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Determinants of Pharmaceutical Innovation: The Role of Technological Opportunities Revisited

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Abstract

Recent empirical contributions emphasize the importance of (potential) market size for the development of new pharmaceuticals. At the same time many scholars point out the importance of scientific advances for the industry's R&D activities. Against this background I analyze the relationship between (potential) market size, technological opportunities, and the number of new pharmaceuticals in the United States. Technological opportunities are operationalized as growth rates of the relevant knowledge stock as proposed by Andersen (1999, 1998). I analyze a unique dataset by using an "entry stock" Poisson quasi-maximum likelihood estimator. The results reveal a rather robust and significantly positive response of the number of new pharmaceuticals, i.e., new molecular entities or new drug approvals, to market size and technological opportunities.

1 Introduction

There has been an extensive and long-running discussion as to whether demand- or supply-side factors determine innovative activities across different industries. The controversy between advocates of the “demand-pull” and those of the “technology-push” theories has been resolved by pointing out the importance of both the information flows of scientific and technical knowledge and information from users of products and processes for innovative activities (Freeman, 1994). Consequently, this paper studies the contribution of demand-side variables (market size) and supply-side variables (technological opportunities) to innovative activities using data from the U.S. pharmaceutical industry. On the one hand, the importance of demand for innovation in this sector has been pointed out by many scholars (e.g., Cerda, 2007; Acemoglu and Linn, 2004). On the other hand, there is much evidence that innovative activities in this sector rely on scientific advances, particularly in the field of biotechnology (e.g., Rasmussen, 2010; McKelvey, 1996; Gambardella, 1995). Hence, the pharmaceutical industry provides an almost ideal case to analyze the importance of demand- and supply-side variables for innovative output.

While researchers studying the determinants of innovation can apply a broad range of usually quite well defined demand-side variables, some important supply-side variables lack a clear definition or operationalization. In particular, the concept of technological opportunities has been found to be a key variable for explaining innovative activities across different industries, but there is no clear consensus concerning its empirical approximation (e.g., Klevorick et al., 1995). Early studies of the importance of technological opportunities relied mostly on industry dummies or survey-based indicators of the importance of different knowledge sources. In contrast to these contributions, I will use a quantitative proxy for technological opportunities, following an idea proposed by Andersen (1999, 1998), and operationalize technological opportunities by the growth rate of the knowledge stock in a given field of research.

The empirical analysis is performed on a unique dataset that encompasses data from different sources. Data concerning new pharmaceuticals comes from the Drugs@FDA database. Market size is constructed using the March Supplement of the U.S. Current Population Survey and the Medical Expenditure Panel Survey (MEPS). Publication data

from the Web of Science databases is used to construct proxies for technological opportunities. The data is analyzed using an “entry stock” Poisson quasi-maximum likelihood estimator (QMLE), as suggested by Blundell et al. (1995), since it accounts for dynamic feedback and unobserved heterogeneity. Moreover, the Poisson QMLE is consistent under the assumption of a correctly specified mean and does not require Poisson-distributed data.

The results indicate a significantly positive response of the number of new pharmaceuticals to market size. This result holds true for new molecular entities as well as for new drug approvals and is rather robust against different specifications of the market size proxy. Technological opportunities have a significantly positive relation with the number of new pharmaceuticals. I find, however, no robust significant relation between technological opportunities in biotechnology and basic research and the number of new pharmaceuticals. This result may be driven by the construction of the database and the knowledge stocks, which may better account for applied research. I take time lags of seven years into account, which corresponds to the average time needed from the first clinical testing of a promising compound to the approval of a new drug. The results suggest no clear-cut relationship between lagged market size, lagged technological opportunities, and the number of pharmaceutical innovations. By instrumenting market size by market size five years previously, I find no evidence for reverse causality.

This paper contributes to the literature in three ways. First, the relationship between demand and pharmaceutical innovation is often analyzed on a rather aggregated level, e.g., drug categories or disease groups. I use instead a more disaggregated level of analysis, namely medical indications. Second, by operationalizing technological opportunities as growth rates of knowledge stocks, I add a quantifiable proxy for this variable to the analysis. Third, the publication data used to construct the knowledge stocks is more closely related to the definition of technological opportunities than are patents or other types of data previously used in the literature. Particularly in a science-based industry such as pharmaceuticals, publications may reflect the possibilities for innovative activities more directly than, e.g., patents, which can be seen as a realization of specific possibilities for innovation.

This paper is structured as follows. Section 2 reviews the related literature on the demand- and supply-side determinants of innovative activities. Section 3 presents the empirical strategy and Section 4 explains the construction of the variables and the different data sources. The empirical results can be found in Section 5. Finally, Section 6 concludes.

2 Related Literature

2.1 Demand and Innovation

The importance of demand in explaining the rate of innovation across sectors has been recognized in economics for many decades. In his seminal contribution, Schmookler (1966) suggested that cycles of capital good patents usually lag behind cycles of capital goods' output and capital expenditures in downstream industries. This finding led to the conclusion that demand side stimuli are the most important for explaining the rate and direction of inventive activities. Along with other early contributions, these results have been criticized in the “demand-push” versus “technology-push” debate. The corresponding studies often lacked a clear definition of demand, neglected supply-side influences, and did not conclusively demonstrate the importance of demand for the rate and direction of innovation (Mowery and Rosenberg, 1979). Replications of Schmookler's (1966) results have pointed to a somewhat weaker relationship between demand and innovative activities than in the original study. However, the relation remains significant in most cases (Scherer, 1982). Furthermore, there may be a mutual dependency between demand and innovation, rather than a clear, unidirectional causality (Kleinknecht and Verspagen, 1990).

Analyzing innovative activities in the United Kingdom, Geroski and Walters (1995) find that variations in demand Granger-cause major innovation counts and patents. Walsh (1984) offers a more differentiated view, by analyzing sub-sectors of the chemical industry in more detail. The results obtained suggest that exogenous major innovations create their own demand, which subsequently leads to a rising number of incremental innovations. Thus, the importance of supply- and demand-side influences may vary over a life cycle. In some industries, heterogeneous demand as well as lead or experimental users play a dominant role in shaping the rate and direction of technological development

(Malerba et al., 2007; Adner and Levinthal, 2001; von Hippel, 1976).

