Diffusion of Medical Innovation: A Case Study of HIV Treatments

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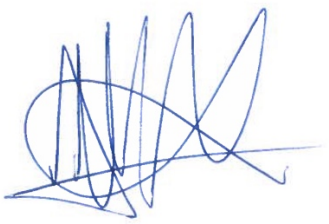

Dr. Andrés Hincapié

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Abstract

This paper uses the OLS regression approach to describe the relationship between supply side and demand side characteristics and diffusion of HIV treatments from 1990-2007. In the past decades, technological advancement has improved the quality of lives of people. There has been extensive study in the area of the pattern of innovation and diffusion of innovation, yet the link between both supply side and demand side characteristics and diffusion of innovation has not been widely discussed. Using longitudinal data from the Multi-Center AIDS Cohort Study (MACS), we find a positive relationship between the quality of HIV treatments and the speed of diffusion and a negative relationship between agents' health status and the speed of diffusion. We also find several variations of this relationship among sub-populations defined by income, race, higher education, and insurance coverage.

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 generates 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 et al. (2017) has explained how consumer demand shapes innovation and its diffusion in the market for HIV treatments. This paper uses part of their model and continues to explore the effect of both supply side and demand side characteristics on diffusion of HIV treatments. We also highlight the role of supply side competition 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 use market-level data, specifically the number of firms and market concentration to illustrate market competitiveness of the U.S. pharmaceutical market over time. In our study, a treatment is a unique set of drugs used by patients. We define the speed of diffusion as the absolute change of market share between two adjacent periods.

We find that HIV treatments that have higher efficacy and less side effects have a higher speed of diffusion. And HIV treatments diffuse faster among generally a less healthy HIV+ MEM (men who have sex with men) population. Furthermore, we are able to capture different relationships between demand side and supply side characteristics and diffusion through interactions of these variables among various sub-populations.

The rest of the paper is organized as follows. 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. In Section V, we present the results. And lastly in Section VI, we conclude with a discussion of the findings.

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 et al.'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 competition on the supply side. Unlike prior literature that captures the relationship between market structure and innovation across industries, we focus on a particular market of HIV treatments. Past literature primarily investigated the impact of competition on innovation, so this paper will examine the relationship between competition and diffusion of innovation.

III. Data

For the purpose of this study, we use two different sources of data to capture market competition and diffusion of innovation respectively. We 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. Survey data are collected semi-annually. 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.

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, blood tests, treatment decisions, insurance coverage, risky sexual 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 et al., 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, and behaviors help us illustrate how diffusion works with respect to different groups of people. We choose the speed of diffusion over the spread of diffusion to capture diffusion of HIV treatments. The speed of diffusion is the change of one treatment's market share between two adjacent periods. As a dynamic measure, the speed 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 speed of diffusion presents another angle to look at this process.

To assess competitiveness of the market for HIV treatments, we access the historical dataset on the financial information of publically-listed pharmaceutical firms through Wharton Research Data Service at the University of Pennsylvania. When facing competitive threats, pharmaceutical firms make strategic moves. 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. The common measures of industry-level competition are Herfindahl-Hirschman index (HHI), the four-firm concentration ratio (CR4) and the eight-firm concentration ratio (CR8).

$$HHI = \sum_{k=1}^{N} {\mu_k}^2$$

$$CR4 = \sum_{k=1}^{4} \mu_k$$

$$CR8 = \sum_{k=1}^{8} \mu_k$$

N = Number of firms competing in the market

μ_{tk} = Market share of firm k

Higher HHI, CR4, and CR8 imply less competition in the market. There is a relationship among HHI, CR4, and CR8. In addition, we recognize several shortcomings of using one of these measures. First, market shares are recorded every fiscal quarter (every three months), whereas our data record patients' semi-annual visits in April and October. Firms' fiscal dates have different corresponding calendar dates. We keep track of the market shares published in the first and third calendar quarter to minimize the time inconsistency. 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 HIV treatments. And the strategies pharmaceutical firms use when interacting with competitors in different therapeutic areas may differ.

A. Summary Statistics

For our preliminary analysis, we first use part of the full MACS public dataset modified by Hamilton et al. (2017). We further extract variables on agents' insurance status (private, public, or no insurance) and combined the extra variables and Hamilton et al.'s dataset. In the end, we generate the means of consumer characteristics for each visit and the means of product characteristics for each product in each visit.

