# Indiscriminate Social Learning among Physicians Providing HIV Treatment

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**Abstract**

Social learning has been identified as an important mechanism for information transfer in the workplace; however, extant research on social learning has been limited to settings where workers can simultaneously observe peers' behavior and the immediate outcome of peers' performance. In these settings, research has identified a beneficial effect from social leaning on workers' performance. The current paper contributes to this growing literature on social learning by identifying the detrimental as well as beneficial effects of social learning on performance in a high-stakes medical context without an immediately observable outcome: physicians' HIV treatment practices. The findings reveal that inexperienced physicians indiscriminately learn proper and improper HIV treatment practices from their more-experienced peers, resulting in differential patient health outcomes depending on experienced peers' task performance. The paper then uses network-structure analysis to identify organizational policies that leverage beneficial social learning effects to help reduce the transmission of improper treatment practices, thereby improving overall treatment performance and subsequent medical outcomes for HIV-infected patients.

**Keywords:** workplace peer effects; social learning; physician behavior; physician patient-sharing networks.

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All errors are my own.

# 1 Introduction

Workers' access to and command of task-specific knowledge is an important determinant of performance in many workplace settings. Social learning has long been theorized to be a key mechanism for information transfer in the workplace (Arrow, 1994), and a better understanding of the influence that social learning can have on task-specific performance will allow for more efficient workplace organization and improved productivity. However, the effect of social learning on overall productivity is difficult to empirically identify. Without the ability to conduct behavioral experiments in many workplace settings, observational methods must overcome several confounding biases to convincingly estimate social learning among workers (Manski, 1993). Additionally, few successful observational studies are able to simultaneously identify the effect of social learning on specific tasks and relate these changes in task performance to workers' overall productivity. Extant research on workplace social learning has identified a beneficial effect on workers' productivity, but the characteristics of these employment settings limit the generalizability of these results.

One common method for describing the effect of social learning on overall productivity is to directly relate changes in peers' productivity to a workers' own productivity. For example, improved teacher training leads to an increase in students' standardized test scores for both participating teachers and their peers (Jackson and Bruegmann, 2009), while the absence of a 'star' researcher reduces the publication success of their academic peers (Azoulay, Zivin, and Wang, 2010). However, in these cases positive workplace peer effects are difficult to clearly disentangle from other forms of social influences, such as peer-induced human capital investment or peer pressure. The challenges faced by these studies of workplace peer effects highlight the importance of observing workers' performance on specific tasks in order to more convincingly identify social learning between workers.

An alternative method for identifying the effect of social learning on overall productivity is to analyze workers' performance on tasks that immediately produce the final output. For example, social learning was found to beneficially impact the monthly sales of beauty products for new salesmen who are able to observe the sales practices of more experienced peers (Chan, Li, and Pierce, 2014), and cardiothoracic surgeons are more successful at minimally invasive cardiac surgery after observing peers' past surgical mistakes (KC, Staats, and Gino, 2013). In these settings, workers

are able to clearly observe the immediate outcome of peers' task performance, which can help to differentiate the successful and unsuccessful practices of their peers. However, when task performance does not produce an immediately observable outcome, social learning may become an unreliable method for acquiring task-specific knowledge and skills. Currently, little is known about the effect of social learning on performance in such workplace settings.

The current paper contributes to the growing literature on workplace peer effects by identifying the detrimental as well as beneficial effects of social learning on task performance in a high-stakes medical context without an immediately observable outcome: physicians' HIV treatment practices. Using a panel dataset of Medicare insurance claims data, this paper can clearly observe physicians' performance of a high-complexity HIV treatment task that is universally recommended for all HIV-infected patients. A physician's performance on this high-complexity task is essential for maintaining the efficacy of a patient's HIV medication regimen and for reducing the risk of HIV transmission, but task performance does not have an immediate impact on HIV-infected patients' health. This allows for the possibility that physicians learn improper HIV treatment practices from observations of peers' poor performance on this high-complexity task.