As to the pharmaceutical industry, it is often argued that demand-side variables determine the rate and the direction of the industry's investment in R&D activities and, consequently, the number of new drugs in different therapeutic categories. Empirical evidence suggests that pharmaceutical companies' R&D decisions are determined by the expected return and cash flow variables, which should be connected with the size of the corresponding markets and with real drug prices (Giaccotto et al., 2005; Grabowski and Vernon, 2000). Expected returns are an important determinant of R&D spending not only for large U.S. but also for Japanese pharmaceutical companies (Mahlich and Roediger-Schluga, 2006). These results support earlier findings, indicating that variables related to the expected returns explain chemical and pharmaceutical firms' R&D intensity (Grabowski, 1968).

Following the empirical evidence on firms' R&D decisions being at least partly shaped by variables affected by market size, one would expect firms to invest in R&D and to introduce new pharmaceuticals, particularly for medical conditions that have a high expected market size and consequently, high expected returns. Acemoglu and Linn (2004) analyze the effect of (potential) market size on new drugs approved by the U.S. Food and Drug Administration (FDA), making use of exogenous changes in the potential market size driven by demographic trends. Their results indicate that a 1 percent increase in the potential market size of a drug category is associated with a 4 to 6 percent increase in the entry of new molecular entities. The response as to new non-generic drugs is approximately 4 percent. Moreover, their results show responses to 5-year leads in market size. Taking the time needed for development into account, pharmaceutical R&D seems to respond to anticipated changes in the market size with a lead of 10 to 20 years. The results are robust against the introduction of controls for a variety of supply-side factors.

Using U.S. demographical data, Cerda (2007) provides additional evidence for the importance of market size for the introduction into the market of new molecular entities. Moreover, the author shows that there are important feedback effects, since new drugs affect the market size through their impact on the mortality rate. Market size related

variables affect not only the introduction of new molecular entities and new non-generics, but also generic entry (Reiffen and Ward, 2005; Morton, 1999).

The importance of market size for the rate and direction of innovative activities related to new drugs has been particularly emphasized regarding diseases which affect individuals in developing countries. Small markets make it less attractive for pharmaceutical companies to engage in research and drug development for the corresponding medical conditions and the appropriate delivery of medications in developing countries (Lichtenberg, 2005a; Kremer, 2002). Similar problems may occur regarding rather rare diseases in developed countries. Supply-side incentives such as tax credits may lead to an increase in innovative activities related to such medical conditions. However, firms may still concentrate on the more prevalent conditions among the rare diseases (Yin, 2008).

2.2 Technological Opportunities and Innovation

The importance of demand-side variables has been contradicted by advocates of the technology-push hypothesis, claiming that scientific and technological progress are the primary drivers of the rate and direction of innovative activities. The generation of new scientific and technological knowledge leads to a steady renewal of the pool of technological opportunities, i.e., an industry's set of possibilities for innovative activities (Klevorick et al., 1995). Technological opportunities reflect the state of knowledge at a particular point in time, which determines the cost and difficulty of successful innovative activities (cf., Jaffe, 1986). Technological opportunities are bound to technological paradigms determining the scope of potential innovations and the effort necessary to achieve these along specific trajectories. New paradigms generate new opportunities for previously infeasible product development and productivity increases. It is, however, the expected economic returns that lead to dedicating resources to the exploitation of the existing opportunities (Dosi, 1988).

The theoretical contributions clearly indicate that technological opportunities are a key factor in explaining (persistent) differences in innovative activities across industries (e.g., Nelson, 1988). However, empirical investigations of this widely accepted view turned out to be more difficult since there is no clear consensus concerning the precise operationaliza-

tion of the concept of technological opportunities (Cohen and Levin, 1989). Consequently, a broad variety of proxies for technological opportunities has been used in empirical research. Many studies rely on industry categories or technology groups using different levels of aggregation. Although these binary variables may capture more than mere differences in technological opportunities, they explain a considerable fraction of inter-industry and inter-firm differences in innovative activities (e.g., Jaffe, 1989a, 1986; Scherer, 1965).

Other studies have relied on survey data addressing the sources of knowledge at the firm or industry level, particularly the importance of various basic and applied sciences for the industries' technological change, as well as the contribution of external knowledge sources, such as universities, suppliers, and customers (Klevorick et al., 1995; Levin et al., 1987). These studies have found that technological opportunities, particularly the closeness to science and extra-industry sources of knowledge, positively affect innovative activities and the rate of technical change (Nelson and Wolff, 1997; Cohen and Levinthal, 1989; Cohen et al., 1987; Levin et al., 1985). Another approach has used patent data to analyze technological opportunities and their development. Andersen (1999, 1998) defines technological opportunities as the growth of the stock of patents in different technology groups. The analysis of technology dynamics reveals opportunity differences across technologies and their changing sources over time.

The pharmaceutical industry is traditionally regarded as an industry with a rather high level of technological opportunities. Particularly, the transformation from "random screening" to a "guided drug discovery" process, and advances in molecular biology and genetic engineering, have opened up new technological opportunities (Galambos and Sturchio, 1998; McKelvey, 1996; Gambardella, 1995). A broad variety of studies have illustrated the importance of scientific research, particularly that conducted in universities and public research institutions, for the creation of new knowledge. This new knowledge leads to a renewal and expansion of the available set of technological opportunities. The set of technological opportunities itself builds a foundation for the development of new pharmaceuticals (e.g., Cohen et al., 2002; Klevorick et al., 1995; Mansfield, 1991; Jaffe, 1989b). In line with these results, public research funding has been found to be another supply-side variable influencing the introduction of new pharmaceuticals to the market, since it

should translate into the generation of new knowledge (Toole, 2012).

Against this background, it seems to be rather surprising that supply-side variables, and among them particularly the concept of technological opportunities, have received relatively little attention from scholars analyzing innovative activities in the pharmaceutical industry. Griliches et al. (1991) show that technological opportunities linked to patent activity are positively related to the pharmaceutical industry's innovativeness. In order to control for different technological opportunities when analyzing the influence of organizational competence on firms' research productivity, Henderson and Cockburn (1994) use dummy variables for therapeutic classes. While clearly focusing on the (potential) market size as the main determinant of pharmaceutical innovation, Acemoglu and Linn (2004) use pre-existing trends in the number of drug approvals to control for scientific opportunities across therapeutic categories.

Despite numerous theoretical arguments emphasizing the importance of technological opportunities for pharmaceutical innovation, difficulties with the operationalization of this concept may be one reason for the marked scarcity of empirical evidence in the literature. By using growth rates of knowledge stocks as a proxy for technological opportunities, as proposed in Andersen (1999, 1998), I will address this shortcoming of the previous empirical literature.

