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Improving HIV/AIDS Care:

Promoting HIV/AIDS Treatment Adherence Through
Physician Peer Effects and Behavioral Incentives for Patients

A dissertation submitted in partial satisfaction

of the requirements for the degree of

Doctor of Philosophy in Economics

by

Chad Daniel Stecher

2017

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ABSTRACT OF THE DISSERTATION

Improving HIV/AIDS Care:
Promoting HIV/AIDS Treatment Adherence Through
Physician Peer Effects and Behavioral Incentives for Patients

by

Chad Daniel Stecher

Doctor of Philosophy in Economics

University of California, Los Angeles, 2017

Professor Dora Luisa Costa, Chair

This dissertation identifies new healthcare policy mechanisms for promoting greater adherence among both physicians and patients to the HIV medication guidelines. The first chapter uses insurance claims data for the sample, compiled by Dr. Arleen Leibowitz, of HIV-infected patients who were insured by Medicare and Medicaid in California between 2007 and 2010 to analyze physicians' adherence to the clinical care guidelines for prescribing HIV medications. The second and third chapters were written in collaboration with Dr. Sebastian Linnemayr, and describe the impact of the Rewarding Adherence Program (RAP) on promoting greater medication adherence among HIV-infected patients in Kampala, Uganda. The second chapter was originally published in *AIDS and Behavior* in May of 2015, and the third chapter was published in *AIDS* in March of 2017.

The first chapter examines the role of physician networks in promoting quality (more adherent) HIV care. Physicians' non-adherence to clinical care guidelines has been observed for many health conditions, and has particularly damaging repercussions for both HIV-infected patients' health and for policies to reduce the domestic HIV epidemic. I identify physician peers through shared patients and develop repeated observations of medication regimen and disease monitoring quality across physicians and patients. Using the structure of physician networks to create instrumental variables, I find heterogeneous effects across peer types. Generalist peers have no effect

on medication decisions, but a one percent improvement in HIV specialist peers' medication regimen quality increases generalists' medication regimen quality by 0.15 percent. Simulations show that improving generalists' network connections to specialists could provide adherent medication regimens to an additional 2,779 patients in California in 2010, reducing the annual number of new infections by 5 percent. These findings illustrate the potential for network connections to diffuse complex treatment protocols and suggest specific mechanisms for reducing the HIV epidemic, which is disproportionately burdening underrepresented demographic communities in the U.S.

The second chapter describes the influence of behavioral decision biases on patients' medication adherence. Behavioral economic theory has been used to study a number of health behaviors such as smoking and drug use, but there is little knowledge of how these insights relate to HIV prevention and care. In this chapter, we present novel evidence on the prevalence of the common behavioral decision-making errors of present-bias, overoptimism, and information salience among 155 Ugandan HIV patients, and quantify their association with lower medication adherence. These findings indicate that behavioral economic tools may be used to screen for future adherence problems and to better design and target interventions addressing these behavioral biases and the associated suboptimal adherence.

The third chapter measures the impact of behavioral economic incentives on combating decision biases and improving patients' HIV medication adherence in sub-Saharan Africa. 155 HIV-positive men and women in Kampala, Uganda aged 19-78 were randomized to 1 of 2 intervention groups or a control group receiving the usual standard of care. Participants in the first intervention group were eligible for prize drawings conditional on attending scheduled clinic appointments; eligibility in the second group was based on antiretroviral medication adherence measured by medical event monitoring system caps. Results from the first nine months of this intervention show statistically significant improvements in the percent of participants who maintain mean adherence rates of 90% or higher in both intervention groups relative to the control. Such behavioral incentives represent a highly cost-effective and scalable mechanism for improving adherence in this region.

The dissertation of Chad Daniel Stecher is approved.

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Sebastian Linnemayr

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Kathleen McGarry

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To the memory of Jimmy Bromberg

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Chapter 1

The Role of Physician Networks in Promoting Quality HIV Care

1.1 Introduction

Physicians' non-adherence to clinical care guidelines has been observed for many health conditions ([McGlynn et al., 2003](#)). Non-adherent treatment of the human immunodeficiency virus (HIV) is particularly damaging for both HIV-infected patients' health and for policies to reduce the domestic HIV epidemic.

While there is no known cure for HIV, antiretroviral therapy suppresses HIV viral replication within a person's body, dramatically improving health, extending life expectancy, and reducing the risk of HIV transmission. However, fewer than 55 percent of HIV-infected patients who were covered by Medicare or Medicaid in California in 2010 received a recommended regimen for a whole year. Thus, improving physicians' quality of HIV care is an important step in increasing the effectiveness of antiretrovirals and reducing disparities in HIV prevalence ([Landovitz, Desmond, and Leibowitz, 2016](#)).

It is known that HIV specialist physicians deliver higher quality (more adherent) HIV care than non-specialists, referred to as "generalist" physicians ([Markson, Cosler, and Turner, 1994](#); [Landon et al., 2005](#)). However, fewer than 30 percent of physicians currently providing treatment to HIV-infected patients in the U.S. are specialists ([Kitahata et al., 2003](#)). Access to a specialist is particularly limited in rural areas and among disadvantaged racial and ethnic populations ([Heslin et al., 2005](#); [Weissman et al., 2015](#)). With roughly 50,000 new HIV infections per year in the U.S., disproportionately occurring among populations with limited access to specialized care and among underrepresented demographic groups, improving the HIV treatment quality of generalists is essential to reducing critical disparities in care ([Centers for Disease Control and Prevention \(CDC\), 2015](#)).

In this paper, I investigate the role that physician networks can play in improving generalists' quality of HIV care. Defining physician peers through shared patients, I test whether generalists learn from the medication practices of their peers and, to the extent they do, test for heterogeneous effects exerted separately among generalist and specialist peers. I then examine how a physician's network position similarly influences HIV care. In this approach, I analyze the impact of physician networks on the quality of HIV disease monitoring, a prerequisite for properly updating patients' medication regimen. I use my results to simulate the potential quality gains in HIV treatment that

can be achieved through improved interaction between specialists and generalists.

This research makes several contributions to the literature. First, I identify physician peer effects for complex treatment outcomes, involving multiple actions on the part of physicians. Previous studies that identified peer effects among physicians focused on treatment behavior that involved a single action, such as employing prostatectomy for men with localized prostate cancer (Pollack et al., 2012) or prescribing particular drug brands (Nair, Manchanda, and Bhatia, 2010). In contrast, this analysis focuses on the quality of HIV care over time and the extent to which physicians tailor the recommended HIV medication regimen to their specific patients. Thus, the peer effects I estimate reflect the extent to which specialized knowledge can be spread through physician networks.

Second, rather than relying on a quasi-experimental research design as in the aforementioned studies, this research illustrates the power of using features of the network structure as described by Bramoullé, Djebbari, and Fortin (2009) to identify peer effects among physicians using an instrumental variables approach. Third, I estimate heterogeneous physician peer effects across physician specialties, whereas previous estimates have not considered differential impacts across physician types. Fourth, the results from the two modeling approaches I employ in this research help show how heterogeneous peer effects can be described through commonly employed network statistics. Finally, I demonstrate how the findings based on these network statistics can inform the optimal design of physician networks in clinical settings where the recommended treatment protocol is complex and requires specialized knowledge.

My data are drawn principally from the census of Medicare and Medicaid insurance claims for HIV-infected patients in California filed between 2007 and 2010.¹ I develop two quality measures from the diagnostic, procedural, and drug prescription codes contained in these data. The first, the quality of an HIV medication regimen, identifies whether the specific drugs used are combined from at least two of five available drug classes, as has been recommended by HIV clinical care guidelines since 1998 (CDC, 1998). The second measure records whether an HIV-infected patient received at least the minimum amount of disease monitoring that is necessary for physicians

¹In the United States, over 50 percent of HIV-infected patients are enrolled in public health insurance plans (Yehia et al., 2014), and approximately 11 percent of all HIV-infected patients reside in California (Office of AIDS, 2016).

to properly select a drug regimen.

The first step of my analysis tests for the presence of significant peer effects between physicians in relation to medication regimen quality. I use repeated observations of new medication prescriptions across physicians and patients to specify a panel linear-in-means model for the impact of peers' medication regimen quality on a physician's own medication regimen quality.² My identification strategy addresses the simultaneity bias inherent in peer effects models, outlined in [Manski \(1993\)](#), in two ways. First, the measure of peers' medication regimen quality only considers the past prescription decisions of physician peers. Second, I employ the medication regimen quality of intransitively connected network peers in an instrumental variables framework (see [Bramoullé, Djebbari, and Fortin \(2009\)](#)). I also develop a novel extension of this empirical method to estimate the heterogeneous peer effects in HIV medication regimen quality across physician peer types.

I find that generalists learn from their specialist peers to more accurately prescribe medication regimens that are adherent with clinical guidelines. On average, a one-percent increase among all peers' past medication regimen quality increases a generalist physician's own medication regimen quality by 0.12 percent. When the peer group is separately defined to consist of only specialists or only generalists, generalist peers have no effect on medication decisions, while a one-percent increase in specialist peers' past medication regimen quality raises generalists' medication regimen quality by 0.15 percent.³ I also find significant peer effects for other prescription behaviors that require specialized clinical knowledge, but do not observe significant effects in the use of specific drug brands or among artificially created physician networks, which further indicates that generalists learn the recommended HIV treatment protocol from their specialist peers.

I also examine the impact of physician peers using common social network statistics that describe physicians' relative position within their network (see [Wasserman and Faust \(1994\)](#); [Barnett et al. \(2012\)](#); [Landon et al. \(2012\)](#)). I investigate peer effects in both medication regimen and

²This model estimates physician, patient, and region-year fixed effects to control for physicians' homophily (i.e. assortative network formation) ([Pollack et al., 2013](#)), patient attributes ([Landovitz, Desmond, and Leibowitz, 2016](#)), and correlated contextual effects ([Schwarcz, Hsu, and Scheer, 2015](#)), which have all been found to influence the quality of care in this setting.

³These elasticities in medication quality are similar in magnitude to workplace peer effects observed between physicians in other clinical settings ([Chan, 2016](#); [Silver, 2016](#)), and across workers in other industries ([Herbst and Mas, 2015](#)).

disease monitoring quality through these methods. I then augment network statistics to describe a physician's network position relative to specialists. I find these specialist-weighted statistics significantly influence a generalists' medication regimen quality, corroborating the previous results. However, increased collaboration among physicians of all types is the only significant contributor to higher quality disease monitoring.

I use my results to estimate the medication regimen quality gains from a simulated health policy that increases generalists' access to specialists within regional health care markets in California ([Wennberg, 1996](#)). My simulations show that improving generalists' network connections to specialists could enable 16 percent of HIV-infected patients in California in 2010 who were not previously virally suppressed by treatment to achieve viral suppression. Because HIV viral suppression dramatically reduces the risk of sexual transmission, this increase in treatment quality reduces the annual number of new infections in California by 5 percent.

This paper proceeds as follows. Section 1.2 discusses existing research on the quality of HIV care, the construction of physician networks, and the identification of peer effects in clinical settings. In Section 1.3, I outline the data construction, sample selection, and measurement techniques used in the analysis. Section 1.4 presents the methods for identifying physician peer effects on medication regimen quality and the impact of network statistics on both medication regimen and disease monitoring quality. In Section 1.5, I describe the observed structure of physician networks constructed in two different samples, and Section 1.6 discusses the estimation results. Section 1.7 simulates how these findings could inform health policy to increase patients' rates of HIV viral suppression, and Section 1.8 concludes.

1.2 Background

1.2.1 HIV Care

There are approximately 1.2 million people currently living with HIV in the United States ([CDC, 2016](#)). Fortunately, antiretroviral therapy can dramatically suppress the presence of the HIV virus in a patient's body, significantly extending life expectancy.⁴ As a result, it has become

⁴The World Health Organization recently estimated that the increased use of antiretroviral therapy has resulted in 7.8 million lives saved globally in the past 15 years alone ([WHO, 2015](#)).

the universally recommended course of treatment for HIV infection and has allowed the disease to be managed as a chronic condition. This treatment additionally minimizes the risk of HIV transmission between sexual partners, so its proper implementation constitutes an important step in ending the HIV epidemic (Cohen et al., 2011; United Nations Joint Programme on HIV/AIDS, 2016).

Among the HIV-infected patients currently receiving antiretroviral therapy in the U.S., however, only 81.1 percent have achieved the optimal HIV viral suppression (CDC, 2014).⁵ Within the estimated 126,241 HIV-infected patients in California who are currently receiving antiretroviral therapy, only 79.7 percent are virally suppressed (Office of AIDS, 2016). Low levels of viral suppression are particularly acute in rural communities (Weissman et al., 2015), and among disadvantaged socioeconomic populations (Landovitz, Desmond, and Leibowitz, 2016).

One important contributor to the reduced effectiveness of antiretroviral therapy is the complexity involved in correctly combining antiretroviral medications. The interactions between HIV medications, potential viral mutations, and a patient's genetics, comorbidities, and medication adherence significantly complicate the proper implementation of this treatment protocol. HIV clinical care guidelines help to outline the appropriate combination of medications, disease monitoring, adherence counseling, and health screenings that should be performed by the physicians involved in an HIV-infected patient's care (Department of Health and Human Services, 2016). Promoting adherence to these guidelines represents one important mechanism for increasing the effectiveness of antiretroviral therapy, improving HIV-infected patients' health, and closing critical rural versus urban and socioeconomic disparities in HIV prevalence (CDC, 2016).

Medical research documents the benefits of physician specialization in adhering to these clinical guidelines, where specialization is defined in terms of both experience and training. Specifically, physicians with large HIV-infected patient caseloads⁶ have been associated with better pa-

⁵An HIV-infected patient is considered virally suppressed when the HIV virus cannot be detected through CD4 T-cell and viral load scans, a level that protects the patient's own health and reduces their likelihood of transmitting the virus to others. Viral load measures the amount of HIV in the bloodstream, usually reported as the number of copies of HIV RNA in a milliliter of blood.

⁶Patient caseload is a common measure of physician specialization, but the specific definitions vary across studies (Handford et al., 2012). In relation to HIV care, specialists are defined by minimum HIV-infected patient caseloads that range from 30 to 100 patients. For this research, HIV specialization identified through clinical experience is defined by an HIV-infected patient caseload greater than or equal to the 95th percentile of all caseloads in a physician's

tient outcomes, measured by survival rates (Kitahata et al., 1996; Kitahata, Van Rompaey, and Shields, 2000), the appropriate initiation of antiretroviral therapy (Handford et al., 2012), and patient satisfaction (Kitahata et al., 2003). Studies comparing patient outcomes across physicians' academic training find that a higher proportion of infectious disease specialists correctly initiate antiretroviral therapy (Landon et al., 2002) and appropriately counsel patients on treatment adherence strategies (Duffus et al., 2003). Specialization has also been significantly associated with improved patient outcomes and treatment quality (Markson, Cosler, and Turner, 1994; Landon et al., 2005). However, fewer than 30 percent of the domestic physicians who provide treatment to HIV-infected patients are specialists (Kitahata et al., 2003).⁷

This research focuses on how physician networks can improve the quality (adherence to clinical guidelines) of HIV care provided by generalists. The analysis estimates network interactions between specialists and generalists,⁸ and examines how closer connections between these two groups can influence the quality of HIV care.

1.2.2 Physician Networks

For these analyses, physician networks are constructed based on patient-sharing relationships observed through health insurance claims. Specifically, network links are recorded between physicians who are listed on an insurance claim for the same patient.⁹ This technique has been used previously to construct network estimates among physicians within hospitals (Barnett et al., 2012), cities (Pollack et al., 2012), and regional health care markets (Landon et al., 2012), and has been validated through additional survey measures of physicians' reported interactions (Keating, Zaslavsky, and Ayanian, 1998; Barnett et al., 2011).

hospital referral region. This measure of specialization translates into a minimum caseload of roughly 40 patients, which is consistent across regions (the standard deviation of the 95th percentile of HIV-infected patient caseloads is approximately 5 patients).

⁷This percentage is also observed within the data informing this research. Table ?? details additional characteristics of the physician population informing these analyses.

⁸HIV specialization will be identified by both academic training (infectious disease specialty) and HIV patient caseload (equal to or greater than the 95th percentile of observed annual caseloads in this sample) throughout this paper.

⁹Networks are constructed only among the physicians performing HIV evaluation and monitoring procedures for this HIV-infected patient sample.

The main hypothesized mechanism for peer effects through sharing patients is that a physician learns from observing the past treatment decisions of other physicians in a patient's records. The peer effects estimated in my first analytic model will capture the aggregate influence of a physician's network that is transmitted through directly connected peers, i.e. the physicians connected through a single patient-sharing link. The choice of medications and the frequency and type of disease monitoring employed by peers may identify new drug regimens, demonstrate an alternative way of combining medications in light of the shared patient's specific health conditions, or suggest additional forms of HIV viral load testing. Of course, physicians interact and learn from their peers in many other forms that are unobserved in these data. Previous research has found that patient-sharing connections identify as much as 82 percent of these unobserved referral and advice relationships between physician colleagues (Keating et al., 2007). Thus, the peer effects estimated within my patient-sharing networks represent only a portion of the true aggregate peer effects between physicians.

Despite only partially observing physicians' interactions, the informal patient-sharing networks inferred from health insurance claim data have been found to predict differences in medical costs (Landon et al., 2012), physicians' practice patterns (Pollack et al., 2013), and patient outcomes (Pollack et al., 2014). In light of the large geographic variation that exists in medical spending (Fisher et al., 2003a,b), the significant role of physician networks in explaining regional differences in treatment costs and intensity highlights the importance that physician relationships have in determining clinical practice patterns and norms (Wennberg, 1996; Landon et al., 2012; Barnett et al., 2012). These recent empirical findings are supported by a long standing medical literature that describes how physicians rely heavily on their peers for patient consultations and for learning about new medications and treatment methods (Coleman, Katz, and Menzel, 1957; Keating, Zaslavsky, and Ayanian, 1998; Gabbay and le May, 2004).

In addition, there is a rich literature in economics that similarly establishes the importance of peer effects on an individual's behavior. For example, a wide range of labor economics studies find that peer effects significantly influence an individual's choice of retirement plans (Duflo and Saez, 2002), migration (Munshi, 2003), technology adoption (Conley and Udry, 2010), and welfare participation (Bertrand, Luttmer, and Mullainathan, 2000). In regards to health behaviors, peers

have been shown to affect an individual’s choice of health insurance (Sorensen, 2006), drug use (Case and Katz, 1991), and diet (Christakis and Fowler, 2007; Trogdon, Nonnemaker, and Pais, 2008). More closely related to this research, researchers have also identified significant peer effects among physicians’ treatment decisions (Coleman, Katz, and Menzel, 1957; Epstein and Nicholson, 2009; Iyengar, Van den Bulte, and Valente, 2011; Nair, Manchanda, and Bhatia, 2010; Molitor, 2014), and workplace productivity spillovers have been identified between physicians in several clinical care settings (Chan, 2016; Silver, 2016).

