When are Patents Traded and Why: A Dynamic Structural Model of Drug Development and Patent Trading*

Jie Fang†

June 13, 2024

Latest Draft Available Here

Abstract

Reallocating patents to firms more proficient in their utilization can improve welfare. Moreover, the timing of such trades significantly impacts innovation outcomes. I construct a unique dataset that captures interactions between patent trades and the drug development within the U.S. pharmaceutical sector, and find that 82% of patents are traded before the associated drug hits the market. Drugs involved in patent trades are also more likely to advance to the launch stage compared to those without patent trades. I construct a dynamic structural model for the development process of a new drug, taking into account crucial factors such as trade dynamics, firms' comparative advantages, transaction costs, and search frictions at various stages of the development process, encompassing discovery, clinical trials, FDA approval, and product launch. The estimation of this model reveals that (i) firms with greater stage-specific experience enjoy reduced development costs at the corresponding stage; (ii) transferring patents to firms with lower development costs enhances the likelihood of a drug advancing to subsequent stages; and (iii) market frictions in patent trading exhibit significant variation across different phases of drug development, with transaction costs reaching their peak before New Drug Application with FDA. Counterfactual analyses show that reducing transaction costs within the patent market at pivotal stages significantly increases the likelihood of drug success and the market value of the drug.

Keywords: Patent trade, Innovation, Drug development outcome, Structural estimation, Market frictions

JEL Codes: O34, O33, C73, L65

*I am deeply grateful to my supervisor Victor Aguirregabiria, Loren Brandt, and Murat Celik for their continual guidance and support throughout this project. I extend particular thanks to Matthew Mitchell, April Franco, Heski Bar-Issac, Eduardo Souza-Rodrigues, Yanyou Chen, and Yao Luo for their insightful comments and suggestions, and to the audience at the 2023 CEA Conference, the 2023 AMES conference, and the 2023 EARIE Conference, as well as the members of the UofT IO group, for their helpful feedback.

†Department of Economics, University of Toronto. Email: jie.fang@mail.utoronto.ca

1 Introduction

Companies often possess distinct comparative advantages at different stages of the innovation and product development process. Some companies excel at generating novel ideas, while others specialize in developing these ideas into market-ready products. This inherent disparity in expertise has made patent trading a pervasive tool for greasing the wheels of innovation, decreasing production costs and increasing the probability of successfully bringing the product to the market. While existing literature attests to inherent frictions within the patent market with substantial welfare implications (Akcigit, Celik, and Greenwood (2016) and Serrano (2018)), it remains unclear how these frictions vary across different stages of development due to a lack of disaggregated data on patent trade timing. As an example, subsidizing patent trades increases patent trade volume, but how much it can improve the likelihood of a successful product launch depends on *when* the patent trading happens in the product development process.

This paper sheds light on the pivotal role of patent trade *timing* at different stages of the drug development process and its critical influence on a drug's successful market launch. To align the timing of patent trade with the corresponding stage of drug development, I leverage the unique characteristics of the pharmaceutical industry. Due to regulatory requirements, pharmaceutical firms must report each phase of drug development to the FDA. This mandatory reporting allows for the mapping of patent trade events within the drug development timeline. This is the first paper to systematically combine data on landmark events during drug development with information on the trade of patents linked to the drug. The new dataset not only enriches our analysis but also provides a valuable resource for broader research, including the study of how patent trading interacts with innovation direction, among others.

My analysis of the data reveals that only 18% of patents are traded after the corresponding drugs reach the market. A majority (over 58%) of patents are traded during clinical trial stages (Phases I, II, and III), with the new patent holder subsequently taking over the development process. When examining the relationship between patent trade and a drug's successful launch, I discover that drugs with patent trades have a higher chance of advancing to the next stage, especially past Phase II. At the extensive margin, drugs associated with patent trades are about 8% more likely to make it to market than those without patent trades.

These findings raise compelling economic questions. First, what factors contribute to the varying distribution of patent trades across stages? Certain stages witness fewer trades, possibly because companies possess similar expertise and skills, reducing the incentive for trade. Alternatively, increased market friction in these stages—due to factors like information disclosure or market thickness—might make trades challenging. Second, there is a notable positive correlation between patent trade and a drug's success rate. This observed increase in success rates might stem from trades ensuring a more suitable pairing of patents with adept developers. Or, it could be the result of selection bias, where superior patents are likely to be traded more often.

To understand how patent market friction changes across the drug development stages and to ascertain the causal effects of patent trading on drug development outcomes, I propose a dynamic structural model. This model endogenizes the decisions of drug development and patent trading, which collectively influence the likelihood of a drug's success and its final value. The model is a dynamic game, with pharmaceutical firms as participants who are eligible to become owners of the drug. Each of these firms is endowed with a vector of experiences, one for each stage in the development of a drug. Stage-specific experience reduces development costs in the corresponding stage and helps in advancing the development of the drug. This disparity in expertise creates significant comparative advantages, creating opportunities for trades. Without a market for patented drug projects, drugs would exclusively be developed by their original patent holders. If development costs at a certain stage become excessive, the company might choose to stop the project. The patent trade market offers an alternative: Firms can sell the drug project to another entity with lower subsequent development costs, boosting the drug's odds of advancing.

Approaching this process as a finite horizon game, with the endpoint being the drug's introduction to the market, I segment the drug development process into distinct stages: discovery, clinical trials (Phase I - small scale; Phase II - medium scale; Phase III - large scale), FDA approval, and market launch. At every stage, firms face a decision: proceed with development, trade the patent, or exit the market. Their choices depend on development costs and returns from patent sales. In an ideal frictionless market, firms would always meet the most compatible buyer who attributes the highest value to the drug. As a result, drugs with promising potential would consistently traded to the best-suited developer for further development. However, market frictions imply that firms do not always encounter the most suitable buyer. And even when they do, the associated transaction costs may deter the transaction from taking place.

When a drug is successfully developed and introduced to the market, it competes with other drugs in the same therapeutic category. At this terminal stage, our model incorporates a demand system for differentiated products. Here, consumer demand is influenced not solely by the drug's characteristics, but also by its final owner. The demand system takes into account both the competitive landscape and the structure of the drug market, aiding in forecasting the value of drugs under development upon their market entry.

The success probability and final value of the drug depends on the owner, or more accurately the sequence of owners. The frictions in the patent trade market are pivotal in this model, affecting whether a beneficial transfer can take place, and consequently whether a drug can eventually progress to the launch stage. The objective of the structural model is twofold: first, to identify where the key frictions sit in the patent market along the development process, and second, to assess how these frictions impact a drug's likelihood of market launch, and its final market value.

My empirical analysis combines several sources of data. The first source records drug development milestones (e.g., discovery, preclinical, Phase I/II/III clinical trails, registration, approval, launch). I focus on small molecule drugs linked to at least one patent granted by the United States Patent and Trade Office (USPTO) between 1980 and 2016, their detailed patent information, including applications

and reassignments if any. From these, I construct an analytical dataset. I first link the drugs to their respective patents and then identify each drug's primary patent based on patent type and application date. The resulting matched dataset encompasses 1,005 small molecule drugs protected by a primary US patent from 1980 to 2016. The final dataset is a longitudinal record of household drug expenditures sourced from the Medical Expenditure Panel Survey (MEPS) spanning 1996 to 2020. I employ this data to assess the market size and value of drugs in their respective therapeutic areas. Using these sources, I construct a unique and comprehensive dataset for the study of drug/patent trade during the drug development process.

The structural model estimation proceeds in three main steps. First, the annual drug expenditure data allows me to estimate a demand model that determines the value of the drug or patent, using the subsample of drugs that are successfully launched in the market. Second, I use a discrete-choice model to estimate the probability distribution of potential buyers, drawing on observed patent transactions and the drug's expected value derived from the demand system. Finally, incorporating drug value and potential buyer estimates, I solve the dynamic game of drug development, trade, and market exit decisions. Through backward induction, I estimate key parameters, such as the patent market's transaction costs and firm-specific development costs at each development stage.

Estimating the structural model yields several key results. First, transaction costs vary across stages, peaking notably prior to FDA registration, and then Phase I clinical and III trail stage . This variation of transaction costs across stages can be attributed to different factors. For instance, pre-Phase I costs are largely influenced by the valuation of the drug's potential and associated risks, given the scant information available. In contrast, the increased cost before Phase III and (later stages) may stem from negotiation complexities related to due diligence processes and agreements concerning trial data and other rights transfers. Second, development cost decreases with the owner's stage-specific experience at critical stages, this finding is consistant with the conjecture that firms are heterogenous in their product development capacities, which affect their decisions. Third, engaging in patent trade such that the buyer's stage-specific experience considerably lowers development costs enhances the chance that the drug moves to subsequent stages. The results support the hypothesis that transferring patents to firms more adept at their development enhances the likelihood of the drug's market launch.

Although patent trades correlate with higher drug launch rates, this relationship is not necessarily causal. For example, it is possible that superior drugs are simply traded more often. To test this hypothesis, I conduct a counterfactual experiment that eliminates patent trades at all stages. Compared to the empirical success rate of 34.6% for drugs without associated patent trades in data that does not account for endogenous selection, a counterfactual estimation considering endogenous selection results in a 38.4% success rate when patent trades are eliminated. The 3.8 percentage point difference reflects the presence of positive selection in the patent market. Nevertheless, even after eliminating the selection effects, we still observe a positive effect of patent trade on the drug's success for most stages.

For policy implications, I explore various hypothetical scenarios to understand the impact of a more efficient market on drug development outcomes. While subsidizing patent trade increases the proba-

bility of patents being traded; its effect on whether the drug successfully launches is stage-dependent. A reduction in transaction costs most notably influences trades occurring prior to FDA registration, which marks a shift from drug development to commercialization and manufacturing. Reducing transaction costs during this phase could boost success rate by 16.6% percentage potentially leading to 12 more drugs entering the market each year. Similar benefits are observed at other pivotal stages, particularly where a transition requires different resources and specializations—like Phase I clinical trial, which marks a transition from lab testing to clinical trials. Facilitating patent trades at these critical stages significantly increases the probability of drugs reaching the market.

Furthermore, enhancing the likelihood of sellers meeting buyers who place a higher value on the drug marginally increases the rate of successful drug development. However, this effect is not as significant as when addressing transaction costs at specific development stages. This suggests that the main friction in the pharmaceutical sector is not the challenge of identifying the optimal buyer, but rather the negotiation frictions that arise after potential buyers are found. Even if sellers encounter the ideal buyer, the complexity and uncertainty inherent in drug patents lead to unavoidable transaction costs during the valuation and negotiation process. Therefore, solely enhancing the search and matching process between sellers and buyers is insufficient.

The rest of the paper is organized as follows. Section 2 provides a review of the relevant literature and outlines my contributions to the field. Section 3 provides institutional details related to the pharmaceutical industry and patent lifecycle. Section 4 describes the data and descriptive evidences. Section 5 develops the theoretical model. Section 6 describes the empirical results and counterfactual exercise. Section 7 concludes and explores at prospective avenues of research. Supplementary estimation checks and data construction details can be found in the Appendix.

2 Literature Review

This paper contributes most directly to the literature on the market for technology and its economic implications. Over recent decades, the market for technology has become a focal point of academic scrutiny. Some key channels are widely studied such as technology licensing (Agrawal, I. Cockburn, and L. Zhang (2015), Arora, Fosfuri, and Gambardella (2001), Gans and Stern (2000), and Cassiman and Veugelers (2006)), technology acquisition via M&A deals (Ahuja and Katila (2001) and Haucap, Rasch, and Stiebale (2019)), and research cooperation(Banerjee and Siebert (2017)). The research on the market for patent and patent trade has surged more recently, since a more research-friendly patent assignment data is released by the USPTO in 2015 and further curated inSerrano (2010).

The economic impact of this market is significant. Researchers have established that the patent market facilitates the reallocation of patents from the original inventors to entities that are better suited to use them (Serrano (2018)), leverage the strategic enforcement right of patents (Galasso, Schankerman, and Serrano (2013), Chien (2011), and Serrano, Chondrakis, and R. Ziedonis (2023)) and more importantly, develop and explore comparative advantages in developing and commercializing an invention (Arora,

Fosfuri, and Gambardella (2001), Gans and Stern (2003), and Arora and Ceccagnoli (2006)). A more efficient market for patent contributes to both higher private and social welfare, and drives economic growth (Akcigit, Celik, and Greenwood (2016) and Arque-Castells and Spulber (2019)) Meanwhile, the literature also documents the inefficiencies and failures in the current patent market (Serrano (2018) and Hagiu and Yoffie (2013)) which is attributed by multiple factors, such as information friction, market thickness, mismatching concern, illiquidity and hold-up issues (Chondrakis, Serrano, and R. H. Ziedonis (2021) and Arora, Fosfuri, and Gambardella (2001)).

While most literature in this topic have centered around the benefits and implications of patent trading in itself, this paper pivots towards a relatively less-explored dimension: the timing of patent trades and their consequent impact on innovation outcomes. The timing of patent trades has been given scant attention. For instance, Serrano, Chondrakis, and R. Ziedonis (2023) delved into the lag between the execution and record date of patent reassignments at the USPTO, investigating the interplay between strategic patent acquisition disclosures, the reputation of enforcers, and imitation costs. This paper, however, approaches the topic from a distinct perspective. It seeks to unpack when, within the product development lifecycle, patents are most frequently traded, and how such timings influence the innovation's trajectory.

The contribution of this paper is twofold. Using the specific setting of pharmaceutical industry, first, I provide the first evidence of when patents are traded in relation to the specific stages of the product development process and how the market friction varies at different stages. Second, I evaluate the direct contribution of patent trade to the project transition across stages and thus shed lights on how reductions in the transaction costs during vairous phases of patent market impact innovation performance and social welfare.

This paper also relates to research on the intellectual property right and innovation in the pharmaceutical sector. Drug development decisions are affected by many factors, such as market competition (Khmelnitskaya (2021), Howard et al. (2015), Filson (2012), Reiffen and Ward (2005), H. G. Grabowski and Vernon (1992), and Caves et al. (1991)), demand shock (Acemoglu and Linn (2004), Blume-Kohout and Sood (2013), and Dranove, Garthwaite, and Hermosilla (2014)), supply side factors (Majewska (2022)), merger and acquisition (H. Grabowski and Kyle (2008), Cunningham, Ederer, and Ma (2021), Letina, Schmutzler, and Seibel (2021), and Ornaghi (2009)) and learning from competitors' failure news (J. L. Krieger (2021)), R&D alliances (Banerjee and Siebert (2017) and Lerner and Merges (1998)), investment type and financial constraints (Budish, Roin, and Williams (2015) and J. Krieger, Li, and Papanikolaou (2022)). Moreover, in the pharmaceutical sector, most research on patents emphasizes strategic patenting by branded companies (H. Grabowski, Brain, et al. (2017), Hemphill and B. N. Sampat (2012), and H. G. Grabowski and Kyle (2007)) and the consequences of imperfect intellectual property rights (Budish, Roin, and Williams (2016), Gaessler and Wagner (2022), Branstetter, Chatterjee, and Higgins (2016), Gilchrist (2016), Y. Zhang (2020), and Gupta (2023)). My project complements this literature by introducing a new model of the drug development process, emphasizing the pivotal role of patent transaction timing. It highlights how patent market frictions impact the probability of new drug introductions.

3 Industry Background

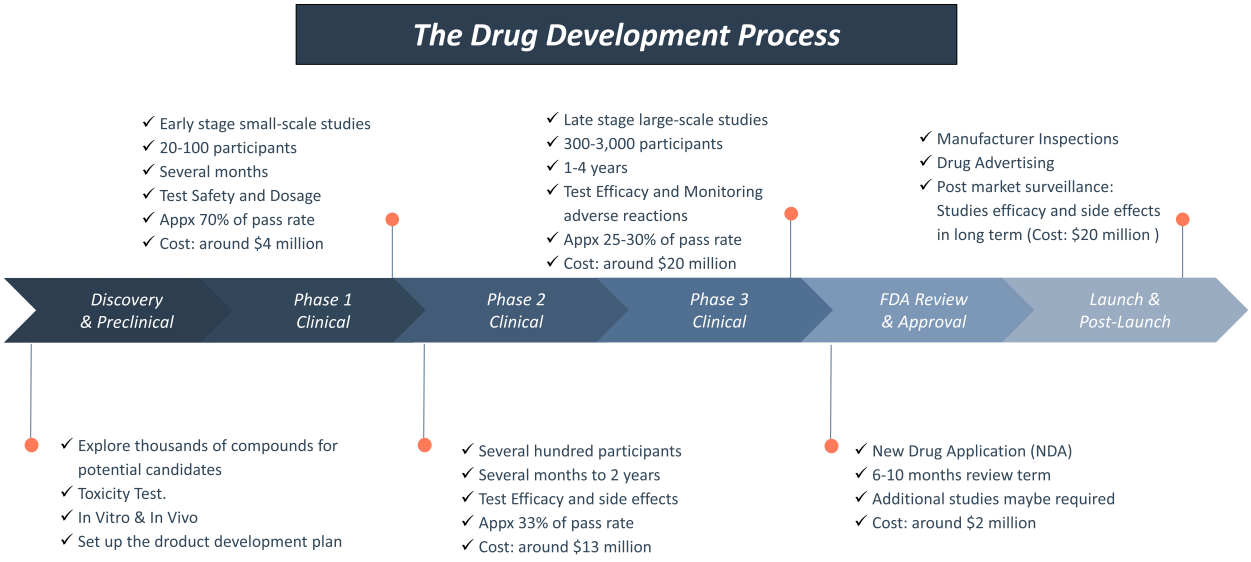
To empirically identify the timing of patent trade and its impact on the innovation outcome, I use the setting of drug development. While scholars have documented that differences in firms' invention and commercialization capabilities drive patent trades (Arora, Fosfuri, and Gambardella (2001) and Arora and Ceccagnoli (2006)), direct evidence on how this directly contributes to project development outcome is still limited. To make valid inferences about this relation requires correct link between a patent and its associated product. Additionally, we should be able to monitor the progression of project development, align the moment of patent trade within this timeline, and follow up on subsequent project choices. The unique features of pharmaceutical drug development makes it a well suit to this context because of its regulatory structure and disclosure requirements. Moreover, the pharmaceutical industry represents an actively innovative industry with significant economic and social impact. This industry's unique characteristics, also leveraged in studies like J. L. Krieger (2021) and Cunningham, Ederer, and Ma (2021), are invaluable for analyses requiring granular project-level data.