3 Empirical Strategy

The empirical analysis draws upon the literature concerning the “demand-pull” versus “technology-push” debate, and takes into account demand- and supply-side factors as the explanatory variables for pharmaceutical innovation. This approach goes beyond recent contributions to the field, which mainly concentrate on the demand-side effects (e.g., Cerda, 2007; Acemoglu and Linn, 2004). Innovation is measured as the number of new drugs approved by the FDA over time.¹ Hence, a Poisson model for the conditional

¹The definition of innovation as a newly approved drug uses the specificities of the innovation process in the pharmaceutical industry. After several phases of pre-clinical and clinical testing, a new drug has to be approved by a regulatory body, the FDA in the United States, before being marketed (see, Gambardella, 1995). This allows of clearly identifying the number of new drugs approved for marketing

mean of new pharmaceuticals can be derived:

$$E [N_{it}|\zeta_i, X_{it}] = \exp(\beta_0 + \beta_1 \ln(MKS_{i,t-a}) + \beta_2 TO_{i,t-b} + \beta C_{i,t-c} + \zeta_i + \mu_t). \quad (1)$$

Here, N_{it} denotes the number of new pharmaceuticals for medical indication i in year t , ζ_i represents time-constant medical indication intercepts capturing heterogeneity among diseases, and X_{it} refers to all explanatory variables at t and earlier. More precisely, $MKS_{i,t-a}$ accounts for the (potential) market size in i at $t - a$, $TO_{i,t-b}$ refers to the corresponding technological opportunities, $C_{i,t-c}$ is a vector of control variables, and μ_t is a set of dummy variables for each year included in the analysis to capture common year specific effects.

Pharmaceutical innovation is a dynamic and non-linear process. Econometric models used to analyze innovative activities in the drug industry have to take this into account. More precisely, dynamic feedback can occur, since scientific breakthroughs in t may influence technological opportunities in t and subsequent years and, hence, innovative output. Given the typical time structure of the industries' R&D and innovative activities, possible effects on innovation may occur around 12 years after the original discovery, or even later. The presence of feedback processes violates the strict exogeneity assumption of conventional fixed or random effects panel estimators. Therefore, I follow Toole (2012) in applying an "entry stock" Poisson QMLE, as suggested by Blundell et al. (1995), which accounts for feedback and unobserved heterogeneity among medical indications. Monte Carlo simulations show that this empirical approach performs quite well if the sample size is rather small and the explanatory variables are highly persistent (Blundell et al., 2002). A high level of persistence over time can be found particularly for the market size measures. According to this approach, Equation (1) can be transformed to

$$E [N_{it}|\bar{N}_{ip}, M_{ip}, \bar{TO}_{ip}, X_{it}] = \exp(\beta_0 + \beta_1 \ln(MKS_{it-a}) + \beta_2 TO_{i,t-b} + \beta C_{i,t-c} + \phi \bar{N}_{ip} + \theta M_{ip} + \rho \bar{TO}_{ip} + \mu_t), \quad (2)$$

where \bar{N}_{ip} denotes the pre-sample mean of new pharmaceuticals, M_{ip} represents the pre-sample prevalence of indication i , and \bar{TO}_{ip} accounts for the pre-sample technological opportunities in i .

in a specific year.

The Poisson QMLE is applied to a population average model in order to estimate (2). The Poisson QMLE is consistent under the assumption of the correct specification of the conditional mean. This implies that the data need not be Poisson distributed (cf., Gourieroux et al., 1984). Throughout the analysis, I use Huber–White robust standard errors in order to account for the possibility of overdispersion and non Poisson-distributed data.

4 Data and Variable Construction

4.1 Pharmaceutical Innovation

Data on new drugs was obtained from the U.S. Food and Drug Administration (FDA) using the Drugs@FDA database.² Each record contains information on the trade name of the drug, its generic name, the components that provide its pharmacological activity, its approval date, and a classification of the newness of the drug formulation. I construct two different proxies for the number of innovations N_{it} . The first follows most of the literature on pharmaceutical innovation, by defining an innovation as a new molecular entity (NME) (Cerda, 2007; Grabowski and Wang, 2006). This measure refers to an active ingredient that has never been marketed before in the United States. Second, I use the number of new drug approvals (NDA) as a broader measure of pharmaceutical innovation. This proxy encompasses NMEs as well as new chemicals derived from marketed active ingredients, new formulations and dosages of already marketed ingredients, and new combinations of marketed ingredients in the year of their approval by the FDA.

The data on new drugs was matched with the diseases or medical indications used in this paper based on their active ingredients which determine their therapeutic use. Therefore, I follow Cerda (2007) in consulting the 19th edition of the Drug Information Handbook published by Lexi-Comp and the American Pharmaceutical Association (Lacy et al., 2010). This handbook is comparable to a pharmaceutical dictionary, providing a list of drugs' active ingredients, the medical conditions the drug is used for, and further information such as adverse effects. I take into account only those medical conditions which can be found on the FDA approved label. Hence, unlabeled and investigational uses are not taken into

²<http://www.fda.gov/Drugs/InformationOnDrugs/ucm135821.htm>

account. For the period 1974 to 2008, 599 unique NMEs and 1,665 unique NDAs have been approved by the FDA in the 203 diseases or medical indications analyzed in this study. However, an NME or NDA may be used as therapy for several medical indications. In this case, an NME or NDA is counted as an innovation for all the medical indications for which it is approved. Figure 1 shows the number of unique NME and NDA throughout the years included in the analysis.³