1.3 Data and Sample Selection

The main sources of data for this study are Medicare and Medicaid fee-for-service health insurance claims for HIV-infected patients filed between 2007 and 2010 in California. County-level contextual data and information about physician characteristics from three other data sources are merged with variables drawn from the insurance claims (see Section 1.3.1). I construct two measures of the quality of HIV care from this combined data set: “Medication Quality” and “Monitoring Quality” (see Section 1.3.2).

These two quality measures describe the HIV treatment protocol administered over different lengths of time and impose different sample restrictions, which leads to the use of two analytic samples described in Section 1.3.3. I construct physician networks separately within these two samples (see Section 1.3.4), and estimate the influence of network peers through two modeling approaches (see Section 1.4).

1.3.1 Primary Data Sources

For this research, I use public health insurance claims for enrollees of fee-for-service (FFS) plans, as managed care claims lack the detailed diagnostic and procedural codes required for confirming a patient’s HIV status and observing individual elements of their clinical care. The FFS claims data outline the care received by HIV-infected patients between 2007 and 2010 in California.¹⁰ I combine these insurance claims data with county-level estimates of median household income from the American Community Survey (ACS), county-specific HIV prevalence statistics

¹⁰The identification of HIV-infected patients among the FFS claims is based on the algorithm developed in [Leibowitz and Desmond \(2015\)](#).

compiled by the California Department of Public Health, Office of AIDS (OA), and physician background information contained in the American Medical Association (AMA) Masterfile.

The historical clinical practice location of each physician contained in the AMA data allows me to place physicians within one of the twenty-four local hospital referral regions (HRRs) in California, as defined by the Dartmouth Health Atlas ([Wennberg, 1996](#)). These regional HRR boundaries are generated by the observed referral patterns between hospitals, and enable more intricate network statistics to be estimated for each physician within these geographical network boundaries. The additional variables obtained from each data source are listed in Table 1.1.

1.3.2 Quality of Care Measures

I derive two main quality measures from these insurance claims data. The first measure, medication quality, identifies whether physicians are correctly administering antiretroviral therapy, the primary treatment mechanism for an HIV-infection.¹¹ Antiretroviral therapy refers to the combination of multiple antiretroviral drugs, which are administered through a daily pill regimen. A recommended antiretroviral prescription contains three active chemical agents drawn from at least two of five available drug classes designed to slow the propagation of the HIV virus. To determine the appropriate combination of drug therapies for a particular patient, physicians must be familiar with a patient's disease history, medication adherence levels, genetic resistances, other interacting drugs, comorbid health conditions, and drug side effect experiences. Each of these factors will inform a physician's selection of an appropriate drug combination, which is drawn from over 200 available drug options. The medication quality measure identifies whether each HIV medication prescription includes a recommended combination of drugs, conditional on containing any HIV drugs.¹²

¹¹After the introduction of potent antiretroviral therapy (ART) in 1996, HIV-infected patients have all been treated with ART to prevent the HIV virus' progression towards AIDS. ART has successfully extended the life expectancy of thousands of HIV-infected individuals, slowed the spread of the HIV virus among many at-risk populations, and nearly eradicated perinatal HIV transmission in the U.S. With the use of perinatal prophylaxis with ART the percentage of infants born to HIV-infected mothers who were perinatally infected with HIV decreased from 25 percent to < 2 percent between 1990 and 2004 ([Van Dyke et al., 2011](#)).

¹²While antiretroviral therapy has served as the main treatment option for HIV infections since 1996, guidelines for the initiation of treatment have varied. Historically, it was believed that antiretroviral therapy was only necessary once HIV replication had reached certain thresholds, measured by the decrease in a patient's CD4 T-cell count and an increase in their HIV viral load, and these thresholds were frequently updated between 2004 and 2015. Instead

I employ this medication quality measure in two ways. First, medication quality is assessed for each new medication prescription. I also calculate medication quality over a calendar year. Specifically, annual medication quality identifies whether a patient received at least one recommended medication combination conditional on filling any HIV prescriptions throughout the calendar year.

The second quality measure, monitoring quality, describes the frequency and type of patient monitoring provided throughout a calendar year. Clinical practice guidelines recommend that patients meet with a physician at least twice annually for HIV checkups where viral load and other health outcomes are assessed.¹³ Conditional on having two or more such visits throughout a calendar year, this measure identifies whether a patient received an appropriate form of disease monitoring during their HIV checkups.¹⁴

1.3.3 Analytic Samples

I derive two analytic samples from the Medicare and Medicaid FFS claims data. I construct the first, “Medicare Only” sample, in order to measure HIV medication quality for individual prescriptions. Specifically, medication quality is assessed for new prescriptions, identified by the prescription’s fill number. This information is only available from Medicare Part D drug claims.

I construct the second, “Medicare Plus” sample, to describe patients’ annual medication and monitoring quality experienced during a calendar year. This sample includes only those patients covered by Medicare or Medicaid for at least one full calendar year between 2007 and 2010. Full-year plan enrollment in a Part D drug plan is also required for all Medicare beneficiaries.

of attempting to measure whether patients were appropriately treated with any form of antiretroviral therapy during this sample time period, which would require additional biological measurements that are unobserved in the insurance claims data, this first quality measure focuses on the adequacy of the combination of HIV drugs prescribed.

¹³During these checkups, physicians should re-evaluate a patient’s HIV medication combination, and assess patients’ treatment adherence and potential side-effects. Additionally, the guidelines recommend that patients undergo two CD4 T-cell count and two HIV viral load scans annually, as well as receive annual testing and immunization for common comorbidities (e.g. flu and tuberculosis) and annual evaluations of their internal organ health (e.g. glucose and lipid level testing).

¹⁴The HIV virus spreads through the body’s CD4 T-cells, which are then destroyed at the end of viral replication. Thus, both CD4 T-cell counts and HIV viral load scans serve to measure the effectiveness of a patient’s HIV drugs, and can be used by physicians to adjust a patient’s particular HIV medication combination. Since these two tests are substitutable, the second quality measure identifies whether either of these methods were used during a patient’s evaluation and monitoring visits during a calendar year of treatment.

Additionally, this sample excludes persons newly diagnosed with HIV during a calendar year, for whom an assessment of their full year of care would be inappropriate. The sample restrictions that yield these two analytic samples are displayed in Table 1.2.

1.3.4 Patient Sharing Networks

Medicare Only Sample

Physicians observed on Medicare Part D drug claims are linked based on writing HIV medication prescriptions for the same patient.¹⁵ However, I do not consider all patient-sharing links when measuring peers' medication quality. For a given physician, only the other physicians who wrote prescriptions for shared patients prior to the last time the patient was seen by the given physician are identified as peers.

Within the Medicare Part D data, I calculate the measure of peers' medication quality as the average medication quality of physicians connected through a single past patient-sharing link. Since the number of observed prescriptions and shared patients grows over time, only links established within the previous twelve months are included in the peers' medication quality measure.¹⁶ Additionally, observations of peers' medication quality are weighted based on their recency to capture the natural decay in information that is likely transmitted from more historical clinical interactions.¹⁷ Finally, I only consider the medication quality of physician peers for patients other than the specific linking patient. Otherwise, a physician who continues the same treatment strategy of prior physicians would automatically appear to have a similar medication quality.

I construct a second set of physician peers' medication quality measurements to test for the presence of heterogeneous peer effects across physician types. As discussed previously, special-

¹⁵The Medicare only sample includes only new prescriptions because the interaction between physicians and their shared patients is the main mechanism for the hypothesized network peer effects. These physician - patient interactions are unlikely to occur at the time of a prescription refill, because refills are most often completed at a pharmacy.

¹⁶To incorporate the information contained in past prescriptions, the Medicare Part D analytic sample begins in 2008 after a full year of prescriptions are observed. This allows the measure of peers' quality to be applied consistently across the remaining sample.

¹⁷The preferred specification for this measure of peers' behavior uses temporal weighting defined as the inverse of the time gap between current and past prescriptions, but I also test alternative weighting procedures and moving average techniques. Additionally, I construct the moving average of peers' behavior over alternative time ranges (6, 18, and 36 months), and the results from these alternative constructions are quantitatively very similar. I present the results for several of these sensitivity analyses in Section 1.6.1.

ization is an important determinant of care quality, yet the majority (78.2 percent) of physicians treating this patient population are generalists.¹⁸ I separately calculate the average medication quality of directly linked generalist and specialist peers to estimate the peer effects exerted by these two physician types.

The measure of peers' medication quality is defined for physician j treating patient i on day d in the following way:

$$\overline{Q_{ijd}} = \sum_{d' < d} \sum_{j' \neq j} \sum_{i' \neq i} \omega_{i'j'dd'} \cdot Q_{i'j'd'}; \quad \text{where}$$

$$\omega_{i'j'dd'} = \frac{L_{i'j'd'} \cdot f(d - d')}{\sum_{d' < d} \sum_{j' \neq j} \sum_{i' \neq i} L_{i'j'd'} \cdot f(d - d')}; \quad \text{and} \quad L_{i'j'd'} = \begin{cases} 1 & \text{if } j', j \text{ are linked through } i' \text{ on day } d' \\ 0 & \text{otherwise} \end{cases}$$

Similarly,

$$\overline{Q_{ijd}^{Type}} = \sum_{d' < d} \sum_{j' \neq j} \sum_{i' \neq i} \omega_{i'j'dd'} \cdot v_{j'}^{Type} \cdot Q_{i'j'd'}; \quad \text{where} \quad \omega_{i'j'dd'} = \frac{L_{i'j'd'} \cdot f(d - d')}{\sum_{d' < d} \sum_{j' \neq j} \sum_{i' \neq i} L_{i'j'd'} \cdot v_{j'}^{Type} \cdot f(d - d')}$$

$\overline{Q_{ijd}}$ is the weighted average medication quality of all peers linked through at least one shared patient in the past twelve months, and $\overline{Q_{ijd}^{Type}}$ separately estimates the weighted average quality of all directly linked generalist and specialist peers, where $Type \in \{General, HIV\}$. The medication quality of physician j' treating patient i' on day d' is recorded by an indicator variable, $Q_{i'j'd'}$, that is equal to one if the prescription adheres a recommended medication combination. These peers' quality measures assume that the HIV medication quality for physicians $j' \neq j$ treating patients $i' \neq i$ on any day $d' < d$ has a diminishing impact on any contemporaneous treatment decision as function of the time gap between current and past prescriptions. I impose this assumption through the weights $\omega_{i'j'dd'}$, where $\omega_{i'j'dd'} = f(d - d')$ and $\frac{\partial f}{\partial d} < 0$. The peers' quality by physician type measure includes an additional component $v_{j'}^{Type}$, which identifies whether a physician peer j' is either a generalist or a specialist.

The biggest concern with this measure is that physician networks are only partially observed through public health insurance claims data. Since I am unable to observe physicians' patient-

¹⁸See Table ?? for additional characteristics of the physicians contained in these analytic samples.

sharing interactions for privately insured HIV-infected patients, the measure of peers' medication quality is likely missing additional signals about the proper HIV medication protocol that physicians are receiving from these unobserved physician peers. Still, the partially observed physician networks previously constructed through public health insurance claims are found to be reflective of regional and hospital-level differences in treatment practices (Barnett et al., 2012; Landon et al., 2012), and over half of all people living with HIV in the U.S. are covered by either Medicare or Medicaid (Yehia et al., 2014). This nonrandom source of measurement error is discussed further in Section 1.6.

Medicare Plus Sample

Physicians observed in the “Medicare Plus” sample are linked based on treating the same patient at any point within a calendar year. This larger physician network additionally includes physicians who prescribed HIV medications to Medicaid enrollees, and physicians who performed other forms of HIV evaluation and monitoring procedures for HIV-infected patients enrolled in either Medicare or Medicaid. I assign the annual medication and monitoring quality experienced by a particular patient equally to all his or her treating physicians within the calendar year.¹⁹ I do not construct similar estimates for the average peers' treatment quality within this second analytic sample however, because the timing of physician and patient interactions cannot be used to describe the direction of information transferred through patient sharing. Instead, I describe peer effects in this setting through a physician's network position, as described by several common network statistics outlined in Section 1.4.2.

1.4 Methods for Estimating Physician Network Effects

I employ two modeling approaches for describing the role of physician networks on the quality of HIV care. I use Equations 1.1 and 1.2 to identify peer effects based on frequent measures of medication quality in the Medicare Only sample (see Section 1.4.1). This approach is informed by econometric theory (Hahn and Newey, 2004; Bramoullé, Djebbari, and Fortin, 2009) and similar

¹⁹Since the two quality dimensions measured in this analysis relate to the primary mechanism for HIV treatment, any physician involved in a patient's HIV care should ensure that the clinical guidelines are being adhered to, even if they were not directly involved in the specific procedure.

regression models previously employed in the labor economics literature (Nair, Manchanda, and Bhatia, 2010; Chan, 2016).

In my second approach, I use Equation 1.3 to estimate the effect of a physician’s network position on annual quality of HIV care in both samples (see Section 1.4.2). This approach allows me to investigate the role of physician networks on both annual medication and monitoring quality, and follows the methods utilized in much of the public health literature (Barnett et al., 2012; Landon et al., 2012). The results from this second approach will identify the important physician relationships for promoting monitoring quality, will help to confirm the findings obtained through Equations 1.1 and 1.2, and will yield empirical evidence for the relationship between these two modeling techniques, commonly employed in different literatures.

1.4.1 Peer Effects in the First Modeling Approach

The first model assumes that the data generating process for medication quality is linear in a set of physician, patient, and network attributes, and is separably influenced by the behavior of a physician’s peers. In Equation 1.1, a single measure for peers’ prescription behavior is included additively, which implicitly assumes that the peer effect is constant across physician types. The probability that the prescription written by physician j for patient i on day d is adherent to the recommended HIV medication guidelines takes the following linear probability functional form:

$$Q_{ijd} = \alpha + \gamma \cdot \overline{Q_{ijd}} + \beta P_{id} + P_i + D_j + N_d + \varepsilon_{ijd}; \quad (1.1)$$

where Q_{ijd} is the binary indicator of medication quality, $\overline{Q_{ijd}}$ is the average past medication quality of all directly linked physician peers (i.e. physicians connected through a single-patient sharing link), P_{id} are time-varying patient characteristics, such as the number of comorbidities, as defined by the Charlson Comorbidity Index (Charlson et al., 1987), P_i and D_j are patient and physician fixed effects, respectively, and N_d are hospital referral region-year indicator variables.

I employ a linear probability model instead of non-linear methods, such as logit or probit, for two main reasons. First, the linear probability model uses fixed effects for patients, physicians, and year-regions to control for the exogenous determinants of treatment quality within each of these units of observation. As the sample size for this estimation grows, so too would the number of

fixed effect estimates, leading to the “incidental parameters problem” which results in inconsistent maximum likelihood parameter estimates (Hahn and Newey, 2004). Second, estimating a full covariance matrix that properly considers nonzero correlations in modeling errors across physicians and patients using maximum likelihood is computationally difficult. Instead, linear probability model estimates describe the marginal effect of local changes from the mean level of peers’ medication quality, and I double-cluster the coefficients’ standard errors over multiple observations of the same physician and the same patient (Petersen, 2009).

I estimate heterogeneous peer effects by including separate measures of peers’ medication quality by physician type. The probability that the prescription written by physician j for patient i on day d is adherent to the recommended medication guidelines takes the following linear probability functional form:

$$Q_{ijd} = \alpha + \gamma^{GEN} \cdot \overline{Q_{ijd}^{General}} + \gamma^{HIV} \cdot \overline{Q_{ijd}^{HIV}} + \beta P_{id} + P_i + D_j + N_d + \varepsilon_{ijd}; \quad (1.2)$$

where $\overline{Q_{ijd}^{General}}$ is the average past medication quality of generalist who are direct peers, and $\overline{Q_{ijd}^{HIV}}$ is the average past medication quality of specialists who are direct peers. Estimates for the parameters (γ^{GEN} and γ^{HIV}) specified by Equation 1.2 are the first to identify heterogeneous peer effects across all network connections, as existing literature exploring heterogeneous peer effects typically analyzes differences across individual relationships (Griffith and Rask, 2014; Yakusheva, Kapinos, and Eisenberg, 2014; Tincani, 2014).

To model physicians’ selection between patient-sharing networks and among their physician peers, Equations 1.1 and 1.2 estimates physician fixed effects (D_j). This strategy treats network selection as a constant physician attribute, which can be thought of as a physician’s taste or preference over professional peers. Additional physician attributes also will influence HIV treatment quality, such as a physician’s educational background, age, and innate skill, and the physician fixed effects estimate the joint influence of all these time-invariant physician attributes on treatment quality.²⁰

Equations 1.1 and 1.2 also includes region-year fixed effects. Region-year identifiers (N_d) are generated for each of the twenty-four hospital referral regions in California in the three years

²⁰The use of fixed effects to model network selection has previously been employed to control for selection among physician networks (e.g. Nair, Manchanda, and Bhatia (2010); Chan (2016)).

of data that inform these parameter estimates. Any regional public health policy campaign or other treatment intervention which simultaneously affected both a physician's and their peers' medication prescriptions will lead to an overestimation of the peer effects (γ , γ^{GEN} , and γ^{HIV}). Fixed effects control for the bias of such correlated confounding effects by estimating the average prescription behavior of all physicians in a given hospital referral region for each year.

The patient fixed effects in Equations 1.1 and 1.2 control for the impact of a patient's demographics on the prescription decision. Once the decision to initiate HIV medication treatment has been made, however, few patient demographics should be incorporated in this decision, since antiretroviral therapy prescriptions take the same general form for all HIV-infected patients (Lan-dovitz, Desmond, and Leibowitz, 2016).²¹ These patient specific fixed effects will capture any residual influence of patients' fixed characteristics on a physician's HIV medication choice, such as the patient's unobserved medication adherence.

One important patient-level determinant of the HIV medication choice is a patient's health status. Genetic drug resistances, viral mutations, and a patient's comorbidities should all direct the selection of a recommended medication combination. While many of these attributes are unobservable in the data, patients' comorbidities are recorded by additional ICD-9 diagnostic codes on each of their health insurance claims. This information informs annual estimates for a patient's number of comorbidities and identifiers for several common mental health conditions,²² which serve as proxies for the patient's personal health and the complexity of their associated medication prescription decision. These are the time-varying patient characteristics included in Equations 1.1 and 1.2 in the vector P_{id} .

The final estimates for the influence of physician peers on HIV treatment quality are based

²¹While the cost of HIV medications can be prohibitively expensive for many patients, all prescriptions in this data set are written for enrollees of Medicare or Medicaid who face similarly subsidized HIV drug prices. Under Medicaid, there was no cost-sharing for most HIV medications during this time period. A dual enrollee of Medicaid and Medicare similarly faced limited cost-sharing. With Medicare only however, cost-sharing was roughly 25 percent of drug costs until annual drug expenses entered into the "donut hole," which refers to a gap in Medicare Part D coverage for a specific range of annual drug expenses. Once annual drug expenditures exceeded a certain threshold, and moved outside of the "donut hole," then cost-sharing was reduced to 5 percent. The additional impact of a patient's personal finances is captured by the patient-level fixed effects.