Figure 1 describes the summary statistics of aggregate demand side characteristics at the market level. Across visit 14 through 47, the average proportion of non-white population is 26%.

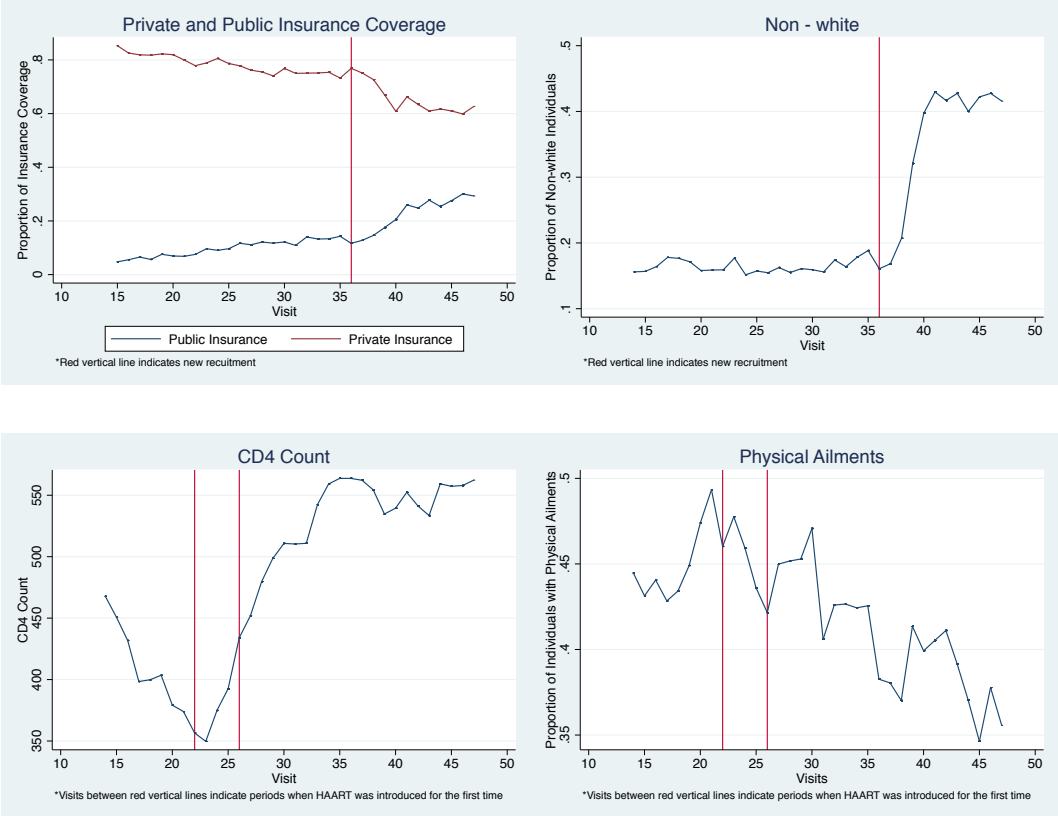
Variation in race is crucial to our analysis of attitudes towards innovative medications. Corbie-Smith (1999) found that African American individuals described distrust of the medical community as a barrier to participation in clinical research. Similar trend might be observed in adoption of new treatments. We divide the population into two racial subgroups, white and non-white. About 66% of the sample received higher education (college and above). 70% of the individuals had private insurance coverage, while 17% had public insurance coverage. 41% of the individuals reported at least one physical symptom, such as unusual bruises lasting at least two weeks, unintentional weight loss of at least 10 pounds, fatigue, diarrhea, fever, night sweats, and tender/enlarged glands for at least 3 days. During each visit, individuals undertake a physical examination that covers several health measurements. Researchers obtain the CD4 count from individuals' blood samples, which indicates the underlying health status. CD4 is a glycoprotein on the surface of immune cells. A depletion of CD4 caused by untreated HIV infection or immune suppression prior to a transplant undermines the immune system. The number of cells per microliter (or cubic millimeter, mm3) of blood is a common measure of blood values, and the normal count of CD4 cells is 500-1200 cells/mm (Hamilton et al., 2017)." The average CD4 count in our sample is 513.