This section provides brief industrial background and highlights the key features of drug patent, supplemented with examples that combine both aspects.

3.1 Pharmaceutical Industry

The development of a branded drug (or patented drug) involves a standard set of structured milestones starting with the discovery or design of potential compounds or molecules. Then, the promising candidates of compounds proceed to preclinical tests, which assess efficacy and toxicity, either in vitro or in vivo. After these preclinical evaluations, successful drug candidates then move to clinical trails on human volunteers after an Investigational New Drug (IND) application filed and approved by FDA. Clinical trials usually consist of three phases. In Phase I, the drug is tested on a small group of healthy volunteers to test safety and dosage. Phase I evaluates the drug's safety and appropriate dosage on a small group of healthy individuals. Phase II tests efficacy and side effects on patients with the targeted disease. This stage spans several months to years. In Phase III, the most large-scale study, enrolls hundreds to thousands of participants to further validate efficacy and monitor adverse reactions, which often lasts several years. The cost and time required for the drug development process are increasing as three clinical phases progress, with a dramatically decreasing pass rate. The overall development for a new molecule drug can take 10 years on average (DiMasi, H. G. Grabowski, and Hansen (2016)). After completing clinical trials, firms can submit a New Drug Application (NDA) to the FDA. This application is meticulously reviewed by both internal and external experts at the FDA, who assess clinical trial results and the firm's manufacturing capabilities. The FDA then decides whether to approve, deny, or request further studies. This review can span several months to two years. Upon FDA approval, the drug hits the market. The development cost for new drugs varies but is substantial, with estimates ranging from $340 million to $2 billion, depending on the type of therapy,

the manufacturing firm, and the methods of estimation.[1] Overall, the drug development process is lengthy, costly and risky. Alongside the clinical trials, pharmaceutical companies also have to engage in additional development activities. These include patent filing (typically during the discovery or preclinical phase),[2] regulatory submissions to the FDA, manufacturing site inspections, and eventually, marketing and advertising as the drug nears or enters the market.



3.2 Drug Patents

The typical intellectual property protection received by a branded drug is either a patent granted by USPTO or regulatory exclusivity granted by the FDA. The two forms of protection operate independently as backups for each other. Patent terms and exclusivity periods may or may not run concurrently, depending on the type of exclusivity at issue (FDA, 2018).[3] Exclusivities offer branded drugs protection from generic competition, either through data exclusivity or marketing exclusivity.

[1] After accounting for costs of failed trials, the most cited studies of drug development cost reported the average cost of getting a new drug into the market was about $1.1 billion in 2003, increasing to $2.8 billion in 2013(DiMasi, H. G. Grabowski, and Hansen (2016) and Adams and Brantner (2006)). A recent study updated the cost in 2018 around $1.3 billion. (Wouters, Mckee, and Luyten, 2009)

[2] There has been a discussion on strategic delay of drug patent application. Given the lengthy development process before FDA approval and marketing, many patented drugs enjoy only a few years of monopoly profits after approval and before patent expiration, paving the way for generic competitors. Delaying the patent application can extend this profitable window. However, if the patent application is postponed too long, the inventor risks losing patent rights either because someone else files first or due to the disclosure of the invention to the public, which has a grace period of only 12 months. For these reasons, patent owners have strong incentives to file patents as early as possible.

[3] https://www.fda.gov/drugs/development-approval-process-drugs/frequently-asked-questions-patents-and-exclusivity

This form of protection is especially vital for drugs that don't qualify for patents. Exclusivities are granted upon marketing approval, hence they don't involve any technology transfers and don't influence decisions or outcomes during the drug development phase. In this paper, given that my objective is to analyze how the timing of technology trade affect innovation outcome, the analysis is confined to branded drugs that are patent-protected.

Drug patents are similar to other types of patents, providing 20 years of protection from the date of USPTO application.[4] The patent application process typically takes on average 24.6 months from the date of the unprovisional application.[5] The patent application process typically takes around 24.6 months from the date of the unprovisional application. It's worth noting that patents can be reassigned even during this pending period, before official patent grant. After a patent has been granted, to maintain its validity, maintenance fees are due at intervals of 3 to 3.5 years, 7 to 7.5 years, and 11 to 11.5 years after the date of issue.

Drug patents typically cover one of the following four aspects: (1) the drug's active ingredient or drug substance; (2) its specific use for treating a certain indication[6]; (3) its formulation, which includes its physical form (e.g. liquid or capsule) and the method of administration (e.g. by mouth or injection); and (4) the production method employed to manufacture the drug (Angell and Reading (2005) and Gupta (2023)). In industries like software, semiconductors, and mobile communications, products and services are complex, integrating numerous patentable interconnected processes and components. For instance, an integrated circuit might involve hundreds of patents. Contrast this situation with the pharmaceutical industry, a patent on a new molecular entity for a specific drug is clear-cut and separate from patents on molecules for other drugs. In the pharmaceutical context, the average drug is protected by approximately 3.4 to 4 patents as listed in the Orange Book. (Gupta (2023) and Ouellette (2010)). Once a molecule or compound is developed, the firm will patent its active ingredient, this patent is considered primary patent that offers the strongest form of protection and contains the key knowledge capital used in the drug development process. Secondary patents, covering one of the other three characteristics, are filed over the course of a drug's development and even after its launch. These patents are mostly filed for the purpose of extending the drug's monopolist position in the market. The clear boundaries between drug patents associated with their use in the specific treatment make it feasible to identify patent-drug links and determine which patent is crucial for the development of a specific drug.

Patent trade plays an important role in the drug development process. For example, Avycaz (ceftazidime-avibactam) was an antibiotic approved by the U.S. Food and Drug Administration (FDA) in February 2015. This prescribed medicine used to treat the symptoms of intra-abdominal infections, urinary tract infections and bacterial pneumonia was protected by seven patent. The primary patent US-8178554 (Heterocyclic compounds, their preparation and their use as medicaments, in particular as

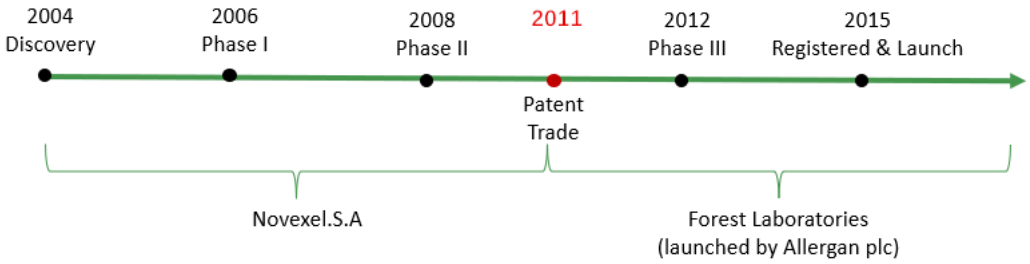
[4]Effective on June 8, 1995, the term of a patent is 20 years from the date on which the application for the patent was filed in the United States. Patents filed before that date has a term of 17 years after the grant date of the patent.

[5]https://www.uspto.gov/help/patent-help#type-application-processes_1208

[6]In the context of drug development, the condition or disease for which a drug is being tested to treat, prevent, or diagnose. It is the specific therapeutic use for which a drug is studied and for which the drug company will later seek approval by regulatory agencies, such as U.S. Food and Drug Administration (FDA).

anti-bacterial agents) was originally invented and owned by Novexel S.A..[7] However, the complexities and high costs associated with drug development and commercialization often lead smaller companies or inventors to transfer their patents to larger firms with the necessary resources. Novexel S.A started the drug development process from discovery in 2004 till Phase II clinical trial in 2008. The patent was then traded to Forest Laboratories Holdings Limited in 2011. Forest Laboratories having the capacity for advanced clinical trials, funding, and infrastructure, took over the development process and conducted Phase III clinical between 2012 to 2014. In 2015, the drug was approved by FDA and launched by Allergan Pharmaceuticals International Limited, which is the parent company of Forest Laboratories.[8] This journey of AVYCAZ, from its inception at Novexel to its final approval under Actavis, highlights the dynamic nature of patent trading in the pharmaceutical industry. The transfer of patents can enable resources and expertise to be optimally utilized, ultimately benefiting patients with the timely introduction of innovative therapies.

Figure 1: Development Milestones of Avycaz



4 Data and Sample Construction

The main goal of this paper is to identify the friction in patent market at different phases and the timing effect of patent trade on the drug development outcome. For this purpose, I construct a comprehensive data set with patent trade observation, drug development histories and measure of market value of drugs. This section provides brief industrial background and describes the various datasets and data construction for the empirical work. More detailed discussion of data construction is documented in Appendix B.

4.1 Data Sources

Patent Application & Trade

[7] Patent US-8178554B2 unprovisional application was officially filed with USPTO on May 10, 2011 under application no.13068399. This application is a division of a serie of U.S. patent appication tracing back to an original international PCT application filed in 2000. Detailed patent application can be found at https://patentimages.storage.googleapis.com/ee/c3/08/204e6083c373c6/US8178554.pdf

[8] The patent was reassigned from Forest Laboratories to Allergan Pharmaceuticals International Limited on December 29, 2020. This is considered as an internal transfer between the subsidaries, which is not the focus on this paper.

The patent granted by USPTO is obtained from PatentsView database. For each granted patent, I retrieve information about the patent number, date of application filing, type of patent, assignee, and patent category.[9] Patent trade information draws from the USPTO Patent Reassignment Data. This data provides details on which patents are being traded, and by whom. The records include a range of patent reassignment reasons including sales, mergers, license grants, government interests, and collateral, etc. Using this information, I am able to classify records to their respective groups. Following the method of data construction in Serrano (2010), this study specifically focuses on standalone patent reassignments.[10] The patent sample period covers 1980 to 2016.

Drug Development Milestones

My primary dataset on drug development records comes from Cortellis, which is owned and managed by Clarivate Analytics. The database includes information on drug candidates in the development process worldwide, among which 48,416 observations for drugs development conducted in U.S. territory (as of May 2023). Cortellis tracks each drug candidate's development process by aggregating information from different sources (e.g. clinical trial registries, patent filings, financial filings, company press releases, academic conferences, and FDA submissions). The database contains detailed development milestones for each drug development process at drug indication level. Notably, it records the date when that stage of development (discovery, preclinical, Phase I/II/III clinical trails, registration, approval, launch) was recorded, the drug's names, the associated developer, the target indication, the country in which that stage occurs. The database also contains pharmaceutical patent information, besides the patent information (e.g. applicant, inventor, IPC codes, priority date, etc.) they also link the patent to the drugs it is used. Cortellis also documents detailed company information ,such as the number of trials the firm has been involved by phases of development. The database is regularly examined and updated by professional analysts and curators.

Drug Market Size

A measure of a patent/drug's potential and realized market value can shed light on the economic implications of patent trades and the ultimate success of the drug. The expected return of the drug is estimated based on the information from the Medical Expenditure Panel Survey's (MEPS) Prescribed Medicines Files and Medical Conditions Files. I obtained these annual data for the 1996-2020 period. The first dataset is used to approximate annual revenue of each drug, while the second is used to construct the outside option for each therapeutic market defined.

[9] Patentview provides multiple types of patent classification standard, namely the cooperative patent classification (CPC), World Intellectual Property Organization (WIPO) technology classification, US patent classification (USPC) and the National Bureau of Economic Research (NBER) technology categories (consistent with that in NBER PDP dataset). In this paper, I use the IPC standard to conduct first round screening of pharmaceutical patent.

[10] A standalone patent reassignment is the reassignment with the change of ownership between distinct entities, which drops the reassignment due to "name change" of the patentee, "security interest" for patent being used as a collateral, the "correction" or "change of address" by patentee, or employee assignments from the inventor to the employer. I also drop the reassignments due to "merger and acquisition".

4.2 Sample Construction

In constructing my final sample, I integrated multiple analytical datasets. The primary dataset focuses on small molecule drugs, specifically those with a non-missing "SMILES" (simplified molecular-input line-entry system) chemical structure. Since my objective is examining the impact of patent trade on drug development outcomes, the sample focuses on these small molecule drugs that are associated with at least one patent. A significant challenge encountered was establishing the drug-patent linkage. My starting point was extracting US patent records and drug development data from Cortellis. Subsequently, these patents were linked to drug development records using drug names. To enhance this matching process, I also incorporated the drug-patent linkage available in the FDA's Orange Book, which lists all relevant patents for FDA-approved drugs.[11]

Regarding the relationship between patents and drugs, a straightforward one-to-one mapping isn't always evident. There exist instances where a singular patent is used in multiple drugs. In such scenarios, each drug's development is treated as an individual record. Conversely, there are situations where multiple patents are associated with a single drug, in this case, we need to differentiate between primary and secondary patents. Those concerning the active ingredient are deemed primary since they shield the drug's fundamental technological attributes. Prior studies have either classified the earliest expiring patents on drugs as primary, given their potentially stronger property rights compared to subsequent filings (Hemphill and B. N. Sampat (2011), Branstetter, Chatterjee, and Higgins (2016), and Gupta (2023)), or engaged in manual patent text reviews to pinpoint active ingredient patents and designate the primary ones, as highlighted in Kapczynski, Park, and B. Sampat (2012). For this study, I refined the patent sample based on three criteria: (i) patents grouped in category 3 "Drugs&Medical" in NBER classification, (ii) patents whose IPC code aligns with at least one of the "A61K/A61P/C01/C07" categories[12] in the USPTO dataset, and (iii) patents whose type labeled as either "product", "drug combination", "formulation", or "new use" with non missing compound name. Following this screening process, if a drug still correlates with several patents, the earliest filed patent is retained.

For these primary patents in the drug sample, I linked their detailed application and reassignment records using the patent numbers from the USPTO dataset. The next task is to pinpoint the timing of patent trades in relation to the drug development timeline.While many drugs have multiple development pipelines for different therapeutic indications, the literature often examines projects at

[11]FDA's Orange Book is widely used in the literature for the study of IP protection for approved drugs (Kapczynski, Park, and B. Sampat (2012) and Gupta (2023)). However, it cannot be solely used in this analysis as it is a selected sample containing only successfully launched drugs, which are not sufficient to study drug development successful rate. Orange Book dataset was digitized by Professor Heidi Williams. Both data for years 1985-2016 and user's guide can be found at https://www.nber.org/research/data/orange-book-patent-and-exclusivity-data-1985-2016

[12]NBER classifies patents into six broad technology categories. The category "Drugs & Medical" involves pharmaceutical products, medical equipment, and other health-related inventions. Patents under this category are very heterogeneous covering medical compounds, medical device, methods of preparation, etc. A further refined classification is needed. To excluding medical equipments and food related data, I restrict the patent sample using more detailed IPC subclass. Based on patent content reviews, the following subclasses are the most relevant for the study of medical compound and molecules: A61K "PREPARATIONS FOR MEDICAL, DENTAL, OR TOILET PURPOSES", A61P "SPECIFIC THERAPEUTIC ACTIVITY OF CHEMICAL COMPOUNDS OR MEDICINAL PREPARATIONS", C01 "INORGANIC CHEMISTRY", C07 "ORGANIC CHEMISTRY"

the indication level. This approach has been used to study the influence of information spillovers on project decisions (J. L. Krieger (2021)), control for firm scale and scope, and evaluate the impact of a firm's experience within a specific therapeutic category on its success rate (Danzon, Nicholson, and Pereira (2005)).