This paper also contributes to an existing literature that has identified physician peer effects in a variety of healthcare settings, but has yet to isolate or quantify the specific role of social learning in shaping these workplace peer effects. Specifically, researchers have shown that physicians who move geographically conform to their new local treatment norms (Molitor, 2018; Epstein and Nicholson, 2009), physicians strategically exert effort in the emergency room based on observations of their peers' workload (Chan, 2016; Silver, 2016), and physicians are influenced by peers when making their prescription drug choice (Nair, Manchanda, and Bhatia, 2010) and adopting new medical procedures (Escarce, 1996; Burke, Fournier, and Prasad, 2007; Coleman, Katz, and Menzel, 1957). In each of these settings however, the authors are not able to identify the specific contribution of social learning to their physician peer effect estimates, and, in most of these cases, social learning can be explicitly ruled out in favor of other behavioral mechanisms such as peer pressure (Molitor, 2018; Epstein and Nicholson, 2009), freeloading (Chan, 2016; Silver, 2016), or mimicking peers' treatment choices (Escarce, 1996; Burke, Fournier, and Prasad, 2007; Coleman, Katz, and Menzel, 1957). Additional qualitative research has described how social learning can shape physicians' behaviors (Schectman et al., 2003; Chaillet et al., 2006), but does not provide

clear evidence for the significance and magnitude of these knowledge transfers. Additionally, these facility-specific estimates are not immediately generalizable to a broader healthcare setting.

Fortunately, studying social learning among physicians in the context of HIV treatment has several important advantages that allow this paper to overcome these previous limitations. First, the primary treatment for an HIV-infection, Antiretroviral Therapy, has been universally recommended by all HIV Clinical Practice Guidelines (CPGs) since its introduction in 1996. This allows for consistent measures of physicians' HIV treatment task performance during the sample period (2007 – 2010). Second, there are several recommended components of Antiretroviral Therapy that are clearly observable in insurance claims data and can be assessed without knowing additional demographic, diagnostic, or other patient-level information. Third, the majority of HIV-infected patients in this sample (65.3 percent in 2010) are treated by a small minority of physicians (17.8 percent in 2010) who have developed expertise in treating HIV-infections. Clinical specialization in this setting is known to improve physicians' adherence to the CPGs (Landon et al., 2002), and non-HIV specialist physicians report that they frequently consult with their more experienced peers on the appropriate HIV treatment for their patients (Keating, Zaslavsky, and Ayanian, 1998; Gabbay and le May, 2004). This frequent transfer of HIV-specific treatment knowledge between HIV specialists and their non-HIV specialist, or *generalist*, peers is directly captured by this paper's modeling approach and presented as evidence of social learning between physicians on their treatment practices.

This paper thus uses observations of physicians' HIV treatment decisions for the population of HIV-infected patients on Medicare to explicitly identify social learning between physicians across healthcare facilities in California. Repeated observations of physicians' HIV treatment decisions for a given patient within a calendar year are used to estimate a panel model that can address many of the common empirical challenges to estimating peer effects through observational data. For this paper, HIV treatment task performance is defined by physicians' adherence to two different CPGs that differ in task complexity. In addition to these HIV treatment performance measures, the insurance data provide robust estimates of physicians' professional networks. This network construction approach mirrors the existing medical and social networks literature that frequently estimates physicians' professional networks from observations of patient-sharing relationships (Pollack et al., 2014; Landon et al., 2012; Agha et al., 2018), and has been vali-

dated against more detailed, survey-based network measurement techniques (Barnett et al., 2011). Based on these observed professional relationships, the model of social learning relates the contemporaneous treatment task performance of a physician to the past treatment performance of their immediate peers who share one or more HIV-infected patients in the sample period.

To control for the wide range of possible confounding variables in this specification, the model includes an extensive set of physician, patient, and region-time fixed effects similar to the worker and firm fixed effects models estimated in Card, Heining, and Kline (2013) and Cornelissen, Dustmann, and Schönberg (2017). Specifically, physician fixed effects are used to account for the potential sorting of high-performing physicians into high-performing peer groups, where the social learning parameter is estimated from within-physician variation in peers' treatment performance. To account for potential correlated, or "contextual," effects that simultaneously impact the treatment performance of both physicians and their peers (Manski, 1993), the model also includes region-year fixed effects. Patient-level fixed effects capture any time-invariant health attributes of a patient that potentially impact the complexity of their HIV treatment. Finally, by estimating the time-varying structure of physicians' full professional networks for this patient population, a novel instrumental variables approach is used to further address the network selection, correlated effects, and reflection problem that is common to all reduced form peer effects estimates (Manski, 1993; Bramoullé, Djebbari, and Fortin, 2009; Aral, 2011). As discussed further in Section 4, the combination of these modeling techniques allows for a new identification strategy of social learning that can be extended to a wide range of other workplace settings using only observational data.