²²Comorbidities are identified using the Charlson Comorbidity Index (Charlson et al., 1987), and mental health disorders are recorded using the Mental Health and Substance Abuse Clinical Classifications Software (Healthcare Cost and Utilization Project, 2016).

on within region, within patient, and within physician variation in peers' prescription behavior and a physician's own adherence to the medication guidelines. That is, holding constant the hospital referral region, the patient, and the physician, changes in peers' adherence between 2007 and 2010 are related to subsequent changes in an individual physician's adherence to the medication guidelines. This measured relationship is independent of regional correlated effects, exogenous physician and patient characteristics, and network selection biases. Linear probability models are estimated using OLS, and instrumental variables estimates are calculated through generalized methods of moments. The level of variation required by this modeling approach highlights the need for an alternative identification strategy when analyzing annual quality of care measured once per calendar year. Table 1.3 outlines the different measures of treatment quality within physician networks available in the two samples.

I employ two strategies to circumvent the “reflection problem,” or the simultaneity bias that occurs when observing both an individual's behavior and the behavior of their peers ([Manski, 1993](#)). The reflection problem in this setting refers to the difficulty in determining whether a physician's own medication quality (Q_{ijd}) is influenced by their peers' behavior ($Q_{i'j'd'}$), or if the direction of causation is reversed. First, I calculate the measure of peers' behavior for prescriptions written on dates prior to the last time a physician interacts with the linking shared patient. By controlling for the timing of prescriptions in this way, a physician's prescription decision on day d would not be expected to influence the past prescriptions of other physicians written on day $d' < d$ through direct interactions with the shared patient. A drawback of this first strategy is that physicians may still interact through shared patients treated on dates relatively close together; for example, physicians may discuss their planned treatment strategy for future patients with their peers.

My second strategy for circumventing this simultaneity bias closely follows the identification strategy in [Bramoullé, Djebbari, and Fortin \(2009\)](#), who detail conditions under which the behavior of a physician's immediate peers can be appropriately instrumented for by the prescription behavior of intransitively connected distal peers, i.e. physicians who are only connected through multiple patient-sharing links. The main criteria for employing this technique are that patient-sharing networks are heterogeneous in size and that not all physician pairs are additionally linked to every

other physician pair in their network. The observed variability in the number of patient-sharing links within the data ensures that these conditions are satisfied.²³ I calculate the measure of distal peers behavior as the average adherence to the recommended HIV medication guidelines among network connections established through three patient-sharing links. In constructing this measure of more distal peers' medication quality, the timing of each written prescription is also taken into consideration in a similar fashion to the methods described previously, which further controls the direction of the estimated peer effects.

1.4.2 Peer Effects in the Second Modeling Approach

The second modeling approach extends this study of physician peer effects to both annual medication and monitoring quality. I measure the relative position of a physician within their local hospital referral region network through the following four network statistics commonly utilized in the social network analysis and public health literatures ([Jackson, 2008](#); [Landon et al., 2012](#); [Pollack et al., 2013](#)):

1. The “adjusted degree” of a physician is the number of links to other physicians divided by the number of patients that a physician shares with any other physician.
2. A physician’s “Katz-Bonacich” centrality is the sum of all their network peers weighted by the number of patient-sharing links required to reach each peer.
3. A physician’s “betweenness” centrality is calculated by first connecting every physician pair through the fewest number of intermediate relationships as possible. For a given physician, their betweenness centrality is then proportional to the number physician pair connections for which they are an intermediary.
4. The “geodesic distance” between any two physicians is the smallest number of patient-sharing links required to connect a physician pair.

Since it has been repeatedly documented in the literature that specialists provide higher quality HIV care, the geodesic distance for each generalist will be computed with respect to their

²³Table 1.5 displays the observed dimensions of the physician patient-sharing network in the medicare only sample composed of Medicare Part D drug claims.

closest specialist peer. Each of the other network structures can also be weighted to further characterize a generalists' network position relative to specialists. Specifically, the "HIV specialist-weighted adjusted degree" only considers a physician's patient-sharing relationships with specialists. Similarly, network links that include specialists factor more prominently into the calculation of "HIV specialist-weighted betweenness" and "HIV specialist-weighted Katz-Bonacich" centralities.

I estimate these network statistics for each annual patient-sharing network measured within a calendar year in both analytic samples (see Table 1.3). The following linear probability model predicts the probability that physician j treating patient i in year t contributes to annual HIV care that is adherent with clinical guidelines:

$$Q_{ijt} = \alpha + \gamma \cdot Net_{jt} + \beta P_{it} + P_i + D_j + T_t + \varepsilon_{ijt}; \quad (1.3)$$

where Q_{ijt} is an indicator equal to one if the annual HIV treatment adheres to the guidelines. The main parameter of interest, γ , estimates the impact of the different network statistics (Net_{jt}) estimated for physician j in year t . This panel model includes additional time-varying patient characteristics (P_{it}), patient and physician fixed effects, P_i and D_j , respectively, and year specific indicator variables (T_t), and ε_{ijt} . I standardize the network statistics, except for geodesic distance, to have a mean of zero and a standard deviation of one, so estimates of γ can be interpreted as the percentage point change in a physician's adherence with the clinical guidelines induced by a one standard deviation increase in their network connectedness as measured by Net_{jt} .

1.5 Observed Quality and Physician Networks

1.5.1 Quality of HIV Care

Table 1.4 shows that there was wide variation in both medication and monitoring quality within the Medicare Only and Medicare Plus samples. Across physicians in the Medicare Only sample, the average adherence to the HIV medication guidelines ranged from 93 percent in Northern California to 84 percent in the Los Angeles area. When the medication quality measure is compared across patients, the regional averages remain the same, but the variance is larger because

several patients only received non-adherent medication prescriptions during this period. Within the Medicare Plus sample, Table 1.4 shows that 89 percent of patients in the Los Angeles area received at least one recommended combination of HIV drugs in a given year.

Despite requiring less specialized HIV knowledge, physicians routinely performed worse on the annual monitoring quality measure. This trend holds across all regions of California, with only 77 percent of patients in the Los Angeles area receiving annual care that is adherent to the disease monitoring guidelines. The small but statistically significant differences in the quality of HIV care observed between regions of California in both analytic samples and across both quality measures corroborates the large literature that documents regional variation in physician practice patterns across the U.S. ([Wennberg and Gittelsohn, 1973](#); [Epstein and Nicholson, 2009](#); [Molitor, 2014](#)).

1.5.2 Physician Network Characteristics

HIV-infected patients are treated regularly by multiple physicians, which creates a rich patient-sharing network within both analytic samples.

Medicare Only Sample

Table 1.5 shows that only 21 percent of physicians prescribing medications were specialists. In 2008, there were 8,385 patients receiving medication prescriptions from 807 physicians, but only 21 percent (166) of the physicians were specialists. Each patient was written a medication prescription by an average of 1.4 physicians, while each physician prescribed medications for roughly 13 patients. These prescribing relationships lead to 10,824 unique physician-patient pairs in 2008, with an average of 3.2 new medication prescriptions written for each physician-patient pair during the year. A typical HIV medication prescription is written for a 30-60 day supply of pills with an option for 3-6 refills, so a patient receiving prescriptions from a single physician would be expected to receive new medication prescriptions between 2 - 4 times per year. The average rate of new prescriptions per patient is roughly 4 per year in this sample, which results from patients seeing multiple physicians and from prescriptions being reformulated in response to a patient's medication adherence and comorbidities.

These prescribing interactions yield connections between a generalist and their specialist peers through roughly 29 percent of their medication prescriptions. Table 1.5 shows that a physi-

cian's average HIV prescription was potentially informed by 8.6 previous physicians' prescription decisions in 2008. Among these 8.6 physician peers, only 2.7 were specialists and, on average, only 27 percent of prescriptions were potentially informed by the past prescription decisions of at least one specialist. Additionally, across all physician links in 2008, 67 percent of generalist physicians were connected to at least one specialist. Statistically equivalent network dimensions are observed within the patient-sharing networks in the Medicare Only sample in 2009 and 2010.

Medicare Plus Sample

Table 1.6 shows that specialists provide only 24 percent of patients annual HIV care. In 2008, there were 13,755 HIV-infected patients receiving annual HIV care from 2,756 physicians, where only 23 percent (626) of physicians were specialists. With a larger number of physicians involved in the annual HIV care of only a few patients, an individual patient in 2008 is treated by an average of 1.6 physicians, while each physician provided annual HIV care to roughly 9 patients.

Similar to the Medicare Only sample, Table 1.6 shows that a generalist is connected with a specialist peer through roughly 29 percent of their patients. In 2008, for each treated patient a physician was linked to an average of 9.6 other physicians. Among these 9.6 physicians, approximately 4.5 were specialists, and on average, 29 percent of all patient-sharing links were with a specialist. Similar to the Medicare Only sample, roughly 69 percent of generalist physicians were connected to at least one specialist in the annual physician network observed in 2008.

Figures 1.1 and 1.2 plot these annual patient-sharing networks observed within Medicare Plus sample in the Palm Springs and San Diego hospital referral regions in 2010, respectively.²⁴ The observed network fragmentation in Palm Springs (as shown by the fewer number of connections between network clusters) and greater connectedness in San Diego foreshadows the empirical findings in this research, as Palm Springs has a lower average medication quality and also has more generalist physicians who are not connected to specialists. The average adherence of physicians to the medication guidelines was 89 percent in Palm Springs and 95 percent in San Diego, while the percent of generalists without any patient-sharing link to an HIV specialist was 33 percent in Palm Springs and only 25 percent in San Diego.

²⁴Annual patient-sharing networks are displayed using the force-directed graphing algorithm defined by [Fruchterman and Reingold \(1991\)](#).

1.6 Estimation Results and Discussion

1.6.1 Estimated Peer Effects through the First Modeling Approach

Significant peer effects in physicians' medication quality are identified through patient-sharing network links. The magnitude of these effects is displayed in Table 1.7 for Equations 1.1 and 1.2 estimated within the Medicare Only sample. The likelihood of adhering to medication guidelines is transformed into percentage points, so estimates of γ , γ^{GEN} , and γ^{HIV} measure the impact of a one percentage point increase in peers' medication quality on the percentage point change in a physician's own medication quality.²⁵ Panel A presents model parameters estimated for only generalists, and Panel B displays estimates among only specialists. For generalists, a ten percentage point increase in all physician peers' medication quality raised the generalist's own adherence by 0.7 percentage points. When the quality of peers who are connected through multiple patient-sharing links is used as an instrumental variable for direct peers' quality, this estimate rises to 1.2 percentage points. The average adherence of generalists to the medication guidelines is 87.3 percent, so an increase of 1.2 percentage points closes roughly 10 percent of the gap in medication noncompliance.

Since the average of physician's individual medication quality and the average peers' medication quality measure are nearly identical, the estimate for γ can alternatively be interpreted as an elasticity: a one percent increase in peers' average medication quality increases a physician's own medication quality by 0.12 percent. This estimate is similar in magnitude to workplace peer effects observed in the emergency room of hospitals, where individuals are found to adopt roughly 11 percent of a productivity increase among their clinical peers (Chan, 2016; Silver, 2016). When work place peer effects are aggregated across a wider range of industries, including sales teams, fruit pickers, scientists, and supermarket cashiers, the average peer effect is also found to be equal to an elasticity of 0.12 (Herbst and Mas, 2015). Finally, the estimate for β in Equation 1.1 finds

²⁵Since observations are recorded across physician and patient pairs $\{j, i\}$ at dates d , standard error estimates of γ are double-clustered at the physician and patient levels (Petersen, 2009). This procedure estimates heterogeneous errors for predictions of the same physician across patients, as well as nonzero covariance terms for residuals of the same physician across different patients, and for residuals of the same patient across different physicians. The results in Table 1.10 are presented with clustering at the physician-patient level, and are robust to alternatively double-clustering on physician and time, which instead assumes that the covariances between different physicians in different years is zero.

that a one standard deviation increase in the average number of comorbidities among a physician's HIV-infected patient caseload, an increase from 0.52 to 1.41 comorbidities, decreases the physician's medication quality by 0.04 percentage points (not displayed in Table 1.7). The relatively small influence of patients' comorbidities on a physician's medication quality further highlights the importance of physician peers in determining medication quality.

Estimates for the heterogeneous peer effects specified by Equation 1.2 are displayed in Columns (2) and (4) of Table 1.7, and show that generalist peers exert little influence on medication decisions, while specialists can significantly improve the medication quality of their generalist peers. Panel A of Table 1.7 presents the OLS estimate for γ^{HIV} , which indicates that a ten percentage point increase in HIV specialist peers' quality raises a generalist's own quality by 0.9 percentage points. The magnitude of both heterogeneous peer effect parameters increase when estimated by instrumental variables methods, which again find that generalist peers' quality has little effect, but a physician's own quality is raised by 1.5 percentage points with a ten percentage points increase in specialist peers' quality.

The beneficial impact of higher quality peers is experienced less by HIV specialists, as shown in Panel B of Table 1.7. Estimates for Equation 1.2 among specialists show that a small and insignificant elasticity exists between changes in the average peers' medication quality of all physician peers on a specialist's own medication quality. Only increases in the average medication quality of specialist peers has a significant effect, where estimates find that a ten percentage point increase in specialist peers' medication quality increases a specialist's own medication quality by 0.6 percentage points. Instrumental variables estimates find that this peer effect between specialists is 0.09. Given that specialists have a higher average medication quality, this indicates that the marginal impact of improved peers' quality diminishes for better physicians. This may also indicate that specialists are less likely to seek advice from and be informed by their physician peers. Thus, improvements in medication quality that can be induced by establishing patient-sharing links to better quality peers are likely to be the greatest among lower quality generalist physicians.

The instrumental variables estimates of Equations 1.1 and 1.2 are generated under conditions of "relevant" and strong instruments for direct peers' medication quality. The underidentification rank tests specified by [Kleibergen and Paap \(2006\)](#) all have Kleibergen-Papp rk statistics above

10, with corresponding chi-squared p-values below 0.001. Additionally, weak identification tests using the Kleibergen-Papp F statistic, based on the Wald version of the rk statistic, are all above 25. These estimates are above the generalized method of moments IV critical values specified in [Stock and Yogo \(2005\)](#), which indicates that the medication quality of physicians connected through three patient-sharing links is a strong predictor of immediate peers' medication quality.²⁶

The larger instrumental variables parameter estimates indicate the significant simultaneity bias that occurs when identifying peer effects through Equations 1.1 and 1.2. Hausman tests for endogeneity further confirm that instrumental variables are necessary in this setting ([Hausman, 1978](#)). As outlined in [Manski \(1993\)](#), the behavior of an individual and their surrounding peer group are closely intertwined. The similar medication quality delivered among physicians' and their peers, and the sporadic observation of an individual physician's measured medication quality in these data, cause the simultaneity bias to attenuate OLS parameter estimates. Thus, the instrumental variables estimates for γ , γ^{GEN} , and γ^{HIV} are the preferred estimates displayed in Table 1.7.

Additional prescription behaviors are examined through Equations 1.1 and 1.2 to further determine whether generalists are learning how to adhere to clinical guidelines from their specialist peers. Prescribing an HIV drug that combines two of three recommended drug classes in a single pill helps to reduce a patient's daily pill burden, promoting medication adherence. While combined HIV drugs are not manufactured for all potential drug combinations, physicians are encouraged to use combined drugs when they are available for their particular patients ([Aberg et al., 2004, 2009](#)). Panel A of Table 1.8 presents estimates for Equations 1.1 and 1.2 used to predict the probability that a generalist prescribes any combined drug. Instrumental variables estimates find that a ten percentage point increase the average likelihood of prescribing a combined drug among all physician peers leads to a 1.3 percentage point increase in the generalist's own probability of prescribing a combined drug. Again, when these effects are separated across peer types, generalist peers exhibit a small and insignificant influence on prescription behavior, while 11 percent of an increase in specialists' use of combined drugs is passed on to their generalist peers.

²⁶Given the complex error structure estimated by double-clustering modeling errors within physicians and patients, these are appropriate tests of this instrumental variables approach.

While physician peers do influence adherence to clinical guidelines, they have no effect on physicians' choice of individual drug brands. Panel B of Table 1.8 displays estimates for the probability of prescribing patients with Epzicom, a particular combined drug that gained Federal Drug Administration approval in 2004. The insignificant effects estimated for this prescription behavior confirm that this modeling approach is not simply capturing generalists continuing the treatment practices of their specialist peers among their shared patients. Since Epzicom is not suitable for all medication regimens, it is expected that the use of Epzicom among a physician's peers should not affect their own likelihood of prescribing Epzicom. Insignificant peer effects are estimated for this specific prescription behavior, despite a statewide increase in Epzicom usage during the sample period (9 percent in 2008 to 12 percent in 2010).²⁷

The peer effect estimates in this paper are robust to alternative methods for constructing the peers' quality measure, defining patient-sharing network links, and estimating the models using regional sub-samples. The peers' medication quality measure computes the average medication quality of peers in the past twelve months, as outlined in Section 1.3.2. Instead of weighting previous prescriptions by the reciprocal of the time gap between past and current prescriptions, Table 1.9 first shows estimates of Equation 1.2 among generalists in the Medicare Only sample under alternative temporal weighting procedures. Weighting peers' quality by the number of days since the past prescription (linear temporal weighting), including only the previous five peers' medication quality observations, or not employing any temporal weights does not diminish the size or significance of the heterogeneous peer effects estimates. Additionally, only defining patient-sharing links between physicians that share at least five patients does not reduce the magnitude of the coefficient estimates. Instead, eliminating physicians who are not as strongly connected with other physicians in the Medicare Only sample increases the impact of peers' quality, which suggests that the number of shared patients is a good measure for the strength of physician's patient-sharing connections. Finally, when peers are randomly assigned, creating an artificial physician network, parameter estimates for Equations 1.1 and 1.2 are not statistically different from zero.

Another possible concern with the estimation methods is that hospital referral region (HRR)-

²⁷ Similar estimates were also obtained when analyzing physicians' use of Atripla, an alternative combined drug that was introduced in 2006.

year fixed effects are unable to control for more localized contextual influences of medication quality. While insignificant peer effect estimates for the adoption of a newly available HIV drug, Epzicom (shown in Table 1.8), suggests that HIV pharmaceutical marketing was not differentially occurring within HRRs, there are other potential regional policies or health care facility specific effects that may be biasing estimates upwards. For example, there are several well documented public health campaigns in California that directly targeted the treatment strategies of physicians during this time period. In San Francisco, a policy called “Test and Treat” was introduced in 2009 which promoted the initiation of antiretroviral therapy for all HIV-infected patients regardless of their HIV virus’ progression (Schwarcz, Hsu, and Scheer, 2015). In highlighting the benefits of early treatment initiation, these campaigns were likely accompanied by additional information about the proper medication combinations, which could have improved physicians’ medication quality. To help better understand the potential bias induced by any such localized treatment intervention, Equation 1.2 is re-estimated within regional subsets of the data. The results in Table 1.9 show that the heterogeneous peer effect estimates maintain their significance and increase in magnitude when either the San Francisco or the Los Angeles metropolitan areas are excluded from the estimation. These two regions represent roughly 20 percent and 29 percent of prescriptions in these data, respectively. The stability of the heterogeneous parameter estimates shows that localized policy within the largest two hospital referral regions is not driving the overall results.