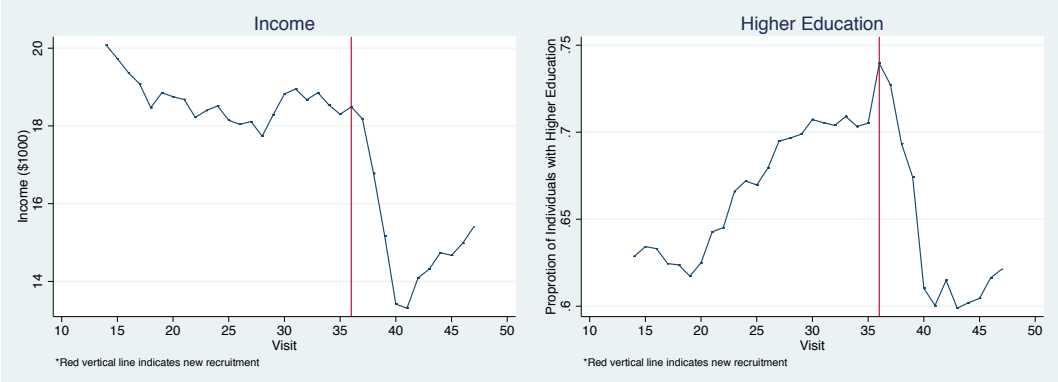
The aggregate demand side characteristics at the market level vary overtime. We observe two major jumps across demand side characteristics in visit 24 (1996) and visit 37 (2001). HAART, a medical breakthrough known as highly active anti-retroviral treatment, was introduced in 1996. HAART is especially effective at controlling CD4 counts, while it also brings significant side effects. In 2001, MACS opened another round of recruitment that focused on more minority and special target groups, which explains the changes in the average socioeconomic status of the participants, such as higher education, race, and income. The new recruitment artificially creates additional variations in the consumer characteristics.

Table 1: Means of Aggregate Demand Side Characteristics, Visit 14-47 (1990 - 2007)

Characteristic	Mean (N = 1188)	Standard Deviation
Higher Education	67%	5%
Private Insurance	70%	10%
Public Insurance	17%	7%
Gross Income	$16,741	$2,098
CD4 Count	513	59
Physical Ailment	41%	3%
Non-White	26%	12%

Figure 1: Change of Consumer Characteristics Overtime





On the supply side, there are 82 distinct treatments that are ever used by individuals in the dataset (Hamilton et al., 2017). As shown on Table 2, on average, a treatment stays in the market for 8.54 visits (approximately 4.27 years). The average change of market share is -0.00025, which is close to zero, as the change of market shares that increase and that of market shares that decrease often cancel out. As medical science evolves overtime, the efficacy and side effects of HIV treatments also change overtime. There is a spike in the rate of diffusion and average efficacy during visit 22-26 during which the HAART was introduced for the first time (Figure 2). The average efficacy and number of products are higher during the post-HAART period. We further separate treatments that have the highest and lowest quality in two dimensions – efficacy and side effects. In general, treatments that have best qualities in terms of efficacy and side effects (top 25 percentile in each visit) diffuse at a lower speed than treatments that have worst qualities (bottom 25 percentile in a visit). Treatments with best qualities during visit 22-26 appear to diffuse at a much higher speed than other treatments, which implies that HAART treatments gained market share very rapidly when they were first introduced (Figure 2). Papageorge (2016) found that sicker HIV+ individuals choose effective treatments like HAART, as those facing low survival rates anticipate high marginal returns to investments in their health stock. When they

become healthier, they are less likely to choose treatments like HAART. Figure 2 seems puzzling as products with better qualities appear to diffuse at a lower speed on average. On the contrary, based on Figure 3, it takes products with better qualities less time to gain market share. Focusing on the products at the top quartile of quality, Figure 3 shows the number of visits that a product of a given quality needs to reach the minimum highest (minmax) share observed in the sample (Efficacy Group: 0.8%; Side Effects Group: 0.4%). Therefore, we control for other demand side and supply side characteristics to further investigate the relationship between product qualities and the speed of diffusion.

