Diffusion of Medical Treatment and Product and Market Characteristics

Senior Honor Thesis Proposal

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I. Introduction

In various product and service markets, innovation leads to substantial changes in product and service quality. The introduction of a new product often brings ground-breaking features that shape our way of living, in a positive direction. Research relating innovation to market structure tends to shed light on how competition drives innovation. Schumpeter (1942) argues that large companies are agents that drive innovation and the economy, since they have more resources to invest in R&D. Maintaining that innovation-oriented market power is a superior driver than the invisible hand and price competition, Schumpeter argues that temporary monopolies created by technological innovation incentivize firms to innovate. The implication is that the relationship between market structure and innovation creates room for policy intervention to encourage innovation by adjusting the market structure and protecting intellectual property, in order to boost economic growth and improve customer welfare.

The next step following innovation is adoption. Adoption is what essentially generates the positive externality and revenue. Though an extensive body of literature has illustrated the drivers for and positive impacts of innovation, there is a lack of understanding of the factors that influence diffusion of innovation. Hamilton (2017) has explained how consumer demand shapes innovation and its diffusion in the market for HIV treatments. This paper will use part of their model and continue to explore the effect of both supply side and demand side characteristics on diffusion of HIV treatments. We would also highlight the role of supply side market structure in diffusion of innovations, which is an area that has not been well understood yet.

Several features of the market for pharmaceuticals make it a suitable context to study the effect of market competitiveness on diffusion of innovation. First, market concentration changes over time. New medical treatments enter the pharmaceutical market after gaining FDA approval

and remain in the market to compete with both existing and more innovative treatments that enter the market later. Second, we can systematically measure the quality of a pharmaceutical product based on the clinical outcome. Clinical records provide us with solid information on the efficacy and side effects of various treatments. We can identify innovation in such treatments based on even a slight increment of the clinical outcome.

We plan to use market-level data, specifically the number of firms, market concentration, or Herfindahl-Hirschman Index (HHI) to illustrate market competitiveness of one particular pharmaceutical market or the U.S. pharmaceutical market over time. In our study, a treatment is a unique set of drugs used by patients. We will define diffusion of a new treatment in a certain period as the speed at which the new treatment gains adoption, and we plan to capture it with the percentage change of the new treatment's market share at one period.

In Section II, we analyze two categories of prior research relating competition to innovation and discuss our contributions to existing literature. In Section III, we explain the data used to extract supply side and demand side characteristics. In Section IV, we describe our empirical model as well as the theoretical background that motivates this model. Finally, in Section V, we provide a preliminary summary of the data and conclude with prospects.

II. Literature Review

There is a lack of literature that links market characteristics on the supply side, especially market structure, with diffusion of innovation. Economists have sought to examine the effect of demand side market concentration on diffusion of new technologies across industries and within a particular industry. Early on, Mansfield (1968) and Romeo (1975) found that technological innovations spread more rapidly in less concentrated industries. Focusing on the diffusion of

automatic teller machines in the banking industry, Hanna and McDowell (1984) identified a positive effect of market concentration on the rate of adoption of this once new technology. Since competition among banks occurs primarily within geographically limited markets, it is possible to investigate diffusion within one industry. By doing so, Hanna and McDowell were able to limit unmeasurable intra-industry differences while allowing varying market conditions.

Another category of literature attempted to understand the relationship between market structure and innovation. Schumpeter (1942) hypothesizes a positive relationship between market concentration and innovation, arguing that large firms in a concentrated market have more resources to invest in R&D. Arrow (1962) proposes a negative relationship. Scherer (1967) presents a model suggesting an inverted-U relationship. Empirical studies yield mixed support for these hypotheses, primarily due to the difficulty of controlling for industry-specific factors, such as regulation, consumer behavior, and product characteristics. The Federal Trade Commission (FTC) increasingly refers to the potential negative effect of competition on innovation to inform policymaking, though economists have not reached a consensus.

