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European Pharmaceutical Industry: A Micro-Econometric Analysis of Growth Dynamics and Production Location

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Thesis submitted to Trinity College, University of Dublin in fulfilment of the requirements for the degree of Doctor of Philosophy (Ph.D.)

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Summary

The aim of this thesis is to investigate the industry dynamics of expansion and the location pattern of the European pharmaceutical industry in the Single Market Programme era using micro-econometric approaches.

Chapter 1 outlines the context and structure of the thesis.

Chapter 2 gives an account of the major data source used for this study - the *Amadeus* database, from which we collect the data on European pharmaceutical firms. The chapter also describes procedures that we construct the dataset on pharmaceutical enterprises and their European subsidiaries.

In Chapter 3, we test whether the growth process of the most dynamic part of the industry - multinational enterprises - obeys Gibrat's law, which states that the growth rate is independent of firm size. Results after two traditional tests generally reveal that the MNEs do not grow in the way indicated by the law - smaller firms grow relatively faster than larger firms do, while the formers follow a more variable growth process. These findings are in line with other empirical literature on the global pharmaceutical industry and on other manufacturing industries. In addition, we find that the MNEs converge to their steady states of size at different speeds, which are negatively correlated with their initial sizes. This mean-reversion mechanism suggests that firms are bounded by the scope of how big they can grow, and it also echoes the existence of firm heterogeneity.

In Chapter 4, we present an econometric procedure to model the growth process of pharmaceutical MNEs. We use the discrete-choice model to estimate the probability of the MNEs to expand, conditioning on their lagged expansion decisions and sizes. Using the primitives of our econometric models and size in the initial period, we can predict the growth trajectory of the MNEs from the initial year up to 14 years later with small error. In addition to the promising outcome from this modelling procedure, we find that a persistent expansion pattern exists in the growth process.

In Chapter 5, we start examining the industry from a location perspective.

We find that, the production location of the industry in fourteen EU-15 countries exhibits a continuously dispersing trend between 1993 and 2002. We decompose one specific dispersion trend measured by the Hirschman-Herfindahl Index into several components associated with various firm life-cycle activities and with different ownership status using firm-level data. The results of the decomposition analysis unveil the substantial contribution from MNEs to the dispersion trend, dwarfing the contribution from non-MNEs.

In Chapter 6, we use the discrete-choice models to identify the country-level determinants of location choice of pharmaceutical MNEs, in terms of where they expand production in existing production subsidiaries and where they start-up new production subsidiaries. We find that, among eleven EU-15 countries, the expanding MNEs prefer countries with high levels of agglomeration in pharmaceuticals, large domestic market of medicines and countries that are close to Brussels, the European pharmaceutical distribution centre. However, somewhat surprisingly, they are not found to be sensitive to the corporate tax rate. In terms of location choice of new subsidiaries creation, the agglomeration in pharmaceuticals, the closeness to Brussels and familiarity with the country are the key country-level factors encouraging MNEs to locate their new subsidiaries in a country, while the size of the domestic market and the corporate tax rate play no role in this type of location choice.

Chapter 7 concludes the whole thesis and suggests some future research directions.

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Chapter 1

Introduction to the Thesis

1.1 Overview of the Thesis

The implementation of the Single Market Programme (SMP) in the European Union (EU) has led gradually to the abolition of non-tariff barriers to trade in goods and services between its member states, and to the free movement of capital and people. This provides researchers with an almost unique opportunity to study the activities of the manufacturing sector following a major institutional shock. We investigate one specific European industry, namely the pharmaceutical industry. We focus on this industry for several reasons: firstly, it is an important industry for the European economy in terms of manufacturing value added and R&D;[1] secondly, the industry was heavily regulated at national level before the SMP era (see Cecchini *et al.*, 1988), and therefore a significant response to the SMP can be expected; thirdly, the industry is dominated by multinational enterprises (MNEs), and hence our investigation can fit well into the growing literature on MNEs, which has developed out of the initial work of Caves (1971) and Dunning (1971).

We examine the industry from two different perspectives, namely, firm growth and the location of production, using firm-level data. In terms of the first perspective, the underlying theoretical framework is the firm growth literature, developed by Sutton (1997, 1998), building on the stochastic growth models in Gibrat (1931) and Ijiri and Simon (1974, 1977). Sutton looks at the firm-growth process as a continuous realisation of independent business opportunities by incumbents or new entrants in an industry. According to Sutton, such independent opportunities can be new geographic markets, business entities that can be acquired and new products. We believe that it makes sense to use this 'independent opportunities' approach to look at the growth process of the pharmaceutical MNEs in the enlarged European market, because the SMP allows footloose MNEs to access pan-Europe opportunities more easily. Motivated by the literature on stochastic growth models, we test one of the growth models, namely, the Gibrat's model using data on pharmaceutical MNEs. The analysis is important because the law is often assumed to hold in many stochastic models of firm growth. We also model the growth (expansion) process of the industry using a discrete-choice model. The modelling approach stems from Sutton's "independent submarket" theory.

In the second part of the thesis, we examine the location of production in the industry. The main theoretical background for this analysis is the New Economic Geography (NEG) literature, which has developed models to explain the non-uniform distribution of economic activities (Krugman, 1991; Venables, 1996; Baldwin, 1999 and Puga, 1999). The NEG models illuminate different mechanisms within the agglomeration

[1] It is the $5th$ largest industry in the European Union in terms of manufacturing value added, amounting to 3.5 per cent and accounts for about 17 per cent of total EU business R&D expenditures (EFPIA 2005).

process of an increasing-return-to-scale (IRS) industry. These mechanisms generate pecuniary benefits, which induce firms in the IRS industry to agglomerate together. The mechanisms include the market/price index linkages (in the Krugman model), the endogenous capital accumulation (in the Baldwin model), and the upstream-downstream linkages (in the Venables-Puga models). All the models assert the connection between the agglomeration and the levels of trade-costs – in effect as trade costs fall, economic activities will become increasingly agglomerated or dis-agglomerated (dispersed). In the context of the study of the European Single Market in this thesis, the NEG models suggest either increased dispersion or agglomeration in the production location of the European pharmaceutical industry.

The NEG models motivate us to study the agglomeration pattern of pharmaceutical production and the determinants of location choice of MNEs in the post-SMP era.

The main focus of the research underlying this thesis is the extensive applications of the state-of-the-art micro-econometric techniques to test some industrial organization and international trade theories using firm-level data. We use the random-parameter or random-effect models, where applicable, to explicitly control for the firm-level heterogeneity. For instance, in the test of Gibrat's law, we use a random-parameter model; hence each MNE will have a unit-specific parameter reflecting its unique growth speed. In modelling the firm growth process, we use three random-effect probit models. The purpose is to alleviate the econometric difficulties in estimation caused by correlations between individual random effects and explanatory variables, or between the individual random effects inter-temporally. The performance of these random-effect probit models is promising. In the location-choice analysis, a random-parameter logit model is used, which allows the effect of some country-level determinants on location choices to vary across MNEs. This specification reflects the MNEs' behaviour in the real world: they response to economic factors differently, depending on their own feature. We use a Bayesian approach in the test of Gibrat's law and in the modelling of firm growth, because it can accommodate random parameter and random effect in the estimation flexibly and efficiently. To our knowledge, the Bayesian approach is not yet popular in empirical industrial-organisation studies. We also use some other advanced econometric tools in the analysis, such as the Copula technique, which helps us to uncover the joint distribution between the number of opportunities a firm captured and the size of the firm in the modelling of firm growth processes.

1.2 Structure of the Thesis

Chapter 2 gives an account of the major data source used for this study – the *Amadeus* database, from which we collect the data on European pharmaceutical firms. The chap-

ter also describes the procedures that we use to identify pharmaceutical enterprises and their pharmaceutical-related subsidiary firms. We also outline how we construct the dataset for the analysis of production location patterns and the determinants of location choice.

The major analysis in the thesis is set out in two parts. In Part I we examine the size-growth relationship and the dynamic expansion of the European pharmaceutical industry. In Part II we examine the production location pattern for the entire industry and the determinants of location choice for the subsidiaries of MNEs in the EU.

Part I contains two chapters. In Chapter 3, we begin by reviewing the firm-growth literature, both theoretical and empirical. In order to examine whether the European pharmaceutical industry grows along the path suggested by theoretical models, for example, Gibrat's model, we undertake two econometric tests on the validity of Gibrat's law for 265 MNEs for the time period from 1990 to 2004.

In Chapter 4, we adopt a stochastic approach to model the growth (expansion) process of the industry. The first task is to estimate the probability of firm's expansion using a random-effect dynamic probit model. The sample examined is the same as in Chapter 3. The second task is to check the performance of the econometric model in predicting the growth trajectory of MNEs. This is done by using the primitives of our probit models and explanatory variables in the initial period to predict the size of MNEs in each successive period.

Part II contains two chapters. In Chapter 5, we begin by reviewing the literature of NEG and the empirical literature of industry location pattern in Europe. We offer some evidence of the dispersing agglomeration trend of pharmaceutical production across fourteen EU-15 countries using four indices. We conduct a decomposition analysis on one index using firm-level data, in hope of identifying the drivers of the dispersion trend.

In Chapter 6, we investigate the country-level determinants of pharmaceutical MNEs' location choices using discrete-choice models. There is a dual focus in this analysis: the location choice of where expansion occurs in existing production subsidiaries and of where new subsidiaries are set up. The two types of location choice are related separately to 222 and 129 subsidiaries, covering eleven EU-15 countries and the time period from 1993 to 2004. In addition to the identification of the determinants, we also link the location choice of MNEs to the SMP and to the predictions of the NEG models.

Chapter 7 concludes the whole thesis and suggests some future research directions.

Chapter 2

Preparation of Micro Data

2.1 Introduction

The analyses of the size-growth rate relationship and industrial expansion dynamics (in Part I), the agglomeration trend and the location choice (in Part II) in the European pharmaceutical industry in the post-SMP era need two related yet different datasets at firm level. The first dataset needs to contain observations of pharmaceutical enterprises, where each enterprise consists of an MNE parent and its pharmaceutical-related subsidiaries (located in Europe). The sizes of subsidiaries are aggregated to generate the size of the enterprise. The second dataset should consist of pharmaceutical production subsidiaries or independent pharmaceutical production firms.[1] Both datasets need to contain following specific details about the subsidiary firms and their MNE (or non-MNE) parents: i) information on the ownership of each subsidiary and its parent, in order to connect each subsidiary firm to a unique ultimate owner; and ii) firm-level production and employment data covering relevant time span. In addition to this common information, the dataset for the analysis of the agglomeration trend and the location choice needs to contain some more information: a) in which country production subsidiary firms or independent firms are located; b) the production and employment data for these firms at an earlier time point and a later time point. Though some subsidiary firms and independent firms may not exist or may no longer be operating in the pharmaceutical industry at the later time point, their information have to be retained;[2] and c) the ownership information of those subsidiary firms at two time points in order to allow the ownership change due to mergers and acquisitions to be tracked.

We construct the two datasets from various data sources. Firm-level data on production, employment, location, the year of incorporation and ownership are collected from a commercial database, "*Amadeus*", which is published by Bureau van Dijk (BvD) Electronic Publishing. The data on the mergers and acquisition (M&A) cases in the European Union come from the Kiel Institute of World Economics in Germany. A list of some of the major M&A cases that took place in the global pharmaceutical industry is shown in Table 2.1. We also obtain information regarding the ownership, and business activities from the websites of the pharmaceutical enterprises as a supplement to the main data sources.

In this chapter we give a brief account of the *Amadeus* database (Section 2.2) and the procedure on how we construct the dataset on production firms (Section 2.3). Section 2.4 contains a brief summary.

[1] The independent firm is defined as a firm does not have owner and subsidiaries.
[2] We will treat these firms as either "died" or "switched industry".

2.2 The *Amadeus* Database

"*Amadeus*" is a large database containing information on the accounts and ownership of medium and large-scale firms based in Europe. This database, which is compiled primarily from company record office data and published company accounts of firms in European countries, is created as a business analysis tool. However, in the absence of pan-European firm-level data, it has recently come to be used for micro-econometric research by economists. For example, Budd *et al.* (2002) analyse profits sharing across borders within multinational companies. Konings and Murphy (2003) investigate European MNEs' employment substitution in home country and other European host countries in response to changes in labour costs in home and host countries. Cuyvers *et al.* (2005) study the impact of FDI and affiliate production in the Central and Eastern European countries on factor demand of their EU parent firms. Navaretti *et al.* (2006) examine the effect of outward investments to low labour-costs countries on MNEs in home country in terms of productivity and employment growth for France and Italy. Mataloni (2007)[3] studies the determinants of location choices of US MNEs through their European operations.

2.2.1 Account Data

The attractiveness of *Amadeus* is that it is one of the few comprehensive databases so far available that can provide researchers with financial accounting information on large numbers of European firms, where the data have been processed to ensure maximum comparability. The latest version of *Amadeus*, as of October, 2008, contains financial information on approximately 11 million public and private firms in 41 European countries. However, the database available to this study has a smaller coverage because of more limited data coverage in earlier years. The 1997 version of the database covers 196,639 firms while the 2005 version covers 1,434,249 firms. BvD uses different inclusion criteria of size to select medium and large-scale firms into different versions of *Amadeus*. The inclusion criteria of size for these two versions are presented in Appendix (Section 2.5).

Its publisher, BvD, combines data from 27 specialist regional information providers (see Table 2A.1 for a list of these providers). The local information providers in Western Europe are some firms that have expert local knowledge of companies. They compile the company register from official sources at local or national level. In some other countries, particularly those in Central Eastern European countries, the information providers collect the data directly from companies due to the difficulty of obtaining the data from government sources as well as the relative unreliability of the data registered

[3]The main data source is the mandatory surveys of the US Bureau of Economics Analysis (BEA) on US MNEs. The location information of US operations in the EU is from *Amadeus*.

with the government.

Because this is ultimately a business analysis tool, BvD collects and updates firm accounts monthly for Balance sheet items and Profit and Loss account items. It also collects other information (e.g. activity, location and ownership etc.) of the relevant firm from its annual report or through direct contact with its staffs. BvD processes all available information on a firm and creates a report for each firm in a uniform format, which contains following items (although the reports' completeness is subject to the information availability):

1. A unique identification number assigned by BvD;[4]
2. Basic information such as nationality, location, legal form, the year of incorporation;
3. Trade description and activity codes: Trade description is in the original language of the country where the firm is located or in English (subject to availability). The activity codes include both a national industry code and a 4-digit EEC code (NACE). The latter is now the compulsory code for all firms in the EU region;
4. A consolidation code indicating if the statement is consolidated, unconsolidated, with the extent of financial data available;
5. The Balance sheet with 25 items (in time series from the earliest year (1993) to the latest year when the data are available);
6. The Profit and Loss account with 25 items (in time series from the earliest year (1993) to latest year when the data are available);
7. Financial ratios calculated by BvD based on the Balance sheet and the Profit and Loss account (26 items in time series from the earliest year (1993) to latest year when the data are available);
8. The shareholders of the firm(corporate shareholders or individual shareholders) and its subsidiaries.

The items in the Balance sheet and the Profit and Loss account are presented in the original currencies. BvD collects exchange rates for 205 countries and regions from

[4]It may not be unique for one firm in different versions of the database if this firm experienced substantial ownership change or changed its name. In such cases BvD assigned a new ID to this firm or modified original ID according to certain rules. These changes become the major difficulty when we try to track the evolution of a firm in different versions of *Amadeus*. See Section 2.3.4 for details.

International Monetary Fund in order to allow users to convert between any currency.[5] We list all items of the Balance sheet, the Profit and Loss account and the financial ratios in Table 2A.2.

2.2.2 Ownership Data

In addition to the standard financial data found in firm accounts, *Amadeus* has an ownership database for every firm included. BvD has generated ownership links between firms located in Europe and their world-wide networks, and as of June, 2005, the database contains over 11 million links providing information on over 6 million firms worldwide. With the help of this database, researchers can track the changes of ownership of firms across time that resulted from the normal share trading activities and active mergers/acquisitions taking place since the mid-1990's, or identify an enterprise group (parent and its subsidiaries). It also facilitates the identification of the nationality of a subsidiary's ultimate owner.

In the ownership database both direct and indirect ownership relationship are revealed. For example, the simplest case is that an information provider reports that entity A (a firm, a government, a known family or an individual etc.) directly owns a certain percentage of voting share in firm B. However, other than this simple case, an information provider may report that entity A exclusively owns firm B and firm B owns, say, 80 per cent shares in firm C. But the A and C's relationship is not revealed. BvD investigates this indirect link between entity A and firm C, then treats firm C as indirectly owned by entity A holding 80 per cent share in firm C.

BvD also makes an effort to identify a firm's ultimate owner (UO). If information reveals that firm A does not have any shareholder, then BvD marks firm A as having "no UO". If firm A has some shareholders, BvD goes upward along firm A's shareholder hierarchy following one link to the shareholder which has the highest voting share in firm A. Then it goes upward again from that shareholder until it reaches the top level of the hierarchy. Only the link with share over 24.99 per cent can be included in such a UO path. BvD specifies the shareholder at the top level as firm A's UO. In case that there are multiple shareholders at this level, BvD specifies the one with the highest share as firm A's UO. In certain case, an information source reveals a shareholder is a UO but does not attaches any specific share to the link between the shareholder and its subsidiary. When BvD goes upward along the shareholder hierarchy and encounters such a UO link (amongst other links with share value attached), this UO link takes priority over all other links.

Following this procedure, BvD specifies a unique ultimate owner for each sub-

[5]Since the time frame of the study begins well before Euro was introduced into international financial market as an accounting currency in 1999, in our constructed dataset all money values are presented in USD.

sidiary. Details of how BvD constructs and organises the ownership data can be found in Bureau van Dijk (2005).

2.2.3 Limitations of *Amadeus*

Although *Amadeus* is the most comprehensive database available to the researchers who want to study various issues of European economy at micro level, it is limited in three particular respects.

Firstly, *Amadeus* does not contain plant-level data for each firm included. Since the raw data are mainly from national company registration administrations and the database was originally designed to serve business analysis purposes, *Amadeus* differs from other large-scale databases[6] being used to study micro behaviour, in that it does not have plant-level information. Since we do not have data on the plants of a firm, we cannot tell how their production distributes geographically in one or multiple countries. This limitation does not cause difficulty in Part I of this thesis because there we are looking at the expansion of pharmaceutical MNEs in the enlarged EU market, assuming the EU market is one single geographic area. However, the limitation prevents us from investigating the location choice of MNEs at region level in Part II. Consequently, we have to use location information on each firm and work on the location choice at country level.

The second limitation lies at the coverage of firms across countries. According to the *Amadeus* help file (the 2005 version), there are two main reasons why the coverage is not complete and particularly poor for some countries.

1. Only firms of certain types of legal form need to submit their accounts to the national company registration administration. These types of firms are usually limited companies or public limited companies (using UK and Irish nomenclature), which have counterparts in other countries, e.g. GmbH and AG in Germany, Sárl and SA in France, Srl and SpA in Italy.

2. Firms may not comply with the legal obligation of filing and the situation varies across countries. In Germany, for instance, according to BvD *"only 10,000 large/medium companies and 25,000 small companies are publishing their account" because "failure to comply with disclosure requirements is not normally a punishable offence; ... There is therefore no guarantee that information will be readily available on smaller and medium-sized companies in particular."*

In addition to the issue of geographic coverage of firms, the coverage of firms is

[6]The databases at plant level include Annual Respondents Database (ARD) file, constructed by the UK Office for National Statistics, US-based Longitudinal Research Database (LRD) and the Irish Central Statistics Office's Census of Industrial Production (CIP), which collects establishment-level data.

generally poorer for the earlier years in the database, with the focus of BvD being on the current data rather than on the time-series preoccupations of economists. But BvD keeps updating *Amadeus* monthly.

The final limitation is that missing data and errors are inevitable. In Section 2.3.3 we discuss the methods used to restore some of the missing values.

2.3 Constructing of the Datasets

2.3.1 Overview of the Procedure

We start collecting data on European pharmaceutical production firms in *Amadeus*, in order to meet the data demand of the second part of the research, which is examining the production agglomeration trend and the location choice of MNEs through their production subsidiary firms. Firstly, we extract and clean the data on both pharmaceutical production subsidiary firms and independent production firms. Secondly, we link each of the subsidiaries to a unique ultimate owner (a parent firm) and all subsidiaries having the same parent are grouped together to form a record of pharmaceutical enterprise. The independent firm is an enterprise in its own right. We are able to identify in this dataset on production firms whether a parent firm is an MNE or not. This is the creation of the dataset on the production firms. In the research on the size-growth relationship and the expansion dynamics of firms, the subjects are MNEs. Accordingly, we expand the data on MNEs which are identified in the dataset on production firms by adding the information on their pharmaceutical-related non-production subsidiaries.[7] The sizes of an MNE's pharmaceutical-related subsidiaries are added up to generate the aggregate size of the MNE. This is the creation of the dataset on enterprises. Because we have to use two versions of *Amadeus* to construct the dataset on production firms, the procedure for creating this dataset is complicated and delicate. Once all pharmaceutical MNEs are identified, it is straightforward to create the dataset on enterprises. Therefore, in the following section, we only describe the procedure used to create the dataset on production firms and delay the discussion of how the dataset on enterprises until Chapter 3, where is relevant.

2.3.2 Determining Time Scope under Investigation

For the dataset on production firms, we need to identify those firms at two time points which are separated by a long time period after 1992. We also need to obtain the production and employment data for those firms in this time period, given the firm was active throughout the time period, was born in the period, left the pharmaceutical in-

[7]They are pharmaceutical wholesale, retail and research and development firms. Moreover, by construction any MNE in our dataset has at least one pharmaceutical production subsidiary firm located in one of the EU-15 countries.

dustry or died in the period. Because BvD only started to assemble the database in the mid-1990's, we use two versions of the database, 1997 and 2005, to construct the 1995 and 2003 sub-datasets respectively. We use these later years because the information providers need time to collect and process data from local administrations and consequently firm-level accounts are published late. Thus looking at the data for the two years in the versions that appear two years later, we get much more complete data. Thus the 1997 version provides good coverage of firms in 1995, while the 2005 version provides good coverage of firms in 2003. This 9-year span is the longest time period we could use in the research.

The coverage of the two versions is somewhat different, reflecting developments in the processing approach of BvD over the period. Since we need to apply the same criteria for the two years, we harmonise the inclusion criteria by applying the inclusion criteria in the 1997 version to the 2005 version to determine which firm should be included in the 2003 sub-dataset.

2.3.3 Searching for Pharmaceutical Production Firms

We search for all pharmaceutical production subsidiary firms or independent firms in the two versions of *Amadeus*. A firm must fulfil the following criteria to be selected:

1. It has at least one of the two 4-digit NACE Rev. 1.1 Industry Code: 2441 (manufacture of basic pharmaceutical products) or 2442 (manufacture of pharmaceutical preparations);

2. It meets the size inclusion criteria in the 1997 version;

3. It has unconsolidated accounts;

4. It is located in one of the following 14 counties: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal, Spain, Sweden, and the United Kingdom.

Each firm is examined carefully for inclusion in the dataset, and some firms are deleted following this examination. For example, on inspection, it appeared that some of the firms selected are wrongly classified as pharmaceutical production firms and in fact they are actually producers of food or medical equipment. This firm-by-firm check was undertaken using the trade description of each firm in the report of *Amadeus*, and then the trade description is further confirmed via the firm's website if available.[8]

[8]We make a great effort to search internet using firm's name to find its or its parent's website. It is usually not difficult to find a firm's website. We find such websites for more than half of the selected firms and fortunately most of the websites have English pages.

After the pharmaceutical firms are selected, we extract data on geographic location, year of incorporation, operational revenue, employment and shareholders/subsidiaries from *Amadeus* for each firm. We have to use operational revenues (in addition to employment) to proxy a firm's production capacity, although usually researchers prefer sales. This is because the data on sales are less complete than those on operational revenues. The operational revenues and employment for the firms selected in the 1997 version are in a time series from 1993 up to 1997 (if available) but only between 1995 and 1996 can the data can be seen as complete and acceptable.[9] The data for the firms selected in the 2005 version are in a time series from 1993 to 2004 and again only data between 1995 and 2003 can be seen as complete and acceptable enough. For those firms in the 2005 version, there are some missing values for operational revenues and employment. For example, one or two blank cells may be found in a time series. In this case, we use the mathematical average of the values in the year before and after the year with missing value to fill in the blank cell. If there are more than two but less than four successive blank cells, we use the data before and after the years with missing values to predict the missing value by assuming a linear growth path. If the missing value exists for more than four successive years, the firm has to be dropped because simple mathematic methods may not be able to restore missing information without introducing significant distortions. Approximately 20 per cent of firms from the 2005 version were dropped for this reason.

Given that the focus of BvD in establishing *Amadeus* is commercial, there is a natural concern about whether the obtained firm-level data are good representation of the European pharmaceutical industry. To address this issue, we sought country-level data on employment and the number of firms in the pharmaceutical industry from other sources for comparative purposes.[10] The first source is the EUROSTAT industry, trade and services data. A second source is the OECD Industry Structural Analysis (STAN) Database, which provides internationally comparable industry-level data. In Table 2.2 the own sample distributions of employment and the number of firms aggregated at country level are compared with those that come from two alternative data sources. Unfortunately, the number of firms is not available in the OECD STAN database. For each of two years (1995 and 2003), the correlation coefficients based on employment and firm numbers (where possible) by country between any two data sources are calculated. The coefficients are all larger than 0.91 for 1995. In 2003 the coefficients between *Amadeus* data and EUROSTAT data are 0.74 and 0.79 respectively

[9] We find that more than 80 per cent of firms selected have data on operational revenues and employment in 1995 and 1996, while before 1995 and after 1996 the percentage drops sharply.

[10] Since there are no figures of operational revenues in EUROSTAT and OECD STAN, we cannot compare the data quality with respect to this item.

for the employment and the number of firms, but it is as high as 0.93 for *Amadeus* data and OECD data in terms of employment. On this basis, we argue that our data can provide a good picture of the European pharmaceutical industry.

2.3.4 Tracking Firms in the Two Sub-datasets

The next step is to track each firm and establish a link between its presences in the 1995 sub-dataset and the 2003 sub-dataset. We also need to identify those firms which had left the industry or died before 2003 and identify those firms were born before 2003. To avoid any potential omission, we use firms in the **1995 sub-dataset** as index and search them in the **2005 version** of *Amadeus*. Then, reversely, we use firms in the **2003 sub-dataset** as index and search them back in the **1997 version** of *Amadeus*. In principle, since BvD assigns a unique ID number for each firm, it should be straightforward to track any firm in two subsets; however, the real situation is that some firms change their ID numbers. The two main reasons for the change of ID are the change of name and re-registration as a new firm following a takeover. One needs to be cautious about the latter case because a re-registered firm is still representing an existing production facility instead of a newly-created one.

Because these complications, we applied six steps to track a firm in two sub-datasets and two versions of *Amadeus*. Below is the example of tracking a firm (called "index firm") of the 1995 sub-dataset in the 2005 version of the database:

1. Look for the firm (called "target firm") with the same ID number in the 2005 version of *Amadeus*;

2. If fails, go to search the target firm in the 2005 version that bears the same name or part of the name of the index firm;

3. If fails, go to search the target firm at the same address in the 2005 version;

4. If fails, go to check the shareholder of the index firm in the 2005 version and look for the possible match in the list of its subsidiaries;[11]

5. If fails, make use of the date of incorporation to cross-check a possible match in the 2005 version (with the aid of other information available, such as ownership, address and trade description, etc.);

6. If fails, the index firm is marked as "untracked".

[11] Usually, we assume that an index firm has the same parent in 2005 as it has in 1997. Sometimes we know who might be the 1997 index firm's parent in 2005, based on information from the mergers and acquisitions database.

Then the above six steps are repeated to track firms in the 2003 sub-dataset back to the 1997 version of the database. If one firm is located in the 1997 version after tracking but has not been included in the 1995 sub-dataset, this firm will be added to the 1995 sub-dataset with its account data from the 2005 version, if available. By this way the 1995 sub-dataset is augmented, in order to obtain the maximum number of observations.[12]

After tracking process is finished, each firm in the two sub-datasets is classified in one of the following six categories:

Cat. 1: Firms continuously staying in the pharmaceutical industry between 1995 and 2003;

Cat. 2: Firms that switched industries and exited the pharmaceutical industry before 2003;

Cat. 3: Firms that switched industries and entered the pharmaceutical industry before 2003;

Cat. 4: Firms that are in the 2003 sub-dataset, but do not have financial data available in 2003, according to the information from the 2005 version of *Amadeus*;[13]

Cat. 5: Firms that were incorporated as a pharmaceutical producer after 1995 (inclusive);

Cat. 6: Firms that were "dead" before 2003 if *Amadeus* indicates they are either inactive, in liquidation or dissolved in the 2005 version.

Cat. 7: If a firm is in one sub-dataset but cannot be located in another one after tracking, it is marked as an untracked firm.

Following this tracking process, we have 1,065 firms in the 1995 sub-dataset and 1,163 firms in the 2003 sub-dataset. In Table 2.3 the breakdown of the firms in the two sub-datasets is given under different categories: 647(648)[14] firms (Cat.1) remained in the pharmaceutical industry between 1995 and 2003; 166 firms (Cat.2) exited from the industry before 2003; 62 existing firms (Cat.3) entered the industry before 2003. Cats. 1 to 3 firms sum up to 875(876), which are tracked firms with data available in both years. Some 24 tracked firms do not have account data in 2003; 177 firms were established after 1995(inclusive); 111 firms were dead before 2003; 55 firms in the 1995 sub-dataset cannot be tracked and 110 firms in the 2003 sub-dataset cannot be tracked.

[12]This practice, to some extent, violates the common inclusion criteria of size we set for the early and late datasets. But considering we are looking at a single industry, we think this practice is acceptable to maximise sample size.

[13]For these firms, *Amadeus* does not provide any information about why there are no financial data available for them.

[14]One firm in 1995 was split into two firms and both of them can be identified in the 2003 sub-dataset. They are still in the same city.

2.3.5 Linking the Subsidiaries to Their Parent

Once the qualified pharmaceutical production subsidiary firms and independent firms are identified, we begin to identify each subsidiary firm's ultimate owner following the same procedure as BvD does in building its ownership database (as described in Section 2.2.2). A subsidiary firm's ultimate owner is deemed as its parent. Consequently, a parent - subsidiary link is identified if a parent firm directly or indirectly owns more than 25 per cent (inclusively) of shares in a subsidiary firm, or the parent firm is marked by BvD as an ultimate owner of the subsidiary firm. This criterion is applied to both domestic parent-subsidiary links as well as to foreign parent–subsidiary links. In terms of the foreign ownership measure, this 25 per cent threshold exceeds what is adopted by International Monetary Fund and OECD to define a foreign directly-owned investment, which states that: "*Foreign direct investment enterprise is 'defined as an incorporated or unincorporated enterprise in which a foreign investor owns 10 per cent or more of the ordinary shares or voting power of an incorporated enterprise or the equivalent of an unincorporated enterprise.*"'[15] We take the higher threshold as we wish to avoid any risk of assigning ownership in the case where minority owners do not have enough control power in their investment.

We also take account of the possible changes in the ownership over time, which are the consequence of active mergers and acquisitions taking place in the pharmaceutical industry between 1990 and 2003. We source information on mergers and acquisitions from pharmaceutical enterprises' official websites, or European Union's antitrust cases database[16] and a specialised M&A database called "DOME (Database on Mergers in Europe)"[17], which is compiled in Germany at the Kiel Institute of World Economics. In some cases a direct query was made to the staff in the company under investigation; however, the response rate to such queries was very low. Besides the above-mentioned information sources, we also consulted the information provided by pharmaceutical industry associations or research organisations (e.g. EFPIA - The European Federation of Pharmaceutical Industries and Associations). The information collected allows us to track the ownership changes of some subsidiary firms over the years, if these firms belong to the pharmaceutical parent firms which are filed in the above information sources. However, we have to admit that, for time reasons, we are only able to identify

[15]Balance of Payments Manual, 5th Edition, IMF (1993, pp.86).

[16]This database is located at http://ec.europa.eu/comm/competition/antitrust/cases/. It contains antitrust cases handled by the European Commission (cases treated under Articles 81 and 82 of the EC Treaty) since 1999.

[17]DOME is a public database that is under examination by the European Commission since 1990. Until the end of 2000 it contains 1,515 M&A cases. Since the database consists of mergers and acquisitions cases examined by the European Commissions, it is biased towards large companies due to the criteria of the European Commission. DOME is available at
http://www.uni-kiel.de/ifw/forschung/dome/dome_e.htm.

a limited portion of the ownership changes and such identified ownership changes mainly took place in the world leading pharmaceutical enterprises.

After the parent-subsidiary links are built for all selected subsidiary firms, the firms having the same ultimate owner are grouped together to form a record of an enterprise. We also classify an independent firm as an enterprise on its own right. Finally, we obtain a collection of 449 pharmaceutical enterprises consisting of 1,047 production firms, which were doing business in the EU-15 countries (excluding Luxemburg), before 2003. These pharmaceutical enterprises are classified into three categories:

1. Multinational enterprise (MNE), which is defined as an enterprise whose parent firm has at least one production subsidiary firm locating in a country other than the country where the parent firm locates. The nationality of an MNE is determined by the location of the parent firm; consequently, an MNE can be a European MNE, a US MNE, a Japanese MNE or an MNE from other country of the world. Since we start building the dataset by searching subsidiary firms in the EU-15 countries, these MNEs, by definition, have at least one subsidiary located in the EU-15.

2. Non-MNE multi-firm enterprise, which is defined as an enterprise whose parent firm has all subsidiary firms (not only its production subsidiaries) located in the same country as the parent does.[18] Again by construction, such enterprise is located in one of the fourteen EU-15 countries.

3. Non-MNE single-firm (independent) enterprise, which is defined as an enterprise consisting only of one production firm and by construction, such an enterprise is located in one of the fourteen EU-15 countries.

In Table 2.4 we present the breakdown of the geographic distribution of 449 enterprises in the EU-15 countries and other countries or regions (by their headquarters' location) and 1,047 production firms in the EU-15 countries. The MNE, Non-MNE multi-firm enterprise and Non-MNE single-firm enterprise are separately reported in the table. Two points are notable:

1. The average number of subsidiaries is 2.81 (799/284) for MNEs and 1.67 (205/123) for Non-MNE multi-firm enterprises;

2. Compared with the subsidiaries located in France, Italy and Spain, the number of German-based subsidiaries is much smaller. This finding is consistent with the fact that German firms are under-represented in *Amadeus* (see Section 2.2.3).

2.4 Summary

In this chapter, we describe the procedures used to construct the dataset on pharmaceutical production firms using a pan-European firm database - *Amadeus*. This dataset

[18]We have to rely on the ownership database in *Amadeus* to check if all firms in an enterprise group are located in the same country.

will be used in the empirical research on production agglomeration and the location choice. The dataset contains data on European pharmaceutical firms in two years, with 1,065 production firms in the 1995 sub-dataset and 1,163 firms in the 2003 sub-dataset. Links are built for 876 (the figure for the 2003 sub-dataset) firms which exist in both 1995 and 2003, plus information of 177 newly-born firms (since 1995) and 111 dead firms (exited between 1995 and 2003).

Using the ownership database of *Amadeus* and other information sources, we identify 284 multinational enterprises and their production subsidiary firms. These enterprises and their subsidiaries form our subjects in the study on the size-growth rate relationship and expansion dynamics (Part I), and production agglomeration and the location choice in the post-SMP era (Part II).

2.5 Appendix: Inclusion Criteria of Size for the 1997 and 2005 Versions of *Amadeus*

A firm can be included in the 1997 version of *Amadeus* if it can meet at least one of three following size criteria:

1. Operational revenues greater than 10 million XEU[19] (approximately 12 million USD);
2. Number of employees greater than 150;
3. Total assets greater than 10 million XEU (approximately 12 million USD).

A firm can be included in the 2005 version of *Amadeus* if it can meet at least one of three following size criteria:

For the UK, Germany, France, Italy, Spain, Ukraine and Russian Federation:

1. Operating revenues equal to at least €1.5 million;
2. Total assets equal to at least €3 million;
3. Number of employees equal to at least 20.

For all other countries:

1. Operating revenues equal to at least €1 million;
2. Total assets equal to at least €2 million;
3. Number of employees equal to at least 15.

[19]XEU is European Currency Unit's ISO code (see ISO 4217:1990- Codes for the representation of currencies and funds).

2.6 Tables

Table 2.1: Major Mergers and Acquisition Cases between 1994 and 2004 in the Global Pharmaceutical Industry

Year	Cases
1994	Johnson & Johnson (US) acquired Clinical Diagnostics (US). Wyeth (US) acquired American Cyanamid (US). Akzo (the Netherlands) merged with Nobel (Sweden).
1995	Pharmacia (Sweden) merged with Upjohn (UK). Glaxo (UK) merged with Burroughs Wellcome (US).
1996	Ciba-Geigy (Switzerland) merged with Sandoz (Switzerland) to create Novartis.
1997	Baxter (US) acquired Immuno AG (Switzerland).
1998	Cardinal Health (US) acquired Scherer Corp. (US).
1999	Johnson & Johnson (US) acquired Centocor (US). Sanofi (France) merged with Synthélabo (France). Hoechst AG (Germany) merged with Rhône-Poulenc (France) to create Aventis. Roche (Switzerland) acquired Genentech (US). Astra (Sweden) merged with Zeneca (UK).
2000	Pfizer (US) acquired Warner-Lambert (US). Glaxo Wellcome (UK) merged with SmithKline Beecham (UK).
2001	Abbott (US) acquired Knoll (Germany). Bristol-Myers Squibb (US) acquired DuPont's pharmaceutical business.
2002	
2003	Pfizer (US) acquired Pharmacia & Upjohn (UK).
2004	Sanofi-Synthélabo (FR) merged with Aventis (FR).

Source: The DOME database and the official websites of the pharmaceutical enterprises.

Table 2.2: The Correlation Coefficients for Employment and the Number of Firms in the Pharmaceutical Industry from *Amadeus*, EUROSTAT and OECD STAN (1995 and 2003)

1995	Employment	Number of Firms
Amadeus/EUROSTAT	0.98	0.99
Amadeus/OECD	0.91	na
OECD/EUROSTAT	0.995	na
2003	Employment	Number of Firms
Amadeus/EUROSTAT	0.74	0.79
Amadeus/OECD	0.93	na
OECD/EUROSTAT	0.95	na

Source: *Amadeus* version 1997 and version 2005; EUROSTAT's Industry, trade and services data; OECD STAN Industry Structural Analysis Database.

Table 2.3: Breakdown of the Tracked and Untracked Firms in the 1995 and 2003 Sub-datasets

	Categories	# in 1995	# in 2003
Active	Cat. 1: Tracked pharmaceutical firms in both 1995/2003 sub-datasets	647*	648*
	Cat. 2: Tracked and was in the pharmaceutical industry in 1995, exited before 2003	166	166
	Cat. 3: Tracked firm that was not in the pharmaceutical industry in 1995, entered the pharmaceutical industry before 2003	62	62
	Cat. 4: Tracked firms but do not have account data in 2003	24	na
	Cat. 5: New firm incorporated after 1995 (inclusive)	na	177
Dead	Cat. 6: Firms were inactive, in liquidation or dissolved in 2003	111	na
Untracked	Cat. 7: Firms in 1995 that cannot be tracked in 2003	55	na
	Cat. 7 : Firms in 2003 that cannot be tracked in 1995	na	110
	Total	1,065	1,163

* One firm in 1995 were split into two firms and both of them can be identified in the 2003 dataset. They are still in the same city.

Table 2.4: Geographic Distribution of Pharmaceutical Enterprises and Production Subsidiaries

		Multinational Enterprise	Domestic Multi-firm Enterprise	Domestic Single-firm Enterprise	Subsidiaries of MNEs	Subsidiaries of Domestic multi-firm enterprise
1	Austria	1	2	1	5	2
2	Belgium	11	1	0	46	4
3	Denmark	10	1	0	17	1
4	Finland	1	1	0	5	1
5	France	47	35	2	227	43
6	Germany	28	8	2	48	12
7	Greece	1	10	2	11	17
8	Ireland	6	2	0	25	2
9	Italy	15	24	30	135	59
10	The Netherlands	5	1	0	12	2
11	Portugal	1	2	3	12	7
12	Spain	21	20	2	135	30
13	Sweden	10	1	0	19	1
14	The UK	25	15	1	102	24
15	Other European countries	21	na	na	na	na
16	US	51	na	na	na	na
17	Japan	14	na	na	na	na
18	ROW	16	na	na	na	na
19	Sum	284	123	43	799	205

Note: ROW = Rest of the World.

Table 2A.1: Information Provider

Information Provider	Country
Creditinfo Czech Republic, s.r.o.	Czech Republic
Chamber of Commerce And Industry of Romania	Romania
COFACE INTERCREDIT	Slovenia
Coface Mope	Portugal
Coface SCRL	France
CreditInform AS	Norway
CreditInfo Group	Iceland
Creditreform Austria	Austria
Creditreform Bulgaria	Bulgaria
Creditreform Croatia	Croatia
Creditreform-Interinfo	Hungary
Creditreform Latvia	Latvia
Creditreform St. Petersburg	Russia
Honyvem	Italy
ICAP	Greece
InfoCredit	Poland
Informa	Spain
Jordans	United Kingdom
Kømandstandens Oplysnings Bureau	Denmark
Krediidiinfo	Estonia
LexisNexis	The Netherlands
Creditreform Belgrade	Serbia and Montenegro
Patikimo Verslo Sistema	Lithuania
Suomen Asiakastieto Oy	Finland
UC	Sweden
Verband der Vereine Creditreform	Germany
Worldbox	Switzerland

Table 2A.2: Financial Items Available in the Firm Report of *Amadeus* (2005 Version)

Item number	Balance sheet	Profit and loss account	Ratios
1	Fixed assets	Operating revenues/turnover	Current ratio
2	Intangible fixed assets	Sales	Liquidity ratio (%)
3	Tangible fixed assets	Costs of goods sold	Shareholders liquidity ratio (%)
4	Other fixed assets	Gross profit	Solvency ratio (%)
5	Current assets	Other operating expenses	Gearing (%)
6	Stocks	Operating P/L	Share funds per employee
7	Debtors	Financial revenue	Working capital per employee
8	Other current assets	Financial expenses	Total assets per employee
9	Cash & cash equivalent	Financial P/L	margin (%)
10	Total assets	P/L before tax	Return on shareholders funds (%)
11	Shareholders funds	Taxation	Return on capital employed (%)
12	Capital	P/L after tax	Return on total assets (%)
13	Other shareholders funds	Extraordinary and other revenue	Interest cover
14	Non current liabilities	Extraordinary and other expenses	Stock turnover
15	Long term debt	Extraordinary and other P/L	Collection period (days)
16	Other non-current liabilities	P/L for period	Credit period (days)
17	Current liabilities	Export turnover	Net assets turnover
18	Loans	Material costs	Costs of employees/operational revenue (%)
19	Creditors	Costs of employees	Operational revenue per employee
20	Other current liabilities	Depreciation	Average cost of employee /year
21	Total shareholder funds & liabilities	Interest paid	Profit per employee
22	Working capital	Cash flow	Cash Flow/Turnover (%)
23	Net current assets	Added value	Gross Margin (%)
24	Enterprise value	EBIT (Earnings before interest and taxes)	EBIT Margin (%)
25	Number of employees	EBITDA (Earnings before interest, taxes, depreciation and amortisation)	EBITDA Margin (%)
26			Export turnover/Total turnover (%)

Part I

Micro-Econometric Applications of Stochastic Firm-Growth Theory

Chapter 3

The Firm-Growth Theory: Literature Review and Applications

3.1 Introduction

Gibrat (1931) postulated a simple stochastic model to explain how the stylised skewed firm-size distribution can be caused. The model implies that there exists a law governing the growth process of any firm that each absolute increment of growth is proportional to firm size, regardless of whether the firm is large or small. Since the 1950's, many stochastic models have been proposed with this law serving as a primary or a partial assumption in explaining firm growth and skewed size distributions. Later, models featuring optimising behaviour based on a game-theory framework were developed in order to bring in more economic sense to the growth theory. Empirical studies on the growth of the firm grew closely with the theoretical progress. We can find multiple studies on firm growth, such as: looking for the best stochastic distribution to fit firm-level data and the stochastic models which can generate such a distribution as well as realistic growth trajectories of the firm; analysing market structure which is the outcome of growth and testing the validity of Gibrat's law for individual industries or the whole economy. In this chapter, firstly, we review the theoretical and empirical literature on firm growth. Secondly, we test Gibrat's law on our firm-level data of the European pharmaceutical industry through two approaches and find that the two tests reject the law for the entire spectrum of firms.

The structure of the rest of the chapter is as follows. In Section 3.2, the theoretical and empirical literature is reviewed. Section 3.3 presents the firm-level data for the European pharmaceutical industry and in Section 3.4, we test the validity of Gibrat's law on the pharmaceutical industry. The last section concludes the chapter.

3.2 Review of Firm-Growth Literature

Gibrat's model is the earliest stochastic framework for modelling firm growth and explaining the skewed size distribution. This model shows that, if proportionate growth rates are drawn from a normal distribution, and these growth rates are multiplicatively accumulated in a firm's growth process, the firm's size (in logarithm form) will follow a normal distribution. In the simplest form (Steindl, 1965; Sutton, 1997), let S_t be the size of a firm (in sales, operational revenues or employment etc.) at time t, and ε_t be the proportionate growth rate:

$$S_t = (1 + \varepsilon_t)S_{t-1} \tag{3.1}$$

If we choose a very short time period for a unit of increment, ε_t must be small so we can use the property of logarithm that $\log(1 + \varepsilon_t) \simeq \varepsilon_t$. After taking logs on both sides we obtain

$$\log S_t = \log S_0 + \varepsilon_1 + \varepsilon_2 + ... + \varepsilon_t \tag{3.2}$$

If the time period goes to infinite, $\log S_0$ would be a negligible part of current size $\log S_t$, hence $\log S_t$ is seen as being generated from the addition of random variables ε_t and it follows a normal distribution with mean mt and variance $\sigma^2 t$, or equivalently, the size S_t has a limiting lognormal distribution.

This model suggests a law that, as described in Ijiri and Simon (1964) *"in its simplest and strongest form"* suggests that, *"year-to-year changes in firm sizes are governed by a simple Markoff process in which the probabilities of the size changes of any specified percentage magnitudes are independent of a firm's present absolute size."*, or in other words, the growth rate of a firm is independent of its size. Since in this stochastic model, the size is increasing proportionately at a growth rate ε, Gibrat's law is also called *"the law of proportionate effect (LPE)."*

Research on firm growth diverged in two major directions. The theoretical direction is to look for the distribution which can fit the skewed firm-size distribution best and the statistical models that can generate such distributions. The empirical direction is to test Gibrat's law using firm-level data. In what follows, we review these two directions separately, but certain overlapping of the two subsections is inevitable.

3.2.1 Theoretical Models of Firm Growth

Early work on the theory behind the evolution of firm size can be dated back to Viner's influential paper in 1932. In this paper he offers a theory that firms' equilibrium sizes are determined by the minimum points on their U-shaped long-term average cost curves. This theory predicts *"a unique size distribution within an industry"* and that *"the size distribution ...is a solution to..., allocate production over firms so as to minimize total cost."* (Lucas, 1978). Viner's deterministic theory received critiques from Lucas (1978) and Simon and Bonini (1958, also in Chapter 7 of Ijiri and Simon, 1977) where the former criticised mainly from the perspective of market operation, while the later argued that the shape of the average cost curve (for instance, decreasing and constant cost curves in Viner, 1932) could not determine the size distribution of the firms. Instead, Simon and Bonini (1958) proposed a stochastic model, based on different assumptions of growth and new-firm entry, which can produce a group of distributions that are able to proxy the size distribution of firms. They introduced the arrival of new firms into a stochastic model resembling Gibrat's model. They started from the assumption of Gibrat's law and demonstrated that a Yule distribution (Yule, 1925)[1] is the steady-state distribution of the upper tail of the size distribution. They further tested the validity

[1]The Yule distribution is a discrete probability distribution. Its probability mass function (pmf) is $\Pr(k) = \rho B(k, \rho + 1)$, where $\rho > 0$, and the interger $k \geq 1$. $B(\cdot, \cdot)$ is a standard Beta function.

of Gibrat's law on US industrial data. The way of testing is implied in Eq. (3.1): if one takes logs on both sides of Eq. (3.1) and plots the logarithms of the sizes in two successive time periods, they should form a 45 degree line and the plot is homoscedastic. Simon and Bonini found that the law holds for the 1955 - 56 period. In addition to that, the actual production data of US steel industry in 1954 fit closely to the production data estimated from a Yule distribution.

Ijiri and Simon (1964, also in Chapter 8 of Ijiri and Simon, 1977) developed a new stochastic process with a major change to that proposed by Simon and Bonini (1958) in that, the strong assumption of Gibrat's law, which states that the probability of any certain percentage of growth is the same for any firm, is replaced by a weaker assumption which assumes that the expectation of a percentage change is independent of firm size strata. This change is necessary to reflect the empirical findings in other researches that there exists a negative correlation between the variance of the growth rate and size, and only the expectation of the growth rate is independent of size (see Hymer and Pashigian, 1962 and Mansfield, 1962).