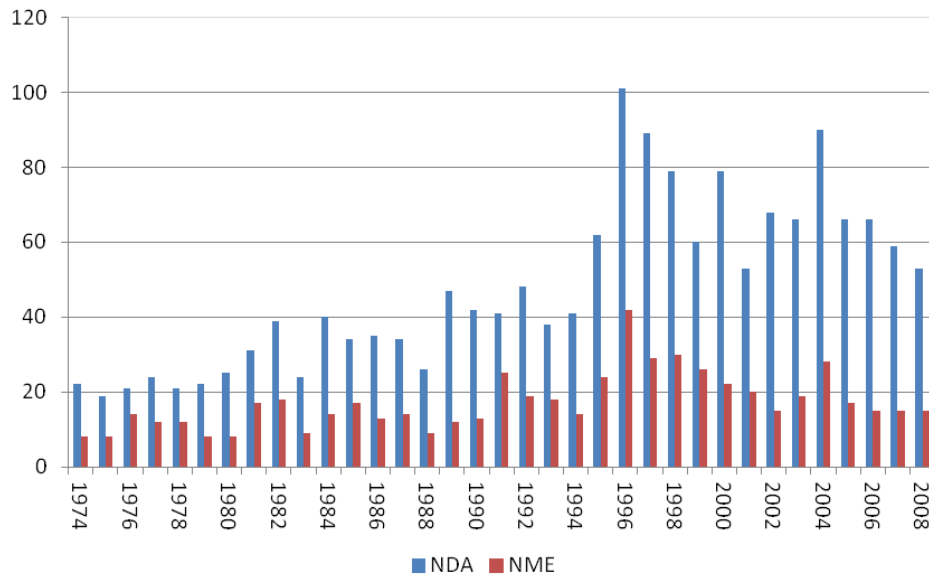


Figure 1: Number of NDA and NME per Year

Source: Drugs@FDA

4.2 Market Size

Similar to related studies, market size is constructed based on demographic data using population sizes in different age groups and individual income. In doing so, I link market size to the potential purchasing power of individuals since a higher income allows higher drug expenditures (cf., Cerda, 2007; Acemoglu and Linn, 2004). There are two arguments for the use of demographic data in the construction of the market size measure. First, drug consumption is likely to change with age. The elderly may spend more on drugs than do younger individuals. However, it is very likely that they are affected by different medical indications than younger members of the population. Second, market size variations due to demographic changes are largely exogenous to scientific achievements, the entry of new

³Table 5 in the Appendix provides more descriptive statistics for the variables used in the analysis

drugs, and the endogeneity of market size and innovation (Acemoglu and Linn, 2004). Therefore, market size per medical indication is proxied by the sum of the purchasing power of five-year age groups a from 0–4 to 85+ for different medical indications, using appropriate weights. More precisely, market size per medical indication i in year t is defined by

$$MKS_{it} = \sum_a \omega_{ia} pop_{at} inc_{at}. \quad (3)$$

Here, ω_{ia} is a weight for medical indication i in age group a , pop_{at} is the total population in age group a at t , and inc_{at} is the individual income of persons in age group a in year t .

Following Acemoglu and Linn (2004), I compute ω_{ia} as the average share of expenditure for drugs assigned to indication i divided by the total individual income of individuals in age group a . To construct this proxy, I use data on drug expenditures and income from the MEPS for the years 1996 to 1998.⁴ I use the 9th revision of the International Classification of Diseases Clinical Modification (ICD-9-CM) published by the National Center of Health Statistics to match the data on the drug spending to the medical indications included in this study. The weights are not time varying, in order to rule out changes caused by new possibilities of diagnosing a disease, new pharmaceuticals to treat it, and other causes of differences in the prevalence rates.

Population sizes per age group and year (pop_{at}) were obtained from the March Supplement of the U.S. Current Population Survey (CPS) provided by the Bureau of the Census for the Bureau of Labor Statistics. The CPS surveys monthly the members of about 50,000 households selected to represent the U.S. non-institutional population. Each member of the surveyed households is assigned to its age group according to the reported age. In addition to the demographic variables, the March Supplement provides information about income. Individual income inc_{at} is proxied by the median of the household income divided by the number of persons in the household. I use this proxy instead of the reported individual income because the latter hardly allows computing meaningful market size measures for those groups who have no or only very little own-income, particularly children, students, and non-working spouses. The income data is adjusted for

⁴This is exactly the timespan used in Acemoglu and Linn (2004). Moreover, it is available for drug expenditure data and for mortality data used as a robustness check.

inflation using the U.S. Consumer Price Index (CPI) for all urban consumers provided by the Bureau of Labor Statistics. It is the logarithms of the market size measures which enter into the regression analysis.

4.3 Technological Opportunities

It is widely accepted in the literature on technological change that technological opportunities play an important role in explaining differences in innovative activities across sectors and over time. However, there is no general consensus concerning the precise definition of this theoretical concept, and particularly its empirical operationalization. Not surprisingly, empirical research has applied a broad variety of indicators for technological opportunities, e.g., industry dummies, survey based measures on the sources of technical advance, and innovation expenditures as share of total expenditures (e.g., Castellacci, 2007; Becker and Peters, 2000; Nelson and Wolff, 1997; Jaffe, 1986; Levin et al., 1985). In this paper, I follow a different approach, proposed by Andersen (1999, 1998) in which the rate of growth of a knowledge stock serves as a proxy for the technological opportunities in a particular technology area. Using this operationalization, high growth rates are associated with high technological opportunities.

The knowledge stock consists of the scientific publications (Pub_{it}) related to medical indication i and published in year t that are assigned to categories related to pharmaceutical research. Publication data was obtained in the following way. A list of 203 medical indications was drawn from the BioPharmInsight database.⁵ Each indication describes a condition or disease which allows of the development of a drug. These medical indications were used to conduct a keyword search in the Web of Science databases (WoS) in order to gather publication data. Publications that contain at least one medical indication in the title have been taken into account. Moreover, I restrict the sample to publications that are related to pharmaceutical research, i.e., that have been assigned to one of the categories “Biochemistry & Molecular Biology”, “Biotechnology and Applied Microbiology”, “Chemistry, Applied”, “Chemistry, Medicinal”, “Medicine, Research & Experimental”, “Pharmacology & Pharmacy”, or “Toxicology”.⁶ I exclude all publications that are not

⁵<http://www.biopharminsight.com/index.html>

⁶A description of these categories can be found at <http://scientific.thomsonreuters.com/mjl/>.

labeled as journal articles. For the period from 1974 to 2008, I obtained 147,092 articles.

Knowledge stocks are created using the perpetual inventory method. The basic idea can be expressed as in Bitzer and Stephan (2007):

$$K_{it} = \lambda_0 Pub_{i,t} + \lambda_1 Pub_{i,t-1} + \dots + \lambda_T Pub_{i,t-T} \quad \text{with } 0 < \lambda \leq 1. \quad (4)$$

Here, λ denotes the share of knowledge of the corresponding vintage that is still in use, and T is the age of the oldest vintage of knowledge still used in t . Assuming geometric depreciation of knowledge, (4) can be transformed into

$$K_{it} = Pub_{it} + (1 - \delta) K_{i,t-1} \quad \text{with } \delta = \frac{\lambda_{\tau-1} - \lambda_{\tau}}{\lambda_{\tau-1}}, \quad (5)$$

where δ is the depreciation rate of the knowledge stock. Following previous work by Cockburn and Henderson (2001), I set δ to 20%.