Table 2: Supply Side Characteristics, Visit 14-47 (1990 - 2007)

Characteristics	Means		
	Overall (N = 1188)	Pre-HAART (N = 104)	Post-HAART (N = 1084)
Number of Products	45.05	13.02	48.13
Efficacy	31.09	-5.91	34.64
Side Effects	-0.40	-0.54	-0.38
Tenure	8.54	2.32	9.04

Figure 2: Average Speed of Diffusion by Efficacy and Side Effects

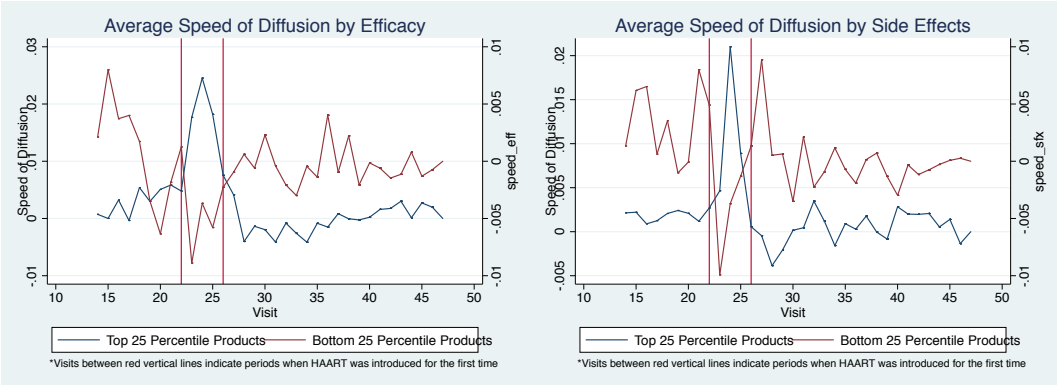
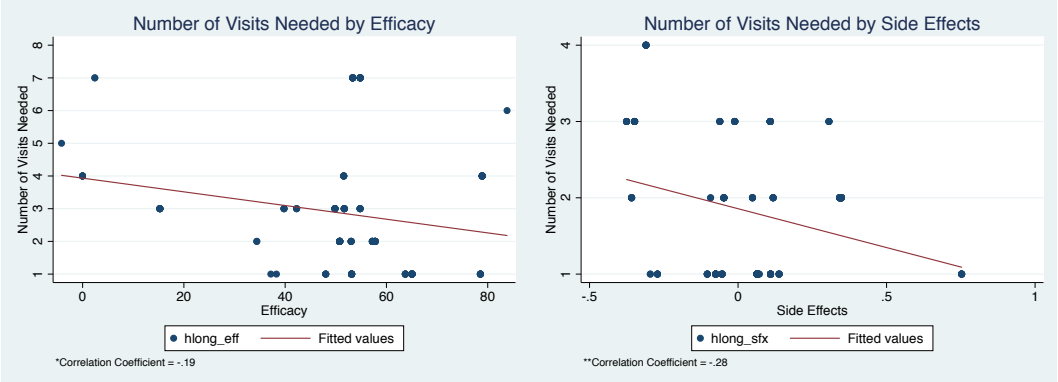


Figure 3: The Number of Visits Needed to Reach Certain Market Share by Efficacy and Side Effects



Note: One outlier observation is dropped. Correlations are robust to dropping the observation.

The change of market share is correlated with consumer characteristics (demand side) (Table 3). Besides, the correlations between demand side characteristics and the change of market share are stronger for products with better quality. Theoretically, the average change of market share approaches zero as the changes of market shares of all products cancel out. In out sample, we consider HIV+ individuals who do not consume any treatment as consumers in the market, so it is possible that market shares of all products increase at the same time as more consumers opt into consuming treatments (Figure 3). Although the relationship between average efficacy and average change of market share is not obvious, our model is able to capture variations across products and visits.

Figure 4: Average Speed of Diffusion by Average Product Qualities (Efficacy and Side Effects)

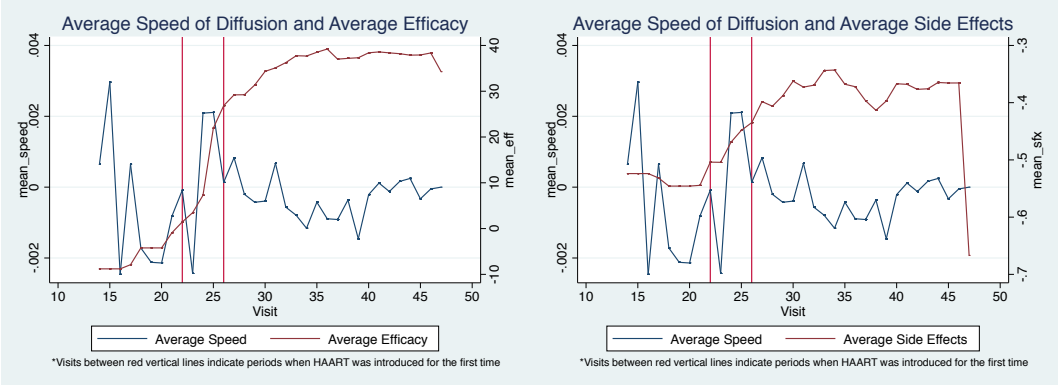


Table 3: Correlation Coefficients between Average Rate of Diffusion and Demand Side Characteristics by Product Quality