In addition to the adoption of a weaker assumption, a serial correlation condition is imposed on the model assuming that the probability of growth of an existing firm is proportional to its weighted sum of past size increments, and the weight is decreasing in the distance of the occurrence of an increment from the current period. Monte Carlo simulation shows that if opportunity comes in a equally-sized block one at a time, the stochastic process can reach an equilibrium distribution of firm size that is close to the Yule distribution.

Meanwhile, Steindl (1965) studied firms' sizes s and their ranks r, and found that the relationship of s and r satisfies the Pareto law[2]. Moreover, fitting US firm data proved that the Pareto distribution[3] is the first approximation to firm size distribution.[4] However, Ijiri and Simon (1974) brought attention to the observed concavity in noting that in the $s - r$ plot, when *Fortune* 1969 data of the largest industrial firms were used, this concavity contradicts the Pareto distribution. They pointed out that greater weight (or in other words, discount factor) given to past increments of size, and mergers and acquisitions can help to explain this concavity.

[2]The Pareto law dictates that the size s and the rank of r of a firm follows a relationship that $sr^{\beta} = A$, where β and A are constants. If we assign rank 1 to the largest firm and rank 2 to the second largest firms and so on, the Pareto law suggests that if firm A's rank is twice as large as that of firm B, the ratio of firm A and firm B's sizes is $2^{-\beta}$. Since the size of the firm at lower rank reduces at a speed governed by the power β, the firms obeying the Pareto law feature a highly-skewed size distribution. The law was named after Italian economist Vilfredo Pareto and it has been widely applied to the studies on the inequality in the distribution of income, event occurence, etc.

[3]The Pareto distribution is a discrete probability distribution. Its probability mass function (pmf) is $\Pr(k) = k^{-\rho}/\varsigma(\rho)$, where $\rho > 0$, and the interger $k \geq 1$. $\varsigma(\cdot)$ is the Zeta function.

[4]Notice here that the upper tail of the Yule distribution resembles that of the Pareto distribution. See Spierdijka and Voorneveld (2007).

In Ijiri and Simon (1967, also in Chapter 9 of Ijiri and Simon, 1977) the idea of the serial correlation between size and the probability of growth was developed. They proposed a model of firm growth that decomposes the growth factor into an industry-level common shock and a firm-specific shock. This decomposition of the growth factor takes into account the implication of Gibrat's law, a Markov process underlining firm growth and the "decaying effects" of firm-specific growth shock over time. By applying the model to large American firms, they estimated the key parameter of the model, the discount factor of sudden growth in the previous period.

Other authors modelled the firm-size distribution from different perspectives. For instance, Lucas (1978) postulated that the size distribution of firms is driven by the underlying distribution of managerial talent among economic agents through out the whole economy. The equilibrium results related to firm growth are derived by applying Gibrat's law literally. The author showed that if managerial talent follows a Pareto distribution, then the size distribution of firms also follows that distribution. Another result after the application of Gibrat's law is that raising the wage rate makes being a manager more costly, therefore more economic agents would like to work as an employee, and consequently raises the average size of firms. Jovanovic (1982) modelled firm growth with a learning process through which small entrants realise their true productive efficiency only after they enter the industry. After the knowledge of true efficiency is revealed, the entrants with low efficiency have to exit and the remaining entrants can survive. This "noisy selection" theory is able to explain the higher and more variable growth rates at the lower tail of the size distribution.

A further development in firm-growth models is in Sutton (1997, 1998). The author borrowed the framework from Ijiri and Simon (1977), but replaced their condition that the probability of a firm taking up a new opportunity is proportional to its size with a weaker condition (Condition 1 in his book) that the probability is non-decreasing in size. The model theorised the idea initialised in Ijiri and Simon (1977) that business opportunities are independent of each other and arrive to incumbents or new firms at the rate of one unit per time period. These independent opportunities can be regarded as submarkets.[5] The intuition of this model goes as follows: In an industry, the business opportunities arrive one at a time and one opportunity can only be captured by either one of the existing firms (incumbents) or a new entrant. If the opportunity is taken up by an existing firm, then this incumbent moves up one level in the rank of size while the total number of firms of the industry remains the same. On the contrary, if the opportunity is taken up by a new entrant, the total number of firms increases by one. Therefore, the evolution of the total number of firms and the size distribution

[5]Klepper and Thompson (2003) postulated a model based on the idea of finitely-lived submarkets that can generate various industrial regularities, i.e., entry, exit and growth.

can be simulated from a binomial distribution under two conditions that specify the probabilities of incumbents or entrants catching a new opportunity.

Condition 1: *"The probability that the next market opportunity is filled by any currently active firm is nondecreasing in the size of that firm"*;

Condition 2: *"The probability p that the next market opportunity is filled by a new entrant is constant over time"*.

As in Sutton (1997, 1998), let N_t denotes the total number of firms and $n_{i,t}$ the number of firms of size i at period t. N_t follows a binomial distribution

$$\Pr(N_t = N) = \begin{pmatrix} t-1 \\ N-1 \end{pmatrix} p^{N-1}(1-p)^{t-N}, \tag{3.3}$$

where p is the probability that a new opportunity is taken up by an entrant. It can be shown that from the above binomial distribution, one can express the probability of N increases by one (the case where a new firm enters), or N remains unchanged (no entry), as a function of N and t. The aim of the model is to show the conditional expectation of $n_{i,t}$ on N_t, $E(n_{i,t}|N_t)$. Based on a special case of Condition 1, namely, the incumbents have the same probability of taking up one new opportunity (Condition 1'), the unconditional expectation of $n_{i,t}$ is

$$\lim_{t\to\infty} E(\frac{n_{i,t}}{1+p(t-1)}) = p(1-p)^{i-1}. \tag{3.4}$$

From the above unconditional expectation, we see the size distribution of firms of size i follows a geometric distribution. This distribution can be further simplified to an exponential distribution if assuming the size x is continuous,[6]

$$f(x) = p\exp(-px). \tag{3.5}$$

The emphasis of the model then is diverted to the derivation of the k-firm concentration ratio for the k largest firms among N firms. By applying Condition (1') and let N and k increase, a lower bound of the k-firm concentration ratio is given by

$$\underline{C}_{k/N} \geq \frac{k}{N}(1 - \ln\frac{k}{N}). \tag{3.6}$$

The lower bound of the k-firm concentration ratio can be visualised by the Lorenz curve. It can be shown that under Condition (1) of inequal probability, the Lorenz curve will bend further away from the diagonal than the curve characterised by the

[6]Let p be a small value, one has $\ln((1-p)^{i-1}) = (i-1)\ln(1-p) \simeq -p(i-1)$. Write $\exp(-p(i-1)) = \exp(-pi)\cdot\exp(p) \simeq \exp(-pi)$ as $p \to 0$. Since $\exp(-pi)$ is the approximation of $(1-p)^{i-1}$, substitute it in Eq. (3.4) and express the size as x, one gets Eq. (3.5).

lower bound.[7]

More recently, some researchers brought the behaviour of optimising agents back into models of firm growth.[8] Ericson and Pakes (1995) modelled the evolution of an industry which solely relies on R&D investment. In such an industry, incumbents make decisions regarding investment in R&D to realise a new opportunity. The economic value associated with a successful realisation of a new opportunity is governed by three stochastic processes i) the firm's belief in its own chance of "success", ii) the belief in its competitor's chance of "success" and iii) an exogenous competitive pressure outside the industry that is imposed on all firms. The investment decision is then made according to the comparison of this value and the opportunity cost of being in the industry. Hence, a firm can either move up to a higher state of "success" if it is able to capture a new opportunity profitably, or be left behind if other firms make successful investments or the firm fails to offset competitive pressure. Continuous failures may lead to the firm exiting the industry. On the other hand, entrant needs first to pay a sunk cost that is non-decreasing in the number of entrants and then make the same investment decision in the next period as an incumbent does. Therefore, the model bears resemblance to Jovanovic's "noise selection" model. The authors showed that the interdependence of firms' investment (and entry) decisions leads to an equilibrium where one firm optimally makes decisions based on the true distribution of

[7]The empirical significance of this lower bound lies in that, once we know the m-firm concentration ratio C_m from published industrial data, we can derive a conditional lower bound of the k-firm concentration ratio D_k of any number k of firms given $k < m$. The performance of the above equation in predicting the lower bound D_k was confirmed using US and German data in Sutton (1998).

[8]A different line of research particularly focusing on the game-theory models of entry into market can also shed light on the theory of the firm. The line started from Bresnahan and Reiss (1990, 1991). In Bresnahan and Reiss (1990), a simultaneous-move game and a sequential-move game of entry are modelled empirically as an ordered discrete-choice of entry. Estimations on geographically-separated US auto markets reveal the effects of market demand and current market structure (in terms of number of dealers) on the evolution of future market structure through entry. Bresnahan and Reiss (1991) estimated the effects of the market size and the number of players on market competition in five US industries (all service industries). They found that the first 2 and 3 entrants change the competition the most, then the influence decreases gradually as the number of entrants increases. Berry (1992) also modelled the entry as a consequence of strategic interaction, but the primary determinant of the entry is firm-level heterogeneity rather than market conditions. The analysis of the US airline industry shows how one source of heterogeneity, amongst others, the airport presence determines airline's entry. The above papers deal with one regularity of firm behaviour, entry, in great detail. Therefore, the approach can be complementary to those stochastic studies which are weak in terms of the mechanism of entry. The limitation of this approach is that it has only be applied to the Oligopoly market.

Some further studies along the same lines of the game theory are listed as follows: Tamer (2003) and Ciliberto and Tamer (2007) both studied the discrete-choice model with multiple equilibriums and the later also applied the method dealing with the multiple equilibriums to the entry of US airline industry; Toivanen and Waterson (2005) modelled entry on market structure for the UK counter-service burger market which is primarily characterised by duopoly. Firms are found entering a geographic market following rival's entry and this pattern is interpreted as a learning effect of a rival's presence; Berry and Tamer (2006) studied the identification of a static and a dynamic entry model; Berry and Reiss (2006) reviewed empirical models of entry and market structure of both homogeneous and heterogeneous firms.

future states which is in turn generated by optimal responses of other firms to the first firm's optimal decision. This perfect Nash equilibrium is of Markov nature because *"...the current state, ..., and the current decision..., are sufficient to completely determine its dynamics..."*(pp. 59). This complex Markov dynamic model is hardly tractable unless one uses numerical simulations[9]. The authors demonstrated simulated outcomes of a homogeneous-product industry which are rich in that they show various features of this simulated industry that are similar to empirical observations such as active and correlated entry and exit, low survival rate of new firms and a highly-skewed size distribution.

Klette and Griliches (2000) developed a model in which a firm's growth is endogenously driven by R&D achievements it accumulated in the past. The independence of growth rate on size is derived under the steady-state condition that the size of the firm and the cost of R&D grow at the same pace, where the size of the firm is measured by its product quality and the rate of innovation is the measure of growth. Thus, the model reconciles R&D-based growth to Gibrat's Law. Moreover, Klette and Griliches' model only allows firms to strategically choose whether or not to conduct R&D in order to deter competitors from entering the market, hence it lacks the richness of the strategic interaction in Ericson-Pakes's models. Klette and Koryum (2004) improved the R&D-based growth model by incorporating the multiproduct nature of firms and the action of exit, which are missing in the early model. Firm growth is decided by a Poisson process where the arrival rate of a successful new innovation is a function of R&D investment and *"its knowledge capital accumulated through past product innovations"* (pp. 3). The model features a growth rate that is independent of firm's initial size before conditioning on survival but is decreasing in the initial size after conditioning on the survival. This growth rate is consistent with the stylised fact on industries discussed in their paper.

3.2.2 Empirical Literature of Firm Growth

Early empirical studies on the size-growth relationship started from Hart and Prais (1956). They used data of quoted companies in the London Stock Exchange (LSE) and found that for small, medium and large firms, their growth rates (the ratio of final size and original size in a 16-year period) closely follow the same normal distribution which is centered at 1. This finding suggests that Gibrat's law holds and no matter which size groups the firms are in, their growth rates are highly likely to be 1 and the distribution of the growth rates are fairly symmetric at the top and bottom tails. The weakness of this research lies in that the sample contains only large and surviving

[9]Pakes and McGuire (1994) developed a simple algorithm to compute the Markov-perfect Nash equilibrium and applied this algorithm to the Ericson-Pakes model of a differentiated-product market.

quoted firms, therefore the study could not address the growth rate of firms that lie at the bottom of the size distribution of the entire industry.

Hymer and Pashigian (1962) used the 1,000 largest US firms and found that average growth rate is not correlated with firm size. However, the variance of the growth rates is negatively correlated with the average size of the firms in different industries. They offered two explanations, either the average cost curve is continually falling, therefore small new entrants suffer from higher risk of exit due to higher costs (together with a higher tendency for high expansion), or, even if the average cost curve is constant, larger firms are more diversified in many different markets, which makes their growth trajectories more stable.

In Mansfield (1962), the author tested Gibrat's law on three American industries, namely steel, petroleum and rubber tire. He classified firms into different size classes by their initial sizes and then calculated the growth rate in each size class. A χ^2 test was used to test if the frequency distributions of the growth rates in different size classes are the same. He found that this hypothesis generally failed to hold. Even if excluding those firms which left the industry (the approach adopted by Hart and Prais, 1956) or those firms whose sizes are smaller than the minimum efficient size (the way adopted by Simon and Bonini, 1958), Gibrat's law still failed to pass the test in more than one half of cases (different industries in different time periods). To explain the finding that small firms generally grow faster but more variable than large firms, he proposed a simple mathematical model. In this model, if a large firm can be viewed as a collection of many small components, the variance of the mean growth rate of the small components is inversely related to the firm's size. As a result, under certain conditions with regards to the death rate of firms, the mean growth rate and its variance are inversely related to the size.[10]

On the contrary, Hart (1962) found evidence, for four UK industries in the 1930's, to support Gibrat's law in terms of average growth rate for firms of different size. However, the hypothesis of same variance cannot be supported using the same data.

Disparity of findings amongst early studies may be attributed to the limitation of the data used, or the proper level of aggregation in definitions of industry/firm. Quandt (1966) pointed out these difficulties facing many studies and that one needs to be confident that the data of a particular industry are generated by a sole stochastic process before the fit between any stochastic distribution and the data can be safely tested. But *"in general one does not know the nature of the stochastic process which generates an industry."*(pp. 417). He further argued that *"...the Law of Proportionate Effect operates*

[10] Another finding is that significant innovation positively contributes to firms' post-innovation growth rate, and those firms' pre-innovation behaviour does not help to explain differences in the growth rates between innovators and non-innovators.

together with such complicated conditions on birth and death as to be incapable of yielding a pure test of the law itself."(pp. 431).

Later, some "*new literature* (termed in Sutton, 1997)" addressed econometric issues in the test of Gibrat's law. Hall (1987) tested the size-growth relationship on publicly traded manufacturing firms in the US in the period between 1976 and 1983. After controlling for biases due to measurement error in initial size and sample selection, the negative relationship between the size and the growth rate is unchanged. Evans (1987) also studied firm survival using a standard sample-selection model. Firm's age has been seen playing a crucial role in determining firm's life-cycle activities, i.e. growth and death. For instance, older firms tend to have a lower growth rate but have a higher chance of survival. After controlling for firm survival, he found that Gibrat's law does not hold for the majority of US industries in his sample.

Taking advantage of a large US plant-level dataset, Dunne *et al.* (1988, 1989) studied firms' entry and exit behaviour as well as their post-entry growth. Similar findings to that of Evans (1987) were concluded in that plant-failure rate declines with size and age, while for those who survive, the growth rates are negatively related to size and age.

Several recent papers study the pharmaceutical industry, thus they offer a good benchmark for our analysis to the same industry.[11] Bottazzi *et al.* (2001) explored the growth dynamics and innovation of the pharmaceutical industry using data on 100 of the world's largest pharmaceutical firms and their products in very fine product categories. Their findings include i) the shape of the growth-rate distribution departs from a Gaussian distribution, thus it rejects the hypothesis that the growth in this industry is generated by a "*pure Gibrat process*", which is driven by independent multiplying growth factors, ii) a negative relationship between the variance of the growth rate and size, iii) innovation and imitation both play important roles in shaping the dynamics of firm growth.

Later in Bottazzi and Secchi (2005, 2006), the same negative correlation between the variance of the growth rate and size is confirmed using some different econometric tests.

Cefis *et al.* (2007) utilised a Bayesian hierarchical linear model to test the assumption of Gibrat's law on 210 pharmaceutical firms from 1987 - 1998. They found evidence that Gibrat's law does not hold on average but it holds for large firms.

Buldyrev *et al.* (2007) developed a model of firm growth which is based on Ijiri and Simon (1977)'s framework and Sutton's "independent submarkets". In this model

[11] All studies discussed here use the same data source : the Pharmaceutical Industry Database (PHID), developed under the European Pharmaceutical Innovation and Regulation Systems (EPRIS) Program at the Centre for the Economic Analysis of Competitiveness, Markets, Regulation (CERM) and the University of Siena.

firm growth is driven by the introduction of new products and the growth in size of the existing products. The probability of an existing firm inventing a new product is proportional to its size and that of a new firm is fixed. The products of an existing firm grow proportionately with a random growth factor. A family of limiting distributions of the growth rate was obtained from their model. They found that among those distributions an exponential power distribution can offer a better fit to the data for the pharmaceutical industry.

To summarise, most of the early empirical studies (before and including Hart, 1962) find that Gibrat's law holds in terms of the size-growth relationship but does not hold for the size-growth variance relationship. However, recent studies (since Hall, 1987) generally agree that the growth rate is not independent of size, especially for the entire size distribution or when survival is taken into account. The pharmaceutical industry is not an exception.

3.3 Data on the European Pharmaceutical Industry and MNEs

As discussed in Chapter 2, we extract account data on pharmaceutical multinationals and their subsidiaries from the "*Amadeus*" database, and identify 284 MNEs. We consider these MNEs who are either incumbents in this industry before 1990 or new entrants, coming into it after 1990. These inclusion criteria strictly comply with Sutton's theory of submarket and firm's size distribution, which only applies to incumbents and new entrants, but is irrelevant to companies who exit. One additional issue of identifying MNE parents is mergers and acquisitions (M&A) in the pharmaceutical industry, which took place frequently in the period under investigation. M&A complicates the identification of an MNE's presence because before two enterprises merged together or one is taken over by the other, they appear as separate businesses in *Amadeus* and as a single enterprise afterwards. This makes it impossible to construct a balanced panel of expansion history.[12] To get around this difficulty, we adopt Bottazzi and Secchi (2005, 2006)'s procedure of treating merged enterprises as a single entity throughout the period under investigation. This "super company" procedure will bias the intertemporal size distribution of firms, but we believe the gain from having a long and balanced panel outweighs the lose due to the bias. Moreover, some MNEs entered the market after 1990, therefore such MNE is treated as "sleeping MNE" at the earlier years of the time period before the year when it really entered. This treatment also helps to obtain a balanced panel.

For each MNE, we identify its subsidiaries which are doing the business related to

[12]Two eminent examples of mergers that took place in the middle of the 1990's are British company AstraZeneca and Swiss company Novartis. British company Zeneca merged with Swedish company Astra in 1999 to create AstraZeneca (located in the UK) and two Swiss companies Ciba-Geigy and Sandoz Laboratories merged in 1996 to create Novartis (located in Switzerland).

the pharmaceutical industry. That is to say, these subsidiaries can be in one or more of three categories of pharmaceutical related activities: i) production; ii) wholesale, retail and dispensing and iii) research and development.[13] The sources of these subsidiaries are either green-field investment generated by the MNE parent itself or acquisition through mergers or takeover. Once all subsidiaries are identified for an MNE, their operational revenues are aggregated to generate the size measure of the MNE. Because for each 19 out of 284 MNEs, the majority of its subsidiaries do not have operational revenues available in *Amadeus*, we have to drop them out. For the remaining 265 MNEs, we allow some of them to have a small amount of subsidiaries without the data of operational revenues in earlier years since 1990. These 265 MNEs consists of the sample for the analysis of the size-growth relationship (this chapter) and the dynamics of expansion (Chapter 4). This sample represents the vast majority of the MNE players in the European pharmaceutical industry who were active before and after the implementation of the Single Market Programme.[14] The Single Market is treated as a single geographic market. Our sample can also be regarded as a good approximation of the major European pharmaceutical producers because during the collection of information for the European enterprises it is hard to find any major pharmaceutical producer that did not expand its business beyond the national borders.

The following two size measures are constructed:

1. $S_{i,t}^{N}$ is the total number of subsidiaries MNE i has established or acquired, regardless of their activities (production, wholesales or research), in year t. This variable is available for all 265 MNEs from 1990 to 2004. By constructing this size variable, we effectively assume the size of each subsidiary is the same and this homogeneity assumption is in line with Ijiri and Simon's assumption of the equally-sized opportunity block (see Section 3.2.1).

2. $S_{i,t}^{S}$ is MNE i's operational revenues.[15] This is calculated by summing up operational revenues of one MNE's pharmaceutical-related subsidiaries for each year. If an MNE has one subsidiary without operational revenues in a specific year, or

[13] In *Amadeus*, business activities are classified by NACE Rev. 1.1 Industry Code. We are primarily looking for the subsidiaries with code 2441 (manufacture of basic pharmaceutical products), 2442 (manufacture of pharmaceutical preparations), 5146 (wholesale of pharmaceutical goods), 5231 (dispensing chemists), 5232 (retail sale of medical and orthopaedic goods) and 7310 (research and experimental development on natural sciences and engineering). We also check some subsidiaries that do not have the above codes if their businesses are actually dealing with pharmaceutical products using information on their pharmaceutical MNE parents' official websites.

[14] According to "The Top 100 Companies" in SCRIP 100 (2005/2006), 78 out of 100 of world's largest pharmaceutical companies are in the sample. We cannot identify the remaining 22 companies and their subsidiaries that are located in the EU (according to *Amadeus*).

[15] Following a usual practice in the Bayesian analysis, $S_{i,t-1}^{S}$ is normalised to follow a $N(0,1)$ distribution in order to guarantee fast convergence to the stable posterior distribution.

an MNE is a "sleeping MNE" in that year, we cannot calculate the aggregate $S_{i,t}^{S}$ for this MNE in the year. We, therefore, consider this MNE as having missing value in the year. Table 3.1 reports how many MNEs in the sample have missing values of operational revenues in each year. As a safe measure we consider that since 1995 the number of MNEs with missing values is low enough and let the panel starting from this year for 265 MNEs. By using this size variable we take into account firm heterogeneity in the analysis.

Descriptive statistics of the sample are provided in Table 3.2 . In this table we see:

- The number of subsidiaries and operational revenues share a similar pattern in their moments, as their standard deviation is larger than their mean. This signals heterogeneity;
- The position of the largest enterprise is very stable as we see Novartis was the largest enterprise in terms of subsidiaries for as long as thirteen years in the sample until it was overtaken by Pfizer in 2003, while Bayer has always shown to be the largest enterprise in terms of operational revenues;
- Approximately 28 per cent of the MNEs are top 100 pharmaceutical companies (73 out of 265); 64 per cent are European enterprises (169 out of 265) and 18 per cent are US enterprises (47 out of 265).

We are aware of the limitation in the scope of this study: the subjects are all MNEs. The choice of the MNEs can be justified by three motivations, i) we are more interested in the most substantial and dynamic component of the European pharmaceutical industry[16], ii) we are interested in the growth of enterprises in the enlarged EU market and non-MNE enterprises did not conduct business beyond national borders, and iii) the MNE sample is closer than the non-MNE sample to the pharmaceutical-enterprise samples used in Bottazzi *et al.* (2001), Bottazzi and Secchi (2005, 2006) and Cefis *et al.* (2007) because they are looking at the leading enterprises which are doing business in multiple countries.[17] Therefore, we believe our analysis will offer more comparable results to theirs if we do not include non-MNEs.

3.4 The Tests of Gibrat's Law

In this section we test Gibrat's law with our data on the European pharmaceutical industry using two approaches. The first approach involves an AR(1) model of size,

[16] Figure 2.4 in Chapter 2 shows that the MNEs account for 63 per cent of all pharmaceutical enterprises we identified in *Amadeus*.

[17] The PHID database used in those studies contains a panel data for the sales of 210 enterprises in seven countries for a long time period from 1987 to 1998. The country set includes five EU countries (France, Germany, Italy, Spain and the UK) and Canada and the US.

which is implied by the growth equation given in Eq. (3.1). This approach has been used in Bottazzi *et al.* (2001) and Cefis *et al.* (2007). The second approach is a size-class test used in Bottazzi and Secchi (2005, 2006).[18] The idea is that: first one calculates the annual growth rate of a firm and then sorts all firms by their sizes. In the next step, the sorted firms are split into equally-sized bins and finally, the average growth rate of each bin is regressed on the average size of each corresponding bin assuming a linear relationship. The slope of this linear relationship can show whether the growth rate is independent of size. The major difference between our study and theirs lies in the samples used, in terms of the geographic coverage, time period and the measure of size (see Footnote 17).

3.4.1 AR(1) Model of Size

Gibrat's stochastic model introduced in Section 3.2 shows this equation $S_t = (1 + \varepsilon_t)S_{t-1}$ (Eq. [3.1]). Considering we have a panel of MNEs where the MNEs are indexed by $i(= 1, 2, 3...N)$, the following equation must exist

$$\log S_{it} = \log S_{i,t-1} + \varepsilon_{it} \, . \tag{3.7}$$

One can write an AR(1) linear function of S_{it} and $S_{i,t-1}$, where ε_{it}, a random and small growth factor, works as an error term with mean zero and variance σ^2.

$$\log S_{it} = \beta_i \log S_{i,t-1} + \varepsilon_{it} \, , \tag{3.8}$$

According to Eq. (3.7), Gibrat's law doesn't hold, if $H_0 : \beta_i = 1$ can be rejected in Eq. (3.8). In Bottazzi *et al.* (2001), β_i is always found to be around unity so Gibrat's law was not rejected. But in Cefis *et al.* (2007), Gibrat's law was rejected for the entire sample but not for large firms. Following Bottazzi *et al.* (2001) and Cefis *et al.* (2007), we normalise the operational revenues of the MNEs. Denote the MNE's size (operational revenues) by $S^S_{i,t}$, then define,

$$s_{it} \equiv \log \left(S^S_{i,t}\right) - \frac{1}{M} \sum_{i=1}^{M} \log \left(S^S_{i,t}\right) \tag{3.9}$$

as normalised size for year t. M is the number of MNEs in each year with reported value of operational revenues. This normalisation is necessary to eliminate the nominal trend of currency.

Substituting s_{it} into Eq. (3.8), we have $s_{it} = \beta_i s_{i,t-1} + \varepsilon_{it}$. In our test, the size is measured by either normalised operational revenues s_{it} or the number of subsidiaries

[18] Bottazzi and Secchi do not give a name to their test, but for convenience we name it as a size-class test according to its nature.

of MNEs S_{it}^N.[19] Bearing Cefis *et al.* (2007)'s finding in mind, we first plot both pairs of (s_{it}, $s_{i,t-1}$) and (S_{it}^N, $S_{i,t-1}^N$) in Figure 3.1 . The figure shows that successive sizes gather around the 45 degree line closely, while the variation of change between two successive sizes is larger for smaller firms.

We employ a Bayesian method which is similar to the method used in Cefis *et al.* (2007) to estimate the AR (1) model. The Bayesian method has following advantages over the traditional econometrics: i) the random-parameter model can easily be accommodated with the Bayesian method; ii), the Bayesian method does not require strong parametric assumptions over the sampling or strong asymptotic theories (Lancaster, 2004) and iii), with the Bayesian method the researcher can use either previously gained or available information on the parameters as priors in the estimation, saving therefore time in the estimation. This is drastically contrasted to the traditional econometrics, which requires researchers to be blind to the data and outcomes. We are mainly encouraged by the first advantage because we want to specify the slope β_i in Eq. (3.8) as unit-specific. This can be easily implemented in a Bayesian statistical package - "WinBugs". We report the average of β_i , $\overline{\beta}$, over the MNEs in the sample in Table 3.3 . We see in the case when the size is measured by the operational revenues, $\overline{\beta}$ is smaller than that of the case when using the number of subsidiaries. All two $\overline{\beta}$s are all significantly different from zero at the 1 per cent significance level. The Wald test rejects that anyone of them is equal to 1 at the 1 per cent level. This is also can be confirmed that the 95 per cent confidence interval of both $\overline{\beta}$s do not contain one.

Since the Bottazzi-Cefis studies find that Gibrat's law holds for large firms, we split the sample into two halves according to the initial size of the MNEs in the beginning of the sample period and repeat the same AR(1) regression.[20] We also apply the AR (1) model on the middle 80 per cent of the MNEs.[21] Table 3.4 reports the results of the subsamples. In Cols. 1, 2 and 3, when the size is measured by operational revenues, the $\overline{\beta}$s of the samples containing the top 50 per cent and the middle 80 per cent of the MNEs are close to the unity, while the $\overline{\beta}$ of the sample containing the bottom 50 per cent of the MNEs is only 0.763. However, the Wald test still rejects $H_0 : \overline{\beta} = 1$ for all three samples. In Cols. 4, 5 and 6, when the size is measured by the number of subsidiaries, the same pattern emerges that the $\overline{\beta}$s of the top 50 per cent and the middle 80 per cent of the MNEs are larger than that for the bottom 50 per cent of the MNEs, while all $\overline{\beta}$s are

[19] We take the logarithm of S_{it}^N but do not demean it because there is no nominal trend in the time series of the number of subsidiaries.

[20] Top or bottom 50 per cent of the sample may not necessarily contain exactly half of the 265 MNEs because either some observations may contain missing values in terms of operational revenues, or the initial number of subsidiaries in 1990 is a discrete value so the whole sample cannot be split evenly.

[21] All MNEs are sorted in ascending order by their initial size. The top and the bottom 10 per cent of the MNEs are excluded. Cefis *et al.* (2007) use the same procedure to eliminate those extreme observations.

not statistically equal to the unity. Therefore, we see the findings in Table 3.3 and 3.4 are robust evidence against Gibrat's law for different size ranges of the pharmaceutical MNEs. In comparison with the Bottazzi-Cefis findings, the βs in Bottazzi *et al.* (2001) for the entire distribution of firms are always statistically close to the unity for each of ten years. However, Cefis *et al.* (2007) finds that *"Overall, these findings do not confirm that Gibrat's law holds on average, over time and across firms."*(pp. 14). But in terms of the top and bottom deciles of MNEs, the law holds in the former case but not in the latter case. We also explore this possibility by examining the two extreme tails - the top and the bottom 10 per cent of our MNE sample and find the same pattern. For example, we have $\overline{\beta} = 1.007$ for the top decile and the Wald test does not reject $H_0 : \overline{\beta} = 1$, while $\overline{\beta} = 0.693$ for the bottom decile and the H_0 is rejected at the 1 per cent level.

The estimated β_is of different sub-samples can also shed light on the issue of mean reversion. The speed of convergence to the steady state of a firm is $1 - \beta_i$ and mean reversion exists if this speed is negatively correlated with the initial size of the firm. We regress $1 - \beta_i$ on the initial size of firms for the top 50, bottom 50 and the middle 80 per cent of the MNEs. Results are presented in Table 3.5 . For all sub-samples with the alternative measures of size, the mean-reversion mechanism is confirmed (except for one sample, Col. 5): small firms adjust to their steady states at a faster speed, while the magnitude of the mechanism is rather weak. Cefis *et al.* (2007) also find that, for the middle 80 per cent of firms, the mean reversion is very weak.[22]

In summary, our findings from the AR(1) test show that Gibrat's law is rejected for the entire sample of the 265 MNEs and the top, bottom halves and the middle 80 per cent of the sample, but it cannot be rejected for the top 10 per cent of the MNEs which are the largest. The mean reversion of the MNEs to their steady states is also confirmed, though very weak. The results are consistent with that of Cefis *et al.* (2007), but not with that of Bottazzi *et al.* (2001).

3.4.2 Bottazzi and Secchi's Size-class Test

Bottazzi and Secchi (BS hereafter) (2005, 2006) studied the size-growth relationship using data containing 198 world's top pharmaceutical MNEs and had evidence that size (sales) is negatively correlated with the standard deviation of the growth rate in different size classes, but not with the mean of the growth rate. These evidence do not invalidate Gibrat's law, but show that small firms are growing at relatively more variable rates, compared with large firms. We replicate their approach in a strict way to make our results comparable to theirs.

[22] They are looking at the relationship between the posterior distribution of $\beta_i < 1$ and the initial sizes of firms in terms of probability distribution, so their result is not perfectly comparable to our result from an OLS regression of $[(1 - \beta_i)|initial\ size]$.

Using the formula of the normalised size shown in Eq. (3.9), we define the logarithm of the growth rate as

$$g_{it} = s_{i,t+1} - s_{it}.$$

Substituting $s_{i,t+1}$ and s_{it} into this formula yields

$$g_{it} = \log\left(S_{i,t+1}\right) - \log\left(S_{it}\right) - \left[\frac{1}{M}\sum_{i=1}^{M}\log\left(S_{i,t+1}\right) - \frac{1}{M}\sum_{i=1}^{M}\log\left(S_{it}\right)\right]$$

and the last term on the right hand side in the bracket is an adjustment term for inflation.

In Figure 3.2 , we present the plot of histograms of the number of subsidiaries $S_{i,t}^N$ (in Figure 3.2 (a)) and the histogram and the empirical density function (EDF)[23] of the normalised operational revenues s_{it} (in Figure 3.2 (b)). We pool the values of the 265 MNEs for the two size variables over the period whenever they are available.

The histogram and the EDF of s_{it} are similar to what have been found in BS (2005, 2006), with one exception that their EDF shows two modes near 0 and 4 but ours shows a smooth distribution. The histogram of $S_{i,t}^N$ is highly skewed to the right. In the pooled values, some of them are zero, which come from new entrants before they entered the market. To make this part of the size distribution more visible, we intentionally replace the value 0 by -10. We also check that the histograms of s_{it} and $S_{i,t}^N$ in each year are stationary, implying that pooling data across the sample period is appropriate.

BS's approach works as follows, one first pools sizes, s_{it} and corresponding growth rates g_{it} for all MNEs and all years available together. Then sort these observations by s_{it} and split all observations into 50 bins. The third step is to calculate the mean, standard deviation, skewness and kurtosis of the observations on the growth rates in each bin. The last step is to fit the following linear model of the growth rate and the size

$$f\left(g|s\right) = \alpha + \beta s,$$

where g are the four moments of the growth rates g_{it} in each bin and s is the mean of the normalised size, s_{it} in the same bin (note subscript i and t are dropped because observations are pooled). With regard to our sample, we split the pooled size observations into 51 bins where each bin contains 36 observations. In addition to the test using the normalised operational revenues, we also use the number of subsidiaries S_{it}^N to proxy size. Because there are more observations of S_{it}^N than s_{it}, we end up with up to 103 bins each containing 36 observations.

[23]The EDF is estimated using the kernel estimate of Gaussian type.

The results of the above linear regressions are reported in Tables 3.6 and 3.7 . We also report Bottazzi and Secchi's results in the same tables.

The main findings in our test are that:

1. In Table 3.6 our results, the mean growth rate and the mean size have a negative linear relationship as β is statistically significant at the 1 per cent level, but β is much weaker than that is reported in BS (2006) ($\beta = -0.11(0.08)$);

2. In Table 3.6 our results, the standard deviation of the growth rate and the mean size have a negative linear relationship and β is significant at the 1 per cent level as well, but this correlation is much weaker than that is reported in BS (2006) ($\beta = -0.21^{***}(0.02)$).

3. Table 3.7 also confirms similar findings shown in Table 3.6 except that statistically significant βs are close to zero and the β associated with the mean growth rate is only significant at the 10 per cent level.

As with the AR(1) test, we split the entire sample into two sub-samples containing the top and bottom 50 per cent of the MNEs by their initial sizes. The same size-class test is done for two sub-samples and the results are reported in Tables 3.8 and 3.9 . In Table 3.8 , the size is s. For the top 50 per cent of the MNEs, there are no significant correlations between the four moments of the growth rate and the size. But for the bottom 50 per cent of the MNEs, the correlation between the mean growth rate and the size is negative with a coefficient of -0.128, which is significant at the 5 per cent level. The correlation between the standard deviation of the growth rate and the size is negative with a coefficient of -0.312, which is significant at the 1 per cent level. In Table 3.9 , the size is S^N. For the top 50 per cent of the MNEs, the correlation between the mean growth rate and the size is positive and significant, but the magnitude of the coefficient is only 0.002. We also see that the skewness and the kurtosis of the growth rate are negatively correlated with the size. Similarly, for the bottom 50 per cent of the MNEs, the same negative correlations between the skewness and kurtosis and the size are found, while there is no correlation between the mean and standard deviation of the growth rate and the size.

In summary, for the entire size distribution of the MNEs, Gibrat's law is rejected because small MNEs grow faster than large MNEs do, but the small MNEs are experiencing more variable growth. Our results are in line with that of BS (2005, 2006) in terms of the standard deviation of the growth rate, but not the mean growth rate. For different measures of the size, Gibrat's law is rejected for either the sub-sample of smaller MNEs or that of larger MNEs.

3.5 Summary and Conclusions

In this chapter we provide a comprehensive review of the firm-growth literature. The focus of the review is on the stochastic models of the firm-size distribution. Originally, stochastic models were used to explain the skewed firm-size distribution (or the skewed distribution of other subjects, such as city size) and the tradition can be dated back to Gibrat (1931). He proposed a simple stochastic process which is able to generate skewed firm-size distribution. Gibrat's process implies a law that the absolute growth of the firm is proportional to firm size, or in other word, the firm growth rate is independent of firm size. Our review shows that, theoretically, earlier models were developed to look for the best stochastic distribution which is able to fit industrial data, for instance, the family of Pareto distributions is usually considered as being capable. Recently, Sutton (1997 and 1998) extended the model of Ijiri and Simon (1964) of the "independent submarkets" and derived a firm-size distribution which is of great empirical significance. Another direction of the firm-growth theory is more focused on the role of the optimising behaviour of firms in determining the industrial growth process and the game-theory framework is often employed to model the entry process. On the empirical side of the literature, several regularities were discovered from the industrial data on the US and the UK. Such regularities include i) the growth rate of smaller firms is higher and more variable than that of larger firms; ii) the active entry and low survival rates of small firms. Gibrat's law is also tested on the industrial data and usually results agree that the law holds for large firms but not for the entire spectrum of firms or small ones.

We offer two tests of Gibrat's law on the European pharmaceutical industry and find that the law can be rejected for the entire and the top, bottom 50 per cent and the middle 80 per cent of the distribution of MNEs by an AR(1) test. The size-class test rejects the law for the entire sample and also the top or bottom half of the sample subject to the size measures. On the contrary, the AR(1) test supports the validity of Gibrat's law for the top 10 per cent of the MNEs. Our findings are broadly consistent with that of several recent studies on the global pharmaceutical industry, while we believe that any difference between our results and theirs comes from the differences in the geographic coverage, size measure and time period of the samples used.

3.6 Tables

Table 3.1: Yearly Number of Missing Values (out of 265 MNEs) in Size Measures as Operational Revenues

Year	90	91	92	93	94	95	96	97	98	99	00	01	02	03	04
Missing	234	235	239	173	103	44	42	34	33	22	17	13	10	7	Note

Note: Since size is lagged by one year, size in 2004 is not used for estimation of entry from 1990 to 2004.

Table 3.2: Statistics of Explanatory Variables

Year	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
Number of subsidiaries*	32 (3.74) [5.35] Novartis	32 (3.97) [5.57] Novartis	32 (4.12) [5.70] Novartis	33 (4.23) [5.77] Novartis	34 (4.46) [5.92] Novartis	34 (4.66) [6.16] Novartis	39 (4.92) [6.48] Novartis	41 (5.15) [6.71] Novartis	47 (5.38) [6.95] Novartis	47 (5.58) [7.10] Novartis	49 (5.92) [7.67] Novartis	49 (6.17) [7.85] Novartis	49 (6.32) [7.94] Novartis	54 (6.49) [8.31] Pfizer	55 (6.63) [8.58] Pfizer
Operational revenues (million USD)+	na	na	na	na	na	27,991 (772.8) [2,527.8] Bayer	30,436 (836.2) [2,779.8] Bayer	34,620 (960.2) [3,260.4] Bayer	34,737 (1,017.4) [3,316.6] Bayer	28,155 (971.0) [3,071.2] Bayer	28,235 (978.9) [3,123.5] Bayer	27,211 (1,065.5) [3,320.1] Bayer	34,384 (1,237.9) [3,883.3] Bayer	38,788 (1,510.2) [4,827.3] Bayer	na
Top MNEs	73	73	73	73	73	73	73	73	73	73	73	73	73	73	73
EU MNEs	169	169	169	169	169	169	169	169	169	169	169	169	169	169	169
US MNEs	47	47	47	47	47	47	47	47	47	47	47	47	47	47	47
OTHER MNEs	49	49	49	49	49	49	49	49	49	49	49	49	49	49	49
Total number of MNEs	265	265	265	265	265	265	265	265	265	265	265	265	265	265	265

Note: * The first value is the maximum of the number of subsidiaries, its mean in (), its standard deviation in [] and the MNE with maximal subsidiaries follows. + The first value is the maximum value of operational revenues, its mean in (), its standard deviation in [] and the MNE with maximal operational revenue follows. Geographic coverage: Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, the Netherlands, Portugal, Spain, Sweden, and UK (excluding Luxembourg).

Table 3.3: AR(1) Model of Size (Entire Sample)

Variable	Size=Operational Revenues	Size=Number of Subsidiaries
$\overline{\beta}$	0.88***	0.925**
	(0.008)	(0.006)
Wald test: $\overline{\beta}$=1	202.8***	172.1***
# of MNEs[a]	221	265

Note: Sample period: 1996 - 2003 if Size is measured by operational revenues, 1991 to 2004 if measured by the number of subsidiaries. a: 44 MNEs have missing observations of operational revenues in 1995. Since the Bayesian statistical package can not handel the missing value at the beginning of the sample period, we can only estimate the model on the rest 221 MNEs. * significant at 10 per cent level, ** significant at 5 per cent level, *** significant at 1 per cent level; standard error in parentheses.

Table 3.4: AR(1) Model of Size (Sub-samples)

	Size=Operational Revenues			Size=Number of Subsidiaries		
Range of MNEs	Top 50 per cent	Bottom 50 per cent	Middle 80 per cent	Top 50 per cent	Bottom 50 per cent	Middle 80 per cent
$\overline{\beta}$	0.936*** (0.005)	0.763*** (0.022)	0.932*** (0.007)	1.01*** (0.004)	0.834*** (0.013)	0.936*** (0.006)
Wald test: $\overline{\beta}$=1	156.8***	119.4***	85.3***	6.5***	161.3***	106.1***
# of MNEs	103[a]	103[a]	166[a]	132[b]	133[b]	213[b]

Note: Sample period: 1996 - 2003 if size is measured by operational revenues, 1991 to 2004 if measured by the number of subsidiaries. a: 59 MNEs have missing observations of operational revenues in 1995. Since the Bayesian statistical package can not handel the missing value at the beginning of the sample period, we can only estimate the model on the rest 206 MNEs. Each of the half sample contains 103 MNEs and the number of the middle 80 per cent of MNEs is 166. b: Top or bottom 50 percent samples may not necessarily contain exactly half of 265 MNEs because initial number of subsidiaries in 1990 is discrete value so the whole sample cannot be split evenly. * significant at 10 per cent level, ** significant at 5 per cent level, *** significant at 1 per cent level; standard error in parentheses.

Table 3.5: Relationship Between the Speed of Mean Reversion (1-β_i) and the Initial Size

	Size=Operational Revenues			Size=Number of Subsidiaries		
Range of MNEs	Top 50 per cent	Bottom 50 per cent	Middle 80 per cent	Top 50 per cent	Bottom 50 per cent	Middle 80 per cent
Dependent Variable: 1-β_i						
Explanatory Variable						
Initial size	-0.013*** (0.002)	-0.069*** (0.005)	-0.023*** (0.004)	-0.024*** (0.003)	-0.021 (0.014)	-0.047*** (0.004)
R^2	0.2585	0.6204	0.1639	0.384	0.018	0.4011
Prob > F	0.0000	0.0000	0.0000	0.0000	0.1215	0.0000
# of MNEs	103[a]	103[a]	166[a]	132[b]	133[b]	213[b]

Note: Sample period: 1996 - 2003 if size is measured by operational revenues, 1991 to 2004 if measured by the number of subsidiaries. a: 59 MNEs have missing observations of operational revenues in 1995. Since the Bayesian statistical package can not handel the missing value at the beginning of the sample period, we can only estimate the model on the rest 206 MNEs. Each of the half sample contains 103 MNEs and the number of the middle 80 per cent of MNEs is 166. b: Top or bottom 50 percent samples may not necessarily contain exactly half of 265 MNEs because initial number of subsidiaries in 1990 is discrete value so the whole sample cannot be split evenly. * significant at 10 per cent level, ** significant at 5 per cent level, *** significant at 1 per cent level; standard error in parentheses.

Table 3.6: Relationship between Size (Operational Revenues) and Variance

	Our results			Bottazzi and Secchi (2006)		
Relationship	β	Std. error	Obs.	β	Std. error	Obs.
Mean of g_{it}–S_{it}^S	-0.036***	0.009	51	-0.11	0.08	50
s.d. of g_{it}–S_{it}^S	-0.062***	0.012	51	-0.21***	0.02	50
Skewness of g_{it}–S_{it}^S	-0.036	0.106	51	-0.12	0.09	50
Kurtosis of g_{it}–S_{it}^S	0.131	0.349	51	-0.03	0.11	50

Note: Time period is from 1995 to 2003. * significant at 10 per cent level, ** significant at 5 per cent level, *** significant at 1 per cent level.

Table 3.7: Relationship between Size (Number of Subsidiaries) and Variance

	Our results			Bottazzi and Secchi (2006)		
Relationship	β	Std. error	Obs.	β	Std. error	Obs.
Mean of g_{it}–S_{it}^N	-0.001*	0.0005	103	-0.11	0.08	50
s.d. of g_{it}–S_{it}^N	-0.003***	0.001	103	-0.21***	0.02	50
Skewness of g_{it}–S_{it}^N	-0.02	0.02	93	-0.12	0.09	50
Kurtosis of g_{it}–S_{it}^N	-0.049	0.154	93	-0.03	0.11	50

Note: Time period is from 1990 to 2003. * significant at 10 per cent level, ** significant at 5 per cent level, *** significant at 1 per cent level.

Table 3.8: Relationship between Size (Operational Revenues) and Variance (Subsamples)

	Top 50 per cent			Bottom 50 per cent		
Relationship	β	Std. error	Obs.	β	Std. error	Obs.
Mean of g_{it}–S_{it}^S	0.014	0.013	59	-0.128**	0.057	43
s.d. of g_{it}–S_{it}^S	0.023	0.018	59	-0.312***	0.111	43
Skewness of g_{it}–S_{it}^S	0.294	0.299	59	-0.214	0.719	43
Kurtosis of g_{it}–S_{it}^S	0.032	0.78	59	-2.893	1.872	43

Note: Time period is from 1995 to 2003. * significant at 10 per cent level, ** significant at 5 per cent level, *** significant at 1 per cent level.

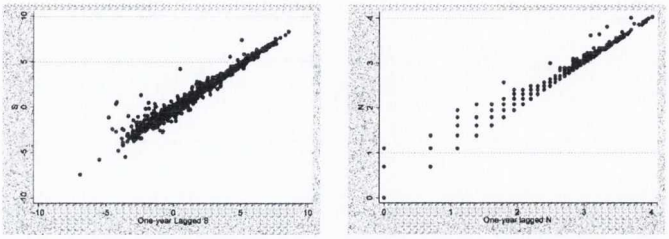
Table 3.9: Relationship between Size (Number of Subsidiaries) and Variance (Subsamples)

	Top 50 per cent			Bottom 50 per cent		
Relationship	β	Std. error	Obs.	β	Std. error	Obs.
Mean of g_{it}–S_{it}^N	0.002***	0.001	100	0.001	0.01	106
s.d. of g_{it}–S_{it}^N	0.0018	0.0011	100	-0.008	0.024	106
Skewness of g_{it}–S_{it}^N	-0.098***	0.023	95	-0.305*	0.162	78
Kurtosis of g_{it}–S_{it}^N	-0.587***	-0.147	95	-2.196*	1.124	78

Note: Time period is from 1990 to 2003. * significant at 10 per cent level, ** significant at 5 per cent level, *** significant at 1 per cent level.

3.7 Figures

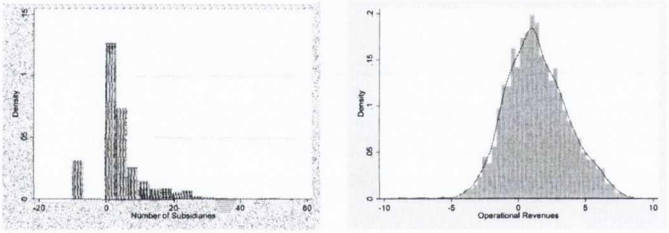
Figure 3.1: Plot of $size_{it}$ vs $size_{i,t-1}$



(a) Size is Normalised Operational Revenues

(b) Size is the Number of Subsidiaries

Figure 3.2: Histogram and Empirical Density Function of Number of Subsidiaries (S^N), Standardised Operational Revenues (S^S).



(a) (S^N)

(b) (S^S)

Gaussian Kernel density. Bin number = 50 for S^S. Bin number = 20 for S^S.

Chapter 4

Modelling and Predicting Dynamic Expansions of Pharmaceutical MNEs[1]

[1]This is a joint work with Doctor Franco Mariuzzo.