According to Andersen (1999, 1998), technological opportunities can be proxied by the rate of growth of the knowledge stock. More formally, technological opportunities can be expressed as

$$TO_{it} = \frac{K_{i,t} - K_{i,t-1}}{K_{i,t-1}} * 100. \quad (6)$$

4.4 Regulatory Stringency

Since the vast majority of new drugs have to be approved by the regulatory authorities, such as the FDA in the United States, the strictness of these authorities influences the number of new drugs that are approved for marketing. Regulatory stringency (*ApprovalLength*) is taken into account by calculating the average number of days needed for FDA approval of a new drug in the therapeutic area, i.e., a broader disease category to which a new drug belongs. More precisely, this is the average time between the submission of a new drug approval to the FDA and its final approval (cf., Grabowski et al., 1978). The data was obtained from the Drugs@FDA database which contains information concerning the original drug application.

4.5 Pre-sample Variables

Following the empirical strategy described in Section 3, pre-sample means were constructed in order to account for unobserved heterogeneity among medical indications.

The pre-sample mean of new pharmaceuticals (\overline{N}_{ip}) is the average number of NMEs or NDAs approved by the FDA from 1940 to 1983 per year:

$$\overline{N}_{ip} = \frac{\sum_{t=1940}^{T=1983} N_{it}}{T - t}. \quad (7)$$

Another source of unobserved heterogeneity may be differences in the prevalence of medial indications. One may account for this aspect by introducing pre-sample market size into the analysis. However, this strategy may bias the results, since pre-sample market size is rather highly correlated with the market size variable. Therefore, I use the mortality rate per medical indication in 1983 to account for differences in the pre-sample prevalence of medial indications:

$$M_{ip} = \frac{\sum_a Death_{it}}{\sum_a pop_{at}} * 100,000 \text{ with } t = 1983. \quad (8)$$

Pre-sample technological opportunities are constructed as the average annual growth rate of the knowledge stock from 1979 to 1983:

$$\overline{TO}_{ip} = \left(\left(\frac{K_{it=1983}}{K_{it=1979}} \right)^{1/5} - 1 \right) * 100 \quad (9)$$

5 Empirical Results

5.1 Determinants of Pharmaceutical Innovation

Table 1 presents the results of the Poisson QML estimation without taking lagged variables into account. In models (1) and (4) I analyze the relationship between market size (MKS_{it}), technological opportunities (TO_{it}), and the number of pharmaceutical innovations, i.e., NME_{it} or NDA_{it} . I find a positive and significant response of the number of new drugs to market size. This result is robust against the introduction of technological opportunities in models (3) and (6). Since market size enters in logarithmic form, we can interpret the coefficient as an elasticity. Consequently, the results presented in Table 1 suggest that a 1% increase in the market size leads to an increase in the number of NME and in the number of NDA by approximately 0.3%. This is considerably smaller than found by other studies. On a more aggregated level, Toole (2012) finds an elasticity between 6.8 and 12.7 and Acemoglu and Linn (2004) find a response rate of 6% to increases in the market size.

As to technological opportunities, I find a positive and significant relation to NME and NDA. The coefficient remains significant also in models (3) and (6), in which the market size is included as well. These results suggest that the number of NME and NDA responds not only to demand- but also supply-side variables. However, the coefficient is rather small, which may be a consequence of the operationalization, as growth rates of knowledge stocks. Regulatory stringency (*ApprovalLength*) is not significantly related to the number of new pharmaceuticals. The estimates for pre-sample mortality M_{ip} do not indicate a significant relation to the number of NME and NDA. Pre-sample technological opportunities \overline{TO}_{ip} show no significant effect on NME or NDA.

Pre-sample drug innovations proxied by the average number of NME (\overline{NME}_{ip}) and NDA (\overline{NDA}_{ip}) prior to the analyzed period are positively and significantly related to the number of new pharmaceuticals. This finding suggest that those medical indications for which a high number of new drugs were introduced in the past still appear attractive for innovation. Past innovations may indicate high profit margins, which make it attractive to introduce novelties in these markets to ensure current and future profits. Another possible explanation may be that a large number of past innovations shows that there has been a large amount of research in the corresponding medical indications, which may build the basis for later discoveries and further exploitation of technological opportunities in subsequent years. The positive response to pre-sample innovations contradicts the empirical evidence presented by Toole (2012), who finds a negative response at a much more aggregated level.

5.2 Time Structure

So far, the analysis does not take into account the specific time structure of the innovation process in the pharmaceutical industry. Subsequent to the discovery of a new promising compound, a considerable period of time is needed in order to pass all stages of pre-clinical and clinical testing and obtain regulatory approval. On average, it takes slightly more than 7.5 years from the first clinical testing to marketing approval. The approval phase itself accounts for around 1.5. years out of this timespan. Before a new compound can enter clinical testing, researchers spend almost 5 years on pre-clinical investigations.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	NME_{it}	NME_{it}	NME_{it}	NDA_{it}	NDA_{it}	NDA_{it}
MKS_{it}	0.3293***		0.3322***	0.3146***		0.3163***
TO_{it}		0.0002**	0.0003**		0.0002***	0.0002***
$ApprovalLength$	-0.0009	0.0006	-0.0008	-0.0008	0.0005	-0.0008*
M_{ip}	0.0029	0.0070***	0.0031	-0.0030	0.0011	-0.0030
\overline{TO}_{ip}	-0.0016	-0.0006	-0.0025	-0.0014	0.0013	-0.0019
\overline{NME}_{ip}	0.5506***	0.4254***	0.5456***			
\overline{NDA}_{ip}				0.6427***	0.5109***	0.6397***
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-8.6975***	-3.1544***	-8.7496***	-7.2651***	-1.8633***	-7.2726***
N	4250	4166	3991	4250	4166	3991
Indications	170	175	168	170	175	168

* $p < 0.01$, ** $p < 0.05$, *** $p < 0.01$

All market size measures enter in logarithmic form into the analysis.

Table 1: Determinants of Pharmaceutical Innovation

Hence, on average, it takes 12.5 years from the discovery of a promising new compound to its approval (DiMasi and Grabowski, 2007).

In Table 2, I use time lags in order to account for delays caused by the specificities of the industry's innovation process. More precisely, I introduce a time lag of 7 years to the market size (models (1), (2), (5), and (6)) and technological opportunities variables (models (3), (4), (7), and (8)). This corresponds to the time needed on average from clinical testing to approval.