The results in this paper improve our understanding of physician peer effects while also making several broader contributions to the literature on social learning in the workplace and organizational policy. First, the observed heterogeneity in peer effects across physicians' clinical specialization for a complex HIV treatment task provides the first convincing evidence of social learning between physicians. Additionally, this paper identifies an indiscriminate social learning process through which inexperienced physicians learn both proper and improper HIV treatment practices from their more-experienced peers. Second, this paper uses estimates of physicians' professional network over time and across facilities to causally identify physician peer effects. This identification strategy is able to capture social learning between physicians that occurs both within and across healthcare facilities, which increases the generalizability of these results. This stands

in contrast to the existing research that relies on either experimental evidence or natural variation in physicians' peer group assignment that occurs within a single healthcare facility. More broadly, this identification strategy outlines how the temporal dynamics of social networks can be used identify the nature of social learning among workers across many different professional settings.

In addition to estimating social learning through observational data, this paper simulates the impact of organizational policies that leverage beneficial social learning effects while reducing the transmission of improper treatment practices to improve patient health outcomes. Specifically, network-structure analysis is used to optimize the position of high-performing HIV specialists within regional networks, and estimate the resulting improvements to treatment practices and health outcomes. Promoting better performance on the high-complexity HIV treatment task also has important benefits for reducing the spread of HIV, thus these policy simulations are additionally able to outline cost-effective methods for combating the domestic HIV epidemic.

This paper proceeds as follows. Section 2 discusses the recommended HIV treatment tasks and describes how physicians' patient-sharing relationships are used to identify professional peers. Section 3 outlines the data sources, sample selection, and measurement techniques used in the analyses. Section 4 discusses the empirical identification strategy. Section 5 presents summary statistics for physicians' estimated professional networks, and Section 6 discusses the estimation results. Section 7 describes the policy simulation exercises, and Section 8 concludes. Additional details on sample construction procedures and the characteristics of patients and physicians in the analytical sample are included in the Appendix.

# 2 Background

## 2.1 Recommended HIV Treatment Tasks

There are approximately 1.2 million people currently living with HIV in the United States (CDC, 2016). These HIV-infected patients are universally treated with antiretroviral (ARV) medications, which can dramatically suppress the presence of the HIV virus in a patient's body, eliminating HIV symptoms and significantly extending life expectancy. Additionally, ARV medication can reduce 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); this reduction in new infections underlies the estimated cost

savings from the simulated policies in Section 7.

All HIV Clinical Practice Guidelines (CPGs) universally recommended that ARV medications be taken in a daily regimen composed of *three* different drugs. As shown in Table 1, a physician can choose from over 35 FDA approved HIV drugs for a patient's drug regimen. However, the adaptability of the HIV virus severely limits the potency and efficacy of any individual drug. This is why a recommended drug regimen is composed of *three* drugs that should be selected from at least *two* different drug classes, where each class suppresses different stages of the HIV viral replication process. By interrupting two different replication stages, a recommended regimen is more robust to frequent HIV viral mutations, and more likely to produce long-term HIV viral suppression.[1]

Among the 1.1 million HIV-infected patients receiving ARV medications in the U.S. in 2009 however, only 75.8 percent had achieved the optimal level of HIV viral suppression targeted by ARV medications (CDC, 2012). Specifically for this paper's sample population, only 69.1 percent of the estimated 125,821 HIV-infected patients in California in 2010 who were being treated with HIV medications were considered virally suppressed (Office of AIDS, 2010).[2] The diminished efficacy of HIV medications is the product of non-adherence to the CPGs by both physicians and patients. While patients' non-adherence is a well-documented problem in the treatment of all chronic conditions (Brown et al., 2016) and many behavioral interventions have been proposed to improve patients' HIV medication adherence (Linnemayr, Stecher, and Mukasa, 2017), physicians' non-adherence can be directly observed in Medicare claims data, and is the focus of this paper's analyses.[3]

In addition to combining HIV medications from at least two different drug classes, hereby referred to as the *high-complexity task*, all HIV CPGs recommend that physicians prescribe a combined HIV drug when appropriate. These combination drugs, highlighted in the second panel of Ta-

[1] An 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.