4.1 Introduction

Gibrat (1931)'s *"law of proportionate effect"* has motivated a growing literature in industrial economics to study and explain skewness in firm size distributions.[2] This firm-growth literature (also known as the stochastic literature on firm size) sees the skewness as the result of a relationship between a firm's size and its rate of growth: if larger firms tend to grow faster (or slower) than their smaller rivals, the size distribution of the firms tend to exhibit more (or less) skewness. The popularity of this literature stands in its strong link with the structure-conduct-performance literature that started with Mason (1939, 1949) and Bain (1951, 1956).

An alternative industrial economics literature adopts a more game theoretical approach: Bresnahan and Reiss (1990, 1991), Berry (1992), Pakes and McGuire (1994), Ericson and Pakes (1995), Tamer (2003), Ciliberto and Tamer (2007), Manuszak and Cohen (2004), Toivanen and Waterson (2005), Berry and Reiss (2006) and Berry and Tamer (2006).

Sutton (1998) has attempted to link these two streams. He proposed an "independent submarkets" model which generates a limiting firm-size distribution of an industry (see the review of this model in Section 3.2.1 of Chapter 3. His main finding is that a lower bound in a Lorenz curve[3] (a minimum degree of inequality in firm size) is the best one can do in explaining firm size distribution. Any distance between actual data and the lower bound can be explained, amongst other things, by the degree of heterogeneity in the arrival of business opportunities.

In this chapter we suggest an approach to model the growth trajectory of the European pharmaceutical industry, which is characterised by the continuous realisation of many unequally-sized opportunities by incumbents. The approach is also used to test Sutton's lower-bound prediction. This approach is based on a simple discrete-choice model where every period firms choose whether or not to capture one of the oppor-

[2]Hart and Prais (1956), Adelman (1958), Simon and Bonini (1958), Hart (1962), Hymer and Pashigian (1962), Mansfield (1962), Steindl (1965, 1968), Ijiri and Simon (1964, 1977), Quandt (1966), Hjalmarsson (1974), Lucas (1978), Hall (1987), Sutton (1997), Bottazzi *et al.* (2001), Bottazzi and Secchi (2005, 2006), Buldyrev *et al.* (2007), Cefis *et al.* (2007).

[3]The Lorenz curve represents a convenient way to represent the size distribution of firms.

tunities that arises. The firms base their optimal decisions on their own profits that depend, amongst other things, on demand shocks, scope economies, and the underlying level of competition. In this way a firm that catches a new opportunity accesses the expansion process, but its actual expansion size only depends on the value associated with the opportunity. The opportunities are therefore heterogeneous and we gauge their heterogeneity by two measures of size: the number of subsidiaries, and operational revenues. In other words the firms choose whether to expand or not and the resulting expansion level is a by-product of their profit realisation.

We have a twofold goal. Firstly, we want to test whether firms' decisions to expand over time during the SMP era are related to their previous expansion and their initial sizes. To this aim we make use of dynamic panel probit models with unobserved heterogeneity, and give robustness to our results by comparing different Traditional and Bayesian approaches. Secondly, we relate the expansion decisions to their resulting sizes. We do this indirectly, by investigating the relationship between the random number of opportunities captured and size. The joint distribution of the number of opportunities a firm caught and its size will be the key in our understanding of firm growth. This is a way to understand whether the firms that have captured more opportunities over time, expand faster. It is also a way to answer a question that can explain skewness. In order to catch this idea, we use a parametric copula approach which allows us to derive the joint distribution (the number of opportunities captured, size) from the empirical marginals of the two variates. Then we simulate the size of any firm by conditioning it on the number of opportunities it earned that period. An important by-product of this procedure is that we can use both the primitives of our dynamic probit estimations and simulations to predict the probability that each firm expands in each subsequent period. One can start predictions in period 1 and extend them up to period T. We use these predictions as a way to check the structure of opportunity-firm size-market concentration.

The European pharmaceutical industry during EU enlargement (1990 - 2004), offers us a valid firm-level dataset. Our dataset has information on opportunities captured

by each of 265 MNEs and on their respective size. We will use two measures of the size:

1. The number of subsidiaries established and acquired before and up to time t, S_t^N;
2. Operational revenues in time t, S_t^S.

We treat the dataset as a balanced panel over the time, assuming new entrants are sleepers from the beginning of the time period until they captured their first opportunity. It is important to mention that our dataset does not provide information on the exit of MNEs, because exitors are not reported in *Amadeus*. This means exit dynamics cannot be studied.

The rest of the chapter is organised as follows: in Section 4.2 we present a simple conceptual model; in Section 4.3 we outline the dynamic panel probit model with unobserved heterogeneity and present Traditional and Bayesian econometric techniques to estimate the model. Section 4.4 describes our data. Our results and predictions are discussed in Section 4.5. Section 4.6 concludes.

4.2 A Conceptual Model

Here we present a conceptual model which is a modified version of that in Berry (1992). The expansion of MNEs can be modelled in a simple way as the discrete choice to expand or not, based on an underlying latent profit relation,

$$y_{it}^* = \psi_{i,t-1} + \alpha_i, \tag{4.1}$$

where the latent profit of MNE i in period t, y_{it}^*, is explained by an idiosyncratic part, α_i, and a function of pre-determined variables, $\psi_{i,t-1}$. MNE i decides to expand in period t, $y_{it} = 1$, if $y_{it}^* \geq 0$; and not to expand, $y_{it} = 0$, otherwise. The actual expansion process occurs by capturing one of the opportunities that arise. The opportunities can be heterogeneous in terms of size, and we expect their difference to reflect, to some extent, differences in profits. For example, when the size is measured by the number of subsidiaries it could be that in a given period an MNE opens up, or acquires, more

than one new subsidiary so that the relation is not necessarily 1:1, as we will discuss later.

With our interest directed towards the dynamics of expansion, $\psi_{i,t-1}$ contains lagged expansion, $y_{i,t-1}$, and observable MNE-specific characteristics such as a vector of time-invariant characteristics, O_i and a lagged measure of size $S^h_{i,t-1}$ (where $h = N$ denotes the number of subsidiaries and $h = S$ denotes operational revenues).[4] The resulting relationship can be expressed as,

$$y_{it} = f(\alpha_i, y_{i,t-1}, S^h_{i,t-1}, O_i). \tag{4.2}$$

Lagged expansion is aimed at capturing any form of persistence in the expansion process and its inclusion is in line with the essential idea in Ijiri and Simon's model of the serial correlation of successive growth (1964)[5]. Applying this model to pharmaceutical data should contribute to our understanding of the European pharmaceutical industry dynamics and the resulting industry concentration. Evidence of a positive effect of the expansion at time $t-1$ on the expansion at time t indicates the sustainability of this industry, or in other words, suggests that the industry is able to generate profits to support its expensive innovative activities through persistent expansion behaviour. In this way, the lagged expansions exert a behavioural effect on current expansion and this effect is termed "true state dependency" in Heckman (1981). However, as is often the case, the examination of dynamics can be blurred by what Heckman (1981) has termed "spurious state dependency". This occurs if unobservable MNE-level effects, α_is are serially correlated over time or are correlated with initial expansion, and these correlations have not been properly controlled for by the researcher. In these cases, the lagged expansion decision will incorrectly capture this unobserved effect and behave as if it is a driving force of the current expansion decision, even if there is no state

[4] O_i contains the nationality of MNEs, for example if they are EU or US based, as well as a variant indicating whether these MNEs are leading pharmaceutical manufacturers in the world. O_i's presence in Eq. (4.2) below is merely functional, in order to meet the technical requirements of instrumental variables and achieve comparability between the econometric models.

[5] The serial correlation assumption states that the probability of growth of an existing firm is proportional to its weighted sum of past increments of size, and the weight is decreasing the further the occurrence of each increment from the current period.

dependence at all. To tackle this problem we adopt a dynamic panel random-effects model. The modelling of the random effects in a dynamic model using the Traditional and Bayesian econometrics approaches is discussed in Section 4.3.

Our choice of the lagged number of subsidiaries, $S^N_{i,t-1}$, and the operational revenues $S^S_{i,t-1}$, as the measures of size, is motivated by Gibrat's law, as reinterpreted in Ijiri and Simon (1964) and Sutton (1997, 1998). Here the authors see new investment opportunities as many equally-sized "islands". Each active MNE in an industry has a certain probability of capturing that opportunity, and subsequently to expand. The size of each MNE is related to the number of opportunities or "islands", it has taken before. This theory imposes that the number of opportunities captured and the size of an MNE have a direct influence on each MNE's propensity to expand. Therefore, Gibrat's law implies that, the probability that a firm captures a new opportunity is proportionate to its size.[6] Visually, as an MNE becomes larger it has more chances to catch new opportunities.

In addition, the lagged observables, $S^h_{i,t-1}$, also influence the probability of expansion in an indirect way, through scope economies, economies of scale in terms of production and R&D, or superior market power that can be gained as MNEs evolve. If the indirect effects of scope economies, economies of scale and market power are growing fast, they may impose an additional "behavioural effect"[7] on future expansion, which can be effectively captured by the lagged expansion variable, $y_{i,t-1}$. Therefore, controlling for $S^h_{i,t-1}$ in the latent profit function is necessary if one wants to estimate state dependence accurately.

4.3 Econometric Methods

4.3.1 A Dynamic Probit Traditional Approach

We employ a dynamic extension of the probit model to address state dependence of MNEs' expansion decisions. Following Wooldridge (2002), we use a generic notation

[6] Gibrat's law has been presented in many forms by different authors depending on how they need to incorporate the law in their models. The one in Sutton (1998) states that *"the firm's proportionate rate of growth is given by a random variable whose mean is independent of the firm's current size"*. Stating the proportionality between the probability and the size is also a meaningful one (Ijiri and Simon, 1964).

[7] It is termed in Heckman (1981).

to model the probability of an MNE i, expanding in the European pharmaceutical market by capturing a new opportunity at year t,

$$\begin{aligned} P\left(y_{it}=1|\alpha_i, y_{i,t-1}, \mathbf{x}_{i,t-1}; \lambda\right) &= \Phi\left(\alpha_i + \rho y_{i,t-1} + \mathbf{x}_{i,t-1}^{'}\beta\right) \\ \lambda &\equiv (\rho, \beta^{'}, \kappa^{'})'; \alpha_i \sim N\left(0, \sigma_\alpha^2\right). \end{aligned} \tag{4.3}$$

The above relationship states that: the probability of expansion at time t is a function of the lagged dependent variable, $y_{i,t-1}$, a vector of all lagged and MNE-specific independent variables, $\mathbf{x}_{i,t-1}$, and unobservables (to us), α_i. This later is intended to capture all unobservable factors that could influence the expansion propensity of an MNE. [8]

The discrete choice of MNEs' expansion modelled in Eq. (4.3) is the result of the linear latent profits expressed in Eq. (4.1). Anytime an MNE finds it can realise a positive y_{it}^* by capturing one of the arisen opportunities, it will do so, $y_{it} = 1$. Hence the full model of expansion can be written as,

$$y_{it}^* = \alpha_i + \rho y_{i,t-1} + \mathbf{x}_{i,t-1}^{'}\beta + u_{it}, \tag{4.4}$$

where u_{it} is an *iid* term distributed as a standard normal.

However, this model faces some difficulties if it is applied in practice, as pointed out in Wooldridge (2002). The assumption of strict exogeneity between all regressors in the right hand side (RHS) of Eq. (4.4) and the unit-specific effect α_i, is required to insure the consistent estimation of the parameters λ as in a traditional static version of the probit model. But this assumption rules out the possibility of introducing a dynamic mechanism in the RHS of Eq. (4.4), since the lagged expansion, $y_{i,t-1}$, is inevitably correlated with time-invariant unit-specific effect α_i, producing the "initial conditions problem". In addition to this difficulty, to consistently estimate the partial effects for independent variables, α_i has to be exogenous to both $\mathbf{x}_{i,t-1}$ and $y_{i,t-1}$ and this assumption is often violated. For example in our case, an MNE's size is influenced

[8] In this equation, we ignore a time-invariant MNE-specific effect, O_i, which is observable. This specification can simplify notation without lossing generality because O_i does not raise econometric difficulty in our probit model. It only controls for the observable part of unit-specific effect with the unobservable part being taken into account by α_i.

by its expansion decisions at current year and past years, and consequently the size is correlated with the unit-specific effect α_i.

In the next sections, we outline two alternative methods for handling the initial conditions problem and the endogeneity.

Wooldridge's Method

Wooldridge (2002) proposes to condition the random effects, α_i, explicitly on the initial value of the dependent variable, y_{i0}, and to the almost full history of the independent variables, $\mathbf{x}_i^{T-1} \equiv (\mathbf{x}_{i1}$ as follows,

$$\begin{aligned} h\left(\alpha_i | y_{i0}, \mathbf{x}_i^{T-1}; \gamma\right) &= \gamma_{[0]} + \gamma_{[1]} y_{i0} + \left(\mathbf{x}_i^{T-1}\right) \gamma_{[2]}, \\ \gamma_{[2]} &\equiv \left(\gamma_{[2]11}, ..., \gamma_{[2]k1}, ..., \gamma_{[2]1,T-1}, ..., \gamma_{[2]k,T-1}\right). \end{aligned} \tag{4.5}$$

Conditioning α_i on $\mathbf{x}_i^{T-1}$ would allow correlation between α_i and the explanatory variables in the model, as suggested by Mundlak (1978) and Chamberlain (1984). However, for each MNE i in our balanced panel, $\mathbf{x}_i^{T-1}$ is a $k(T-1) \times 1$ vector of independent variables and this configuration causes inefficiency in estimation. Mundlak (1978) and Chamberlain (1984) suggested replacing the full time series of the independent variables with their time-means, in order to reduce the number of excessive regressors. So that,

$$\overline{\mathbf{x}}_{i[-1]} \equiv \frac{1}{T-1} \sum_{t=2}^{T} \mathbf{x}_{i,t-1}.$$

Such that Eq. (4.5) can be rewritten as,

$$h\left(\alpha_i | y_{i0}, \mathbf{x}_i^{T-1}; \gamma\right) = \gamma_{[0]} + \gamma_{[1]} y_{i0} + \left(\overline{\mathbf{x}}_{i[-1]}\right) \overline{\gamma}_{[2]}, \quad \overline{\gamma}_{[2]} = \left(\overline{\gamma}_{[2]1}, ..., \overline{\gamma}_{[2]k}\right)'.$$

Once α_i is conditioned, the task of finding a joint density function of y_{it}, for $t = 1, 2, ..., T$, is transformed into the task of finding the joint density function of y_{it}, for $t = 2, 3, ..., T$, conditional on the initial value y_{i0} and the regressors $\overline{\mathbf{x}}_{i[-1]}$. The conditional joint distribution of $(y_{i2}, y_{i3}, ..., y_{iT})$ can be expressed as an integral with the random

effects being integrated out,

$$f\left(y_{i2}, y_{i3}, ..., y_{iT}|y_{i0}, y_{i,t-1}, \mathbf{x}_i^{T-1}; \gamma, \lambda\right) = \int_{-\infty}^{\infty} \left[\begin{array}{c} f\left(y_{i2}, y_{i3}, ..., y_{iT}|\alpha_i, y_{i,t-1}, \mathbf{x}_{i,t-1}; \lambda\right) \cdot \\ h\left(\alpha_i|y_{i0}, \mathbf{x}_i^{T-1}; \gamma\right) d\alpha_i \end{array} \right] \tag{4.6}$$

The advantages of the above approach are: i) it is easy to find the conditional density of α_i given y_{i0} and $\mathbf{x}_i^{T-1}$, and it is also computationally easy to estimate maximum likelihood estimators using regular statistical package[9], ii) the average partial effect for every regressors can be computed, iii) it can be easily extended to the Bayesian case as we will see later.

Heckman's Method

Heckman (1981) proposes an alternative approach to handle the initial conditions problem. He suggests finding the joint distribution for a time series of binary outcomes $(y_{i2}, y_{i3}, ..., y_{iT})$ by specifying two conditional distributions $\Phi_0\left(y_{i0}|\mathbf{x}_i, \alpha_i, \eta\right)$, for y_{i0}, and $f_1\left(\alpha_i|\mathbf{x}_{i,t-1}, \theta\right)$, for α_i. Substituting into Eq. (4.6) the two conditional distributions and integrating the product with respect to α_i, we recover the joint distribution of $(y_{i2}, y_{i3}, ..., y_{iT})$ conditional only on $\mathbf{x}_{i,t-1}$,

$$f\left(y_{i2}, y_{i3}, ..., y_{iT}|y_{i,t-1}, \mathbf{x}_{i,t-1}; \lambda\right) = \int_{-\infty}^{\infty} \left\{ \begin{array}{l} \Phi_0\left(\cdot\right)^{y_{i0}} \left[1 - \Phi_0\left(\cdot\right)\right]^{(1-y_{i0})} \cdot \\ \prod_{t=2}^{T} \Phi\left(\cdot\right)^{y_{it}} \left[1 - \Phi\left(\cdot\right)\right]^{(1-y_{it})} \end{array} \right\} f_1\left(\alpha_i|\mathbf{x}_{i,t-1}; \theta\right) d\alpha_i. \tag{4.7}$$

The likelihood to be maximised across the whole time span is

$$L = \prod_{i=1}^{M} f\left(y_{i2}, y_{i3}, ..., y_{iT}|\mathbf{x}_{i,t-1}; \lambda\right),$$

where M is the number of MNEs in the panel. To apply this approach we use a Stata add-in programme *redprob*, which is provided by Stewart (2006), and described in Stewart (2007). In this programme, the conditional distribution $\Phi_0\left(\cdot\right)$ is approximated by a reduced-form linear function of the initial latent profit,

$$y_{i0}^{*} = \mathbf{z}_{i0}^{'}\eta_1 + \eta_2\alpha_i, \quad \eta_1 = \left(\eta_{11}, ..., \eta_{1k}\right)^{'}.$$

[9]We use a Stata command of cross-section time-series probit model - *xtprobit*.

where $\mathbf{z}_{i0}$ is a vector containing the exogenous instruments along with $\mathbf{x}_{i0}$. The parameter η_2 measures the correlation between the initial condition and the unit-specific effect. This program evaluates the integral (Eq. 4.7) by Gaussian-Hermite quadrature assuming that $\alpha_i \sim N\left(0, \sigma_\alpha^2\right)$.

4.3.2 A Dynamic Probit Bayesian Approach

The Bayesian approach has not become popular in the industrial-organisation research, but its flexibility and computational easiness encourage us to use it. Particularly, the random-effect models can easily be accommodated using the Bayesian approach; plus it has the advantage that it does not require solving prohibitive high-dimension integrals, as in Traditional econometric models. Unlike Traditional econometrics, the Bayesian approach does not require strong parametric assumptions over the sampling or strong asymptotic theories (Lancaster, 2004). In addition, the Bayesian approach uses either previously gained or available information on the parameters of the model as priors in the estimation, saving therefore time in the estimation. This is drastically contrasted to the Traditional econometric approach, which requires researchers to be blind to data and outcomes.

Bayesian modelling and computation of the discrete-choice model have been studied in various papers (see Chib, 1992, Albert and Chib, 1993 and Chib and Greenberg, 1996). Amisano and Giorgetti (2005) use a Bayesian approach to study expansion into submarkets and diversification across seven developed countries for the global pharmaceutical industry.

In the probit model in Eq. (4.3), we are interested in the parameters $\lambda \equiv (\rho, \beta')'$, but we must specify the unit-specific α_i to accommodate random effects. Using the Bayesian approach, we can write the joint posterior distribution of the parameters of interest (and those of no interest) conditional on the data $\mathbf{z}_{it} = \left(y_{it}, y_{i,t-1}, \mathbf{x}_{i,t-1}\right)$ as,

$$p\left(\lambda, \alpha_i | \mathbf{z}_{it}\right) \propto p\left(\mathbf{z}_{it} | \lambda, \alpha_i\right) p\left(\lambda, \alpha_i\right), \tag{4.8}$$

where $p\left(\mathbf{z}_{it} | \lambda, \alpha_i\right)$ is the likelihood of $\mathbf{z}_{it}$ and $p\left(\lambda, \alpha_i\right)$ is the prior distribution of random parameters. We also assume that α_i is independent of λ. This expression reads

like "the conditional joint posterior distribution of λ and α_i is proportional to $(\propto)$, the product of the likelihood of the data $\mathbf{z}_{it}$ conditional on λ and α_i, and their priors". Intuitively, if the posterior joint distribution of λ and α_i conditional on the data $\mathbf{z}_{it}$ is known, the task of estimating the parameters of interest is nothing more than simulating the joint posterior distribution of λ and α_i. However, as pointed out in Chib and Greenberg (1996), $p(\mathbf{z}_{it}|\lambda,\alpha_i)$ is intractable, because its discrete nature does not allow normalisation, and hence $p(\lambda,\alpha_i|\mathbf{z}_{it})$ cannot be easily simulated. On the other hand, if we condition a latent variable y^*, as well as λ and α_i on the data $\mathbf{z}$, Expression (4.8) becomes,

$$p(y_{it}^*, \lambda,\alpha_i|\mathbf{z}_{it}) \propto p(\mathbf{z}_{it}|y_{it}^*, \lambda, \alpha_i)\, p(y_{it}^*|\lambda, \alpha_i)\, p(\lambda, \alpha_i)\,.$$

Although the (posterior) distribution $p(y_{it}^*, \lambda, \alpha_i|\mathbf{z}_{it})$ is complicated, the conditional distributions $p(y_{it}^*|\lambda, \alpha_i, \mathbf{z}_{it})$ and $p(\lambda, \alpha_i|\mathbf{z}_{it})$ are easy to simulate (Albert and Chib, 1993).

$$\begin{aligned} p(y_{it}^*|\lambda, \alpha_i, \mathbf{z}_{it}) &= p(y_{it}^*|\rho, \beta, \alpha_i, y_{it}, y_{i,t-1}, \mathbf{x}_{i,t-1}) \\ &\propto \phi(y_{it}^*)_{i=1\ t=2}^{M\ \ T} \left[\begin{array}{l} I(y_{it}{=}1)\, I\left(\rho y_{i,t-1}{+}\mathbf{x}_{i,t-1}\beta{+}\alpha_i ¿ 0\right) + \\ I(y_{it}{=}0)\, I\left(\rho y_{i,t-1}{+}\mathbf{x}_{i,t-1}\beta{+}\alpha_i \leq 0\right) \end{array} \right], \end{aligned} \tag{4.9}$$

and,

$$\begin{aligned} p(\lambda, \alpha_i|\mathbf{z}_{it}) &= p(\rho, \beta, \alpha_i|y_{it}, y_{i,t-1}, \mathbf{x}_{i,t-1}) \\ &\propto \phi(\rho)\,\phi(\beta)\,\phi(\alpha_i)\cdot \\ &\quad {\scriptstyle i=1\ t=2}^{M\ \ T} \left\{ \begin{array}{c} \Phi\left(\rho y_{i,t-1} + \mathbf{x}_{i,t-1}\beta + \alpha_i\right)^{y_{it}} \cdot \\ \left[1 - \Phi\left(\rho y_{i,t-1} + \mathbf{x}_{i,t-1}\beta + \alpha_i\right)\right]^{(1-y_{it})} \end{array} \right\}, \end{aligned} \tag{4.10}$$

where $I(\cdot)$ in Expression (4.9) and (4.10) is an indicator function for $y_{it} = 1$ and $y_{it} = 0$ and $\phi(y_{it}^*)$, $\phi(\rho)$, $\phi(\beta)$ and $\phi(\alpha_i)$ in Expression (4.10) are all prior density functions which reflect the subjective beliefs of the researcher.

We utilise the Gibbs sampling to simulate the parameters $\lambda \equiv (\rho, \beta')'$ and α_i and it

proceeds with following steps:

1. Choose the initial values of ρ, β and α_i;
2. Sample y_{it}^* for $i = 1, 2, ..., M$ from a conditional normal distribution $\begin{pmatrix} y^*|\rho, \beta, \alpha_i, \\ y_{it}, y_{i,t-1}, \mathbf{x}_{i,t-1} \end{pmatrix}$ that is truncated on the left if $y_{it}^* > 0$, $y_{it} = 1$, and on the right if $y_{it}^* \leq 0$, $y_{it} = 0$;
3. Sample ρ, β, α_i, from the normal distribution $(\rho, \beta, \alpha_i | y_{it}, y_{i,t-1}, \mathbf{x}_{i,t-1})$,where the means ρ, β, are equalised to $(\mathbf{XX})^{-1}\mathbf{Xy}^*$ and variance $(\mathbf{XX})^{-1}$, where $\mathbf{X} \equiv (\mathbf{X}_1, \mathbf{X}_2, ..., \mathbf{X}_M)$ and $\mathbf{X}_i$ is a $(k \times T)$ matrix of all explanatory variables $\left(y_{i,t-1}, \mathbf{x}_{i,t-1}\right)$.
4. Repeat steps 1 to 3 ns times. The number ns should be large enough to guarantee the posterior distribution of the parameters of interest to converge to a stationary state.

We use the Bayesian statistical package "WinBUGS" to implement our Bayesian analysis. The analysis will use the specification in Wooldridge's method. In this way we make our Bayesian results comparable to those of the Traditional econometrics approaches.

4.4 Data and Variables

In Chapter 3 we describe how we collect and compile the data of 265 pharmaceutical MNEs which were active in the EU market from 1990 to 2004. We make two assumptions in order to obtain a balanced panel dataset: i) we treat a merged company as a single entity, i.e., a "super company"[10], ii) new entrants are treated as inactive incumbents until the year they took up their first opportunity. This "sleeping incumbents" assumption is made on the basis that new entrants only account for 12 per cent of the total 265 MNEs.

Of these 265 pharmaceutical MNEs, we collected information on their subsidiaries, amounting to 1,772, existing and active up to 2004. Detailed information on the sample is provided in Table 4A.1 . Specifically, in the time period 1990 - 2004 we observe

[10]This is the assumption adopted by Bottazzi and Secchi (2006).

827 new subsidiaries established or acquired. These subsidiaries are in one or more of three categories of business activities: i) production, ii) wholesaler, retailer or dispensing and iii) research and development. The sources of these subsidiaries are either green-field investments by MNE parent companies themselves or acquisitions through mergers or takeovers. The expansion of the MNEs in each year is defined as a binary variable equal to one if an MNE has at least one pharmaceutical-related subsidiary established or acquired in that year and zero, otherwise. New-entrant MNEs are treated as holding zero opportunities prior to their first expansion in the market. Of the 265 MNEs over the 15-year period, we count 564 expansion observations. This is denoted as the number of opportunities captured by the MNEs. Dividing the new subsidiaries by the expansion observations, we get an average of 1.47 (827/564) subsidiaries per opportunity. This number reveals the discrepancy between the Ijiri and Simon's model of the "independent islands" and real data (Ijiri and Simon [1964, 1977] assumed that opportunities are equally-sized.). This empirical difficulty warrants some "bridging technique" to link the number of opportunities to the number of subsidiaries, for instance, our copula approach.

Our idea of treating acquired and new own-established subsidiaries indifferently is justified by the fact that either green-field investments or acquisitions reflect each MNE's willingness and actions of expansion. Expansions through both platforms are all influenced by industry-level trends such as relocation of business activities or adjustments to the Single Market. Consequently, acquired or new own-subsidiaries are components of the industrial dynamics.

Descriptive statistics on MNEs expansion and changes in their size are presented in Table 4A.1 .

Here we point out some important facts from Table 4A.1 :

a) The standard deviation of size change (either proxied by the number of subsidiaries or operational revenues) is larger than its mean.[11] This fact signals a high level of heterogeneity in the expansion process;

[11] The mean value is reported in parenthesis, and the standard deviation in squared brackets.

b) In 1996 and 2000, there are two peaks in established or acquired subsidiaries (71 and 90, in curly bracket); but the sum of increases in operational revenues does not reflect the same pattern;

c) Row 3 shows that less than 20 per cent of the MNEs expanded by at least one subsidiary every year.[12]

The explanatory variables we use in estimations are the following:

1. $y_{i,t-1}$ is one-year lagged dependent variable, which equals 1 if some subsidiaries were established or acquired in year $t-1$, i.e., the MNE captured an opportunity in the previous period.

2. $S^N_{i,t-1}$ the total number of subsidiaries MNE i has established or acquired, regardless of their activities, in the previous period; and its squared term, $S^{N2}_{i,t-1}$. Any positive effect of the number of subsidiaries $S^N_{i,t-1}$ may be counteracted by external and internal factors. Externally, the availability of new business opportunities may be scarce, because the European market for the pharmaceutical products has been well-established for many decades: some big players in this industry have been in Europe for more than one hundred years. Therefore, an MNE having many subsidiaries may merely indicate well-exploited opportunities. Internally, as the number of subsidiaries increases, managerial costs or transaction costs also rise, raising the long-run average costs of the MNEs.[13] These possible negative connections motivate us to include a squared term of $S^N_{i,t-1}$ and wish this term will capture the non-linearity in the size-growth relationship.

3. $S^S_{i,t-1}$ is MNE i's one-period lagged size measured by operational revenues[14]. This is calculated by summing up operational revenues of one MNE's pharmaceutical-related subsidiaries for each year. As we discuss in Section 3.3, Chapter 3, some

[12]Since the focus of this study is to look at the overall dynamic pattern of expansion for the industry, we do not explore who was active in expansion, for instance, did smaller or younger MNEs tend to expand more frequently? We agree that this question leads to another research direction.

[13]Diseconomies of scale are discussed in Williamson (1975), and tested in Canback (2004).

[14]Following usual practice in Bayesian analysis, $S^S_{i,t-1}$ is standardised to follow a $N(0,1)$ distribution in order to guarantee fast convergence to the stable posterior distribution in the Gibbs' sampling.

MNEs do not have the value of aggregated operational revenues.[15] To ensure the reliability of the data we restrict this measure of size to the period 1995 onwards. Also in this definition of size we include a squared term, $S_{i,t-1}^{S2}$, to catch any non-linearity.

4. Three dummy variables are also included to fulfill the requirement of instruments required by Heckman's method. They are TOP_i which is equal to one if an MNE belongs to the top 100 pharmaceutical companies in the world rank in 2004 (SCRIP 100, 2005/2006), and EU_i or US_i which are equal to one for those MNEs that have headquarters located either in the EU or the US. These instruments are added as explanatory variables to Wooldridge's and Bayesian approaches, so as to make the results from the different models comparable.

5. Initial conditions of the explanatory variables are also included: $y_{i,90}$, $S_{i,90}^{N}$, $S_{i,90}^{N2}$ (or $y_{i,95}$, $S_{i,95}^{S}$, $S_{i,95}^{S2}$ respectively), where $S_{i,90}^{N}$, $S_{i,90}^{N2}$, $S_{i,95}^{S}$ and $S_{i,95}^{S2}$ are serving as instrument variables in Heckman's method;

4. Time mean variables, $\overline{S_i^h}$, and $\overline{S_i^{h2}}$, $h = \{N, S\}$.

The statistics on the explanatory variables are reported in Table 3.2 and described in Section 3.3 of Chapter 3. As mentioned previously, in our estimations the time span of the data differs when the size is measured by the number of subsidiaries or by operational revenues. In the former, the data are available for the entire period 1990 - 2004. However, the presence of the initial conditions and the lagged dependent variables force us to use data from 1992 only. When the size is measured by operational revenues, the sample span reduces to 1995 - 2003 and, estimations can only begin from 1997.

At the last part of this section, we discuss the histogram of the number of opportunities[16]

[15]See Table 3.1 in Chapter 3 for a list of how many MNEs in the sample have missing values for operational revenues in each year.

[16]The number of opportunities S_{it}^{n} is the sum of $y_{it}(=1)$ for MNE i in year t and before up to 1980. We know for each subsidiary of an MNE when it was incorporated. We decide to use 1980 as the cut-off point because i) amongst 1,772 subsidiaries identified, 1,096 of them were incorporated after 1980; ii) we do not wish to extent the time period too early because Amadeus does not record firms which exited and

S^n (Figure 4A.1 (a)), the number of subsidiaries S^N (Figure 4A.1 (b)) and operational revenues S^S (Figure 4A.1(c) with the kernel estimates of the empirical density function [EDF]), which are plotted in Figure 4A.1, where data are pooled over the entire period whenever they are available. We find that: i) the histograms of S^n and S^N are highly skewed to the right, ii) the distribution of the normalised S^S is close to a normal distribution.[17]

4.5 Results

4.5.1 Size Proxied by the Number of Subsidiaries

In this section we measure size by the number of subsidiaries opened/acquired. Two models are estimated using different econometric approaches.

Model 1:

$$\begin{aligned} P(y_{it} &= 1|y_{i,t-1}, S^N_{i,t-1}, O_i, \alpha_i; \lambda, \gamma, \eta) \\ &= \Phi(\rho y_{i,t-1} + \beta_1 S^N_{i,t-1} + \psi + \overline{\gamma}_{[2]}\overline{S^N_i} + \eta_{11} S^N_{i,90} \\ &\quad + \eta_{12} TOP_i + \eta_{13} EU_i + \eta_{14} US_i + \alpha_i + u_{it}) \end{aligned} \tag{4.11}$$

where O_i collects all time-invariant MNE-specific effects. We make use of a pooled probit and a Heckman approach to estimate Model 1. Results are reported in Cols. 1 and 2 of Table 4.1. The results including the squared terms $S^{N2}_{i,t-1}$, $\overline{S^{N2}_i}$ and $S^{N2}_{i,90}$ are reported in Cols. 1 and 2 of Table 4.2.

Model 2:

$$\begin{aligned} P(y_{it} &= 1|y_{i,t-1}, S^N_{i,t-1}, O_i, \alpha_i; \lambda, \gamma, \eta) \\ &= \Phi(\rho y_{i,t-1} + \beta_1 S^N_{i,t-1} + \psi + \gamma_{[1]} y_{i,90} + \overline{\gamma}_{[2]}\overline{S^N_i} \\ &\quad + \eta_{12} TOP_i + \eta_{13} EU_i + \eta_{14} US_i + \eta_2 \alpha_i + u_{it}) \end{aligned} \tag{4.12}$$

We make use of Wooldridge's method and a Bayesian approach to estimate Model

hence we are less confident in the identification of the existence of subsidiaries in the earlier years. We are aware that this practice is somewhat arbitrary.

[17] In this plot operational revenues are normalised: we take the logarithm of it and then demean it. This way of normalisation is used in Bottazzi and Secchi (2005, 2006). We follow their way so that we can replicate their test of Gibrat's law, see Appendix (Section 4.7.1).

2. The results of Model 2 with or without the squared terms are reported in Col. 3 and 4 of Tables 4.1 and 4.2 respectively. To obtain the estimates of the Bayesian approach, we run the Gibbs sampling for 50,000 iterations in two chains based on different sets of initial values. The first set of the initial values is non-informative because all parameters are set as zero while the second set is the estimates from the Traditional econometrics. Visual inspection of the two chains suggests that for all parameters convergence is achieved after 30,000 iterations. Formal convergence diagnosis is done by using the test proposed in Brooks and Gelman (1998)[18] and it shows that generally after 35,000 iterations convergence is achieved for all parameters of interest. Therefore, we discard the first 40,000 draws and calculate the posterior value of each parameter based on the last 10,000 draws.

When comparing the pooled probit model with the other random-effects models, we need to recall that the former treats observations as belonging to a single cross-section. In this way the temporal correlation between unobservable unit-specific effects is ignored and the terms α_i and true error term u_{it} are treated as a composite error term,

$$c_{it} = \alpha_i + u_{it}.$$

The implication is that the pooled probit uses as normalisation of the error term $\sigma_c^2 = 1$, whereas the other random-effects models adopt $\sigma_u^2 = 1$. Therefore, the random-effects coefficients need to be multiplied by a factor of $\sqrt{1-\iota} = \sigma_u/\sigma_c$ to make them comparable to those of the pooled probit (see Arulampalam, 1999).[19]

In terms of the lagged dependent variable $y_{i,t-1}$, the pooled probit model over-estimates more significantly the level of state dependence. The Bayesian approach is the one that offers the most conservative but significant estimate of lagged expansion. This can be seen as evidence that the Bayesian approach outperforms the Tradi-

[18] Brooks and Gelman (1998) modified the method introduced in Gelman and Rubin (1992) to monitor the convergence of the simulated parameters. The Brooks and Gelman's statistics is the ratio of the between and within variances of multiple chains of simulations. The ratio has the property that if it is close to one, it indicates convergence is achieved for the multiple chains.

[19] $\iota = Corr\left(u_{it}, u_{is}\right) = \frac{\sigma_\alpha^2}{\sigma_\alpha^2 + \sigma_u^2}$, for $s, t = 2, 3, ..., T; s \neq t$, which is the equicorrelation between the error in two time periods. Since ι is bounded between 0 and 1, $\sqrt{1-\iota}$ is smaller than 1. Thus if ρ of Heckman's method or Wooldridge's method is multiplied by $\sqrt{1-\iota}$, it would be reduced.

tional econometrics approach in terms of controlling for random effects, since from the Bayesian analysis we can obtain the exact estimates from the simulation of the posterior distributions of parameters, whereas in Traditional econometrics, the maximum-likelihood estimates (MLEs) are computed using mathematical approximations (Lancaster, 2004).

To evaluate the effect of state dependence, we calculate the average partial effect (APE), by constructing counter-factual outcome probabilities and calculating these in the states $y_{i,t-1} = 0$ and $y_{i,t-1} = 1$; with associated explanatory variables $\mathbf{x}_{i,t-1} = \left(S^N_{i,t-1}\right)$ or $\mathbf{x}_{i,t-1} = \left(S^N_{i,t-1}, S^{N2}_{i,t-1}\right)$ and their respective time-mean values $\overline{\mathbf{x}}_{(-1)i}$ (Wooldridge, 2006 and Stewart, 2006). We compute the following probabilities (based on Heckman's method for example),

$$\widehat{p}_{(1)} = \frac{1}{M(T-1)} \sum_{i=1}^{M} \sum_{t=2}^{T} \Phi\left[\left(\widehat{\rho} + \mathbf{x}_{i,t-1}\widehat{\beta} + \overline{\mathbf{x}}_{i[-1]}\widehat{\overline{\gamma}}_{[2]}\right)\sqrt{1-\widehat{\iota}}\right]$$

$$\widehat{p}_{(0)} = \frac{1}{M(T-1)} \sum_{i=1}^{M} \sum_{t=2}^{T} \Phi\left[\left(\mathbf{x}_{i,t-1}\widehat{\beta} + \overline{\mathbf{x}}_{i[-1]}\widehat{\overline{\gamma}}_{[2]}\right)\sqrt{1-\widehat{\iota}}\right].$$

The Average Partial Effects (APEs), $\left(\widehat{p}_{(1)} - \widehat{p}_{(0)}\right)$, are reported in percentages at the bottom of Tables 4.1 and 4.2 . They are all at similar levels, except those from the pooled probit model, which are larger. This potentially shows how much state dependence in the pooled probit model is spurred by the correlation between the error terms, as well as between α_i and the initial condition $y_{i,90}$. However, ι, the coefficient of inter-temporal correlation reported in Heckman and Wooldridge's methods exhibits no statistical significance. The dependence of the initial condition $y_{i,90}$ on α_i, η_2 is also insignificant using Heckman's method (see Section 4.3.1). Therefore, we can conclude safely that these groups of probit models are not plagued by the econometric issues discussed earlier.

Turning to the estimates of the lagged number of subsidiaries $S^N_{i,t-1}$, the four models all estimate a statistically significant negative effect of $S^N_{i,t-1}$ of similar magnitude (Tables 4.1-4.2). In Table 4.2, we observe that adding a squared term $S^{N2}_{i,t-1}$ leads to an increase in the effect of lagged expansion, $y_{i,t-1}$, in all four models. The effect of

$S^N_{i,t-1}$ also changes drastically (having a higher negative impact on expansion now). The coefficient of $S^{N2}_{i,t-1}$ is statistically significant but generates only a weak effect.

We calculate the APEs on expansion derived from a marginal change in the numbers of subsidiaries for the Heckman's and Wooldridge's methods without and with $S^{N2}_{i,t-1}$. The interest lies in two questions:

1. Do the APEs of $S^N_{i,t-1}$ differ between MNEs in different size strata? This question is directly motivated by our empirical evidence of Gibrat's law and that of other studies set in Chapter 3, where there is a negative correlation between growth rate and size.

2. How do the effects of $S^N_{i,t-1}$ evolve?

In order to answer the first question, we calculate the APEs for the 265 MNEs in four quartiles specified by the initial number of subsidiaries, $S^N_{i,90}$.[20] They are defined, for the MNEs in the same size stratum, as the average change in the probabilities of expansion, resulting from the change in S^N_i in two successive years. The particular trend of APEs responds to the second question and allows us to track the growth path of MNEs over natural time divisions (between two years), rather than by arbitrarily assigned marginal changes of S^N, e.g., $N \rightarrow N+1$.

Since S^N grows over time, a cumulative APE, CAPE, is more suitable to demonstrate the inter-strata differences and intra-strata evolution in the effect of S^N. The first four figures (a-d) in Figure 4.1 show the CAPEs of S^N, as they result from the Wooldridge's and Heckman's methods, both with and without the squared term. Two figures in the first row show the CAPEs from two models without the squared term S^{N2}. Looking at Figure 4.1 (a), the effects of S^N do differ alot across the four size strata. Negative effects of the first three strata are close to each other, running from zero to about $-$ 8 per cent over time; on the other hand the negative effect for the largest firms in the fourth stratum is much larger than that of the other three strata,

[20] Because of the discrete nature of $S^N_{i,90}$, the quartiles do not have equal amount of MNEs in them. The first quartile contains 23 percent of MNEs, with $S^N_{i,90} = 0$; the second quartile 28 percent, with $S^N_{i,90} = 1$; the third quartile 22 percent, with $S^N_{i,90} = \{2, 3, 4\}$; and the last quartile 27 percent, with $S^N_{i,90} \geq 5$.

and it grows at a faster pace up to over − 20 per cent in 2004 (Figure 4.1 (b) shows the same pattern). Turning to the figures in the second row, where a squared term S^{N2} is added, it is hard to explain why the CAPEs of the last three strata in Figure 4.1 (d) cluster, while they spread almost evenly in Figure 4.1 (c). Though Figure 4.1 (c-d) share a negative growth pattern, the effects of S^N differ significantly once we distinguish between small and large MNEs.

On the basis of the CAPE plots, we see there exists a negative relationship between MNEs' size and their probabilities of expansion, which is the answer for question 1. The answer for question 2 is that, the CAPE curves for the MNEs in the four size strata evolve with a similar pattern: they are firstly lowering and as they are approaching the end of the sample period, they becomes flatter. In particular, the CAPE curves become almost flat for the smaller MNEs towards the end of the sample period, indicating that as new opportunities are added to the MNEs over time, the effect of the next new opportunity on an MNE becomes zero, in terms of the probability of capturing a new opportunity. This finding is evidently suggesting the existence of a steady state in firm growth trajectory, for the MNEs in each size strata. However, for the largest MNEs in the fourth strata, the curves only become flatter but not yet reach a steady state towards the end of the sample period (this tendency is visible in Figure 4.1 (a), Figure 4.1 (c) and Figure 4.1 (d), but not in Figure 4.1 (b)). Such tendency is clearer in Figure 4.1 (c) and Figure 4.1 (d) than in Figure 4.1 (a) and Figure 4.1 (b), due to the positive effect of the squared term $S^{N2}_{i,t-1}$(see Tables 4.1 -4.2).

We attempt to interpret the finding in this way: the smaller MNEs have higher probability than the larger MNEs of capturing a new opportunity and this is in line with the higher growth rate and active entry behaviour at the lower tail of the firm size distribution, which is often found in other empirical studies in the firm-growth literature[21]. In terms of the growth path, the MNEs with different initial sizes seem to converge to different steady states and the smaller MNEs have a faster speed of converging. This finding is also in line with the mean-reversion mechanism identified

[21]See Section 3.2.2 in Chapter 3 for the review on those empirical studies.

by the AR(1) tests in Section 3.4.1 of Chapter 3, although in that case the steady state is in terms of real size, and in the current case it has a probability sense. In addition, the non-linear CAPE curves can also be related to diseconomies of scale and market power. Taking the largest MNEs for example, they are facing size disadvantages, which are resulted from diseconomies of scale, such as rising managerial costs or transaction costs in a large enterprise. However, they can overcome the size disadvantages by engaging in mergers and acquisitions, in order to gain superior market power. If they can gradually overcome the disadvantages, their growth trajectories may converge to a steady state, as those smaller MNEs do. For this logic, we expect to see the CAPE curve of the largest size strata to become flat in the four figures, if the time period can be extended further.

4.5.2 Size Proxied by Operational Revenues

This definition of size, S^S, introduces richer heterogeneity. As mentioned in our data description, the sample period is restricted to the time span 1995 - 2003. S^S replaces S^N in the models given in Eq. (4.11) and (4.12). The initial year becomes 1995.

Results are reported in Tables 4.3 and 4.4 . In both tables, we find that for the three methods (Heckman, Wooldridge and Bayesian), the coefficients of $y_{i,t-1}$ are much smaller than those in the long sample and are only statistically significant at the 10 per cent level (although not significant for the Bayesian method). Again the pooled probit model overestimates state dependence significantly. The APEs of lagged expansion are reported at the bottom of Tables 4.3 and 4.4 . The APE in the pooled probit model is at least twice as large as the ones from the other three models. An inspection of the coefficients related to the inter-temporal correlation between the error terms, ι, and the correlation between α_i and $y_{i,95}$, η_2, reveals that the source of overestimation comes from the former correlation because only ι is statistically significant. This finding justifies our choice of the random-effects models to correct for the econometric issues discussed in our econometric section.

Turning to the effect of lagged operational revenues, $S^S_{i,t-1}$, it shows a negative but insignificant effect on expansion using three methods (Heckman, Wooldridge and

Bayesian) in Table 4.3 . Moreover, in Table 4.4 , while $S^S_{i,t-1}$ shows a positive but insignificant effect, $S^{S2}_{i,t-1}$ shows a negative and insignificant effect. The coefficients of $\overline{S^S_i}$ are significantly positive using both Heckman and Bayesian methods (Table 4.3), $\overline{S^S_i}$ and $\overline{S^{S2}_i}$ do not have significant coefficients in Table 4.4 for three methods (Heckman, Wooldridge and Bayesian).

CAPEs are plotted in Figure 4.1 (e-h). The general result coming from the figures is that the CAPE curves of MNEs in the first three strata cluster together and fluctuates marginally around the zero probability line. On the contrary, the CAPE curve of MNEs belonging to the largest stratum departs from the other three towards negative probabilities, indicating heterogeneity among the largest MNEs and the smaller ones. However, we have to bring attention to the fact that the maximum CAPE is never beyond $-$ 1 per cent. On the basis that the coefficients of $S^S_{i,t-1}$ and $S^{S2}_{i,t-1}$ are not all statistically significant, and the predicted CAPEs are much weaker than those for the number of subsidiaries S^N, we suggest the plots of CAPEs of operational revenues can only be seen as indicative.

The initial condition $y_{i,95}$ has positive coefficients in the Wooldridge's and Bayesian methods and they are all significant at the 1 per cent level. It may be difficult to interpret its true effect on expansion because it is time invariant, but the positive effect is as expected if MNEs that expanded in the first period might be more likely to expand in the future. Another explanation for the significant and positive coefficient is that, $y_{i,95}$ may absorb the effects of S^S, which is surprisingly lacking significance.

To summarise the main findings using the two measures of firm size, we see that:

1. The state dependence of the expansion decisions is confirmed using both measures: the predicted average effect of the lagged expansion on the probability of current expansion ranges from 5 to 16 per cent;

2. If the size of MNEs is measured by the number of subsidiaries each of them has, the probability that the MNEs expand by an additional opportunity is negatively related to their sizes and this decreasing effect is rather considerable. We also

find a converging trend in the growth trajectories of the MNEs to different steady states, being associated to their initial sizes;

3. The negative size effect on the probability of expansion runs against one key assumption of Sutton's "independent submarkets" model, where the probability of a firm catching an opportunity is assumed as non-decreasing in the size. However, when the size is measured by a more heterogeneous measure - operational revenues, this assumption is not invalidated. Therefore, we believe that it is still premature to claim that the "independent submarkets" model is not able to reconcile with the growth of the European pharmaceutical industry, or to say that a dynamic probit model is not suitable for proxying industry growth. Instead, in the next section we propose a prediction procedure to show how the dynamic probit model works well in predicting industry growth by combining the probability and the size of expansion.

4.5.3 Predictions

In this section we make use of the primitives of the dynamic probit estimations and perform a forecasting experiment of MNEs' expansion. Considering the size proxied by the number of subsidiaries and operational revenues separately.

Size Proxied by the Number of Subsidiaries

When size is proxied by the number of subsidiaries, we find a strong positive relationship with the number of opportunities (see Figures 4.2 and 4.3). Figure 4.2 brings up an interesting result: there is a tendency of the cumulative density functions (CDFs) of the two random variables to overlap for values below their respective median, and diverge for values above (with the number of subsidiaries growing larger than the number of opportunities). An effect that is certainly more noticeable over time, as stressed further in Figure 4.3 . This later is obtained by plotting the Kernel estimations of the cumulative densities of the two variates against each other.[22] The strong positive relationship between the two random variables is a key factor that leans our choice of

[22]We have employed a normal kernel function with a window parameter (bandwidth) related to the number of points in each random variable.

the parametric copula towards a Gaussian one. Our decision to utilise a bivariate copula[23] to recover the joint distribution relies on our ultimate need to simulate values for the two correlated variates. The procedure requires first to have an estimate of their CDFs. For that we use the Kaplan-Meier estimator and account for the variables being discrete. We then employ these estimations to fit the linear correlation parameters[24]. In the first column of Table 4.7 , the very high positive correlation between the two variables is unveiled. The final step of this approach makes use of the correlation parameters to simulate values for the two variates (see Figure 4.4). We simulate $1,000$ pairs of the opportunities and the number of subsidiaries by inverting the joint bivariate Gaussian distribution with the fitted correlation coefficient, $\widehat{\rho}$. Next, we exploit the expected number of opportunities (rounded) variable generated in the probit estimations. The number of subsidiaries results from conditioning our simulations to these expected number of opportunities.