Models (1) and (5) show a significant and positive relationship between the lagged market size and the number of NME and NDA. In models (2) and (6), in which contemporary and lagged market size are introduced simultaneously, the coefficients of the lagged market size turn out to be negative. However, contemporary and lagged market size are not significantly related to the number of NME and NDA in this case. These findings may indicate that market size when the project started, as well as the forecast of the market size when the new drug is introduced to the market, play a role in pharmaceutical R&D decisions. However, the estimation results do not allow for any clear-cut conclusion as to which market size measure dominates the decision.

Regarding technological opportunities, the results suggest differences between NME and

NDA. The coefficients of TO_{it-7} are positive, but not significantly associated to the number of NME. In the case of NDA, the results suggest that contemporaneous and lagged technological opportunities are significantly and positively related to the number of new pharmaceuticals. This finding may indicate that the development of NDA builds upon a slightly different knowledge base than the more innovative NME. Past technological opportunities seem to be less important for the development of the more innovative NME. In general, the results for the control variables are comparable to those presented in Table 1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	NME_{it}	NME_{it}	NME_{it}	NME_{it}	NDA_{it}	NDA_{it}	NDA_{it}	NDA_{it}
MKS_{it}		1.3370	0.3444***	0.3457***		0.7309	0.3514***	0.3521***
MKS_{it-7}	0.3375***	-1.0035			0.3474***	-0.3847		
TO_{it}	0.0003***	0.0003***		0.0003**	0.0002***	0.0002***		0.0002***
TO_{it-7}			0.0002	0.0002			0.0002*	0.0002*
$ApprovalLength$	-0.0011*	-0.0010*	-0.0012*	-0.0012*	-0.0009*	-0.0009*	-0.0009*	-0.0009*
M_{ip}	0.0032	0.0029	0.0032	0.0032	-0.0036	-0.0039	-0.0046	-0.0046
\overline{TO}_{ip}	-0.0022	-0.0027	-0.0023	-0.0021	-0.0015	-0.0018	-0.0015	-0.0014
\overline{NME}_{ip}	0.5340***	0.5428***	0.5315***	0.5354***				
\overline{NDA}_{ip}					0.6177***	0.6232***	0.6214***	0.6243***
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-8.6722***	-8.7788***	-8.7829***	-8.8204***	-7.7737***	-7.8400***	-7.8847***	-7.9121***
N	2964	2964	2817	2817	2964	2964	2817	2817
Indications	168	168	167	167	168	168	167	167

* $p < 0.01$, ** $p < 0.05$, *** $p < 0.01$

All market size measures enter in logarithmic form into the analysis

Table 2: Determinants of Pharmaceutical Innovation With Time Lags

In order to account also for the pre-clinical phase, I use 12 year time lags for market size and technological opportunities.⁷ The results are rather similar to those presented in Table 2. However, lagged technological opportunities have a non-significant coefficient. Hence, technological opportunities at the beginning of the pre-clinical research phase are not significantly related to the number of NME and NDA. A possible explanation for this finding may be found in the high uncertainty accompanying pharmaceutical R&D. High technological opportunities at the beginning of the pre-clinical research phase may lead to extensive exploration, but most of the possible compounds do not obtain mar-

⁷The results can be found in Appendix A.2.

ket approval. In contrast, a high level of technological opportunities at the beginning of the clinical research phase may enable pharmaceutical companies to improve promising compounds that may have a higher probability of finally obtaining market approval.

5.3 Robustness Checks

Table 3 presents several robustness checks. As pointed out by Acemoglu and Linn (2004), changes in the insurance coverage of drug expenditures can be another source of market size variation. In order to proxy drug expenditure coverage, I multiply the market size measure by the fraction of privately insured persons in age group a at time t , (ins_{at}). The data was obtained from the Medical Expenditure Panel Survey (MEPS), a large scale survey of U.S. families and individuals, their medical providers, and employers. Equation 3 can be modified to $\widetilde{MKS}_{it} = \sum_a \omega_{ia} pop_{at} inc_{at} ins_{at}$. Models (1) and (7) present the regression analysis using \widetilde{MKS}_{it} . The results are rather similar to the results presented above. As in Table 1, I find a positive and significant response for NME and NDA to both market size and technological opportunities. The results stay qualitatively the same if the insurance coverage encompasses also other types of health insurance.

In models (2) and (8) in Table 3, market size is constructed using weights representing the average fraction of individuals dying because of a specific indication divided by the total number of deaths in an age group for the years 1996 to 1998 (cf., Cerda, 2007). Again, the weights are not time varying, in order to rule out changes in the use of drugs for a certain medical indication due to price and quality changes as well as the introduction of new pharmaceuticals. The data on multiple causes of death in the United States was obtained from the National Vital Statistics System of the National Center of Health Statistics. The results suggest a positive but not significant relation between market size and the number of new pharmaceuticals. Technological opportunities are again positively associated with the number of NME and NDA.

In (3) and (9), technological opportunities are constructed by only taking biotechnology publications into account. These are journal articles assigned to the categories “Biochemistry & Molecular Biology” and “Biotechnology and Applied Microbiology” in the WoS databases. Whereas the market size variable is still significantly positive related to the

number of NME and NDA in this setting, the coefficient for technological opportunities is insignificant. In models (4) and (10), I employ only basic research articles to construct technological opportunities using the CHI classification of journals (Hamilton, 2003). The CHI classification categorizes each article according to the type of research prevalent in the journal in which it was published. Taking only “basic biomedical research” into account, the response of the number of new pharmaceuticals to market size remains significantly positive whereas the coefficient for technological opportunities is insignificant for NDA in model (10). The insignificance of basic research and biotechnology technological opportunities may be caused by the construction of the publication database. Since a keyword search for medical indications was used, the data may capture mainly applied research and only a few basic and biotechnology research papers building the basis for new pharmaceuticals for several medical indications. In particular, the data may not include new research methods which encompass a considerable amount of innovation in biotechnology and may be more indirect in how they affect the number of new pharmaceuticals. Moreover, the relevant knowledge stocks for basic research may differ from the ones for more applied research.