Goettler and Gordon (2011) investigated the oligopolistic competition between Intel and AMD and showed that the rate of innovation in product quality would increase and consumer surplus would decrease when Intel is the sole player. Also through studying durable consumer goods, Carranza (2010) found no effect of competition between average firms on the quality and quantity of introduced products in the market of digital cameras. But Carranza also noted that more products would be introduced and the average quality of new products would decrease, when firms compete with a cost or demand average.

On the supply side, price and product qualities, often indicated by perceived usefulness and user experience, partly determine adoption of new products (Pagani, 2003; Horst, 2005). Frambach

and Schillewaert (2002) suggested that marketing communication indirectly influences the probability that an innovation would be adopted. In a dynamic market, firms make competitive responses to change these determinants of diffusion of new products. Therefore, our hypothesis posits that competition influences diffusion of innovations. On the demand side, empirical studies have shown that consumer characteristics, such as age, gender, and education, impact diffusion of innovation, so we also integrate these demand side features into our model (Marenya and Barrett, 2007; Adesina, 2000). Studies showing the negative impact of perceived risks on product adoption also lead us to suspect that those willing to engage in risky behaviors might be more risk-taking and therefore tend to accept new treatments of unknown risks (Kim, 2008).

Following Hamilton's approach to study the effect of consumer demand on innovation, this paper aspires to characterize the relationship between both demand side and supply side characteristics and diffusion of innovation with an emphasis on the role of market structure on the supply side. Unlike prior literature that captures the relationship between market structure and innovation across industries, we follow Hamilton's route to focus on a particular market of HIV treatments. Past literature primarily investigated the impact of competition on innovation, so this paper will be a next step forward to examine how competition influences diffusion of innovation.

III. Data

For the purpose of this study, we will use two different sources of data to capture market competitiveness and diffusion of innovation respectively. We will use the public data set from the Multi-Center AIDS Cohort Study (MACS) to describe diffusion of innovation, demand side characteristics, and supply side characteristics. The MACS is an ongoing longitudinal survey of

HIV infection in men who have sex with men (MSM) initiated in 1984 and conducted at Baltimore, Chicago, Pittsburgh, and Los Angeles. Survey data are collected semi-annually.

The MACS dataset is particularly suited for extraction of both product (supply side) and consumer (demand side) characteristics. Surveys contain extensive questions concerning HIV+ men's self-reported health, physical ailments reflecting side effects of treatments, blood tests, treatment decisions, insurance coverage, out-of-pocket treatment expenditures, health behaviors, and sociodemographic information. These variables provide us with an extensive set of measures for supply side and demand side features. And since observations are patients at each time period, we are also able to extract both market-level and product-level information used for our analysis.

Patients' self-reported health and medical examination results indicate treatment's quality that includes efficacy and side effects. We can therefore obtain product-level supply side characteristics. We use CD4 count, the number of white blood cells per cubic millimeter of blood, to measure the objective immune system health (Hamilton, 2017). Changes of CD4 count implies whether the treatment is efficacious, which can be used to partly indicate the quality of a treatment. Individuals without HIV infection usually have a CD4 count within the normal range of 500 and 1500. A count below 500 indicates that the immune system has begun to deteriorate due to HIV virus but can still function such that the individual is not symptomatic. An individual is diagnosed to suffer from AIDS if CD4 count drops below around 300. At this point, the immune system becomes unable to fight infections.

Patients' sociodemographic information, insurance coverage, spending on treatment, attitudes, and behaviors help us illustrate how diffusion works with respect to different groups of people. A potential concern is that different insurance plans cover different groups of drugs. In order to minimize such bias affecting consumer behavior, we could control for the type of

insurance as well as financial hardship faced by patients, which are documented in the dataset. Furthermore, we choose the rate of diffusion over the spread of diffusion to capture diffusion of AIDS treatments. The rate of diffusion is the percentage change of one treatment's market share between two adjacent periods. As a dynamic measure, the rate of diffusion illustrates how fast a treatment gains adoption. Defined as the market share of one treatment at a particular period, the spread of diffusion is a static measure of how wide a treatment spreads. The number of patients, the potential adopters, varies over time. The absolute market share of a treatment is insufficient to capture adoption at the market level. Meanwhile, in a more competitive market, it is intuitive that one treatment has lower market share. Using the rate of diffusion presents another angle to look at this process.