Our prediction exercise can only start in 1992, for the model requires both initial conditions in 1990, and predetermined lagged variables (inclusive of size) in 1991. We then employ the primitives of the model and predict the expected number of opportunities captured by each MNE up to 1992.[25] In addition we avail of the simulated number of the subsidiaries captured up to that year, resulting from the procedure outlined above. This allow us extending our predictions to 1993, since the lagged size is now available. We can now predict the expected number of opportunities captured by each MNE up to 1993 and the procedure repeats up to period T (2004).[26] Once the exercise is completed, we compute the coefficient of determination between the predicted number of subsidiaries and the actual (observed) number of subsidiaries. Table 4.5 reveals, under different probit models, the high goodness of fit of our approach.

Finally, we wish to relate our ability to predict the expansion of MNEs to Sutton's

[23]The bivariate copula approach is described in Appendix (Section 4.7.2).

[24]See Figure 4.10 (top) for a plot of our fitted Gaussian bivariate copula CDF.

[25]We do not account for individual heterogeneity of being a Top, US or EU MNE, given the parameters from the models are all non-significant (see results in Tables 4.1 and 4.2).

[26]In 1993 we add to the total number of opportunities captured up to 1991, the (non rounded) expected number of opportunities captured in 1992 and the (non rounded) expected number of opportunities captured in 1993. The rounded value of the resulting total will be our expected number of opportunities captured by each MNE up to 1993. The same logic can be extended up to year T.

lower bound and the firm-growth literature. We address the linkage of our predictions to the firm-growth literature in Appendix (Section 4.7.1). Figure 4.5 plots the concentration Lorenz curves and Sutton's lower bounds for years covering almost the entire period. From the figure we notice two important facts: i) Sutton's lower bound (the dotted line) is almost always satisfied; ii) The predicted concentration curve (the solid line) is, in most years, very close to the actual concentration curve (the dashed line) and when it departs, it does it by moving away from the lower bound, suggesting a slight overprediction of MNEs' opportunity heterogeneity.[27]

Size Proxied by Operational Revenues

The procedure described in the previous section can also be applied to size proxied by (standardised) operational revenues. We compare the CDF of the two variates and notice that in Figure 4.6 that in almost all domains a smooth increase in the number of opportunities is not followed by an increase in the size. Only in the last 10 - 20 per cent of the domain do the number of opportunities and the size track each other. This interesting pattern is more obvious now in Figure 4.7 . A 45 degree line would exhibit a pattern of opportunity-homogeneity, with the implication that the more opportunities an MNE captures, the larger that MNE would be. Instead, Figure 4.7 highlights a rather unexpected characteristic: large heterogeneity in opportunities seems to be peculiar to those MNEs that have captured a small number of opportunities. In order to catch the particular relationship, we adopt a parametric Gumbel copula approach, which has the idiosyncrasy of capturing positive correlations in the upper tail of the distribution.

We report our estimates of the dependence coefficient, along with its confidence interval, in the second column of Table 4.7 . We use those estimates to recover the joint distribution (S^S and S^n) and subsequently simulate the number of opportunities and the standardised operational revenues, as shown in Figure 4.8 . The final step is to predict MNE growth for the period 1997 - 2003. As before, we use our predictions to evaluate the goodness of the various specifications adopted. Table 4.6 shows the coef-

[27] Higher heterogeneity is equivalent to more skewed distribution of the opportunities, which leads Lorenz curve to bound further away from the 45 degrees line.

ficients of determination used to embed a peculiar trend. The suggested methodology seems to better predict long-run growth. We need however to be careful in interpreting this result. Our interpretation of the trend in Table 4.6 is that the large heterogeneity and independence (between S^S and S^n) that are peculiar to small MNEs (Figure 4.8) reduces over time, as MNEs grow. This implies that simulation errors are expected to decrease over time.

Finally, we again relate our results to Sutton's lower bound and defer their linkage in terms of the firm-growth literature to Appendix (Section 4.7.1). We plot the concentration Lorenz curves and Sutton's lower bound (Figure4.9) and observe that both actual and predicted concentration are well apart from Sutton's lower bound, thus indicating a good level of heterogeneity.

4.6 Conclusions

Following Ijiri and Simon (1964)'s "islands" model, Sutton's "independent submarkets" model suggests that the growth process of an industry can be seen as a continuous realisation of opportunities by incumbents and new entrants. Sutton assumes that the probability of any incumbent catching the next opportunity is non-decreasing in its size, and fixed for new entrants. His model then generates the limiting distribution of firm size and demonstrates the empirical significance of such a distribution in gauging the market structure of an industry (Sutton, 1997 and 1998). In addition to its ability to predict industry growth, the model suggests a potential direction for modelling firm growth empirically. We put forward an extension to this idea. We make use of a discrete-choice model and estimate the probability that a firm expands by capturing a new opportunity, and then link it to its heterogeneous size dimension, with the aim of predicting the long-term growth process of the industry. Specifically, we employ a dynamic probit model and condition the probability of expansion on the MNEs' size as well as on their lagged expansion.

The effect of the lagged expansion can shed light on the potential state dependence in the firm growth process. We find that the state dependence between current expansion and lagged expansion in the industry is modest in the period of the SMP era, and

be more specific, the expansion in the previous year increases the probability of current expansion by approximately 5 to 16 per cent. Although no comparable research is available, we argue that this is an indication that the pharmaceutical industry in the European Union is at a stable state. This finding enriches our understanding of the dynamics of the European pharmaceutical industry.

Firm size is also seen as an important determinant of expansion probability. When the size is measured by the number of subsidiaries, we find that it imposes a negative effect on the MNE's ability to expand, or in other words, to capture a future opportunity. The magnitude of the negative effect of the number of subsidiaries is also found to be larger for larger MNEs, and vice versa. We also find that MNEs with different initial sizes are converging to respective steady state of growth, in terms of the probability of expansion. These findings are consistent with those of the tests of Gibrat's law, presented in Chapter 3. Moreover, the negative effect of the number of subsidiaries is in contrast to the "non-decreasing" condition utilised in Sutton's model. But, if the size is measured by operational revenues, its effect is no longer statistically significant.

Starting from the primitives of our econometric models and explanatory variables in the initial period, we are able to predict the growth trajectory of MNEs up to 13 years later. There is an important lesson here. We use a very simple approach that relates MNEs' decisions to their size. If we proxy size by the number of subsidiaries we see that we are able to predict well MNEs' expansion behaviour. If asked in 1990 to produce a forecast of MNE expansion and are given the total number of opportunities available every period, we can predict the size 14 years ahead with a minimal error (that accounts for less than 20 per cent of the variability). The outcome is less satisfactory when the size is proxied by standardised operational revenues. In this case, if we are asked in 1995 to predict MNE expansion up to 2003, the error would be larger (that accounts for more than half of the variability).

Sophisticated econometric methods are used in this study to prevent unobserved random effects of MNEs from contaminating the estimation of state dependence. We use two Traditional and a Bayesian approaches on the dynamic probit model to control

for the initial conditions problem and endogeneity caused by the random effects. The results are robust.

4.7 Appendix

4.7.1 Replication of Bottazzi and Secchi's Size-Class Test Using Predicted Size

We are interested in whether the predicted operational revenues $\widehat{S}_{it}^{S}$ and the number of subsidiaries $\widehat{S}_{it}^{N}$ can reveal the same size-variance relationship estimated in Section 3.4.2, Chapter 3. Therefore, we repeat BS's size-class test using[28] $\widehat{S}_{it}^{S}$ and $\widehat{S}_{it}^{N}$. Results are reported in Tables 4A.2 and 4A.3. Compared the βs of the mean growth rate-size correlation (the first column in both tables) to that in Tables 3.6 and 3.7 in Chapter 3, we see that no matter the model includes squared terms or not, the βs are always negative and statistically significant and in particular, if the size is measured by the number of subsidiaries, the βs in Table 4A.3 are very close to that in Table 3.7 , Chapter 3. However, the significant negative β for the standard deviation-size correlation in Tables 3.6 and 3.7 of Chapter 3 can only be confirmed in Table 4A.2 , the model without the squared terms.

In addition to the size-class test, we can visually check how well the predicted number of opportunities, subsidiaries and operational revenues match the actual data. In Figure 4A.1 , we present the plot of histograms of the number of opportunities S^n (Figure 4A.1 (a)), the number of subsidiaries S^N (Figure 4A.1 (b)), and the normalised operational revenues S^S (Figure 4A.1(c), with the kernel estimate of the EDF).

In terms of the predicted values, in Figure 4A.1(d) and Figure 4A.1(g), $\widehat{S}^n$ (from the models without and with the squared terms) show the same highly skewed distribution, while the maximum number of the predicted opportunities are more than twice of the actual opportunities. Figure 4A.1(e) and Figure 4A.1(h) show the histogram of $\widehat{S}^N$, which almost perfectly mirror that of S^N. In Figure 4A.1(f) and Figure 4A.1(i) show $\widehat{S}^S$ and we see quite poor fit. We believe it is due to the insignificant coefficients of

[28] Since we standardise operational revenues in order to make it follows a $N(0,1)$ distribution, we need to first convert $\widehat{S}_{i,t}$ into the operational revenues in original unit (thousand USD) and normalise it in the way described in Section 3.4.1 of Chapter 3.

S^S in the dynamic probit model (see Tables 4.3 and 4.4). Based on these facts, we conclude that our dynamic probit model with the number of subsidiaries as size measure is proved to be the best one to model the firm growth for the pharmaceutical industry, which is also in line with the prediction exercise in Section 4.5.3.

4.7.2 The Copula

The copula is a technique used to relate multivariate joint distributions to their one-dimensional margins, and is particularly suitable both for non-normal data and for the marginals coming from different parametric families. It was first introduced by Hoeffding (1940) but it is commonly associated to Sklar (1973).

Although the copula approach can be generalised to the multivariate case, we confine in this chapter our attention to its bivariate parametric case and define a copula as follows, let F be a bivariate cumulative distribution function for random variables R_1 and R_2 and respective one-dimensional margins are F_1 and F_2, then there exists a bivariate distribution function, denoted as copula, C, such that,

$$F(r_1, r_2) = C(F_1(r_1), F_2(r_2); \theta),$$

where θ is a parameter that measures the dependence between the marginals. Let now $U(0,1)$ be a uniform distribution and u_1 and u_2 uniformly-distributed variates, so that, $r_1 = F_1^{-1}(u_1) \sim F_1$ and $r_2 = F_2^{-1}(u_2) \sim F_2$. Hence,

$$F(r_1, r_2) = F\left(F_1^{-1}(u_1), F_2^{-1}(u_2)\right) = C(u_1, u_2; \theta).$$

This means that if $r \sim F$, and F is continuous then $(F_1(r_1), F_2(r_2)) \sim C$, and if $U \sim C$, then $\left(F_1^{-1}(u_1), F_2^{-1}(u_2)\right) \sim F$. Therefore a bivariate copula is defined as a bi-dimensional CDF whose support (random variables) is contained in $[0,1]$ and whose margins are uniform on $[0,1]$.[29]

We are interested in the joint distribution (the number of opportunities and size), where the size can be either measured by the number of subsidiaries, S^N, or opera-

[29] For a more detailed description of the copula we refer to Trivedi and Zimmer (2007).

tional revenues, S^S. We base our choice of the parametric copula on the relationship between the random variables (the number of opportunities and the size). The kernel representation of the relationship of the number of opportunities and the number of subsidiaries, Figure 4.3, shows a strong positive relation between the two variables, suggesting us to adopt a Gaussian copula,

$$\begin{aligned} C(u_1, u_2; \theta) &= \Phi_G\left(\Phi^{-1}(u_1), \Phi^{-1}(u_2); \theta\right) \\ &= \int_{-\infty}^{\Phi^{-1}(u_1)} \int_{-\infty}^{\Phi^{-1}(u_2)} \frac{1}{2\pi\sqrt{(1-\theta^2)}} \exp\left[-\frac{\left(s^2 - 2\theta st + t^2\right)}{2(1-\theta^2)}\right] dsdt, \end{aligned}$$

where Φ is the CDF of the standard normal marginal distribution and $\Phi_G(u_1, u_2)$ is the standard bivariate normal distribution with dependence parameter θ.

On the other side the kernel representation of the relationship of the number of opportunities and the operational revenues, Figure 4.7, presents a strong positive correlation only at higher values, suggesting therefore a Gumbel copula to be more appropriate,

$$C(u_1, u_2; \theta) = \exp\left[-\left(\widetilde{u}_1^{\theta} + \widetilde{u}_2^{\theta}\right)^{1/\theta}\right],$$

where $\widetilde{u}_j = -\log(u_j)$, $j = 1, 2$ with $\theta \in [1, \infty)$.[30]

[30] A value of $\theta = 1$ indicates independence between F_1 and F_2.

4.8 Tables

Table 4.1: Dynamic Random-Effect Probit Model without Squared Terms, Sample Period: 1990 - 2004

Variable	Pooled Probit	Heckman	Wooldridge	Bayesian
Lagged Expansion ($y_{i,t-1}$)	0.414*** (0.075)	0.361*** (0.084)	0.372*** (0.084)	0.307*** (0.080)
Lagged Number of Subsidiaries ($S^N_{i,t-1}$)	-0.137*** (0.018)	-0.135*** (0.018)	-0.136*** (0.018)	-0.133*** (0.018)
Time Mean Number of Subsidiaries ($\overline{S^N_i}$)	0.180*** (0.017)	0.178*** (0.018)	0.177*** (0.018)	0.177*** (0.018)
Initial Expansion ($y_{i,90}$)	-	-	-0.050 (0.087)	-0.053 (0.099)
Initial Number of Subsidiaries ($S^N_{i,90}$)	0.028 (0.018)	0.035* (0.021)	-	-
TOP	0.446* (0.247)	0.420 (0.260)	0.088 (0.081)	0.091 (0.092)
EU	0.284 (0.288)	0.287 (0.301)	-0.057 (0.085)	-0.056 (0.095)
US	0.394 (0.322)	0.377 (0.337)	0.038 (0.098)	0.041 (0.111)
Constant	-1.752*** (0.116)	-1.767*** (0.118)	-1.742*** (0.136)	-1.780*** (0.138)
Time Dummies	yes	yes	yes	yes
ι	-	0.026 (0.022)	0.021 (0.022)	-
η_2	-	2.009 (2.558)	-	-
Average Partial Effect of Lagged Expansion (%)	14.3	12.7	12.9	10.8
Log-likelihood	-1229.5	-1336.1	-1226.6	-1205

Note: * significant at 10 per cent level, ** significant at 5 per cent level, *** significant at 1 per cent level; standard error in parentheses. ι is the coefficient of inter-temporal correlation between u_{it}. η_2 measures correlation between the initial condition and the unit-specific effect α_i.

Table 4.2: Dynamic Random-Effect Probit Model with Squared Terms, Sample Period: 1990 - 2004

Variable	Pooled Probit	Heckman	Wooldridge	Bayesian
Lagged Expansion ($y_{i,t-1}$)	0.552*** (0.078)	0.550*** (0.079)	0.547*** (0.079)	0.484*** (0.082)
Lagged Number of Subsidiaries ($S^N_{i,t-1}$)	-0.568*** (0.043)	-0.568*** (0.043)	-0.567*** (0.043)	-0.568*** (0.042)
Lagged Squared Number of Subsidiaries ($S^{N2}_{i,t-1}$)	0.008*** (0.001)	0.008*** (0.001)	0.008*** (0.001)	0.008*** (0.001)
Time Mean Number of Subsidiaries ($\overline{S^N_i}$)	0.630*** (0.043)	0.629*** (0.043)	0.635*** (0.044)	0.640*** (0.044)
Time Mean Squared Number of Subsidiaries ($\overline{S^{N2}_i}$)	-0.008*** (0.001)	-0.008*** (0.001)	-0.008*** (0.001)	-0.009*** (0.001)
Initial Expansion ($y_{i,90}$)	-	-	-0.121 (0.087)	-0.123 (0.100)
Initial Number of Subsidiaries ($S^N_{i,90}$)	0.157*** (0.054)	0.414 (2.091)	-	-
Initial Squared Number of Subsidiaries ($S^{N2}_{i,90}$)	-0.007** (0.003)	-0.017 (0.087)	-	-
TOP	0.380 (0.249)	0.973 (4.966)	0.048 (0.080)	0.050 (0.091)
EU	0.169 (0.298)	0.440 (2.338)	-0.086 (0.084)	-0.093 (0.095)
US	0.368 (0.329)	0.943 (4.775)	0.005 (0.096)	0.001 (0.109)
Constant	-2.345*** (0.140)	-2.345*** (0.140)	-2.308*** (0.154)	-2.355*** (0.159)
Time Dummies	yes	yes	yes	yes
ι	-	0.000 (0.001)	0.000 (0.000)	-
η_2	-	183.959 (1332.585)	-	-
Average Partial Effect of Lagged Expansion (%)	16.2	16.2	15.9	14.6
Log-likelihood	-1157.2	-1261.3	-1154.5	-1148

Note: * significant at 10 per cent level, ** significant at 5 per cent level, *** significant at 1 per cent level; standard error in parentheses. ι is the coefficient of inter-temporal correlation between u_{it}. η_2 measures correlation between the initial condition and the unit-specific effect α_i.

Table 4.3: Dynamic Random-Effect Probit Model without Squared Terms, Sample Period: 1995 - 2004

Variable	Pooled Probit	Heckman	Wooldridge	Bayesian
Lagged Expansion ($y_{i,t-1}$)	0.453*** (0.089)	0.192* (0.112)	0.194* (0.111)	0.150 (0.109)
Lagged Size ($S^s_{i,t-1}$)	-0.106 (0.131)	-0.095 (0.138)	-0.099 (0.141)	-0.109 (0.143)
Time Mean Size ($\overline{S^s_i}$)	0.275** (0.134)	0.297** (0.144)	0.241 (0.147)	0.257* (0.152)
Initial Expansion ($y_{i,95}$)	-	-	0.397*** (0.123)	0.415*** (0.131)
Initial Size ($S^s_{i,95}$)	-0.005 (0.088)	0.006 (0.090)	-	-
TOP	0.803*** (0.232)	0.776*** (0.235)	0.168 (0.114)	0.171 (0.124)
EU	0.730** (0.302)	0.741** (0.304)	-0.172 (0.123)	-0.176 (0.132)
US	0.404 (0.343)	0.401 (0.344)	0.012 (0.143)	0.012 (0.153)
Constant	-1.144*** (0.098)	-1.185*** (0.107)	-1.175*** (0.149)	-1.194*** (0.158)
Time Dummies	yes	yes	yes	yes
ι	-	0.158*** (0.045)	0.121*** (0.043)	-
η_2	-	0.284 (0.386)	-	-
Average Partial Effect of Lagged Expansion (%)	17.3	8.2	7.2	5.9
Log-likelihood	-788.9	-892.8	-769.8	-725.5

Note: * significant at 10 per cent level, ** significant at 5 per cent level, *** significant at 1 per cent level; standard error in parentheses. ι is the coefficient of inter-temporal correlation between u_{it}. η_2 measures correlation between the initial condition and the unit-specific effect α_i.

Table 4.4: Dynamic Random-Effect Probit Model with Squared Terms, Sample Period: 1995 - 2004

Variable	Pooled Probit	Heckman	Wooldridge	Bayesian
Lagged Expansion ($y_{i,t-1}$)	0.413*** (0.090)	0.186* (0.112)	0.187* (0.111)	0.137 (0.108)
Lagged Size ($S^s_{i,t-1}$)	-0.040 (0.259)	0.013 (0.266)	0.009 (0.270)	0.060 (0.257)
Lagged Squared Size ($S^{s2}_{i,t-1}$)	-0.006 (0.025)	-0.011 (0.026)	-0.011 (0.026)	-0.018 (0.025)
Time Mean Size ($\overline{S^s_i}$)	0.435* (0.264)	0.450 (0.277)	0.323 (0.284)	0.288 (0.273)
Time Mean Squared Size ($\overline{S^{s2}_i}$)	-0.029 (0.027)	-0.030 (0.028)	-0.016 (0.028)	-0.012 (0.027)
Initial Expansion ($y_{i,95}$)	-	-	0.355*** (0.123)	0.374*** (0.133)
Initial Size ($S^s_{i,95}$)	0.354 (0.331)	0.336 (0.335)	-	-
Initial Squared Size ($S^{s2}_{i,95}$)	-0.068 (0.093)	-0.059 (0.096)	-	-
TOP	0.679 (0.247)	0.673*** (0.248)	0.104 (0.117)	0.107 (0.125)
EU	0.666** (0.303)	0.676** (0.305)	-0.190 (0.122)	-0.197 (0.127)
US	0.321 (0.348)	0.324 (0.348)	-0.026 (0.143)	-0.032 (0.151)
Constant	-1.111*** (0.099)	-1.140*** (0.107)	-1.104*** (0.152)	-1.119*** (0.154)
Time Dummies	yes	yes	yes	yes
ι	-	0.140*** (0.044)	0.115* (0.043)	-
η_2	-	0.176 (0.444)	-	-
Average Partial Effect of Lagged Expansion (%)	15.9	7.2	6.9	5.4
Log-likelihood	-781.6	-886.1	-767.4	-725.4

Note: * significant at 10 per cent level, ** significant at 5 per cent level, *** significant at 1 per cent level; standard error in parentheses. ι is the coefficient of inter-temporal correlation between u_{it}. η_2 measures correlation between the initial condition and the unit-specific effect α_i.

Table 4.5: Coefficient of Determination of Growth Predictions - Size Proxied by Number of Subsidiaries

Year	No squared terms				Squared terms			
	Pooled	Heckman	Wooldridge	Bayesian	Pooled	Heckman	Wooldridge	Bayesian
1992	0.97	0.97	0.97	0.97	0.97	0.96	0.97	0.97
1993	0.97	0.97	0.97	0.97	0.97	0.96	0.97	0.97
1994	0.95	0.95	0.96	0.96	0.95	0.94	0.96	0.96
1995	0.95	0.95	0.95	0.95	0.95	0.93	0.95	0.95
1996	0.92	0.93	0.92	0.92	0.92	0.90	0.92	0.92
1997	0.90	0.90	0.91	0.90	0.90	0.89	0.91	0.92
1998	0.85	0.84	0.90	0.90	0.82	0.82	0.90	0.92
1999	0.90	0.90	0.87	0.87	0.87	0.79	0.88	0.88
2000	0.87	0.87	0.86	0.87	0.87	0.85	0.87	0.87
2001	0.83	0.83	0.84	0.84	0.84	0.81	0.78	0.84
2002	0.83	0.83	0.82	0.83	0.85	0.80	0.78	0.81
2003	0.85	0.84	0.84	0.85	0.85	0.73	0.80	0.83
2004	0.84	0.84	0.83	0.82	0.86	0.79	0.80	0.83

Table 4.6: Coefficient of Determination of Growth Predictions - Size Proxied by Standardised Operational Revenues

Year	No squared terms				Squared terms			
	Pooled	Heckman	Wooldridge	Bayesian	Pooled	Heckman	Wooldridge	Bayesian
1997	0.18	0.18	0.17	0.17	0.17	0.17	0.16	0.16
1998	0.22	0.22	0.23	0.23	0.21	0.22	0.23	0.23
1999	0.29	0.29	0.26	0.26	0.28	0.27	0.27	0.26
2000	0.35	0.29	0.30	0.30	0.33	0.27	0.30	0.30
2001	0.40	0.41	0.41	0.41	0.42	0.48	0.42	0.42
2002	0.43	0.44	0.40	0.40	0.42	0.42	0.40	0.40
2003	0.51	0.45	0.38	0.38	0.46	0.45	0.40	0.40

Table 4.7: Estimated Correlation Coefficient, $\widehat{\rho}$

Year	$\widehat{\rho}$ Number of Subsidiaries	$\widehat{\rho}$ Operational Revenues
1992	0.97	na
1993	0.97	na
1994	0.97	na
1995	0.98	na
1996	0.97	na
1997	0.97	5.75 (5.26, 6.25)
1998	0.97	5.65 (5.17, 6.13)
1999	0.97	5.89 (5.40, 6.38)
2000	0.97	5.91 (5.43, 6.40)
2001	0.97	5.97 (5.50, 6.44)
2002	0.95	5.54 (5.13, 5.94)
2003	0.95	5.52 (5.13, 5.91)
2004	0.95	na

$\widehat{\rho}$ for i) Gaussian copula's if size is proxied by number of subsidiaries and ii) Gumbel copula's if size is proxied by standardised operational revenues. Confidence interval is in bracket.

Table 4A.1: Statistics of Subsidiaries and Expansion by MNEs

Year	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004
New subsidiaries established or acquired by each MNE*	4 (0.23) [0.61] {61}	8 (0.23) [0.73] {60}	3 (0.16) [0.45] {42}	1 (0.11) [0.31] {29}	3 (0.23) [0.53] {61}	4 (0.19) [0.54] {51}	5 (0.27) [0.71] {71}	4 (0.22) [0.62] {59}	6 (0.24) [0.67] {63}	4 (0.20) [0.52] {53}	17 (0.34) [1.42] {90}	7 (0.25) [0.72] {65}	4 (0.15) [0.50] {40}	15 (0.17) [0.99] {44}	15 (0.14) [1.01] {38}
Changes in operational revenues (million USD)+	na	na	na	na	na	na	3,805 (91.4) [381] {18,456}	19,353 (166.6) [1,375] {35,151}	3,602 (80.4) [322] {17,440}	5,420 (6.2) [584] {1,404}	3,970 (44.4) [300] {10,652}	10,567 (110.3) [788] {27,358}	7,173 (211.4) [757] {53,895}	15,192 (293.3) [1,205] {74,510}	na
≥1 new subsidiaries expansion %	16.2	15.5	12.9	10.9	18.5	14.3	16.9	15.1	16.2	15.9	17.8	15.9	10.9	9.5	6.4
1 new subsidiary expansion %	11.7	12.1	10.2	10.9	14.3	10.9	10.9	10.2	11.7	12.8	13.2	10.6	8.3	7.2	4.5
2 new subsidiary expansion %	3	2.3	2.3	0	3.8	2.3	3.4	3.4	3	2.3	2.3	3.8	1.5	1.9	1.1
>2 new subsidiary expansion %	1.5	1.1	0.4	0	0.4	1.1	2.6	1.5	1.5	0.8	2.3	1.5	1.1	0.4	0.8
Expansion	61	60	42	29	61	51	71	59	63	53	90	65	40	44	38

Note: * The first value is the maximum number of new subsidiaries established or acquired by any MNE, the mean of this item is in (), then standard deviation in [] and sum of all new subsidiaries in {}.

+ Size is measured by operational revenue. The first value is the maximum change in size of any MNE, the mean of this item is in (), then standard deviation in [] and sum of all changes in size {}.

We only report these statistics from 1995 as too many missing data for the previous years. The number of MNEs with missing size data is reported in Table 3.1

Geographic coverage: Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, the Netherlands, Portugal, Spain, Sweden, and the UK (excluding Luxembourg).

Table 4A.2: Relationship of Size-Variance: Size is Predicted Operational Revenues

	$\widehat{S}_{it}$ from model without squared term			$\widehat{s}_{it}$ from model with squared term		
Relationship	β	Std. error	Obs.	β	Std. error	Obs.
Mean of g_{it}–$\widehat{S}_{it}$	-0.136***	0.021	44	-0.058***	0.014	43
s.d. of g_{it}–$\widehat{S}_{it}$	-0.143***	0.038	44	-0.01	0.014	43
Skewness of g_{it}–$\widehat{S}_{it}$	-0.064	0.072	44	-0.18	0.115	43
Kurtosis of g_{it}–$\widehat{S}_{it}$	-0.11	0.28	44	-0.469	0.442	43

Note: * significant at 10 per cent level, ** significant at 5 per cent level, *** significant at 1 per cent level. 36 MNEs in one Bin. Data are pooled for year 1997 to 2002.

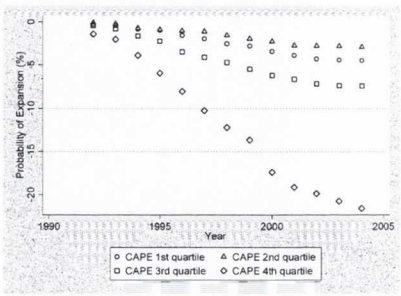
Table 4A.3: Relationship of Size-Variance: Size is Predicted Number of Subsidiaries

	$\widehat{N}_{it}$ from model without squared term			$\widehat{N}_{it}$ from model with squared term		
Relationship	β	Std. error	Obs.	β	Std. error	Obs.
Mean of g_{it}–$\widehat{N}_{it}$	-0.003***	0.001	89	-0.002***	0.0003	89
s.d. of g_{it}–$\widehat{N}_{it}$	-0.001	0.001	89	0.001	0.001	89
Skewness of g_{it}–$\widehat{N}_{it}$	-0.068***	0.01	89	-0.113***	0.016	88
Kurtosis of g_{it}–$\widehat{N}_{it}$	-0.051*	0.029	89	-0.159**	0.078	88

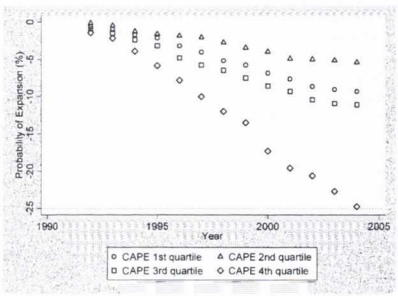
Note: * significant at 10 per cent level, ** significant at 5 per cent level, *** significant at 1 per cent level. 36 MNEs in one Bin. Data are pooled for year 1992 to 2003. Predicted N_{it} is logrised to get $\widehat{N}_{it}$ but not demeaned.

4.9 Figures

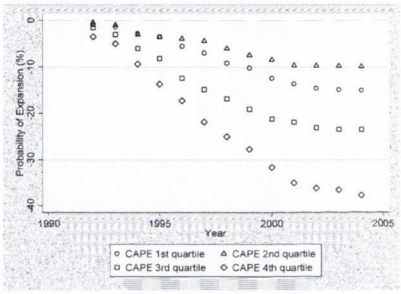
Figure 4.1: Cumulative Average Partial Effects of Number of Subsidiaries (S^N) and Standardised Operational Revenues (S^S).



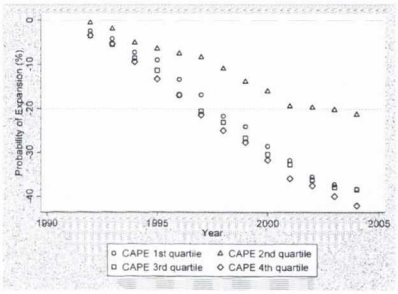
(a) Wooldridge no squared terms (S^N)



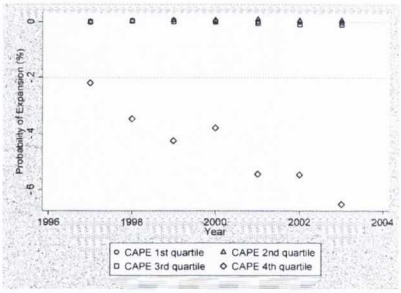
(b) Heckman no squared terms (S^N)



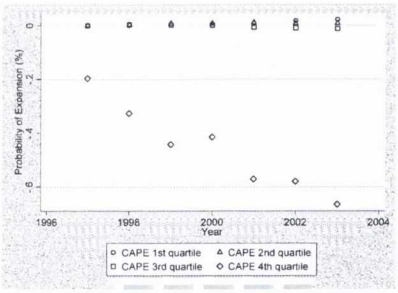
(c) Wooldridge with squared terms (S^N)



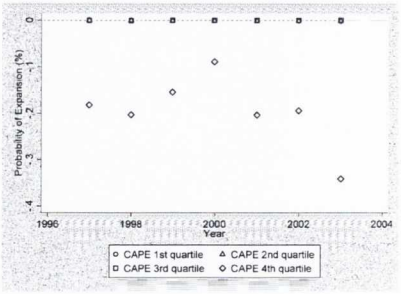
(d) Heckman with squared terms (S^N)



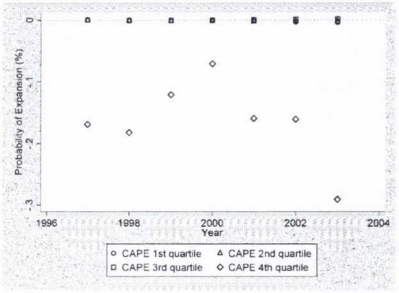
(e) Wooldridge no squared terms (S^S)



(f) Heckman no squared terms (S^S)

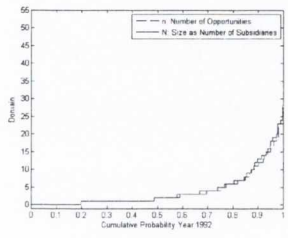


(g) Wooldridge with squared terms (S^S)

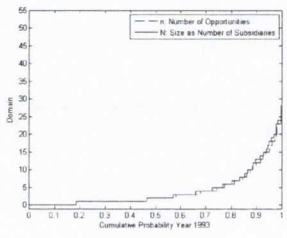


(h) Heckman with squared terms (S^S)

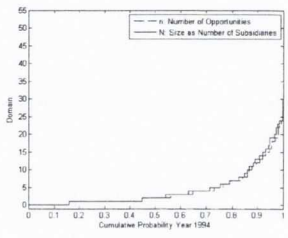
Figure 4.2: Cumulative Density Functions of Number of Opportunities(S^n) and Number of Subsidiaries(S^N).



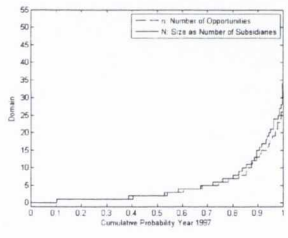
(a) Year1992



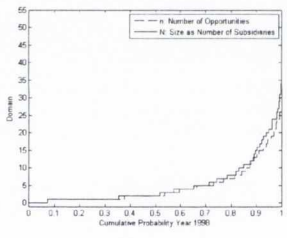
(b) Year1993



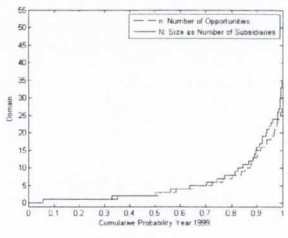
(c) Year1994



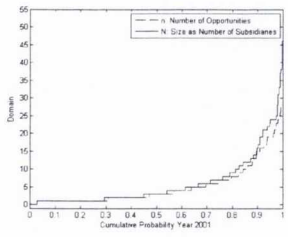
(d) Year1997



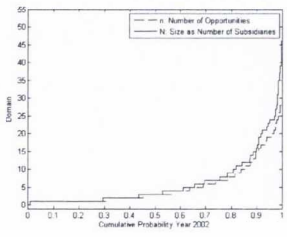
(e) Year1998



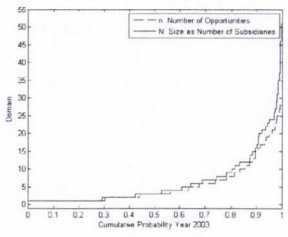
(f) Year1999



(g) Year2001

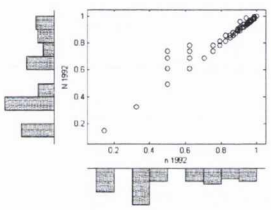


(h) Year2002

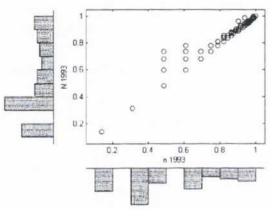


(i) Year2003

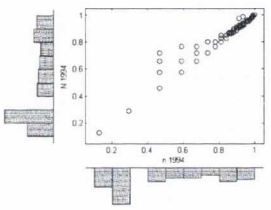
Figure 4.3: Kernel Density Number of Opportunities Plotted versus Kernel Density Number of Subsidiaries.



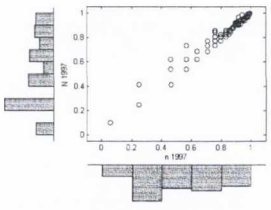
(a) Year1992



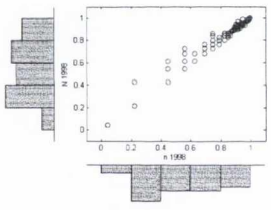
(b) Year1993



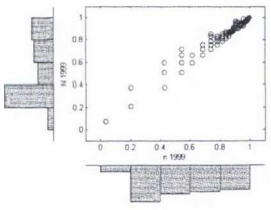
(c) Year1994



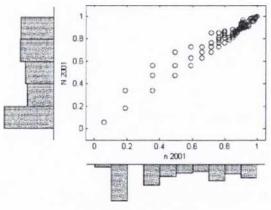
(d) Year1997



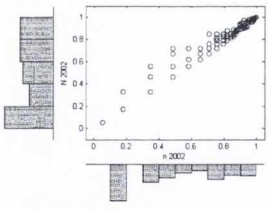
(e) Year1998



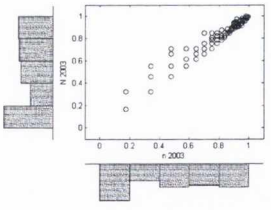
(f) Year1999



(g) Year2001

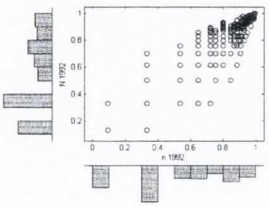


(h) Year2002

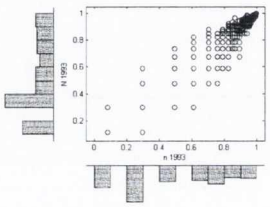


(i) Year2003

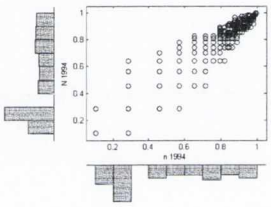
Figure 4.4: Kernel Density Simulated Number of Opportunities versus Kernel Density Simulated Number of Subsidiaries.



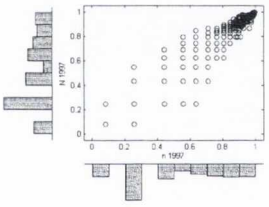
(a) Year1992



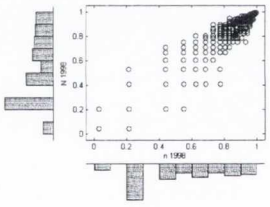
(b) Year1993



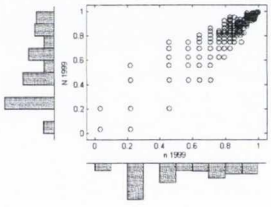
(c) Year1994



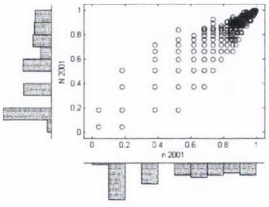
(d) Year1997



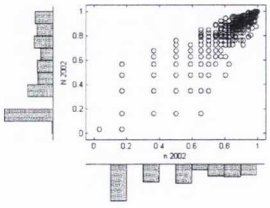
(e) Year1998



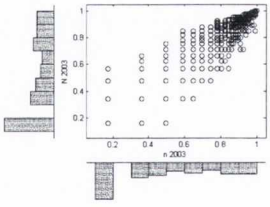
(f) Year1999



(g) Year2001

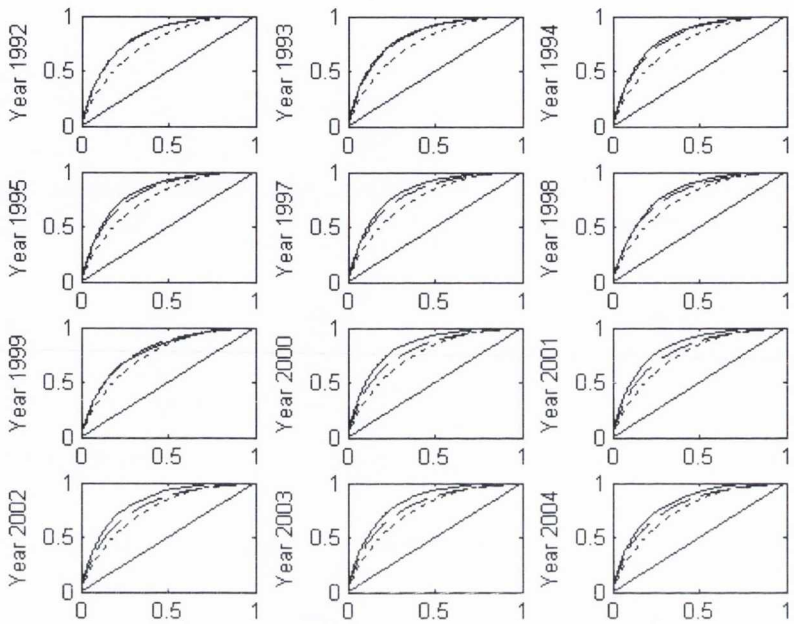


(h) Year2002

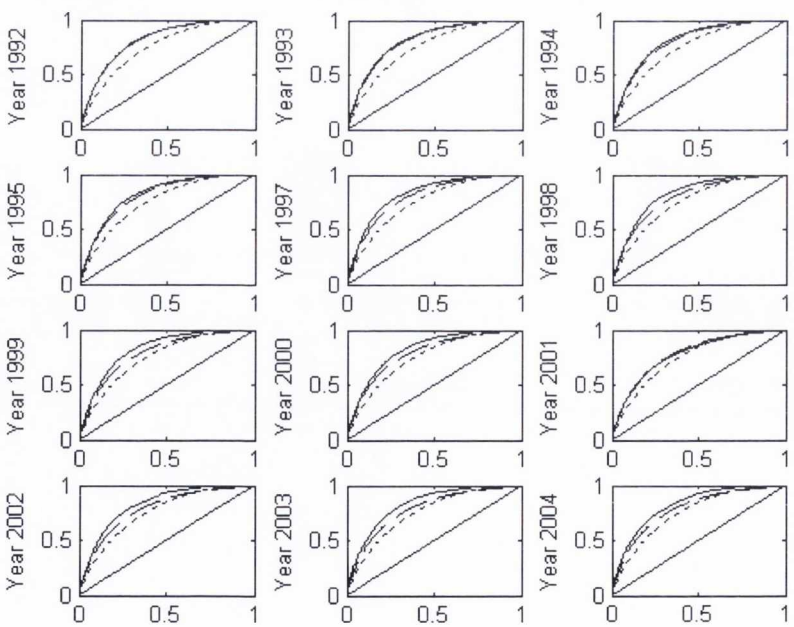


(i) Year2003

Figure 4.5: Lorenz Concentration Curves(Number of Subsidiaries).*



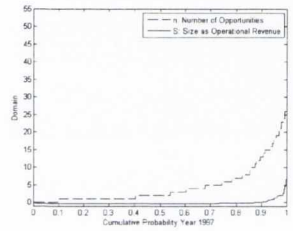
(a) Number of subsidiaries without squared term



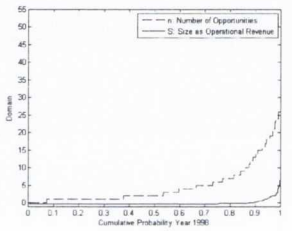
(b) Number of subsidiaries inclusive of squared term

*The diagonal line is the symmetric case; the dotted line is Sutton's lower bound; the solid line is the predicted number of subsidiaries; the dashed line is the actual number of subsidia

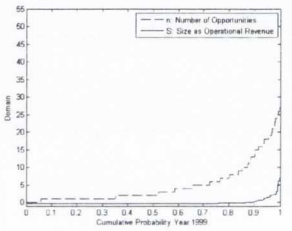
Figure 4.6: Cumulative Density Functions of Number of Opportunities(S^n) and Standardised Operational Revenues(S^S).



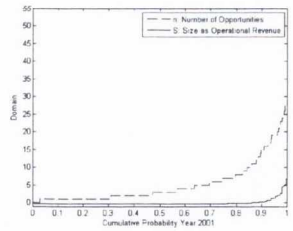
(a) Year1997



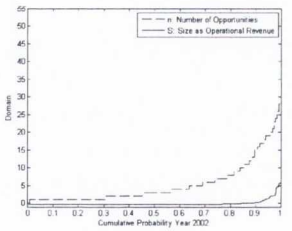
(b) Year1998



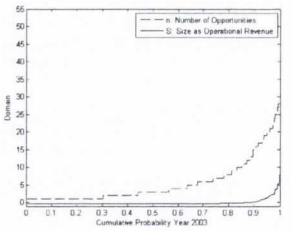
(c) Year1999



(d) Year2001

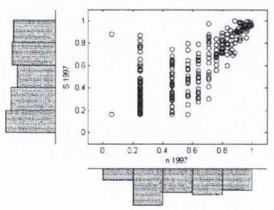


(e) Year2002

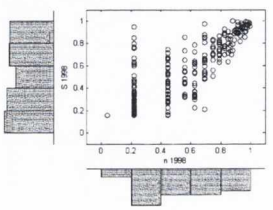


(f) Year2003

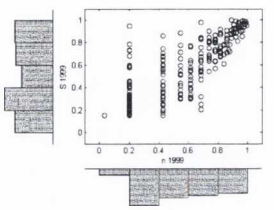
Figure 4.7: Kernel Density Number of Opportunities Plotted versus Kernel Density Standardised Operational Revenues.



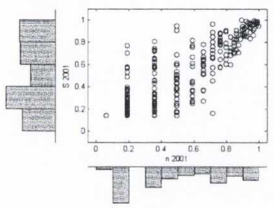
(a) Year1997



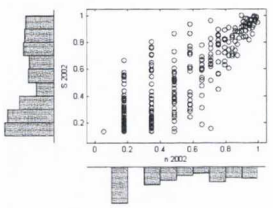
(b) Year1998



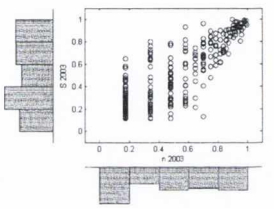
(c) Year1999



(d) Year2001

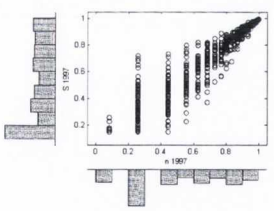


(e) Year2002

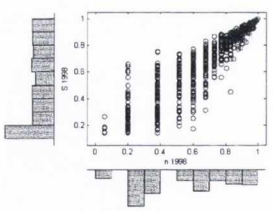


(f) Year2003

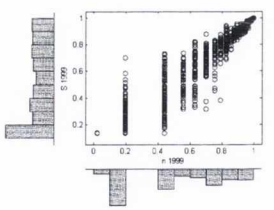
Figure 4.8: Kernel Density Simulated Number of Opportunities versus Kernel Density Simulated Standardised Operational Revenues.