However, in this study, where I regard the drug-patent relationship as a singular entity, using the indication level presents challenges. Firstly, firms often explore multiple indications, with many not progressing beyond early stages, such as preclinical trials or Phase I. If we solely focus on patent trades at the indication level, there's a potential misinterpretation. For instance, a patent trade could occur after a specific indication has failed, but this doesn't necessarily denote a negative impact on the overall drug development. When assessing the effect of patent trades on drug success rates or transition probabilities across phases, this could introduce bias. Secondly, when evaluating a patent's value, it may no longer correspond with the drug's anticipated worth. To address this, I'm focusing on the development status that reached the furthest stage for each drug. As an example, if a drug had three indications—with one reaching Phase I, another Phase III, and the third being launched—I would use the launched indication as the reference point for the drug's development timeline, regardless of the sequence of the other two. The linked dataset contains 1,005 small molecule drugs, each protected by at least one patent, documenting their drug development and patent activities from 1980 to 2016.

Next, I created a drug-therapy link to determine the therapeutic market that each drug targets. The FDA-approved drugs can be categorized using the World Health Organization's Anatomical Therapeutic Chemical (ATC) classification system.[13] Due to sample size constraints, I aggregated the approved drugs into 23 therapeutic markets using their ATC2 classifications. Some drugs might fall under multiple ATC categories. In such instances, I determined the primary ATC group based on the technology class (TC) code from the MEPS dataset. However, a challenge arises when attempting to define therapeutic markets for drugs still in development, as both ATC and TC codes are generally assigned for approved drugs. For these developmental drugs, I rely on information regarding their therapy area, indications, and technologies sourced from the Cortellis database. While Cortellis' therapy area definitions don't align perfectly with the ATC standard themselves, we can leverage this data to anticipate the therapeutic market as defined in our study.

To predict the therapy market for drugs still in development, I need to first merge the relevant datasets that have been constructed. I began by connecting the approved drugs from the Cortellis drug development database to the Orange Book data, using both patent numbers and drug names as reference points.[14] Because of discrepancies in drug naming across the two datasets, I also referenced the drug's key ingredient. A match is validated only when both the trade name and key ingredients align. For unmatched entries, I manually cross-referenced them using the FDA's official Drugs@FDA-Approved Drugs list.[15] Next, I connected the Orange Book data with the MEPS data using the NDA application

[13] ATC is a hierarchical classification system based on the drug's therapeutic, pharmacological and chemical properties. Drugs are classified in groups at five different levels. There are 14, 94, and 269 groups at ATC1 (1st level), ATC2 (2nd level) and ATC3 (3rd level) ,respectively.

[14] Orange Book only documents non expired patents associated with the approved drug. Therefore, we need to have a further match using drug names.

[15] https://www.accessdata.fda.gov/scripts/cder/daf/index.cfm?event=browseByLetter.page&productLetter=A

Table 1: Description of Drug Development and Patent Trade Distribution

	N	N_with patent trade
Whole sample	1005	131
By highest-stage		
Discovery&Preclinical	200	29
Phase I clinical	63	8
Phase II clinical	200	21
Phase III clinical	127	11
FDA Registration	56	6
Launch	359	56

number.[16] Finally, I merged these datasets using the triplet of drug-patent number, NDA application number, and therapy market. Then, leveraging the therapy market definitions for approved drugs and their associated Cortellis therapy area and indication details, I predicted the therapeutic market for drugs under development.

My final dataset covers drug development projects initiated from 1980 to 2016. It focuses on 1,005 drugs that I successfully linked to a US-granted primary patent. For each of these drugs, I tracked ownership, developmental stages, associated dates and developers. If a drug was discontinued midway, I recorded the highest stage reached. For drugs that reached market, I have data on their launch dates and annual revenue up to 2020. If a patent was traded, details on the assignor, assignee, and execution date are documented. Additionally, this dataset is enriched by integrating developer information from the Cortellis database. Both the drug developers and patent traders in our sample are connected to company-specific details using name matching algorithm. This includes metrics such as the number of drugs in development, owned patents, participated deals, and trials categorized by phase.

Table 1 provides descriptive information on the main sample, which includes the entire sample, drugs with patent trades, by highest status. (Number of patent trades by therapeutic market can be found in Appendix) During the sample period, I observe 1,005 drug-patent pair, among which 131 of them has been recorded with standalone patent trade for at least once. Among those traded, 29.7% observe multiple trade, thus I have a total of 177 patent trade observations. The Table further breaks down drugs by the highest stage attained. 35.7% of patented drugs reached launch stage over the sample period, the number is slightly higher for drugs with patent trades, which is 42.7% (56 over 131 drugs). Moreover, over half of the companies originate just one patented drug during this period, and 70% of companies originate two or fewer drugs. When narrowed to drugs with patent trades, these figures are even more pronounced: of the companies that began a drug's development and later sold it, 85% had initiated only one drug.

After completing the matching process, I identified 383 drugs that reached the launch stage. However, only 141 of them had revenue/sales information available in the MEPS dataset. This discrepancy

[16]Note that one single NDA application number may correspond to multiple NDC (same drug, formula but with different package). For the use of expected return of a certain drug, we should aggregate these multiple NDC into one to account for its return.

arises from two main reasons: first, some drugs had small market sizes, making them likely to be overlooked in survey data; second, the MEPS dataset covers the period from 1996-2022. As a result, drugs approved too early and discontinued before this timeframe remain unaccounted for. For the drugs missing revenue data, I will estimate their expected returns using the same methodology applied to drugs still in development.

4.3 Descriptive Evidence

Table 2 showcases the distribution of patent trades by various drug development stages. In subsequent sections of this paper, I will group the drug discovery and pre-clinical phases together following papers in this literature. Both these stages are primarily concerned with the screening, testing, refinement, and optimization of new molecules in a laboratory setting. Collectively, they will be referred to as the "discovery" phase.

Several insights can be drawn from the table. First, patents can be traded at any phase of the drug development process. Looking into details, only 18% of patent trades occur after a drug has been launched in the market. Approximately 74% of patent trades take place before the completion of the full clinical trial. The majority of patent trades, amounting to 24.3%, are observed between the end of early discovery phases and the start of Phase I clinical trials. When assessing the average size of the patent seller (quantified by the number of active drugs they're developing) across stages, it's evident that developers with a smaller portfolio tend to sell their patents during the preliminary stages of drug development. This observation aligns with our hypothesis that companies have comparative advantages at different stages of drug development, creating opportunities for patent trades. It is also consistent with established notions and findings within the drug development literature. Often, smaller firms pioneer innovative drug projects, many of which are later acquired and further developed by larger pharmaceutical entities (Cunningham, Ederer, and Ma (2021) and I. M. Cockburn (2004)).

Table 2: Distribution of Patent Trade by Drug Development Stage

	N	Percentage	Cumulative	avg. size of seller
Before Discovery&Preclinical	10	5.6%	5.6%	6
After Discovery until Phase I (small-scale tests)	43	24.3%	29.9%	9
After Phase I until Phase II (medium-scale tests)	20	11.3%	41.2%	19
After Phase II until Phase III (large-scale tests)	31	17.5%	58.8%	110
After Phase III until FDA registration (final tests)	27	15.3%	74.0%	91
After FDA registration until Launching	14	7.9%	81.9%	105
Post-Launch	32	18.1%	100.0%	58
Total	177	100%		

Note: The number in this table accounts for multiple trade cases. The average size of seller is measured by the number of active drugs in the development of the developers.

Next, I examined the relationship between patent trading and drug transition probabilities in Table 3. The table presents drug transition probabilities based on their patent trade status. The left block

lists drugs progressing to each stage, grouped by those with and without patent trades. The middle part shows the empirical distribution of the highest stage that a drug reaches. For instance, for all drugs with patent trade during the development process, 42.7% are eventually launched in the market. This ratio is 8.1 percentage point higher than the 34.6% for drugs without patent trade. The right side indicates the probability of quit at each stage. For example, of the drugs that reached Phase III clinical trials and were traded at any stage prior, 22.3% were discontinued and thus did not succeed. Overall, drugs with traded patents tend to have lower probabilities of quit, particularly post-Phase II.

Table 3: Percentage of Quit at Each Stage

	Remaining Patent		Dist. of Highest Stage		Prob. of Quit	
Stages	no trade	with trade	no trade	with trade	no trade	with trade
Before Phase I Clinical	874	131	19.6%	22.1%	19.6%	22.1%
Before Phase II Clinical	703	102	6.3%	6.1%	7.8%	7.8%
Before Phase III Clinical	648	94	20.5%	16.0%	27.6%	22.3%
Before Registration	469	73	13.3%	8.4%	24.7%	15.1%
Before Launching	353	62	5.7%	4.6%	14.2%	9.7%
Launched	303	56	34.6%	42.7%		

In summary, the descriptive evidence reveals key insights. Firstly, patents are actively traded throughout all stages of drug development, with a majority of trades happening before the completion of clinical trials. This active trading behavior exhibits variations: the frequency differs across stages, and smaller entities tend to sell their patents during early development stages. Furthermore, there's a positive correlation between the likelihood of a drug advancing to the next development stage and its associated patent being traded, a trend which is more obvious in the later stages of development.

There is concern about a 'killer motive' in acquiring patents to block potential competitors, especially when the buyer already has similar drugs on the market or in development. Cunningham, Ederer, and Ma (2021) documented this phenomenon in the pharmaceutical industry, finding that drug projects are less likely to be developed when they overlap with the acquirer's existing products. In my study of 131 drug projects with traded patents, 54 were discontinued post-trade. I investigated whether the buyers were incumbents in the therapeutic class, either with drugs launched or in development. Initially, only 18% of these trades involved buyers with a market-launched drug in the same class. The discontinuation rate for these incumbents was 29.2%, compared to 43.9% for non-incumbents (Table 4). When including drugs in development, the discontinuation rate was 38.8% for incumbents versus 42.7% for non-incumbents. These findings reveal lower or similar discontinuation rates for incumbents compared to non-incumbents, suggesting that 'killer purchases' may not be a significant concern in this context.

Table 4: Probability of Quit After Trade (Incumbent or Not)

	Trade & Quit	Trade & Cont	Prob. of Quit
Drugs in Market			
Incumbent	7	17	29.2%
Non Incumbent	47	60	43.9%
Drugs in market or development			
Incumbent	19	30	38.8%
Non Incumbent	35	47	42.7%

The different findings between Cunningham, Ederer, and Ma (2021) and this study might stem from the acquisition form. While they examined drug project discontinuation post-merger and acquisition (M&A), this study focuses on standalone patent trades. Two factors may explain the variance in results. Firstly, M&A often involves the transfer of multiple patents, where some projects might be secondary to the acquisition's primary goal. In this case, an overlapping project that is unfamiliar to the acquirer is less likely to continue unless it offers significant advantages over existing ones. Secondly, acquisitions might be more effective in fully eliminating competition than purchasing single projects. In acquisitions, the competitor is entirely absorbed, whereas buying single projects leaves room for the original owner to develop similar patents, posing future competition.

Table 5 presents a statistical summary of the firms' experience at various stages, measured by the number of trials they have conducted at each stage.[17] The data reveal significant variability in firms' experience across stages. On average, there is a trend showing that as stages progress, the number of trials with which firms have experience tends to decrease.

Table 5: Distribution of Firm's Experience Across Stages

Stage	Obs	Mean	Std. Dev.	Min	Max
Phase I trials	120	115.9	324.4	1	2268
Phase II trials	126	131.2	347.5	1	2150
Phase III trials	120	83.5	242.8	1	1590
Phase IV trials	95	72.4	185.1	1	1282

The empirical evidence shed light on the interplay between patent trading and the drug development process. It reveals the critical role patent trading has on drug transition decisions, with varying likelihoods at different stages. Multiple factors may affect the likelihood of patent trade at different stages, include company homogeneity and patent market friction. For instance, there's a notable 24% of patent trades observed before Phase I, compared to a mere 11% before Phase II. Two possible forces might explain this variance. Firstly, companies might possess comparable expertise in drug development between Phase I and Phase II, reducing the incentive for trade. Alternatively, increased

[17] Phase IV clinical is known as post-marketing surveillance or post-marketing studies, takes place after a drug has been approved by FDA and is already on the market. It serves as an indicator of a firm's expertise in launching drugs.

patent market friction during this stage might hinder transactions, even when companies display a strong interest in trading. To disentangle these influencing factors and understand the true impact of patent trade on drug transition probability, and to gauge its effectiveness in mitigating market friction across various drug development stages, a comprehensive structural model will be introduced in the subsequent section.

The empirical evidence is informative in understanding the relationship between patent trade and drug development process. It shows that patent trade plays an important role in the drug transition decisions and the likelihood of patent trade varies across stages. Multiple factors affect the likelihood of patent trade at different stages, such as homogeneity of companies and patent market friction. For example, I observe 24% patent trade happening after discovery before Phase I, while only 11% occurs after Phase I. The reasons behind this difference can be either that companies possess similar skills and capabilities of drug development after Phase I before Phase II compared to discovery to Phase I such that there's less potential for trade, or that the patent market friction at this stage is relatively higher than other stages such that transactions are hard to achieve. To disentangle different factors influencing patent trade, examine its causal impact on drug transition probability and test the efficiency of reducing market friction across drug development stages, I introduce a structural model that incorporate these crucial features in the next section.

5 Model

To answer the empirical questions discussed above, I propose here a dynamic model of patent trading and drug development, which determines two main outcomes: the probability of success and the final value of a drug. Within this model, I assume that each firm initially possesses a patented drug, along with other expertise and complementary knowledge capital essential for advancing the drug through various development stages. It's worth noting that this expertise and knowledge capital may vary between stages. For example, a firm may have rich experience in Phase I clinical trial but possess limited expertise in Phase III. The costs associated with drug development at each stage are contingent upon the firm's specific expertise level for that stage. Furthermore, differences in expertise among different firms at each stage create distinct comparative advantage of firms throughout the drug development process.

In the absence of alternative owners, if the development costs at certain stage become too high for the owning firm, the drug development process is stopped. Now let's consider a scenario in which drugs, along with their patents, can be traded among potential owners (typically the pharmaceutical companies). The existence of comparative advantage among these firms creates opportunities for mutually beneficial trades. The market for patent trade offers the original owner the option to sell the drug to someone with lower development cost for the subsequent stages, thereby increasing the likelihood of the drug progressing to the next phase of development. In a frictionless market, drugs with positive final values would either be developed by a single owner or transferred through a sequence of owners, ultimately reaching successful development. However, in the reality, patent trade involves

various costs, including factors like information asymmetry, and transaction cost, etc. While some drugs may indeed progress to the next stage of development if traded, the transaction costs could impede such trade, potentially causing the drug's development to stall at its current stage. The objective of this model is twofold: firstly, to identify the transaction cost associated with different stages of the development process, and secondly, to assess how these frictions impact the probability of success of the drug.

In this model, consider each firm is a drug that protected by a patent. The firms produces drugs using patents (knowledge capital) and variable inputs. At each development stage, these firms have the choices of selling their patents, investing in drug development or quitting the market. These choices are influenced by the firm's drug development cost and the transaction cost associated with trade in the patent market. There are finite number of firms in the market, each has potential to become a drug developer. These firms are heterogeneous in their drug development experience and commercialization capacity. This difference directly affects the success rate of drug development at each stage and ultimately determines the final value of a drug.

(a). Setup

The model follows a finite horizon $t = 0, 1, 2, ..., T$ as illustrated in Figure 2. At period 0, a firm, says i, owns patented drug project j.[18] At this stage, the original drug project is commonly patented, substantial development investments are required to bring the drug into the market, which is costly and uncertain. Each firm i is endowed with a vector of experiences $\boldsymbol{e}_{it} = (e_{i1}, e_{i2}, ..., e_{iT})$ that are exogenously given at the beginning and constant over time.

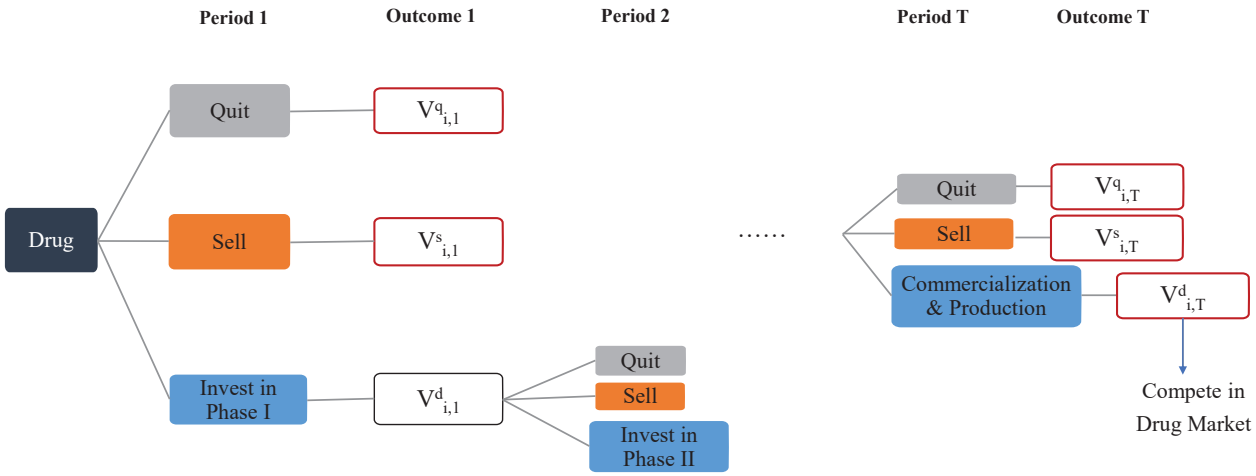
In period 1, the drug owner i faces three potential decisions: to invest in Phase I clinical trials, to sell the drug , or to quit the market without any further action. If the firm i opts to quit or sell, then the game of this drug ends for firm i at period 1. If firm i chooses to invest in its development, it receives an associated value of developing, denoted as $V^d_{i,1}$. Then in period 2, the firm confronts a similar set of choices: to invest, to sell, or to quit. If the drug is sold by firm i to another firm i' , then in the succeeding period, firm i' will encounter the analogous decision points: whether to invest in Phase I, to sell the drug, or to quit. This sequence of game proceeds up till the final period T, provided that investment decisions are continually made. By the terminal period T, drug j will have passed all the requisite development phases, reaching the commercialization and production stage. In this terminal period, the firm must decide whether to commercialize the approved drug independently, to sell it to another entity for production, or to abstain from any action.