[2] Even lower levels of viral suppression were experienced by rural communities (Weissman et al., 2015) and among disadvantaged socioeconomic populations (Landovitz, Desmond, and Leibowitz, 2017) where the access to specialized HIV care has historically been the most limited (Bozette et al., 1998)

[3] The mechanisms proposed in this paper for improving physicians' performance of these CPGs are not expected to entirely improve the efficacy of HIV medications, and the confounding impact of patients' non-adherence is accounted for in the simulated policy effects described in Section 7.

ble 1, contain two or more active agents in a single pill, reducing patients' daily pill burden, which is known to increase patients' medication adherence (Buscher et al., 2012). In 2007, there were three FDA approved combination pills. Determining whether any of the three combination drugs is suitable for a given patient requires less disease-specific knowledge then the high-complexity task, identifying an optimal drug regimen from the over 6,000 different drug combinations in the top panel of Table 1, so physicians' performance of this secondary CPG task will be referred to as the *low-complexity task*.

Table 2 shows how HIV CPGs help physicians determine an appropriate treatment in several common clinical scenarios, such as harmful interactions between HIV drugs, potential HIV viral mutations, and a patient's genetics, comorbidities, and medication adherence rates.[4] In all scenarios, the prescribed medication regimen should still contain drugs from multiple classes and use a combined ARV drug when feasible. Physicians' performance of both the high-complexity and low-complexity tasks are necessary for increasing the effectiveness of ARV medications, improving HIV-infected patients' health, and closing critical geographic and socioeconomic disparities in domestic HIV prevalence (CDC, 2016).

Medical research has documented the benefits of physician specialization in performing both the high- and low-complexity HIV treatment tasks, where specialization is defined in terms of both clinical experience and academic training. Specifically, physicians with large HIV-infected patient caseloads have been associated with better patient 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 by physicians' academic training find that a higher proportion of infectious disease specialists correctly initiate ARV medications (Landon et al., 2002) and appropriately counsel patients on treatment adherence strategies (Duffus et al., 2003). For this paper, HIV specialization is identified by both academic training (infectious disease academic specialty) and HIV patient caseload ($\geq 95^{\text{th}}$ percentile of observed annual caseloads in this sample).[5] These criterion are used to categorize physicians into two groups, *HIV specialists* and *generalists*, which is consistent with

[4] For example, patients that test positive for specific genetic mutations (e.g. HLA-B*5701) should not be treated with certain medications (e.g. abacavir), and patients with osteoporosis should not be treated with other ARV medications (tenofovir disoproxil fumarate).

[5] The $95^{\text{th}}$ percentile of observed annual caseloads is roughly equal to 42 patients in this sample.

definitions used by the medical literature.[6] This paper's main model of workplace peer effects divides peers by these groups, and their heterogeneous influence on physicians' performance of the high- and low-complexity HIV treatment tasks are used to test for the presence of social learning in this workplace setting.

## 2.2 Physicians' Professional Networks

Physicians' professional networks are constructed based on observed patient-sharing relationships in Medicare insurance claims. Specifically, network links are recorded between physicians performing HIV evaluation and monitoring procedures for the same HIV-infected patient.[7] This technique has been previously used 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 professional interactions (Keating, Zaslavsky, and Ayanian, 1998; Barnett et al., 2011).

Physicians' patient-sharing networks are used to identify their social interactions in the workplace. Previous research has found that these patient-sharing connections identify as much as 82 percent of the unobserved referral and advice relationships between physician colleagues (Keating et al., 2007). Moreover, patient sharing may serve as a direct mechanism for social learning in this setting. Since ARV medications are the universally recommended treatment for an HIV infection, physicians are likely to review clinical charts and past prescriptions before prescribing a new drug regimen. Observing peers' past treatment decisions for a shared patient provides a salient example of how to perform both the high- and low-complexity HIV treatment tasks given the shared patient's specific health status, and thus is the main channel for social learning being investigated in these analyses.

These informal patient-sharing networks observed through health insurance claim data have been found to predict many important health care outcomes. Specifically, these network estimates have helped to explain differences in medical costs (Landon et al., 2012), physicians' practice patterns (Pollack et al., 2013; Agha and Zeltzer, 2018), and patient outcomes (Pollack et al., 2014). In light of the large geographic variation that exists in medical spending (Skinner, 2011), the significant role of physician networks in explaining regional differences in treatment costs and intensity

[6] The results of this paper are robust to small changes in these definitions for *specialists* and *generalists*.