Two additional methodological concerns require additional discussion. First, the use of a linear probability model for the binary measure of medication quality may lead to biased parameter estimates of Equations 1.1 and 1.2 if the true relationship between an individual physician’s medication quality and their peers’ medication quality is nonlinear around the mean medication quality. Despite the documented bias in estimating panel non-linear models with fixed effects (Hahn and Newey, 2004), a panel probit functional form was also specified for Equations 1.1 and 1.2. The parameter estimates identified through this method are not statistically different from those presented in Table 1.7 and are of the same significance, which supports the use of linear probability model estimates for describing the marginal effect of changes in peers’ quality local to the average medication quality.

An equally important source of bias in the parameter estimates of Equations 1.1 and 1.2

comes from the partial observation of physicians' patient-sharing network. A complete census of public health insurance records was compiled for all HIV-infected patients in California, but patient-sharing relationships established through privately insured patients are unobserved in these data. Given the observed homophily of physicians by practice style, i.e. assortative network formation (Pollack et al., 2013; Molitor, 2014), and the fact that better outcomes are observed among privately insured patients, this measurement error is likely depressing the peers' quality measure for higher quality physicians.²⁸

The panel nature of this data helps to reduce the bias induced from partially observing peers' quality. When first differences are used to identify the impact of an independent variable that is measured with error, the corresponding attenuation bias is increasing in the serial correlation of true value and decreasing in the correlation of the noise (error) over time. Since the unobserved physicians are likely of a higher quality with a smaller variation in their quality of HIV care, the correlation in measurement error over time is hypothesized to be larger than the serial correlation of true peers' quality. Estimates of the panel linear probability models specified by Equations 1.1 and 1.2 are therefore subject to a smaller measurement bias than if estimated in a static model. The estimated magnitude of these parameters corroborates this hypothesis, since the previously cited literature estimates similarly sized workplace peer effects across different industries (Herbst and Mas, 2015).

1.6.2 Estimated Peer Effects through the Second Modeling Approach

Significant physician peer effects are also identified by network statistics that describe physicians' relative network position. Table 1.10 displays the OLS estimates of Equation 1.3 estimated in the Medicare Plus sample, where columns (1) and (2) present the estimated physician network effects on annual medication quality and adherence to the annual disease monitoring guidelines, respectively. The mean of each network statistic within the Medicare Plus sample (presented in column (5) of Table 1.10) shows that the average geodesic distance of all generalist physicians to the closest specialist is 1.13 patient-sharing links. Additionally, the average HIV specialist-weighted

²⁸Measurement error in determining a physician's medication quality is an additional source of possible bias. However, the quality metric developed by Leibowitz and Desmond (2015) is conservatively employed in this analysis to ensure that physicians are not incorrectly associated with non-adherent HIV care. This may artificially inflate the quality measured for worse physicians, which would further attenuate the model parameter estimates.

adjusted degree among all physicians is 0.38, which indicates that for every 100 shared patients, physicians are collaborating with 38 specialists. The HIV specialist-weighted Katz-Bonacich and betweenness centrality statistics additionally describe physician's relative access to specialists, where the Katz-Bonacich centrality uses the peer effects parameter (γ^{HIV}) identified previously by Equation 1.1 to weight each patient-sharing link.²⁹

Increases in a physician's geodesic distance to a specialist, HIV specialist-weighted adjusted degree, and HIV specialist-weighted Katz-Bonacich and betweenness centrality all improve the physician's likelihood of adhering to the recommended medication regimen. Reducing the number of patient-sharing links to the closest specialist by one increases medication quality by 2.64 percentage points. Additionally, a one standard deviation increase in a physician's HIV specialist-weighted adjusted degree, which corresponds to an increase from the mean of 38 directly linked specialists to 85 specialists for every 100 shared patients, increases the likelihood of adhering to the medication guidelines by 1.38 percentage points. Finally, a one standard deviation increase in a physician's HIV specialist-weighted Katz-Bonacich and betweenness centrality increases medication quality by 0.18 percentage points.

While the un-weighted network statistics calculated across all physician types do not show a significant impact on a physician's medication quality, these general network statistics are significant predictors of appropriate disease monitoring. Specifically, an increase of one standard deviation in a physician's un-weighted adjusted degree, which corresponds to an increase from the mean of 91 directly linked physicians of all types to 168 direct physician links for every 100 shared patients, increases monitoring quality by 1.55 percentage points. A one standard deviation in a physician's betweenness centrality can also raise monitoring quality by 1.52 percentage points. With only 86.4 percent of physicians in this sample adhering to the monitoring guidelines, an increase in 1.52 percentage points translates into a 11.2 percent reduction in the percent of non-adherent physicians.

The general sign and significance of the parameter estimates obtained through Equation 1.3 support the peer effects identified earlier through Equations 1.1 and 1.2. It is not immediately

²⁹Under this method, each link is scaled to equal 0.15, which is why the average Katz-Bonacich centrality (0.14) is lower than the average adjusted degree (0.38) despite the Katz-Bonacich centrality measure including more patient-sharing links.

clear however, which of the network statistics should be expected to have the greatest impact on physicians' quality of HIV care. As discussed by [Wasserman and Faust \(1994\)](#) and [Borgatti and Molina \(2003\)](#), many different network statistics are commonly employed in the social networks literature. The recent results of [Calvó-Armengol, Patacchini, and Zenou \(2009\)](#) show that the Nash equilibrium strategy for a generalizable peer-effect game is proportional to an agent's Katz-Bonacich centrality.³⁰ However, this mathematical connection between peer effect estimates and Katz-Bonacich centrality is characterized for a theoretical game in which the aggregate behavior of all peers is what informs an individual's actions. In contrast, the results of this research suggest that only specialist peers exert a significant influence on their peers' medication quality, and the findings presented in Table 1.10 show that multiple network statistics are able to capture this heterogeneous effect when specifically weighted for specialist connections.

To better compare the results across the two analytic samples and corresponding modeling strategies, I replicate the methods employed in Equation 1.3 within the Medicare Only sample of Medicare Part D drug claims. Specifically, patients' individual drug claims are used to construct the annual medication quality measure which identifies whether a recommended medication combination was prescribed for the patient at least once in a given year. Additional annual outcome variables are constructed to identify whether any combined HIV drugs were prescribed, and whether the patient was ever prescribed Epzicom. The results from estimating Equation 1.3 across these annual measures within the Medicare Only sample are presented in Table 1.11.

Two important differences exist between the estimates of Equation 1.3 generated within the Medicare Only versus Medicare Plus samples. First, annual medication quality is lower in the Medicare Only sample. Table 1.11 shows that the 88.1 percent of patients received at least one recommended medication prescription in the Medicare Only sample, compared to 93.2 percent in the Medicare Plus sample. These lower outcomes are partially the result of the better medication quality observed among the Medicaid patient population, but also may reflect the imprecise assignment of annual patient outcomes among the physicians in the Medicare Plus sample. The Medicare Plus sample includes physicians who may not be directly involved in the prescription decisions for

³⁰Additional theoretical results have also identified a link between peer effects and an agent's smallest eigenvalue ([Bramoullé, Kranton, and D'amours, 2014](#)).

a patient's HIV treatment, which will raise the average medication quality if patients treated by many physicians also experience higher quality.

The second difference between analyses within the Medicare Only versus Medicare Plus samples is that Equation 1.3 estimates smaller effects for the HIV specialist-weighted network statistics on physicians' annual medication quality within the Medicare Only sample. Since the Medicare Only sample contains only the physicians who were directly prescribing HIV medications, these estimates should be closer in magnitude to the peer effects estimated previously in Equations 1.1 and 1.2.

To compare the estimated coefficients generated by the two modeling approaches, I use the average difference in medication quality between generalists and specialists to approximate the increase in peers' medication quality that would be induced by a one standard deviation increase in specialist-weighted adjusted degree. Table 1.11 shows that the effect of such an increase, from 87 to 143 direct specialist peers for every 100 shared patients, is 0.94 percentage points. Based on the peer effect parameter γ shown in Table 1.7, this same increase in direct specialist links would increase medication quality by 0.86 percentage points. Thus, the estimates of medication quality on network statistics within the Medicare Only sample are the preferred parameter estimates.

A similar pattern in physician peer effects is observed within the other prescription behaviors previously examined in Section 1.6.1. Table 1.11 shows that while none of the HIV specialist-weighted network statistics predict Epzicom usage, a reduction of one patient-sharing link between a generalist physician and the closest specialist increases the generalists' likelihood of treating a patient with a combined drug by 1.61 percentage points. Similarly, a one standard deviation increase in physicians' HIV specialist-weighted Katz-Bonacich centrality and betweenness centrality increases their probability of prescribing a combined drug by 0.14 and 0.31 percentage points, respectively, while these same network statistics have no effect on Epzicom usage.

Overall, the results from Equation 1.3 help to confirm the heterogeneous peer effects estimated through Equation 1.2 on medication quality, and help to extend these analyses to better understand the determinants of proper HIV disease monitoring. Specifically, a one standard deviation increase in physicians' un-weighted adjusted degree can increase adherence to the disease monitoring guidelines by 1.55 percentage points. This indicates that more physician collabora-

tion in HIV-infected patients' care can improve the delivery of routine components of the HIV treatment protocol. Existing public health research corroborates these findings, where physician collaboration and the network centrality of generalist physicians predicts increased medical testing ([Barnett et al., 2012](#); [Landon et al., 2012](#)).

1.7 Simulated Physician Network Redesign

The peer effects identified through both modeling approaches highlight the importance of generalists' connections to specialists for promoting medication quality. This simulation exercise relocates specialists within each regional network to increase generalists' access to specialists, and then estimates the increase in the medication quality based on the simulated HIV specialist-weighted Katz-Bonacich centrality. Specifically, I hold fixed the observed patient-sharing links between all physicians of the largest clustered network in each of twenty-four hospital referral regions (HRRs) in California in 2010,³¹ and then relocate the specialists in each network to more well-connected, central positions. I perform these simulations using two different methods for identifying central network positions. The first simulation places all specialists in the positions with the largest degree (number of direct patient-sharing links), and the second simulation places specialists at the positions that minimize the geodesic distance to all other physicians. Intuitively, the first simulation maximizes specialists' number of direct peers, while the second simulation considers all patient-sharing connections. I employ these methods as opposed to solving for the network positions that maximize the HIV specialist-weighted Katz-Bonacich centrality, because these two methods are easier to approximate through policy in an actual clinical setting.

The two simulation methods produce opposite results for the largest clustered physician network in the Los Angeles area. Figure 1.3 plots the results of these simulations, where Figure ?? places specialists at the positions with the largest degree, and Figure ?? re-positions specialists by minimizing the geodesic distance to all other physicians. After specialists are relocated, the average medication quality within the region is estimated based on physicians' simulated HIV specialist-weighted Katz-Bonacich centrality and the estimates of Equation 1.3 presented in Table

³¹The largest regional network cluster is identified through the "fast and greedy" clustering algorithm ([Clauset, Newman, and Moore, 2004](#)) within each hospital referral region.

1.11. Relocating specialists to positions based on degree reduces the average regional medication quality by 3.8 percentage points, while the simulation using geodesic distance increases the average medication quality by 2.3 percentage points.

The simulated results in Los Angeles highlight the potential costs associated with rearranging existing patient-sharing connections. When I relocate specialists based on degree, this increases the number of immediate patient-sharing links for each specialist, but also reduces many generalists' access to any specialist. Conversely, by minimizing network distances, this simulation method provides some level of specialist connection for all generalist physicians. Given the number of patients in the Los Angeles area, the simulated 2.3 percentage point increase in medication quality by minimizing distance corresponds to providing adherent medications for an additional 845 HIV-infected patients. Another way to achieve this level of improvement in regional quality is by adding new specialists to the network. If all physicians were left in their original position and new specialists were placed in the positions that minimize the geodesic distance to all other physicians, then it would require a minimum of 6 new HIV specialists to achieve a 2.3 percentage point increase in average medication quality.

Figure 1.4 plots the results of these two simulations performed within the largest clustered network in all twenty-four HRRs. For each network, Figure 1.4a plots the change in average medication quality resulting from both simulation methods and Figure 1.4b displays the network's size and density, where density measures the number of existing network links divided by the number of possible links. These results confirm that the simulations by geodesic distance yield the larger improvements to regional medication quality. These simulated quality improvements are greatest within small, dense networks, because smaller networks are more likely to have central network positions that can provide some access to specialists for all generalist physicians. When the regional improvements in medication quality are aggregated in terms of the number of HIV-patients treated within each region of California in 2010, the total increase in quality translates into adherent medication prescriptions for an additional 2,779 patients. This increase in adherent prescriptions could have enabled 16 percent of patients who were not previously virally suppressed through treatment to achieve viral suppression.

In addition to improving health, viral suppression among HIV-infected patients reduces the

rate of transmission. Research has found that the risk of sexual transmission of the HIV virus is reduced by 96 percent when the HIV-positive partner is virally suppressed (Cohen et al., 2011). Given the observed forms of HIV transmission in California during this period, the simulated increase in virally suppressed patients could have reduced the annual number of new infections by 5 percent, which is roughly 250 fewer infections each year. In terms of health care costs, this represents a present discounted cost savings of roughly \$82 million.³² Even when the cost of increasing a specialists' annual caseload is taken into consideration,³³ this is a highly cost-effective policy for reducing the HIV epidemic in the U.S.

Existing efforts to increase physicians' treatment quality have focused on supplemental medical training. The peer effects identified by Equations 1.1 and 1.2 quantify the significant positive externalities in treatment quality that would be experienced by physicians' peers as a result of this additional training. However, training alone is still likely to have a smaller impact on aggregate health outcomes than redesigning physician networks at existing levels of adherence by specialists. Based on the largest peer effect observed between specialists and their generalist peers, if training all specialists led to fully adherent care, raising their average medication quality by 11 percentage points, this would increase their generalist peers' quality by only 1.6 percentage points. The combined impact of these improvements would yield adherent prescriptions for only 1,221 additional HIV-infected patients during this sample period. Moreover, previous attempts to improve physicians' treatment quality through Continuing Medical Education programs have not produced large effects, and have never resulted in fully adherent care (Lin et al., 1997; Marinopoulos et al., 2007).

Improving generalists' network connections to specialists in these simulations is one method for spreading specialized treatment knowledge within a regional network. An alternative and potentially more cost-effective mechanism might be to implement an electronic prescription guide that corrects non-adherent combinations as they are being written. The HIV treatment goals for 2017 – 2021 outlined by the California Department of Public Health, Office of AIDS call for an

³²The present discounted cost of a lifetime of HIV care for a 35-year-old patient is \$326,500 (Schackman et al., 2015).

³³The increased annual caseload for specialists under these simulations is an average of three additional generalist connections and approximately 117 annual patient visits, which has a total present discounted cost of \$33 million (Elliott et al., 2014).

increased use of electronic health records to improve HIV care continuity ([Office of AIDS, 2016](#)). Expanding the capacity of these data collection and analytic efforts to identify and correct non-adherent prescriptions might be a more effective way to inform generalists' treatment practices than relying on informal physician networks.

1.8 Conclusion

Physician peer effects on medication regimen and disease monitoring quality underlie potential policy mechanisms for improving HIV-infected patients' health and reducing socioeconomic disparities in HIV care. Instrumental variables estimates for a panel model of physicians' medication regimen quality show that a one-percent increase in specialists' medication regimen quality improves the quality of their generalist peers by 0.15 percent. Using a modeling approach that employs common network statistics to describe physicians' relative network position, I find that increased collaboration among physicians of all types is the only significant network contributor to higher quality disease monitoring. Simulations show that improving generalists' network connections to specialists could enable 16 percent of HIV-infected patients who were not previously virally suppressed to achieve viral suppression. The subsequent 5 percent reduction in annual HIV transmission rates makes this a highly cost-effective method for reducing the HIV epidemic in the U.S.

In general, these findings emphasize the importance of physician interactions in spreading new medical knowledge and diffusing quality standards. The presence of a significant peer effect on medication regimen quality indicates that specialized knowledge is shared through physician network connections. Within rural areas or socioeconomic populations with limited access to specialized care, health policymakers can reduce disparities in treatment quality for many health conditions by improving generalists' connectedness with specialists. Increased connections between generalists and specialists can be formalized by insurers or physician organizations through referral networks or mandated specialist consultations, which will likely facilitate larger improvements to generalists' treatment quality than relying on passive connections through shared patients.

Table 1.1: Data Sources and Variables

<i>Source</i>	<i>Variables</i>
Medicare & Medicaid insurance claims	ICD-9 diagnostic and procedural codes NDC prescription drug codes Patient demographics NPI physician identifiers CCW patient identifiers
American Community Survey (ACS)	Median household income
CA Dept. of Public Health; Office of AIDS	HIV prevalence
American Medical Association (AMA)	Physician demographics Primary practice location Clinical specialty

Note: ICD-9 refers to the International Classification of Diseases, 9th Revision, and NDC are the National Drug Codes that uniquely identify each human drug product in the United States. NPI are unique ten-digit National Provider Identifiers and CCW are the Chronic Conditions Data Warehouse beneficiary identifiers.

Table 1.2: Analytic Samples

	(1) Medicare Only Sample	(2) Medicare Plus Sample
<i>Source:</i>	Medicare Part D Claims	All Medicare + Medicaid Claims
<i>Initial Sample</i>		
# of Patients	11,219	31,879
# of Physicians	1,386	6,463
Measurement Restrictions		
New HIV prescription ID	Required	Not required
Initial HIV diagnosis	Anytime	Prior to measured calendar year
Insurance plan enrollment	Any length	Full calendar year
Quality Measures Computed		
Medication Quality	✓	
Annual Medication Quality	✓	✓
Annual Monitoring Quality		✓
<i>Final Analytic Sample</i>		
# of Patients	11,219	16,164
# of Physicians	1,386	3,496

Note: Both analytic samples are composed of only fee-for-service health insurance plan types. Medication quality is measured for every prescription, while annual medication quality identifies whether at least one recommended HIV medication combination was received within a calendar year. Annual monitoring quality measures whether the appropriate frequency of disease monitoring occurred within a calendar year.

Table 1.3: Physician Network Statistics Computed

	(1) Medicare Only Sample	(2) Medicare Plus Sample
Average of Peers' Past Medication Quality		
All physicians	✓	
Generalist peers	✓	
HIV specialist peers	✓	
General Network Statistics		
Adjusted degree	✓	✓
Betweenness centrality	✓	✓
Katz-Bonacich centrality	✓	✓
HIV Specialist-weighted Network Statistics		
Geodesic distance to HIV specialist	✓	✓
HIV specialist-weighted Adjusted degree	✓	✓
HIV specialist-weighted Betweenness	✓	✓
HIV specialist-weighted Katz-Bonacich	✓	✓

Note: All network statistics are estimated at the physician level. Regional-level network statistics are computed as the average physician-level network statistic for all physicians within the indicated region.

