-0.49	0.35
	(0.11)	(0.16)
DHKAP	-0.46	-1.04
	(0.16)	(0.29)
HKAP	0.05	-0.14
	(0.03)	(0.04)
log(GDP)	-0.32	0.96
	(0.20)	(0.29)
log(POP)	0.17	-0.77
	(0.11)	(0.17)
log(ENERGY)	0.81	0.37
	(0.10)	(0.15)
DOPEN	-1.51	0.80
	(0.19)	(0.32)
(1-DOPEN)*OPEN	0.07	0.69
	(0.17)	(0.30)
log(SIZE_FW)	0.44	0.77
	(0.06)	(0.10)
log(COST_FW)	-0.07	-0.12
	(0.03)	(0.05)
NOVELTY	-0.13	-0.19
	(0.05)	(0.08)
(1-DPROCPAT)*log(PROCPAT)	-0.13	-0.03
	(0.03)	(0.05)
DPROCPAT	-0.61	-0.22
	(0.25)	(0.41)
log(KFW)	0.42	-0.02
	(0.06)	(0.10)
Delta	0.59	0.81
	(0.04)	(0.90)
Log Likelihood	-4066.67	-1882.84
No of Observations	5282	5282

Note: Standard errors are in parenthesis. DELTA is the negative binomial overdispersion parameter, so that the variance to mean ratio is (1 + DELTA)/DELTA. All regressions include sector dummies and dummies for geographical areas of country

Table 9: *Investment in chemical plant (values)*: *Max. Likelihood Estimates of Equation (12)*

	EQUATION	
Variable	**Number of Plants**	**Average Investment (value)**
Constant	-5.40	1.55
	(1.27)	(0.32)
DOIL	0.05	
	(0.05)	
DGAS	-0.13	
	(0.07)	
DHKAP	-0.19	
	(0.09)	
HKAP	-0.01	
	(0.02)	
log(GDP)	-0.03	
	(0.11)	
log(POP)	0.02	
	(0.0.6)	
log(ENERGY)	0.45	
	(0.08)	
DOPEN	-0.51	
	(0.13)	
(1-DOPEN)*OPEN	0.05	
	(0.12)	
NOVELTY	-0.08	-0.04
	(0.03)	(0.05)
(1-DPROCPAT)*	-0.07	-0.05
log(PROCPAT)	(0.02)	(0.04)
DPROCPAT	-0.36	0.27
	(0.15)	(0.28)
log(SIZE_FW)	0.19	-0.01
	(0.05)	(0.07)
log(COST_FW)	-0.06	0.70
	(0.02)	(0.03)
log(KFW)	0.33	0.16
	(0.06)	(0.08)
Log Likelihood	-4802	
No of Observations	5282	

Notes: Standard errors are in parenthesis. Both equations include sector dummies and dummies for geographical areas of country which are not reported here.