In (5) and (11) I use a 10% depreciation rate of the knowledge stock when constructing the proxy for technological opportunities. The coefficients for technological opportunities are positive and significant for NME and NDA. Hence, the technological opportunities measure seems to be robust against changes in the depreciation rate. Market size is still positively and significantly related to the number of new pharmaceuticals. In regression models (6) and (12) I use a Poisson QML estimation with fixed effects for medical indications. In these models, the market size measure is insignificant. This result is rather surprising but may be the consequence of the fixed effects model. Since I run the analysis on a rather disaggregated level, there are a considerable number of medical indications for which no NME or NDA was introduced over the entire period of analysis. These indications are not taken into account in the fixed effects estimation, and this may have consequences for the results. Nevertheless, the proxy for technological opportunities is significantly positively related to the number of NME and NDA. Moreover, the results presented in Table 1 are generally robust to the use of ten year age groups in the construction of the market size proxy and linear depreciation of the knowledge stock over a

five year period.

A further concern might be that larger markets attract more public or private research, generating higher technological opportunities. One may check for these feedback effects by taking only rare diseases into account, since there are only a few market incentives to develop medications for them. However, the number of rare diseases in the sample is quite small and the corresponding Poisson models do not converge.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent Variable	NME_{it}	NME_{it}	NME_{it}	NME_{it}	NME_{it}	NME_{it}	NDA_{it}	NDA_{it}	NDA_{it}	NDA_{it}	NDA_{it}	NDA_{it}
MKS_{it}	0.3255***	0.0601	0.3393***	0.3250***	0.3362***	0.5940	0.3452***	0.0070	0.3354***	0.3121***	0.3278***	1.0149
TO_{it}	0.0003***	0.0002**	-0.0000	0.0008**	0.0013***	0.0007***	0.0003***	0.0002***	-0.0000	0.0005	0.0008**	0.0004***
$ApprovalLength$	-0.0013*	0.0005	-0.0009	-0.0011*	-0.0011*		-0.0008	0.0005	-0.0005	-0.0009**	-0.0011**	
M_{ip}	0.0007	0.0041	0.0028	0.0031	0.0032		-0.0046	0.0007	-0.0035	-0.0024	-0.0030	
\overline{TO}_{ip}	-0.0036	-0.0020	0.0031	-0.0070	-0.0050		-0.0033	0.0012	0.0047	-0.00241	-0.0163	
\overline{NME}_{ip}	0.5088***	0.4495***	0.5240***	0.5272***	0.5543***							
\overline{NDA}_{ip}							0.6251***	0.5142***	0.6578***	0.6312***	0.6233***	
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-8.1387***	-4.3928***	-8.8269***	-8.4010***	-8.5758***		-7.6390***	-2.0039**	-7.8283***	-7.0144***	-7.1325***	
N	2169	4162	3191	3827	3368	3474	2169	4162	3191	3827	3368	3801
Indications	168	175	155	168	173	144	168	175	155	168	173	158

* $p < 0.01$, ** $p < 0.05$, *** $p < 0.01$

All market size measures enter in logarithmic form into the analysis

In models (1) and (7) market size is multiplied with the share of privately insured individuals in an age group at t ,

(2) and (8) market size is constructed using weights representing the average share of individuals dying because of i ,

(3) and (9) take only biotechnology publications into account when constructing technological opportunities,

(4) and (10) only basic research publications into account when constructing technological opportunities,

(5) and (11) use an 10% depreciation rate of the knowledge stock used for TO_{it} ,

(6) and (12) use Poisson QML estimation with fixed effects

Table 3: Robustness Checks

5.4 Reverse Causality

As pointed out by Kleinknecht and Verspagen (1990), there may be a mutual dependency between market size and innovation instead of a unidirectional causality. Particularly in the pharmaceuticals industry, new products may introduce the potential for reverse causality. Lichtenberg (2005b, 2004) shows that new drugs contributed to the longevity increase observed in many countries over the past few decades. Hence, through their impact on consumers' life expectancy, new drugs lead to an endogenous growth of pharmaceutical markets (Cerda, 2007). However, Acemoglu and Linn (2004) argue that the drug-induced changes in the population sizes are quite small relative to overall demographic changes. Nevertheless, they propose a strategy to address this issue. Following their approach, I instrument current market size by the corresponding market size five years earlier. More precisely, I use the size and income of those 70–74 years old in 1984 to instrument for population size and income of those 75–79 years old in 1989. The population size and the income of those 70–74 years old is highly correlated with the size and the income of those 75–79 years old five years later, but it is unaffected by new pharmaceuticals which were approved in the meantime.

In the empirical analysis of this instrumental-variable I use a Generalized Methods of Moments (GMM) estimator for the pooled Poisson regression. Standard errors are bootstrapped with 1000 replications and clustered on the indication level. The results are presented in Table 4. These results are quite similar to the baseline results in Table 1. The number of new NME and NDA responds positively to market size. However, the coefficients for technological opportunities are insignificant. Consequently, I find no evidence that the problem of reverse causality arises in the analysis.

6 Conclusion

Recent empirical contributions have stressed the importance of the (potential) market size for the development of new pharmaceuticals. At the same time, many scholars have emphasized the changes in the industry's R&D process, from “random screening” to “guided

	(1)	(2)	(3)	(4)
Dependent Variable	NME_{it}	NME_{it}	NDA_{it}	NDA_{it}
MKS_{it}	0.2391***	0.2502***	0.1845***	0.2063***
TO_{it}		0.0001		0.0001
$ApprovalLength$	-0.0004	-0.0004	-0.0002	-0.0002
M_{ip}	0.0000	0.0011	-0.0029	-0.0023
\overline{TO}_{ip}	-0.0022	-0.0029	-0.0013	-0.0027
\overline{NME}_{ip}	1.0977***	1.0557***		
\overline{NDA}_{ip}			1.3883***	1.3190***
Year Dummies	Yes	Yes	Yes	Yes
Constant	-7.3557***	-7.4919***	-5.9523***	-6.2739***
N	4250	3991	4250	3991
Indications	170	168	170	168

* $p < 0.01$, ** $p < 0.05$, *** $p < 0.01$

All market size measures enter in logarithmic form into the analysis

Market size is instrumented with market size of the same age cohort five years earlier.

Table 4: Determinants of Pharmaceutical Innovation GMM Estimation

drug development”, and have pointed to the importance of advances in molecular biology and related fields for the industry’s technological opportunities and innovative capabilities. Against this background, I have analyzed the relationships between (potential) market size, technological opportunities, and the number of new pharmaceuticals in the United States. This empirical analysis is based on a unique dataset combining data from different sources. In the analysis, I use an “entry stock” Poisson quasi-maximum likelihood estimator (QMLE), as suggested by Blundell et al. (1995).