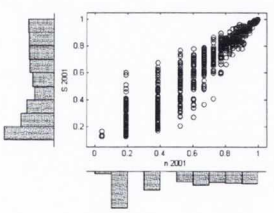
(a) Year1997



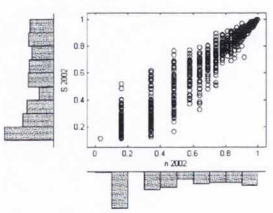
(b) Year1998



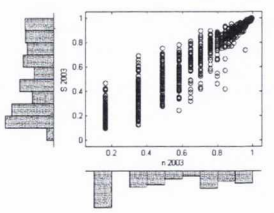
(c) Year1999



(d) Year2001

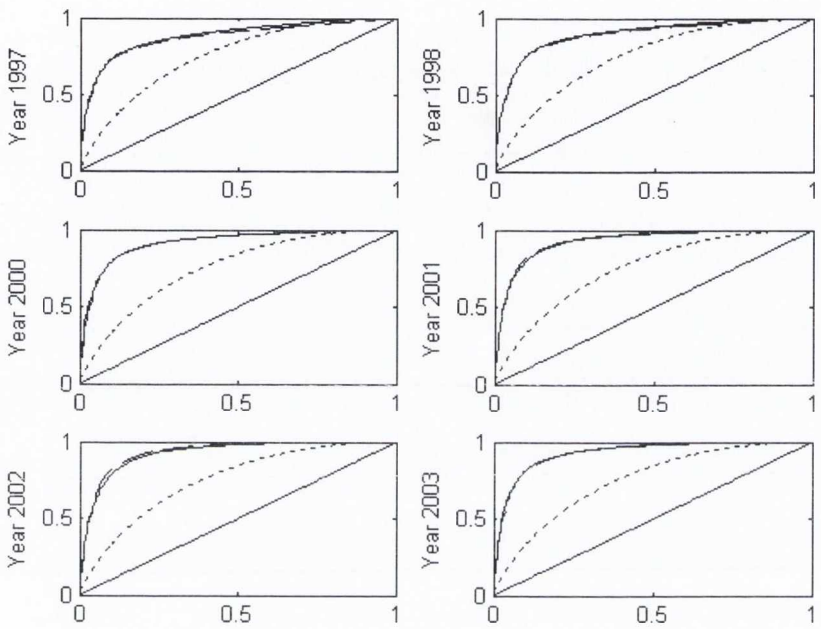


(e) Year2002

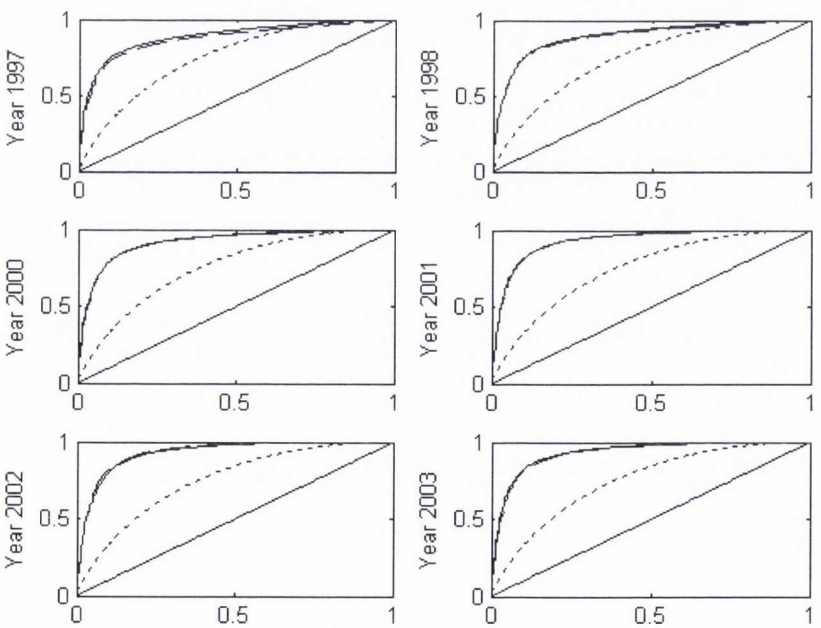


(f) Year2003

Figure 4.9: Lorenz Concentration Curves(Operational Revenues).*



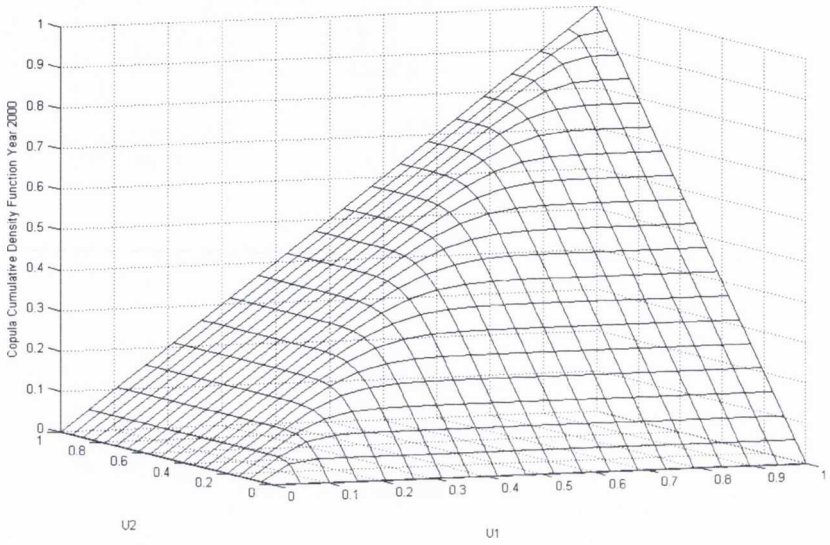
(a) Standardised operational revenues without square term



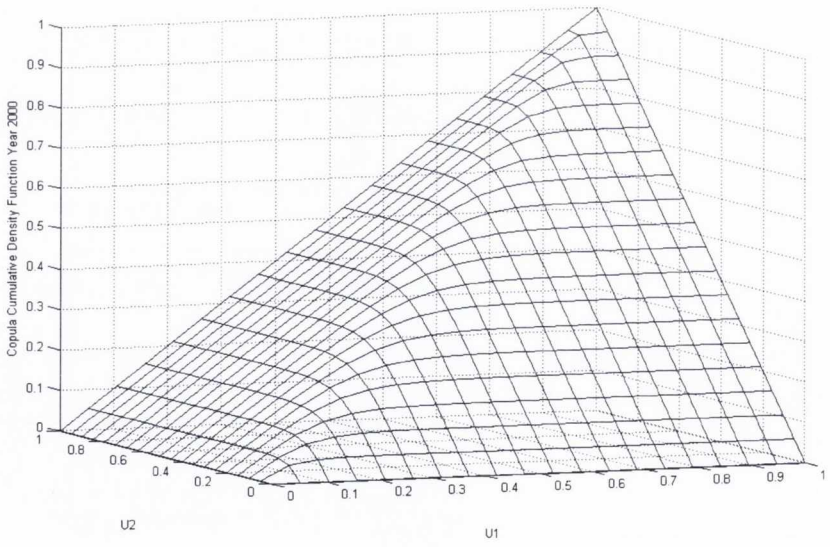
(b) Standardised operational revenues inclusive of square term

*The diagonal line is the symmetric case; the dotted line is Sutton's lower bound; the solid line is the predicted number of subsidiaries; the dashed line is the actual number of subsidiaries.

Figure 4.10: Copulas Cumulative Density Function (Year 2000).

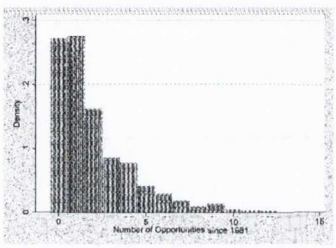


(a) Gaussian copulas for size proxied by number of subsidiaries

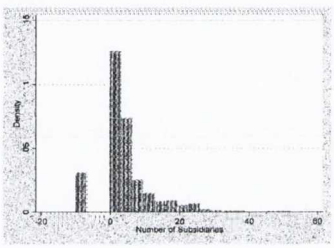


(b) Gumbel copulas for size proxied by standardized operational revenues

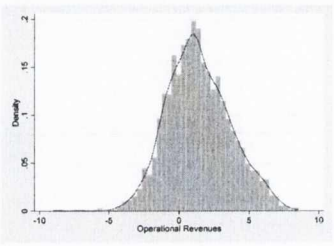
Figure 4A.1: Histogram and EDF of Number of Opportunities(S^n), Number of Subsidiaries(S^N) and Standardised Operational Revenues (S^S).



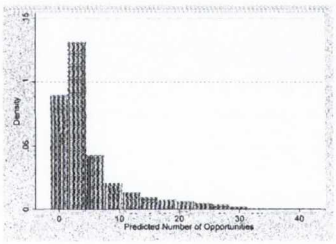
(a) (S^n)



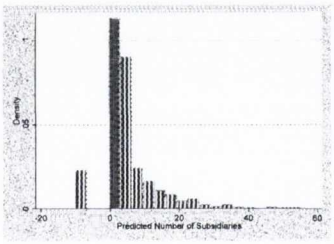
(b) (S^N)



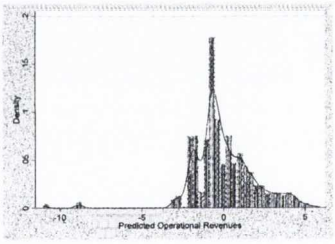
(c) (S^S)



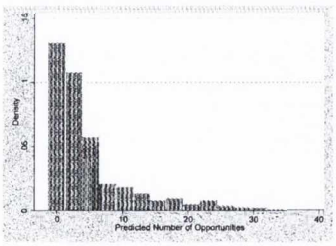
(d) ($\widehat{S}^n$ without squared terms)



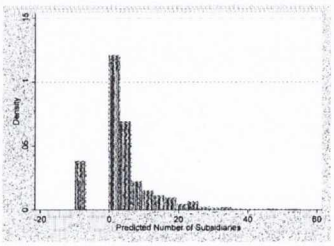
(e) ($\widehat{S}^N$ without squared terms)



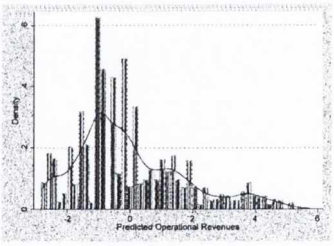
(f) ($\widehat{S}^S$ without squared terms)



(g) ($\widehat{S}^n$ with squared terms)



(h) ($\widehat{S}^N$ with squared terms)



(i) ($\widehat{S}^S$ with squared terms)

Gaussian Kernel density. Bin number = 50 for S^S and $\widehat{S}^S$. Bin number = 20 for S^n, $\widehat{S}^n$, and S^N, $\widehat{S}^N$.

Part II

Examining the Location Pattern of Pharmaceutical Production

Chapter 5

A Decomposition of the Agglomeration of Pharmaceutical Production in the EU-15 Countries

5.1 Introduction

The activities of MNEs have been widely studied by economists over the past several decades, with the commencement of this literature dating back to Caves (1971, 1982) and Dunning (1971). One much-researched issue, amongst others, is the geographic distribution of production of MNEs. This issue is explored in the more general context of seeking to explain why and how the distribution of industry production within a country or an area (for instance, the EU) is not uniform, where the production of MNEs constitutes a major component of industry production, as, say, in the EU. This chapter explores these two questions by studying a specific sector - the pharmaceutical industry in the context of European integration in the 1990's. The focus is placed on both MNEs and non-MNEs, expecting to reveal heterogeneous contributions of their activities, given the fact that the MNEs are considered to be more footloose than non-MNEs.

In the first part of this chapter, we mainly review the literature of New Economic Geography (NEG), for which the central theme is the geographic distribution of economic activities. The review will shed light on the first question, namely, the non-uniform geographic distribution of industry production. The underlying context of the European economic geography is the integration process that started in the late 1950's. The ongoing process reached its new level after 1992, when the Single Market Programme (SMP) was implemented. This event resulted in the gradual abolition of non-tariff barriers (NTBs) for trade between the member states of the EU and consequently led to a significant fall in EU trade costs. This provides a natural context for using the NEG theory as it focuses on the close connection between industrial location across countries and inter-country trade-cost levels. For instance, some NEG models predict that as trade costs fall, increasing returns to scale (IRS) industries will agglomerate initially but then disperse across countries. Other models argue that the agglomeration continues, with the periphery losing to the core. Empirical research also provides some evidence regarding the location pattern of European industries over this period, so this literature is also reviewed.

In the second part of the chapter, we address the second question through a decomposition analysis. We present a time series of the geographic distribution of production, which takes place in the pharmaceutical MNEs and non-MNEs in the EU. The time series is in the form of four indices measuring the geographic agglomeration across the EU-15 countries. We find a generally dispersing agglomeration trend over the post-SMP era. The trend of one agglomeration index (the Hirschman-Herfindahl Index) is evaluated using a decomposition technique. Be more specific, the trend, beginning in 1995 and ending in 2003, is decomposed into twelve elements at firm level, which can be mapped on a two-dimension coordinate of industry production - one dimension is the ownership of MNEs and non-MNEs, while the other is firm life-cycle activity, which, namely, includes, birth of new enterprise, birth of new subsidiary, expansion/contraction, sector-switch and closure. Using the firm-level data described in Chapter 2, we find that expansion/contraction, sector-switch and closure of MNEs are three major drivers of the dispersing agglomeration trend while the birth of new subsidiaries of MNEs is the major counterforce of such trend.

The review of the NEG literature and the decomposition analysis not only provide insight into the location side of industrial dynamics in the pharmaceutical industry, but also serve as a backdrop for the modelling of location choices of MNEs in the next chapter.

The chapter is organised as follows. Section 5.2 gives an account of NEG models and discusses their implications for industry location in the context of European integration; the related empirical literature on the distribution of industry is also reviewed. Section 5.3 presents the agglomeration trend and the decomposition analysis. In Section 5.4, the chapter is summarised and conclusions drawn.

5.2 Review of NEG Models and Related Empirical Evidence

The growth of economic regionalism in the past decade has increased interest in what happens to economic activities when countries come together in customs-union type arrangements, for instance, the European Union. A major focus of that interest lies in what it does to the location of production, between the customs union and the rest of

the world and within the customs union itself. It is not surprising then that we saw in the 1990's the growth of the New Economic Geography literature, and a resurgence of interest in studying what determines the location of production (see Fujita *et al.*, 1999). In the European context, these issues were seen as important in trying to ascertain whether production would become more centralised at the European core, at the expense of a declining periphery (see Braunerhjelm *et al.*, 2000). In this review, we look at some important theoretical models and empirical studies in the NEG literature, in terms of their predictions and the empirical evidence for Europe in relation to its patterns of production location.[1]

5.2.1 New Economic Geography (NEG) Models

The major NEG models, such as Krugman (1991), Baldwin (1999), Venerable (1996) and Puga (1999), aim to explain the geographic distribution of economic activities, on the assumption that manufacturing sector exhibits increasing returns to scale (IRS)[2]. Firms in the IRS sector generate pecuniary externalities, causing them to agglomerate together in particular regions. While the assumption of IRS production is common to all models, the models differ in other assumptions they make, for example, regarding the degree of factor mobility (inter-sectoral and inter-regional) and the direction of trade costs. For example, Krugman (1991) considers a two-region framework, where manufacturing sector, which enjoys IRS, and agriculture sector (featuring constant-

[1] Alongside the development of the NEG literature has been the literature that grew naturally out of Caves (1971) and Dunning (1971), who focused on MNEs as business entities, in contrast to previous literatures which modelled foreign direct investment in a more sectoral way. As that literature developed, MNEs were seen as locating to get close to markets (market-driven), in order to strengthen market position and reduce trade costs, or locating so as to reduce production costs (cost-driven), so that they can source more cheaply for the home market. The former is associated with the organisation of the MNEs activities on a horizontal basis, whereas the latter is seen as being more vertical in its focus. This latter links particularly to the agglomeration literature, as the presence of existing industry is seen as a source of potential for spillovers, etc. More recently, the increasing fragmentation of global production and the growth of export platforms (see Ekholm *et al.*, 2007) have indicated that the motives of MNEs are more complex than had previously been assumed. In practice they often involve a hybrid of both horizontal and vertical drivers. These arise because MNEs operate in a range of product areas and operate across multiple rather than just two countries. Recent literature is seeking to address this – see, for example, Baltagi, Egger and Pfaffermayr (2007). This is highly relevant to the pharmaceutical industry where individual plants are likely to be producing both for local markets (possibly both national and EU) as well as for global markets. It also points to the important interactions between trade patterns and MNE locations, echoing Vernon's (1966) product-cycle approach again.

[2] There are other two important assumptions: imperfect competition and transportation costs. Due to the interests in this study, we discuss the trade costs later but not the imperfect competition.

returns-to-scale (CRS) production technology) exist in both regions. He supposes that, when some historical event happens initially that leads one manufacturing worker to move from one region to another region, this movement increases the demand for goods in the receiving (or "core") region. Manufacturing firms reinforce this initial move by following the worker to the core region because of its larger market size (usually termed as "backward linkage" or "demand linkage"). This relocation of the manufacturing sector reduces the price index (due to savings on trade costs[3]) in the core region and raises its real wage rates. Thus more workers are further encouraged to move to the core region (usually termed as "forward linkage" or "supply linkage"). Since this market size-production linkage is a self-reinforcing process, the final equilibrium in the model shows that the manufacturing sector and workers agglomerate in the core region, while leaving the agriculture sector in the other ("periphery") region.

While this type of circular causality is the essence of all NEG models, other models are constructed using different agglomeration mechanisms. Venables (1996) suggests that the producers of final products prefer to cluster close to the producers of intermediate products in order to reduce production costs and, similarly, the producers of intermediate products prefer to locate close to the producers of final products. Therefore, even without perfect inter-region mobility of labour, continuous agglomeration can occur driven by regional clustering of production units, which are linked upstream or downstream.[4] Baldwin (1999) uses a similar framework to that in Krugman's model, but focuses on endogenous capital accumulation - if some exogenous event helps to raise the profits of manufacturing firms in one region but to reduce the profits of the manufacturing firms in the other region, the rate of return in the former region begins to increase and leads to more activities in this region. As a consequence, the manufacturing sector in the first region will expand at expense of the agriculture sector, by absorbing agriculture workers. The reverse happens in the other region -

[3]If manufactured products are available locally instead of having to be imported from the other region, the trade costs of importing can be saved.

[4]Krugman and Venerable (1995) uses a simplified version of the upstream-downstream linkages in a core-periphery framework, assuming the final product in a sole industry in the model can be consumed by workers, or used by other firms in the same industry as intermediate input.

the manufacturing sector shrinks and workers move to the agriculture sector. In this model, inter-regional labour mobility is not needed to generate the core-periphery outcome. Puga (1999) develops a model based on Krugman's core-periphery model, into which he incorporates the upstream-downstream linkages. This model demonstrates the agglomeration processes of the manufacturing sector across two regions under the assumptions that either manufacturing workers are inter-regionally mobile or immobile.

Despite differences in the mechanisms employed in the NEG models, they all imply that industrial agglomeration in one or more regions is closely connected with trade costs between regions (e.g., transportation costs, tariffs, non-tariff barriers and customs efficiency, etc.), and is influenced by balance between agglomeration forces and dispersion forces (i.e., high labour cost, high land rental and severe competition in the intermediate and final products markets.). Generally, these models generate two different patterns of relationship between the industrial agglomeration and the trade costs: a monotonic relationship or a non-monotonic (bell-shaped) relationship, depending on their assumptions of labour mobility. The monotonic outcomes in Krugman (1991) and Baldwin (1999) are linked to the assumption of inter-regional labour mobility, which is illustrated in Figure 5A.1. The x-axis shows the trade-cost level, ranging from $\tau = 2$ (maximum trade costs) to $\tau = 1$ (zero trade costs) and the y-axis shows the shares of the IRS industry in two regions.[5]

At the right end of the figure, when trade costs between the two regions are extremely high, manufacturing firms prefer to stay and serve the region where they were incorporated. Krugman assumes a special case where the IRS industry is evenly distributed across these two regions at high levels of trade costs. As trade costs fall, industrial agglomeration stays unchanged until the trade costs cross the critical values of the τ_s. As one moves through the critical trade-cost values, the industry begins to agglomerate in one region and which region receives the whole industry depends on

[5] τ denotes a Samuelson-type iceberg cost. If one wants to import one unit of a good from region A into region B, then one needs to ship τ ($\geqslant 1$) units of that good , since $\tau - 1$ melts down during the trip, i.e., $\tau - 1$ is the trade cost. Therefore, $\tau = 1$ means no trade costs are incurred.

the exogenous shock or so called "historical event"[6]. At these low trade costs manufacturing firms can locate anywhere and serve other regions without incurring any additional costs. While the excess demand for labour in the receiving region generates a wage gap between two regions, as long as labour mobility can eliminate the inter-regional wage gap, then other firms follow and eventually, complete industrial agglomeration in one region is reached.

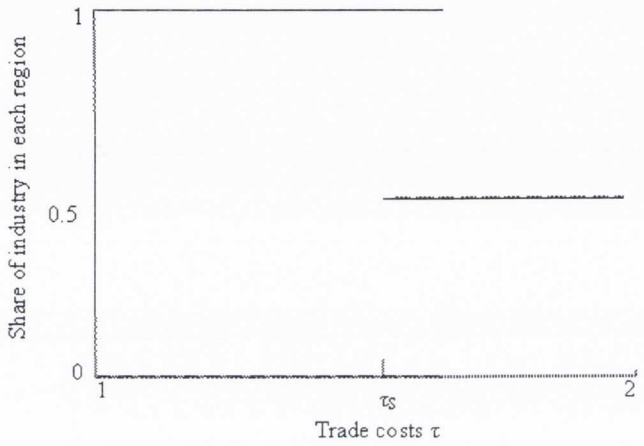


Figure 5A.1: Monotonic Relationship between Agglomeration and Trade Costs in Krugman (1991) and Baldwin (1999)

By contrast, the immobile labour assumption in the Venables (1996) and Puga (1999) models creates a dispersion force to counteract agglomeration benefits, so the industry-agglomeration process goes through five stages under different levels of trade costs and shows a non-monotonic relationship. It is illustrated in Figure 5A.2. In Stage 1, when trade costs are very high, serving the other region is not economically profitable and hence firms in manufacturing industry distribute evenly across two regions. As trade costs fall, the industry begins to agglomerate (Stage 2) in one region and if the costs continue to fall, then complete agglomeration is reached between two critical values of trade costs (Stage 3). As the trade costs fall further, the agglomeration begins to decline (Stage 4). Because, with inter-regional labour immobility, the wage gap between the agglomerated and un-agglomerated regions causes more losses for the firms

[6]For example, suppose the authority in one region introduces a tax incentive for firms that increase their net profits, this will be the region into which the firms move into.

than the agglomeration benefits they receive (from either the large market or the proximity of upstream or downstream industries). Consequently, it drives previously agglomerated industry back to the less agglomerated periphery region. When the trade costs fall by enough (Stage 5), the industry distributes evenly in the two regions again.

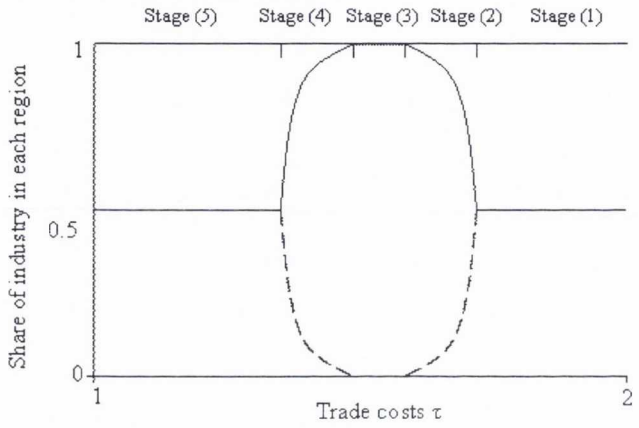


Figure 5A.2: Non-monotonic Relationship between Agglomeration and Trade Costs in Venables (1996) and Puga (1999)

Beyond the scope of the market effect and the industrial linkage, Baldwin and Krugman (2004) introduces the policy element, namely, the corporate tax rate into the core-periphery framework. Their model illuminates how corporate tax competition between the core and periphery regions (or countries) is influenced by the existence of the agglomeration rent. Instead of a "race to bottom" tax competition between two regions, the government of the core region, where the whole IRS industry locates, can charge an equilibrium tax rate higher than that of the periphery region and still keep the industry, as long as the tax burden for individual firms does not overweigh the agglomeration rent they are enjoying in the core region.

A main drawback of the above-mentioned models (except Baldwin, 1999) lies in that they adopt the Cobb-Douglas and the constant-elasticity-of-substitution (CES) utility functions. Such complex mathematical forms prevent the authors from obtaining analytically trackable solutions for the equilibrium states of agglomeration. Another line of NEG models were developed using simple utility forms, such as quasi-

concave (introduced in Flam and Helpman, 1987), quasi-linear or quadratic functions. These models, other than Baldwin (1999), include Robert-Nicoud (2002), Ottaviano (2002)[7] and Forslid and Ottaviano (2003) [8].

Some surveys and applications of the NEG models can be found in Ottvaino and Puga (1998), Neary (2001) and Baldwin *et al.* (2003).

5.2.2 Empirical Literature on Industry Location in Europe

Research, based on sectoral-level data, on industry location in Europe in the period prior to the SMP has found mixed evidence of industrial agglomeration. Using data on 11 European countries and 18 industries (including the chemical industry) between 1980 and 1990, Brülhart and Torstensson (1996) found that the indices of IRS are positively correlated with the locational Gini coefficients, which suggests that industries with higher levels of IRS are more concentrated in the selected European countries. Noting the significant non-tariff barriers between the EU countries, they suggest that IRS industries will become more concentrated after 1990 if non-tariff barriers cease to hinder free trade. Amiti (1998, 1999) found similar results - during the period between 1968 and 1990, industries (including the pharmaceutical industry) characterised by high scale economies and the high proportions of intermediate goods in production showed an increase in geographical concentration across EU-12 countries. In contrast, using the Gini coefficient of concentration, Midelfart-Knarvik *et al.* (2002) found the diverse trends of concentration across industries, with a very slow process of dispersion in geographic distribution for manufacturing sectors overall from the 1970's to the 1990's.[9]

Turning to the more recent period, Aiginger and Davies (2004) and Aiginger and Pfaffermayr (2004) examined the geographic concentration of industries in the EU for the period up to 1998. They found, for the post-SMP era, industrial concentration declined across 14 EU countries. They suggest this evidence is consistent with a non-

[7] Both models feature upstream-downstream linkages, while the former assumes skilled labour is inter-regional mobile and the latter assumes perfect inter-regional mobility of capital.

[8] It is a core-periphery model featuring skilled mobile workers and unskilled immobile workers.

[9] Specifically, in the case of the medium and high IRS industries (including the chemical industry), they find a diminishing trend in the geographic concentration in central European countries.

monotonic relationship, i.e., the left part of the arc in the bell-shaped curve in Figure 5A.2, where decreasing transport costs leads to dispersion. Brülhart and Traeger (2005) finds that European manufacturing sector has become geographically more concentrated, relative to the geographic distribution of aggregate employment in the time frame from 1975 to 2000, while relative to the distribution of physical space, it has become less concentrated. In particular, the relative geographic concentration of chemicals to the aggregate employment does not experience statistically significant changes during the period.[10] Overman *et al.* (2003) and Combes and Overman (2004) provide comprehensive surveys of studies on this topic.

The NEG models can provide insights into the location pattern of European industries and in particular, the pharmaceutical industry. In the European Union, the major elements of trade costs - tariffs and quotas - were removed between the initial six members at the end of the 1960's and then between those members and new members. However, there were no major changes in non-tariff barriers, which continued to grow until the launch of the Single European Market Programme, which announced the abolition of NTBs in the whole EU with effect from 1993. In this context of decreasing trade costs, the NEG models predict that the agglomeration level of IRS industries in the European Union can either be strengthened (Figure 5A.1 and Stage 2 in Figure 5A.2) or be weakened (Stage 4 in Figure 5A.2). Because the pharmaceutical industry features high IRS[11], we argue that these possible outcomes regarding agglomeration apply in this industry. Clearly, the question of whether the agglomeration of the European pharmaceutical industry was strengthened or weakened in the past decade depends on the level of trade costs prior to and after 1993. Unfortunately, because there is no benchmark by which to judge how high the level of trade costs was, one cannot tell the precise stage of agglomeration process in the pharmaceutical industry in Figure 5A.2. Moreover, recent empirical evidence shows a dispersion trend in geographic concen-

[10]The statistical significance of changes in concentration index is evaluated by bootstrap tests. Authors do not provide separate concentration index (relative to physical space) for chemicals.

[11]Brülhart (1998) ranks the pharmaceutical industry as a high economies-of-scale industry following the classification of Pratten (1988). Brülhart and Torstensson (1996) and Midelfart-Knarvik *et al.* (2002) rank the chemical industry as a high IRS industry.

tration of manufacturing sector as a whole in Europe, but no such evidence available at the sub-sector level. In the rest of this chapter, we take a straightforward approach to measure and analyse the actual agglomeration trend in the pharmaceutical industry in the post-SMP era.

5.3 European Pharmaceutical Industry: Agglomeration Trend and Decomposition

5.3.1 Overview

We present four agglomeration indices using aggregate production and employment data (OECD) to show the overall dispersing agglomeration trend over time in the European pharmaceutical industry. Naturally, question arises as what are the MNEs and non-MNEs' contributions to the overall dispersing trend, or be more specific, what are the contributions from various firm life-cycle activities, namely, birth of new enterprise, birth of new subsidiary, expansion/contraction, sector-switch and closure took place in the MNEs and non-MNEs to the trend. To answer these questions, we recalculate one agglomeration index using firm-level data (*Amadeus*, described in Chapter 2) for two years (1995 and 2003) and find the same dispersing trend. Then a decomposition technique is applied to breakdown the change of the index between the two years into components associated with above-mentioned activities for the MNEs and non-MNEs. The decomposition analysis provides us with a forensic picture of how the geographic distribution of industry production, for a specific industry, changed in the EU in the post-SMP era with active contributors to the change being pinpointed.

5.3.2 Agglomeration Trend between 1993 and 2002 - OECD Data

We use four indices to measure the geographic concentration (agglomeration)[12] of production of the pharmaceutical industry in 14 EU countries from 1993 to 2002.[13] The

[12]The terms concentration and agglomeration are used interchangeably in this chapter and both refer to the absolute or relative distribution of industry production in a given geographic area (the EU member states in this chapter, as well as in this thesis).

[13]Due to data availability, we can only calculate cross-country indices for 14 EU countries from 1993 to 2002. These countries are Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal, Spain, Sweden, and the UK.

indices are the Hirschman-Herfindahl Index (HHI)[14], the Theil Index[15], the Location-Gini coefficient of concentration[16] and the Ellison-Glaeser (E-G) Index[17] (Ellison and Glaeser, 1997). The HHI and the Theil index are traditional inequality measures because they have simple mathematical forms and straightforward economic meaning, as well as the nice property of being decomposable. The Location-Gini coefficient is also a commonly used index to measure inequality but it cannot be decomposed.[18] The most sophisticated index, the E-G Index is regarded as superior to the other indices measuring inequality in industrial distribution as it takes into account the part of geographic concentration that is caused by the size distribution at plant, or in our case, firm level.[19]

Pharmaceutical production is measured by gross output and the number of employees, using data from the OECD STructural ANalysis (STAN) database. Four figures of these indices are shown in Figure 5.1 at the end of this chapter. In Figure 5.1(a), the HHIs for pharmaceutical production are plotted along with that of deflated GDP for comparison. Figure 5.1(a) clearly shows a decreasing trend in the agglomeration of pharmaceutical production, especially in terms of gross output. During the same period, the geographic concentration of GDP is virtually unchanged, which suggests that the decreasing trend in the agglomeration of pharmaceutical production is not

[14]The Hirschman-Herfindahl Index is defined as $HHI = \sum_{i=1}^{N} s_i^2$, where s_i is the production share of country i, and N is the number of countries under investigation.

[15]The Theil Index is defined as $\frac{1}{N}\sum_{i=1}^{N} \frac{x_i}{\overline{x}} \ln(\frac{x_i}{\overline{x}})$, where x_i is pharmaceutical production in country i, $\overline{x} = \frac{1}{N}\sum_{i=1}^{N} x_i$, and N is the number of countries. This index is bounded between $\ln N$ (highly concentrated) and 0 (evenly distributed).

[16]The Gini coefficient of concentration is defined as the area between the Lorenz curve and 45 degree line in a space where s_i, the pharmaceutical production share of country i in the data, is cumulated on the y-axis and the number of countries cumulated on the x-axis with the equal interval of width $1/N$. The countries are ranked by s_i. Haaland et al. (1999) and Midelfart-Knarvik et al. (2002) applied this index to European industries.

[17]Ellison and Glaeser define the Index as follows: Let s_i and x_i be the share of employment of industry k and the share of total employment in the ith geographic region of I regions respectively; z_j be the share of employment in the jth plant of J plants for the industry k. G, the raw geographic concentration index of the industry k for I regions, is defined as $\frac{\sum_i (s_i - x_i)^2}{1 - \sum_i x_i^2}$. The HHI of the plant-level concentration is $H = \sum_j z_j^2$. The E-G Index is defined as $\gamma = \frac{G - H}{1 - H}$.

[18]See Bourguignon (1979) for the proof of the non-decomposability of the Gini coefficient.

[19]If an industry consists of a small number of plants and the production is highly concentrated in a few of them, purely random distribution of these plants in a set of geographic regions may lead to highly concentrated geographic pattern.

simply a mirror of the trend of economic agglomeration. In Figure 5.1(b) and Figure 5.1(c) we can see the Theil Indices and the Location-Gini coefficients all reveal the same dispersing trend. In particular, the trend revealed by the Location-Gini coefficients of concentration is in line with that in Midelfart-Knarvik *et al.* (2002), where they use the same concentration measure (the Gini coefficient) and the OECD STAN database to find the trend in dispersion in the European pharmaceutical industry before the 1990's. The E-G indices in Figure 5.1(d) show conflicting agglomeration trends, with the gross output indexes dispersing until the middle of the time period and then becoming more concentrated, while the employment index shows a continuously dispersion trend.[20] One possible explanation is that the change of employment and gross output only track each other in the earlier part of the period, while in the later part the labour productivity grows faster in some countries.

In summary, overall the balance of the evidence is in favour of dispersion rather than concentration, i.e., Venables/Puga rather than Krugman/Baldwin.

5.3.3 Decomposition of the Agglomeration Trend - the *Amadeus* Data

The observed dispersion trend at aggregate level in the European pharmaceutical industry raises questions as to what extent MNEs and non-MNEs have contributed to this change respectively and to what extent it is done by various firm life-cycle activities. To address these two questions, we decompose the change of the HHI between the beginning year and the ending year into twelve components associated with different activities in firm life cycle and with MNEs or non-MNEs by their ownership. We use a decomposition method of the HHI available in Dumais *et al.* (2002).

The OECD STAN data are only available at country-industry level, but not at firm level. Therefore, we use *Amadeus* and extract firm-level data that contain information rich enough for us to conduct a decomposition analysis. The details of how we collect and prepare the data is described in Chapter 2. First, we recalculate the HHI for the industry in 1995 and 2003 respectively using the above-mentioned firm-level data (aggregated at country level), and the geographic scope is again 14 EU-15 member states.

[20] The index approaching (deviating from) 0 means more (less) dispersion.

The years 1995 and 2003 are the earliest and the latest for which we can obtain reliable employment and output data from *Amadeus*, which will be used to proxy production level. The new HHIs show that the level of agglomeration is lower in 2003 than in 1995. In terms of the employment level, it was 0.1634 in 1995 and dropped to 0.1537 in 2003, while in terms of output, which is proxied by operational revenues[21], was 0.1639 in 1995 and 0.1559 in 2003. These finding are in line with the HHIs and the location trend based on the aggregate data shown in the previous section.

Turning to the decomposition, as described in Chapter 2, we have a collection of tracked pharmaceutical firms (the production subsidiaries of MNEs, non-MNEs multi-firm enterprises, and non-MNE single-firm enterprises) whose employment or output data are available for 1995 and 2003. These firms are classified into five categories, each of them corresponds to one of the activities in firm life cycle as mentioned before. The same classification is used in Dumais *et al.* (2002). We further classify the parent companies of the subsidiaries as being either an MNE or a non-MNE. This is an important dichotomy because the data show that while MNEs are dominant in this industry, non-MNEs are still an important part in terms of firm number (see Table 2.4 in Chapter 2). With the help of detailed information, we are able to breakdown the dispersion trend along two dimensions - activities and ownership.

Dumais *et al.* (2002) Decomposition Method

Dumais *et al.* (2002) proposes a method to decompose a HHI of production concentration across plants into components associated with different activities in firm life cycle. This method can be readily applied to the HHI of the production concentration across countries.

Suppose we use employment level to proxy production level. Let e_{it} be the employment level of country $i (i = 1, 2, \ldots, N)$ in one industry (e.g. the pharmaceutical industry) at time t and N is the number of countries. The share of i^{th} country's em-

[21] Ideally we need the output of pharmaceutical products of each firm. But this financial item is not available in *Amadeus*. We turn to sales, but unfortunately the data availability of sales value is generally very poor. Therefore, we have to rely on operational revenues (turnover), which is good in terms of completeness, to proxy output.

ployment in total employment in this industry is $s_{it} = e_{it}/E_t$ and $E_t = \sum_i^N e_{it}$. HHI is then $\sum_i^N s_{it}^2$, $i = 1, 2, ..., N$. Define the changes of one country's share over time as $\triangle s_{it} = s_{i,t+1} - s_{it}$ and $\tilde{s}_{it} = s_{it} - \frac{1}{N}$ as the excess share a country has against the share if the industry were distributed evenly across all countries.

Consider a regression of the change of one country's employment share in time t and $t+1$ is a function of the excess employment share

$$s_{i,t+1} - s_{it} = \triangle s_{it} = \alpha + \beta \tilde{s}_{it} + \varepsilon_{it} \tag{5.1}$$

where ε_{it} is an identical independent distributed (IID) error term, so $\sum_i^N \varepsilon_{it} \tilde{s}_{it} = 0$. In addition, $\alpha = 0$ because the left hand side (LHS) variable is in the form of first difference.

Note that $\sum_i^N \tilde{s}_{it}^2 = \sum_i^N (s_{it} - \frac{1}{N})^2 = HHI_t - \frac{1}{N}$, the difference of HHIs in year t and $t+1$ is

$$\begin{aligned}
HHI_{t+1} - HHI_t &= \sum_i^N \tilde{s}_{i,t+1}^2 - \sum_i^N \tilde{s}_{it}^2 \\
&= \sum_i^N [(s_{i,t+1} - \frac{1}{N})^2 - (s_{it} - \frac{1}{N})^2] \\
&= \sum_i^N [2(s_{i,t+1} s_{it} - s_{it}^2 - s_{i,t+1}\frac{1}{N} + s_{it}\frac{1}{N}) + (s_{i,t+1} - s_{it})^2] \\
&= \sum_i^N [2((s_{i,t+1} - s_{it})s_{it} - (s_{i,t+1} - s_{it})\frac{1}{N}) + (s_{i,t+1} - s_{it})^2] \\
&= \sum_i^N [2(s_{i,t+1} - s_{it})(s_{it} - \frac{1}{N}) + (s_{i,t+1} - s_{it})^2].
\end{aligned}$$

Substituting Eq. (5.1) into the above formula we have

$$
\begin{aligned}
HHI_{t+1} - HHI_t &= \sum_i^N [2(\widehat{\beta}\tilde{s}_{it} + \widehat{\varepsilon}_{it})\tilde{s}_{it} + (\widehat{\beta}\tilde{s}_{it} + \widehat{\varepsilon}_{it})^2] \\
&= \sum_i^N [(2\widehat{\beta} + \widehat{\beta}^2)\tilde{s}_{it}^2 + (2 + 2\widehat{\beta})\widehat{\varepsilon}_{it}\tilde{s}_{it} + \widehat{\varepsilon}_{it}^2] \\
&= (2 + \widehat{\beta})\widehat{\beta}(HHI_t - \frac{1}{N}) + \sum_i^N \widehat{\varepsilon}_{it}^2.
\end{aligned} \tag{5.2}
$$

Define the change of a country's share due to the j^{th} $(j = 1, ..., J)$ category of firm life-cycle activities by

$$
\triangle s_{it}^j = \frac{e_{i,t+1}^j}{E_{t+1}} - \frac{e_{it}^j + s_{it}(E_{t+1}^j - E_t^j)}{E_{t+1}} = \frac{\triangle e_{it}^j - s_{it} \triangle E_t^j}{E_{t+1}}. \tag{5.3}
$$

Let $\sum_j^J \triangle e_{it}^j = \triangle e_{it}$ and $\sum_j^J \triangle E_t^j = \triangle E_t$, then Eq. (5.3) satisfies an adding-up property that $\sum_j^J \triangle s_{it}^j = \triangle s_{it}$.

If one estimates the parameters of the regression (Eq. 5.1) for the country-level share changes corresponding to the j^{th} category

$$
\triangle s_{it}^j = \alpha^j + \beta^j \tilde{s}_{it} + \varepsilon_{it}^j, \tag{5.4}
$$

the following equalities must hold: $\widehat{\beta} =_j^J \widehat{\beta}^j$ and $\widehat{\varepsilon}_{it} =_j^J \widehat{\varepsilon}_{it}^j$. Substitute these two equalities into Eq. (5.2):

$$
\begin{aligned}
HHI_{t+1} - HHI_t &= \sum_j^J [(2 + \widehat{\beta})\widehat{\beta}^j (HHI_t - \frac{1}{N})] + \sum_j^J (\sum_i^N \widehat{\varepsilon}_{it}\widehat{\varepsilon}_{it}^j) \\
&= \sum_j^J [(2 + \widehat{\beta})\widehat{\beta}^j (HHI_t - \frac{1}{N}) + \sum_i^N \widehat{\varepsilon}_{it}\widehat{\varepsilon}_{it}^j] \\
&= \sum_j^J \triangle HHI_t^j.
\end{aligned} \tag{5.5}
$$

The change of HHI between year t and $t + 1$ is decomposed into J components associated with different categories of activities in firm life cycle. This result is slightly

different from the one in Dumais *et al.* (2002) where $\sum_{i}^{N} \widehat{\varepsilon}_{it} \widehat{\varepsilon}_{it}^{j}$ in the second step in Eq. (5.5) can be further expressed as ${}_{i}^{N} \widehat{\varepsilon}_{it}^{j2} +_{i} \widehat{\varepsilon}_{it}^{j} (_{l \neq j} \widehat{\varepsilon}_{it}^{l})$.

In the above derivation for decomposition, we use employment as our baseline measure of production. However, this measure may be distorted by the difference in labour productivity across countries. Since output is a natural alternative but it also suffers from potential measurement problem due to price differences between countries, we use both employment and output levels in the decomposition analysis.

Results of Decomposition

Following Dumais *et al.* (2002), changes in the HHI between 1995 and 2003 can be decomposed into the following five categories: i) birth of new enterprises, ii) birth of new subsidiaries in continuing enterprises, iii) expansion or contraction in continuing subsidiary[22], iv) sector-switch (into and out of the pharmaceutical industry) by continuing subsidiaries, and v) closure of subsidiaries.[23] We also distinguish between subsidiaries that have an MNE parent or a non-MNE parent. Therefore, we have ten components associated with the five categories and the two ownership types. In addition to these components, there are some cases for two activities (expansion/contraction and sector-switch) where a subsidiary having a non-MNE parent in 1995 but having an MNE parent in 2003 or vice versa.[24] We find 130 subsidiaries went from a non-MNE parent to an MNE parent but only two subsidiaries went through the reverse process.[25] Therefore, one should bear in mind that these switching cases are almost equivalent to the change from a non-MNE parent to an MNE parent. The immediate implica-

[22]There are 43 single-firm enterprises in our dataset (see Table 2.4, Chapter 2). By definition these enterprises are non-MNEs. We denote a firm in the single-firm enterprise as a subsidiary of this enterprise. Using this term we can use one phrase - the subsidiaries of MNE or non-MNE parent - for both the subsidiaries and the single-firm enterprises, thus make writing easy.

[23]The birth of new enterprises and the birth of new subsidiaries are treated separately because it is easy for us to find information about the year of incorporation of a new enterprise/subsidiary. But it is technically difficult for us to judge wether the disappearance of a subsidiary in the data means its parent (enterprise) was also closed. Therefore, we do not further distinguish subsidiaries or enterprises in the activity of closure.

[24]This change may due to the facts that a subsidiary is acquired by an MNE or its non-MNE parent becomes an MNE.

[25]In one case a subsidiary's parent company switching its status from non-MNE to MNE and in the other case, the subsidiary itself changed its parent. We do not separate these cases further.

tion is that even if the production of these subsidiaries grew at the same pace with the overall growth in the European pharmaceutical industry (so these subsidiaries would not contribute to share change in countries where they are located), their ownership switching would overstate or understate the contribution of MNEs to the agglomeration trend in terms of expansion/contraction and sector-switch. We isolate these cases and collect them in two additional components - expansion/contraction in switching MNEs and sector-switch in switching MNEs. After this step we end up with twelve components. Table 5.1 gives a description of the number of subsidiaries in each of the five categories, distinguishing by parent status, including MNE, non-MNE or switching MNE. The number of business entities under "1995" and "2003" shows the quantity of that were successfully tracked. For instance, the first row under "2003" shows that 16 new MNEs and 14 non-MNEs were established between 1995 and 2003. The second row shows that 118 subsidiaries of MNEs and 28 subsidiaries of non-MNEs were established between 1995 and 2003. The third row shows that 385 subsidiaries of MNEs exist in both 1995 and 2003 experiencing expansion or contraction during this period, while there are 166 such subsidiaries of non-MNEs and 96 subsidiaries with parents changed status. The forth row of sector-switch can be read in the same way like the third row and the row of closure shows 69 subsidiaries of MNEs and 42 of non-MNEs died after 1995. It is obvious that expansion/contraction took place in MNEs accounts for the largest portion of changes among subsidiaries. Table 5.2 shows the geographic breakdown of subsidiaries by country and parent status. In all countries, except Italy and Portugal, the number of subsidiaries of MNEs increased to different extents. In terms of the subsidiaries of non-MNEs, the number of such subsidiaries decreased in Belgium, Finland, France, Italy and Portugal, while it increased in Austria, Denmark, Germany, Greece, Spain and the UK. The numbers were the same in Ireland, the Netherlands and Sweden. Under the column item "Switching", large numbers of subsidiaries switched from non-MNE parent to MNE parent in France, Italy, Spain and the UK. The last row of Table 5.2 reveals that the total number of subsidiaries of MNEs increased by approximately 10 per cent but the number of subsidiaries of non-MNEs

remained the same.

Table 5.3 reports results for the regressions Eq. (5.1) and Eq. (5.4). For all firm life-cycle activities, the βs for excess share, $\tilde{s}_{it}$, are the same using employment or output levels. Negative coefficients indicate that the excess share in a country discouraged the country from gaining a great share in the 9-year period, although small sample size casts some doubt over the credibility of the estimates. Turning to the regression results corresponding to the twelve components, our estimates reveal counteracting forces at play. Regardless of whether the production level is measured by employment or output, the excess share of a country negatively affects MNEs, non-MNEs and switching MNEs in the activities of new enterprise birth, expansion and contraction, sector-switch and closure[26], however, the excess share encourages a country's share to increase through the new subsidiaries born in continuing MNEs or non-MNEs. The findings can be summarised as follows: the new enterprises tend to start up in less agglomerated countries (with low production share s_{it}); the expansion in the continuing subsidiaries of MNEs or non-MNEs in the less agglomerated countries dominates the same process took place in the agglomerated countries (with high production share);[27] the switches into the pharmaceutical industry from other industries in the less agglomerated countries dominate the same processes in the agglomerated countries; the closure is more likely to take place in the agglomerated countries, which reduces their production shares and finally, continuing MNEs or non-MNEs tend to start up new business in the agglomerated countries.

Table 5.4 reports the decomposed contributions to the overall change of the HHIs due to the five activities in MNEs, non-MNEs and switching MNEs. Twelve components are presented as percentage changes which are able to be summed up to the overall percentage change of the HHIs. For example, the HHIs in terms of employment level was 0.1633(631) in 1995 and dropped to 0.1536(847) in 2003, the overall

[26]There is only one exception, which is the subsidiaries in switching MNEs switching sectors when the production level is measured by employment.

[27]There are more employment and output expansion in countries with low production share, while less such expansion took place in countries with high production share. Therefore, the production shares associated with the expansion increase in the previous low-share countries due to the expansion, while the reverse took place in the previous high-share countries.

percentage change is approximately − 5.9 per cent. In Table 5.4, corresponding components show that the birth of new enterprises only contributes a small amount to this dispersion trend, but the contribution from the birth of new subsidiaries in MNEs is stronger, which counteracts the dispersion trend. However, the aggregate contributions of expansion/contraction, sector-switch and closure dominates the change in agglomeration trend and directs the whole process to dispersion. Leave the birth of new subsidiaries aside, in each of the remaining four categories, it is evident that MNEs, non-MNEs and switching MNEs all work in the same direction but the contribution of MNEs is far greater than those of other two.[28]

If the HHIs are calculated with output level, there is an approximately − 4.9 per cent net decrease of the HHIs (from 0.1639(4138) to 0.1558(8848)). The same patterns of the decomposed contributions appear. For instance, MNE's contribution is − 2.814 to the overall dispersion trend and that from non-MNEs and switching MNEs are − 1.512 and − 0.587, respectively.

The above decomposition analysis reveals the significant dominance of the MNEs' activities in shaping the European economic geography of the pharmaceutical industry. However, caveats and limitations should be noted:

In terms of the source of our firm-level data - *Amadeus*, we find that:

1. The firms in Germany are under-represented for institutional reasons as described in Chapter 2;

2. We have some worries about the consistency of the classification of NACE industry codes over time. As the firm-level data are extracted from several issues of *Amadeus* over an 9-year time frame. Continuous improvement of data quality, as the publisher states, itself may result in inconsistencies with regard to the identification of NACE classifications. As discussed in Chapter 2, great efforts were made to recover the true classification of all firms but the main information source is still *Amadeus*. This is of particular concern in relation to the large

[28]The contribution of MNEs is − 4.823 to the overall dispersion trend if we sum up components 1, 3, 5, 8 and 11. Non-MNE's contribution is − 0.775 if we sum up components 2, 4, 6, 9 and 12. And the remaining contribution comes from switching MNEs at only − 0.352 (the sum of components 7 and 10).

contribution from MNEs' subsidiaries switching sectors between 1995 and 2003 (Component 8 in Table 5.4).

3. We are only able to use information on firms that are large enough to meet three size criteria (see Appendix (Section 2.5) in Chapter 2). Hence, if there is discrepancy between OECD's picture of the European pharmaceutical production and our picture of it, such discrepancy may be mainly caused by the exclusion of smaller firms, which are usually non-MNEs. But we still believe our results successfully pinpoint the major driver of the agglomeration trend: MNEs. The exclusion of smaller firms merely helps to uplift the contributions of the MNEs, rather than undermine them.

The limitation lies in the agglomeration index (HHI) used and decomposed in the study. It is suggested that the E-G Index is superior to the HHI in that it is able to control for the noise in the agglomeration measure which is attributed to the uneven distribution of production across firms, which may randomly distribute across countries. Given its complicated form, we start from a decomposition of the HHI but an extension to the E-G Index is worth.