Table 1.4: Regional Variation in the Quality of HIV Care Across California

<i>Quality Measures</i>	(1) Northern CA	(2) San Francisco	(3) Central CA	(4) Los Angeles	(5) Southern CA
Medicare Only Sample: Medicare Part D drug claims					
<i>Medication quality</i>					
<u>Physician-level</u>					
Mean	93.0	91.0	88.2	84.1	89.7
Std. deviation	(15.01)	(16.65)	(18.92)	(22.39)	(18.00)
Median	99.5	98.1	94.3	91.9	98.1
25 th pctl.	90.9	87.8	85.4	78.6	84.9
N	139	317	194	373	201
<u>Patient-level</u>					
Mean	93.0	91.0	88.2	84.1	89.7
Std. deviation	(22.58)	(25.32)	(27.13)	(30.54)	(27.47)
Median	100.0	100.0	100.0	100.0	100.0
25 th pctl.	95.8	96.7	95.4	94.6	93.2
N	1118	2801	1358	2964	1987
Medicare Plus Sample: All Medicare + Medicaid claims					
<i>Annual Medication quality</i>					
<u>Physician-level</u>					
Mean	95.6	94.2	91.0	89.3	93.6
Std. deviation	(17.3)	(18.5)	(23.9)	(25.9)	(20.1)
Median	100.0	100.0	100.0	100.0	100.0
25 th pctl.	99.3	98.9	99.1	95.7	97.3
N	395	823	626	1229	694
<i>Annual Monitoring quality</i>					
<u>Physician-level</u>					
Mean	87.9	84.5	86.1	77.3	93.5
Std. deviation	(28.3)	(28.0)	(29.5)	(37.1)	(20.9)
Median	100.0	100.0	100.0	100.0	100.0
25 th pctl.	94.6	81.3	92.3	66.7	96.4
N	395	823	626	1229	694

Note: This table outlines the regional average quality of HIV care among HIV-infected patients in California between 2007 and 2010. Medication quality in the Medicare Only Sample measures whether individual prescriptions contain a recommended HIV medication combination. In the Medicare Plus Sample, medication quality identifies whether at least one recommended HIV medication combination was prescribed within a calendar year. Monitoring quality measures whether the appropriate frequency of disease monitoring occurred within a calendar year. These five regions are defined by aggregating the twenty-four hospital referral regions identified in California by Wennberg (1996).

Source: Medicare and Medicaid insurance claims for HIV-infected patients in California between 2007 and 2010.

Table 1.5: Physician Network Defined in the Medicare Only Sample

	(1) 2008	(2) 2009	(3) 2010
<i>Population</i>			
# of patients	8,385	9,326	9,390
# of physicians	807	953	937
# of HIV Specialists	166	202	204
<i>Network Dimensions</i>			
Physicians per patient	1.4 (0.7)	1.4 (0.6)	1.4 (0.7)
Patients per physician	13.4 (17.9)	12.5 (17.8)	13.0 (19.5)
# of patient + physician pairs	10,824	11,906	12,144
Observations of same patient + phys. pair	3.2 (2.6)	3.1 (2.5)	3.1 (2.3)
<i>Network Link Characteristics</i>			
Physician links per prescription	8.6 (6.3)	8.5 (5.8)	8.6 (6.3)
HIV Specialist links per prescription	2.7 (2.2)	2.9 (2.2)	2.8 (2.4)
% of all links with an HIV Specialist	27.4 (44.6)	29.4 (45.6)	28.7 (45.2)
% of all links within same HRR	80.9 (21.5)	80.3 (20.9)	80.6 (20.7)
<i>Generalists' Link Characteristics</i>			
% Generalists with any HIV Specialist links	66.8 (47.1)	64.7 (47.8)	64.7 (47.8)

Note: This table outlines several dimensions of the patient-sharing network constructed within the Medicare Only Sample composed of only Medicare Part D HIV drug claims.

Source: Medicare Part D drug insurance claims for HIV-infected patients in California between 2007 and 2010.

Table 1.6: Physician Network Defined in the Medicare Plus Sample

	(1) 2008	(2) 2009	(3) 2010
<i>Annual Population</i>			
# of patients	13,755	13,838	13,989
# of physicians	2,756	3,105	3,369
# of HIV Specialists	626	764	845
<i>Network Dimensions</i>			
Physicians per patient	1.6 (0.9)	1.6 (1.0)	1.6 (1.0)
Patients per physician	8.8 (27.5)	8.5 (27.9)	8.2 (25.6)
<i>Network Link Characteristics</i>			
Other physician links per patient	9.6 (28.8)	10.1 (39.5)	9.7 (35.9)
HIV Specialist links per patient	4.5 (26.7)	4.4 (28.6)	4.1 (32.5)
% of all links with an HIV Specialist	29.0 (46.3)	27.8 (44.0)	27.2 (44.9)
% of all links within same HRR	67.9 (46.7)	61.7 (48.6)	62.4 (48.4)
<i>Generalists' Link Characteristics</i>			
% Generalists with any HIV Specialist links	68.9 (46.3)	71.1 (47.7)	69.0 (48.0)

Note: This table outlines several dimensions of the patient-sharing network constructed within the Medicare Plus Sample, which contains both Medicare and Medicaid insurance claims.

Source: Medicare and Medicaid insurance claims for HIV-infected patients in California between 2007 and 2010.

Table 1.7: Physician Peer Effects on Medication Quality

HIV Medication Quality		(1)	(2)	(3)	(4)
		OLS	IV		
<i>Panel A: Generalists only</i>	Mean 87.34 (SD 34.32)				
All physician peers		0.07*** (0.025)		0.12** (0.051)	
Generalists			0.00 (0.031)		0.01 (0.047)
HIV Specialists			0.09** (0.042)		0.15** (0.069)
<i>Panel B: HIV Specialists only</i>	Mean 89.94 (SD 32.59)				
All physician peers		0.01 (0.016)		0.05 (0.021)	
Generalists			0.00 (0.017)		0.01 (0.019)
HIV Specialists			0.06* (0.026)		0.09* (0.032)
Physician Fixed Effects		✓	✓	✓	✓
Patient Fixed Effects		✓	✓	✓	✓
Region + Year Fixed Effects		✓	✓	✓	✓
Time-varying Patients' Health Status		✓	✓	✓	✓

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. (Standard errors are double-clustered over multiple observations of the same physician and the same patient.)

Note: This table present OLS and IV estimates of the panel linear probability models specified by Equations 1.1 and 1.2, where coefficient estimates measure the percentage point change in medication quality that results from a one percentage point increase in peers' average medication quality. Peers' average medication quality is calculated as a weighted average over the past twelve months of the HIV medication quality for the patients treated by directly linked physicians, where weights are the reciprocal of the time gap between the current observation and past prescription. This measure of peers' average medication quality is instrumented for by the average quality among intransitively connection peers.

Source: Medicare Part D drug claims for HIV-infected patients in California (2007-2010), and ACS and OA county-level characteristics.

Table 1.8: Physician Peer Effects on Other Prescription Behaviors

Other Outcomes	(1)	(2)	(3)	(4)
	OLS			IV
<i>Panel A: Combined ARV usage</i> Mean 56.41 (SD 39.41)				
All physician peers	0.07* (0.032)		0.10* (0.047)	
Generalists		0.02 (0.011)		0.03 (0.021)
HIV Specialists		0.08* (0.036)		0.11* (0.043)
<i>Panel B: Epzicom usage</i> Mean 11.06 (SD 31.76)				
All physician peers	0.06 (0.036)		0.07 (0.051)	
Generalists		-0.00 (0.012)		0.02 (0.023)
HIV Specialists		0.01 (0.024)		0.02 (0.037)
Physician Fixed Effects	✓	✓	✓	✓
Patient Fixed Effects	✓	✓	✓	✓
Region + Year Fixed Effects	✓	✓	✓	✓
Time-varying Patients' Health Status	✓	✓	✓	✓

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. (Standard errors are double-clustered over multiple observations of the same physician and the same patient.)

Note: This table present OLS and IV estimates of the panel linear probability models specified by Equations 1.1 and 1.2, where coefficient estimates measure the percentage point change in other prescription behaviors that result from a one percentage point increase in peers' average corresponding prescription behavior. Peers' average prescription behavior is calculated as a weighted average over the past twelve months of the specific prescription behavior performed for the patients treated by directly linked physicians, where weights are the reciprocal of the time gap between the past and current prescription. This measure of peers' average prescription behavior is instrumented for by the average behavior among intransitively connection peers. These estimates are generated among generalists within the Medicare Only Sample.

Source: Medicare Part D drug claims for HIV-infected patients in California (2008-2010), and ACS and OA county-level characteristics.

Table 1.9: Robustness: Physician Peer Effects on Medication Quality

Weighting Past Medication Quality		(1)	(2)
		OLS	IV
<i>Linear temporal weighting</i>	Mean 87.34 (SD 34.32)		
Generalists		0.00 (0.017)	0.01 (0.019)
HIV Specialists		0.08* (0.034)	0.13* (0.050)
<i>Past five observations only</i>			
Generalists		0.02 (0.012)	0.03 (0.020)
HIV Specialists		0.10** (0.030)	0.18** (0.041)
Patient-sharing Link Strength			
<i>Five or more shared patients only</i>	Mean 89.12 (SD 32.13)		
Generalists		-0.01 (0.011)	-0.03 (0.012)
HIV Specialists		0.10* (0.035)	0.19** (0.051)
Regional Subsamples			
<i>Without San Francisco</i>	Mean 85.97 (SD 31.54)		
Generalists		0.04* (0.016)	0.05 (0.026)
HIV Specialists		0.09* (0.035)	0.17** (0.055)
<i>Without Los Angeles</i>	Mean 88.71 (SD 32.44)		
Generalists		0.02 (0.018)	0.03 (0.028)
HIV Specialists		0.10** (0.039)	0.16** (0.053)
Physician Fixed Effects		✓	✓
Patient Fixed Effects		✓	✓
Region + Year Fixed Effects		✓	✓
Time-varying Patients' Health Status		✓	✓

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. (Standard errors are double-clustered over multiple observations of the same physician and the same patient.)

Note: This table presents OLS and IV estimates of the linear probability model specified by Equation 1.2 that predicts physicians' HIV medication quality under alternative temporal weighting procedures for the calculation of peers' medication quality, a stronger cutoff for recording patient-sharing links, and regional sub-samples. Specifically, estimates are generated when separately excluding the Los Angeles and San Francisco metropolitan areas, which represent roughly 29.3 percent and 19.5 percent of prescriptions, respectively. These estimates are generated among generalists within the Medicare Only Sample.

Source: Medicare Part D drug claims for HIV-infected patients in California (2007-2010), and ACS and OA county-level characteristics.

Table 1.10: Physician Peer Effects Measured through Network Statistics in Medicare Plus Sample

	(1) Medication Quality	(2) Monitoring Quality	(3) Any Comb. Drug	(4) Epzicom Usage	(5)
Mean Outcome (sd)	93.2 (25.2)	86.4 (34.3)	88.9 (31.4)	17.7 (38.2)	Avg. Dependent Variable
Geodesic dist. to HIV Specialist	-2.64*** (0.87)	1.12 (0.73)	-1.94** (0.91)	-0.23 (0.60)	1.13 (0.89)
<i>HIV Specialist-weighted Statistics</i>					
Adjusted Degree	1.38** (0.62)	0.84 (0.50)	0.06 (0.03)	-0.11 (0.06)	0.38 (0.47)
Katz-Bonacich centrality	0.18* (0.08)	0.15 (0.08)	0.10 (0.06)	0.09 (0.07)	0.14 (0.36)
Betweenness centrality	0.18* (0.08)	0.50 (0.26)	0.38 (0.21)	0.40 (0.27)	1.80 (2.15)
<i>General Network Statistics</i>					
Adjusted Degree	-0.49 (0.27)	1.55** (0.63)	-0.25 (0.17)	0.17 (0.11)	0.91 (0.77)
Katz-Bonacich centrality	0.14 (0.08)	0.11 (0.09)	0.14 (0.08)	-0.17 (0.10)	0.48 (0.21)
Betweenness centrality	-0.11 (0.07)	1.52*** (0.61)	0.02 (0.01)	0.16 (0.07)	21.18 (24.84)
Physician Fixed Effects	✓	✓	✓	✓	
Patient Fixed Effects	✓	✓	✓	✓	
Region Fixed Effects	✓	✓	✓	✓	
Time-varying Patients' Health Status	✓	✓	✓	✓	
Observations	41,695	40,941	41,695	41,695	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. (Standard errors are double-clustered over multiple observations of the same physician and the same patient.)

Note: This table presents OLS estimates for the panel linear probability model specified by Equation 1.3, where coefficient estimates measure percentage point changes in HIV medication quality and disease monitoring quality, Columns (1) and (2) respectively, that result from a one standard deviation increase in the indicated network statistic. Columns (3) and (4) measure the likelihood of prescribing any combined drug and specifically prescribing Epzicom. Each network statistic is standardized to have a mean of zero and a standard deviation of one, except for the geodesic distance to an HIV specialist.

Source: Medicare and Medicaid insurance claims for HIV-infected patients in California (2007-2010), ACS and OA county-level characteristics, and AMA Masterfile data.

Table 1.11: Peer Effects Measured through Network Statistics in Medicare Only Sample

	(1) Medication Quality	(2) Any Comb. Drug	(3) Epzicom Usage	(4)
Mean Outcome (sd)	88.1 (21.7)	61.3 (29.0)	11.3 (19.6)	Avg. Dependent Variable
Geodesic dist. to HIV Specialist	-1.64*** (0.74)	-1.61** (0.71)	-0.13 (0.60)	1.56 (0.62)
<i>HIV Specialist-weighted Statistics</i>				
Adjusted Degree	0.94** (0.41)	0.43* (0.20)	-0.29 (0.18)	0.87 (0.56)
Katz-Bonacich centrality	0.16** (0.07)	0.14* (0.06)	0.17 (0.11)	0.14 (0.10)
Betweenness centrality	0.15* (0.05)	0.31* (0.14)	0.39 (0.21)	3.15 (6.13)
<i>General Network Statistics</i>				
Adjusted Degree	-0.29 (0.18)	-0.43 (0.26)	0.15 (0.21)	1.19 (0.66)
Katz-Bonacich centrality	0.12 (0.08)	0.12 (0.09)	-0.13 (0.10)	0.15 (0.30)
Betweenness centrality	0.31 (0.16)	0.12 (0.11)	0.13 (0.14)	21.90 (20.87)
Physician Fixed Effects	✓	✓	✓	
Patient Fixed Effects	✓	✓	✓	
Region Fixed Effects	✓	✓	✓	
Time-varying Patients' Health Status	✓	✓	✓	
Observations	31,885	31,885	31,885	

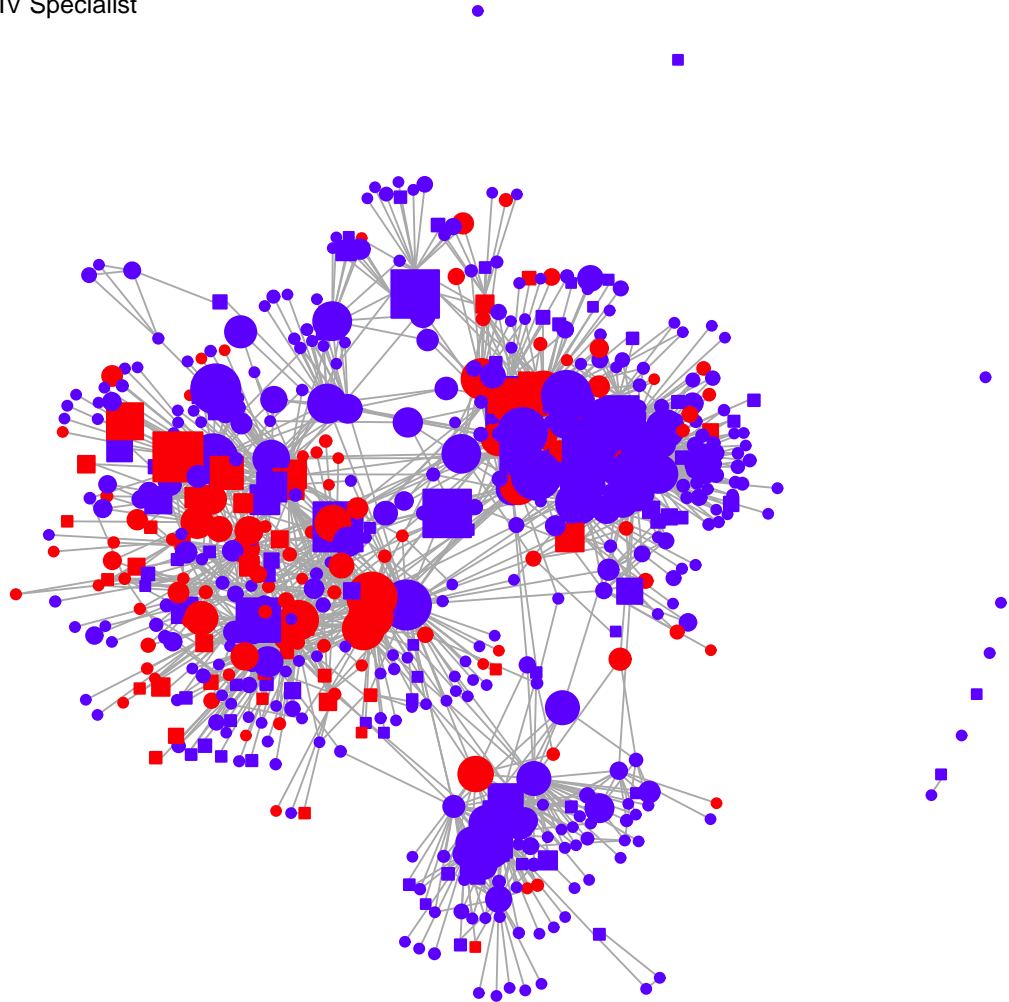
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. (Standard errors are double-clustered over multiple observations of the same physician and the same patient.)

Note: This table presents OLS estimates for the panel linear probability model specified by Equation 1.3 in medicare only sample, where coefficient estimates measure the percentage point change in HIV medication quality, Column (1), that results from a one standard deviation increase in the indicated network statistic. Columns (2) and (3) measure the likelihood of prescribing any combined drug and specifically prescribing Epzicom, respectively. Each network statistic is standardized to have a mean of zero and a standard deviation of one, except for the geodesic distance to an HIV specialist.

Source: Medicare Part D drug claims for HIV-infected patients in California (2007-2010), and ACS and OA county-level characteristics.