In this model, the drug and its associated patent are intrinsically linked, meaning a sale of the patent also signifies a sale of the drug. A firm's decision depends on several factors: the anticipated value of the drug, costs specific to the investment stage, transaction costs associated with patent trading, and the potential value from exiting the market. For clarity in notation, I will omit the subscript j

[18]The assumption here is that the patents are exogenously assigned to firms, with each drug having already passed the discovery screening which has potential to be put in clinical tests.

when describing the model. Nonetheless, it's crucial to remember that each observation and decision is specific to an individual drug j level.

Figure 2: Illustration of Firm's Decisions in the Model



(b). Value of Choices

At the beginning of each period t, firm i observes the cost shocks τ and κ^d, as well as the distribution of potential buyers. Firm i enters the market to meet the potential buyer. Firm i can meet and negotiate with only one potential buyer per stage. The likelihood of firm i' be the optimal buyer b is based on its expected value of the drug $V_{i't}$, characteristics of firm i and i' and market-specific features. Assuming there is a random shock ε^ρ associated with the search, and it it follows Type 1 EV distribution, the probability that a firm i' is the best buyer has the following form :

$$Pr(b_t = i'|\boldsymbol{x}) = \frac{exp(\boldsymbol{x}'_{i't}\mu + \rho V_{i't})}{\sum_k exp(\boldsymbol{x}'_{kt}\mu + \rho V_{kt})} \tag{1}$$

In an ideal market with no search frictions, we would expect the buyer to always be the firm that values the drug the most. This would mean that the model parameter ρ associated with the buyer's valuation is extremely high ($\to \infty$), and the vector of parameters μ would be 0. Any deviation from this ideal scenario indicates the presence of market frictions, such that the optimal buyer might not

necessarily be the firm with the highest valuation. The parameter ρ is exogenously determined in the market, reflecting the prevailing search technology. After observing the potential buyer b and assessing the potential surplus from a trade, firm i chooses from the discrete options represented by (d, s, q) based on the expected outcomes.

Once the buyer and seller meet, they negotiate the price p_{it} using the Nash bargaining framework. The value derived from the trade for the firm i is

$$V_{it}^s = p_{it} - (\tau_t + \varepsilon_{it}^s) \tag{2}$$

where τ_t is the stage-specific transaction cost in the secondary patent market, and ε_{it}^s, zero mean shocks in the transaction costs which are independently and identically distributed over time. Suppose the buyer's bargainning power is ω, the price $p_{it} = (1-\omega)V_{bt} + \omega \cdot [max\{V_{it}^d, V_{it}^q\} + \tau_t]$. For the details on the derivation of the price, see the appendix.

The expected value of investing in drug development at period t is the difference between the expected continuation value and the associated investment cost for that development stage. The investment cost follows the form $\kappa_{it}^d = \kappa_t^0 - \kappa_t^1 ln(e_{it} + 1)$ .This equation indicates that the investment at each stage consists of two components: the consistent stage-specific average investment cost κ_t^0 which remains the same for all firms, and a firm-specific cost $\kappa_t^1 ln(e_{it}+1)$. This latter component is influenced by e_i^t , the number of trials firm i has conducted for t-stage trials, thus capturing the firm's particular experience at that stage. The parameter κ_t^1 reflects the heterogeneity in investment cost across firms. Note that since firm's experience e_{it} is exogenously given at the beginning, the stage costs $\kappa_{it}^d = (\kappa_{i1}^d, \kappa_{i2}^d, ..., \kappa_{iT}^d)$ are also known to all the firms since period $t = 0$. Therefore, the value of engaging in drug development can be written as:

$$V_{it}^d = \beta_t \mathbb{E}(V_{i,t+1}) - (\kappa_{it}^d + \varepsilon_{it}^d) \tag{3}$$

Lastly, when the firm chooses to quit the market, it receives a value of quitting denoted as V_{it}^q. Given that this is a finite game, the terminal value of the drug is determined by market demand. When a drug successfully reaches the market, the revenue is derived from its sales within the respective therapeutic market. Assuming that the value from commercialization takes the logarithmic form of the revenue generated, it depends on the drug's therapeutic market, and the attributes of the firm. Hence, the terminal value of the drug can be expressed as:

$$V_{iT}^d = ln(R(\boldsymbol{x}_{iT})) \tag{4}$$

Firm i's value function at period t is defined as:

$$V_{it} = max\left\{V_{it}^d, V_{it}^s, V_{it}^q\right\}$$

At every stage, firms evaluate the expected terminal value of their drug, adjusting their calculation based on a vector of discount factors $\beta_t \in (0,1)$. They do so with rational expectations regarding the market's evolution and a foresighted estimation of the time it would take to launch from various starting stages. These assumptions are strong but useful in making the model both tractable and computationally feasible for the estimation. First, while there are lots of uncertainties inherent in drug development, firms can draw on previous experiences and timelines of similar drugs to form an understanding of the average time to success from their current development stage. This aids in determining the expected discount rates β_t when firms calculate their expected value at different stages[19] and anticipate the market structure at the time of entry. Furthermore, the model suggests that firms can accurately predict future market demand early on. It's worth noting that pharmaceutical companies have a track record of market trends and adjusting to the demand. Researchers have documented that firms sensitively response to competitor's failure news, these adjustments typically relate to factors like investment costs and success probabilities, rather than being directly influenced by market demand.

The model incorporates two types of transaction costs related to patent trade. The first appears in identifying a potential buyer. Ideally, in a hypothetical market without searching friction, we expect that the buyer would be always the firm with the highest valuation of the drug. This implies that the model parameter ρ associated with the buyer's value converges to ∞. Any deviation from this indicates the existence of market friction such that the buyer is not necessarily the firm with the highest valuation. The second type of transaction cost. symbolized as τ, appears in the firm's decision of trade, investment and quit, after the potential buyer has been pinpointed. This is a cost at the extensive margin in the sense that it affects the firm's overall payoff and thus decisions, but does not affect the quality of the match between buyer and seller (which was already determined in the first step). Costs like administrative fees, commissions, or legal charges fall under this category. The model will identify both these costs and investigate their roles in affecting firm's decisions and the eventual drug outcome.

(c). Equilibrium

This is a finite-horizon dynamic discrete game. Firms initiate with a drug protected by a patent that has passed the discovery and preclinical stage. Every firm's experience at each stage, denoted as $\boldsymbol{e}_t$ is commonly known.

In each period, firms observe the transaction cost τ_t and their private cost shocks $\varepsilon_{it} = (\varepsilon^d_{it}, \varepsilon^s_{it}, \varepsilon^q_{it})$, and choose one of the three actions: develop, sell, or quit $a_{it} = (d, s, q)$ aiming to maximize their expected profits V_{it}.

An equilibrium in this dynamic game can be described in terms of of $N \times T$ strategy functions $\Phi_{it}(\boldsymbol{x}_{it})$, which is a mapping from the space of state variables $(x_{it}, \varepsilon_{it})$ into the action space $\{d, s, q\}$. In

[19] Here I follows the expected discount rate at different stages estimated in Aryal et al. (2022).

equilibrium, we have

$$\Phi_{it}^{*} = \underset{a \in \{d,s,q\}}{argmax} \left\{ V_{it}^{d}, V_{it}^{s}, V_{it}^{q} \right\}$$

In this dynamic game, the optimal strategy of a firm i at stage t depends on the optimal strategies of other firms at stage $t' > t$. This is because the value of trade for a firm i at stage t depends on the continuation value of other firms. To make the optimal decisions in period t, firm i needs to know not only its own expected value of the drug, but also continuation value of the drug of all other firms. For instance, if the experience of one firm is changed, this will change the strategy functions of all the firms.

Despite the dynamic features, this model has a unique equilibrium. This is a finite-horizon game. Starting with the terminal stage T, given the final value of the drug of each firm, the continuation values for every firm are uniquely defined. Consequently, the probability distribution of the optimal buyer, the trade value, and all conditional choice values for every choice at the terminal stage T are uniquely determined for each player. This means that each firm's optimal strategy function $\Phi_{iT}^{*}(\boldsymbol{x}_{iT})$ is uniquely determined. Leveraging this result, we can use backward induction to prove that the strategy functions for every firm at each stage are uniquely defined. Thus, the dynamic game has a unique Markov Perfect equilibrium.

The previous proof of equilibrium has already illustrated that deriving the unique equilibrium can be achieved through backward induction. I calculate the best response function of all firms from the last period T all the back to period 1. That is to say, to determine firm i's best response function at stage t, it's necessary to know the continuation values of all firms in the market for period t. These continuation values are derived from the optimal strategies of every firm at stages t' greater than t. In this manner, we should be able to write the expected value functions from period T all the way back to period 1 and solve for every firm's optimal decisions at each stage.

6 Structural Estimation

In the following section, I will first describe the estimation method employed for the structural estimation. Subsequently, I will present and discuss the estimation results and the implications drawn from counterfactual analyses.

6.1 Estimation

My empirical approach takes three steps. First, I estimate the system of demand for drugs based on their therapeutic market. Second, I calculate the expected value of the drug implied by the demand estimates and use the terminal value in the determination of buyer to estimate the searching friction ρ.

Third, I embed these demand estimates and searching cost into the dynamic discrete game of continue, sell and quit, which I solve to estimate the cost of drug investment and transaction cost in patent trade.

First, for the demand estimation, the drug sample in the dynamic model is restricted to small molecule drugs under the patent protection. This is a limited subsample of all drugs selling in the US market. First, there are many drugs using other technologies, such as macromolecule. Second, some small molecule drugs not eligible for patent are protected under other forms of protection, such as exclusivity right. Third, generic drugs are not considered in our sample, but they account for substantial market share in certain therapy market, which should not be neglected. Therefore, in the demand estimation, we should take into account all drugs in the market. The sample covers the expenditure of US household on drugs over 1996 to 2020 period. I first group the drugs into their main therapeutic market, and then conduct the demand analysis at therapy-year level.

The therapy market is defined using ATC2 code and TC (therapeutic classification in MEPS, from Multum Lexicon database), the same way as the therapy class for the working sample. When there are multiple ATC2 class, the drug is grouped to the main therapy class using TC information.

The outside option is approximated by the drug prescription rate for each therapy. MEPS provides Medical Condition data information from 1996-2020. This information is collected along with drug prescription and expenditure info from the survey. In medical condition files, MEPS documents health condition issue reported by households and coded them based on ICD-9 or ICD-10 code. These are the detailed disease classification code used by medical system which contains more than 300 categories, then MEPS collapsed the codes into broad condition categories (e.g 56 in 1996). For each broad health issue, it estimates the number of medical events happened, including Doctor Office visits, ER visits, inpatient stays, outpatient events, home health events, and prescription medicines. Any type of visits/events related to a certain medical condition can be considered as the potential population affected by such disease. Given these information, the drug treatment rate in each therapy is approximated by the number of prescribed medicine purchases associated with a particular condition over the total number of medical events in that therapy area. The distribution of therapy class in the demand system and more detailed outside option construction can be found in Appendix 8.2.4.

Demand estimation follows multinomial logit form. The market is defined at year-therapy-level. The market share of drug j in therapy m is defined as :

$$s_j = \frac{exp(\boldsymbol{x}'_{jiT}\alpha)}{1 + \sum_{k=1}^{J} exp(\boldsymbol{x}'_{kiT}\alpha)} \tag{5}$$

Following Berry (1994), with normalization of utility function $s_0 = \frac{1}{1+\sum_{k=1}^{J} exp(\boldsymbol{x}'_{kiT}\alpha)}$, we have $log(s_j) - log(s_0) = \boldsymbol{x}'_{jiT}\alpha$.

Second, once the demand estimation of drugs is done, we could use the demand estimates to calculate the expected return of any drug j for any developer i, regardless of the drug being launched or not.

I define a drug's expected value as the logarithm of the sum of its first five year's revenue generated since the date of marketing $V_{ji} = log(R(\boldsymbol{x}_{ji}))$,

where Here I borrowed the average time to launch from each stage as a starting point in the literature $R = \sum_{y=0}^{4} Revenue_{y_{marketing}+y}$, with $y_{marketing}$ is the year of marketing for the drug. This specification is based on two considerations. First, the return of the new drug introduced in the market may not reach the peak at the first year of launching as it may need some time to learn the market and grow. This learning effect can be better captured when I control for the age effect of the drug and take into account several years of revenue since the marketing date. Second, FDA granted 5 year data exclusivity to new molecular entities (NMEs) drugs, this exclusivity rights guarantee that generic competition is typically not possible for this type of drugs for the first five years after the drug is approved, even absent patents or the patent expires earlier than this date.[20]

The determination of optimal buyer depends on the expected value of the drug owned by potential buyers $V_{ji't}$ and the buyers' other characteristics $\boldsymbol{x}_{i't}$, such as the number of drugs that have been developed for the stage at which the drug he is going to buy. With the assumption of Type I EV distribution of cost shock ε^{ρ}, we could use the functional form defined in equation (1) to first estimate the searching parameter ρ , and second use the estimate to predict the expected value of buyer $V_{ji}^{b} = \sum P_{ji'} \cdot \hat{V}_{ji'}$. With Nash bargaining, the agreed price of the patent is determined as $p_{ji} = \omega V_{ji}^{b} + (1 - \omega) V_{ji}^{d}$.[21]

In the last step of estimation, I use the demand estimate and searching parameter (α, ρ) as given, embed them into the dynamic discrete game model and solve it by backward induction. The goal of this step is to obtain estimates for the key cost parameters $(\tau_t, \kappa_t^0, \kappa_t^1)$ by maximum likelihood. The ML estimate is the vector that maximizes the likelihood of observing the actual choice probabilities in the data for each stage. The ML estimators for the development cost (κ_t^0, κ_t^1) and transaction cost τ_t for each stage t are

$$arg \max_{\tau_t, \kappa_t^0, \kappa_t^1} ln \left[P(N_{T,}^{d} N_T^{s}, N_T^{q}) \right]$$

$P(N_{T,}^{d} N_T^{s}, N_T^{q})$ is the joint likelihood for stage T of observing data $(N_{T,}^{d} N_T^{s}, N_T^{q})$, with each element representing the number of developing, selling and quitting respectively. Note that the last stage is post-launch, firms have completed the drug development and FDA approval process, thus at this stage, we only have two observed choices: commercialize (develop) or sell.

Normalize the value of quit to 0, then the expected value of drug j for firm i at stage $T-1$ is

$$\hat{V}_{jiT-1} = log(exp\{0\} + exp\{\beta_{T-1} * \hat{V}_{jiT} - C^{c}{}_{T}\} + exp\{\beta_{T-1} * \hat{V}_{jb_{jiT}T} - C_{jiT}^{s}\})$$

[20] Similar method and first time generic entry after the fifth year discussion can be found in Kapczynski, Park, and B. Sampat (2012) and Hemphill and B. N. Sampat (2012)

[21] In the estimation, I assume seller and buyer have equal negotiation power with $\omega = 1 - \omega = 0.5$.

Using the calculated $\hat{V}_{jiT-1}$ for each drug, I conduct the same ML estimation for stage $T-1$ and so on.[22]

Sources of Identification:

Parameters to estimate in this model are $\theta = (\alpha, \mu, \rho, \kappa_t^0, \kappa_t^1, \tau_t)$

The static demand estimates α (and hence the implied expected value of drugs V_{jiT} from the demand estimation using MEPS data. Demand estimation follows multinomial logit form. The market is defined at year-therapy-level. The market share of drug j in therapy m is defined as :

$$s_j = \frac{exp(\boldsymbol{x}'_{jiT}\alpha)}{1 + \sum_{k=1}^{J} exp(\boldsymbol{x}'_{kiT}\alpha)} \tag{6}$$

Following Berry (1994), with normalization of utility function $s_0 = \frac{1}{1+\sum_{k=1}^{J} exp(\boldsymbol{x}'_{kiT}\alpha)}$, we have $log(s_i) - log(s_0) = \boldsymbol{x}'_{jiT}\alpha$.