[7] See Appendix for a more detailed discussion of the selection of physicians from the Medicare claims records.

highlights the importance that physician relationships have in determining clinical practice patterns and norms (Wennberg and Cooper, 1996; Landon et al., 2012; Barnett et al., 2012). Additionally, recent research has documented the specific contribution of physicians' beliefs in determining the large regional variation observed in health care costs and treatment practices (Cutler et al., 2019). 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). This paper will use the heterogeneity in physician peer effects across HIV specialization and treatment task complexity to identify the presence of social learning through patient-sharing interactions, and then will use these estimates to suggest organizational policy that can improve aggregate performance.

# 3 Data

## 3.1 Data Sources

The main source of data for this paper are fee-for-service (FFS) Medicare Inpatient, Outpatient, Hospice, and Part D drug claims for all HIV-infected patients filed between 2007 and 2010 in California.[8] In 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), making this an important and significant sample population to study and inform policy design. I use Medicare insurance claims for FFS plan enrollees only, because these data contain the detailed diagnostic and procedural codes necessary for confirming a patient's HIV status and observing physicians' performance of the high- and low-complexity HIV treatment tasks. The final panel data set of Medicare claims contains repeated observations of physicians' performance on the HIV treatment tasks for each patient, as well as detailed information about patients' changing health status.

This selected sample of physicians and patients affects the results in one potentially important dimension. Estimating physicians' professional networks only for shared Medicare patients introduces an important source of measurement error when identify peer physicians, which I dis-

[8] Identifying HIV-infected patients through the FFS claims is based on an algorithm developed in Leibowitz and Desmond (2015). See Appendix for more details on the sample construction.

cuss further in Section 6. Patient selection however, can be addressed using the detailed diagnostic codes available in the data. Since the estimation strategy employs patient-level fixed effects to control for time-invariant patient characteristics, such as genetics and historical health status, changes in a physician's HIV treatment for a given patient can measured conditional on a patient's time-varying health status.

I combine these insurance claims data with physician background information contained in the American Medical Association (AMA) Masterfile. The annual primary 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 and Cooper, 1996). These regional HRR boundaries are generated by the referral patterns between hospitals, and enable me to control for potential correlated (or contextual) effects that may be impacting all physicians simultaneously within a particular geographical region. The complete set of variables drawn from each data source are listed in Table 3.

## 3.2 Physician Networks

Physicians observed on FFS Medicare Part D drug claims are directly linked to one another in the network if they write an HIV medication prescription for the same patient. Only Part D claims for patients' *new* prescriptions are used to construct this patient-sharing network, because most prescription refills occur at a pharmacy and rarely necessitate physician decision-making or professional interactions. Thus, physician peers are identified by treating one or more shared HIV patients during the sample time period. Since this paper is specifically estimating the social learning that occurs through sharing patients, patient-sharing connections formed after an observed treatment decision are not considered. Thus, for a given physician, only the other physicians who wrote prescriptions for shared patients prior to the contemporaneous patient visit are identified as peers.

Within the FFS Medicare Part D data, I calculate a measure of peers' performance on the high- and low-complexity HIV treatment tasks as the average performance 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' performance measure. Thus the analytic sample begins in 2008 after a full year of

prescriptions are observed. This allows the measure of peers' performance to be applied consistently across the remaining three years of data in the sample. Additionally, observations of peers' performance are weighted based on their recency to capture the natural decay in information transmitted from more historical clinical interactions.[9] Finally, I only consider peers' treatment choice for patients who are not shared between peer physicians. Otherwise, a physician who continues the same treatment strategy of prior physicians for their shared patient(s) would automatically appear to have similar HIV treatment task performance. Similarly, this removes the possibility that a physician transfers all (or some of) their patients to their peers who simply continue their prior treatments.

I construct a second set of peers' task performance measures to test for the presence of heterogeneous peer effects across physicians' clinical specialization. As discussed previously, HIV specialization is important determinant of treatment practices, yet the majority (73.3 percent) of physicians treating this patient population are generalists.[10] So, I calculate the average treatment task performance separately among specialist and generalist peers to estimate the peer effects exerted by these two physician groups.