5.4 Summary and Conclusions

The Single Market Programme was implemented in 1993 aiming to abolish remaining non-tariff barriers in the integrated European market. In the context of this major institutional change that drastically reduced trade costs in the EU, it was expected that industries would respond to these changes in different dimensions. One dimension is the geographic distribution of industrial production across the EU member states. The New Economic Geography literature provides insights into the connection between trade-cost levels and the distribution of economic activities, hence it is crucial for us to understand and predict industry responses. In this chapter, we reviewed some important models of the NEG literature. Krugman's model stresses the product and labour market effects on the agglomeration patterns of IRS industries. Baldwin's model focuses on regional endogenous capital accumulation. Both models predict a monotonic

trend in industrial agglomeration: initially evenly distributed IRS industry in two regions will agglomerate in only one region if trade costs become low enough. Venables' and Puga's models illuminate the role of upstream-downstream linkages in shaping industry location patterns. Moreover, both models predict a non-monotonic trend of agglomeration under different levels of trade costs. Venables-Puga's models differ from Krugman-Baldwin's in that the former assume that labour is immobile inter-regionally. This limits the supply of labour in the agglomerated region and causes the agglomerated industry to leave when trade costs are low enough. Considering the features of European labour market, we see Venables-Puga's models as being better tools that can help us to understand the geographic distribution of industry across the EU.

We then look at the agglomeration pattern of one particular European industry - pharmaceuticals, and find evidence at an aggregate level that a dispersion trend in agglomeration emerged in this industry over the post-SMP era. To gain a good understanding of the driving forces behind this trend, we use firm-level data to decompose the trend into twelve components along two dimensions of firms: by ownership, i.e., MNE or non-MNE parents and by the activities of firm life cycle. We find that the activities that took place in the MNEs contribute substantially to the overall dispersion trend but in opposite ways. Specifically, the birth of new MNEs, expansion and contraction, sector-switch and closure in the MNEs reduce agglomeration, while the birth of new subsidiaries in the MNEs strengthens the agglomeration. On the other hand, the contribution to the dispersion trend from non-MNEs is much smaller. The decomposition analysis articulates the crucial role the MNEs played in the shaping of the agglomeration pattern in the EU.

The NEG models and our decomposition analysis can serve as two guidelines for further detailed firm-level analysis. The former illuminates the direction of industry agglomeration and central mechanisms behind such movement. Based on these models, we suggest that one may investigate the effect of the agglomeration level on individual firm's behaviour and other factors related to the agglomeration process in the pharmaceutical industry, for instance, the market size, labour market conditions,

the upstream-downstream linkages, transportation and accessibility to the enlarged EU market. Based on the decomposition results, we suggest that we need to focus on MNEs' activities, and in particular, two activities need separate analysis: the expansion/contraction and the birth of new subsidiaries. In the next chapter we present a firm-level analysis on the location choice of MNEs in the EU closely following the above-mentioned guidelines.

5.5 Tables

Table 5.1: Breakdown of Pharmaceutical Enterprises and Subsidiaries in 1995 and 2003 by Parent Status

	1995			2003		
Category	MNE	Non-MNE	Switching	MNE	Non-MNE	Switching
Birth of new enterprise	na	na	na	16	14	na
Birth of new subsidiary	na	na	na	118	28	na
Expansion/Contraction	385	166	96	385	166	96
Sector-switch	152	40	36	152	40	36
Closure	69	42	na	na	na	na
Sum	606	248	132	671	248	132

Table 5.2: Geographic Distribution of Pharmaceutical Enterprises and Subsidiaries in 1995 and 2003 by Parent Status

	1995			2003		
Country	MNE	Non-MNE	Switching	MNE	Non-MNE	Switching
Austria	3	2	0	5	3	0
Belgium	32	5	8	38	4	8
Denmark	9	0	2	15	1	2
Finland	2	3	0	5	1	0
France	175	52	37	190	45	37
Germany	39	9	3	45	14	3
Greece	7	18	2	9	19	2
Ireland	16	2	1	24	2	1
Italy	120	94	30	105	89	30
The Netherlands	9	2	2	10	2	2
Portugal	11	12	3	9	10	3
Spain	103	29	27	108	32	27
Sweden	8	1	4	15	1	4
The UK	72	19	13	89	25	13
Sum	606	248	132	667	248	132

Table 5.3: Regression Results of Production Share Changes Due to Various Activities of Firm Life Cycle

			Employment			Output		
Category	Component		β	R_2	# of Obs.	β	R_2	# of Obs.
All activities			-0.11	0.106	14	-0.11	0.091	14
			(0.093)			(0.101)		
Birth of new enterprise	MNE	1	-0.003**	0.38	14	-0.001	0.159	14
			(0.001)			(0.001)		
	Non-MNE	2	-0.002	0.088	14	-0.001	0.113	14
			(0.001)			(0.001)		
Birth of new subsidiary	MNE	3	0.007	0.005	14	0.025	0.066	14
			(0.03)			(0.027)		
	Non-MNE	4	0.005*	0.232	14	0.002	0.068	14
			(0.003)			(0.002)		
Expansion/Contraction	MNE	5	-0.093	0.051	14	-0.083	0.054	14
			(0.116)			(0.101)		
	Non-MNE	6	-0.004	0.014	14	-0.004	0.085	14
			(0.009)			(0.004)		
	Switching	7	-0.005	0.06	14	-0.006	0.069	14
			(0.006)			(0.006)		
Switch	MNE	8	-0.009	0.011	14	-0.012	0.077	14
			(0.024)			(0.012)		
	Non-MNE	9	-0.005	0.093	14	-0.006	0.197	14
			(0.005)			(0.003)		
	Switching	10	0.002	0.005	14	-0.002	0.01	14
			(0.007)			(0.005)		
Closure	MNE	11	-0.003	0.003	14	-0.019	0.149	14
			(0.016)			(0.013)		
	Non-MNE	12	-0.0002	0.0002	14	-0.003	0.095	14
			(0.004)			(0.003)		

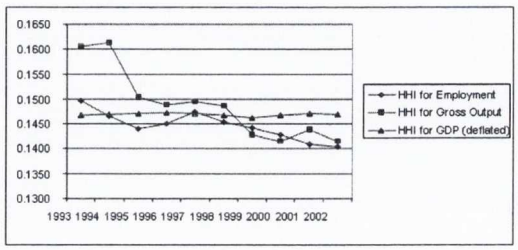
Note: Overall β is estimated by regression Eq. (5.1) : $\triangle s_{it} = \alpha + \beta \tilde{s}_{it} + \varepsilon_{it}$;
βs of various regularities are estimated by regression Eq. (5.4) : $\triangle s^j_{it} = \alpha^j + \beta^j \tilde{s}_{it} + \varepsilon^j_{it}$;
* significant at the 10 per cent level, ** significant at the 5 per cent level; standard error in parentheses.

Table 5.4: Decomposition of Changes in Geographic Concentration Due to Various Activities of Firm Life Cycle

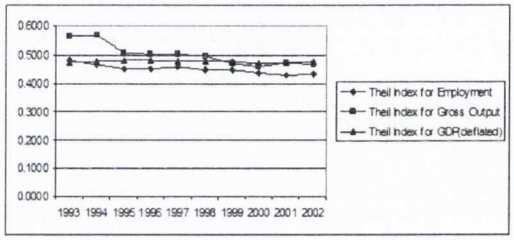
			Employment	Output
Percentage change in the HHIs 1995 - 2003: All activities			-5.924	-4.912
Percentage change due to:				
		Component		
Birth of new enterprise	MNE	1	-0.321	-0.095
	Non-MNE	2	-0.136	-0.107
	.....	.....	.....	.....
Birth of new subsidiary	MNE	3	1.533	3.98
	Non-MNE	4	0.436	0.058
	.....	.....	.....	.....
Expansion/Contraction	MNE	5	-2.781	-2.16
	Non-MNE	6	-0.1	-0.429
	Switching	7	-0.295	-0.516
	.....	.....	.....	.....
Switch	MNE	8	-2.11	-1.921
	Non-MNE	9	-0.754	-0.637
	Switching	10	-0.057	-0.071
	.....	.....	.....	.....
Closure	MNE	11	-1.114	-2.618
	Non-MNE	12	-0.221	-0.397

5.6 Figures

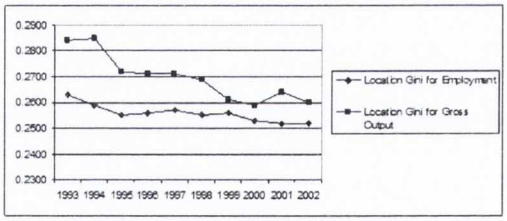
Figure 5.1: Four Agglomeration Indices of Pharmaceutical Production in Selected European Countries, 1993 - 2002. Source: (OECD STAN Data, the *Amadeus* Database, EU15, excl. Luxembourg).



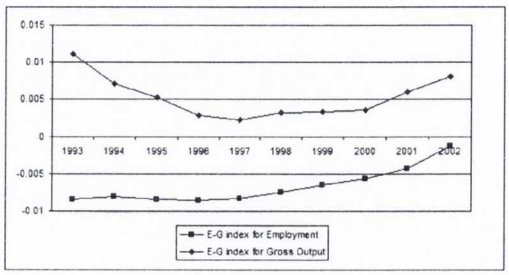
(a) Hirschman-Herfindahl Index



(b) Theil Index



(c) Location-Gini Coefficient



(d) Ellison-Glaeser Index

Chapter 6

The Location Choice of Pharmaceutical MNEs in the Enlarged EU Market[1]

[1]This chapter is developed from a joint working paper with Professor Frances Ruane.

6.1 Introduction

Implementation of the Single Market Programme (SMP) in the European Union (EU) after 1992 resulted in the abolishment of non-tariff barriers (NTBs) for trade between member states of the EU and as consequently, trade-cost levels in the EU are at an unprecedented low point. In the context of lowering trade costs, the models of New Economic Geography (NEG) predict different directions of agglomeration in the increasing returns to scale (IRS) industry. The Krugman (1991) and Baldwin (1999) models predict that as trade costs decrease between two regions, the IRS industry will agglomerate in one region. On the contrary, Venables' (1996) and Puga's (1999) models show that the IRS industry will initially agglomerate in one region but then disperse across regions.

On the empirical side, we know from our investigation of the European pharmaceutical industry in Section 5.3.3, Chapter 5 that:

1. The overall location pattern of pharmaceutical production exhibited a dispersion trend in the EU-15 member states in the post-SMP era.

2. The major drivers of this dispersion trend are multinational enterprises (MNEs).

3. Various activities of MNEs contributed to the overall trend in different directions and to different degrees. Expansion/contraction in MNEs, MNEs switching into the pharmaceutical industry and the closure of subsidiaries of MNEs are the sources that encourage the dispersion trend, while the birth of new subsidiaries in MNEs offsets the trend.

In this chapter we attempt to link the predictions of the NEG models with the location trend in the following way: the dispersion trend means that pharmaceutical production is shifted from countries with a high level of agglomeration in the industry to countries with a low level of agglomeration, consequently, a previous high level of agglomeration of a country can be seen as exerting a negative effect on the movement of production. This correlation can be effectively estimated with a discrete-choice framework where MNEs make the decision of where to locate their production. On the basis

of this logic, we analyse the location-choice decisions of the pharmaceutical MNEs in 14 EU member states in the 1990's and try to answer the first empirical question,

1. Does the agglomeration of the pharmaceutical industry in a country increase or decrease its probability of being chosen by MNEs?

If the previous agglomeration has a negative impact on the probability, it will provide evidence on the observed dispersion trend (at aggregate level) from a firm's perspective and also reinforce the Venables-Puga prediction of the stage of dispersion given lowering trade costs (see Stage 4 in Figure 5A.2 of Chapter 5). Otherwise, a positive impact will reinforce the common rationale that firms tend to agglomerate, as shown in various NEG models discussed in Chapter 5.

In addition to the effect of agglomeration, we are also interested in the second question:

2. Are there any other country-level characteristics which can influence the location choices of MNEs?

And finally we want to explore the third question:

3. Do MNEs respond differently to country-level characteristics when they make location choices associated with production expansion and new-subsidiary creation, as suggested by the decomposition analysis.

Question 3 also rises from the fact that the firm-level data in *Amadeus* show that the change in pharmaceutical production in existing firms was roughly six times that of new firms during the period from 1993 to 2003[2], hence we need to study production relocation (in terms of expansion) in the existing firms and the new-subsidiary creation separately.

We make use of two discrete-choice models – the conditional logit model (CLM) and the mixed logit model (MXL). The results show that, in terms of the location choice

[2] A new firm is defined as a firm being established after 1993 and its production value in 2003 is used for comparison.

of MNEs in relation to production expansion, high levels of agglomeration in the pharmaceutical industry increase a country's probability of being chosen by MNEs. Thus, the finding supports the rationale of NEG models that an agglomeration force is at play in the distribution of industrial activities. In contrast, agglomeration in the chemical industry seems to work as a deterrent to production expansion and the negative effect is particularly prominent in the second period of the sample period (1999 - 2003). In addition, MNEs are also found to prefer countries with large market size and better motorway density, however, some other factors, which are usually found to have a impact in the location-choice literature, such as the corporate tax rate, labour costs and labour quality, do not have significant effects for the entire sample period, but some of them play roles in the second half of the period. On the other hand, the agglomeration effect is less evident for location choices associated with new-subsidiary creation, but if a country is close to Brussels or being familiar to an MNE through an existing plant or headquarters being located in that country, the MNE is more likely to choose the country. We also find significant variation in the ways that MNEs that differ in their nationality and intended sizes of production expansion or newly-built production capacity respond to some country-level characteristics.

The chapter is organised as follows. Section 6.2 reviews empirical literature of location choice, while Section 6.3 discusses the empirical methods and data used; Section 6.4 presents and discusses the results for the location choice of production expansion and new-subsidiary creation. In section 6.5, the chapter is summarised and conclusions drawn.

6.2 Review of Empirical Literature

A growing literature focuses on the modelling of the location choice of firms directly, using discrete-choice models. Some of the early research examined the location choice of firms in the US[3], while more recently there have been several studies of location choice within individual European countries.[4] Of particular relevance to our work are

[3]See Bartik (1985), Friedman *et al.* (1992), Woodward (1992), Head *et al.* (1995, 1999) and Shaver (1998).

[4]See Barrios *et al.* (2002) for Ireland, Crozet *et al.* (2003) for France, Hogenbirk and Narula (2004) for the Netherlands, and Békés (2005) for Hungary.

studies on the location choice of MNEs across several European countries, at region[5] and country level: for example, Devereux and Griffith (1998) for US MNEs in 3 European countries; Basile *et al.* (2003) on EU and US MNEs' investments in 55 NUTS 1 regions in 8 EU countries; Head and Mayer (2004) for Japanese firms in 9 EU countries at the NUTS 1 level; Disdier and Mayer (2004) for French MNEs in Western Europe and Eastern Europe; Defever (2006) for MNEs' investment projects in 23 European countries and Mataloni (2007) for US MNEs in the EU.

Agglomeration forces are seen as playing an important role in many studies. For example, Bartik (1985), Head *et al.* (1995) and Mataloni (2007) find that the existence of regional manufacturing activities encourages new manufacturing investments. In addition to that, foreign MNEs are more likely to set up their new plants in the locations where business already exist from the same country or even the same business group.[6] However, the results are not uniform for regions within countries[7] and across countries within the EU.[8]

The influence of local goods markets on the probability of one region or country being chosen by MNE investors is confirmed in most research. The effect of the integrated EU market is also verified indirectly by studies on Ireland and Hungary, which find that MNEs prefer to locate in proximity to the major ports and airports in Ireland (Barrios *et al.*, 2002), and in Hungary they prefer the places that are close to the western borders (Békés, 2005), in order to access to a broader market.

The influence of policy factors is explored by researchers, with the corporate tax rate typically as a focus. Although the evidence generally indicates a significant nega-

[5]Regional level studies are normally conducted at different NUTS level. NUTS stands for Nomenclature of Territorial Units for Statistics, the official regional classification system developed by EUROSTAT to facilitate regional study in the European Union. Current version of the NUTS classifies 25 member states at the NUTS 0 (country level), and then further decomposes these countries into 89 regions at the NUTS1 level, 255 regions at the NUTS2 level and 1,221 regions at the NUTS3 level.

[6]For example, Japanese firms tend to locate in the regions with other firms from the same industrial group, or Keiretsu.

[7]For example, Hogenbirk and Narula (2004) find that when comparing the Randstad region (the agglomerated region containing large cities, major ports and airports) with the rest of the Netherlands, the presence of local business seems to work as a deterrent for new foreign establishments.

[8]Disdier and Mayer (2004), using data on French MNEs, find that industrial agglomeration is less important as a factor influencing their location-choice decisions in Central and Eastern Europe than in Western Europe.

tive relationship between the tax rates and the attraction of foreign investments, some researchers find that taxes have a relatively modest impact (e.g., Friedman *et al.*, 1992 and Crozet *et al.*, 2003). The correlation is even found to be positive in some specifications in Shaver (1998). Differences in the research findings on the impact of the corporate tax rates on FDI are generally due to differences in the precise tax measures used[9], differences in actual tax burdens across industries[10], and differences in the way in which the tax effects are conditional on other variables.[11]

The evidence on the importance of labour-market conditions to location choice is mixed. For example, wage rates are found to be negatively associated with FDI inflows or new establishments (Bartik, 1985; Friedman *et al.* 1992, etc), but the effect may also be positive or insignificant (Devereux and Griffith, 1998; Head *et al.*, 1999; Barrios *et al.*, 2002 and Mataloni, 2007). Since the NEG models clearly indicate that higher wage rates hinder the movement of economic activities, several arguments are proposed to explain this discrepancy between theories and empirical evidence. One argument suggests that wage rates work as a signal on the quality of labour, and consequently foreign MNEs may be happy to accept high wages to secure skilled labour.[12] Another argument is that the positive wage effect on FDI merely reflects an "industry bias" or "skill bias". For instance, Békés (2005) suggests that MNEs are most likely to be in the high-tech sectors where the wage is high or, they are bringing superior technologies to host countries and consequently are hiring more skilled or managerial workers than

[9]The corporate tax rates can be measured in different ways. The most frequently used tax rate is the statutory tax rate (see Head and Mayer, 2004, Bénassy-Quéré *et al.*, 2005). This rate ignores actual tax practices (e.g., fiscal incentives) in different countries and MNEs' responses to them. The average tax rate based on actual firm-level tax data also has been increasingly used in panel studies. However, as Devereux and Griffith (2002) point out, the average tax rate is a backward-looking rate whereas investment should be based on the effective tax rate, which is estimated using the relevant parameters at the time the real investment is made. Using this tax rate, Devereux and Griffith (1998), in a study of a panel of US firms locating in European markets, find that their effective tax rate has a negative impact.

[10]Many European governments target high-tech industries so that they can avail of more tax incentives, or equivalently, have lower tax burdens than the rest of industry. Unfortunately, there are no studies in the existing literature that controls for this effect.

[11]For example, the impact of taxation on FDI may depend on market size, the agglomeration of business activities and labour-market conditions, and these are taken account of in very different ways in various studies, reflecting their particular focuses.

[12]Moreover, Guimaraes *et al.* (2002) argue that wage effects may be significant between countries but not necessarily important across regions within one country if investors have already decided on the country in which to invest.

domestic firms.

Other factors affecting the location decisions of MNEs are R&D capacity (positive effect in Neven and Siotis, 1996 and Blonigen, 1997); infrastructure (positive in Woodward, 1992; Holl, 2004 and Basile *et al.*, 2003) and the availability of government support such as EU structural funds and state aids/promotion (positive effect in Friedman *et al.*, 1992 for US; Shaver, 1998 for US, Barrios *et al.*, 2002 for Ireland and Basile *et al.*, 2003 for the EU).

Firm heterogeneity is also found to be important in the location decisions of MNEs, and is reflected in the determinants of location choice for MNE parents from different countries (or continents). For example, Basile *et al.* (2003) find that, when investing in EU countries, US MNEs treat regions within a country as equivalent substitutes, whereas the location decision of EU MNEs respond to regional differences. Also, Hogenbirk and Narula (2004) find US and Japanese MNEs prefer the Randstad region in the Netherlands, while EU MNEs prefer the regions which border other EU countries.

6.3 Empirical Methods and Data

6.3.1 A Discrete-Choice Framework

As described in Section 6.1, the agglomeration trend in the pharmaceutical industry can be studied indirectly by looking at that to what extent the previous agglomeration of pharmaceutical production within countries affects MNEs' location choices. Consider a discrete-choice framework in which MNEs need to make investment decisions regarding where to expand their existing production capacity, or where to build new production facilities. The probability of a country being chosen as a location is determined by how attractive the country is to an MNE in terms of observable characteristics. Suppose the previous agglomeration of pharmaceutical production in one country is such a potential determinant. A dispersing trend of agglomeration suggests some forces are discouraging firms from being close to each other, for instance, severe competition for market share, production resources and labour, or congestion costs of traffic and pollution. Therefore, countries with a larger portion of previous phar-

maceutical production may become less favourable to the MNEs. Consequently the probability of such countries being chosen by the MNEs to invest will be lower and investments will go to those countries with less production. On the basis of this logic, if we can find any effect of the previous agglomeration on the location choice, it would provide evidence to support or challenge our findings about the roles of production expansion and new-subsidiary creation in the dispersion trend as shown in the decomposition analysis in Chapter 5. In addition, we are also interested in whether the NEG models' argument about the agglomeration effect can be supported – they are, a positive effect leading to increasing agglomeration in the Krugman-Baldwin and the Venables-Puga models, or a negative effect under certain ranges of trade costs leading to dispersion as shown in the Venables and Puga models.

The first discrete-choice model we use is McFadden's conditional logit model. McFadden (1974) models discrete choices in terms of an individual $i(i = 1, ..., I)$ making a choice among J alternatives to maximise his/her perceived utility (U_{ij}) conditional on the characteristics (X_{ij}) of each alternative. The perceived utility generated by the individual i from choosing alternative j can be expressed as

$$U_{ij} = X'_{ij}\beta + \varepsilon_{ij}, \tag{6.1}$$

where X_{ij} is a vector of alternative j's characteristics, which are observable to the individual as well as to the researcher; β is a vector of coefficients measuring the influence of these characteristics on the individual's utility and ε_{ij} is the unobservable random element of the individual's utility.

McFadden proposes that, if (and only if) the random element ε_{ij}, $\forall j = (1, ..., J)$ follows a type I extreme value distribution, independently and identically (IID) across I individuals and J alternatives, the probability of alternative k being chosen over other alternatives can be expressed as

$$\Pr(y = k|1, ..., J) = \frac{\exp(X'_{ik}\beta)}{\sum_{j=1}^{J} \exp(X'_{ij}\beta)}. \tag{6.2}$$

From Eq. (6.2), one has

$$\frac{\Pr(y=k)}{\Pr(y=l)} = \frac{\exp(X'_{ik}\beta)}{\exp(X'_{il}\beta)} = \exp(X'_{ik} - X'_{il})\beta. \tag{6.3}$$

Eq. (6.3) shows that the ratio of two probabilities is only determined by the explanatory variables of two alternatives k and l, but irrelevant to that of other alternatives. Therefore, this structure of the probability function gives rise to the *Independence from Irrelevant Alternatives* (IIA) property, which means that the choice of an individual between any two alternatives is not influenced by any other alternatives. IIA can be easily tested because it implies that if any one of the alternatives is irrelevant to the rest in the choice set, dropping it will not result in inconsistent estimates. Based on this implication, Hausman and McFadden (1984) proposed a specification test for the validity of IIA. In terms of the location-choice model, to perform the Hausman test for one country, one needs to exclude this country from the choice set and run the CLM for the remaining countries, and then compare the estimates with estimates for the full set of countries using a Chi-square test. One can exclude one country at a time in turn to perform Hausman tests for every country.

It is often found that IIA cannot hold. In some cases, an individual's preference towards some particular alternatives among others may create an unobserved common utility for those particular alternatives, if such preference cannot be explicitly controlled. This unobserved utility causes cross-alternative correlation and hence the violation of IIA. For example, US MNEs may prefer to invest in English-speaking countries, and this preference causes the utilities generated from choosing the UK and Ireland to correlate with each other. Consequently, for a US MNE, the probability ratio of choosing the UK and Germany (see Eq. 6.3) contains a factor of English language, which is correlated with the profit generated in Ireland. Although English language is an obvious factor, sometimes researchers cannot be confident whether they have controlled for all factors, so the unobserved preferences of individuals are inevitable. We use a recently-developed mixed logit model (MXL) to tackle this problem (see Train, 2003 for an extensive discussion of this model). The MXL specifies the utility function

as follows,

$$U_{ij} = X'_{ij}\beta_i + \varepsilon_{ij}, \tag{6.4}$$

where β_i is a vector of coefficients for the alternative-specific characteristics X_{ij} associated with individual i, and ε_{ij} is an unobserved error term following an IID extreme value distribution. β_i is assumed to be distributed randomly across all individuals and has a density function of $f(\beta)$. One way to specify this cross-individual variation is to assume a nest structure of individuals. That is to say, individuals are nested in hierarchies indexed by $h(h = 1, \ldots, H$ and $H <= I)$ and the heterogeneous responses of individuals to X_{ij} are varying across hierarchies but not within hierarchies. Consequently, the variation in an individual's preferences towards alternatives' characteristics is accommodated in the utility function.[13] This hierarchical assumption has been applied to research on students' academic performance where students are nested in schools or on patients' death rate where they are nested in hospitals. The probability of alternative k being chosen by individual i over J alternatives is an integral of the ratio of utility derived from alternative k to the sum of utilities derived from all alternatives over the density function of β_i:

$$\Pr_i(y = k|1, ..., J) = \int \frac{\exp(X'_{ik}\beta_i)}{\sum_{j=1}^{J} \exp(X'_{ij}\beta_i)} f(\beta) d\beta_i. \tag{6.5}$$

If one rewrite the ratio of probabilities (Eq. 6.3) using this form of probability function, "*the denominators of the logit formula are inside the integrals and therefore do not cancel*" (Train, 2003), hence, all explanatory variables of J alternatives are in the ratio and the correlation between alternatives is allowed.

Since β_i reflects idiosyncratic preferences of individuals towards each alternative and is usually assumed to follow a normal distribution (see Revelt and Train, 1998 and Ben-Akiva and Bolduc, 1996), the density function can be expressed as $f(\beta|\mu, \sigma^2)$, where μ is the mean of the normal distribution and σ^2 is the variance. These two

[13] In effect, the CLM is a special case of the MXL where β_i is assumed to be fixed for every individual.

parameters have to be estimated to evaluate the effect of an alternative-specific characteristic on individuals' utilities.

In this chapter we will estimate the mean β and variance σ^2 for the explanatory variables that are set to have a random parameter. The estimation is done by a STATA[14] add-in programme "GLLAMM" (see Rabe-Hesketh *et al.*, 2004).[15] We assume there is an MNE parent-subsidiary hierarchy structure, where MNE parents make their decisions through their multiple subsidiaries and the random parameter β_is of explanatory variables vary across MNE parents.

6.3.2 Data Description

Our study is focused on the location choice of MNEs taking place between 1993 and 2004 in the pharmaceutical industry[16] in the EU-15 countries (excluding Luxemburg).[17] We include all MNE subsidiaries, irrespective of parents' nationality. Two types of location choices are considered. The first type is the choice of location amongst existing high-expansion subsidiaries at which production is to expand[18], where high-expansion subsidiaries are defined as those with above-median rates of output growth.[19] Because most of the existing subsidiaries expanded their output at different growth rates during the last decade, it is to be expected that subsidiaries would expand at higher growth rates in the more attractive country locations, and thus to identify the determinants of those countries one needs to choose high-expansion subsidiaries. We use above-median growth rate of all existing pharmaceutical subsidiaries as the criterion to determine high-expansion subsidiaries. The second type is the choice of location for new start-up subsidiaries. We analyse these two types separately for two reasons: first,

[14]The version 10.

[15]GLLAMM stands for Generalised Linear Latent And Mixed Models and it can estimate a class of multi-level latent variable models including the MXL.

[16]The pharmaceutical industry is defined according to NACE Rev.1.1 industry code at 3-digit level. The 3-digit NACE code for the pharmaceutical industry is 244 and two 4-digit codes are assigned to its sub-industries: 2441 (manufacture of basic pharmaceutical products) or 2442 (manufacture of pharmaceutical preparation).

[17]They are Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal, Spain, Sweden, and the United Kingdom.

[18]The terms subsidiary (ies) or firm (s) are used interchangeably throughout this chapter since they are equivalent in the sense that all firms studied in this chapter are subsidiaries.

[19]Output is proxied by operational revenues.

our decomposition analysis reveals that these two types of choices work in opposite directions in the location trend, thus they might respond to the country-level agglomeration and other variables in different ways. Second, though they are both vehicles of production relocation, they reflect different considerations for the MNEs. In particular, expanding production in an existing subsidiary generally involves negligible sunk costs compared with starting up a new subsidiary.

MNEs' expanding and new subsidiary firms are identified in *Amadeus*. Each subsidiary is linked to an ultimate MNE shareholder as its MNE parent, and all ultimate MNE parents defined in this way are independent of each other. Such clean "parent - subsidiary links" allow us to study ownership effects on the location choice of MNEs (through subsidiaries) later.[20]

The year 1993 is chosen to distinguish between the existing subsidiaries and new subsidiaries, so no pharmaceutical firm exists in both samples. Moreover, since the accounts of subsidiaries in *Amadeus* from 1995 are better (in terms of completeness) than those in 1993, we calculate the growth rates of output of every existing pharmaceutical subsidiary for the period between 1995 and 2003. After applying certain size criteria[21], we initially find 725 existing subsidiaries, which were established before 1993. Further investigation allows us to identify 444 subsidiaries out of 725 that have complete production data in both 1995 and 2003, which are necessary for one to calculate the scale of production change. The "high-expansion" sample contains 222 subsidiaries in the EU-15.[22] The "new-subsidiary" sample contains the 129 new subsidiaries that were established between 1993 (inclusive) and 2004 in EU-15.[23]

[20]By defining an ultimate owner as having the largest share in a firm, we avoid the complication of joint ventures. According to the ownership database in Amadeus, there is only one joint-venture case where two parents have exactly 50 per cent shares each in a subsidiary, which is Bracco Spa, an Italian company owned equally by E.MERCK (Germany) and Brafin Finanziaria Spa (Italy). We treat Bracco Spa as the subsidiary of E.MERCK because E.MERCK is a leading European pharmaceutical MNE, while the NACE industry code of Brafin Finanziaria Spa is not available in Amadeus and we are not able to get information about its trading activities from other sources.

[21]Because data for small firms are generally poor in Amadeus, we only choose those firms that can meet at least one of the three size criteria: operational revenues greater than 12 million USD, or number of employees greater than 150, or total assets greater than 12 million USD.

[22]These firms were located in only 11 of the EU-15 countries: Belgium, Denmark, France, Germany, Greece, Ireland, Italy, Portugal, Spain, Sweden, and the UK.

[23]These new firms were established in only 11 of the EU-15 countries: Austria, Belgium, Denmark,

Tables 6A.1 and 6A.2 summarise the descriptive statistics and location distribution (by parent nationality) of the high-expansion subsidiaries, while Tables 6A.3 and 6A.4 summarise the descriptive statistics and location distribution (by parent nationality) of the new subsidiaries.[24] Comparing mean and median values for the high-expansion subsidiaries, we can see that the distribution of employees, operational revenues and fixed assets is skewed towards larger subsidiaries; the distribution of age is skewed towards older subsidiaries; and the distribution of growth rates is skewed towards fast-growing subsidiaries. For the new subsidiaries, the same features can be observed, except in the case of age which is skewed towards younger subsidiaries.

Turning to the geographic distribution of firms, we see that France, Italy, Spain and the UK account for the majority of high-expansion subsidiaries during the period between 1995 and 2003, while France, Spain and the UK account for the majority of new firms established. We also note that, relative to land and population size, both Belgium and Ireland account for a significant number of new firms. The relatively low representation of Germany amongst the high-expansion subsidiaries may in part be due to the fact that German firms are underrepresented in *Amadeus*.[25]

We acknowledge the limitation of our data in that the geographic resolution is at country level, rather than at region level. Because there is no plant-level data available in *Amadeus*, if a firm has multiple plants located in different regions in a country, we are not be able to pinpoint the exact locations of all these plants. It is also often found that some large manufacturers have their national headquarter firms located and registered in the capital of a country, but the plants under the control of the headquarter firms are spread in different regions of the country. Therefore, assuming all productions of a multi-plant headquarter are taking place in the capital region will inevitably lead to biased estimates with respect to the effects of agglomeration and market size (if they are measured at region level). We try to compensate this limitation using some

Finland, France, Germany, Ireland, Italy, Spain, Sweden, and the UK.

[24] The MNE parent's nationality is decided by its headquarter's location.

[25] According to the help file in *Amadeus*, *"Failure to comply with disclosure requirements is not normally a punishable offence; ... Consequently, only about 10-20% of 450,000 companies actually do so. There is therefore no guarantee that information will be readily available on smaller and medium-sized companies in particular."*

industry-specific explanatory variables, which are not available at region level.

6.3.3 Explanatory Variables

Based on the existing location choice literature and on the NEG theories we construct three sets of explanatory variables: industry-specific country-level variables, generic country-level variables and firm-specific variables.

Industry-Specific Country-level Variables

Agglomeration Variables: Agglomeration of the pharmaceutical industry at country level is the primary focus of this study. Following other studies, two types of agglomeration variables are constructed. The first agglomeration variable is intended to measure absolute agglomeration. It is the number of both domestic and foreign-owned firms, [*PHAR*], in the pharmaceutical industry. We only consider firms which can meet certain size criteria[26] (i.e., they are large firms), since the total number of firms may absorb the country-level fixed effects which have been internalised in a country's pharmaceutical industry. Such as the history and relative advantage of producing pharmaceuticals, or institutional arrangement and business tradition which encourage the creation of small firms.[27] As a robustness check, we also use a second agglomeration variable, the number of foreign-owned firms in each country, [*PHAR2*]. The foreign-owned firm is defined as the firm with foreign ownership of at least 25 per cent. We expect this variable to capture the country-level characteristics that were internalised in the location decisions made by foreign MNEs. In addition to the absolute variables, we use total manufacturing as a reference point in each case to create relative variables of agglomeration [*PHARSHR*] and [*PHARSHR2*] because the absolute agglomeration variables correlate with other country-level characteristics.[28]

Because some of the agglomeration effects in connection with the location choices come from the upstream-downstream linkages, we need to take account of the possi-

[26] It is the same size criteria which are applied to the selection of existing firms in Section 6.3.2.

[27] Due to the data constraint, we have to confine our focus on the subsidiary firms that can meet certain size criteria. Therefore, the impact of small firms are deemed as being less relevant in our study.

[28] PHARSHR is the share of firms in the pharmaceutical sector in that of all manufacturing sectors, where firms are constrained to both domestic and foreign-owned ones with size criteria applied. PHARSHR2 is defined in the similar way but firms are constrained to the foreign-owned ones.

bility that the pharmaceutical industry may co-locate with the chemical industry. We include two corresponding chemical-industry (excluding the pharmaceutical industry) agglomeration variables, namely, the number of domestic and foreign-owned large firms [*CHEM*] (with the same size criteria applied) and that of foreign-owned firms [*CHEM2*]. A positive relationship is expected.[29] The corresponding relative measures for the chemical industry are created on the same basis as the pharmaceutical sector variables as [*CHEMSHR*] and [*CHEMSHR2*].

Market Variables: We choose the national consumption of drugs and medicines (million USD) as a variable to proxy national market size [*MKSIZE*] in each country. We want to test whether, after the implementation of the SMP since 1993, the national market size still matters to MNEs looking for a location at which to expand production or build up new facilities. We also include a market-concentration variable [*MKSHARE*] to proxy competition and to test whether competition in the pharmaceutical market at country level influences the location decisions of MNEs. Our measure is the share of top 25 firms at the national pharmaceutical market in terms of sales.[30] Baldwin (1995) and Barbosa (2003) suggest that in a highly-concentrated market, incumbent firms enjoy high price-cost margins and are motivated to deter new entrants from entering into the market. Therefore, this variable is only included in the model for the new-subsidiary sample and we suggest that it may negatively affect location choices of starting up new subsidiaries.

According to the NEG literature, usually firms are assumed to be attracted by both the size of a local market as well as the ability to access other markets from this local market. This gives rise to the concept of "market potential", which is introduced in Harris (1954) as the inverse distance-weighted market size. Considering that market potential is more suitable to capture the correlation of demand between two regions within a country through their distance to each other, we believe our country-level location observations are not fine enough to allow us adopting the market-potential

[29] The NEG theories strongly support such a positive relationship since there is no perceived negative consequence for pharmaceuticals from competition on product market with chemicals. Though, we are aware of potential competition on the labour market and pollution permit from these two industries.

[30] From Gambardella *et al.* (2000).

measure. However, we will include a geographic-distance variable in the hope of capturing the spatial correlation between countries. The variable will be described later.

Pharmaceutical Labour Costs: To take account of national differences in production costs, labour costs per employee [*LCOST*] in the pharmaceutical industry in each country is derived from the OECD STAN database. Assuming that we can account for quality, we expect a negative effect from LCOST.

Generic Country-level Variables

Labour quality: To control for labour quality we include the percentage of workers having completed tertiary education in the total manufacturing workforce [*EDU3*]. Results in the related empirical studies lead us to believe that if EDU3 captures the skills component fully, we expect a positive effect of EDU3.

Corporate tax rate: We use the effective average tax rate [*EATR*] generated by Devereux and Griffith (2003) to measure corporate tax rates. EATR is superior to the statutory tax rate as it takes account of various financial factors that a hypothetical investment project will face in a discrete location-choice context.[31] We expect a negative effect on output expansion and new start-up.[32]

Geographic variables: In the NEG theories, trade costs are conceived as a mixture of various factors that hinder the free movement of goods between countries, e.g., tariffs and quotas, non-tariff barriers, customs inefficiency, transportation costs, etc. However, it is not possible to find a simple variable that can take account of all of these costs.[33] Instead, we focus on a proxy for transportation costs, namely, the Euclidean distance between countries or regions. We use the distances [*DIST*] of each country's capital city from Brussels to measure trade costs from each country to access the entire EU market. Brussels is chosen as it is seen by many leading pharmaceutical MNEs as the key distribution centre in Europe.[34] We expect that the larger is the distance from

[31] These financial factors include: the statutory tax rate, the fixed asset-deprecation rate, the interest rate and the inflation rate.

[32] Devereux and Griffith (1998) tested a panel of US MNEs' location choices across three European countries and found that the effective tax rate had a negative impact on the probability of a country being chosen.

[33] We focus on distance only on the grounds that other trade costs have been reduced by the SMP.

[34] An industry specialist identified this institutional feature of the market.

one country's capital to Brussels, the higher the costs of accessing the integrated European market for a manufacturer from this country and thus the lower the probability of this country being chosen.

Following Bartik (1985), Woodward (1992) and Hogenbirk and Narula (2004), we also include land mass [*AREA*] in specifications for the new-subsidiary sample in order to control for the dart-board concept, i.e., the larger is the land mass of a country, the more new investments it can take if all other country-level characteristics are the same.

Infrastructures: The quality of infrastructure is measured by motorway density (km per million inhabitants) which is derived from EUROSTAT and OECD database. We expect a positive relationship between location choices.

MNE-specific Country-level Variable

Familiarity: A familiarity variable [FAM] is generated for each firm in the new-subsidiary sample. It equals 1 for a country if a new firm in that country has an MNE parent or sister subsidiary already located in that country.[35] Potentially, this indicator variable might capture the knowledge of an MNE on the business environment of a particular country, the MNE's intra-country upstream-downstream linkages, or its marketing network in that country. Familiarity is confirmed as having a positive impact on MNEs' overseas investments in Rangan (2000), who finds that MNEs invest more in 'familiar' countries. Mataloni (2007) also finds a positive correlation between this variable and the location choices of US MNEs in the EU.

Firm-Heterogeneity Variables

Because firm heterogeneity is found to be important in the location decisions of MNEs[36], we construct four firm-heterogeneity variables and interact them with country-level variables to isolate the responses of different firms to country-level characteristics. It should be noted that this firm heterogeneity is different from cross-MNE parent variation in β_i in the MXL, since the latter can only be estimated as variance, not as an

[35] By this definition, FAM can be regarded as a hybrid variable at both country-level and firm-level.

[36] Basile *et al.* (2003) and Hogenbirk and Narula (2004) examine the firm heterogeneity among the US, Japanese and EU MNEs.

exact effect.

Firm ownership: Two dummy variables, [*EU*] and [*US*] are created to capture the nationality of the MNE parent: an EU MNE parent and a US MNE parent, respectively.[37] In addition, a dummy variable [*TOP*] is created for those firms belonging to the top 50 global pharmaceutical MNEs (rank comes from SCRIP 100, 2005/2006), to capture the dominance of these particular MNEs in the development of the European market.[38]

Firm production size: An MNE's decision to increase production may take the form of an expansion in production in one or more subsidiaries or the creation of one or more new subsidiaries in countries having certain characteristics. These choices may be influenced by the scale of increase intended. By interacting the size of production increment with a country-level characteristic, we may identify the effect of this characteristic on location choice associated with different levels of production size. A production-size variable [*SIZE*] is obtained from *Amadeus*. For a high-expansion subsidiary, this variable equals the difference in its operational revenues between 2003 and 1995. For a new firm, it equals its operational revenues in the third year following the year in which that new firm was incorporated on the basis that a firm needs time to reach its designed production capacity.

All country-level variables and firm-heterogeneity variables are listed along with their sources and expected signs in Table 6B.1 .

6.3.4 Specifications of Models

All explanatory variables enter the CLM and the MXL models in logarithm form except those variables that are already in percentage form, such as *PHARSHR/2*, *CHEMSHR/2*, *EATR*, *MKSHARE* and *EDU3*. The use of logarithms allows us to interpret the estimated coefficients as elasticities[39], while the coefficients of variables included in per-

[37] MNE parent's nationality is decided by the location of their headquarters.

[38] Some 17 out of the 50 top pharmaceutical MNEs in the world are US MNEs, while another 17 MNEs are European MNEs.

[39] Another aim of taking logarithms of the explanatory variables is to solve a technical problem in the regression. GLLAMM cannot handle random-parameter variables that have a large variation in values, e.g., across country variation in market size and pharmaceutical production are large enough to cause this problem. Although this is just a requirement for the MXL, for the purpose of comparison, we also

centage form can also be converted into elasticities (see the next section and Appendix (Section 6.6) for details). For the high-expansion sample, most country-level variables enter the model as their average values, based on as many years as are available over the sample period, with agglomeration variables lagged by one year to reduce endogeneity.[40] For the new-subsidiary sample, where possible, all country-level variables are lagged by one year prior to the year when the subsidiary was established, in order to minimise the simultaneity problem and to account for the fact that decisions to locate are influenced by what happens in the period prior to the investment.

In order to estimate random parameters in the most efficient way in the MXL, *PHAR/2*, *CHEM/2*, *PHARSHR/2*, *CHEMSHR/2*, *MKSIZE* and *EATR* are set as having random parameters because we are mainly interested in their effects, while other explanatory variables are set as having fixed parameters.[41]

Thus the two baseline models of the CLM and the MXL for the high-expansion sample and the new-subsidiary sample respectively are:

High-expansion sample

$$\begin{aligned}\Pr(y = j|1, ..., J) \\ = \Lambda(\beta_1 \ln MKSIZE_j + \beta_2 EATR_j + \beta_3 \ln DIST_j + \beta_4 \ln LCOST_j \\ + \beta_5 EDU3_j + \beta_6 \ln MOTDEN_j + \varepsilon_j).\end{aligned} \tag{6.6}$$

use logarithms in the CLM.

[40] Expansion took place over the period from 1995 to 2003 and it was continuously influenced by the country-level variables and their changes in every year; therefore variables in any single year cannot capture their aggregated effects on expansion.

[41] GLLAMM utilises a numerical simulation technology to maximise the log-likelihood for the MXL, which implies a heavy computation load. Generally the computation load is proportional to the sample size and increases exponentially with the number of the random parameters involved in the estimation. Technical issues on the estimation and simulation methods are discussed in Train (2003) and Rabe-Hesketh *et al.* (2004). Further information about GLLAMM is available at www.gllamm.org.

New-subsidiary sample

$$\begin{aligned}
&\Pr(y = j|1, ..., J) \qquad (6.7)\\
&\quad = \Lambda(\beta_1 \ln MKSIZE_j + \beta_2 EATR_j + \beta_3 \ln DIST_j + \beta_4 \ln AREA_j\\
&\quad + \beta_5 \ln LCOST_j + \beta_6 EDU3_j + \beta_7 MKSHARE_j + \beta_8 \ln MOTDEN_j\\
&\quad + \beta_9 FAM_j + \varepsilon_j).
\end{aligned}$$

After the baseline models are estimated, alternative agglomeration variables are added into the models. In addition, to study cross-firm variations in response to the country-level characteristics, four firm-heterogeneity variables will be interacted with each of the explanatory variables. Each interaction term will be included in the models separately in order to avoid multi-collinearity between them. Details of how we estimate the interaction terms are described in the relevant section later.

6.4 Results

Before describing the results, we first explain how estimated coefficients can be interpreted so as to have straightforward economic interpretations. We derive the average probability elasticity (APE) of an explanatory variable which is in logarithmic form by differentiating Eq. (6.6) or (6.7) with respect to the variable. The same method is also used in Head *et al.* (1995) and Head and Mayer (2004). The APE is given by

$$\beta_k(1 - \frac{1}{J}),$$

where β_k is the coefficient of the variable of interest and J is the number of alternative countries in the choice set. In this study, there are eleven countries in the alternative set, so this implies the coefficients on the logarithmic variables need to be multiplied by 0.91 to get the APE. The derivation of the APE is given in Section 6.6.

Some variables are in percentage form, and their APEs have to be calculated with the aid of statistical packages. Details are given in Appendix (Section 6.6).

The familiarity variable FAM is a dummy variable taking values of 0 or 1. To calculate its APE, we firstly calculate two counter-factual outcome probabilities with FAM

being 0 or 1 in Eq. (6.7) using the statistical package. Then the difference between the two probabilities is averaged over MNEs and countries to obtain the APE.

6.4.1 Results of the CLM and the MXL for the High-expansion Sample

CLM: Entire Period

In Table 6.1 we report the results of the baseline model of the CLM and its variations with four alternative agglomeration variables being added separately. These agglomeration variables are all related to the number of domestic and foreign-owned firms. The data cover the time period from 1995 to 2003.[42]

The baseline model Eq. (6.6) is reported in Col. 1. The market size (lnMKSIZE) shows a positive effect on the probability of a country being chosen by MNEs and the coefficient is statistically significant at the 1 per cent level. The coefficient has a corresponding APE that if the market size of drugs and medicines increases by 1 per cent in an average country, the probability of the country being chosen by MNEs will increase by 1.1 per cent. This is consistent with what we expect and with results found in other studies, namely, market size still matters in the Single Market despite the fact that the additional costs of transaction across national borders are supposed to be negligible. The coefficient of the effective average tax rate (EATR) is statistically significant and negative with an APE of approximately -3.4 per cent. The distance from Brussels (lnDIST) has a negative effect, which suggests MNEs were more likely to expand production in those countries that are closer to the European "market hub" Brussels. This result is consistent with MNEs in the post-SMP era taking the integrated EU market into account as well as the national market.

Labour costs (lnLCOST) are found to have a statistically significant negative effect (the APE is approximately -1.2 per cent) on location choice. This significant effect is presented even when labour quality (EDU3) is controlled for, although EDU3 does not have a significant effect. lnMOTDEN, serving as a proxy for the development of infrastructure, is found to have a positive effect.

[42] We present the estimations using the number of foreign-owned firms as the agglomeration variables in Tables 6C.1 - 6C.9 and will discuss them in Section 6.4.3.

So far, several determinants of location choice are identified. However, we have one concern over the robustness of these effects because, as mentioned in Section 6.3.2, Germany-based firms are underrepresented in *Amadeus* and consequently in our high-expansion sample. Such selection-bias may distort the estimation of effects of some variables which are particularly large or small in the biased country. We address this concern by including a Germany dummy variable in the baseline, in the hope that it will control for the Germany fixed effect.[43] The results are reported in Col. 2. Not too surprisingly, because German firms are underrepresented, the dummy variable has a strong negative coefficient and it is significant at the 1 per cent level. To our surprise, in terms of the other explanatory variables, the effects of four of them disappear, including the tax rate. This change demonstrates the consequence of the selection bias. Because Germany has the highest tax rate amongst all alternative countries, the low presence of German subsidiary firms exaggerates the negative effect of the tax rate. On the other hand, the effect of market size remains and labour quality gains an expected positive effect. This result suggests that it is necessary to control for the selection bias in German subsidiary firms in our sample.

In Cols. 3 to Col. 6, we report the results of models with four alternative agglomeration variables added in one at a time. In Cols. 3 and 4, the number of domestic and foreign-owned firms (lnPHAR) and its share form (PHARSHR) show positive effects. The former is statistically significant at the 1 per cent level while the later only at the 10 per cent level. These results suggest that, given that trade costs were lower and possibly still decreasing in the post-SMP era, the potential agglomeration force on the location choice of MNEs did work in a systematic direction. This is consistent with the Krugman-Baldwin models (Figure 5A.1 in Chapter 5) and also consistent with the Venables-Puga models (Figure 5A.2 in Chapter 5) but only in the range where trade costs are moving from a very high to a medium level – in other words, before congestion costs arise.