Then, using the expected vale of drugs and the characteristics of sellers and buyers in the observed trades, I obtain the searching parameters (μ, ρ) from the determination of buyer estimation and the probability distribution of optimal buyer. As such, I can estimate the expected value of selling the drug V^s . These first two steps are completed outside the dynamic estimation framework. The expected value of continuation, expected value of selling, together with the observed continue/sell/quit choices at each stage of drug development process are used for identifying the key cost parameters $(\kappa_t^0, \kappa_t^1, \tau_t)$ in the dynamic game.

For example, a large transaction cost τ_t will decrease the predicted value of selling the drug, and hence decrease the trade probability $P_t(sell)$ with respect to the probability of quitting $P_t(quit)$. Similarly, a higher fraction of firms choosing to trade at stage t will lead to a lower estimate of $\hat{\tau}_t$. Likewise, large development cost κ_t^0 and κ_t^1 will decrease $P_t(develop)$ with respect to $P_t(quit)$. The variance of $\boldsymbol{e}_{it}$ across firms help identify κ_t^o and κ_t^1 separately. Therefore, the observed fractions of drug development over quit and selling over quit will differently pin down $\hat{\kappa}_t^d$ and $\hat{\tau}_t$ in the MLEs.[23]

G. Ellison and S. F. Ellison (2011) also study incumbents' strategic motives in the pharmaceutical industry, but they focus on investment and advertising choices to deter entry. In their setting, the

[22]For the drugs in the development, we need to estimate its expected time of entering the market as the market structure evolves over time. I've referenced the literature to use the average time to launch from each stage as a starting point: Discovery: 10.1 years/ Phase I clinical: 8.1 year / Phase II clinical: 6.6 year / Phase III clinical: 4.1 year / FDA application: 1.1 year(Aryal et al., 2022). For example, if we observe a drug's latest development stage is Phase III conducted in 2001, then the expected marketing year is 2005 and we use the whole market size in 2005 for therapy class this drug is in. For drugs expected to enter the market after 2016 (given the 5 year revenue defined in current setting, the latest market revenue that we could observe is 2016), I use the growth rate of market size over 2010-2015 to predict the later year market.

[23]To make it more clear, taking the logarithm of division of the probabilities of two choices gives us

$$ln(P_{it}^d/P_{it}^q) = -\kappa_t^o - \kappa_t^1 \boldsymbol{e}_{it} + V_{it}^d - V_t^q$$
$$ln(P_{it}^s/P_{it}^q) = -\tau_t + p_{ii't} - V_t^q$$

Normalizing $V_t^q = 0$, the two fractions of observed choices and observables (or calculated continuation value from previous steps used as observables here) help us identify the key parameters in the structural model.

strategic motive is identified by the nonmonotonicity of investment with respect to market size, whereas in ours, it is identified by the lack of development of overlapping acquired projects.

6.2 Empirical Results

6.2.1 Demand Estimation

Given the data limitation, the market size and market share are determined using annual revenue of each drug. The set of explanatory variables $\boldsymbol{x}_{iT}$ includes both firm and drug characteristics. This includes the count of Phase IV clinical trials which gauges a firm's post-launch expertise, and the age of the drug, measured from its year of entry, helps account for any learning effects over time.[24] Therapy class fixed effect is controlled.

Table 6 presents the demand estimates (detailed estimates including therapy market effect can be found in Appendix 8.2.5). The findings highlight that a firm's prior experience in launching drugs favorably impacts the drug's market share. Additionally, coefficients tied to a drug's age reveal a significant learning effect. As a drug enters the market, its share typically increases in the initial years, suggesting adaptability and market understanding. However, over an extended period, its market share may decline, possibly due to the introduction of new competitors in the market.

Table 6: Drug Demand Estimation

Variables	coefficient
# Phase4 trials	0.001***
log(age)	1.60***
$\log(\text{age})^2$	-0.46***
Constant	-6.43***
Therapy FE	Yes
Observations	6,701
Adjusted R^2	0.22

6.2.2 Determination of Buyer

The potential buyer is determined using a discrete choice (logit) model. The model yields an estimate of $\rho = 0.75$. This implies that with every one-unit rise in the drug's valuation, the likelihood of firm i' becoming a potential buyer increases by a factor of 2.12 (calculated as $e^{0.75}$). While this result indicates that firms with higher drug valuations are more inclined to be potential buyers, it's not a

[24]Firms are identified by aligning the labeler name in the MEPS data with the corresponding name in the Cortellis database. This required a thorough cleaning process, including manual checks for any inconsistencies or misspellings. Out of 560 labelers, we successfully matched 455. For those unmatched—primarily public institutions or smaller companies with missing data— their shares are added to outside options.

guarantee. This variability underscores the inherent frictions in the patent trade market, highlighting that sellers might not always connect with the most suitable buyer for their drug.

Table 7: Discrete Choice Estimation of Buyers

Determination of buyer	
ρ	0.75 (0.28)
obs	177
Prob>χ^2	0.017

6.2.3 Investment and Transaction Cost

Table 8 shows the MLEs of the transaction costs τ, stage-specific development costs κ^o and experience-based development cost parameter κ^1. Standard errors are presented in the parentheses[25][26]. The estimates suggest that the transaction costs peak before FDA registration and Phase I clinical trial stages, followed by Phase III clinical trial. The factors that drive up the transaction costs at these stages might be different. In the early stages like Phase I, the limited available information about a drug's potential introduces high uncertainty. This necessitates higher valuation and investigation efforts and often involves discussions about "risk premium", resulting in elevated negotiation and transaction costs. On the other hand, while the drug's potential becomes clearer by the time of trades preceding Phase III and FDA reviews, due diligence costs soar. Firms need to review past trial data and address any outstanding rights or agreements linked to the drug. A high-potential drug might also attract more interested buyers, further complicating negotiations. These elements collectively contribute to the increased transaction costs during these different phases.

Regarding development costs, the model indicates that the development costs are negative relative to the cost of discontinuation (given value of quitting is normalized to 0) except for the FDA registration

[25]In the estimation process, due to the presence of measurement errors in the e_{it} variable, and given that e_{it} for some large pharma companies are excessively high, I've adjusted the scale of the variable by using $e^*_{it} = e_{it}/2$ to ensure more accurate data interpretation.

[26]In the estimation, I assume that the variance of ε is constant across stages up to $T-1$, and in the last stage T. It doesn't impose additional assumptions with respect to the variance at the last stage. Since the shock follows iid Extreme Value Type I distribution, for any stage up to $T-1$, the variance of $\varepsilon(trade) - \varepsilon(quit)$ and variance of $\varepsilon(cont) - \varepsilon(quit)$ are the same, suggesting the difference $\varepsilon(cont) - \varepsilon(trade)$ has the same variance. The difference between the last stage T and stages up to $T-1$ is the constant term μ. For stages before last stage, we are identifying $\mu_{trade} - \mu_{quit}$ and $\mu_{cont} - \mu_{quit}$with μ_{quit} being normalized to 0, while at the last stage, we can only identify $\mu_{cont} - \mu_{trade}$. This specification will not affect the magnitude and interpretation of the parameters but will only affect how we counduct conterfactual exercises in the next section.

In practice, I conducted a two-step estimation approach. In the first step, I estimated the parameters at each stage via independent MLE. This yielded consistent estimates, enabling the construction of the expected continuation value of the drugs at each stage. In the second step, I imposed the restriction that the scale parameter σ remains constant across stages and estimated all the parameters jointly in a single MLE, which improves the efficiency of the estimates. The estimates suggest that $1/\sigma$ is not very precisely estimated. In the robustness checks, I assessed the correlation between the variable associated with the model (V) and other explanatory variables. As V was not strongly correlated with other variables, I conducted a constrained MLE by imposing the constraint $1/\sigma \geq 1/\sigma^*$ such that other parameters are not sensitive to the change of σ. This gives the value of $1/\sigma^* = 0.3$. Imposing this constraint incurs minimal penalty in terms of maximum likelihood, and the precision of other parameters is less affected. Note that the magnitude of σ suggests the presence of other unobservable factors that could influence firms' choices, which will be an interesting topic for future exploration.

stage. $\kappa^0 < 0$ does not necessarily mean a negative development cost. Rather, this suggests that these drugs demonstrate significant potential up to this stage, withdrawing from the current development is more damaging than the costs associated with continued development. The parameter κ^1 correlates with a firm's stage-specific experience. A negative value of κ^1 denotes that a firm's accrued experience substantially diminishes development costs.

Table 8: Structural Estimation of Cost Parameters

Stage	τ/σ	κ^o/σ	κ^1/σ
Before Phase I	3.04 (0.39)	-0.58 (0.26)	-0.13 (0.05)
Before Phase II	1.82 (0.38)	-1.83 (0.26)	-0.14 (0.07)
Before Phase III	2.87 (0.29)	-0.37 (0.18)	-0.13 (0.04)
Before FDA Regist.	4.06 (0.87)	1.60 (0.77)	-0.03 (0.05)
After launch		-2.66 (0.37)	-0.32 (0.18)
$1/\sigma = 0.3(0.11)$			

Note*: At the terminal stage, the drug has already been approved and launched in the market, thus there is no observation of quit any more. Since we can only observe two choices, the transaction costs τ and stage-specific development costs κ^0 can not be separately identified. The estimates presented in the table is the stage-specific cost relative to transaction cost κ^0-τ.

The cost parameters are estimated relative to the logarithm of revenue. The current functional form of the firm's payoff suggests that transaction costs can be interpreted as an ad valorem tax on the expected annual return of the patent. If we consider the transaction cost proportional to the revenue received, and define the firm's utility as $U = (p \cdot (1 - t_\tau))$ with the rate of transaction cost $t_\tau \leq 0$, then taking the logarithm of both sides gives $V^s = \frac{1}{\sigma} log(U) = \frac{1}{\sigma} log(p) + \frac{1}{\sigma} log(1 - t_\tau)$. This implies that the estimated parameter can be represented as $\tau = \frac{1}{\sigma} log(1 - t_\tau)$. Rearranging the equation, we obtain the rate of transaction cost in terms of the expected revenue: $t_\tau = 1 - exp(\frac{\tau/\sigma}{1/\sigma})$.

Given the estimates, transaction costs can be interpreted as the percentage of the expected annual revenue of the drug across stages, as shown in Table 9. Across all stages, transaction costs are approximately equal to one year's expected revenue of the drug at that stage. Most of the revenue generated by a novel drug comes from the period during which it enjoys monopolistic power in the market. The actual monopoly terms can vary across drugs, influenced by the duration of drug development and the number of secondary patents associated with them. Based on recent literature, the average actual monopoly term of a novel NCE drug is about 13.3 years[27], implying that the transaction cost of patent trading is approximately 7.5% of its expected lifetime revenue.

[27]In Gupta (2022), the average initial monopoly term is 11.1 years, and the potential monopoly term is 17.9 years (if all secondary IP were fully enforced). The actual effective monopoly life from branded launch to generic entry is 13.3 years

Table 9: TC as ad valorem tax

Stage	t_τ as % of annual revenue
Before Phase I	99.99%
Before Phase II	99.76%
Before Phase III	99.99%
Before FDA Regist.	99.99%

Given the estimates, we can calculate the stage-specific probability of taking a particular action a_{ijt} for each drug j:

$$\begin{aligned} P(a_{it} = develop) =& exp[V_{it}^d - \kappa_{it}^d]/A \\ P(a_{it} = trade) =& exp[V_{it}^s - \tau_t^s]/A \\ P(a_{it} = quit) =& exp(0)/A \end{aligned}$$

where

$$A \equiv exp[V_{it}^d - \kappa_{it}^d] + exp[V_{it}^s - \tau_t^s] + exp(0)$$

Since the paper focuses on comparing the development outcomes of traded and non-traded patents, we have abstracted from other forms of collaboration, such as licensing or joint ventures. The choice of "develop" in the model implies development either by the original owner or through licensing or other collaborations. Therefore, we should be careful about the interpretation. We are comparing the average effect of developing drugs under different forms—either independently or collaborately—against the results when patents are traded.

6.2.4 Selection Effect and Causal Effect of Patent Trade

Table 10: Analysis of Selection Effect

Drug's Success Rate		
With Trade (data)	No Trade (data)	No Trade (model)
42.7%	34.6%	38.4%

Based on the estimates, we can test for the impact of selection effect on the drug's success. Table 10 shows drug's success rate without patent trades in the data and under model prediction. In the

data, we have an empirical success rate of 35.6% ($Pr(Success) = Pr(trade) * Pr(success|trade) + Pr(no\,trade) * Pr(success|no\,trade) = 0.13 \times 0.427 + 0.97 \times 0.346$). Without accounting for endogenous selection, eliminating patent trade is equivalent to setting $Pr(trade) = 0$, which gives us a success rate of $Pr(success) = 34.6\%$. This implies a reduction of 1 percentage point in $Pr(success)$. The last column shows the hypothetical scenario that if we increase the transaction costs such that no trade happens at any stage. In this counterfactual scenario, I estimate the success rate accounting for the endogenous selection into trade, resulting in $Pr(success) = 38.4\%$. This difference of 3.8 percentage points ($0.384 - 0.346 = 0.038$) in success rate between two scenarios reflects the effect of endogenous selection into trade. Removing endogenous selection results in a higher $Pr(success)$ for drugs without patent trade. This result implies a positive selection of patents into trade. When investigating the average expected value of drugs at their final development stage between traded and non-traded groups, we observe that patents with higher expected value of the drug are more likely to be traded during the development stages (before drug approval). While after the development process is completed, this difference in expected value vanished. Particularly, once the drug has been launched in the market, firms seem more inclined to retain drugs with higher value.[28]

Next, I simulate the development path of drugs to identify the causal effect of patent trade while eliminating selection effects. To achieve this, I hypothesize that all drugs in the sample initially start at stage t under their original ownership. I then simulate the success rate of these drugs when trade is either allowed or prohibited at stage t. Table 11 presents the simulated success rates under both the 'With Trade' and 'No Trade' scenarios. By starting all drugs at stage t, we eliminate the selection into development effect. Additionally, by ensuring the drugs are developed by their original owners, we avoid any change in ownership before stage t, thereby excluding trade effects from earlier stages. Consequently, the difference observed in the last column between the two scenarios represents the average treatment effect of patent trade, conditional on the drug's ownership at stage t, after selection bias has been removed. For instance, the direct effect of patent trade prior to FDA Registration on the drug's success rate, after removing the selection effect, is 1.6 ppt. This causal effect itself is relatively small. The pass rate of the drug at each stage is quite low even when developed by the most sophisticated developers. A 1.6 ppt increase before FDA registration stage implies approximately 8-9 additional drugs passed the approval stage during the sample period

From the analysis presented in the table, we observe that patent trade has positive effect on a drug's success even after removing selection effects for most stages, except for Phase II. The largest effect occurs for trade before FDA registration, followed by a weaker positive effect before Phase I and III clinical trials. This finding contrasts with the empirical probabilities of discontinuation observed for drugs within patent trade and without trade groups as shown in Table 3. For instance, the discontinuation probability for drugs without patent trade is 5.3 ppt higher than that for drugs with patent trades at the Phase III clinical stage. However, this discrepancy is largely attributable to selection and trade effects from earlier stages. Once the selection effect is removed, the pure effect of patent trade before Phase III is only 0.3 ppt.

[28] A detailed table comparing the values of drugs between the two groups bys stage can be found in the Appendix.

Table 11: ATE of Patent Trade on Drug's Success Rate across Stages

	Drugs starting since stage t		
	With Trade	No Trade	Trade Effect
Stage	[1]	[2]	[1]-[2]
Before Phase I	39.6%	39.4%	+ 0.2 ppt
Before Phase II	46.6%	47.7%	- 1.1 ppt
Before Phase III	51.0%	50.7%	+ 0.3 ppt
Before FDA Registration	68.6%	67.0%	+ 1.6 ppt

The results also suggest that patent trading before Phase II clinical trials has a negative effect on the drug's success. This finding suggests that a change of ownership at this stage decreases the chance of success for the drugs. Upon examining the probability of decisions at each stage allowing and shutting down trade, I found that trades before stage t decrease the probability of quitting at that stage, except for Phase II. For Phase II clinical trials, the probability of quitting is higher with trade compared to cases without trade. Detailed P(quit) for causal effect check is in the Appendix.