		Product Quality			
		Efficacy		Side Effects	
	Population	Top Products	Bottom Products	Top Products	Bottom Products
	Rate of Diffusion				
CD4 Count	-0.127	-0.620	0.280	-0.412	-0.225
Physical Ailments	-0.051	0.221	-0.212	0.148	0.108
Higher Education	-0.179	-0.216	0.081	-0.130	0.012
Income	-0.074	0.016	0.091	0.042	0.245
Private Insurance	-0.126	0.127	-0.050	0.087	0.132
Public Insurance	0.099	-0.106	-0.086	-0.128	-0.248

As introduced above, the sample includes a new wave of recruitment that focuses on minority population in 2001, which creates additional variations in demand side characteristics. Racial composition is the main variable that changed in 2001. We find that the speed of diffusion varies across different sub-populations (Table 4).

Table 4: Average Speeds of Diffusion across Different Populations by Product Qualities

		Product Quality			
		Efficacy		Side Effects	
	Population	Top Products	Bottom Products	Top Products	Bottom Products
	Rate of Diffusion				
Full Sample	-0.00025	0.00162	-0.00055	0.00132	0.00000
White	-0.00022	0.00161	-0.00056	0.00154	0.00012
Non-white	-0.00021	0.00191	-0.00053	0.00078	-0.00068
Higher Education	-0.00032	0.00139	-0.00056	0.00120	-0.00003
No Higher Education	-0.00010	0.00201	-0.001	0.00148	-0.00013
High Income	-0.00023	0.00153	-0.00056	0.00131	0.00013
Low Income	-0.00029	0.00179	-0.00055	0.00134	-0.00035
Private Insurance	-0.00048	0.00126	-0.00035	0.00120	0.00020
Public Insurance	-0.00058	0.00234	-0.00043	0.00075	-0.00057
No Insurance	-0.00016	0.00220	0.00047	0.00004	0.00026

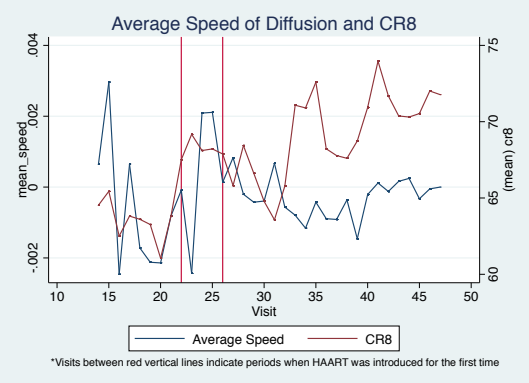
We further calculated three different concentration ratios for all publicly listed pharmaceutical manufacturers, Herfindahl-Hirschman Index (HHI), CR4, and CR8 (Table 5).

Table 5: Summary Statistics: Concentration Ratios, Visit 14-47 (1990 - 2007)

Type of Concentration Ratio	Concentration Ratio of Publicly Listed Pharmaceutical Manufacturers	Standard Deviation
HHI	734	48
CR4	43	2
CR8	69	3

In our sample, the concentration ratios showed an upward trend with moderate fluctuations during 1990 – 2007, which is consistent with existing analysis of competition in the pharmaceutical market (Figure 6). Goettler and Gordon (2011) argue that the market becomes more innovative when the market transforms from duopoly to monopoly, which may suggest a positive correlation between market concentration and diffusion of innovative products. However, markets with extremely high market concentration (duopoly and monopoly) may function differently, and demand side characteristics also affects diffusion of innovation.