The final independent variables describing peers' treatment performance of the high-complexity $(H)$ and low-complexity $(L)$ HIV treatment tasks are defined for physician $j$ treating patient $i$ in region $r$ on day $d$ with a caseload $\Omega_j$ over the past 12 months in the following way:

$$\overline{Q_{\{H,L\}ijrd}} = \sum_{d'<d} \sum_{j' \neq j} \sum_{i' \notin \Omega_j} \omega_{i'j'dd'} \left( Q_{\{H,L\}i'j'rd'} \right) \; ; \quad \text{where}$$

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

Similarly,

$$\overline{Q^T_{\{H,L\}ijrd}} = \sum_{d'<d} \sum_{j' \neq j} \sum_{i' \notin \Omega_j} \omega_{i'j'dd'} \cdot \upsilon^T_{j'} \left( Q_{\{H,L\}i'j'rd'} \right) \; ; \quad \text{where} \quad \omega_{i'j'dd'} = \frac{L_{i'j'd'} \cdot f(d-d')}{\sum_{d'<d} \sum_{j' \neq j} \sum_{i' \notin \Omega_j} L_{i'j'd'} \cdot \upsilon^T_{j'} \cdot f(d-d')}$$

[9] The 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.

[10] See Table A2 for additional characteristics of the physicians contained in this sample.

$\overline{Q_{\{H,L\}ijrd}}$ is the weighted average treatment task performance of all peers linked through at least one shared patient in the past twelve months, and $\overline{Q^T_{\{H,L\}ijrd}}$ separately estimates the weighted task performance of all directly linked generalist and specialist peers, where $T \in \{Generalist,\ HIV\ Specialist\}$. The HIV treatment task performance of physician $j'$ treating patient $i'$ on day $d'$ is recorded by an indicator variable that is equal to one if the prescription adheres to the recommended high-complexity task $\left(Q_{Hi'j'rd'}\right)$ or low-complexity task $\left(Q_{Li'j'rd'}\right)$. These peers' performance measures assume that the treatment choice for physicians $j' \neq j$ treating patients $i' \notin \Omega_j$ on 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' performance by physician specialization includes an additional component $\upsilon^T_{j'}$, which identifies whether a physician peer $j'$ is either a generalist or an HIV specialist.

# 4 Identification Strategy

The model of physician peer effects assumes that the data generating process for physicians' treatment performance is linear in a set of physician, patient, and regional attributes, and is separably influenced by the behavior of a physician's peers. A linear probability model is used to describe the likelihood of physicians' adherence to the recommended high- and low-complexity treatment tasks because the model specifies fixed effects at the patient, physician, and regions-year levels. Since the number of fixed effect parameters would increase with more observations of these data, maximum likelihood parameter estimates would be inconsistent due to the "incidental parameters problem" (Hahn and Newey, 2004). Additionally, estimating the full covariance matrix using maximum likelihood in this setting is computationally difficult. Linear probability model estimates in this paper are used to describe the marginal effect of local changes from the mean level of peers' treatment performance.

In Equations 1 and 2, a single measure of peers' treatment task performance is included additively, which is calculated across all physician types. The probability that the prescription written for patient $i$ by physician $j$ in region $r$ on day $d$ is adherent to the recommended high-complexity treatment task $\left(Q_{Hijrd}\right)$ or low-complexity treatment task $\left(Q_{Lijrd}\right)$ take the following

linear probability functional forms:

$$Q_{Hijrd} = \alpha + \gamma_H \cdot \overline{Q_{Hijrd}} + \beta_H P_{id} + P_i + D_j + N_{rd} + \varepsilon_{ijrd} \tag{1}$$

$$Q_{Lijrd} = \alpha + \gamma_L \cdot \overline{Q_{Lijrd}} + \beta_L P_{id} + P_i + D_j + N_{rd} + \varepsilon_{ijrd}; \tag{2}$$

where $Q_{\{H,L\}ijrd}$ is a binary indicator of successful high- and low-complexity task completion, $\overline{Q_{\{H,L\}ijrd}}$ is the average past performance of the high- and low-complexity tasks among all directly linked physician peers (i.e. physicians connected through one or more shared patients), $P_{id}$ are time-varying patient characteristics, such as the number of comorbidities, $P_i$ and $D_j$ are patient and physician fixed effects, respectively, and $N_{rd}$ are hospital referral region-year indicator variables.