The empirical estimates reveal a significantly positive response of the number of new pharmaceuticals, i.e., new molecular entities or new drug approvals, to market size and technological opportunities. In the robustness checks, the market size measures lose significance when mortality data is used in its construction and when the PQML fixed effects model is used. As a further robustness check, I constructed the technological opportunities proxy by taking only biotechnology or basic research publications into account. The results from this indicated no significantly robust positive relation between these two variants of the technological opportunities measure and the number of new pharmaceuticals. When taking the specific time structure of the pharmaceutical R&D process into account by including time lags of seven years into the analysis, I found no clear-cut relationship

between lagged market size, lagged technological opportunities, and the number of new pharmaceuticals.

Overall, the results suggest a quite robust and significantly positive relation between the (potential) market size and the number of new pharmaceuticals. These results are in line with recent contributions by Cerda (2007) and Acemoglu and Linn (2004). I found no evidence for a reverse causality between market size and the number of new pharmaceuticals. Regarding technological opportunities, I found a significantly positive relation with the number of new drugs. This result supports earlier studies indicating the importance of technological opportunities in themselves and the scientific progress which is an important source of new opportunities for pharmaceutical innovation (e.g., Toole, 2012; Lim, 2004; Griliches et al., 1991). Nevertheless, the results for technological opportunities need further analysis of the role of advances in biotechnology and basic research for the development of new pharmaceuticals.

Since my results suggest that the (potential) market size influences the rate and direction of innovative activities in pharmaceuticals, policy makers might introduce and continue programs creating incentives for the development of drugs for medical indications which are associated with rather small markets. Nevertheless, these programs have to take into account the fact that private R&D investment is rather concentrated in the bigger markets among the small ones (Yin, 2008). Since the results indicate a positive association between technological opportunities and the number of new pharmaceuticals, public support of scientific research directed to certain diseases may enhance the relevant technological opportunities and consequently the number of new pharmaceuticals. Moreover, public research funding may lead to quality improvements in terms of the safety and efficacy of new drugs. Recommendations concerning the support of different research types to increase the number of new pharmaceuticals need further evaluations of the role of biotechnology and basic research. Regarding regulatory stringency, the empirical analysis does not suggest that reductions in this stringency would be an appropriate method for spurring pharmaceutical innovation.

A Appendix

A.1 Descriptive Statistics

		Mean	Std. Dev.	Min	Max	Observations	
NME_{it}	overall	0.1458128	0.440	0.000	5.000	N	5075
	between		0.212	0.000	1.880	n	203
	within		0.386	-1.734	3.266	T	25
NDA_{it}	overall	0.5239409	1.113	0.000	12.000	N	5075
	between		0.726	0.000	4.760	n	203
	within		0.845	-3.236	11.324	T	25
MKS_{it}	overall	18.18052	1.973	10.887	23.256	N	4800
	between		1.970	11.222	22.948	n	192
	within		0.172	17.667	18.803	T-bar	25
TO_{it}	overall	15.29261	175.750	-20.000	9074.948	N	4786
	between		41.838	-20.000	487.966	n	200
	within		171.707	-492.673	8602.275	T-bar	23.93
$ApprovalLength$	overall	545.0301	143.466	201.267	780.136	N	5075
	between		143.806	201.267	780.136	n	203
	within		0.000	545.030	545.030	T	25
M_{ip}	overall	5.455496	18.628	0.000	127.006	N	4775
	between		18.675	0.000	127.006	n	191
	within		0.000	5.455	5.455	T	25
\overline{TO}_{ip}	overall	8.13265	13.113	-16.349	96.463	N	4675
	between		13.147	-16.349	96.463	n	187
	within		0.000	8.133	8.133	T	25
\overline{NME}_{ip}	overall	0.6217778	0.662	0.000	6.000	N	5075
	between		0.664	0.000	6.000	n	203
	within		0.000	0.622	0.622	T	25
\overline{NDA}_{ip}	overall	0.8076554	0.762	0.000	6.000	N	5075
	between		0.763	0.000	6.000	n	203
	within		0.000	0.808	0.808	T	25

Table 5: Descriptive Statistics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) MKS_{it}	1						
(2) TO_{it}	-0.0317*	1					
(3) $ApprovalLength$	0.2823***	-0.0267	1				
(4) M_{ip}	0.2007***	-0.0050	0.1576***	1			
(5) \overline{TO}_{ip}	0.1054***	-0.0480**	0.0343*	0.0366*	1		
(6) \overline{NME}_{ip}	0.1311***	-0.0289*	-0.0116	0.0355*	0.1080***	1	
(7) \overline{NDA}_{ip}	0.2065***	-0.0239	0.0096	-0.0059	0.1149***	0.9025***	1

* $p < 0.01$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Correlations

A.2 Additional Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	NME_{it}	NME_{it}	NME_{it}	NME_{it}	NDA_{it}	NDA_{it}	NDA_{it}	NDA_{it}
MKS_{it}		0.9085	0.3413***	0.3436***		0.7943	0.3584***	0.3599***
MKS_{it-12}	0.3269***	-0.5845			0.3464***	-0.4500		
TO_{it}	0.0003***	0.0003***		0.0003**	0.0003***	0.0003***		0.0003***
TO_{it-12}			-0.0022	-0.0021			-0.0001	-0.0001
$ApprovalLength$	-0.0013*	-0.0012*	-0.0016**	-0.0016**	-0.0008	-0.0008	-0.0009*	-0.0009*
M_{ip}	0.0008	0.0005	0.0013	0.0013	-0.0046	-0.0049	-0.0057	-0.0057
\overline{TO}_{ip}	-0.0035	-0.0040	-0.0031	-0.0030	-0.0032	-0.0037	-0.0023	-0.0023
\overline{NME}_{ip}	0.4992***	0.5099***	0.4814***	0.4863***				
\overline{NDA}_{ip}					0.6147***	0.6255***	0.6070***	0.6116***
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-8.2348***	-8.4603***	-8.4407***	-8.4926***	-7.7385***	-7.9334***	-7.9770***	-8.0133***
N	2169	2169	1985	1985	2169	2169	1985	1985
Indications	168	168	163	163	168	168	163	163

* $p < 0.01$, ** $p < 0.05$, *** $p < 0.01$

All market size measures enter in logarithmic form into the analysis

Table 7: Determinants of Pharmaceutical Innovation With 12-year Time Lags

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