To assess competitiveness of the market for AIDS treatments, we will continue to search for outside market-level data that contain information about the number and relative size of pharmaceutical firms as well as market concentration. When facing competitive threats, pharmaceutical firms make strategic. Competition within the pharmaceutical market as a whole may cause firms to invest more in areas that influence diffusion of products, such as marketing, R&D, and distribution channels. Two common measures of industry-level competition are Herfindahl-Hirschman index (HHI) and the four-firm concentration ratio (CR4).

$$HHI = \sum_{i=1}^{N} {s_i}^2$$

$$CR4 = \sum_{i=1}^{4} s_i$$

N = Number of firms competing in the market

s_i = Market share of firm i

Higher HHI and CR4 imply less competition in the market. HHI appears to be a more precise measure since it takes into account all firms, and there is a relationship between HHI and CR4. In addition, we recognize several shortcomings of using one of these measures. First, market shares are often recorded annually, whereas our data record patients' semi-annual visits. Second, the effect of market concentration of the overall pharmaceutical industry might differ from the true effect of market concentration of the particular market for AIDS treatments. And the strategies pharmaceutical firms use when interacting with competitors in different therapy areas may differ.

Summary Statistics

For our preliminary analysis, we use part of the full MACS public dataset modified by Hamilton (2017). We will further extract variables of our interest from the original MACS public dataset. The full MACS dataset covers information on 6,972 individuals at 49 semi-annual visits for a total of 111,271 observations. Each observation is labeled with subject ID and serial number of the visit. By using CD4 cutoff, Hamilton excluded HIV- individuals, leaving 47,753 observations. They dropped observations without information on gross income and out-of-pocket treatment costs at earlier visits and observations after visit 47 for robustness in the reporting of survival. The restrictions above leave them with 29,523 observations and 2,420 individuals. Then they dropped observations missing more than one of the variables of interest. In the end, the remaining sample contains 1,719 individuals and 16,851 total observations. After applying a different set of restrictions later with respect to our intended analysis, we should expect a different sample that has enough observations.

Figure 1 describes the summary statistics. Among 1,719 individuals in our restricted sample, 68% are White, 22% are Black, and 9% are Hispanic. Variation in race is crucial to our

analysis of diffusion among different sub-populations. Corbie-Smith (1999) found that African American individuals described distrust of the medical community as a barrier to participation in clinical research. Similar trend might be observed in adoption of new treatments. About 86% of the sample finished high school, and 23% received some graduate school education. The variation in labor supply observed in this sample aligns with previous literature on medication choice using the MCS dataset. 74% of the sample report that they have worked at least once, and 68% report that they have been out of the labor market at least once.

Figure 1: Summary Statistics: Selected Subjects, Visit 14-47 (1990-2007)

Subjects	Mean, Restricted Sample of 1719 Subjects
Black	0.22
Hispanic	0.09
White	0.68
High School	0.14
Some College	0.29
College	0.34
Graduate	0.23
Ever Work	0.74
Ever Not Work	0.68

IV. Empirical Model

This section outlines a model of diffusion of innovation in the market for HIV treatments, which involves multiple concepts borrowed from the study on the relationship between consumer demand and diffusion of innovation by Hamilton (2017). As we will study how market competition along with other factors on the demand side and the supply side affect diffusion, we propose the following preliminary econometric model with our measure of diffusion on the left hand side and both supply side and demand side characteristics on the right hand side. In practice, consumers refer to the performance of products in the previous period to make purchasing decisions; diffusion

from period t-1 to period t depends on the characteristics of consumers at period t, since those are who actually adopt or abandon the products. We specify the following reduced-form model that summarizes the relationship between diffusion of innovation and factors of our interests. Diffusion is denoted Y_{it}. The factors include lagged market structure $\mathbb{C}_{t-1}$, lagged product qualities $\mathbb{P}_{it}$, and market-level aggregate consumer characteristics $\mathcal{F}_t$.