Figure 5: Average Speed of Diffusion and Concentration Ratio (CR8)



IV. Empirical Model

This section outlines a model of diffusion of innovation in the market for HIV treatments, which involves multiple concepts introduced in the study on the relationship between consumer demand and diffusion of innovation by Hamilton et al. (2017). As we study how market competition along with other factors on the demand side and the supply side affect diffusion, we propose the following 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 to make purchasing decisions; diffusion from period t-1 to period t depends on the characteristics of consumers at period t, since consumers at period t are who actually adopt or abandon the products. We specify the following reduced-form OLS regression model that summarizes the relationship between diffusion of innovation and factors of our interests. Diffusion is denoted Y_{tk}. The factors include supply side characteristics S_{tk} and demand side characteristics D_t. Supposedly, the measure of diffusion is a function of supply side characteristics and demand side characteristics. We also added selected interactions between supply side characteristics and demand side characteristics to capture more variations. The full model we plan to use for estimation is listed below, and detailed explanation of the variables follows:

$$Y_{tk} = S_{tk}\theta^S + D_t\theta^D + S_{tk}D_t\theta^{SD}$$

Y_{tk}: Change of market share/rate of diffusion of product k from period t-1 to period t

S_{tk}: Supply side characteristics of product k at period t

D_t: Aggregate demand side characteristics of all consumers at period t

The change of market share captures the absolute change of market share of a product from period t-1 to t. The change of market share can be either positive or negative, as products can either

gain or lose market shares. We count all HIV+ individuals in the survey at period t as consumers, including those who participate in clinical trials or do not consume any treatment. Therefore, the market shares of all products at period t can rise or fall simultaneously. The mean speed is -0.025.

$$\mu_{tk} = \frac{\#\ of\ individuals\ using\ treatment\ k\ at\ period\ t}{\#\ of\ individuals\ at\ period\ t}$$

$$Y_{lt} = \mu_{tk} - \mu_{(t-1)k}$$

A. Supply Side Characteristics | S_{tk}

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. Efficacy and side effects are two main dimensions of a pharmaceutical product's quality. Hamilton et al. modeled efficacy and side effects of treatments in the sample, based on the health outcomes and the type of treatment used by the agent conditional on the agent's health status (CD4 counts and physical ailments) in last period (2017). The efficacy and side effects of a product are constant over time. Based on the summary statistics, products diffuse at a higher rate when they are just introduced to the market, and then diffusion slows down. We use tenure, defined as the length of time a product has been in the market, to capture such variations. Due to the limited access to price information, we include other measures such as insurance status in the consumer characteristics in the next section. Supply side characteristics are labeled S_{tk}.

$$S_{tk} = \{c_t, \varepsilon_k, h_k, \delta_{tk}\}$$

c_t: Concentration ratio at period t

ε_i: Treatment efficacy of treatment k

h_t: Treatment side effect of treatment k

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

B. Demand Side Characteristics | D_t

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 are able to present how a treatment diffuses in markets with different overall consumer characteristics. Harris et al. argued that there is an underrepresentation of racial minority individuals in clinical trials of new medications, and the reason might be that African American and other minority individuals were used to test new treatments that had adverse influence on their health (1996). The MACS dataset specifies 8 types of insurance plans, including Medicare, Medicaid, HMO (Health Maintenance Organization), group private insurance, individual private insurance, Veterans Administration coverage, campus/campus-Veterans Administration coverage, and other private health insurance plans. We categorize them into private and public insurance coverage. Medicare, Medicaid, Veterans Administration coverage, and campus/campus-Veterans Administration coverage are public insurance plans, and the rest are private insurance plans. Demand partly depends on price in the pharmaceutical market. Due to the availability of historical price information on the treatments, we did not include price in the model. Although part of unexplained variations on the left-hand side may come from price, our model partly captures the variations, since price is related to the tenure and quality of the product. As indicated in Figure 1, consumer characteristics at the market level vary overtime. For each visit, the consumers in the market are different, so we only capture current consumer characteristics. Aggregate consumer characteristics D_t describes the demand side characteristics.

$$D_t = \{\kappa_t, \lambda_t, \omega_t, \eta_t\}$$

κ_t: Average CD4 count at period t

λ_t: Proportion of individuals having public insurance plans at period t

φ_t: Proportion of individuals having private insurance plans at period t

η_t: Proportion of non-white population at period t

C. Interactions | $S_{kt}D_t$

Table 3, Table 4, and Figure 4 indicate that the rate of diffusion follows different trend among products with different qualities, specifically efficacy and side effects. In order to capture such difference, we interact aggregate consumer characteristics (demand side) and product characteristics (supply side) with product efficacy and side effects. Therefore, the interpretation of the results from such interactions is that the marginal effect of consumer and product characteristics vary based on efficacy and side effects of the product.

V. OLS Regression Results

In this section, we illustrate and explain our findings from the OLS regression approach. We first present the regression results using the baseline model (Table 6). We further discuss our findings from the race sub-groups – white and non-white, income subgroups, insurance type subgroups, and education level subgroups. In the end, we conducted additional analysis in which observations during the visits when HAART was introduced are dropped from the regression, as a robustness check.