However, our agglomeration variables to proxy the upstream-downstream link-

[43] Dropping Germany from the choice set yields the same results. But we keep Germany for the sample size issue.

ages between the pharmaceutical industry and the chemical industry do not show significant effects in Cols. 5 and 6. Therefore, this finding does not support the argument in the Venables-Puga models that the agglomeration force is generated by the upstream-downstream linkages among industries, at least for these two particular industries.

Turning to other country-level variables, lnMKSIZE shows a positive and significant effect in three out of four specifications (Cols. 2 - 4).[44] The APEs range from 0.8 to 1 per cent for a 1 per cent increase in the value of this variable. This is consistent with what we observe in the baselines. The coefficients of EATR are statistically insignificant in four specifications nor does it have the expected negative sign in Cols. 4 and 6. This finding further reinforces our concern that the selection bias of German subsidiary firms is causing the exaggeration of the negative tax-rate effects while in fact the corporate tax rate plays no role in the location choice of pharmaceutical MNEs in terms of production expansion. We think the non-effect of the tax rate can be interpreted in this way: usually the corporate tax rate is found to be an important driver negatively affecting the location choice of investments(see related studies reviewed in Section 6.2), our contradictory finding may be regarded as evidence of how apt the pharmaceutical MNEs are in relocating profits between countries through internal transactions in their local branches. Therefore, they are less sensitive to the differences between national tax regimes when making the decisions of where to expand production. The distance from Brussels also has statistically insignificant effect. Labour quality is marginally significantly positive in Col. 5, while motorway density has positive effects in Cols. 3 and 4. Finally , the Germany dummy variable has a much larger coefficient than most other variables and is significant at the 1 per cent level in all four specifications.

To briefly summarise the findings so far: we identify three out of eleven explanatory variables as the key determinants of location choice of MNEs in terms of production expansion in the 9-year period – they are agglomeration, market size and motor-

[44]The non-significant coefficient of the market size is probably caused by the very high correlation of lnMKSIZE and lnPHAR, which is larger than 0.9. The use of the relative measure of agglomeration would alleviate this issue.

way density.

CLM: Two-period Analysis

One question that may arise is whether these determinants exert the same influences over the entire post-SMP era? Particularly for the agglomeration of pharmaceuticals, the E-G indices in Figure 5.1 (d), Chapter 5, measured by gross output, show that a dispersing trend appears first until 1997 and then an agglomerating trend ensues up to 2002. This finding assures a two-period analysis. The entire sample period is divided equally into two sub-periods, which are 1995 - 1999 and 1999 - 2003 respectively. High-expansion subsidiaries in these two sub-periods are re-identified separately using the same definition as given in Section 6.3.2. The high-expansion subsidiaries are not identical in the two sub-periods and country choice sets are also not identical, which will reflect potential differences in the determinants of location choice across the two sub-periods, if there is any.[45] The results of the two-period analysis are reported in Table 6.2. In Cols. 1 and 2, we report the results of the specifications with PHARSHR and the Germany fixed effect.[46] We replace PHARSHR with CHEMSHR and repeat the analysis again. The results are reported in Cols. 5 and 6. Comparing the two sub-periods reveals the following results:

1. Agglomeration in pharmaceuticals does not show any statistically significant effect in both periods. On the other hand, the negative effect of agglomeration in chemicals is evident in the later period (Col. 6);

2. The effect of the market size is consistently positive in all specifications, and the pattern is that it is slightly stronger in the later SMP period than in the earlier period;

3. The effect of the distance from Brussels is significantly negative in the later period (Cols. 2 and 6) with some variation in the significance level;

[45] In the earlier period we locate 219 high-expansion subsidiaries and the country choice set is exactly the same as that of the entire period; in the later period there are 219 high-expansion subsidiaries and Austria is added into the previous 11-country choice set.

[46] We do not use the specifications with the absolute agglomeration variables because of the strong correlation between each of them and market size.

4. The effects of labour costs and labour quality show consistent patterns and worked in the expected way in the later period, while they did not play a role in the earlier period;

5. Motorway density only shows significantly positive effects in Col. 2, and this effect does not exhibit any consistent inter-temporal pattern. Also the corporate tax rate only has a marginally significant effect in Col. 2. Therefore, we are not able to draw any definite conclusions about their effects in the two sub-periods.

The partition point, 1999, is chosen arbitrarily because it is the mid-point of the entire period. But robustness tests were also done using two other partition points - 1998 and 2000, and similar patterns are found.

The two-period analysis reveals a richer picture of how MNEs responded to the institutional changes in the EU: instead of relocating their existing production capacity immediately upon the implementation of the SMP, the MNEs were still attracted by the national market size. Not until in the later period, seven years after 1992, did they begin to look for the places that were close to the European geographic centre (hence close to the enlarged EU market), with lower labour costs and higher labour quality. Moreover, in the later period they shifted production from the countries that are agglomerated in chemicals to countries with less agglomerated chemicals. Negative effect of agglomeration in chemicals provides some evidence of negative agglomeration effects at play.[47] We propose two interpretations for this finding: first, the upstream-downstream linkages between the pharmaceutical and chemical industries were strong. But as pharmaceutical R&D and production process become more and more complicated and specialised due to the intensive applications of bio-technologies (Ørnskov and Dukes, 1992, Gambardella, 2000 and SCRIP 100, 2005/2006), the linkages become weaker. Instead, the two industries may be competing for resources such as serviced land, skilled workers or pollution permits. Therefore, it is possible to observe the negative agglomeration effect from the presence of chemicals. Second, in

[47]The negative agglomeration effect is also found in Hogenbirk and Narula (2004) that the capital region of the Netherlands, the presence of local business seems to work as a deterrent for new foreign establishments.

Chapter 5 we analyse the dispersion trend in the geographic distribution of the pharmaceutical industry, but in this Chapter it is challenged by the estimated positive agglomeration effect inside pharmaceuticals. However, suppose this dispersion trend is not confined to the pharmaceutical industry only, but is also true for the chemical industry as a whole, we may be able to observe a negative response of pharmaceuticals to the agglomeration of chemicals, which is actually reflecting the overall trend in the broad chemical industry. We think the agglomeration patterns of each component of the chemical industry deserve more exploration, though it is beyond our research scope in this thesis.

Overall, the inter-temporal patter of determinants suggest that the progress of the SMP in terms of this industry was slow and trade costs were still strong enough between the EU member states so as to lock the MNEs effectively in the existing locations until the later period. Interestingly, even in the later period from 1999 to 2003, we still see that MNEs were attracted by the national markets' characteristics, suggesting that there was something hindering the free movement of pharmaceutical products that has not yet been abolished.

CLM: Exploring Firm Heterogeneity

We introduce firm ownership and size effects into the CLM by interacting either the ownership dummies or the size with each of the explanatory variables, in the hope of identifying the heterogeneous responses of MNEs to the country-level characteristics. Because the interaction terms are highly correlated with each other, they enter the model separately.[48] Since there are four firm-heterogeneity variables and ten country-level variables, in total forty estimations are made.[49] Only the statistically significant coefficients of the interaction terms are reported in Table 6.5 , along with the major effects of the corresponding country-level variables.

Because we are examining the effect of the interaction terms, we decide to be stricter

[48] Usually the coefficient of correlation for any pair of interaction terms is higher than 0.8.

[49] The specification used is the one with PHARSHR. We repeat the same analysis for the specifications using lnPHAR, lnCHEM and CHEMSHR. The results show very similar heterogeneous effects of country-level variables as those reported in Table 6.5. Therefore, we do not report them.

when we identify those statistically significant effects. Hence, our attention is restricted to the nine interaction terms whose coefficients' 95 per cent confidence intervals do not contain zero. Looking at the major and interaction effects in the context of EU MNEs (Regressions 3, 4 and 5), we find that, in terms of their production-expansion decisions, they respond relatively more positively to motorway density, while relatively less positively to agglomeration in pharmaceuticals and chemicals. The elasticity interpretation can also be applied to the interaction terms. Notice here that we interpret the effect of the interaction variables in an unusual way. We do not report the combined effect of the major effect and the interaction effect because often the major effect is not statistically significant. So the interaction effect is singled out and interpreted as a marginal APE (marginal in the sense that the dummy variable changes its value from 0 to 1). Simply to say, the marginal APE of a dummy variable, such as EU, US or TOP MNE, equals $\rho_X(1-\frac{1}{J})$, where J is the number of countries in the choice set and ρ_X is the coefficient on interaction term (the derivation of this marginal APE is presented in Appendix (Section 6.6). The interpretation of the marginal APE, in the case of being an EU MNE, is that if motorway density in an average country increases by 1 per cent, the probability of this country being chosen by an EU MNE will be 0.8 per cent higher than the same probability by a non-EU MNE. Similarly, the EU MNEs have a 0.6 per cent lower probability of choosing the countries that are agglomerated in pharmaceuticals or chemicals.

Interestingly, however, we see in Regression 6 that US MNEs respond relatively negatively to motorway density, with an APE of approximately -0.7 per cent. The results of Regressions 8, 9 and 10 suggest that the top 50 global pharmaceutical MNEs are less likely to expand in countries with higher labour quality, higher motorway density and higher relative presence of chemical firms, relative to non-top MNEs.

In Regressions 14 and 15, when SIZE, which measures the dimension of production expansion, is interacted with lnDIST and lnLCOST respectively, the coefficients of interaction terms are all significant at the 5 per cent level. Because SIZE is a continuous variable, we evaluate its interaction effect as a marginal APE by taking the

second derivative of the APEs of lnDIST or lnLCOST with respect to SIZE and averaging it over all MNEs and countries (see Appendix Section 6.6). The marginal APE of SIZE in terms of lnDIST is -0.1 per cent, which states that: given the size of production expansion increases by 1 per cent and the distance of a country is 1 per cent further away from Brussels, the probability of an MNE choosing this country will be 0.1 per cent lower. Though the marginal effect is small, it still suggests that an MNE experiencing greater production expansion tend to prefer the country which is closer to Brussels more. This evidence reinforces the negative effect of the distance in Table 6.1, suggesting MNEs were taking the integrated European into account.

The marginal APE of SIZE in terms of lnLCOST is 0.35 per cent, indicating that an MNE experiencing greater production expansion tend to prefer the country which has higher labour costs more. This positive effect, while is opposite to what one would generally expect, can be explained by the signal theory of labour costs that labour costs work as an indicator of labour quality. Hence, suppose large production expansion would be associated with higher technological level, the MNEs expecting a large expansion are willing to pay high wages on the understanding that the higher pay secures better quality workers (see Békés, 2005).

MXL: Entire Period

As discussed in Section 6.3.1, sometimes the correlation exists between alternative countries due to unobserved country-level characteristics, which results in the violation of IIA. One is able to detect such violation using the Hausman test of IIA. The test is performed for the specifications using the absolute and relative measures of agglomeration (Cols. 3, 4, 5 and 6, Table 6.1) and the results of one specification are reported in Table 6.6 for every country excluded, while the Hausman test on the other specifications produce similar results. χ^2 statistics show that when Germany[50] and Sweden are excluded from the country set, the estimates are significantly different from the es-

[50]The χ^2 statistics for Germany is -31.25. Long and Freese (2006, pp. 244-245) suggest that negative χ^2 statistics normally mean that IIA is not violated. But based on the obvious differences of the estimates from two specifications with and without Germany, we are not ready to accept this explanation but believe that the differences, rather than the χ^2 statistics, are evidence of the violation of IIA.

timates using the complete country set. We conclude that the IIA property cannot hold for the two countries, and the MXL is needed to tackle the correlation problem.

We estimate the MXL using the specifications with the Germany fixed effect (the same as in Cols. 3 to 6, Table 6.1). The results of the MXL are reported in Table 6.8. From Cols. 1 to 4, if we look at the six variables that are set as having random parameters (lnPHAR, lnCHEM, PHARSHR, CHEMSHR, lnMKSIZE and EATR), the MXL estimates are similar to those estimated by the CLM (Table 6.1) in terms of the significance level and the magnitude of the coefficients. One exception is PHARSHR in Col.2, which lose its significance. A close look at the estimates reveals that wherever there is a difference between the estimates of the CLM and MXL, the estimates of the MXL have a lower significance level. This raises the question as to whether the two models give systematically different estimates. The cross-firm variances, σ^2 , of six random-parameter variables at the hierarchy of MNE parent are reported in the same table following the coefficients with their standard errors. Only the variance of the coefficient associated with lnMKSIZE is significant at the 1 per cent level for five out of eight specifications, which means that the effect of market size on MNEs is varying significantly. But these coefficients all lie in the 95 per cent confidence interval of the same coefficient estimated using the CLM (Table 6.1).[51] On the other hand the variances of the coefficients on the other random-parameter variables are all statistically insignificant. This evidence indicates that there is no significant difference between the estimates from the two models.

The comparison of the CLM and the MXL suggests that a model with only fixed parameters, such as the CLM, is suitable for our study. Some relevant studies, such as Defever (2006) also utilises the MXL (together with the CLM) to study the location choice of MNEs in the enlarged EU and finds that the two models produce similar outcomes. Hence, we conclude that by comparing the two discrete-choice models, the application of the CLM and its specification is justified.

[51] This criterion is adopted in Haan (2004) on the comparison of the performance of the CLM and MXL in a study on individuals' labour-supply decisions. He finds that the two models' outcomes do not differ significantly.

Taking the results for high-expansion location choices together, they can be linked to the implications of the NEG theory and the Single Market Programme:

1. Agglomeration in the pharmaceutical industry was preferred by MNEs when making location decisions with regard to production expansion. The positive effect is shown in the entire sample period. This finding is in line with both the Krugman-Baldwin and the Venables-Puga predictions of the agglomeration trend given decreasing trade costs. At the same time the agglomeration in the chemical industry has a negative impact on the probability of an average country being chosen by MNEs and this effect is particularly evident in the later period, indicating that pharmaceutical production has been relocated to locations with a lower presence of chemical firms. Hence this finding does not support the upstream-downstream linkages at work between the pharmaceutical and chemical industry, as suggested in the Venables-Puga models. In terms of the heterogeneous responses of MNEs to agglomeration, we find that EU MNEs and TOP MNEs are less likely to expand production in countries with higher levels of agglomeration in chemicals. Moreover, the EU MNEs also respond negatively to agglomeration in pharmaceuticals (for the entire sample period). The evidence reinforces our argument of weakening linkages between pharmaceuticals and chemicals;

2. National market size attracted MNEs for both the entire period and the two subperiods, while locations close to the European pharmaceutical distribution centre were only preferred by MNEs in the later period. Midelfart-Knarvik *et al.* (2002) noted a dispersion trend in pharmaceutical production away from the European geographic centre, Belgium for the period prior to 1990.[52] Our finding from a firm's perspective, suggests the contrary outturn, i.e., we have no evidence of a dispersion trend in pharmaceuticals after the implementation of the SMP. Although the general expectation in the post-SMP era is that national mar-

[52]Specifically they noted that *"12% of Drugs & Medicines production moved out of Germany and Italy and this production was primarily absorbed by Denmark, the UK, Ireland and Sweden."*(pp.235).

kets would not matter any more, our analysis suggests that the two markets both at the national level and European level were both important considerations to MNEs. Moreover, our finding that MNEs tend to locate in locations that are closer to the European pharmaceutical distribution centre and prefer better motorway infrastructure suggests the growing importance of logistics, which may have influenced the relocation of pharmaceutical production achieved by MNEs in Europe.

6.4.2 Results of the CLM and the MXL for the New-subsidiary Sample

CLM: Entire Period

The results of the CLM for the new-subsidiary sample are reported in Table 6.3, where the first two columns present the results of the baseline models, the next four columns present the baseline models with alternative agglomeration variables included and the last four columns include the country-level fixed effects. The sample period is from 1993 to 2004. The overall results of the baseline models reveal that fewer of the explanatory variables are found to have significant effects compared with the high-expansion sample (Cols.1 and 2), and the selection bias associated with German subsidiary firms does not appear (Col. 2). For instance, only the distance from Brussels and the familiarity of MNEs to the local business environment show the expected effects.

In Cols. 3 to 6, with the alternative agglomeration variables added in the baseline, we find that the pharmaceutical agglomeration has a positive effect on the location choice of MNEs in terms of where to build new establishments, independent of whether agglomeration is measured in an absolute or relative manner. The chemical agglomeration shows a negative effect in Col. 6, although it is only significant at the 10 per cent level. In terms of other explanatory variables, they generally do not have significant effects, with the exception of the distance from Brussels and the labour quality which have some marginally significant effects in Col. 6. In particular, the fact that market size does not have a significant effect is surprising because it contrasts with the findings in many other location-choice studies with respect to new business entities. The familiarity variable (FAM) has a statistically significant coefficient and the coeffi-

cient is stable across all specifications. The APE of FAM reveals that, being familiar with a country increases the probability of choosing it by approximately 2 per cent. This familiarity effect is not as substantial as one may perceive, but still suggests that risk aversion plays a role in the decision-making process of MNEs in terms of where to locate new subsidiaries. One explanation for the low magnitude of the effect is that, from the data collected, we see that many large MNEs already had a wide presence in most EU-15 countries. Therefore whether an MNE is familiar with local environment is not a critical factor because the MNE will typically have several locations which it already has plants. We are worrying that the FAM variable may absorb the other variables' effects. As a robustness check we run the same models without FAM yielding very similar results, suggesting that identifying fewer determinants is not caused by the inclusion of FAM. Finally, we find that the Germany fixed effect is not significant, except in Col. 6.

Since not all possible determinants are included, the omitted-variable issue perhaps is especially worthy of exploration. We do so by including country-level fixed-effect dummy variables in addition to the Germany fixed-effect dummy in the four specifications. Because of colinearity between some country-level fixed-effect variables and the explanatory variables, some fixed-effect variables are dropped. However, we manage to retain the Germany fixed-effect variable and all three key variables – agglomeration, market size and tax rate. The results of the models with the country-level fixed effects are reported in Cols. 7 to 10. The pharmaceutical agglomeration variables lose their significances but lnCHEM gains a surprisingly high positive coefficient. Considering the variations in the significance level and the coefficient, we doubt whether the agglomeration in both industries does have any effect on the location choice of the new-subsidiary creation.

On the other hand, marginally significant effects of the distance from Brussels (Cols. 8 and 10) and motorway density (Col. 9) do not provide any convincing evidence of their true effects. However, the familiarity variable has consistently positive effects across all four specifications and the coefficients are all significant at the 1 per

cent level.

CLM: Two-period Analysis

The entire sample period is divided equally into two sub-periods, which are 1993 - 1998 and 1999 - 2004 respectively. Cols. 1 and 2 of Table 6.4 report the results of the specifications with PHARSHR being the agglomeration variable for the two sub-periods and those of the specifications containing CHEMSHR are reported in Cols. 3 and 4. Since the Germany fixed effect is not significant as seen in Table 6.3, we do not run the regressions with the Germany fixed effect only, but instead including the country-level fixed effects (including that of Germany[53]) all together.[54] In what follows we present the main findings of the pattern from two sub-periods:

1. Pharmaceutical agglomeration appears to have a significantly negative effect in the later period only but chemical agglomeration does not have a significant effect in either period;

2. Market size, the corporate tax rate, land mass, labour costs, labour quality and motorway density do not have significant effects in either periods (with the exception of the distance which shows a positive effect once in the later period, Col. 2. It is only significant, however, at the 10 per cent level.);

3. Market competition (MKSHARE) shows a positive and significant effect in two specifications in the earlier period, while its negative effect in the later period is not significant. According to Baldwin (1995) and Barbosa (2003), this positive effect may arise from the high price-cost margin at the highly-concentrated market. However, they also argue that in the highly-concentrated market the incumbent firms will be motivated to deter new entrants from entering into the market. Our findings support the price-cost margin effect, but not the "deterrent effect";

4. The familiarity variable appears to exert a positive effect consistently in both the earlier and later period.

[53] In Cols. 1 and 3 the Germany fixed-effect dummy is dropped due to high colinearity.
[54] One reference country is excluded to avoid perfect colinearity.

Caution is needed when interpreting these findings because the sample size in each sub-period is reduced significantly. Robustness checks have been performed using different partition points (1999 and 2000) and similar inter-temporal patterns are found.

CLM: Exploring Firm Heterogeneity

We estimate the models of the new-subsidiary sample with the interaction terms and the results are reported at the end of Table 6.5. In Regressions 17 and 18 we see that EU MNEs prefer high motorway density and, if newly-established subsidiaries have a large production capacity, their MNE parents demonstrate a weak preference for the country with which they are familiar. However, for both interaction effects, the 95 per cent confidence intervals contain zero. As such, we are unable to draw any definite conclusions from these findings.

MXL: Entire Period

In Table 6.7, the Hausman tests are reported. If Belgium, the UK[55] and Italy are excluded from the country choice set, the IIA property can be rejected. Therefore, we carry on the MXL estimations. Because the Germany fixed effect is largely not significant in Table 6.3, we only estimate the MXL using the specifications with as many of country-level fixed effects as possible (the same as in Cols. 7 to 10 in Table 6.3) in order to reduce the computational load. Estimates of the MXL are reported in Table 6.9. Compared with estimates in Table 6.3 (Cols.7 to 10), we now find that, only the agglomeration variables and the familiarity variable have significant coefficients, while the distance from Brussels and motorway density do not have any significant effect. The significant pharmaceutical agglomeration effect (Col. 1) when the country-level fixed effects are controlled for is in contrast to the results from the CLM. The positive effect of chemical agglomeration (Col. 3) has similar magnitude as that in Col. 9 of Table 6.3, hence we are less confident to accept this unexceptional large effect.

The variance of the coefficient of lnMKSIZE are significant in Cols. 1 and 3, but the coefficients still lie in the 95 per cent confidence interval of the coefficient from the

[55]The χ^2 statistics of Belgium is -66.31, and for the UK it is -1.14. For the same reason as described in Footnote 50, we believe that when Belgium and the UK are excluded from the choice set, IIA is violated.

CLM estimations, indicating the estimates of lnMKSIZE by the two models do not differ from each other significantly. Hence, we conclude that, generally the two models produce similar outcomes, as was the case for the high-expansion sample, while additional evidence of the effect of the pharmaceutical agglomeration is gained from the advanced model.

We summarise the main findings for the new-subsidiary sample as follows:

1. Agglomeration in the pharmaceutical industry has a significantly positive impact on the location choice of MNEs (in the MXL);

2. We do not find evidence that MNEs were attracted by the national market of pharmaceuticals, but rather they were more likely to locate their new subsidiaries in countries that are close to Brussels. Moreover, if we divide the entire sample into two sub-periods, this "distance-effect" seems to occur in the later sub-period;

3. Being familiar with the local business environment of a country is an important factor for MNEs in deciding whether to establish new subsidiaries in that country, though its effect is not strong.

6.4.3 Robustness Check of Agglomeration Effects

In the above analysis we use the number of both domestic and foreign-owned pharmaceutical or chemical firms as the agglomeration variables. This definition of agglomeration can capture the effect of a broad presence of business activity in said industries, but we are also interested in the relationship among foreign-owned firms. Therefore, as a robustness check, we repeat the analysis using one set of alternative agglomeration variables - the number of foreign-owned firms in both industries (see Section 6.3.3 for the definition of these alternative variables).

The results of the models including these alternative agglomeration variables are reported in Tables 6C.1 - 6C.9. In Tables 6.7 and 6.7 we summarise the major results of the robustness analysis, with the focus being placed on the agglomeration effect. The main findings are described as follow,

High-expansion Sample

1. Looking at the first row of Table 6.7 , which summarises the results of the CLM for the entire sample period, if agglomeration is measured by the total number of large pharmaceutical firms (Col. 1), we can see stable agglomeration effects for both absolute and relative measures. While in Col. 2, when agglomeration is measured by the number of foreign-owned firms, pharmaceutical agglomeration effect remains in only one specification. The stronger effects of the broadly-defined agglomeration variables can be expected and they confirm that pharmaceutical MNEs were attracted by business presence and linkage building at wider industry presence of both domestic and foreign-owned firms, rather than by the presence of foreign-owned pharmaceutical firms;

2. The second row summarises the findings of the two-period analysis. Interestingly, we see that only the total number of domestic and foreign-owned large firms consistently capturing the negative effect of chemical agglomeration in the later period (Col. 1), while the number of foreign-owned firms fails to reveal consistent agglomeration effects in different specifications;

3. The third row summarises the findings of the heterogeneous responses of MNEs to the country-level variables. Noticeably, EU MNEs are found being less likely to prefer agglomeration in both industries if the agglomeration variable is measured by the total number of large pharmaceutical firms (Col. 1), but not if the variable is measured by the number of foreign-owned firms (Col. 2). Nevertheless, in case of total firms, MNEs engaging in larger scale production expansion are indifferent to agglomerated countries, while in case of foreign-owned firms, such MNEs less prefer higher agglomeration in both industries;

4. In the fifth row, we summarise the major findings of the MXL model. Two sets of agglomeration variables all reveal the positive effect of pharmaceutics. Again a possible explanation is the broadly-defined agglomeration measures. The other main difference between the two analyses is that in the first one, the variance

of effect of market size is statistically different from zero in most of the specifications; however the variance is not statistically different from zero in the other analysis.

New-subsidiary Sample

1. For the entire sample period (Row 1, Table 6.7), both agglomeration measures fail to reveal consistent agglomeration effects in different specifications, whether the country-level fixed effects are included or excluded;

2. In terms of the two-period analysis (Row 2), both agglomeration measures show the same inter-temporal pattern of the agglomeration effects;

3. In Row 3, no heterogeneous response of MNEs with respect to the industrial agglomeration is found if the agglomeration is measured by the total number of firms (Col. 1), but if measured by foreign-owned firms, MNEs conducting larger scale expansion are seen to have a lesser preference for locations with the presence of other foreign-owned pharmaceutical firms in both industries. This finding echoes what we find for the heterogeneous responses of the high-expansion sample;

4. The MXL also reveals one major difference between the two analyses - the significant variances of coefficient of market size appear in the first analysis but not the latter one.

To draw conclusion regarding the robustness check of the agglomeration effects, we find that i) for the location choice of production expansion, only the broader definition of pharmaceutical agglomeration provides consistent evidence of its positive impact, and ii) for the location choice of new subsidiaries, we are less certain about the existence of agglomeration effects.

6.4.4 Comparison with Other Location-choice Studies

As discussed in Section 6.2, there are many similar studies on the location choice using discrete-choice models. We choose six studies to serve as a reference point for our

results. They are chosen because they are recent and look at the location choice of MNEs in the EU or Europe. To make the comparison easy to follow, we summarise their subjects of investigation, empirical methods and main findings alongside ours in Table 6.11 and briefly discuss the effects and magnitudes of the identified determinants with emphasis set on the agglomeration variables, market size and the corporate tax rate.

Devereux and Griffith's (1998) findings are summarised in Col. 1 of Table 6.11. They were primarily interested in the effects of various corporate tax rates on the location choice of US MNEs among France, Germany and the UK. They find that the average probability elasticity of choosing these three countries with respect to the effective average tax rate (EATR) ranges from -0.4 to -1.7 per cent. By contrast, our corresponding findings are that the EATR has no effect on MNEs in the location choice of production expansion and new firm creation.

In Col. 2, Basile *et al.* (2003) find positive effects of agglomeration (the APEs are at about 0.4 per cent, while our APEs of the same-industry agglomeration can go up to 0.7 per cent (Col. 7, Table 6.1) and mixed effects of GDP and market potential (the inverse distance-weighted GDP). They also find positive effects of the effective corporate tax rate on the location choice of EU MNEs in 55 EU regions. They point out that this might be due to the fact that some high tax-rate countries attract a large amount of subsidiaries compared with other countries featuring low tax rate, if not equal.

In Col. 3, Head and Mayer (2004) use the number of domestic establishments or Japanese-owned affiliates to proxy the agglomeration effect. The estimated APEs of the agglomeration variables are usually lower than 1 per cent. But their network variable - the number of affiliates of the same Japanese parent – has a larger APE at about 1.2 to 1.4 per cent. Interestingly, our dummy variable, capturing familiarity, also has a relatively strong effect at about 2 per cent, thus confirming the potential importance of business networks and risk aversion in terms of the location of new subsidiaries. They also find that the APE of market potential is about 1.1 per cent, which is very close to our estimation of the APE of market size, yet the variable is not comparable to our

more precise measure of market size by a particular product. The effect of the statutory tax rate is that a one percentage point increase will lead to a decrease in the probability of being chosen by Japanese firms by about 5 per cent.

Disdier and Mayer (2004), summarised in Col. 4, do not include the corporate tax rate in their location-choice model of French MNEs in Western and Eastern Europe. Their agglomeration variable proxies only the local presence of French affiliates, which has an APE of about 0.4 to 0.8 per cent. Their market size variable is country-level GDP, which has an APE of between 0.2 to 0.4 per cent.

In Col. 5, Defever (2006) considers the effects of market potential and agglomeration. His estimates of market potential lead to APEs with a magnitude of up to 1.9 per cent. His agglomeration variables of production firms at sectoral level have APEs at about 0.2 to 0.6 per cent.

In Col. 6 we summarise Mataloni's (2007) study on US MNEs in the EU. His results confirm the consistent positive effects of agglomeration at both country and region level, with coefficient of around 0.5. He also finds that GDP has a positive effect at country and regional level if the conditional logit model is used, but these effects disappear or even become negative in the nested logit model. The statutory tax rate is found to have no effect in the conditional logit model but shows some positive effect in one sub-sample when using the nested logit model.

In summary, given significant variations in the above-mentioned studies, with respect to location-choice sets, econometric methods and the emphasis of the investigation, consensus is generally reached in terms of the effects of agglomeration, market and the corporate tax rate on MNEs' location choice in the enlarged EU. Our findings are consistent with these effects in terms of the same-industry agglomeration and the market size, but not in terms of the tax rate.

6.5 Summary and Conclusions

In this chapter we make use of a discrete-choice framework to study the location choices of pharmaceutical MNEs in the post-SMP era in the EU. The goals of the study are three-fold: firstly, we wish to examine the dispersion trend in the geographic dis-

tribution of pharmaceutical production from a firm's perspective, by looking at how individual MNEs respond to the previous agglomeration status of a country; secondly, we wish to identify country-level determinants in the location choice of MNEs and thirdly, the location choice associated with production expansion and new-subsidiary creation need separate analysis.

Econometric analysis is based on two samples of pharmaceutical subsidiaries of MNEs in Europe. The first sample consists of subsidiary firms that experienced high levels of output expansion in the period between 1995 and 2003, and the second sample consists of new subsidiary firms that were established after 1993.

The main findings with respect to agglomeration are summarised as follows:

1. At least for the major element of production relocation, namely, the expansion of output by existing producers, our findings confirm the prediction of NEG models that an increasingly agglomerated stage as the trade-costs level is reduced. However, one source of agglomeration forces, the upstream-downstream linkages (features in the Venables-Puga models), is not supported, but rather contradicted by the negative effect that we find;

2. The firm-level evidence provided by our location-choice model cannot be reconciled with the findings of the decomposition analysis because the former does not agree on the latter that the production expansion of MNEs was contributing to the aggregate dispersion trend while MNEs' new subsidiaries were discouraging it. We argue that this discrepancy between the two analyses is due to the fact that in the location-choice analysis we only examine half of the existing subsidiaries, i.e., those that were undergoing high-level production expansion. However, the location-choice analysis, on its own, provides us with useful insights about how agglomeration works.

Other important findings which may have implications for the Single Market Programme are that, in the case of MNEs expanding production in their existing subsidiaries, the local markets continue to be important, while the enlarged EU market is

important in the later period. On the other hand, MNEs are more likely to establish their new subsidiaries closer to Brussels but are not influenced by the local market.

We also find the positive effect of motorway density and labour quality, while the negative effect of labour costs in the case of production expansion. And MNEs prefer to locate their new subsidiaries in familiar countries. In terms of ownership and the size dimension of location choice, MNEs respond differently to some country-level characteristics. With respect to the econometric methods, the traditional conditional logit model is not outperformed by the more advanced mixed logit model. This finding suggests that we can rely on the simple and much less computationally-intensive model in future studies.

This research contributes to the location-choice literature in two ways. It contains, to our knowledge, the first completed study of multi-country location choices, measured in terms of output expansion, of multi-country MNEs.[56] Secondly, it is an early application of the MXL to location choice studies, and provides a comparison with the CLM analysis.

The policy implications of this study are: first, we find the hysteretic impact of the SMP on the pharmaceutical industry, which is more significant in the period from 1999 to 2003 because in that period MNEs prefer the access to the enlarged EU market more. This evidence can be useful in the evaluation of effect of the SMP. Second, there are two lessons that are relevant to individual countries that wish to attract the pharmaceutical industry, i) the effectiveness of using tax incentives to attract more investment in this particular sector is questionable, as MNEs do not respond to the corporate tax rate in any way. Hence, industrial policy makers may need to find some new incentives, and ii) because the MNEs that differ in their nationalities and intended production sizes respond differently to various country-level characteristics, the policy markers may need to tailor-make promotion schemes to different potential investors, rather than rely on the one–size-fits-all scheme.

Our analysis is not without its limitations. First, we only manage to obtain pro-

[56] Raymond Mataloni in his 2007 working paper studies the location choice of production expansion of US multinationals in Europe.

duction data for 444 out of 725 existing subsidiaries and 129 newly-established subsidiaries, and therefore the small sample size is a concern. One possibility is to incorporate the two samples. But we feel this is not a good solution to expand sample size. This is because the identification of a new subsidiary is straightforward, but the identification of a high-expansion subsidiary relies on the cut-off point[57] of the growth rate, which is decided subjectively, the two samples are not perfectly comparable. Second, the geographic resolution of our study is at country-level, which is governed by the source data - *Amadeus*, while currently, region-level data are more popular in the location-choice literature. However, we compensate for this limitation by making use of some carefully-compiled industry-level variables, such as the market size of pharmaceuticals and labour costs, which are not available at region-level.

6.6 Appendix: Derivation of the Average Probability Elasticity (APE)

A convenient way to interpret the effect of a continuous explanatory variable x on the probability of location choice is to use the elasticity of this variable. We can average the probability over all countries in the choice set and all MNEs that make choices in order to generate an "average probability elasticity (APE)" E_x, which has a straightforward economic meaning that for a one per cent increase in the value of an explanatory variable x, the probability of an average country being chosen by an MNE will increase by E_x per cent, if the coefficient of this variable is positive, or vice versa if the coefficient is negative, assuming all other variables keep constant. To obtain the APE in a conditional logit model, we need first to use the natural logarithm of x in the probability function, Eq. (6.8) shown below and differentiate it. The probability function is

$$\Pr(y_i = k | \ln x_{i1}, \ln x_{i2}, ... \ln x_{iJ}) = \frac{\exp(\beta \ln x_{ik})}{\sum_{j=1}^{J} \exp(\beta \ln x_{ij})} \tag{6.8}$$

In this function, we let $i = 1, 2, ..., I$ for all MNEs and $j = 1, 2, ..., J$ for all countries in the choice set and $y_i = k$ means country k is chosen by MNE i. We then write the

[57] We use the above-median growth rate to define high-expansion firms.

elasticity in terms of x_{ik} as follows,

$$E_{x_{ik}} = \frac{\partial \Pr(ik)}{\Pr(ik)} / \frac{\partial x_{ik}}{x_{ik}}. \tag{6.9}$$

The right hand side (RHS) of Eq. (6.9) is rewritten to get

$$E_{x_{ik}} = \frac{x_{ik}}{\Pr(ik)} \cdot \frac{\partial \Pr(ik)}{\partial x_{ik}}, \tag{6.10}$$

which is expanded by substituting Eq. (6.8) into it and taking the partial derivative w.r.t x_{ik} to get

$$\begin{aligned}
E_{x_{ik}} &= x_{ik} \frac{\sum_{j=1}^{J} \exp(\beta \ln x_{ij})}{\exp(\beta \ln x_{ik})} \left[\frac{\exp(\beta \ln x_{ik}) \beta \frac{1}{x_{ik}} \left(\sum_{j=1}^{J} \exp(\beta \ln x_{ij}) \right) - \beta \frac{1}{x_{ik}} \exp(\beta \ln x_{ik}) \exp(\beta \ln x_{ik})}{\left(\sum_{j=1}^{J} \exp(\beta \ln x_{ij}) \right)^2} \right] \\
&= \beta \frac{\sum_{j=1}^{J} \exp(\beta \ln x_{ij}) - \exp(\beta \ln x_{ik})}{\sum_{j=1}^{J} \exp(\beta \ln x_{ij})} \\
&= \beta(1 - \Pr(ik)).
\end{aligned}$$

In the next step we average all $E_{x_{ik}}$ over I MNEs and J countries to get the average probability elasticity E_x,

$$\begin{aligned}
E_x &= \frac{1}{I \cdot J} \sum_{i=1}^{I} \sum_{j=1}^{J} E_{x_{ik}} \\
&= \frac{1}{I} \sum_{i=1}^{I} \left\{ \frac{1}{J} \sum_{j=1}^{J} E_{x_{ik}} \right\} = \frac{1}{I} \sum_{i=1}^{I} \left\{ \frac{1}{J} \left[(\beta(1 - \Pr(i1)) + \beta(1 - \Pr(i2)) + ... + \beta(1 - \Pr(iJ)) \right] \right\} \\
&= \beta \frac{1}{I} \sum_{i=1}^{I} \left\{ \frac{1}{J} \left[J - 1 \right] \right\} = \beta \frac{1}{I} \sum_{i=1}^{I} (1 - \frac{1}{J}) = \beta \frac{1}{I} (I - \frac{I}{J}) \\
&= \beta(1 - \frac{1}{J}).
\end{aligned}$$

A variable in percentage form, like the corporate tax rate can also be expressed as a probability elasticity by the same derivation. Let's replace $\beta \ln x_{ij}$ in Eq. (6.8) with γtax_{ij} and then expand the corresponding Eq. (6.10) to get

$$E_{tax_{ik}} = tax_{ik} \frac{\sum_{j=1}^{J} \exp(\gamma tax_{ij})}{\exp(\gamma tax_{ik})} \frac{\exp(\gamma tax_{ik})\gamma \left(\sum_{j=1}^{J} \exp(\gamma tax_{ij}) \right) - \gamma \exp(\gamma tax_{ik}) \exp(\gamma tax_{ik})}{\left(\sum_{j=1}^{J} \exp(\gamma tax_{ij}) \right)^2}$$

$$= \gamma tax_{ik}(1 - \Pr(ik)).$$

Obviously, to derive a simple expression of the APE from the above formula is impossible due to the presence of tax_{ik}, so we need to use a statistical package to calculate the APE once all $\Pr(ik)$s are predicted after estimation.[58] This method of generating the APE can be applied to other variables that are in percentage form or ration form.

The next step is to derive the APE of x if it is interacted with a firm-level heterogeneity variable z_i where our interest still lies in the APE of x. The APE is derived in the following way. First rewrite Eq. (6.8) to get Eq. (6.11)

$$\Pr(y_i = k | \ln x_{i1}, \ln x_{i2}, ... \ln x_{iJ}, z_i) = \frac{\exp(\beta \ln x_{ik} + \rho z_i \ln x_{ik})}{\sum_{j=1}^{J} \exp(\beta \ln x_{ij} + \rho z_i \ln x_{ij})} \tag{6.11}$$

Notice that z_i does not enter the probability equation on its own because there is no within-(MNE)group variation of a firm-level heterogeneity variable, it is unidentifiable and will be dropped from the conditional logit model automatically.

A similar derivation of Eq. (6.10) with necessary changes to the model specification will result in following probability elasticity w.r.t. x_{ik}

$$E_{x_{ik}}^{int} = (\beta + \rho z_i)(1 - \Pr(ik)) \tag{6.12}$$

[58] Another common practice calculates APE by evaluating it at the mean value of the tax rate over all countries and MNEs. With this specification, a simple expression of APE can be derived. It is $\gamma \overline{tax}(1 - \frac{1}{J})$.

where the superscript int indicates that the elasticity is for x_{ik} and its interaction with another variable, say an MNE-specific z_i. Again we can use a statistical package to calculate the APE once the $\Pr(ik)$ is predicted after estimation.

One may also be interested in the marginal effect of z_i imposed on the APE of x, the MAPE E_x^M. The MAPE states that, given a one per cent increase in the value of x, the marginal change of z_i will change the probability of an average country being chosen by an MNE by E_x^M per cent.

To derive the MAPE, first we sum Eq. (6.12) to get the within-group APE for MNE i

$$\frac{1}{J}\sum_{j=1}^{J} E_{x_{ik}}^{int} = (1-\frac{1}{J})\beta + (1-\frac{1}{J})\rho z_i \tag{6.13}$$

Consequently, within any group of i, the marginal APE due to a change from z_i^2 to z_i^1 is $E_x^{M_J} = (1-\frac{1}{J})\rho\triangle z_i$, where $\triangle z_i = z_i^2 - z_i^1$.

In the case that z is a dummy variable, a marginal change of z_i would be from 0 to 1 and this change leads to a within-group i marginal APE of x_i equals $(1-\frac{1}{J})\rho$. Then we can average $(1-\frac{1}{J})\rho$ over I groups to get E_x^M, which equals $(1-\frac{1}{J})\rho$ as well.

In the case that z is a continuous variable, we take the second derivative of Eq.(6.12) w.r.t z_i, which is

$$\frac{\partial E_{x_{ik}}^{int}}{\partial z_i} = [(\beta+\rho z_i)(1-\Pr(ik))]_{z_i}^{'}.$$

The resulting formula of the marginal APE can be evaluated using a statistical package over all the MNEs and all the countries.

6.7 Tables

Table 6.1: CLM: Determinants of the Location Choice, High-expansion Sample Time Period: 1995 - 2003

Explanatory Variable	Col. 1	Col. 2	Col. 3	Col. 4	Col. 5	Col. 6
lnPHAR			0.685***			
			(0.259)			
PHARSHR				0.301*		
				(0.161)		
lnCHEM					0.178	
					(0.382)	
CHEMSHR						-0.164
						(0.213)
lnMKSIZE	1.178***	1.079***	0.343	0.868***	0.956***	1.144***
	(0.150)	(0.132)	(0.276)	(0.152)	(0.293)	(0.155)
EATR	-0.148***	-0.015	-0.02	0.012	-0.027	0.023
	(0.023)	(0.045)	(0.036)	(0.039)	(0.053)	(0.065)
lnDIST	-0.299**	0.067	0.076	0.289	0.006	0.055
	(0.145)	(0.176)	(0.158)	(0.201)	(0.222)	(0.171)
lnLCOST	-1.381**	-0.612	-0.056	0.722	-0.835	-0.68
	(0.549)	(0.535)	(0.531)	(0.825)	(0.734)	(0.519)
EDU3	0.016	0.035**	0.017	0.007	0.031*	0.07
	(0.016)	(0.015)	(0.016)	(0.021)	(0.017)	(0.049)
lnMOTDEN	0.705***	0.298	0.690***	0.535**	0.373	0.101
	(0.195)	(0.196)	(0.239)	(0.234)	(0.253)	(0.323)
Germany fixed effect	no	-2.093***	-1.499***	-1.956***	-1.919***	-2.8***
		(0.559)	(0.523)	(0.507)	(0.679)	(1.066)
Log-likelihood	-436.4	-427.2	-422.5	-425.6	-427.1	-426.9
Prob > χ2	0.000	0.000	0.000	0.000	0.000	0.000
Pseudo R2	0.1803	0.1975	0.2063	0.2006	0.1977	0.198
# of Firms	222	222	222	222	222	222

Note: * significant at 10 per cent level, ** significant at 5 per cent level, *** significant at 1 per cent level; standard error in parenthesis.

Table 6.2: CLM : Determinants of the Location Choice, High-expansion Sample; Two Periods

	Pharmaceutical agglomeration		Chemical agglomeration	
Explanatory Variables	Col. 1	Col. 2	Col. 3	Col. 4
	1995 - 1999	1999 - 2003	1995 - 1999	1999 - 2003
PHARSHR	0.267	-0.105		
	(0.163)	(0.152)		
CHEMSHR			-0.024	-0.546**
			(0.055)	(0.215)
lnMKSIZE	0.917***	1.389***	1.138***	1.497***
	(0.152)	(0.192)	(0.164)	(0.168)
EATR	0.013	-0.113*	-0.011	0.076
	(0.036)	(0.058)	(0.037)	(0.075)
lnDIST	0.41*	-0.498**	0.154	-0.550***
	(0.226)	(0.232)	(0.208)	(0.184)
lnLCOST	0.911	-2.267**	-0.554	-2.525***
	(0.902)	(0.886)	(0.790)	(0.653)
EDU3	0.026	0.056**	0.047	0.123***
	(0.023)	(0.023)	(0.031)	(0.035)
lnMOTDEN	0.312	0.686***	0.075	-0.035
	(0.207)	(0.263)	(0.293)	(0.386)
Germany	-2.068***	-1.315**	-2.117***	-3.996***
fixed effect	(0.510)	(0.576)	(0.553)	(1.145)
Log-likelihood	-416.8	-422.9	-418	-420.4
Prob $> \chi 2$	0.000	0.000	0.000	0.000
Pseudo R2	0.2064	0.2228	0.2041	0.2275
# of Firms	219	219	219	219

Note: * significant at 10 per cent level, ** significant at 5 per cent level, *** significant at 1 per cent level; standard error in parenthesis.

Table 6.3: CLM : Determinants of the Location Choice New-subsidiary Sample Time Period: 1993 - 2004

Explanatory Variables	Col. 1	Col. 2	Col. 3	Col. 4	Col. 5	Col. 6	Col. 7	Col. 8	Col. 9	Col. 10
lnPHAR			0.937**				3.056			
			(0.371)				(1.953)			
PHARSHR				0.269**				-1.42		
				(0.132)				(1.256)		
lnCHEM					-0.68				11.048***	
					(0.603)				(3.702)	
CHEMSHR						-0.342*				-0.597
						(0.176)				(0.722)
lnMKSIZE	0.046	-0.063	-0.777	0.258	0.841	0.248	-5.173	-5.676	-5.874	-5.538
	(0.553)	(0.573)	(0.681)	(0.616)	(0.978)	(0.612)	(4.432)	(4.472)	(4.575)	(4.438)
EATR	-0.023	-0.005	0.026	0.024	0.015	0.032	0.009	0.013	-0.049	0.03
	(0.029)	(0.036)	(0.04)	(0.04)	(0.041)	(0.04)	(0.046)	(0.045)	(0.049)	(0.052)
lnDIST	-0.903**	-0.973**	-0.711	-0.427	-0.565	-0.863*	-1.816	-5.329*	4.814	-5.51*
	(0.453)	(0.465)	(0.453)	(0.503)	(0.565)	(0.46)	(3.467)	(3.139)	(4.461)	(3.246)
lnAREA	0.751	0.877	0.86	0.483	0.466	0.654	3.081	7.038	-2.087	6.425
	(0.542)	(0.567)	(0.573)	(0.591)	(0.66)	(0.583)	(4.741)	(4.363)	(5.290)	(4.285)
lnLCOST	-0.766	-0.915	-0.429	-0.146	-0.476	-0.282	1.073	0.783	0.854	0.517
	(0.943)	(0.962)	(1.015)	(1.045)	(1.023)	(1.018)	(2.044)	(2.058)	(2.05)	(2.124)
EDU3	0.032	0.03	0.04	0.056	0.077	0.114*	0.001	-0.027	-0.128	0.03
	(0.042)	(0.041)	(0.045)	(0.044)	(0.058)	(0.061)	(0.081)	(0.085)	(0.091)	(0.086)
MKSHARE	-0.009	-0.021	0.035	0.019	-0.012	-0.028	0.108	-0.022	0.013	0.031
	(0.035)	(0.038)	(0.044)	(0.042)	(0.039)	(0.04)	(0.114)	(0.115)	(0.113)	(0.108)
lnMOTDEN	-0.121	-0.185	0.157	-0.077	-0.423	-0.25	1.404	1.682	3.684*	0.934
	(0.246)	(0.253)	(0.316)	(0.278)	(0.331)	(0.269)	(1.871)	(1.856)	(2.026)	(2.035)
FAM	1.169***	1.157***	1.104***	1.11***	1.139***	1.113***	1.14***	1.123***	1.161***	1.122***
	(0.246)	(0.247)	(0.248)	(0.248)	(0.248)	(0.247)	(0.251)	(0.248)	(0.251)	(0.249)
Germany fixed effect		-0.461	0.249	-0.365	-1.075	-1.757**	4.993	4.824	-4.012	5.673
		(0.53)	(0.587)	(0.531)	(0.772)	(0.848)	(5.319)	(5.543)	(6.419)	(5.388)
Country fixed effects	no	no	no	no	no	no	yes	yes	yes	yes
Log-likelihood	-248.7	-248.3	-244.9	-246.3	-247.7	-246.3	-242.9	-244.1	-240.1	-244.4
Prob > $\chi 2$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Pseudo R2	0.196	0.1973	0.2084	0.2038	0.1993	0.2036	0.2146	0.2108	0.2239	0.21
# of Firms	129	129	129	129	129	129	129	129	129	129

Note: * significant at 10 per cent level, ** significant at 5 per cent level, *** significant at 1 per cent level; standard error in parenthesis.