$$Y_{it} = \{\mathbb{C}_{t-1}, \mathbb{P}_{it-1}, \mathcal{F}_t\}$$

The full model we plan to use for estimation is listed below, and detailed explanation of the variables follows:

$$Y_{it} = \beta_0 + \beta_1\mu_{it-1} + \beta_2\varepsilon_{it-1} + \beta_3\pi_{it-1} + \beta_4\iota_{it-1} + \beta_5\alpha_{it-1} + \beta_6\delta_{it-1} + \beta_7 h_t + \beta_8\alpha_t + \beta_9\,\nu_t + \beta_{10}\kappa_t + \beta_{11}\lambda_t + \beta_{12}\,\omega_t + \varepsilon_{it}$$

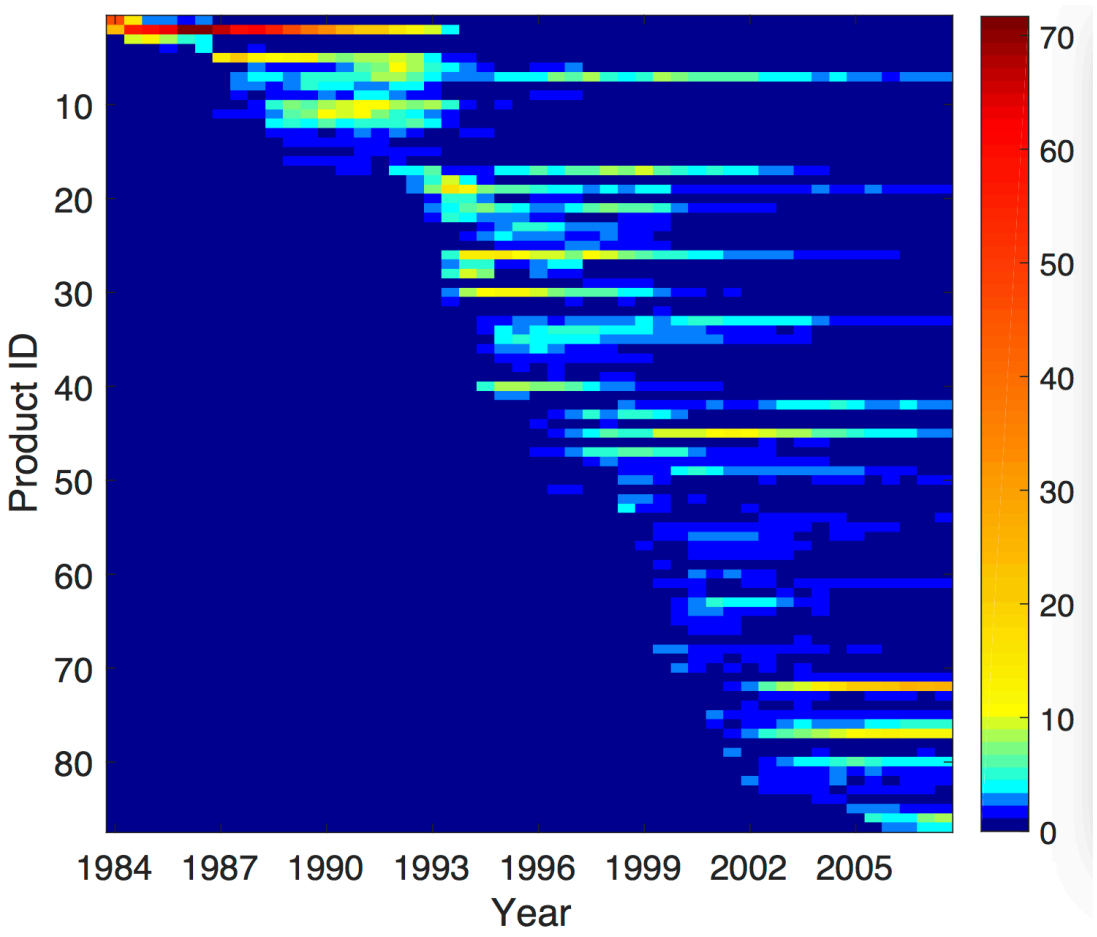
A. Diffusion

As suggested in the discussion of the data source, it is essential to construct a measure of diffusion which captures the dynamics of this process. Diffusion is denoted Y_{it} and summarizes the percentage change of market share of treatment *i* at period *t*. Market share of treatment *i* at period *t* is indicated by μ_{it} and calculated as a dynamic measure, based on the proportion of patients receiving treatment *i* at period *t*.

$$\mu_{it} = \frac{\#\ of\ participants\ using\ treatment\ i\ at\ period\ t}{\#\ of\ participants\ at\ period\ t}$$

$$Y_{it} = \frac{\mu_{it} - \mu_{it-1}}{\mu_{it-1}}$$

Hamilton (2017) illustrated diffusion of AIDS treatments over time with the following heat map.



B. Supply Side

Because original diffusion theories posit that the quality of the product itself is one of the determinants of diffusion, we include product-level characteristics in our model. Product quality is labeled $\mathbb{P}_{it}$. side effects π_{it}, relative quality (ranking) of treatment ι_{it}, relative advantage of treatment α_{it}, and length of time the treatment has been in the market δ_{it}.

$$\mathbb{P}_{it} = \{\varepsilon_{it}, \pi_{it}, \iota_{it}, \alpha_{it}, \delta_{it}\}$$

ε_{it}: Treatment efficacy of treatment i at period t, defined as average percentage change of CD4 count from period t-1

π_{it}: Side effects of treatment i at period t, defined as percentage change of the physical ailment variable from period t-1

ι_{it}: Relative quality of treatment i at period t, defined as the ranking of treatment efficacy

α_{it}: relative advantage of treatment i at period t, defined as the percentage difference between treatment efficacy of treatment i and that of the treatment ranked lower

δ_{it}: length of time treatment i has been in the market at period t

C. Demand Side