Figure 1.1: Physician Network in Palm Springs, CA

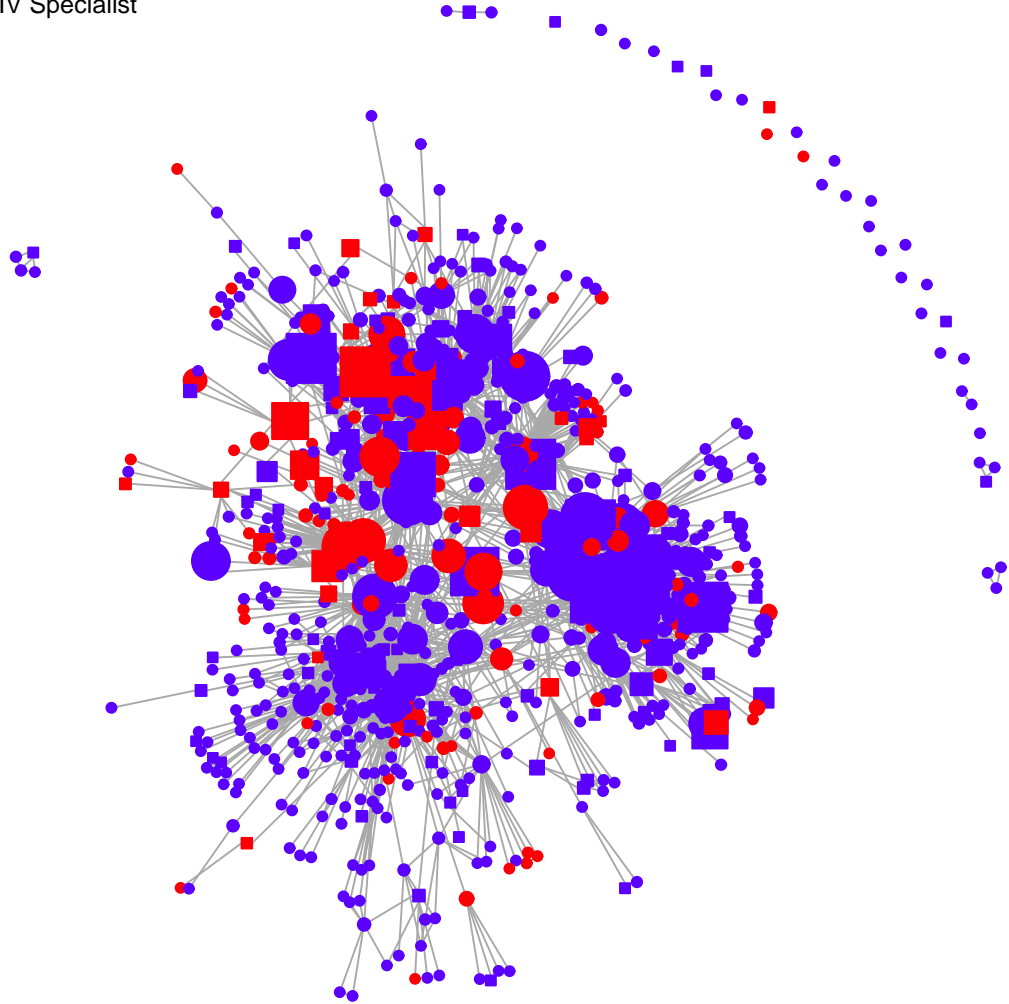
- Adherent Generalist Physician
- Non-adherent Generalist Physician (bottom 25th pctl. medication quality)
- Adherent HIV Specialist
- Non-adherent HIV Specialist



Note: Physician network in Palm Springs, CA. Shapes distinguish physician specialty, size indicates the physician's relative HIV-infected patient caseload, and color identifies a physician's average medication quality in 2010. The percent of physicians in Palm Springs adhering to medication guidelines is 88.6 percent, which is lower than the statewide average of 90.8 percent.

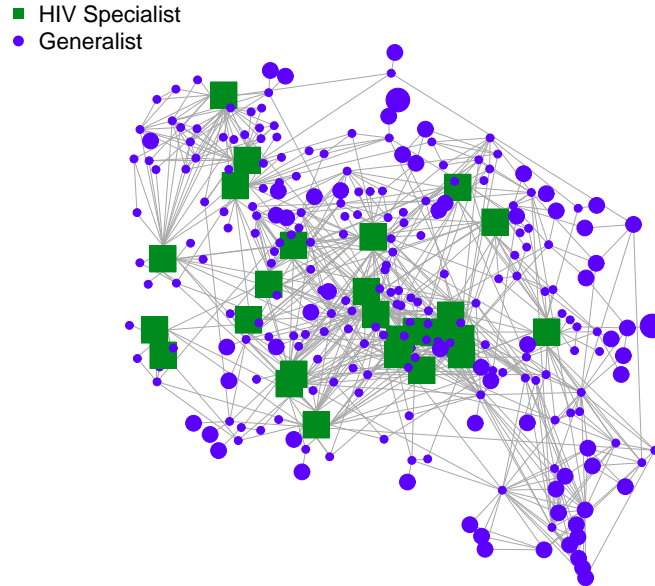
Figure 1.2: Physician Network in San Diego, CA

- Adherent Generalist Physician
- Non-adherent Generalist Physician (bottom 25th pctl. medication quality)
- Adherent HIV Specialist
- Non-adherent HIV Specialist

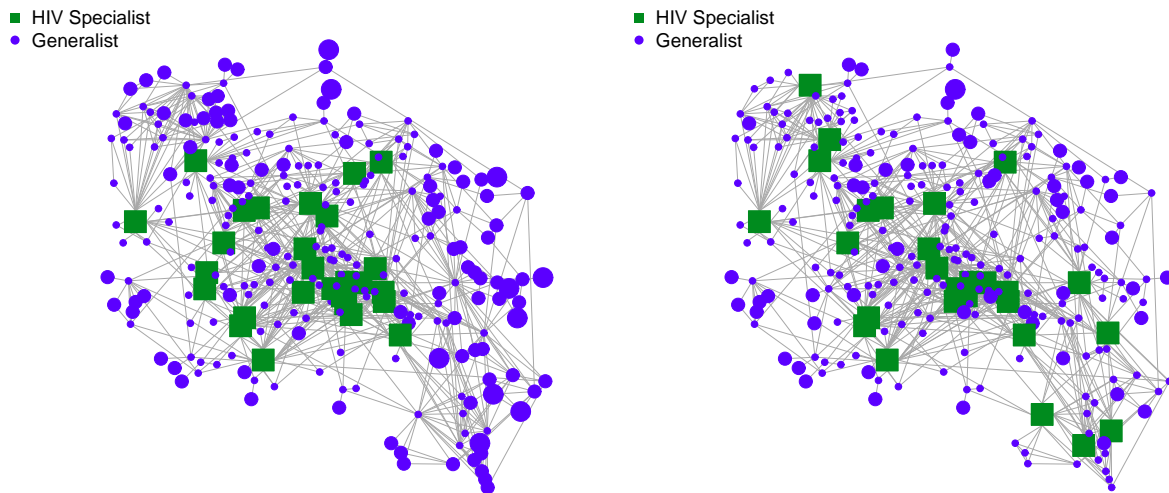


Note: Physician network in San Diego, CA. Shapes distinguish physician specialty, size indicates the physician's relative HIV-infected patient caseload, and color identifies a physician's average medication quality in 2010. The percent of physicians in San Diego adhering to medication guidelines is 95.0 percent, which is higher than the statewide average of 90.8 percent.

Figure 1.3: Simulated Network Redesign in Los Angeles, CA



(a) Original network: 92.0% of physicians adhere to the medication guidelines.

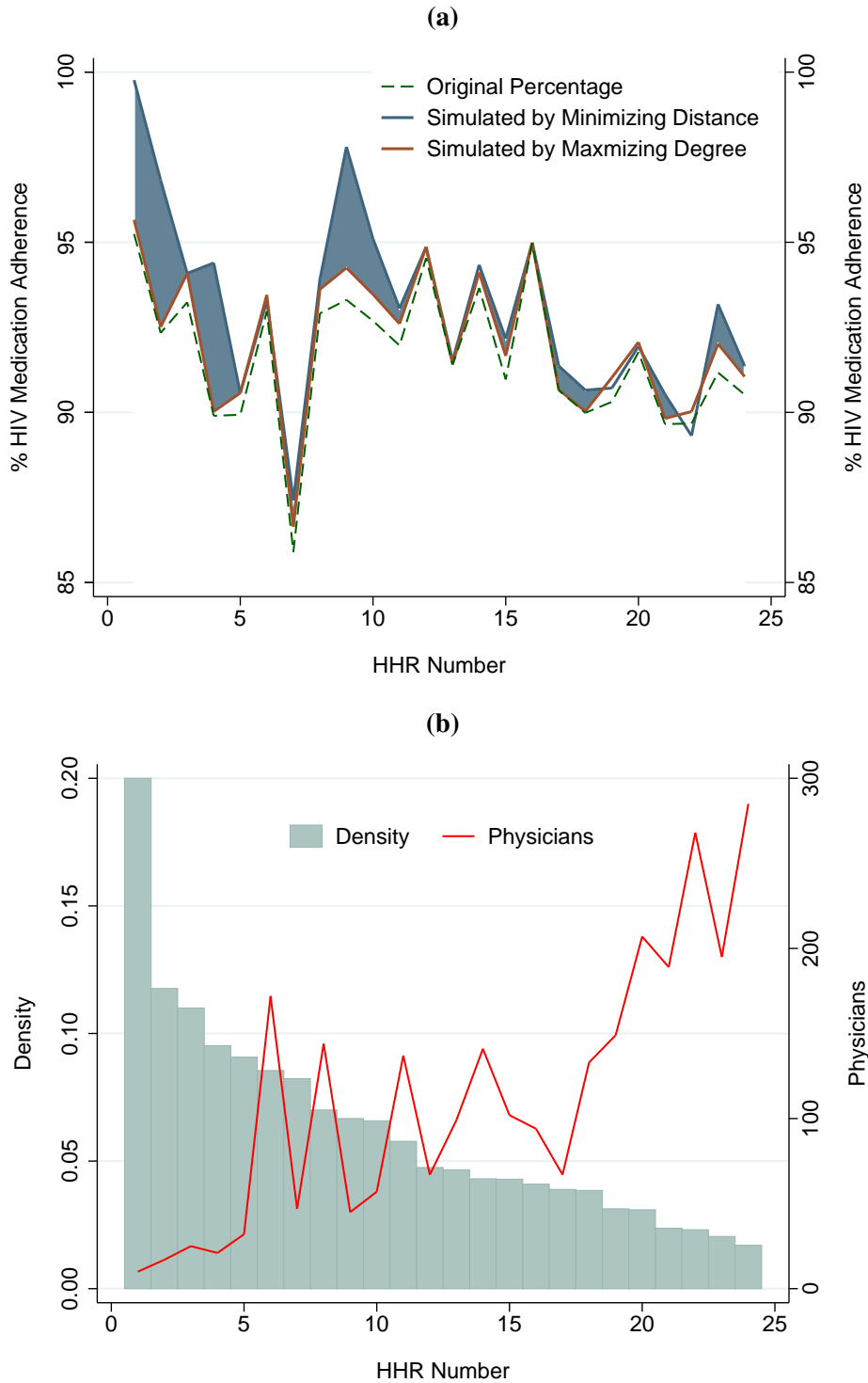


Simulated by degree:
88.2% network adherence.

Simulated by distance:
94.3% network adherence.

Note: Figure 1.3a plots the largest clustered physician network in the Los Angeles hospital referral region, where specialists are represented by green squares and generalist physicians are blue circles sized by their geodesic distance to the nearest specialist. Figures ?? and ?? plot simulated networks where specialists are positioned based on maximizing degree and minimizing geodesic distance to as many generalists as possible, respectively.

Figure 1.4: Improved Adherence to Medication Guidelines Under Simulations



Note: The shaded area in Figure 1.4a highlights the increase in medication quality by minimizing geodesic distance relative to simulations that maximize specialists' degree. HRR networks are ordered by density (number of patient-sharing links divided number of possible network links) as shown in Figure 1.4b.

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Chapter 2

The Impact of Behavioral Biases on Medication Adherence

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Behavioral Economics Matters for HIV Research: The Impact of Behavioral Biases on Adherence to Antiretrovirals (ARVs)

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Abstract Behavioral economics (BE) has been used to study a number of health behaviors such as smoking and drug use, but there is little knowledge of how these insights relate to HIV prevention and care. We present novel evidence on the prevalence of the common behavioral decision-making errors of present-bias, overoptimism, and information salience among 155 Ugandan HIV patients, and analyze their association with subsequent medication adherence. 36 % of study participants are classified as present-biased, 21 % as overoptimistic, and 34 % as having salient HIV information. Patients displaying present-bias were 13 % points ($p = 0.006$) less likely to have adherence rates above 90 %, overoptimistic clients were 9 % points ($p = 0.04$) less likely, and those not having salient HIV information were 17 % points ($p < 0.001$) less likely. These findings indicate that BE may be used to screen for future adherence problems and to better design and target interventions addressing these behavioral biases and the associated suboptimal adherence.

Keywords Behavioral economics · Medication adherence · HIV · Antiretroviral therapy · Developing countries · Uganda

Introduction

People commonly fail to act in their own self-interest and behave in ways they later regret such as overeating or smoking [1–3]. Behavioral economists study why and in

what circumstances individuals display such decision-making errors or “biases” [4–8]. Insights from behavioral economics (BE) have been applied to study a number of diseases and health behaviors [9], but to date, none have explored HIV. BE is grounded in Traditional Economics (in particular the premise that people make decisions based on costs and benefits) but enriches this framework with insights from psychology. It also shares some characteristics with existing health behavior theories; like Social-cognitive Theory, it starts from the premise that expectations of future events and outcomes are important determinants of behavior [10]. Similarly, it recognizes the importance of beliefs in shaping behaviors stressed in the Health-Belief model [11]. With the Health-Belief model, it shares the recognition that people have limited cognitive capacity and may sometimes feel overwhelmed when carrying out a complex task [12]. Overall, BE is a systematic framework to investigate human actions that recognizes the importance of the behavioral determinants outlined across different health behavior theories. BE posits that people make decisions based on their costs and benefits, but contrary to the Traditional Economics model recognizes that people do not access all available information when making a decision (information salience), are overly confident in their capacity to carry out a task (overoptimism), and face difficulties sticking to their decisions (present-bias) [13]. A trademark of BE is the focus on measurement and quantification of these biases in a simple fashion. For example, compared to the related concept of time preference as used in an HIV context by Préau et al., the BE concept of present-bias as executed commonly is evaluated using only a handful of questions as compared to the 61 items in Zimbardo’s Stanford Time Perspective scale [14]. Questions identifying BE biases could therefore be a more feasible, much-needed tool to screen for likelihood of

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optimal medication adherence for HIV and other chronic conditions [15].

In what follows, we briefly discuss some key biases that have been found to influence behavior for chronic conditions, and discuss why we believe that these likely also matter for ARV adherence. We then present novel empirical evidence from a sample of HIV clients in Uganda showing that BE biases are common and negatively correlated with subsequent Medication Event Monitoring System (MEMS)-cap measured adherence. We end with a discussion of the results and in the conclusion encourage more research to further study these biases and their association with adherence.

The Importance of BE Biases for Chronic Health Behaviors

We focus on three key behavioral biases that have been found to influence health behaviors for other chronic conditions [9] and that we hypothesize may also be important to components of ARV adherence:

Present-Bias

A key behavioral bias is present-bias, which is the tendency of people to give into current temptation at the price of beneficial future outcomes [16]. For example, a seminal article by Benartzi found that people tend to delay the decision to save (e.g., to forego current consumption in exchange for future benefits) to a tomorrow that—when turning into today—is again pushed off [17]. Chronic HIV care management requires a similar decision, as health is conditional on daily pill-taking with immediate costs such as social stigma, side-effects, and financial costs. The benefits of optimal ARV adherence that include a healthier and longer life, on the other hand, manifest only in the distant future. We therefore hypothesize that patients displaying present-bias will display lower adherence, as they overly discount the future benefits of adherence and may see their actions guided mainly by its daily costs.

Overoptimism

Being overly confident in one's ability to stick to a planned behavior has been found to have important negative consequences for a wide range of behaviors [18]. For ARV adherence, this bias may manifest itself as patients not taking appropriate steps to assure their taking the medicine on time or not taking it at all; for example, most patients in our sample set phone alarms that subsequently prove insufficient to assure optimal adherence. We hypothesize that patients displaying overoptimism will show lower

adherence than their peers with more realistic expectations regarding their future adherence behavior. A closely related bias is overplacement, which is being overly confident in one's own behavior relative to that of a reference group [19], which may be a particularly good indicator of being too confident and not taking enough precaution to ensure high adherence.

Information Salience

Behavioral economists have found that people act on the information that first comes to mind rather than on all the relevant information available [18]. This can lead to people being guided by relatively recent experiences, or those that were experienced by friends and that were particularly memorable. For example, people tend to buy earthquake insurance following an earthquake in their area, even though this occurrence does not change the underlying probability of an earthquake occurring [20]. We argue that HIV as a health threat may not be very salient (e.g., on top of their minds) for people living with HIV, in particular for those who have been on ARV for a number of years as is the case for the sample described below. Such patients often enjoy good health and no longer experience health improvements from taking their medication, therefore the benefits of ARV may become relatively invisible/less salient over time, leading them to fail to perceive adhering to the pill regimen as a priority. We expect that for patients who have received positive feedback on the ARV medication's health benefits from peers at the HIV clinic this information is salient, leading to higher adherence.

Methods

The data for this article come from the Rewarding Adherence Program (RAP) that uses variable rewards to improve ARV adherence and retention in care. The program attempts to reduce present-bias and increase information salience by providing small prizes allocated by a drawing at each clinic visit conditional on keeping scheduled clinic appointments (treatment group 1) and high ARV adherence measured by MEMS caps (treatment group 2). The study was implemented as a small randomized controlled trial (RCT) with about 50 participants in each of the two treatment groups and the control group, which received standard clinical care and answered the survey but did not take part in the prize drawings.

RAP is currently being implemented at Mildmay Uganda, an NGO in the capital Kampala. At the time of enrollment into the RAP program, patients completed a baseline survey before being informed of their randomized treatment assignment and before they were exposed to the

intervention. This survey consisted of 11 different modules measuring a variety of characteristics such as patient demographics, household characteristics, or community environment. BE biases were also collected as part of this baseline survey as described below, and form the basis for the analysis in this paper. Eligible participants (18 years of age or older, taking ARVs for at least 2 years, having adherence problems (either self-reported or otherwise indicated in the medical records data) in the last 6 months, willing to follow and able to understand the study procedures) were asked to provide written consent in their preferred language (English or Luganda) that included the survey data collection and use of MEMS caps. RAP was approved by the HSPC Board at RAND (2012-0372), the IRB review board at Mildmay, and the Uganda National Science Counsel (UNCST).

Measurement of BE Biases

Present-Bias

The survey used the common method of asking clients to make a choice between hypothetical rewards that varied in size depending on the delay of payment [21]. The survey question stated: “Imagine you can win a lottery prize and have to choose between receiving 50,000 US\$ tomorrow, or 75,000 US\$ in one year. Which would you choose?”. Respondents who chose the immediate reward rather than the more distant, larger reward were subsequently classified as present-biased. This method has been validated across many cultural settings [6], and this particular question was designed for a similarly, resource-poor environment [22].

Overoptimism

Respondents were asked to report the likelihood of forgetting at least one dose in the next month based on a four point Likert-type scale, and to make the same judgment about the likelihood of *other clients* at the clinic to measure overplacement. As displaying adherence problems in the 6 months preceding the survey was one of the enrollment criteria for the RAP intervention, we expected study participants to realize that on average they are likely to display lower adherence than most other clinic patients. Patients therefore were classified as overconfident if they assigned themselves a lower likelihood of forgetting pill doses relative to the other clients in the clinic.