To determine the baseline model, we tested different combinations of right-hand side variables. We started with including only the indicators for market competition, CR8 and the

number of competing products in the market. In the following OLS regression models we tested, we added a set of product characteristics, a set of consumer characteristics, and a set of interactions. Throughout the process, we excluded variables whose effects are not statistically significant. In addition, we standardized the arbitrary variables that have inconsistent units. All the right-hand side variables are rescaled to have a standard deviation of one.

Table 6: OLS Regression Results (Full Sample)

Variables	**f1**	**f2**	**f3**	**f4**	**f5**
CR8	0.00003	-	-	-	-
Number	0.00000	-	-	-	-
Efficacy	-	0.00056**	0.00056*	0.00026	-
Side Effects	-	0.00047*	0.00048*	0.00054**	0.00059**
Tenure	-	-0.00117***	-0.00131***	-0.00122***	-0.00128***
CD4	-	-	-0.00057	-0.00184***	-0.00174***
Physical Ailments	-	-	-0.00032	-0.00079**	-0.00081**
Income	-	-	-0.00014	-	-
Higher Education	-	-	-0.00038	-	-
Private Insurance	-	-	-0.00005	-	-
Public Insurance	-	-	0.00125	-	-
Non-white	-	-	-0.00120	-	-
CD4*Efficacy	-	-	-	-0.00242***	-0.00245***
Physical Ailments*Side Effects	-	-	-	0.00005	-
Efficacy*Non-white	-	-	-	0.00116***	0.00112***
Side Effects*Non-white	-	-	-	0.00005	-
Constant	-0.00214	-0.00025	-0.00025	0.00060**	0.00063**

***: 99% confidence level; **: 95% confidence level; *:90% confidence level

Table 7: OLS Regression Results (Visit 22-26 dropped)

Variables	f5
Side Effects	0.00041*
Tenure	-0.00105***
CD4	-0.00067
Physical Ailments	-0.00052
CD4*Efficacy	-0.00130***
Efficacy*Non-white	0.00097***
Constant	0.00006

***: 99% confidence level; **: 95% confidence level; *:90% confidence level

A. Full Sample

The coefficients of CR8 and the number of available products appear not to be statistically significant (Table 6). This contrasts with our assumption that HIV treatments diffuse faster in a more concentrated market. The lack of statistical evidence can be due to the fact that we used external financial information of all publically listed pharmaceutical manufacturers. In future studies, it is more reasonable to focus on competition within a specific therapeutic area, HIV, for example.

We then perform OLS regression analyses with different sets of demand-side characteristics, supply-side characteristics, and interactions. The coefficients of most demand-side characteristics that are not measures of health status are not statistically significant. Therefore, we exclude them from our baseline OLS model and conduct further OLS regression analyses among different sub-population defined by these measures.

Based on the results from the baseline OLS regression model, it is clear that HIV treatments that have less side effects tend to diffuse at a higher speed. For one standard deviation increase in the standardized measure of side effects, which indicates better quality in terms of less side effects, the speed of diffusion increases 0.059 percentage points (2.36 times of the average speed of diffusion). And the coefficient is statistically significant at 95% confidence level. There is also a

negative relationship between the tenure and the speed of diffusion, which confirms our summary statistics. For one standard deviation increase in tenure, the speed of diffusion decreases 0.128 percentage points (5.12 times of the average speed of diffusion). On the demand side, HIV treatments tend to diffuse at a lower speed in a population in which the average CD4 count is higher and the proportion of individuals with physical ailments is higher. For one standard deviation increase in the average CD4 count, the speed of diffusion decreases 0.174 percentage points (6.96 times of the average speed of diffusion). For one standard deviation increase in the proportion of individuals with physical ailments, the speed of diffusion decreases 0.081 percentage points (3.24 times of the average speed of diffusion). Furthermore, the coefficient of the interaction of CD4 count and efficacy of the treatment also implies that HIV treatments that are more efficacious diffuse at a lower speed in a population that have a higher CD4 count. This relationship confirms our findings in Figure 3. In a market where HIV+ population are generally healthier, the market share of treatments changes at a lower rate. This result is consistent with Papageorge (2016), as more efficacious products diffuse at a lower speed in healthier population, perhaps because there are tradeoffs between efficacy and other characteristics, such as side effects or dosage frequency.