Table 6.4: CLM : Determinants of the Location Choice, New-subsidiary Sample; Two Periods

	Pharmaceutical agglomeration		Chemical agglomeration	
Explanatory Variables	Col. 1	Col. 2	Col. 3	Col. 4
	1993 - 1998	1999 - 2004	1993 - 1998	1999 - 2004
PHARSHR	1.042 (1.415)	-6.973** (2.947)		
CHEMSHR			-0.409 (1.077)	2.59 (2.62)
lnMKSIZE	3.313 (2.640)	-4.566 (5.598)	2.167 (1.79)	-3.676 (5.804)
EATR	0.142 (0.113)	-0.151 (0.138)	0.153 (0.112)	-0.204 (0.142)
lnDIST	3.519 (3.252)	-8.15* (4.95)	1.941 (3.913)	4.829 (8.519)
lnAREA	-3.013 (2.776)	8.734 (5.705)	-1.579 (1.967)	3.03 (6.167)
lnLCOST	2.663 (6.328)	-2.254 (4.686)	2.094 (6.475)	-0.78 (4.438)
EDU3	0.303 (0.252)	-0.062 (0.286)	0.282 (0.255)	0.374 (0.274)
MKSHARE	0.467** (0.219)	-0.434 (0.426)	0.525** (0.244)	-0.242 (0.335)
lnMOTDEN	0.412 (2.931)	1.814 (5.604)	-1.015 (1.9)	-1.038 (5.41)
FAM	0.729** (0.331)	1.591*** (0.404)	0.714** (0.33)	1.604*** (0.4)
Germany fixed effect		-3.546 (8.241)		4.2 (6.99)
Country fixed effects	yes	yes	yes	yes
Log-likelihood	-138.7	-88.7	-138.9	-91.2
Prob > $\chi 2$	0.000	0.000	0.000	0.000
Pseudo R2	0.2488	0.2882	0.248	0.2688
# of Firms	77	52	77	52

Note: * significant at 10 per cent level, ** significant at 5 per cent level, *** significant at 1 per cent level; standard error in parenthesis.

Table 6.5: CLM: Selected Interactions of Firm Heterogeneity with Country-level Variables from Multiple Regressions High-expansion Sample (1995 - 2003) and New-subsidiary Sample (1993 - 2004)

	Major Effect		Interaction Effect	Does 95 per cent confidence interval contain zero ?
High-expansion Sample				
Regression 1 EU (dummy) interacts with lnLCOST	lnLCOST	1.397 (0.93)	EU*lnLCOST	-0.914* (0.533)	yes
Regression 2 EU (dummy) interacts with EDU3	EDU3	-0.016 (0.025)	EU*EDU3	0.036* (0.022)	yes
Regression 3 EU (dummy) interacts with lnMOTDEN	lnMOTDEN	-0.027 (0.298)	EU*lnMOTDEN	0.907*** (0.317)	no
Regression 4 EU (dummy) interacts with lnCHEM	lnCHEM	0.714 (0.458)	EU*lnCHEM	-0.629** (0.255)	no
Regression 5 EU (dummy) interacts with lnPHAR	lnPHAR	1.224*** (0.374)	EU*lnPHAR	-0.617** (0.271)	no
Regression 6 US (dummy) interacts with lnMOTDEN	lnMOTDEN	0.741*** (0.254)	US*lnMOTDEN	-0.836** (0.34)	no
Regression 7 US (dummy) interacts with lnCHEM	lnCHEM	0.124 (0.382)	US*lnCHEM	0.573* (0.304)	yes
Regression 8 TOP (dummy) interacts with EDU3	EDU3	0.031 (0.024)	TOP*EDU3	-0.046** (0.021)	no
Regression 9 TOP (dummy) interacts with lnMOTDEN	lnMOTDEN	0.85*** (0.29)	TOP*lnMOTDEN	-0.618** (0.31)	no
Regression 10 TOP (dummy) interacts with CHEMSHR	CHEMSHR	-0.046 (0.22)	TOP*lnCHEMSHR	-0.229** (0.095)	no
Regression 11 SIZE interacts with PHARSHR	PHARSHR	1.303** (0.589)	SIZE*PHARSHR	-0.088* (0.05)	yes
Regression 12 SIZE interacts with lnMKSIZE	lnMKSIZE	-0.242 (0.605)	SIZE*lnMKSIZE	0.099* (0.053)	yes
Regression 13 SIZE interacts with EATR	EATR	-0.313* (0.171)	SIZE*EATR	0.029* (0.015)	yes
Regression 14 SIZE interacts with lnDIST	lnDIST	1.585** (0.657)	SIZE*lnDIST	-0.111** (0.053)	no
Regression 15 SIZE interacts with lnLCOST	lnLCOST	-3.586* (1.954)	SIZE*lnLCOST	0.385** (0.163)	no
Regression 16 SIZE interacts with lnCHEM	lnCHEM	-1.109 (0.798)	SIZE*lnCHEM	0.116* (0.065)	yes
New-subsidiary Sample				
Regression 17 EU (dummy) interacts with lnMOTDEN	lnMOTDEN	0.982 (1.872)	EU*lnMOTDEN	0.569* (0.328)	yes
Regression 18 SIZE interacts with FAM	FAM	3.266** (1.295)	SIZE*FAM	-0.208* (0.124)	yes

Note: * significant at 10 per cent level, ** significant at 5 per cent level, *** significant at 1 per cent level; standard error in parenthesis.

Table 6.6: Hausman Test for the CLM: High-expansion Sample

#	Country excluded	$\chi 2$ Statistics	Conclusion
1	Belgium	2.33	IIA cannot be rejected
2	Denmark	5.49	IIA cannot be rejected
3	France	8.34	IIA cannot be rejected
4	Germany	-31.25	IIA cannot be rejected
5	Greece	4.85	IIA cannot be rejected
6	Ireland	0.22	IIA cannot be rejected
7	Italy	0.51	IIA cannot be rejected
8	Portugal	0.01	IIA cannot be rejected
9	Spain	4.42	IIA cannot be rejected
10	Sweden	19.21**	IIA rejected
11	UK	1.25	IIA cannot be rejected

Note: * significant at 10 per cent level, ** significant at 5 per cent level, *** significant at 1 per cent level; H0: Difference in coefficients of models for subset and full set of countries is not systematic.

Table 6.7: Hausman Test for the CLM: New-subsidiary Sample

#	Country excluded	$\chi 2$ Statistics	Conclusion
1	Austria	1.68	IIA cannot be rejected
2	Belgium	-66.31	IIA cannot be rejected
3	Denmark	3.62	IIA cannot be rejected
4	Finland	2.76	IIA cannot be rejected
5	France	7.74	IIA cannot be rejected
6	Germany	1.56	IIA cannot be rejected
7	Ireland	0.46	IIA cannot be rejected
8	Italy	19.68**	IIA rejected
9	Spain	1.34	IIA cannot be rejected
10	Sweden	4.47	IIA cannot be rejected
11	UK	-1.14	IIA cannot be rejected

Note: * significant at 10 per cent level, ** significant at 5 per cent level, *** significant at 1 per cent level; H0: Difference in coefficients of models for subset and full set of countries is not systematic.

Table 6.8: MXL: Determinants of the Location Choice, High-expansion Sample; Time Period: 1995 - 2003

Explanatory Variables	Col.1	Col. 2	Col. 3	Col. 4
lnPHAR	0.688**			
	(0.337)			
Variance	*0.036*			
	(0.186)			
PHARSHR		0.233		
		(0.188)		
Variance		*0.003*		
		(0.017)		
lnCHEM			0.288	
			(0.470)	
Variance			*1.576*	
			(1.266)	
CHEMSHR				-0.033
				(0.247)
Variance				*0.002*
				(0.008)
lnMKSIZE	0.402	0.977***	1.048***	1.177***
	(0.336)	(0.223)	(0.365)	(0.171)
Variance	*0.001*	*0.04****	*1.3****	*0.055****
	(0.022)	*(0.009)*	*(0.094)*	*(0.008)*
EATR	-0.022	0.006	-0.003	-0.004
	(0.042)	(0.047)	(0.080)	(0.080)
Variance	*0.002*	*0.004*	*0.014*	*0.009*
	(0.005)	*(0.007)*	*(0.012)*	*(0.01)*
lnDIST	0.079	0.265	0.221	0.129
	(0.162)	(0.205)	(0.288)	(0.196)
lnLCOST	-0.142	0.379	-0.599	-0.572
	(0.550)	(0.962)	(0.822)	(0.562)
EDU3	0.02	0.016	0.043**	0.046
	(0.017)	(0.024)	(0.019)	(0.054)
lnMOTDEN	0.682***	0.473*	0.356	0.261
	(0.247)	(0.257)	(0.304)	(0.362)
Germany fixed effect	-1.583***	-2.145***	-2.437***	-2.463**
	(0.604)	(0.644)	(0.893)	(1.166)
Log-likelihood	-422.3	-425.2	-424.2	-426.1
# of Firms	222	222	222	222

Note: * significant at 10 per cent level, ** significant at 5 per cent level, *** significant at 1 per cent level; standard error in parenthesis.

Table 6.9: MXL: Determinants of the Location Choice, New-subsidiary Sample; Time Period: 1993 - 2004

Explanatory Variables	Col.1	Col. 2	Col. 3	Col. 4
lnPHAR	4.448**			
	(1.966)			
Variance	*10.194*			
	(11.726)			
PHARSHR		-1.367		
		(1.284)		
Variance		*0.014*		
		(0.085)		
lnCHEM			13.717***	
			(4.219)	
Variance			*3.204*	
			(4.306)	
CHEMSHR				-0.526
				(0.763)
Variance				*0.067*
				(0.135)
lnMKSIZE	-4.739	-5.528	-5.573	-4.947 F
	(4.601)	(4.511)	(4.640)	(4.578)
Variance	*6.22****	*0.007*	*1.096****	*0.014*
	(0.68)	*(0.009)*	*(0.226)*	*(0.026)*
EATR	-0.016	0.014	-0.063	0.023
	(0.067)	(0.046)	(0.057)	(0.059)
Variance	*0.033*	*0.000*	*0.014*	*0.002*
	(0.041)	*(0.001)*	*(0.017)*	*(0.006)*
lnDIST	-0.706	-5.180	6.793	-5.025
	(3.543)	(3.195)	(4.659)	(3.396)
lnAREA	1.656	6.863	-4.199	5.837
	(4.834)	(4.410)	(5.457)	(4.431)
lnLCOST	0.593	0.780	0.310	0.715
	(2.235)	(2.069)	(2.207)	(2.223)
EDU3	0.094	-0.022	-0.132	0.033
	(0.101)	(0.088)	(0.101)	(0.089)
SHARE	0.041	-0.022	-0.048	0.042
	(0.145)	(0.116)	(0.123)	(0.111)
lnMOTDEN	0.942	1.592	1.733	0.813
	(2.001)	(1.955)	(2.707)	(2.129)
FAM	1.161***	1.115***	1.067***	1.167***
	(0.281)	(0.251)	(0.279)	(0.266)
Germany fixed effect	3.459	4.640	-7.689	5.094
	(5.818)	(5.600)	(6.772)	(5.509)
Country Fixed effects	yes	yes	yes	yes
Log-likelihood	-241.7	-244	-239	-244.1
# of Firms	129	129	129	129

Note: * significant at 10 per cent level, ** significant at 5 per cent level, *** significant at 1 per cent level; standard error in parenthesis.

Table 6.10: Summary of the Robustness Check: High-expansion Sample

	Agglomeration Variable A	Agglomeration Variable B
CLM, entire sample period (Table 6.1, Table 6C.1)	Positive pharma. aggl. effects in Cols. 3 and 4 for both absolute and relative measures; Motorway density shows significant positive effect in Cols. 1, 3 and 4; All other variables generally show similar effects like what in the other analysis.	Positive pharma. aggl. effect only appears in Col. 4 for relative measure; Motorway density only shows significant positive effect in Cols. 1 and 3; All other variables generally show similar effects like what in the other analysis.
CLM, Sub-periods (Table 6.2, Table 6C.2)	Negative chem. aggl. effect in the later period (Cols. 6); Market size has consistent positive effect in all 4 spec.; Distance shows marginally significant positive effect in the earlier period and negative effect in the later period; Labour costs show consistent negative effect in the later period while labour quality shows consistent positive effect in the later period; Motorway density shows positive effects in the later period (not consistent in different spec.).	Positive pharma. aggl. effect in both periods; Market size has consistent positive effect in all 4 spec.; Distance shows no effect in the earlier period and but consistent negative effect in the later period; Labour costs show consistent negative effect in the later period while labour quality shows positive effect in the later period (not consistent in different spec.); Motorway density shows no consistent effect in different spec..
CLM, Firm heterogeneity (Table 6.5, Table 6C.5)	EU MNEs less prefer aggl. (pharma. and chem.), while prefer better motorway density;	EU MNEs prefer better motorway density;

US MNEs less prefer better motorway density;	US MNEs less prefer better motorway density;
Top MNEs less prefer better labour quality, better motorway density and higher chem. aggl.;	Top MNEs less prefer better labour quality and better motorway density;
Larger expansion prefers being close to Brussels, higher labour costs.	Larger expansion prefers larger market size, being close to Brussels, higher labour costs, less prefer pharma. and chem. aggl., respond less negatively to tax rate.

Hausman (Table 6, Table A4.6)	Reject IIA for Germany and Sweden.	Reject IIA for Belgium, Germany and Sweden.
MXL, entire sample period (Table 6.8, Table 6C.8)	Positive pharma. aggl. effects in Cols. 1; The variance of the markets size's effect is significantly different from zero in Cols. 2-4; EDU3 has positive effect in Cols. 3; Motorway density has positive effects in Cols. 1 and 2.	Positive pharma. aggl. effect only in Col. 2; no chem. aggl. effect; The variances of the markets size's effect are all not significantly different from zero; All other explanatory variables do not have effects.

Agglomeration variable A: The number of domestic and foreign-owned large firms in the pharmaceutical (chemical) industry. See Section 6.3.3 for detailed definition.

Agglomeration variable B: The number of foreign-owned firms in the pharmaceutical (chemical) industry. See Section 6.3.3 for detailed definition.

Table 6.11: Summary of the Robustness Check: New-subsidiary Sample

	Agglomeration Variable A	Agglomeration Variable B
CLM, entire sample period (Table 6.3, Table 6C.3)	No consistent pharma. or chem. aggl. effects (for both absolute and relative measures); All other variables generally show similar effects like what in the other analysis, if any.	No consistent pharma. or chem. aggl. effects (for both absolute and relative measures); All other variables generally show similar effects like what in the other analysis, if any.
CLM, Sub-periods (Table 6.4, Table 6C.4)	Pharma. aggl. has negative effect in the later period only. Chem. aggl. shows no effect; Consistently positive effect of competition in the earlier period (Cols. 1 and 3); Consistently positive effect of the familiarity variable; All other variables generally show similar effects like what in the other analysis, if any.	Pharma. aggl. has negative effect in the later period only. Chem. aggl. shows no effect; Consistently positive effect of competition in the earlier period (Cols. 1 and 3); Consistently positive effect of the familiarity variable; All other variables generally show similar effects like what in the other analysis, if any.
CLM, Firm heterogeneity (Table 6.5, Table 6C.5)	No significant heterogeneity effect found.	Larger new firm less prefers pharma. and chem. aggl.
Hausman (Table 6.7, Table 6C.7)	Rejected for Belgium and Italy.	Reject IIA for France and Italy.

MXL, entire sample period (Table 6.9, Table 6C.9)	Positive pharma. and chem.. aggl. effects in Cols. 1 and 3; The variance of markets size's effect is significantly different from zero in Cols. 1 and 3.	Positive chem. aggl. effects in Col. 3; The variance of markets size's effect is not significantly different from zero; Negative distance effect and positive country size effect in Col. 2.

Agglomeration variable A: The number of domestic and foreign-owned large firms in the pharmaceutical (chemical) industry. See Section 6.3.3 for detailed definition.

Agglomeration variable B: The number of foreign-owned firms in the pharmaceutical (chemical) industry. See Section 6.3.3 for detailed definition.

Table 6.12: Comparison with Other Location-choice studies

	D&G (1998)	B (2003)	H&M (2004)	D&M (2004)	D (2005)	M (2007)	Our Results
Object	US MNEs' new establishments (firms)	New foreign subsidiaries (EU and US parents)	Japanese MNEs' new subsidiaries	French MNEs' subsidiaries	MNEs	US MNEs	Pharmaceutical MNEs
Time frame	1980 - 1994	1991 - 1999	1984 - 1995	1980 - 1999	1997 - 2002	1996 - 2003	1993 - 2004
Location-choice set	France, Germany and the UK	55 regions in 8 EU countries	57 regions in 9 EU countries	19 countries in Western and Eastern Europe	23 countries in the enlarged Europe	55 regions in 7 EU countries	14 EU countries
Econometric method	Nested multinomial logit	Nested logit	Nested logit	Conditional and nested logit	Conditional and mixed logit	Conditional logit and nested logit	Conditional logit and mixed logit
No. of observations	597 establishments	5,761 subsidiaries	452 subsidiaries	1,843 affiliates	11,000 investment projects	682 subsidiaries	222 high-expansion subsidiaries / 129 new subsidiaries
A. Agglomeration							
Industry Production	+						
Industry Demand	+						
Number of Manu. Plants		+			Mostly NS, significant for production/R&D projects		+ in expansion sample, NCS in new-subsidiary sample
Number of foreign-owned firms		+					NCS in expansion sample and new-subsidiary sample
Number of domestic establishments			+				
Number of Japanese affiliates			+				
Number of French affiliates				+			
Dummy of functional co-aggl.					Effects vary for different functions		
Location quotient of employment						+ in CLM and NLM	

B. Market size and potential							
Inverse distance-weighted GDP		+ or - depending on specifications	+		Mostly +		
GDP		Mostly +	+	+	+	+ in CLM, NS or - in NLM	
Krugman's market potential			+				
Per capita GDP				Mostly - in CLM, but NS in MXL			
Consumption of medicines							+ in high-expansion sample, NS in new-subsidiary sample
C. Tax and costs							
Effective average tax rate	-						NS in high-expansion sample and new-subsidiary sample
Statutory tax rate	-		-			NS in CLM, NS or - in NLM	
Cost of capital	-						
Effective tax rate		Mostly +					
Exchange rate volatility				-			
D. Distance							
Distance between capital cities				-			- in both samples
E. Labour market condition							
Unit labour costs or wage rate	NS	+ (only at 10 per cent level)	NS	-	Mostly NS, only significant in one specification	- in CLM, + in NLM	NS in high-expansion sample and new-subsidiary sample
Tax wedge on labour		-					
Unemployment rate		+	-	Mostly + in CLM, but NS in MXL		- in CLM and NLM	
Social charge rate			-				

Tertiary education attainment					+		Mostly NS in both samples
Second. education attainment						+ in CLM, NS in NLM	
F. Infrastructure							
Infrastructure index	Mostly +						
Motorway density							+ in high-expansion sample, mostly NS in new-subsidiary sample
G. Familiarity							
Number of firms controlled by the same parent	+	+					
Dummy of existing presence of the same parent						+ in CLM, NS in NLM	+ in new-subsidiary sample
H. Institutional Factors							
Structural Funds	+	NS					
Cohesion Funds	+						
Institutional quality			+				
Governance effectiveness					Mostly +		

Abbreviations:

D&G (1998) = Devereux and Griffith (1998)
B (2003) = Basile *et al.* (2003)
H&M (2004) = Head and Mayer (2004)
D&M (2004) = Disdier and Mayer (2004)
D (2005) = Defever (2005)
M (2007) = Mataloni (2007)

CLM = conditional logit model
NLM = nested logit model
MXL = mixed logit model
NS = no significant effect
NCS = no consistently significant
(Indicating the effect is not significant when the country - level fixed effects are included in the specification.)

Table 6A.1: Summary Statistics on the High-expansion Sample

Existing Pharmaceutical Firms Experiencing Above-median Growth in Terms of Operational revenues between 1995 and 2003, Value in 2003, Number=222

Variable	Mean	Median	Std.dev	Min	Max
No. of Employees	754.2	287	1,292.7	11	10,076
Operational revenues (thousand USD)	462,365.5	98,443	939,702.1	2,523	6,669,416
Fixed Assets (thousand USD)	314,650.4	25,870	1,635,887.7	8	18,724,261
Age (to 1993)	28.1	23	22	3	120
Growth Rate of Operational revenues (Ratio of Operational revenues in 2003 to Operational revenues in 1995)	23.6	3.2	183.1	2.1	2,601

Table 6A.2: Geographic Distribution of Firms in the High-expansion Sample (by Ownership)

	Location					
Ownership	Belgium	Denmark	France	Germany	Greece	Ireland
EU MNE parent	6	4	46	5	4	2
US MNE parent	3	0	10	2	1	0
Other non-EU MNE parent	1	0	8	1	0	1
Sum	10	4	64	8	5	3
	Italy	Portugal	Spain	Sweden	UK	Sum
EU MNE parent	21	7	39	2	12	148
US MNE parent	10	1	8	0	13	48
Other non-EU MNE parent	9	0	3	0	3	26
Sum	40	8	50	2	28	222

Table 6A.3: Summary Statistics on the New-subsidiary Sample

New Pharmaceutical Firms Established between 1993 and 2004, Value in 2003, Number=129					
Variable	Mean	Median	Std.dev	Min	Max
No. of Employees	297	150	456	3	2,960
Operational revenues (thousand USD)	120,077	43,209	292,028	1	2,244,221
Fixed Assets (thousand USD)	44,310	12,399	109,078	0	841,936
Age (to 1993)	6.5	7	3	1	11

Table 6A.4: Geographic Distribution of Firms in the New-subsidiary Sample (by Ownership)

	Location					
Ownership	Austria	Belgium	Denmark	Finland	France	Germany
EU MNE parent	1	6	2	3	29	5
US MNE parent	0	4	0	0	9	2
Other non-EU MNE parent	0	2	1	1	9	2
Sum	1	12	3	4	47	9
	Ireland	Italy	Spain	Sweden	UK	Sum
EU MNE parent	4	4	11	4	7	76
US MNE parent	3	2	0	1	4	25
Other non-EU MNE parent	2	0	3	0	8	28
Sum	9	6	14	5	19	129

Table 6B.1: List of Country-Level Variables and Firm-Heterogeneity Variables

Variable	Description	Expected sign	Source
	Country-level Variables		
PHAR/2	Number of domestic and foreign-owned firms in the pharmaceutical sector./Number of foreign-owned firms in the pharmaceutical sector with foreign owner has at least 25 per cent share.	?	OECD STAN industry data
PHARSHR/2	Share of domestic and foreign-owned firms in the pharmaceutical sector to that of total manufacturing sectors./Share of foreign-owned firms in the pharmaceutical sector (with foreign owner has at least 25 per cent share) to that of total manufacturing sectors. See Footnote 27 for details.	?	OECD STAN industry data
CHEM/2	Number of domestic and foreign-owned firms in the chemical sector. / Number of foreign-owned firms in the chemical sector with foreign owner has at least 25 per cent share.	+	OECD STAN industry data
CHEMSHR/2	Share of domestic and foreign-owned firms in the chemical sector to that of total manufacturing sectors./Share of foreign-owned firms in the chemical sector (with foreign owner has at least 25 per cent share) to that of total manufacturing sectors.	+	OECD STAN industry data
MKSIZE	National consumption of drugs and medicines (millions USD, deflated to base year 1994).	+	OECD Health Data
MKSHARE	Market share of top 25 corporate in national pharmaceutical market (not including the Netherlands)	-	IMS International
LCOST	National labour compensation per worker in the pharmaceutical industry (euros). Labour compensation is defined as "wages as well as the costs of supplements such as employer's compulsory pension or medical payments. "	-	OECD STAN industry data
EDU3	National share of workers with a tertiary level education in manufacturing workforce (per cent).	+	Eurostat
EATR	National effective average tax rate (per cent) created by Devereux and Griffith (2003).	-	The Institute for Fiscal Studies
DIST	Geographic distance from capital city to Brussels (km).	-	CEPII's dyadic
AREA	Land mass (sq. km) excluding water area.	+	CIA World Factbook 2006
MOTDEN	Motorway density in km per million inhabitants.	+	EUROSTA/OECD
FAM	Dummy variable =1 if for a firm, there are at least one other firm from the same MNE existed in a country, or a firm is located in the same country with the parent company.	+	Ownership Database in Amadeus
	Firm-Heterogeneity Variables		
EU	Dummy variable=1 if EU MNE parent.		Amadeus
US	Dummy variable= if US MNE parent.		Amadeus
TOP	Dummy variable=1 if the top 50 global pharmaceutical MNEs (2004 rank by sales).		SCRIP 100 (2005/2006), compiled by KPMG
SIZE	Operational revenues change between 1995 and 2003.		Amadeus

Robustness Check using Alternative Agglomeration Variables

Table 6C.1: CLM: Determinants of the Location Choice, High-expansion Sample Time Period: 1995 - 2003

Explanatory Variable	Col. 1	Col. 2	Col. 3	Col. 4	Col. 5	Col. 6
lnPHAR2			0.567			
			(0.501)			
PHARSHR2				0.178*		
				(0.106)		
lnCHEM2					-0.102	
					(0.414)	
CHEMSHR2						0.027
						(0.04)
lnMKSIZE	1.178***	1.079***	0.480	1.078***	1.169***	1.124***
	(0.15)	(0.132)	(0.535)	(0.143)	(0.387)	(0.155)
EATR	-0.148***	-0.015	-0.01	-0.004	-0.01	-0.021
	(0.023)	(0.045)	(0.042)	(0.046)	(0.05)	(0.048)
lnDIST	-0.299**	0.067	0.085	-0.096	0.064	0.01
	(0.145)	(0.176)	(0.170)	(0.203)	(0.177)	(0.2)
lnLCOST	-1.381**	-0.612	-0.042	-0.569	-0.634	-0.732
	(0.549)	(0.535)	(0.701)	(0.574)	(0.547)	(0.594)
EDU3	0.016	0.035**	-0.005	0.016	0.04	0.031*
	(0.016)	(0.015)	(0.038)	(0.019)	(0.028)	(0.016)
lnMOTDEN	0.705***	0.298	0.759*	0.166	0.2	0.264
	(0.195)	(0.196)	(0.45)	(0.215)	(0.442)	(0.203)
Germany fixed effect	no	-2.093***	-2.154***	-1.936***	-2.113***	-1.953***
		(0.559)	(0.54)	(0.567)	(0.564)	(0.611)
Log-likelihood	-436.4	-427.2	-426.6	-425.8	-427.2	-427
Prob > $\chi 2$	0.000	0.000	0.000	0.000	0.000	0.000
Pseudo R2	0.1803	0.1975	0.1987	0.2001	0.1975	0.1979
# of Firms	222	222	222	222	222	222

Note: * significant at 10 per cent level, ** significant at 5 per cent level, *** significant at 1 per cent level; standard error in parenthesis.

Robustness Check using Alternative Agglomeration Variables

Table 6C.2: CLM : Determinants of the Location Choice, High-expansion Sample; Two Periods

	Pharmaceutical agglomeration		Chemical agglomeration	
Explanatory Variables	Col. 1	Col. 2	Col. 3	Col. 4
	1995 - 1999	1999 - 2003	1995 - 1999	1999 - 2003
PHARSHR2	0.196*	0.321**		
	(0.102)	(0.147)		
CHEMSHR2			0.058	0.054
			(0.043)	(0.037)
lnMKSIZE	1.111***	1.315***	1.194***	1.405***
	(0.141)	(0.164)	(0.163)	(0.175)
EATR	-0.011	-0.036	-0.031	-0.100*
	(0.036)	(0.062)	(0.042)	(0.057)
lnDIST	-0.027	-0.571***	0.045	-0.489**
	(0.223)	(0.212)	(0.225)	(0.211)
lnLCOST	-0.355	-1.695**	-0.644	-2.013***
	(0.622)	(0.666)	(0.671)	(0.670)
EDU3	0.019	0.003	0.025	0.037**
	(0.025)	(0.024)	(0.025)	(0.016)
lnMOTDEN	0.052	0.356	0.115	0.628**
	(0.197)	(0.311)	(0.188)	(0.265)
Germany fixed effect	-1.815***	-1.427**	-1.709***	-1.135*
	(0.563)	(0.578)	(0.644)	(0.598)
Log-likelihood	-416.2	-420.7	-417.1	-422.1
Prob > $\chi 2$	0.000	0.000	0.000	0.000
Pseudo R2	0.2075	0.227	0.2057	0.2244
# of Firms	219	219	219	219

Note: * significant at 10 per cent level, ** significant at 5 per cent level, *** significant at 1 per cent level; standard error in parenthesis.

Robustness Check using Alternative Agglomeration Variables

Table 6C.3: CLM : Determinants of the Location Choice New-subsidiary Sample Time Period: 1993 - 2004

Explanatory Variables	Col. 1	Col. 2	Col. 3	Col. 4	Col. 5	Col. 6	Col. 7	Col. 8	Col. 9	Col. 10
lnPHAR2			0.663*				0.425			
			(0.340)				(1.905)			
PHARSHR2				-0.016				-1.524		
				(0.250)				(1.008)		
lnCHEM2					0.691				4.238	
					(0.573)				(3.044)	
CHEMSHR2						-0.133**				-0.745
						(0.065)				(0.580)
lnMKSIZE	0.046	-0.063	-0.325	-0.07	-0.625	0.071	-5.428	-6.982	-6.233	-4.961
	(0.553)	(0.573)	(0.619)	(0.585)	(0.749)	(0.582)	(4.558)	(4.636)	(4.508)	(4.447)
EATR	-0.023	-0.005	0.015	-0.005	-0.002	0.011	0.008	0.018	-0.018	0.03
	(0.029)	(0.036)	(0.039)	(0.037)	(0.037)	(0.037)	(0.046)	(0.045)	(0.049)	(0.048)
lnDIST	-0.903**	-0.973**	-0.697	-0.973**	-1.006**	-0.638	-4.107	-7.537*	-2.569	-4.143
	(0.453)	(0.465)	(0.458)	(0.465)	(0.45)	(0.453)	(3.668)	(3.864)	(3.375)	(3.034)
lnAREA	0.751	0.877	0.572	0.877	0.893	0.491	5.695	11.386*	3.192	3.941
	(0.542)	(0.567)	(0.584)	(0.567)	(0.562)	(0.574)	(5.221)	(5.840)	(4.895)	(4.656)
lnLCOST	-0.766	-0.915	-1.246	-0.942	-1.964	-0.921	1.001	0.754	1.015	0.638
	(0.943)	(0.962)	(1.016)	(1.058)	(1.333)	(0.968)	(2.053)	(2.044)	(2.04)	(2.074)
EDU3	0.032	0.030	0.029	0.031	0.008	0.079*	0.006	-0.02	-0.079	0.075
	(0.042)	(0.041)	(0.042)	(0.045)	(0.044)	(0.046)	(0.08)	(0.084)	(0.102)	(0.096)
MKSHARE	-0.009	-0.021	0.024	-0.023	-0.002	-0.044	0.03	-0.047	-0.034	0.099
	(0.035)	(0.038)	(0.044)	(0.057)	(0.041)	(0.041)	(0.112)	(0.112)	(0.114)	(0.123)
lnMOTDEN	-0.121	-0.185	0.216	-0.175	0.237	0.062	1.576	1.622	2.303	0.891
	(0.246)	(0.253)	(0.34)	(0.299)	(0.434)	(0.283)	(1.859)	(1.913)	(1.956)	(1.935)
FAM	1.169***	1.157***	1.105***	1.158***	1.139***	1.126***	1.133***	1.151***	1.154***	1.114***
	(0.246)	(0.247)	(0.247)	(0.248)	(0.247)	(0.247)	(0.249)	(0.249)	(0.250)	(0.249)
Germany fixed effect	no	-0.461	-0.532	-0.5	-0.528	-1.511**	6.044	-0.432	1.941	4.885
		(0.53)	(0.528)	(0.825)	(0.532)	(0.758)	(5.948)	(5.365)	(6.27)	(5.403)
Country fixed effects	no	no	no	no	no	no	yes	yes	yes	yes
Log-likelihood	-248.7	-248.3	-246.4	-248.3	-247.6	-246.3	-244.7	-243.5	-243.8	-243.9
Prob > $\chi 2$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Pseudo R2	0.196	0.1973	0.2034	0.1973	0.1996	0.2038	0.2089	0.2128	0.212	0.2116
# of Firms	129	129	129	129	129	129	129	129	129	129

Note: * significant at 10 per cent level, ** significant at 5 per cent level, *** significant at 1 per cent level; standard error in parenthesis.

Robustness Check using Alternative Agglomeration Variables

Table 6C.4: CLM : Determinants of the Location Choice, New-subsidiary Sample; Two Periods

	Pharmaceutical agglomeration		Chemical agglomeration	
Explanatory Variables	Col. 1	Col. 2	Col. 3	Col. 4
	1993 - 1998	1999 - 2004	1993 - 1998	1999 - 2004
PHARSHR2	-2.328 (2.338)	-6.017** (2.581)		
CHEMSHR2			-0.620 (0.807)	-0.594 (1.554)
lnMKSIZE	2.132 (1.607)	-4.682 (5.892)	3.932 (3.143)	-6.664 (5.544)
EATR	0.154 (0.111)	-0.133 (0.144)	0.146 (0.110)	-0.167 (0.147)
lnDIST	2.865 (3.222)	-4.624 (4.782)	3.592 (3.286)	-3.641 (4.829)
lnAREA	-3.008 (2.409)	3.139 (5.984)	-4.822 (4.609)	5.608 (5.707)
lnLCOST	3.260 (6.502)	-0.463 (4.546)	2.096 (6.316)	-1.404 (4.432)
EDU3	0.224 (0.268)	0.111 (0.272)	0.309 (0.254)	0.320 (0.285)
MKSHARE	0.665** (0.292)	-0.191 (0.358)	0.720* (0.377)	-0.231 (0.336)
lnMOTDEN	-3.502 (2.921)	0.229 (6.172)	-0.713 (2.024)	-0.598 (5.112)
FAM	0.729** (0.330)	1.594*** (0.404)	0.711** (0.329)	1.589*** (0.399)
Germany fixed effect	na na	0.437 (8.08)	na na	4.036 (7.023)
Country fixed effects	yes	yes	yes	yes
Log-likelihood	-138.7	-88.7	-138.9	-91.2
Prob > χ2	0.000	0.000	0.000	0.000
Pseudo R2	0.2488	0.2882	0.248	0.2688
# of Firms	77	52	77	52

Note: * significant at 10 per cent level, ** significant at 5 per cent level, *** significant at 1 per cent level; standard error in parenthesis.

Table 6C.5: CLM: Selected Interactions of Firm Heterogeneity with Country-level Variables from Multiple Regressions High-expansion Sample (1995 - 2003) and New-subsidiary Sample (1993 - 2004)

		Major Effect		Interaction Effect	Does 95 per cent confidence interval contain zero ?
High-expansion Sample					
Regression 1 EU (dummy) interacts with lnMKSIZE	lnMKSIZE	1.308*** (0.202)	EU*lnMKSIZE	-0.324* (0.191)	yes
Regression 2 EU (dummy) interacts with lnLCOST	lnLCOST	0.179 (0.737)	EU*lnLCOST	-0.998* (0.561)	yes
Regression 3 EU (dummy) interacts with lnMOTDEN	lnMOTDEN	-0.385 (0.277)	EU*lnMOTDEN	0.914*** (0.318)	no
Regression 4 EU (dummy) interacts with lnCHEM2	lnCHEM2	0.136 (0.431)	EU*lnCHEM2	-0.383* (0.198)	yes
Regression 5 US (dummy) interacts with lnMOTDEN	lnMOTDEN	0.387 (0.241)	US*lnMOTDEN	-0.848** (0.343)	no
Regression 6 US (dummy) interacts with lnCHEM2	lnCHEM2	-0.21 (0.42)	US*lnCHEM2	0.431* (0.233)	yes
Regression 7 TOP (dummy) interacts with PHARSHR2	PHARSHR2	0.263** (0.117)	TOP*PHARSHR2	-0.188* (0.111)	yes
Regression 8 TOP (dummy) interacts with EDU3	EDU3	0.039* (0.022)	TOP*EDU3	-0.043** (0.021)	no
Regression 9 TOP (dummy) interacts with lnMOTDEN	lnMOTDEN	0.49* (0.28)	TOP*lnMOTDEN	-0.62** (0.31)	no
Regression 10 SIZE interacts with PHARSHR2	PHARSHR2	1.229*** (0.446)	SIZE*PHARSHR2	-0.092** (0.038)	no
Regression 11 SIZE interacts with lnMKSIZE	lnMKSIZE	-0.239 (0.663)	SIZE*lnMKSIZE	0.116** (0.058)	no
Regression 12 SIZE interacts with EATR	EATR	-0.357** (0.175)	SIZE*EATR	0.032** (0.016)	no
Regression 13 SIZE interacts with lnDIST	lnDIST	1.063* (0.621)	SIZE*lnDIST	-0.099** (0.05)	no
Regression 14 SIZE interacts with lnLCOST	lnLCOST	-5.259*** (1.941)	SIZE*lnLCOST	0.421** (0.171)	no
Regression 15 SIZE interacts with lnCHEM2	lnCHEM2	-1.34 (0.822)	SIZE*lnCHEM2	0.106* (0.06)	yes
Regression 16 SIZE interacts with CHEMSHR2	CHEMSHR2	0.444** (0.208)	SIZE*CHEMSHR2	-0.036** (0.018)	no
New-subsidiary Sample					
Regression 17 EU (dummy) interacts with lnMOTDEN	lnMOTDEN	1.151 (1.862)	EU*lnMOTDEN	0.572* (0.329)	yes
Regression 18 SIZE interacts with PHARSHR2	PHARSHR2	-0.642 (1.098)	SIZE*PHARSHR2	-0.092** (0.045)	no
Regression 19 SIZE interacts with CHEMSHR2	CHEMSHR2	-0.384 (0.598)	SIZE*CHEMSHR2	-0.039** (0.017)	no

Note: * significant at 10 per cent level, ** significant at 5 per cent level, *** significant at 1 per cent level; standard error in parenthesis.

Robustness Check using Alternative Agglomeration Variables

Table 6C.6: Hausman Test for the CLM: High-expansion Sample

#	Country excluded	$\chi 2$ Statistics	Conclusion
1	Belgium	13.93*	IIA rejected
2	Denmark	2.12	IIA cannot be rejected
3	France	1.73	IIA cannot be rejected
4	Germany	24.77***	IIA rejected
5	Greece	2.34	IIA cannot be rejected
6	Ireland	1.26	IIA cannot be rejected
7	Italy	0.83	IIA cannot be rejected
8	Portugal	0.22	IIA cannot be rejected
9	Spain	1.8	IIA cannot be rejected
10	Sweden	21.25***	IIA rejected
11	UK	0.00	IIA cannot be rejected

Note: * significant at 10 per cent level, ** significant at 5 per cent level, *** significant at 1 per cent level; H0: Difference in coefficients of models for subset and full set of countries is not systematic.

Robustness Check using Alternative Agglomeration Variables

Table 6C.7: Hausman Test for the CLM: New-subsidiary Sample

#	Country excluded	$\chi 2$ Statistics	Conclusion
1	Austria	2.14	IIA cannot be rejected
2	Belgium	0.84	IIA cannot be rejected
3	Denmark	4.88	IIA cannot be rejected
4	Finland	4.27	IIA cannot be rejected
5	France	16.43*	IIA rejected
6	Germany	13.97	IIA cannot be rejected
7	Ireland	3.56	IIA cannot be rejected
8	Italy	42.7***	IIA rejected
9	Spain	1.75	IIA cannot be rejected
10	Sweden	1.62	IIA cannot be rejected
11	UK	1.74	IIA cannot be rejected

Note: * significant at 10 per cent level, ** significant at 5 per cent level, *** significant at 1 per cent level; H0: Difference in coefficients of models for subset and full set of countries is not systematic.

Robustness Check using Alternative Agglomeration Variables

Table 6C.8: MXL: Determinants of the Location Choice, High-expansion Sample; Time Period: 1995 - 2003

Explanatory Variables	Col.1	Col. 2	Col. 3	Col. 4
lnPHAR2	0.402			
	(0.531)			
Variance	*0.018*			
	(0.087)			
PHARSHR2		0.214*		
		(0.122)		
Variance		*0.058*		
		(0.943)		
lnCHEM2			-0.072	
			(0.420)	
Variance			*0.000*	
			(0.000)	
CHEMSHR2				0.075
				(0.064)
Variance				*0.039*
				(0.033)
lnMKSIZE	0.758	1.296***	1.237***	1.376***
	(0.611)	(0.233)	(0.400)	(0.259)
Variance	*0.021*	*0.207*	*0.066*	*0.27*
	(0.075)	*(0.224)*	*(0.094)*	*(0.28)*
EATR	-0.015	-0.05	-0.019	-0.058
	(0.052)	(0.06)	(0.058)	(0.089)
Variance	*0.008*	*0.008*	*0.01*	*0.012*
	(0.009)	*(0.01)*	*(0.011)*	*(0.013)*
lnDIST	0.115	-0.210	0.098	-0.118
	(0.175)	(0.241)	(0.180)	(0.319)
lnLCOST	-0.292	-0.816	-0.654	-0.857
	(0.763)	(0.590)	(0.537)	(0.702)
EDU3	0.010	0.012	0.041	0.021
	(0.042)	(0.020)	(0.028)	(0.020)
lnMOTDEN	0.630	0.159	0.251	0.262
	(0.475)	(0.224)	(0.449)	(0.227)
Germany fixed effect	-2.331***	-1.835***	-2.336***	-2.079**
	(0.666)	(0.698)	(0.699)	(0.817)
Log-likelihood	-425.8	-424.2	-426.3	-424
# of Firms	222	222	222	222

Note: * significant at 10 per cent level, ** significant at 5 per cent level, *** significant at 1 per cent level; standard error in parenthesis.

Table 6C.9: MXL: Determinants of the Location Choice, New-subsidiary Sample; Time Period: 1993 - 2004

Explanatory Variables	Col.1	Col. 2	Col. 3	Col. 4
lnPHAR2	1.381			
	(2.326)			
Variance	*10.851*			
	(7.201)			
PHARSHR2		-1.530		
		(1.013)		
Variance		*0.001*		
		(0.04)		
lnCHEM2			6.023*	
			(3.589)	
Variance			*2.278*	
			(4.07)	
CHEMSHR2				-0.731
				(0.588)
Variance				*0.000*
				(0.005)
lnMKSIZE	-3.298	-6.941	-6.594	-4.928
	(4.688)	(4.641)	(4.604)	(4.459)
Variance	*8.579*	*0.008*	*1.483*	*0.013*
	(5.314)	*(0.051)*	*(2.656)*	*(0.075)*
EATR	0.003	0.017	-0.057	0.029
	(0.058)	(0.047)	(0.061)	(0.049)
Variance	*0.006*	*0.001*	*0.006*	*0.000*
	(0.007)	*(0.003)*	*(0.008)*	*(0.001)*
lnDIST	-1.978	-7.51*	-2.069	-4.136
	(4.025)	(3.867)	(3.548)	(3.054)
lnAREA	2.723	11.327*	2.061	3.948
	(5.629)	(5.839)	(5.147)	(4.671)
lnLCOST	0.683	0.669	0.441	0.589
	(2.426)	(2.075)	(2.334)	(2.096)
EDU3	0.044	-0.019	-0.126	0.074
	(0.100)	(0.085)	(0.116)	(0.097)
SHARE	0.044	-0.053	-0.056	0.093
	(0.119)	(0.115)	(0.127)	(0.127)
lnMOTDEN	0.940	1.444	2.306	0.841
	(2.268)	(2.095)	(2.282)	(1.978)
FAM	1.158***	1.150***	1.219***	1.111***
	(0.277)	(0.253)	(0.283)	(0.251)
Germany fixed effect	2.686	-0.631	0.264	4.794
	(6.275)	(5.464)	(6.911)	(5.419)
Country fixed effects	yes	yes	yes	yes
Log-likelihood	-239.9	-243.4	-243	-243.9
# of Firms	129	129	129	129

Note: * significant at 10 per cent level, ** significant at 5 per cent level, *** significant at 1 per cent level, standard error in parenthesis.

Chapter 7

Conclusions

7.1 Conclusions

As a consequence of the Single Market Programme (1993) abolishing non-tariff barriers between member states, the EU-wide market has become much more integrated. In advance of the SMP, it was expected that some manufacturing industries, especially those featuring high scale economies, would respond significantly to the integrated market. The market integration was seen as creating opportunity for businesses in these industries to achieve greater scale and to shift to the most cost-effective locations to produce for the integrated market.

Within this broad context, we examine two aspects of change in the European pharmaceutical industry, an IRS industry, using state-of-the-art micro-econometric methods and firm-level data. The first aspect is firm growth. In Chapter 3, we test whether the growth process of the most dynamic part of the industry – multinational enterprises - obeys Gibrat's law, which states that the growth rate is independent of size. Results after two traditional tests reveal that the MNEs do not grow in the way indicated by the law. In plain language, we find that smaller firms grow relatively faster than larger firms do, while they follow a more variable growth process. These findings are in line with that of the empirical literature on the global pharmaceutical industry and on other manufacturing industries. In addition we find that the MNEs converge to their steady states of size at different speeds, which are negatively correlated with their initial sizes. This mean-reversion mechanism suggests that firms, upon their birth, are bounded by the scope of how big they can grow, and it also echoes the existence of firm heterogeneity.

In Chapter 4, we develop a modelling technique to model the growth process of pharmaceutical MNEs. The technique stems from Sutton's "independent submarket" theory, which looks at the firm-growth process as a continuous realisation of independent business opportunities by incumbents or new entrants. We use the discrete-choice model to estimate the probability of the MNEs to expand, conditioning on their lagged expansion decisions and sizes. Using the primitives of our econometric models and size in the initial period, we can predict the growth trajectory of the MNEs from the

initial year up to 14 years later with small error. In addition to the promising outcome from this modelling technique, we find that a persistent expansion pattern exists in the growth process, which suggests the industry is able to generate profits in order to support its expensive R&D activities.

In Chapter 5, we start examining the industry from a location perspective. We find that, the production location of the industry in fourteen EU-15 countries exhibits a continuously dispersing trend between 1993 and 2002, as the production moved from previously agglomerated countries to less agglomerated countries. The result is in line with the New Economic Geography models' predictions regarding agglomeration, in the face of significant reductions in trade costs. We decompose one specific dispersion trend measured by the Hirschman-Herfindahl Index into several components associated with various firm life-cycle activities and with different ownership status using firm-level data. The results of the decomposition analysis unveil the substantial contribution from MNEs to the industry trend, dwarfing the contribution from non-MNEs.

In Chapter 6, we use the discrete-choice models to identify the country-level determinants of location choice of pharmaceutical MNEs, in terms of where they expand production in existing production subsidiaries and where they start-up new production subsidiaries. We find that, among eleven EU-15 countries, the expanding MNEs prefer countries with high levels of agglomeration in pharmaceuticals, large domestic market of medicines and countries that are close to Brussels, the European pharmaceutical distribution centre. However, somewhat surprisingly, they are not found to be sensitive to the corporate tax rate. In terms of location choice of new subsidiaries creation, the agglomeration in pharmaceuticals, the closeness to Brussels and familiarity with the country are the key country-level factors encouraging MNEs to locate their new subsidiaries in a country, while the size of the domestic market and the corporate tax rate play no role in this type of location choice.

The implications of the findings on location side of the industry are two-fold: firstly, the MNEs did actively respond to the SMP in the way predicted by the NEG models and by European policy makers – they were seeking both agglomeration benefits

and the easiness of access to the enlarged EU market; secondly, policy makers may need to take into account the identified country-level determinants when drawing up foreign-investment promotion plan. In particular, they may need to reassess the use of country-specific tax incentives, if our result that pharmaceutical MNEs hardly react to the corporate tax rate, are correct.

7.2 Future Research Directions

Some potential avenues for further research emerged during the course of current studies, and we now look at these in turn.

Whereas in Chapter 3 we used a dynamic probit approach to model the growth process of the pharmaceutical industry, we could explore other approaches. For example, another way to model this discrete process of expansion is the count-data model with selection mechanism (Greene, 1994). In this approach, we would need to start by estimating the probability of a firm to expand by capturing a new opportunity using a logit/probit model. [This step is similar to our probit-model approach in Chapter 3.] Once those firms that can expand (with positive probability) are identified, we need to estimate the size of the opportunity conditioning on firm characteristics[1], such as size and nationality. In this case we would assume that the size of the opportunity is generated from a Poisson process. This step contrasts sharply with what we do in Chapter 3, where the size of the opportunity is estimated using its joint distribution with the size of firm. We finished a static version of the count-data model, and will introduce the dynamic mechanism into it as a nature extension.

In terms of location choice analysis, we currently model regarding location choice of MNEs at country level. An obvious extension is to model the location choice at regional level. As empirical studies show, when MNEs seek a region to locate their business, they typically evaluate country-level characteristics and region-level characteristics sequentially. In terms of our analysis, we would seek to investigate whether the pharmaceutical MNEs follow the same decision-making procedure. However, to do this, we would have to overcome firstly the difficulty caused by data limitation,

[1]It is defined as the number of subsidiaries associated with each opportunity.

which is described in Section 2.2.3 of Chapter 2.

Another possibility is to examine the location choice in the EU-27 countries, given the deepening integration process. We expect significant differences between the "old" member states and the new ones, in terms of labour costs and quality, institutional structures, infrastructures and geographic distance to the European centre, will reveal rich pattern in the location decisions of MNEs.

Finally, if we can find solutions to the shortage of regional data, we believe that it would be worthwhile exploring the behaviour of those non-MNE multi-firm enterprises and independent enterprises[2], as they account for 37 per cent of the pharmaceutical enterprise population that we identified (the remaining 63 per cent of the population are MNEs, see Table 2.4 in Chapter 2). We expect their growth process and location-choice patter may differ from that of the MNEs, due to their relatively smaller size, and their presumed commitment to operate within national borders.

[2]In Chapter 2 they are termed as "domestic multi-firm enterprise" and "domestic single-firm enterprise" respectively.

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