Information Salience

Patients were asked whether they know people who have benefited from ARVs (as a reminder of the benefits of

ARVs), and whether they have a close friend or family member who has died from AIDS (which would make the serious consequences of non-adherence more salient). We do not report results for the latter measure as the large majority of the sample (over 90 %) responded in the affirmative, indicating the generalized nature of the HIV epidemic in Uganda.

Adherence Measures

Participants at baseline were provided with a MEMS cap that electronically records the date and time a pill bottle is opened, and were instructed to bring it with them for each clinic or study visit, at which point the adherence data were abstracted. Such an objective measure of adherence has been found to give a more accurate picture of adherence compared with self-reports that are easily manipulated and often overstated [23]. Objectively measuring adherence is particularly important in the current study where eligibility for participating in the prize drawing is conditional on high adherence (treatment group 2). Adherence so measured may differ from actual adherence if participants do not consistently use the caps, which we tried to control for by adjusting the measured adherence by self-reported pocketing or taking of medication from sources other than the MEMS cap. A second possible source of error in this measure is if people open the MEMS cap but do not actually swallow the pill. This would typically occur if people are trying to ‘game the system’. While we cannot control for this possibility, we can largely abstract from this problem for the control group and intervention group 1 as their eligibility in the lottery was not conditional on adherence but only on timely clinic visits.

MEMS data from the first 4 months of study participation are used to calculate the adherence outcome variable; we exclude the first month where we observe significantly higher adherence for all participants that is likely due to the novelty of being part of the study and focus our analysis on months two through four when we hypothesize that the novelty of using a MEMS cap would have worn off. Our main outcome variable is the fraction of clients displaying mean adherence of at least 90 %, where mean adherence is calculated as (# of actual bottle openings/# of prescribed bottle openings). While current regimens seem to be less forgiving than older ones [24], high and consistent adherence is certainly more conducive to viral suppression, and we therefore think that such a cut-off level is justified. Moreover, recent research has shown high risks for the development of disease resistant strains and advanced disease progression at mean adherence rates below 90 % [25, 26].

Approach

Data were analyzed with Stata/SE version 10.1. Statistical significance is reported for levels between 0.10 and 0.01 for hypothesis testing and regression coefficient estimates. Summary statistics are reported as frequency counts (%), and regression results present maximum likelihood estimation (MLE) coefficient estimates for probit regressions along with standard errors. Baseline results were compared among behavioral biases using chi-squared testing within the pooled sample of observations between months two and four. This method is well suited to the binary nature of the outcome variable and the non-normality of the underlying distribution of adherence behavior in the sample. To control for observable patient characteristics, probit regression results provide a secondary analysis of adherence behavior across biases.

Adherence as the primary RAP outcome is likely impacted by the intervention over time. During the first 4 months of the study, RAP's impact would be little felt as few clients would have participated in a prize drawing during that time. We also repeated the analysis using the control group only (that did not receive the intervention) to ensure that the results observed are not driven by the RAP intervention. Furthermore, as the impact of the biases on ARV adherence can be expected to be muted by RAP (in particular present-bias that is directly targeted by the RAP rewards), our results constitute a lower bound estimate for these effects.

Results

Sample Characteristics (Table 1)

Table 1 presents summary statistics of the sample's demographics and tests whether characteristics such as gender, age, and education status are equally distributed among the two intervention groups and the control group as would be expected in a RCT. These observable

characteristics do not show statistically significant differences between the groups; however, present-bias is higher in the control group compared to the treatment group 2, and overoptimism is more prevalent in the control group than in treatment group 1.

Prevalence of BE Biases in the Sample (Table 1)

Present-Bias

36.3 % of respondents chose an immediate hypothetical reward over a larger reward in 1 year, and are therefore classified as present-biased.

Overoptimism

89 % of patients believe they are unlikely to miss a dose in the month following the baseline survey despite being recruited because of recent adherence problems. 20.7 % of clients believe that they have a better chance than the other patients at Mildmay clinic to fully adhere in the following month, indicating that they suffer from the bias of overplacement and leading to their being classified as overoptimistic.

Information Salience

More than 33 % of patients have received positive feedback on the effectiveness of the ARV medication from other HIV patients.

Association of Behavioral Economics Biases with Subsequent ARV Adherence (Table 2)

The biases presented in Table 1 may influence patients' decision-making and consequently their adherence behavior. Table 2 provides empirical evidence on the impact of these biases on the fraction of patients taking 90 % or more of their medication.

Table 1 Behavioral bias prevalence across treatment groups

Variable	Full sample (1)	Control (2)	Treatment 1 (3)	Treatment 2 (4)	Control vs. treatment 1 Two-sided <i>p</i> value (5)	Control vs. treatment 2 Two-sided <i>p</i> value (6)
Female	62.4 %	62.0 %	60.8 %	66.7 %	0.901	0.624
30 years or younger	24.2 %	30.0 %	19.6 %	24.1 %	0.230	0.501
At least primary education	52.3 %	52.0 %	54.9 %	50.0 %	0.773	0.840
Present-biased	36.3 %	48.0 %	33.3 %	29.6 %	0.136	0.0551*
Optimism	89.0 %	90.0 %	84.3 %	92.6 %	0.399	0.642
Overoptimism	20.7 %	30.0 %	11.8 %	20.4 %	0.0239**	0.262
Information salience	33.6 %	30.0 %	41.2 %	29.6 %	0.245	0.968
Sample size (N)	155	50	51	54		

The *p* values indicate two-sided *t* test significance at the 10 % (*), 5 % (**), and 1 % levels (***)

Table 2 Behavioral bias impact on adherence

Variable	Fraction above 90 % adherence with bias (1)	Fraction above 90 % adherence without bias (2)
Present-biased	28.0 %***	41.4 %
Optimism	38.4 %*	25.0 %
Overoptimism	29.4 %	38.8 %
Saliency	48.3 %***	31.1 %

Indicated chi-squared significance at the 10 % (*), 5 % (**), and 1 % (***) levels

Present-Bias

Patients who more heavily weigh the immediate costs of pill-taking than its future benefits are 13.4 % points less likely to attain mean adherence rates of at least 90 % ($p = 0.006$).

Overoptimism

Participants who report being ‘very likely’ to fully adhere in the next month are 13.4 % points more likely to have mean adherence rates equal or above 90 % ($p = 0.07$). The 20.7 % of patients who believe that they are more likely to show optimal adherence relative to others (i.e. those displaying overplacement), have an 9.4 % points lower chance to display 90 % adherence ($p = 0.11$).

Information Saliency

The percentage of patients with mean adherence rates of 90 % or greater increases from 31.1 to 48.3 % for those who recently received positive feedback about the HIV medication from other patients ($p = 0.001$).

In Table 3, we investigate the association of the same BE biases with adherence when controlling for the observable characteristics of gender, age, and education of the participants to examine whether the behavioral biases exert an additional influence on adherence that cannot be inferred from these observable characteristics. Each column in the table represents a separate regression of adherence

on the respective bias when controlling for the observable characteristics. We find that present-bias and information saliency remain statistically significant; overoptimism has a negative impact on adherence that is however not statistically significant.

Robustness Check: Results in the Control Group

Above we discussed the potentially confounding influence of participation in the RAP program and uneven distribution of bias prevalence between control and treatment groups on adherence. We therefore repeated the analyses for the control group only ($n = 50$) that is not subjected to the intervention. The results confirm that patients with present-bias have a significantly lower mean adherence and are 15.3 % points less likely to achieve adherence over 90 % ($p = 0.02$). Similarly, the same patterns in adherence across patients’ overoptimism and information saliency discussed above continue when restricting our analysis to this subgroup, but the small sample size limits the power of statistical inference.

Discussion

In this paper, we argue that the characteristics of HIV as a chronic disease make it likely that the systematic decision-making errors (‘biases’) of people living with HIV significantly interfere with optimal ARV adherence, and that measuring these biases and their association with ARV adherence is an important research topic. We focus on three key biases identified in the BE literature: present-bias (the tendency many people display of preferring immediate rewards to temporally more distant ones), overoptimism (excessive confidence in the ability to stick to a planned behavior), and information saliency (the tendency of people to act on information that is more readily available). Our hypotheses that we subsequently test are that present-bias leads to lower adherence as adherence has current costs (stigma, financial costs, ...) but the benefits of taking pills only manifest in the distant future (improved life expectancy and life quality). We also hypothesize that overoptimism may lead people not to implement enough

Table 3 Behavioral bias impact on adherence controlling for observable patient characteristics

	Present-biased (1)	Optimism (2)	Overoptimism (3)	Saliency (4)
BE bias	-0.791 (0.404)**	0.912 (0.634)	-0.531 (0.492)	0.933 (0.406)**
Gender	-0.814 (0.423)*	-0.893 (0.426)**	-0.860 (0.427)**	-0.794 (0.423)*
Age	0.544 (0.199)***	0.544 (0.200)***	0.524 (0.201)***	0.512 (0.199)**
Education	0.177 (0.385)	0.270 (0.386)	0.209 (0.388)	0.134 (0.385)

Maximum likelihood estimation coefficient results and standard errors (in parenthesis) along with indicated significance at the 10 % (*), 5 % (**), and 1 % levels (***)

precautions to take their daily drug dose(s) resulting in lower adherence, and that the long-term and relatively invisible nature of HIV reduces its information salience, making it likely for people to put the demands of daily life before HIV, again leading to lower adherence.

We then go on to test for the presence of these biases using commonly used, simple survey measures. We find that these biases are prevalent in a sample of clients in HIV care in an urban clinic in Uganda; more importantly, we find that these biases are associated with lower subsequent ARV adherence. These results represent the first empirical evidence for the importance of BE in studying ARV adherence, an area in need of further research and understanding, in particular in resource-limited settings [27]. While the biases empirically confirm the hypotheses we started out with, there was one unexpected finding: optimistic clients (i.e. those who think that they have taken good precautions to make sure to adhere to their regimen) manage to show higher adherence than their more pessimistic peers, indicating that some confidence in one's ability to adhere to the medication regimen is actually beneficial. However, if patients are too confident in their ability to adhere (those who suffer from overplacement, i.e. the tendency to overstate their own ability to adhere compared to the general clinic population), they seem to not create an environment susceptible to good adherence and display lower adherence.

Our results point to several potential uses of BE for improving ARV adherence: first, BE biases could be a low-cost, quick way to screen for patients who are likely to show low adherence and are thus in need of additional adherence support. However, how useful biases are as a screening tool depends on the extent to which they cannot be inferred from observable characteristics such as age, gender or education that have been found to be associated with adherence and that are likely used by providers to infer the likelihood of a patient to show good adherence [28]. Our findings do indicate that BE biases are not systematically correlated with age, gender, or education, and therefore provide additional information that a provider would not be able to gather based on these observable client characteristics.

Our findings also point to the potential use of BE as way to design interventions that use the biases identified as entry points. For example, the finding that participants with present-bias display lower adherence indicates that interventions such as the RAP program may be able to improve adherence by providing short-term rewards to adherence. Similarly, the finding that information salience is associated with improved adherence suggests the importance of increasing the tangibility of the costs of non-adherence and benefits of adherence. This could for example take the form of reminders about the importance of adhering to the ARV regimen at times such as on weekend nights when

individuals may be engaging in activities (drinking, drug use, ...) that can lead them to forget to take their drugs.

Limitations of the study include that it is relatively small in size and may be contaminated by the RAP study that took place after the information on the biases was collected at baseline. However, the results for the control group that was not exposed to the intervention are equally robust. As this subsample consists of only 50 patients, the ability to detect any significant differences in mean adherence underscores the robustness of our results.

Conclusion

This paper presents first empirical evidence that BE can shed new light on ARV adherence behaviors. The finding that BE biases are common and are associated with subsequent ARV adherence supports the view of BE as a novel and low-cost way to screen for people in HIV care who are likely to show suboptimal adherence. We therefore encourage future research on the topic of BE biases and their impact on adherence using larger samples, using studies with the sole purpose of investigating the role of biases (i.e. not measuring biases as part of an intervention study), utilizing refined survey tools to detect biases, and using experiments in controlled settings to gain further insights. If the promising result in this study holds in these later studies, it would offer a simple tool to screen for clients likely needing additional treatment support. BE is increasingly being used to design and refine behavioral interventions for a range of (health) behaviors, and based on this literature and our results, we hope that BE methods can improve interventions for HIV-related behaviors as well. The RAP study discussed in this paper will provide first such evidence when it is completed in late 2015.

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Chapter 3

Behavioral Economic Incentives to Improve Medication Adherence

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Behavioral economic incentives to improve adherence to antiretroviral medication

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Objective: Fixed incentives have been largely unsuccessful in improving adherence to antiretroviral medication. Therefore, we evaluate whether small incentives based on behavioral economic theory can increase adherence to antiretroviral medication among treatment-mature adults in Kampala, Uganda.

Design: A randomized control trial design tests whether providing small incentives based on either attending timely clinic visits (intervention group 1) or achieving high medication adherence (intervention group 2) can increase antiretroviral adherence. Antiretroviral adherence is measured by medical event monitoring system (MEMS) caps.

Methods: Overall, 155 HIV-infected men and women age 19–78 were randomized into one of two intervention groups and received small prizes of US \$1.50 awarded through a drawing conditional on either attending scheduled clinic appointments or achieving at least 90% antiretroviral adherence. The control group received the usual standard of care.

Results: Preliminary results based on pooling the intervention groups showed individuals receiving incentives were 23.7 percentage points more likely to achieve 90% antiretroviral adherence compared with the control group [95% confidence interval (CI), 6.7–40.7%]. Specifically, 63.3% (95% CI, 52.9–72.8%) of participants in the pooled intervention groups maintained at least 90% mean adherence during the first 9 months of the intervention, compared with 39.6% (95% CI, 25.8–54.7%) in the control group.

Conclusion: Small prize incentives resulted in a statistically significant increase in antiretroviral adherence. Although more traditional fixed incentives have not produced the desired results, these findings suggest that small incentives based on behavioral economic theory may be more effective in motivating long-term adherence among treatment-mature adults. Copyright © 2017 Wolters Kluwer Health, Inc. All rights reserved.

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Keywords: behavioral economics, HIV, medication adherence, Uganda

Introduction

Antiretroviral therapy has improved the life expectancy of HIV-infected patients dramatically [1–4]. However, the success of these drugs is dependent on high medication adherence, which is a difficult behavior for patients to maintain not only in Uganda but worldwide [5–8]. The growing evidence of suboptimal adherence is pronounced among patients who have been on antiretroviral medication for a number of years and have been found to take ‘drug holidays’ from their antiretroviral regimen when they feel overwhelmed by daily pill taking [9]. These gaps in adherence dramatically reduce the

effectiveness of antiretroviral medication, and highlight the importance of motivation and self-control in fighting treatment fatigue.

For many health behaviors, people have difficulty following through on their good intentions and end up in situations they later regret, such as overeating or smoking [10,11]. Behavioral economists interpret these situations as people overly discounting the future and giving in to short-term temptation at the expense of long-term benefits [12]. Such ‘present bias’ is particularly damaging for chronic conditions such as HIV/AIDS where the benefits of a healthier and longer life occur in

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the distant future, but the costs of taking antiretroviral drugs are incurred daily [13].

Incentives, such as conditional cash transfers [14] or contingency management style payments of large monetary value that have a long tradition in the psychology literature [15], show promising but sometimes mixed results [16]. In the field of HIV, recent studies using large conditional rewards to prevent HIV [17–19] and link HIV-infected individuals to HIV care have not delivered the desired results [20], and novel, more effective ways to provide incentives are needed.

Behavioral economics suggests that instead of the magnitude of the incentive, the way incentives are delivered – and at what time intervals – significantly determines their effectiveness [13]. Small incentives provided frequently and close to observations of the desired behavior may be more effective than larger, infrequent payments at increasing an individual's internal motivation and sustaining behavioral improvements [21]. Some recent studies in the field of HIV have begun to apply smaller, more frequent incentives to increase the uptake of safe male circumcision [22] and mother-to-child HIV transmission care [23]. Incentives allocated by a drawing may be more effective than equivalent fixed payments [24,25] by leveraging the motivational power and joy of games of chance. Such incentives also leverage overestimation bias to reduce the cost of the intervention, as individuals respond more to these small incentives relative to a larger fixed payment [26,27].

The 'Rewarding Adherence Program' (RAP) described in this paper examines whether providing small incentives allocated by a drawing conditional on either attending timely clinic visits (intervention group 1) or achieving high medication adherence (intervention group 2) can increase antiretroviral adherence among 155 adult clients in HIV care in Uganda. We did not test the relative effectiveness of incentives as traditionally used (i.e. those of relatively large, fixed monetary value) versus those inspired by behavioral economics after discussions with the implementing clinic who decided that larger incentives would not be sustainable or acceptable to clinic leaders. In this article, we report on the effects over the first 9 months of a 26-month study that is currently ongoing.

Methods

Study setting

RAP was implemented at Mildmay Uganda, an HIV clinic in Uganda's capital Kampala that provides antiretroviral therapy to over 11 000 clients and has been caring for HIV-infected Ugandans for over 17 years.

Study design and participants

Ethics approval was obtained from RAND's Human Subjects Protection Committee, the Research Ethics Committee at Mildmay clinic, and the Uganda National Council for Science and Technology. There were no adverse events reported in any of the study groups.

Clients of the Mildmay clinic were eligible for participation if they were at least 18 years of age, had documented adherence problems (either missed at least one clinic visit in the last 6 months or self-reported adherence problems), and were on antiretroviral medication for at least 2 years; these criteria were chosen as we hypothesized that small incentives may be particularly appropriate for treatment-mature clients who likely have overcome more structural barriers to adherence (such as transportation costs or lack of appropriate food) and for whom motivational barriers are likely of key importance. Based on a list of all clients conforming to these study eligibility criteria, potential participants were randomized to either one of two intervention groups or the control group in a 1:1:1 ratio. Written informed consent was then obtained in the patient's preferred language. Afterwards, consenting participants completed a 45 min baseline survey that measured respondents' demographics, socioeconomic status, and health history. Recruitment took place between March and August 2013.

Of the initial 201 eligible Mildmay clients, 46 approached by the study coordinator were not recruited because of refusal, scheduling problems, language barriers, and other circumstances, until the final study sample size of 155 participants was reached. These participants were evenly divided between the three study groups, and sample attrition during the first 9 months of the RAP program was equally experienced across groups. Figure 1 outlines the flow of study participation during the recruitment phase and the first 9 months of the project.

Intervention groups

After completing the baseline survey, participants were informed of their random assignment to either of the intervention groups, whereby participants were eligible for small incentives, or to the control group. Eligibility for in-kind incentives allocated by a drawing was based on timely clinic visits – that coincide with drug refills at the clinic pharmacy – for intervention group 1 and antiretroviral adherence of 90% or higher for intervention group 2. Intervention group 1 was included at the request of our local partner to test whether incentives could be successfully implemented without the cost-intensive use of medical event monitoring system (MEMS) caps to measure adherence. The control group received the usual standard of care.