In a population with a higher proportion of non-white individuals, more efficacious HIV treatments diffuse at a higher speed, which is in contrary to previous literature and summary statistics. In addition, we conducted a separate analysis on a more restricted sample in which observations during visit 22-26 are dropped, in order to account for the shock caused by the introduction of HAART treatments. CD4 count and physical ailments lost their statistical significance, while coefficients of other variables and interactions only changed slightly in magnitude (Table 7).

B. Sub-population Analyses

Table 8 summarizes the results from the baseline OLS regression model, regarding sub-populations. We analyzed four main categories of demand side characteristics: income, race, higher education, and insurance status. For income, we used the median gross income of all observations, $16,102, as a threshold to assign individuals into the high income and low income groups. Assignment into other sub-populations was based on the criteria mentioned in the Section III.

In the analysis of the high income and low income sub-populations, all coefficients remained statistically significant. The speed of diffusion decreases more among low income individuals than among high income individuals, given same level of increase in average CD4 count and product efficacy. It is possible that more efficacious treatments cost more and that low income individuals are more price-sensitive. A difference between white and non-white populations is that the coefficients of side effects and physical ailments are not statistically significant in the non-white population. This can be attributed to the fact that the original sample is predominantly white, and there was an increase of non-white individuals in the sample only after the new recruitment during which the qualities of HIV treatments had already improved.

Table 8: OLS Regression Results (Sub-populations)

Variables	Sub-populations								
	High Income (>=$16102)	Low Income (<$16102)	White	Non-white	Higher Education	No Higher Education	Private Insurance	Public Insurance	Uninsured
Side Effects	0.00057**	0.00065*	0.00063**	0.00058	0.00058**	0.00063*	0.00058	0.00063	-0.00010
Tenure	-0.00118***	-0.00121***	-0.00117***	-0.00099**	-0.00117***	-0.00137***	-0.00136***	-0.00129*	-0.00112
CD4	-0.00165***	-0.00154***	-0.00136***	-0.00170***	-0.00135***	-0.00158**	-0.00221***	-0.00119	0.00026
Physical Ailments	-0.00081*	-0.00089*	-0.00069*	0.00013	-0.00057*	-0.00037	-0.00241***	-0.00020	-0.00047
CD4*Efficacy	-0.00238***	-0.00268***	-0.00178***	-0.00236***	-0.00246***	-0.00220***	-0.00251***	-0.00298***	-0.00447**
Efficacy*Non-white	0.00120***	0.00147***	-	-	0.00125***	0.00072	0.00090	0.00187*	-0.00053
Constant	0.00061**	0.00050	0.00062**	0.00067	0.00051*	0.00074*	0.00053	0.00026	0.00094

***: 99% confidence level; **: 95% confidence level; *:90% confidence level

VI. Conclusion

This paper has established a OLS regression model that analyzes descriptively the relationship between demand side and supply side characteristics and the diffusion of HIV treatments. Through OLS regression models using historical data on HIV+ MSM (men who have sex with men) and publically listed pharmaceutical firms, we find a relationship between product and market characteristics including both consumer characteristics and competition at the industry level and diffusion of HIV treatments.

On the supply side, the regression results suggest that there is no statistical evidence indicating a relationship between market concentration and the speed of diffusion. This contradicts our assumption. A unique feature about the pharmaceutical market is that competition often happens within a very specific therapeutic area, so the results in our study might be inconsistent with previous findings and our assumption due to the lack of access to data capturing competition within the HIV therapeutic area. Furthermore, HIV treatments that are more efficacious and have less side effects diffuse at a higher speed. HIV treatments' market shares increase more when they are new in the market, and diffusion decelerates as the tenure of the treatment increases.

On the demand side, we find that in a healthier population with a higher average CD4 count and lower proportion of individuals that suffer from physical ailments, the speed of diffusion is lower. In particular, among a population with a lower average CD4 count and a higher proportion of non-white individuals, more efficacious HIV treatments diffuse at a higher speed. These results are in accord with previous studies indicating that demand for medical treatments shifts as patients' health status changes.

We then applied the baseline OLS regression model to conduct analyses on several sub-populations defined by demand side characteristics including race, income, higher education, and

insurance coverage. Since the coefficients of most demand side characteristics that are not indicators of health status are not statistically significant, such additional analyses served as a supplement to the analysis of the baseline model and provided insights about how HIV treatments diffuse among populations with different characteristics.

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