I estimate heterogeneous peer effects by including separate measures of peers' treatment task performance by physician type. The probability that the prescription written for patient $i$ by physician $j$ in region $r$ on day $d$ is adherent to the recommended high-complexity treatment task $\left(Q_{Hijrd}\right)$ or low-complexity treatment task $\left(Q_{Lijrd}\right)$ take the following linear probability functional forms:

$$Q_{Hijrd} = \alpha + \gamma_H^{GEN} \cdot \overline{Q_{Hijrd}^{General}} + \gamma_H^{HIV} \cdot \overline{Q_{Hijrd}^{HIV}} + \beta_H P_{id} + P_i + D_j + N_{rd} + \varepsilon_{ijrd} \tag{3}$$

$$Q_{Lijd} = \alpha + \gamma_L^{GEN} \cdot \overline{Q_{Lijrd}^{General}} + \gamma_L^{HIV} \cdot \overline{Q_{Lijrd}^{HIV}} + \beta_L P_{id} + P_i + D_j + N_{rd} + \varepsilon_{ijrd}; \tag{4}$$

where $\overline{Q_{\{H,L\}ijrd}^{General}}$ is the average past treatment performance of generalist who are direct peers, and $\overline{Q_{\{H,L\}ijrd}^{HIV}}$ is the average past treatment performance of specialists who are direct peers. Estimates for the parameters $\gamma_{\{H,L\}}^{GEN}$ and $\gamma_{\{H,L\}}^{HIV}$ specified by Equations 3 and 4 identify the heterogeneity in peer effects exerted across physician types and treatment task complexity.

This model employs several sets of fixed effect parameters to control for the main sources of bias inherent to peer effects estimation (Manski, 1993; Bramoullé, Djebbari, and Fortin, 2009; Aral, 2011). First, to control for the possibility that physicians' choose their peers based on their HIV treatment performance, often referred to as network selection or *homophily*, Equations 1 – 4 estimate physician-level 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 physi-

cian'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 decisions.[11]

Equations 1 – 4 also include region-year fixed effects. Region-year identifiers ($N_{rd}$) are generated for each of the twenty-four hospital referral regions in California in the three years of data that inform these parameter estimates. Any regional public health policy campaign or other treatment intervention which simultaneously affected both a physician and their peers' treatment practices will lead to an overestimation of the peer effects $\left(\gamma_{\{H,L\}},\ \gamma^{GEN}_{\{H,L\}},\ \text{and}\ \gamma^{HIV}_{\{H,L\}}\right)$. These region-year fixed effects control for the bias of such correlated confounding effects by estimating the average performance of all physicians in a given hospital referral region for each year.

The patient-level fixed effects in Equations 1 – 4 capture the impact of patients' time-invariant characteristics on a physician's HIV treatment decision, such as the patient's genetics, demographics, and unobserved medication adherence behavior. Time-varying patient health characteristics ($P_{id}$) contain identifiers for several common mental health conditions and patients' number of comorbidities, as recorded by the ICD-9 diagnostic codes.[12] These measures serve as proxies for patients' personal health and the complexity of their associated HIV treatment decision.

The final estimates for the influence of physician peers on HIV treatment task performance are based on within-region, within-patient, and within-physician variation in peers' treatment performance and a physician's own performance of the recommended the high- and low-complexity treatment tasks. That is, holding constant the hospital referral region, the patient, and the physician, changes in peers' performance between 2007 and 2010 are related to subsequent changes in an individual physician's performance on the high- and low-complexity tasks.

Finally, I combine two strategies to address the "reflection problem," or the simultaneity bias, which positively biases peer effect estimates from linear models that relate changes in individual behavior to changes in peers' behavior (Manski, 1993). The reflection problem in this setting refers to the difficulty in determining whether a physician's own treatment practices $\left(Q_{\{H,L\}ijrd}\right)$ are influenced by their peers' behavior $\left(Q_{\{H,L\}i'j'rd'}\right)$, or if the direction of causality is reversed. To overcome this bias, I first calculate the measure of peers' treatment behavior for dates prior

[11] The use of fixed effects to model network selection among physicians has been repeatedly used in the peer effects literature (e.g. Nair, Manchanda, and Bhatia (2010); Chan (2016)).

[12] Comorbidities 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).

to the last time a physician interacts with the linking shared patient (denoted $d''$). By controlling for the timing of treatment decisions in this way, a physician's own treatment decision on day $d$ would not be influenced the decisions of other physicians written on days $d'$ that occur between $d''$ and $d$, $d' \notin [d'', d]$. 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. Additionally, patient-sharing links also may identify more frequent, unobservable social interactions between physicians, which additionally contribute a positive bias to the peer effects estimates, so the second strategy addresses this potential bias.