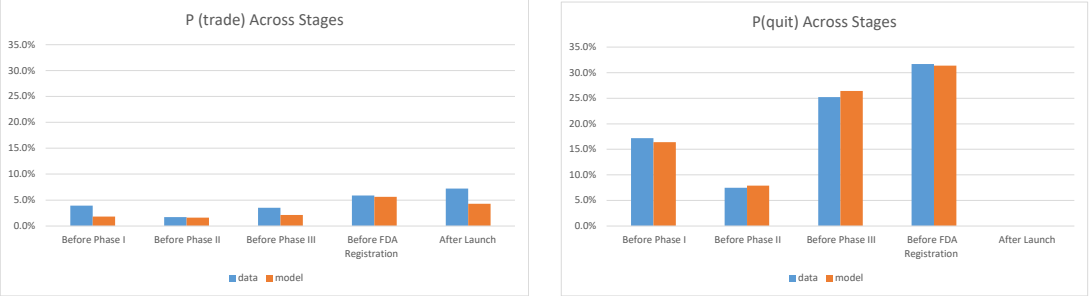
Several potential alternative explanations exist for the negative effect of patent trade before Phase II clinical trials. One possible explanation is the efficacy of data and knowledge transfer. At this stage, the new owner needs to thoroughly understand the previous work done on the drug, including the rationale behind the drug's development, any findings from preclinical studies, and the proposed clinical development plan. Any incompleteness or misrepresentation during the transfer can negatively impact the new owner's development decisions. However, there is not yet sufficient evidence proving that data and knowledge transfer is specifically inefficient before Phase II.

Another alternative explanation is optimal project selection. Specifically, for firms with multiple drug development projects, the buyer might strategically and optimally compare the projects and only continue with the most promising ones. Since our model assumes a single drug developer, we do not take into account the drug pipeline optimization effect. A related alternative explanation is similar to "killer acquisitions", in which acquirers have a strong incentive to acquire and terminate overlapping innovation ex ante. Though we do not find systematic evidence of the killer purchase phenomenon by comparing the discontinuation rate for incumbents and non-incumbents, this killer incentive might be more evident during this specific early stage as it is not too costly to do so. This finding is consistent with the literature, suggesting that the effect of acquiring drug projects varies across stages. For example, Siebert and Z. Tian (2020) also documents the evidence that project transition rate from Phase I to Phase II clinical trials is lower for merging firms comaring to non-merging firms. They argue that M&A in the early development phases serves to replenish firms' drug pipelines, while acquiring drug development and technology in the late stages of the development process has a stronger effect on pushing the drug into the market.

6.2.5 Model Fit

Figure 3 suggests that the estimated model fits the data reasonably well, predicting the conditional probability of trade and discontinuation across stages. While there is some discrepancy between the observed data and predicted probabilities, the overall magnitudes and trends across stages provide a reasonable benchmark for comparing firms' decisions under different counterfactual scenarios in Section 6.3.

Figure 3: Probability of Choices at Different Stages (model v.s. data)



6.3 Counterfactual

In this section, counterfactual exercise is to be conducted to see how firms' drug development outcome and payoffs change if the exogenous transaction cost in the patent market changes. More specifically, this exercise explores two hypothetical scenarios: (i) reduce the transaction cost associated with patent trades, and (ii) improve the searching quality.

6.3.1 Subsidize Patent Transactions

In this part, I will examine the impact of reducing transaction costs τ at various stages on the drug success rate, considering the firm's optimal decision probabilities. To do so, I hypothetically reduce the transaction costs by different levels (50% or fully eliminated) from each stage and compare the impacts on drug transition rates and the ultimate success rate.

Practically, I solve the model for a new MPE in each counterfactual scenario and use the equilibrium choice probabilities to run 500 simulations for each drug. Table 12 shows the average success rate of all drugs under different scenario. On average the model predicts that a drug beginning post-discovery stage have a 39.6% chance of success, which is close to the empirical success rate of 35.7%.

Reducing transaction costs at specific stages significantly increases the probability of trade for that stage, however, its impact on the final success rate varies across stages. Comparing the results in column [2], when transaction costs are fully removed during critical moments – such as before FDA

registration – we observe significant jumps in success rates to 56.3% , marking a 16.7 ppt improvements. We also observe a positive effect of patent trade before Phase I and III stage, free of transaction costs at this stage increases success rate to 40.7%. These stages share similar features that could explain this significant improvement: the inputs and skills needed for the drug development before and after are very different. For example, The reason why reducing transaction cost helps for trade before FDA registration stage is that this stage marks the transition from drug clinical trial tests to commercialization and manufacturing stages. Companies that are specialized in the drug development may not be able to efficiently commercialize and manufacture the drug as the infrastructure, expertise and regulatory compliance are very different. Phase I marks the transition from lab tests to clinical trials, many original patent owners are small labs and individuals that lack resources for clinical trials. Facilitating trades before this stage help more drugs enter the trials.

For drugs traded after launch, only the difference between development cost and transaction cost $(\kappa^0 - \tau)$ is identified in the model. For this stage, we cannot estimate the impact of an absolute change in transaction cost. However, we can estimate the impact of relative change using other stages as benchmark. For example, suppose τ^{CF}_{launch} changes such that the percentage change of differences under the counterfactual and baseline after launch is the same as the percentage change of difference in Phase I when transaction cost before Phase I reduces by half $(\tau^{CF}_{PhaseI} = 50\%\,\tau_{PhaseI})$:

$$\frac{\kappa^0_{launch} - \tau^{CF}_{launch}}{\kappa^0_{launch} - \tau_{launch}} = \frac{\kappa^0_{PhaseI} - \tau^{CF}_{PhaseI}}{\kappa^0_{PhaseI} - \tau_{PhaseI}}$$

Row [5] in Table 12 presents the counterfactual using Phase I as a benchmark. Counterfactual results using other stages as benchmarks show similar results, indicating a positive impact of reducing transaction costs after launch on the drug success rate (details in the Appendix). Although firms cannot quit after launch, reducing transaction costs at this stage still has a positive effect on the drug's success rate. This result suggests the forward-looking behavior of firms. By anticipating trade after launch, which is less costly, firms increase the chance of continuation during the development stages.

Table 12: Probability of Success: Remove TC at Different Stages

	CF Scenario	P(success)	
		$\tau \downarrow 50\%$	$\tau \downarrow 100\%$
[0]	Baseline	39.6%	39.6%
[1]	Before Phase I	39.9%	40.7%
[2]	Before Phase II	39.2%	37.9%
[3]	Before Phase III	39.9%	40.7%
[4]	Before FDA registration	44.7%	56.3%
[5]	After Launch*	40.1%	40.9%
[6]	TC (all stage)	56.0%	56.0%

When transaction costs change at stage t, forward-looking firms adjust their decisions not only at that stage but also at others. Tables 13 and 14 show the probabilities of trade and quitting for all

stages under different counterfactual scenarios. Lowering transaction costs at stage t affects the trade probability at that stage but not elsewhere. However, it decreases the quitting probability not only at stage t (except for Phase II) but also at earlier stages. This dynamic effect suggests that when firms anticipate lower transaction costs in the future, they may be more likely to continue development at current stages, as selling the drug at a future stage would be easier and cheaper.

Table 13: Dynamic Effect: P(trade) by Removing TC at Different Stages

		P (trade) by stage ($\tau\downarrow$100%)				
	CF Scenario	Bef Phase I	Bef Phase II	Bef Phase III	Bef FDA Reg	Aft Launch
		[1]	[2]	[3]	[4]	[5]
[0]	Baseline	1.6%	1.6%	2.0%	5.4%	4.3%
[1]	Before Phase I	25.0%	1.6%	2.0%	5.5%	4.4%
[2]	Before Phase II	1.6%	9.0%	2.0%	5.3%	4.4%
[3]	Before Phase III	1.5%	1.6%	26.8%	5.4%	4.3%
[4]	Before FDA Reg.	1.6%	1.6%	2.1%	76.7%	4.3%
[5]	After Launch	1.6%	1.6%	2.1%	5.7%	27.9%
[6]	TC (all stage)	25.0%	8.9%	26.6%	77.2%	28.2%

Table 14: Dynamic Effect: P(quit) by Removing TC at Different Stages

		P (quit) by stage ($\tau\downarrow$100%)				
	CF Scenario	Bef Phase I	Bef Phase II	Bef Phase III	Bef FDA Reg	Aft Launch
		[1]	[2]	[3]	[4]	[5]
[0]	Baseline	16.5%	7.9%	26.4%	31.3%	0.0%
[1]	Before Phase I	13.7%	8.0%	26.4%	31.5%	0.0%
[2]	Before Phase II	16.1%	12.9%	26.2%	31.2%	0.0%
[3]	Before Phase III	16.2%	7.4%	24.5%	31.5%	0.0%
[4]	Before FDA Reg.	16.2%	7.4%	20.0%	10.0%	0.0%
[5]	After Launch	16.4%	8.0%	26.0%	29.4%	0.0%
[6]	TC (all stage)	13.1%	12.0%	19.6%	9.4%	0.0%

While reducing transaction cost for trades before Phase II clinical trials increases patent trades, it has negative effects on drug's successful development. This result is consistent with the negative causal effect we found in the estimation. As the probability of quit is higher with traded patent compared to nontraded ones at Phase II. There are two possible reasons here. One is that trade at this stage reallocate the drugs to firms who has better capability at the current stage but not as capable in the subsequent development stages. With more trades happening before Phase II, it may happen that these drugs are not able to be further transferred to right hands due to the existence of transaction cost during the later stages.

If this assumption holds true, then allowing frictionless patent trade during the subsequent stages should lead to a decrease in the probability of quitting before Phase II, bringing it closer to the baseline level and resulting in an overall positive effect on the drug's success. To test this hypothesis, I removed transaction costs for patent trade not only before Phase II, but for all stages afterward (scenario [2] in Table 12). First, the simulation results suggest a drug's success rate of 53.9%, which is higher than the baseline success rate of 39.6%. Second, the probability of quitting before Phase II is 12%, 1 ppt lower than the cases where only transaction costs before Phase II are removed, but still higher than the baseline probability of 7.9%. This result suggests that the conjecture that firms who are good at conducting Phase II trials might perform worse in the later stages could only partially explain the story. Overall, drugs are more likely to enter into Phase II trials if kept under the same ownership as Phase I.

Table 15: Probability of Quit for Phase II clinical trial

	CF Scenario	P(success) $\tau \downarrow 100\%$	P (quit) by stage ($\tau\downarrow 100\%$) Bef Phase I	Bef Phase II	Bef Phase III	Bef FDA reg	Aft Launch
			[1]	[2]	[3]	[4]	[5]
[0]	Baseline	39.6%	16.4%	7.9%	26.4%	31.4%	0.0%
[1]	Before Phase II	37.8%	15.9%	13.0%	26.3%	31.6%	0.0%
[2]	Remove TC since Phase II	53.9%	15.5%	12.0%	19.9%	10.2%	0.0%
[3]	Remove TC (all stage)	56.0%	13.1%	12.0%	19.6%	9.4%	0.0%

Pushing this perspective even further, if transaction costs were eliminated across all stages, the likelihood of drug development success increases to 56%. which is 0.3 percentage point lower than targeting trade before FDA regsitration stage mainly due to the significant negative effect of patent trade before Phase II clinical trials. Such finding suggests that for the purpose of increasing drug's success rate, a uniform patent trade subsidy has positive effect, but might not be very cost effective as the impact of trade is not constant over stages.

For the cost benefit analysis, I simulated the drug development path in the sample and calculated the predicted change of annual revenue in the drug market under different scenarios. Moreover, relying on the number of new molecular entities (NMEs) drugs approved by the U.S. FDA since 1990 to 2015[29], I approximate the number of additional new drugs introduced into the market per year under different scenarios. Table 16 shows the results under different scenarios, with changes in revenue represented in billion dollars. Fully subsidizing patent trade before FDA registration increases the success rate of drug development from 39.6% to 56.3% (Table 16). Based on the number of new molecular entities (NMEs) approved by the FDA per year, this translates to the introduction of an additional 12 new drugs annually, generating an additional $23.5 billion in annual revenue in the drug market. It's

[29]The number of new molecular entities (NMEs) approved by the U.S. Food and Drug Administration (FDA) varies across years, over the period of 1990 to 2015, the range is between 20 to 45 , with an average of 29.5 new drugs approved per year.

worth noting that this figure, calculated using the simulated sample, may vary slightly from a simple accounting method (multiplying the number of additional drugs by the average drug revenue), as the drugs affected under different counterfactuals may have different expected values.

In the last column, I compared the average expected annual revenue of the drugs under different scenarios. The numbers show the difference from the baseline. We can observe that the expected value of the drugs introduced into the market due to facilitating patent trade is slightly lower than the original cases, but the difference is less than 1% for most cases except for drugs traded before FDA registration. The expected revenue of the drugs introduced into the market by subsidizing trade before FDA registration is, on average, 3.6% lower than the baseline cases. This finding aligns with the positive selection effect identified in the previous results.

Table 16: Welfare Analysis of Subsidizing Patent Trade

	CF Scenario	P(success)	△ drugs per year	△ revenue	Change of drug value
[0]	Baseline	39.6%	–	–	–
[1]	Before Phase I	40.7%	0.9	3.5	-0.23%
[2]	Before Phase II	37.9%	-1.2	-1.2	0.03%
[3]	Before Phase III	40.7%	1.0	3.1	-0.72%
[4]	Before FDA registration	56.3%	12.4	23.5	-3.60%
[5]	After Launch	40.9%	1.0	2.7	-0.72%
[6]	All Stages	56.0%	12.2	26.2	-4.20%

These counterfactual experiments suggest that subsidizing patent trade at critical stages can generate significant positive social gains. The largest effect is observed for trade before FDA registration. Fully subsidizing patent trade increases the drug's success rate by 42.2%, generating an additional $23.5 billion in annual revenue in the pharmaceutical market. Despite transaction costs amounting to approximately 78% of the annual $log(Rev)$, the potential benefits extend beyond the increase in the firm's payoff. We anticipate even greater social welfare effects for at least two reasons. First, firms maximize their own expected profit when making trade and development decisions, primarily derived from the drug's returns during the patent protection period. However, after the drug's patent expires and generic alternatives enter the market, consumers could benefit further by getting access to the drug at even lower prices. Second, successful drug development may have positive spillover effect, stimulating knowledge sharing and facilitating subsequent drug development processes. Although a comprehensive analysis of these factors is beyond the scope of this paper, I interpret this result as a conservative estimate of the welfare benefits that a more efficient patent market could generate.

6.3.2 Patent Exchange

An important hindrance in patent trading is the challenge of searching and matching: sellers often struggle to identify the ideal buyer to finalize a transaction. Currently, U.S. patent trading operates

primarily through IP Brokerage firms, online platforms, and Patent Assertion Entities (PAEs). Some prominent firms even have dedicated in-house IP management teams that engage direct searches and sales. While the patent market thrives with the presence of varied private entities, these platforms, though facilitating patent transactions, are not without their own set of issues. Hagiu and Yoffie (2013) offers an extensive review of the challenges faced by patent marketplaces in the U.S., including those involving patent brokers, NPEs, and patent aggregators.

Given the unique nature of patent trading—marked by high levels of uncertainty and information asymmetry—a centralized patent exchange platform could potentially ameliorate search-related frictions and address the illiquidity problems inherent in fragmented markets. For instance, China has been progressively establishing patent exchanges across various regions since 2006. Introducing these centralized patent exchanges has notably amplified patent trading activities and fostered specialization among buyers and sellers based on their comparative advantages, as highlighted by Han, Liu, and X. Tian (2022). Consequently, predicting a patent trading environment with reduced search frictions and enhanced matching can provide insights into the potential benefits of establishing a marketplace that efficiently connects patent buyers and sellers.

To delve into this hypothesis, I undertake a counterfactual analysis that increases the probability of a seller encountering a potential buyer who places a higher value on the drug. In essence, if sellers are more likely to engage with buyers who recognize and appreciate the drug's inherent value, transactions are poised to become more frequent and straightforward, even if transaction costs remain unchanged. A heightened transaction rate, coupled with the increased possibility of advancing the drug to subsequent stages of development, should, in theory, boost the overall success rate. This counterfactual scenario provides insights into how optimizing matching mechanisms can influence drug development trajectories.

For this purpose, I consider a counterfactual exercise that increases the the probability of a seller encountering a potential buyer who places greater value on the drug. When sellers connect with such buyers, the likelihood of trade becomes stronger, even if transaction costs remain unchanged. As the transaction rate increases and the drug has a greater likelihood of progressing through the subsequent stages of development after trade, we anticipate an increase in the overall probability of success. This counterfactual scenario provides insights into how optimizing matching mechanisms can significantly influence drug development outcomes.

Table 17 shows the success rate and probability of trade across stages under baseline and when ρ is increased by 8 units . The success rate is slightly increased to 33.2% which is very negligible. The result suggests that the difference of drug valuation between the optimal buyer and current buyer (expected buyer from the distribution) is not large enough to overcome the TC barrier to make the impossible transaction possible. Another possibility is that in the pharmaceutical industry, the key friction in the patent market is not about meeting the optimal buyer. The number of players with patented drugs that passed discovery stage is not that large such that searching or matching barrier is not as high as we imagined. The key friction occurs during the negotiation after the meeting. Even the seller meet the optimal buyer, due to the private information of the patent and the uncertainty

of the drug, the transaction costs due to the complex valuation and negotiation is inevitable. That's why only improving the searching and matching between seller and buyer is not enough.