Since a product diffuses among all potential adopters, it is more relevant to measure demand side characteristics at the market level. By including these indicators in the model, we will be able to present how a treatment diffuses among a particular group of potential adopters. Aggregate consumer characteristics $\mathcal{F}_t$ describes the demand side characteristics.

$$\mathcal{F}_t = \{h_t, \alpha_t, \nu_t, \kappa_t, \lambda_t, \omega_t\}$$

h_t: Average self-reported health at period t

α_t: Proportion of individuals having received higher education at period t

ν_t: Proportion of individuals having insurance plans that cover any AIDS treatment at period t

κ_t: Proportion of individuals engaging in risky sexual behavior at period t

λ_t: Proportion of non-white population at period t

ω_t: Average income at period t

V. Preliminary Analysis and Prospects

This paper aims at demonstrating the effect of demand side and supply side characteristics on diffusion of innovations in the market for pharmaceuticals, with an emphasis on the effect of

supply side market structure, which is an area that few economists have studied. Currently, we have established a preliminary empirical model and acquired data that we plan to use to capture diffusion and some supply side and demand side characteristics. We are in the process of searching for market-level data that we can exploit to assess market structure. Potential sources of such data include the number of firms that produce relevant drugs and market concentration of the U.S. pharmaceutical market. Upon accessing the public dataset of the MACS, we are able to obtain some preliminary results and summary statistics. Furthermore, we will conduct a more in-depth literature review to complete the empirical model.

There are several potential threats to the robustness of our model. First, multicollinearity might lead to unstable parameter estimates that make it difficult to assess the effect of independent variables on diffusion. Our model includes multiple measures of the supply side and demand side characteristics. We will test the correlation between relevant measures to further adjust our model. Second, it is arbitrary to assume market concentration and product characteristics at period t-1 affects diffusion at period t. We will investigate how often patients reevaluate the quality of a treatment and switch to a different treatment because of quality of the treatment.

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