The eligibility for incentives in intervention group 1 was defined as attending the clinic appointment on the

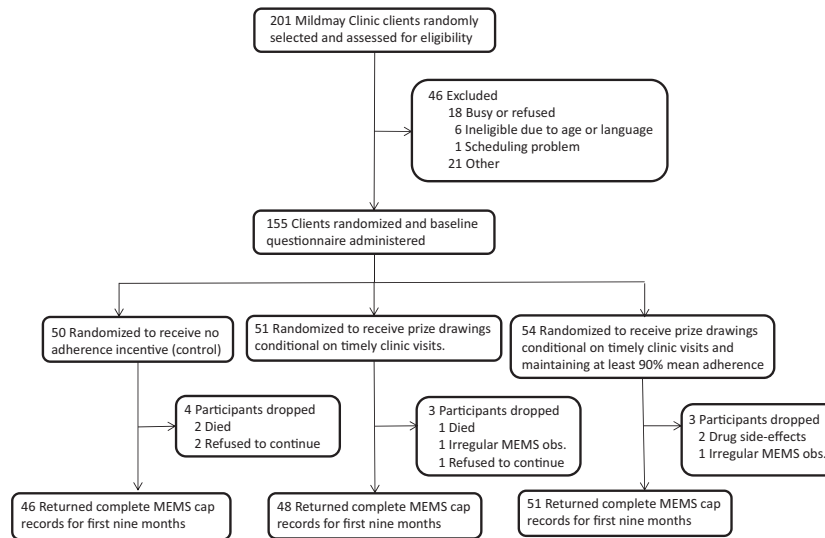


Fig. 1. Flow of study participants for the Rewarding Adherence Program study. MEMS, medical event monitoring system.

scheduled day and was verified by the study coordinator who checked the client’s scheduling booklet. Clients who visited the clinic before their scheduled visit would only become eligible again based on the date for their following appointment. If the client was overdue by 3 days or more, the study coordinator would first verify that the participant had not come to the clinic without being seen by study personnel, and if not, then a new schedule for clinic appointments was established. Eligibility was then determined based on this new schedule, which maintained an approximate 2-month gap between appointments (the observed time between clinic visits during the study period was approximately 52 days for all three groups). The eligibility for incentives in intervention group 2 was defined as being more than 90% adherent and was confirmed by downloading patients’ latest MEMS data.

Eligible participants would then draw a number out of a bag with cards numbered 1 through 6, and would receive the in-kind incentive if they drew a ‘6.’ They were offered the choice of one of three items (to avoid boredom, as some patients were expected to win more than once): a coffee mug, an umbrella, or a water bottle. All three items had a monetary value of about 6000 Ugandan shillings, or approximately \$1.50 USD. The incentives and other intervention parameters were developed in collaboration with key stakeholders as part of an extensive formative phase preceding the intervention.

Primary outcome adherence measurement

Given evidence in the medical literature that adherence levels of 80–100% are necessary to achieve viral suppression [28–32], and levels above 90% significantly reduce the likelihood of virologic failure and drug

resistance [33], the main outcome of interest was achieving 90% adherence or higher.

A MEMS cap was placed on the pill bottle containing antiretroviral medication for all participants of this study. The MEMS cap electronically records the time and date of each bottle opening. Clients were asked to bring the MEMS cap to each clinic visit to download their adherence data. Participants were encouraged to take their medication only from the pill bottle with the MEMS cap. Of note, as it was important to determine if a lower cost approach could be used to increase adherence, eligibility for participating in the prize drawing in intervention group 1 was based on timely clinic attendance only. However, providing the intervention group 1 and the control group with MEMS caps not only assured that we could use a fully comparable adherence measure for all three groups, but also largely eliminated any potential confounding effects brought about by the use of MEMS caps.

Statistical analyses

We conducted an impact analysis to compare the proportion of participants with 90% mean adherence or higher in each intervention group to the control group using probit regression analysis, and F-tests were used to compare the treatment impact between intervention group 1 and intervention group 2. Kernel densities were used to additionally compare the distribution of patients’ mean adherence in each study group using the Epanechnikov kernel function with equal bandwidths for each group. The analysis also estimated probit models adjusted for participant’s age, educational attainment, sex, wealth, marital status, and physical and mental health. Age was defined in years and was measured as an integer, and education was defined as a binary variable indicating

whether the participant had completed at least primary education. Participants' wealth was measured by an asset index defined as the sum of affirmative responses to the ownership of 10 common household items. These 10 items represent the most common household items included in the Demographic and Health Survey's (DHS) Uganda survey [34], and the asset index places equal weight on participants' self-reported ownership of each item. Marital status was defined as a binary variable indicating whether the participant was married at the time of the baseline survey. Physical and mental health were defined by participants' responses on a 5-point Likert-type scale to the statements: 'My health keeps me from working at a job, doing work around the house, or going to school,' and 'Over the past 2 weeks, I have felt down, depressed, or hopeless.' All statistical tests were two-sided and performed using Stata version 14.0 (StataCorp. LP, College Station, Texas, USA). Coefficient standard errors were estimated using heteroskedasticity robust procedures for all linear regression specifications.

The planned sample size for the intervention was 150, with 50 participants in each study group. Power calculations indicated that with a sample size of 50 per study group and 45% of participants in the control group maintaining mean adherence rates equal to or above 90%, there would be 80% power to detect a difference in the proportion of participants with high mean adherence as small as 17% between study groups. At the time that power calculations were performed, there were no data available on the actual mean adherence rates of patients at the Mildmay HIV clinic, but self-reported measures indicated that fewer than half of clients were maintaining at least 90% mean adherence.

Results

Baseline data

Baseline demographic characteristics of participants were similar across the three study groups (Table 1). Roughly half of the participants had at least completed their primary education (53%). The majority of clients in this sample (63%) were women, which is representative of the total client population at the Mildmay clinic that is also predominantly female, and participants were on average 39 years old. Median monthly disposable income was US \$58 [interquartile range (IQR), \$29.20–\$87.20] of which travel costs to the clinic represented roughly 5%; median travel costs were US \$2.90 (IQR, \$2.03–\$4.35), according to the prevailing exchange rate of 1 USD to 3450 Ugandan Shillings. The average participant's household contained 4.7 (SD 2.8) members, and 49% of participants were married at the time of the baseline survey. Roughly 12% of participants are physically limited by their health, and over 65% have had feelings of depression or hopelessness.

Table 1 also illustrates that the randomization procedure successfully led to a balanced sample across the control and intervention groups. The only significant differences occurred between the control group and intervention group 1, where two-sided *t*-tests indicated that the fraction of participants being married was lower and the percentage of participants who had completed primary school was higher in intervention group 1 (*P* values of 0.10 and 0.06, respectively). This difference in educational attainment across study groups is not correlated with participants' self-reported knowledge of the HIV treatment protocol or observed mean adherence rates so it is unlikely to bias the impact analyses. In light of these small

Table 1. Balanced demographics across study groups.

	Full sample (<i>N</i> = 155)	Control (<i>N</i> = 50)	Intervention groups	
			Group 1 (<i>N</i> = 51)	Group 2 (<i>N</i> = 54)
Men, no. (%)	57 (37)	19 (38)	20 (39)	18 (33)
Age, mean (SD), years	39 (10.3)	37.4 (9.8)	40.1 (10.9)	39.3 (10.0)
Education, no. (%)				
Some primary education or none	74 (48)	24 (48)	23 (45)	27 (50)
Completed primary education	63 (41)	23 (46)	19 (37)	21 (39)
Greater than primary education	18 (12)	3 (6)	9 (18)	6 (11)
Wealth based on asset index, mean (SD) ^a	5.0 (2.0)	4.8 (2.0)	5.3 (2.1)	4.9 (2.0)
Own home, no. (%)	115 (74)	35 (70)	39 (76)	41 (76)
Monthly disposable income, median (IQR), US \$ ^b	58.00 (29.00–87.00)	43.50 (23.20–79.75)	58.00 (34.80–87.00)	58.00 (34.80–87.00)
Travel cost to HIV clinic, median (IQR), US \$	2.90 (2.03–4.35)	2.90 (2.03–4.35)	2.90 (2.90–4.35)	2.90 (1.74–4.35)
Married, no. (%)	76 (49)	21 (42)	30 (59)	25 (46)
Household size, mean (SD)	4.7 (2.8)	4.3 (2.5)	5.1 (3.1)	4.7 (2.8)
Health limits physical activity, no. (%)	18 (12)	9 (18)	4 (8)	5 (9)
Feelings of depression or hopelessness, no. (%)	102 (66)	33 (66)	34 (67)	35 (65)

^aWealth was measured using an asset index defined as the sum of affirmative responses to questions about ownership of 10 household items. These 10 items represent the most common household items included in the Demographic and Health Survey's (DHS) Uganda survey and the index places equal weight on participants' self-reported ownership of each individual item.

^bBecause of varying exchange rates, US dollar conversions (from Ugandan shillings) are approximate, and are based on the prevailing rate of 1 USD to 3450 Ugandan Shillings during this study period.

and generally statistically insignificant observable differences between intervention groups, the preferred analytic specification for analysis is the unadjusted regression model comparing mean adherence rates between intervention groups and the control group. To account for the small changes in baseline variables between the three groups, however, we also present results controlling for the main observable demographic differences between intervention groups, and find that the demographic controls are statistically insignificant in all regression models.

Impact of behavioral economic incentives on antiretroviral adherence

Table 2 shows the impact of the incentives on mean adherence rates separately for the two intervention groups, as well as when the intervention groups are combined. Although adherence in the control group was 80.9% [95% confidence interval (CI), 74.8–87.1%], those in the intervention group 1 show adherence that was 88.3% (95% CI, 84.7–91.9%), which is 7.4% higher, and those in intervention group 2 had a mean adherence level of 86.7% (95% CI, 81.9–91.6%). In the unadjusted regression, these differences in mean adherence are statistically significant only for intervention group 1, and marginally significant at conventional significance levels for the combined treatment groups.

These intervention impacts were unlikely to be experienced equally by all members of the target population for this study. For example, small incentives are likely to be least effective for clients with structural adherence barriers such as high clinic commuting costs or family/social stigma. To investigate the heterogeneity of intervention effects, Fig. 2 displays the observed distribution of 9-month mean adherence rates across each study group. The kernel density distributions are estimated using equal size bandwidths and the Epanechnikov kernel function. This figure shows that the intervention impacts are most pronounced around the 90% mean adherence threshold, which suggests that the

outcome measure of the proportion of clients maintaining at least 90% mean adherence is likely capturing the key impact of the behavioral change induced by RAP.

Table 3 presents the probit regression results for a binary outcome measure that takes on the value of 1 for clients who show at least 90% adherence over the first 9 months of RAP, and shows positive improvements in both intervention groups. Although 39.6% (95% CI, 25.8–54.7%) of the participants in the control group showed a mean adherence level of at least 90%, the fraction in the combined intervention groups was 63.3% (95% CI, 52.9–72.8%). Probit regression analysis indicates that those in either one of the intervention groups were more likely to have adherence of at least 90%; (intervention group 1 marginal effect, 21.5%; 95% CI, 0.9–42.1%; intervention group 2 marginal effect, 26.2%; 95% CI, 6.2–46.3%), and this increase was statistically significant at the 5% level among both intervention groups. The effects are larger in intervention group 2 than in intervention group 1, but this difference is not statistically significant (P value = 0.45; 4.7%; 95% CI, –0.4 to 9.8%). Results from the adjusted probit regression analyses were similar, with slightly smaller increases in the marginal effects estimated (intervention group 1 marginal effect, 20.5%; 95% CI, –1.3 to 42.3%; intervention group 2 marginal effect, 24.8%; 95% CI, 4.0–45.7%), and only the intervention group 2 marginal effect is statistically significant at the 5% level (P value = 0.02). Additional adjusted regression models were estimated using the measures of physical and mental health status, and the inclusion of these additional variables does not alter the magnitude or significance of the estimated intervention effects.

Discussion

In this study, we present evidence that it is feasible and effective to use small behavioral economics incentives to

Table 2. Impact of incentives on mean antiretroviral adherence over 9 months.

	Control	Intervention groups			<i>P</i> value for test of equality ^c
		Group 1	Group 2	Groups 1 + 2	
No. of participants	48	46	52	98	
Mean adherence % (95% CI)	80.9 (74.8–87.1)	88.3 (84.7–91.9)	86.7 (81.9–91.6)	87.5 (84.4–90.5)	
Unadjusted ^a impact (95% CI)	1 (Reference)	7.4 (0.3–14.4)	5.8 (–1.9 to 13.6)	6.6 (–0.2 to 13.3)	0.510
<i>P</i> value		0.040	0.140	0.057	
Adjusted ^b impact (95% CI)	1 (Reference)	6.4 (–0.7 to 13.5)	4.7 (–2.9 to 12.3)	5.2 (–1.6 to 11.9)	0.511
<i>P</i> value		0.077	0.225	0.131	

CI, confidence interval.

^aResults from ordinary least squares (OLS) regression model of mean adherence during the first 9 months of Rewarding Adherence Program with indicators of intervention groups (control group is the reference standard).

^bResults from OLS regression model with indicators of intervention groups and controls for age, sex, education, wealth, and marital status.

^c P value from F-test of equality between treatment group 1 and treatment group 2.

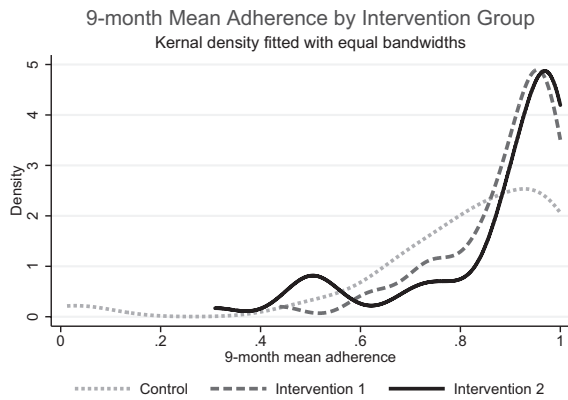


Fig. 2. Observed distribution of 9-month mean adherence.

increase antiretroviral adherence. Using in-kind prizes valued at less than \$2 USD, the intervention resulted in a 23.7 percentage point increase in the fraction of clients showing mean adherence of 90% or higher. These improvements were made using items valued at roughly half of the cost of travel to the HIV clinic, which represent significantly smaller transfers than employed in most other interventions targeting antiretroviral adherence [16]. These beneficial effects occurred both in intervention group 2, in which adherence was directly incentivized, and intervention group 1 in which participants were eligible for prize drawings if they came to the clinic on their scheduled appointment days. This finding is important as it indicates that such an intervention may not have to rely on expensive MEMS cap-based adherence measurement to increase adherence, but can instead be based on timely clinic attendance, which is easier and less costly to verify. However, we do find some evidence that direct adherence incentivization may be more effective, but a fully powered study is necessary to

provide more conclusive evidence on this question. Interventions leading to increased adherence can be cost-effective if they lead to lower levels of adherence support needed, and subsequently lower rates of drug resistance and the need to switch to expensive (and in sub-Saharan Africa not always available) second or third-line treatment. Given the low payouts used in our intervention we expect that it is likely cost-effective, which we intend to test in the fully powered trial based on the current study.

The RAP study is to our knowledge the first to use small incentives based on insights from behavioral economics and allocated by a drawing for improving antiretroviral adherence, and contributes to a growing body of literature that uses such incentives to improve chronic health behaviors [35,36]. Our study suggests that designing incentives based on behavioral economic insights can increase their effectiveness, and get beyond the often at best mixed results of recent interventions aimed at behavioral change in the HIV field based on traditional, fixed incentives of relatively large monetary value. A larger, fully powered study is needed to confirm these early promising results, and would allow the results to additionally detect demographic subgroup differences to shed light on the characteristics of patients most likely to benefit from the intervention. In the current study, those with already relatively high (but not optimal) adherence seem to be benefitting disproportionately from the intervention, which is in line with our hypothesis that for our sample of treatment-mature clients motivational rather than structural barriers are addressed by the small incentives offered. A larger study would also be able to quantify the potentially differential treatment impact across participants' behavioral biases, which our study was not powered to detect. In particular, clients' present bias may play an important role for medication adherence in chronic conditions, and such clients may also be

Table 3. Impact of incentives on reaching 90% mean antiretroviral adherence over 9 months.

	Control	Intervention groups			P value for test of equality ^c
		Group 1	Group 2	Groups 1 + 2	
No. of participants	48	46	52	98	
Mean adherence above 90%					
No.	19	28	34	62	
% (95% CI)	39.6 (25.8–54.7)	60.9 (45.4–74.9)	65.4 (50.9–78.0)	63.3 (52.9–72.8)	
Unadjusted ^a					
ME (95% CI)	1 (Reference)	21.5 (0.9–42.1)	26.2 (6.2–46.3)	23.8 (6.4–41.2)	0.453
P value		0.040	0.010	0.007	
Adjusted ^b					
ME (95% CI)	1 (Reference)	20.5 (–1.3 to 42.3)	24.8 (4.0–45.7)	21.2 (3.0–39.4)	0.457
P value		0.065	0.020	0.023	

CI, confidence interval; OR, odds ratio.

^aMarginal effects from probit regression model of attaining at least 90% mean adherence during the first 9 months of Rewarding Adherence Program with indicators of intervention groups (control group is the reference standard).

^bMarginal effects from probit regression model with indicators of intervention groups and controls for age, sex, education, wealth, and marital status.

^cP value from F-test of equality between treatment group 1 and treatment group 2.

particularly likely to respond to the relatively short-term rewards underlying the current intervention [37].

There are several limitations to our study. First, it does not have a biological endpoint such as viral load for cost reasons, which should be a goal for a larger study. Although adherence was measured using MEMS caps, which is currently one of the most accurate ways to measure adherence, we cannot exclude the possibility that some participants consciously manipulated the pill bottle openings to increase their chances of receiving the incentives. However, as we observe similar adherence improvements in the group incentivized for keeping their scheduled clinic appointments, this seems to be a limited problem. Second, the incentives provided were in-kind and of very small monetary magnitude (umbrellas, coffee mugs, water bottles). We can therefore not speak to the (potentially greater) effectiveness of different types of incentives (such as cash versus in-kind), or larger prizes that may still be cost-effective. Third, as this article provides evidence of the impact of incentives for the first 9 months of an ongoing study, we cannot verify the longer term effects of these incentives, or whether any effects persist after the incentives are withdrawn. The evaluation of treatment effects over the full 20 months study duration and 6 months postintervention will be better positioned to investigate such effects. However, being able to improve adherence over 9 months using in-kind incentives that cost \$1.50–2 USD is a significant achievement.

In conclusion, small in-kind incentives based on insights from behavioral economics were found to result in improved adherence to antiretrovirals over 9 months among HIV-positive, treatment-mature adults in HIV care in a clinic in Kampala, Uganda. These adherence improvements were experienced by participants in an intervention group eligible for incentives based on MEMS caps-measured adherence directly, as well as participants in a group that received incentives for timely clinic visits. The impact of offering different incentive types and amounts will require further research.

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Conflicts of interest

There are no conflicts of interest.

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