Table 17: P(success) under different ρ scenario

		P (trade) by stage ($\rho \uparrow$)				
CF Scenario	P(success)	Bef Phase I	Bef Phase II	Bef Phase III	Bef FDA Reg.	Aft Launch
		[1]	[2]	[3]	[4]	[5]
Baseline $\rho(= 0.75)$	39.6%	1.6%	1.6%	2.0%	5.4%	4.3%
Increased $\rho(= 8.75)$	39.7%	1.6%	1.6%	2.1%	5.3%	4.4%

7 Conclusion

This paper sheds light on the pivotal role of patent trades during the drug development process, emphasizing that the timing of such trades critically influences a drug's success rate. While the advantages of patent trading, such as optimizing resource allocation and promoting comparative advantage-based specialization, are well recognized, the precise implications of trade timing have remained limited due to data constraints. By leveraging a unique dataset and solving a dynamic model capturing both drug development and patent trading decisions, this study underscores that most patents change hands before a drug's full development cycle concludes. Empirical findings suggest that pharmaceutical entities exhibit distinct comparative advantages at varied developmental stages. This, in turn, affects their investment costs and thus development decisions. Moreover, market frictions are not uniformly distributed across the development timeline, due to information asymmetry and market liquidity. The finding suggests that transaction costs peak before New Drug Application with FDA, followed by Phase I clinical trials. These pivotal phases demand very different areas of expertise, distinct from prior stages.

Counterfactual analysis demonstrates considerable potential for welfare improvements through increasing patent market efficiency. The findings suggest that patent searching might not be the primary barrier in this market, and we should instead focus on the transaction costs related to negotiation and investigation of patented drugs. Moreover, the impact of patent trade on the drug's success rate depends on the development stage, indicating that a uniform subsidy towards all transactions might not be the most effective approach. A cost-effective policy would aim to reduce transaction costs at stages that most significantly influence drug development outcomes. Remarkably, fully subsidizing patent trades at the critical friction stages (before FDA registration stage) can enhance a drug's success rate by approximately 16.6 percentage, which would translate to the introduction of an additional 12 drugs per year. This observation aligns with established literature, suggesting that a smoother market fosters patent trades among firms that can optimize their utilization, leading to better innovative results. While these insights are primarily derived from the pharmaceutical industry, the core economic

implications examined are applicable across industries where the success of innovation is contingent upon diverse expertise throughout the product development process, often held by distinct firms.

This paper provides compelling evidence that the timing of patent trades profoundly influences drug development outcomes. The results indicate that a firm's decision regarding drug development is influenced by its specific investment costs at various stages and the prevailing frictions in the patent market. Enhancing the efficiency of the patent market substantially increases the success rates of new drugs.

Several interesting questions naturally arise from this paper. First, various methods exist for technology transfer (i.e. licensing, joint venture), leading to the question of how different collaborative approaches in drug development might coincide with patent trades, collectively shaping innovation outcomes. Second, a prevailing debate concerns the trading of patents purely for competitive or preemptive motives, stifling further development. Though current evidence suggests that the phenomenon of these so-called "killer purchases" is less prevalent in standalone patent acquisitions than in full company takeovers, it warrants closer scrutiny, especially when considering policies to subsidize patent trades. While I am actively working on these issues, a full exploration of these topics and a more comprehensive welfare analysis is still underway and will be detailed in my future research.

References

Acemoglu, Daron and Joshua Linn (2004). "Market size in innovation: theory and evidence from the pharmaceutical industry". In: *The Quarterly journal of economics* 119.3, pp. 1049–1090.

Adams, Christopher P and Van V Brantner (2006). "Estimating the cost of new drug development: is it really $802 million?" In: *Health affairs* 25.2, pp. 420–428.

Agrawal, Ajay, Iain Cockburn, and Laurina Zhang (2015). "Deals not done: Sources of failure in the market for ideas". In: *Strategic management journal* 36.7, pp. 976–986.

Ahuja, Gautam and Riitta Katila (2001). "Technological acquisitions and the innovation performance of acquiring firms: A longitudinal study". In: *Strategic management journal* 22.3, pp. 197–220.

Akcigit, Ufuk, Murat Alp Celik, and Jeremy Greenwood (2016). "Buy, keep, or sell: Economic growth and the market for ideas". In: *Econometrica* 84.3, pp. 943–984.

Angell, Marcia and Kate Reading (2005). *The truth about the drug companies: How they deceive us and what to do about it*. Random House Trade Paperbacks New York.

Arora, Ashish and Marco Ceccagnoli (2006). "Patent protection, complementary assets, and firmsâ incentives for technology licensing". In: *Management science* 52.2, pp. 293–308.

Arora, Ashish, Andrea Fosfuri, and Alfonso Gambardella (2001). "Markets for technology and their implications for corporate strategy". In: *Industrial and corporate change* 10.2, pp. 419–451.

Arque-Castells, Pere and Daniel F Spulber (2019). "Measuring the Private and Social Returns to R&D: Unintended Spillovers versus Technology Markets". In: *Northwestern Law & Econ Research paper* 18-18.

Aryal, Gaurab et al. (2022). "Valuing Pharmaceutical Drug Innovations: An Event Study Approach". In: *Working Paper*.

Banerjee, Tannista and Ralph Siebert (2017). "Dynamic impact of uncertainty on R&D cooperation formation and research performance: Evidence from the bio-pharmaceutical industry". In: *Research Policy* 46.7, pp. 1255–1271.

Berry, Steven T (1994). "Estimating discrete-choice models of product differentiation". In: *The RAND Journal of Economics*, pp. 242–262.

Blume-Kohout, Margaret E and Neeraj Sood (2013). "Market size and innovation: Effects of Medicare Part D on pharmaceutical research and development". In: *Journal of public economics* 97, pp. 327–336.

Branstetter, Lee, Chirantan Chatterjee, and Matthew J Higgins (2016). "Regulation and welfare: evidence from paragraph IV generic entry in the pharmaceutical industry". In: *The RAND Journal of Economics* 47.4, pp. 857–890.

Budish, Eric, Benjamin N Roin, and Heidi Williams (2015). "Do firms underinvest in long-term research? Evidence from cancer clinical trials". In: *American Economic Review* 105.7, pp. 2044–2085.

– (2016). "Patents and research investments: Assessing the empirical evidence". In: *American Economic Review* 106.5, pp. 183–187.

Cassiman, Bruno and Reinhilde Veugelers (2006). "In search of complementarity in innovation strategy: Internal R&D and external knowledge acquisition". In: *Management science* 52.1, pp. 68–82.

Caves, Richard E et al. (1991). "Patent expiration, entry, and competition in the US pharmaceutical industry". In: *Brookings papers on economic activity. Microeconomics* 1991, pp. 1–66.

Chien, Colleen V (2011). "Predicting patent litigation". In: *Texas Law Review* 90, p. 283.

Chondrakis, George, Carlos J Serrano, and Rosemarie H Ziedonis (2021). "Information disclosure and the market for acquiring technology companies". In: *Strategic Management Journal* 42.5, pp. 1024–1053.

Cockburn, Iain M (2004). "The changing structure of the pharmaceutical industry". In: *Health Affairs* 23.1, pp. 10–22.

Cunningham, Colleen, Florian Ederer, and Song Ma (2021). "Killer acquisitions". In: *Journal of Political Economy* 129.3, pp. 649–702.

Danzon, Patricia M, Sean Nicholson, and Nuno Sousa Pereira (2005). "Productivity in pharmaceutical–biotechnology R&D: the role of experience and alliances". In: *Journal of health economics* 24.2, pp. 317–339.

DiMasi, Joseph A, Henry G Grabowski, and Ronald W Hansen (2016). "Innovation in the pharmaceutical industry: new estimates of R&D costs". In: *Journal of health economics* 47, pp. 20–33.

Dranove, David, Craig Garthwaite, and Manuel Hermosilla (2014). *Pharmaceutical profits and the social value of innovation*. Tech. rep. National Bureau of Economic Research.

Ellison, Glenn and Sara Fisher Ellison (2011). "Strategic entry deterrence and the behavior of pharmaceutical incumbents prior to patent expiration". In: *American Economic Journal: Microeconomics* 3.1, pp. 1–36.

Filson, Darren (2012). "A Markov-perfect equilibrium model of the impacts of price controls on the performance of the pharmaceutical industry". In: *The RAND Journal of Economics* 43.1, pp. 110–138.

Gaessler, Fabian and Stefan Wagner (2022). "Patents, data exclusivity, and the development of new drugs". In: *Review of Economics and Statistics* 104.3, pp. 571–586.

Galasso, Alberto, Mark Schankerman, and Carlos J Serrano (2013). "Trading and enforcing patent rights". In: *The RAND Journal of Economics* 44.2, pp. 275–312.

Gans, Joshua S and Scott Stern (2000). "Incumbency and R&D incentives: Licensing the gale of creative destruction". In: *Journal of Economics & Management Strategy* 9.4, pp. 485–511.

– (2003). "The product market and the market for âideasâ: commercialization strategies for technology entrepreneurs". In: *Research policy* 32.2, pp. 333–350.

Gilchrist, Duncan S (2016). "Patents as a spur to subsequent innovation? Evidence from pharmaceuticals". In: *American Economic Journal: Applied Economics* 8.4, pp. 189–221.

Grabowski, Henry G and Margaret Kyle (2007). "Generic competition and market exclusivity periods in pharmaceuticals". In: *Managerial and Decision Economics* 28.4-5, pp. 491–502.

Grabowski, Henry G and John M Vernon (1992). "Brand loyalty, entry, and price competition in pharmaceuticals after the 1984 Drug Act". In: *The journal of law and economics* 35.2, pp. 331–350.

Grabowski, Henry, Carlos Brain, et al. (2017). "Pharmaceutical patent challenges: company strategies and litigation outcomes". In: *American Journal of Health Economics* 3.1, pp. 33–59.

Grabowski, Henry and Margaret Kyle (2008). "11. Mergers and alliances in pharmaceuticals: effects on innovation and R&D productivity". In: *The economics of corporate governance and mergers*, p. 262.

Gupta, Charu (2023). "One product, many patents: Imperfect intellectual property rights in the pharmaceutical industry". In: *working paper*.

Hagiu, Andrei and David B Yoffie (2013). "The new patent intermediaries: platforms, defensive aggregators, and super-aggregators". In: *Journal of Economic Perspectives* 27.1, pp. 45–66.

Han, Pengfei, Chunrui Liu, and Xuan Tian (2022). "Does trading spur specialization? evidence from patenting". In: *Evidence from Patenting (October 11, 2022)*.

Haucap, Justus, Alexander Rasch, and Joel Stiebale (2019). "How mergers affect innovation: Theory and evidence". In: *International Journal of Industrial Organization* 63, pp. 283–325.

Hemphill, C Scott and Bhaven N Sampat (2011). "When do generics challenge drug patents?" In: *Journal of Empirical Legal Studies* 8.4, pp. 613–649.

– (2012). "Evergreening, patent challenges, and effective market life in pharmaceuticals". In: *Journal of health economics* 31.2, pp. 327–339.

Howard, David H et al. (2015). "Pricing in the market for anticancer drugs". In: *Journal of Economic Perspectives* 29.1, pp. 139–162.

Kapczynski, Amy, Chan Park, and Bhaven Sampat (2012). "Polymorphs and prodrugs and salts (oh my!): an empirical analysis of âsecondaryâ pharmaceutical patents". In: *PLoS one* 7.12, e49470.

Khmelnitskaya, Ekaterina (2021). "Competition and Attrition in Drug Development". PhD thesis. University of Virginia.

Krieger, Joshua L (2021). "Trials and terminations: Learning from competitorsâ R&D failures". In: *Management Science* 67.9, pp. 5525–5548.

Krieger, Joshua, Danielle Li, and Dimitris Papanikolaou (2022). "Missing novelty in drug development". In: *The Review of Financial Studies* 35.2, pp. 636–679.

Lerner, Josh and Robert P Merges (1998). "The control of technology alliances: An empirical analysis of the biotechnology industry". In: *The Journal of Industrial Economics* 46.2, pp. 125–156.

Letina, Igor, Armin Schmutzler, and Regina Seibel (2021). "Killer acquisitions and beyond: policy effects on innovation strategies". In: *University of Zurich, Department of Economics, Working Paper* 358.

Majewska, Gosia (2022). "Incentivizing novelty in antibiotic development". In: *working paper*.

Ornaghi, Carmine (2009). "Mergers and innovation in big pharma". In: *International journal of industrial organization* 27.1, pp. 70–79.

Ouellette, Lisa Larrimore (2010). "How many patents does it take to make a drug-follow-on pharmaceutical patents and university licensing". In: *Mich. Telecomm. & Tech. L. Rev.* 17, p. 299.

Reiffen, David and Michael R Ward (2005). "Generic drug industry dynamics". In: *Review of Economics and statistics* 87.1, pp. 37–49.

Serrano, Carlos J (2010). "The dynamics of the transfer and renewal of patents". In: *The RAND Journal of Economics* 41.4, pp. 686–708.

– (2018). "Estimating the gains from trade in the market for patent rights". In: *International Economic Review* 59.4, pp. 1877–1904.

Serrano, Carlos J, George Chondrakis, and Rosemarie Ziedonis (2023). "Acquiring Patents in Secret: the Strategic Disclosure of Patent Transactions". In: *Working paper* 79, p. 463.

Siebert, Ralph and Zhili Tian (2020). "Dynamic Mergers Effects on R&D Investments and Drug Development across Research Phases in the Pharmaceutical Industry". In:

Wouters, O, M Mckee, and J Luyten (2009). "Estimated Research and Development Investment Needed to Bring a New Medicine to Market". In: *JAMA* 323.9, pp. 844–853.

Zhang, Yang (2020). "Does market exlcusivity improve access to drugs? The case of US anti-ulcer drug market". In: *Working paper*.

8 Appendix A:

8.1 Derivation of Nash Bargaining Price

Upon meeting of the potential buyer, the value function of the buyer V_{bt} is known to the drug owner i. Let p_t be the price of the patent. Denote BS and SS as buyer's surplus and seller's surplus respectively. Assume that transaction cost τ is paid by the seller, then thus the two surplus are defined as

$$BS = V_{bt} - p_t$$
$$SS = p_t - max\{V_{it}^d, V_{it}^q\} - \tau$$

Total surplus can be written as

$$TS = V_{bt} - max\{V_{it}^d, V_{it}^q\} - \tau$$

Suppose ω is the buyer's bargaining power, seller's surplus can be re-written as :

$$SS = (1-\omega)(V_{bt} - max\{V_{it}^d, V_{it}^q\} - \tau)$$

Thus the price of the patent can be derived as

$$p_t = (1-\omega)V_{bt} + \omega \cdot [max\{V_{it}^d, V_{it}^q\} + \tau]$$

8.2 Additional Empirical Results

8.2.1 Distribution of Patent trade over time

The sample spans from 1980 to 2015, and it displays temporal variation in the number of patent trades. As illustrated in the Figure 4, there was a marked increase in patent trades post-2000, comprising approximately 86% of the sample. Table 18 showcases the distribution of the highest drug development stages associated with patent trades within each period. Although there may be period-specific variations in the highest stages achieved, the overall distribution remains relatively stable over time.

Figure 4: Distribution of Patent Trade over Years

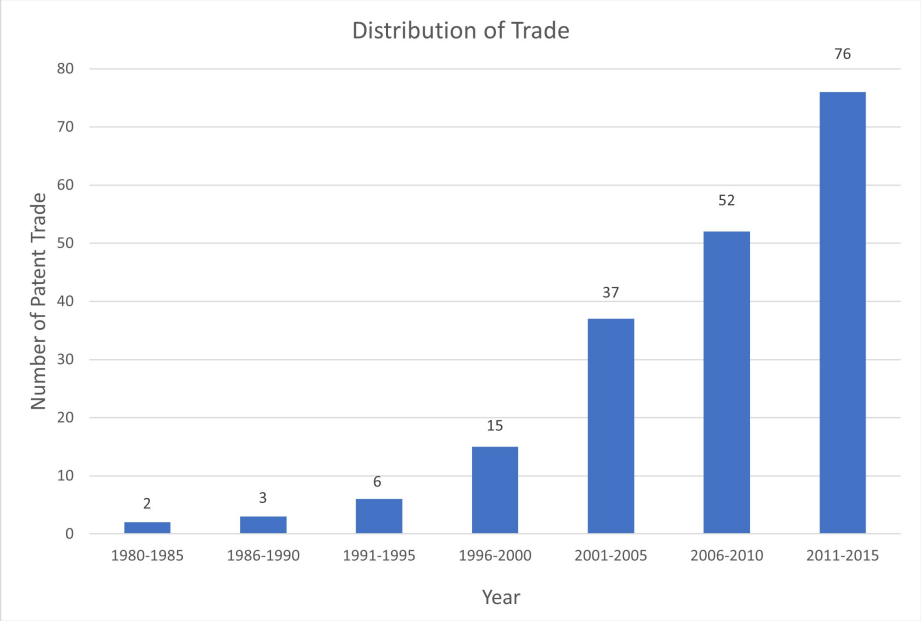


Table 18: Success Rate of Drugs with Patent Trade, by period

	Distribution. of Highest Stage			
Stages	Full Sample	1980-2000	2001-2010	2011-2015
Before Phase I Clinical	22.1%	17.4%	27.5%	20.9%
Before Phase II Clinical	6.1%	8.7%	9.8%	0.0%
Before Phase III Clinical	16.0%	17.4%	7.8%	20.9%
Before Registration	8.4%	4.4%	9.8%	9.3%
Before Launching	4.6%	0.0%	7.8%	4.7%
Launched	42.7%	52.2%	37.3%	44.2%

8.2.2 RF Evidence of Patent Selection into Trade

Regarding the selection of patent into trade. The model prediction suggests an success rate of 32.3% , even lower than the empirical success rate of 34.6% for drugs without patent trade.

Table 19 below shows the reduced form regression of success dummy on trade dummy. The first column shows the basic regression. The probability of reaching launch stage is 8.1 percentage points higher for drugs with patent trade than for those without trade, holding other factors constant. Column (2) and (3) added the control #indications (number of indications the drug's development is involved, more indications show higher potential of the drug), therapy_prescription rate (the drug prescription rate of that therapy, which I used to control therapeutic class), and the #indication_launch (number of indications that reached launch stage). Comparing the parameter associated with trade dummy, after controlling for observables, the effect becomes even larger and more significant, which is consistent with the finding from model prediction. So the higher success rate of the drugs with patent trade has little to do with the selection issue.

Table 19: RF Evidence of patent selection

Dummy_success	(1)	(2)	(3)
Dummy_trade	0.081*	0.091**	0.095**
	(0.04)	(0.04)	(0.04)
#Indications		0.022***	0.027***
		(0.00)	(0.00)
therapy_prescription rate			0.78***
			(0.09)
#indications (launch)			
Constant	0.35***	0.26***	-0.24***
	(0.02)	(0.02)	(0.06)
N	1005	1005	1004
R^2	0.003	0.053	0.125

Standard errors in parentheses * p<0.1, ** p<0.05, *** p<0.01

8.2.3 Statistic summary

Table 20: Description of Drug Development and Patent Trade Distribution, by Therapy Market

	N	N_with patent trade
Whole sample	1005	131
By therapeutic market		
Gastrointestinal	92	9
Diabetes	24	2
Hematologic	34	3
Cardiovascular	42	7
Hypertension	10	0
Hyperlipidemia	3	0
Dermatological	12	3
Acne	6	0
Genitourinary	57	5
Urological	7	0
Endocrine/Metabolic	27	2
Infection	137	26
Cancer	264	34
Musculoskeletal	11	2
Gout	2	1
Analesics/Anesthetics	32	4
Epilepsy	15	4
Parkinson	11	2
Psycholeptic-related	17	2
Psychoanaleptics	20	1
Other Nervous system drugs	137	18
Respiratory	30	4
Ophthalmic	15	2

8.2.4 Construction of Outside Option, by therapy market

To approximate the treatment rate with prescribed medications for specific conditions, I look at the frequency of prescribed drug purchases linked to each condition. This approach helps us estimate the treatment rate within each therapeutic area, offering insight into alternative treatment options. Nevertheless, the health conditions recorded in the MEPS database do not align perfectly with the therapeutic markets delineated in our study. To address this discrepancy, I referenced the health condition events from 1996 within MEPS, aligning them with our defined therapeutic markets through a manual mapping process. We then estimated the rate of drug use by dividing the total number of prescriptions by all recorded medical events associated with a particular disease. The outside option for a certain therapy market is $(1 - drug\,prescription\,rate)$, that is, the proportion of individuals with the potential for the disease who did not have a prescription drug purchase. Table 21 presents the finally estimated rate. The first column lists the therapeutic markets as established in our study, the second column displays the estimated drug prescription rate.

Table 21: Drug's Prescription Rate by Therapy Market

Therapy Market	Drug Prescription Rate
Gastrointestinal	0.674
Diabetes	0.827
Hematologic	0.454
Cardiovascular	0.786
Hypertension	0.946
Hyperlipidemia	0.800
Dermatological	0.751
Acne	0.751
Genitourinary	0.763
Urological	0.776
Endocrine/Metabolic	0.837
Infection	0.668
Cancer	0.371
Musculoskeletal	0.585
Gout	0.585
Analesics/Anesthetics	0.781
Epilepsy	0.861
Parkinson	0.81
Psycholeptic-related	0.668
Psychoanaleptics	0.69
Other Nervous system drugs	0.668
Respiratory	0.848
Ophthalmic	0.449

Table 22: Therapy Classification and Full Sample in Demand Estimation

Therapy Name	Freq.	Percent	Cum.
Gastrointestinal	265	6.18	6.18
Diabetes	117	2.73	8.9
Hematologic	47	1.1	10
Cardiovascular	416	9.7	19.7
Hypertension	170	3.96	23.66
Hyperlipidemia	124	2.89	26.55
Dermatological	450	10.49	37.04
Acne	14	0.33	37.37
Genitourinary	215	5.01	42.38
Urological	65	1.52	43.89
Endocrine/Metabolic	109	2.54	46.43
Infection	440	10.26	56.69
Cancer	85	1.98	58.67
Musculoskeletal	341	7.95	66.62
Gout	24	0.56	67.18
Analesics/Anesthetics	125	2.91	70.09
Epilepsy	201	4.69	74.78
Parkinson	45	1.05	75.83
Psycholeptic-related	221	5.15	80.98
Psychoanaleptics	333	7.76	88.74
Other Nervous system drugs	45	1.05	89.79
Respiratory	256	5.97	95.76
Ophthalmic	182	4.24	100
Total	4,290	100	

8.2.5 Demand Estimation with Therapy Class

Table 23: Demand Estimation of Drugs

	N[1]
#phase4_trials	0.001***
log(age)	1.60***
log(age)^2	-0.46***
therapy class	**therapy**
A03/Gastrointestinal	0
A10/Diabetes	3.24***
B/Hematologic	2.19***
C/Cardiovascular	2.31***
C07_09/Hypertension	3.63***
C10/Hyperlipidemia	1.03***
D/Dermatological	0.41***
D10/Ance	2.49***
G/Genitourinary	1.21***
G04/Urological	3.11***
H/Endocrine/Metabolic	3.56***
J/Infection	0.063
L/Cancer	0.62***
M/Musculoskeletal	0.57***
M04/Gout	4.34***
N01/Analesics/Anesthetics	2.08***
N03/Epilepsy	1.99***
N04/Parkinson	3.65***
N05/Psycholeptic-related	1.49***
N06/Psychoanaleptics	0.91***
N07/Other Nervous system	3.79***
R/Respiratory	0.82**
S/Ophthalmic	1.44***
Constant	-6.43***
Observations	6,701
R-squared	0.22

8.2.6 Comparison of Drug's Value between Traded and Non-Traded Groups

Table 24 displays the expected value ($V_T = log(Rev)$) of drugs at their final development stage for both traded and non-traded drugs across different stages. The data suggest that drugs with higher market values are more likely to be traded during the early stages, specifically before Phase I. Conversely, starting from Phase II, the trend reverses; drugs that were traded tend to have lightly lower average expected market values. This comparison focuses on the ex-post market value of the drug.

Table 24: Mean value of drugs with/without trade

	Expected value of the drug	
Stages	trade	no trade
Before Phase I Clinical	18.32	17.77
Before Phase II Clinical	17.62	17.64
Before Phase III Clinical	17.37	17.65
Before Registration	17.56	17.58
Launched	16.95	17.56

8.2.7 Probability of Quit Across Stages: Traded and Non-Traded Drugs

Table 25 compares the probability of quit for drugs in the causal effect counterfactual (discussed with Table 11). Assuming that all drugs in the sample initially start at stage t under their original ownership, the table shows the simulated probability of quit at each stage when trade is either allowed or prohibited at stage t. From the table, we can see that the effect of trade mainly comes from the stage affected. For Phase I, III clinical trials, and FDA registration, allowing trade decreases the likelihood of the drug discontinuing development at those specific stages. However, allowing trade before Phase II clinical trial increases the likelihood of the drug discontinuing development at that stage.

Table 25: Mean value of drugs with/without trade

	P (quit)			
Stages	Phase I	Phase II	Phase III	FDA Registration
Phase I - trade	16.1%	8.5%	26.1%	31.4%
Phase I - no trade	16.6%	8.5%	26.1%	31.3%
Phase II - trade		8.5%	26.1%	31.4%
Phase II - no trade		6.9%	26.2%	31.3%
Phase III - trade			26.1%	31.4%
Phase III - no trade			26.5%	31.3%
FDA Regist - trade				31.4%
FDA Regist - no trade				33.0%

8.2.8 Counterfacutal of Transaction Cost at Last Stage

In the counterfactual analysis, I examine the scenario of reducing transaction costs at the final stage in such a way that the relative change between development costs and transaction costs $\kappa^0_{launch} - \tau^{CF}_{launch}$ is proportional to the change in Phase I clinical trial. Table 26 presents the counterfactual results using other stages as benchmarks. The impacts on the drug's success rate are similar, with the use of the FDA registration stage leading to the highest impact.

$$\frac{\kappa^0_{launch} - \tau^{CF}_{launch}}{\kappa^0_{launch} - \tau_{launch}} = \frac{\kappa^0_t - \tau^{CF}_t}{\kappa^0_t - \tau_t}$$

Table 26: Probability of Success: Change of TC at Last Stage

	Benchmark Stage	P(success)	
		$\tau \downarrow 50\%$	$\tau \downarrow 100\%$
[1]	Phase I	40.1%	40.9%
[2]	Phase II	39.8%	40.1%
[3]	Phase III	40.1%	41.0%
[4]	FDA Registration	40.9%	44.4%

9 Appendix B: Data Construction

9.1 Firm Name-Matching Algorithm

In order to create a more precise list of firms and link firms between Cortellis and PRD datasets, a firm name-matching algorithm is employed to clean the string variables for the assignor and the assignee of all unnecessary indicators and company type abbreviations. If the cleaned assignor and assignee strings are equal, they are considered the same firm. The firm name-matching algorithm follows the methods in Akcigit, Celik, and Greenwood (2016). Details about the algorithm can be found in their Appendix. The firm name-matching algorithm is run on Cortellis CompanyName and PRD assignor / assignee, duplicates are dropped and a full list of firms (id) is created using cleaned names from both datasets. All observations for which assignor and assignee can be uniquely identified are used in this study. The subsidaries associated with a parent company can also be identified using Cortellis Company dataset.

9.2 Patent Reassignment Database

For PRD dataset, there is 190,580 transaction records related to the pharma patents that appears in PDP dataset. But PRD reassignment records include the first time assignment (application), so 181,996 records with "initial owner = assignee" are dropped. Different from Akcigit, Celik, and Greenwood (2016), internal transfer records are identified and dropped using two criteria: assignee equal to assignor, AND employer assignment indicator equal to 1.

9.3 Drug-Patent Link

This study specifically targets patents identified by a "US-" prefix, which are traceable within the USPTO database. These contrast with patents prefixed by "WO-" which are filed through the PCT application process and managed by WIPO but do not have automatic recognition under U.S. patent law. To associate patents with drugs, we employ two methods: The first method involves extracting patent details directly from drug development records. However, this approach has limitations as the patent documentation is often incomplete, frequently only listing "WO-" prefixed patents.The second method entails gathering patent data independently and then correlating these patents with the drugs they are utilized in, thereby linking patent information to drug data. This linkage is facilitated through drug names. It's important to acknowledge that a single patent may apply to several drugs. Therefore, we treat each drug development instance as an individual record to ensure accuracy in our analysis.

9.4 Therapy Class Identification

To calculate a drug's potential earnings, it's crucial to identify its therapeutic market and competitors. Approved drugs are linked to an ATC code upon their release, which indicates the organ or system they target (first digit) and their pharmacological or therapeutic properties (second digit). In the MEPS survey data post-2002, drugs are additionally assigned a Therapy Class (TC) code based on MULTUM secondary data. However, drugs that are still in development stages lack an ATC classification, necessitating alternative methods to forecast their market returns.

The Cortellis database offers detailed information about the therapy areas and indications for each drug, yet the categorization can sometimes be broad or inconsistent. For instance, a therapy area might be as generic as "Neurology/Psychiatric," making it challenging to pinpoint a precise therapeutic field. The indications provided for drugs can range from very specific conditions, like "Stage II melanoma," to broader terms, and occasionally multiple indications might overlap, referring to closely related diseases.

In my approach, I use the established ATC2 codes and the associated therapy areas and indications of approved drugs as a basis to decide the probable therapy areas for drugs currently in development. This is constrained by the limited variety of ATC2 codes represented in the approved drugs within my sample, with only certain codes appearing, and some represented by a sparse number of observations. Consequently, the therapeutic markets I identify are based on an aggregation of several ATC2 categories. To refine this classification, I integrate the therapeutic class (TC) variable from the MEPS dataset, which offers an additional layer of therapeutic classification derived from the Multum Lexicon database. For instance, in the category of ATC A, which encompasses drugs for the alimentary tract and metabolism, there exist 16 distinct sub-categories at the ATC2 level. However, only 7 of these appear within the approved drug sample. These ATC2 categories are further condensed into two broader therapy markets: one for diabetes and another for gastrointestinal drugs. This grouping is corroborated by the TC codes from Multum, ensuring a consistent therapeutic market classification.

Certain drugs may be associated with multiple ATC2 codes, as the World Health Organization's *Guidelines for ATC classification and DDD assignment 2018* suggests that "ATC codes are often assigned according to the mechanism of action rather than therapy. An ATC group may therefore include medicines with many different indications, and drugs with similar therapeutic use may be classified in different groups." As a result, a single ATC category could encompass medications with a wide range of indications, and drugs with similar therapeutic applications might be classified under different ATC groups. Given this, it is possible for a single drug to be linked with various ATC codes, and similarly, a drug may be applicable for a range of indications, with no systematic correlation between the two. For instance, a drug listed under J01 - ANTIBACTERIALS FOR SYSTEMIC USE might also fall under S01 - OPHTHALMOLOGICALS if it is indicated for ocular infections. In instances where a drug spans across multiple therapeutic categories, my approach is to assign it to a more general class, such as anti-infectives, to provide a broader, inclusive categorization.

Following the outlined criteria for data cleaning, every drug currently in development has been allocated a therapy market according to its specific therapy area and active indications. To verify the precision of this therapy market allocation, I reviewed the assigned markets of approved drugs that already possess an ATC2 code. The analysis reveals a high degree of consistency, with 119 out of 133 therapy classifications aligning with their corresponding ATC2 classifications.

9.5 OrangeBook-NBER NDC Drug Code Link

I initially link patents from Cortellis with those in the Orange Book using their patent numbers. This method leaves 288 drugs whose patents could not be linked to those listed in the Orange Book. To address the unmatched launched drugs, I propose two verification methods: First, I extract the drug names from Cortellis, which typically reflect the active ingredient, and match these to the ingredient variable in the Orange Book. Subsequently, we can verify the match by comparing it to the trade names listed in "other drug names" records. A match is confirmed only if both the key ingredients and trade names align. Second, for those that remain unmatched due to potential typos or discrepancies, a manual examination is necessary. The aim is to acquire the application numbers of these drugs to align them with the MEPS-NDC data. For this purpose, I consult the "other drug names" field for trade names, which are then cross-referenced with the Orange Book, the NDC Directory, and the FDA's official database[30] to secure the NDA application numbers. In cases where the drug trade name is uncertain, I check with the Drugs@FDA database of approved drugs[31] for further verification.

After matching the drugs listed in the Orange Book to the MEPS-NDC using their NDA application numbers, I observed that a single NDA number can correspond to multiple NDCs, reflecting various packaging options for the same drug formulation. To accurately estimate the expected return of a specific drug, it is essential to consolidate these NDC entries into a single record. For the MEPS dataset, aggregation should be performed at the application number level, since the ATC and therapy class typically remain consistent for drugs under the same application number—the variations are mainly in format or dosage. This aggregation should also consider the labeler name, as multiple labelers may market the same drug, sometimes under the same application number but with different market entry timings. If labeler names differ, we should identify if the initial entry belongs to the brand name owner and, if so, retain only that entry for our analysis.[32]

After this matching process, we have identified 383 drugs that have reached the market launch phase. However, only 141 of these have revenue or sales information available in the MEPS dataset. The discrepancy arises for two main reasons: first, some drugs may have small market sizes and thus are not captured by survey data; second, the MEPS coverage period is from 1996 to 2022, which means drugs approved before this period and discontinued early are not recorded. For the drugs missing from this dataset, I plan to estimate their expected returns using the same methodology applied to the drugs still in development.

[30] https://www.accessdata.fda.gov/scripts/cder/daf/
[31] https://www.accessdata.fda.gov/scripts/cder/daf/index.cfm?event=browseByLetter.page&productLetter=A
[32] In the cases examined, the initial entry tends to be the brand-name drug, with subsequent entries being generics.