In addition to controlling for the timing of treatment decisions, I also instrument for the performance of a physician's immediate peers with the treatment performance of intransitively connected peers (Bramoullé, Djebbari, and Fortin, 2009). These are the peer physicians who do not share patients with a given physician (thus are not immediate peers), but do share patients with the physician's immediate peers. The main criteria for employing this technique are that patient-sharing networks are heterogeneous in size and that not all physician peers are linked to each other (Rock, Aral, and Taylor, 2016). The observed variability in the number of patient-sharing links within the data ensures that these conditions are satisfied. I calculate the measure of intransitive peers' performance as the average treatment performance of the recommended high- and low-complexity tasks among physicians connected through three patient-sharing links. In constructing this measure of intransitively connected peers' performance, the timing of each treatment decision is also taken into consideration in a similar fashion to the methods described above, which further controls the direction of the estimated peer effects.

Figure 1 further details how the patient-sharing relationships are used to identify both immediate peers and intransitively connected peers. First, the physicians who share one or more patients are considered immediate peers, and the historical performance of these immediate peers are used to construct the primary measure of peers' treatment task performance, $\overline{Q_{ijrd}}$. The peers who do not share patients with a given physician nor that physician's immediate peers are considered intransitively connected peers, connected by two patient-sharing links. The performance of peers who are intransitively connected through three patient-sharing links, as displayed in Figure 1b, is used to instrument for the performance of immediate peers in this model. Linear probability mod-

els are estimated using ordinary least squares, and instrumental variables estimates are calculated through generalized methods of moments.

# 5 Summary Statistics

## 5.1 HIV Treatment Tasks

Table 4 shows that there is wide regional variation in physicians' performance of both the high- and low-complexity HIV treatment tasks during this sample period. Across five aggregate regions of California, the average performance of the recommended high-complexity treatment task ranges from 93 percent in Northern California to 84.3 percent in the Los Angeles area. Among all physicians ($N = 1,030$), the average performance of the high-complexity treatment task was 88.8 percent ($SD = 19.72$), and the bottom $25^{th}$ percentile of physicians had successful performance rates of 84.8 percent or lower.

Since many of the combined ARV pills had been recently approved by the FDA,[13] and because a combined ARV pill is not always available for a given patients' medication regimen, the average performance of the recommended low-complexity treatment task was significantly lower for all physicians. Across the five aggregate regions of California, the average performance of the low-complexity task ranges from 57.8 percent in Southern California and San Francisco to 52.3 percent in Los Angeles. Among all physicians ($N = 1,030$), the average performance of the low-complexity treatment task was 56.4 percent ($SD = 31.76$), and the bottom $25^{th}$ percentile of physicians had performance rates of 29.9 percent or lower. The insignificant regional differences in this low-complexity task suggest that the necessary HIV treatment knowledge for completing this task was more easily and quickly diffused across the state. Conversely, many of the regional differences in physicians' performance of the high-complexity task are statistically significant, suggesting that local peers have more of an influence on this treatment decision.

## 5.2 Physician Network Characteristics

Table 5 outlines two key patterns in physicians' patient-sharing networks observed in these data. First, fewer than 25 percent of the physicians prescribing HIV medications were HIV spe-

[13] The FDA approval date for the combined ARV pills most commonly prescribed in this sample period are the following: *Atripla* (July 12, 2006), *Epzicom* (August 2, 2004), *Truvada* (August 2, 2004).

cialists. Second, over 30 percent of generalist physicians did not share patients with a single HIV specialist. The average performance of the high-complexity treatment task is significantly lower for these generalist physicians who do not have an immediate HIV specialist peer, and the modeling estimates presented in Section 6 help to further quantify the beneficial impact of HIV specialist peers. Table 5 additionally shows physicians' treat an average of 13 patients in 2010, while patients are treated by an average of 1.4 physicians. The average number of treatment decisions made by a given physician for the same patient is roughly three per year, and it is this variation in treatment task performance observed within physician-patient pairs that identifies peer effects in these models.

Figures 2 and 3 plot the annual patient-sharing networks observed in the Palm Springs and San Diego hospital referral regions in 2010, respectively.[14] The observed network fragmentation in Palm Springs (as shown by the larger distance between network clusters) relative to San Diego foreshadows the empirical findings in this research, as Palm Springs had a lower average performance of the high-complexity treatment task and also has more generalist physicians who are not linked to HIV specialists. The average performance of the high-complexity treatment task was 89 percent in Palm Springs and 95 percent in San Diego, while the percent of generalists who do not share patients with an HIV specialist was 33 percent in Palm Springs and only 25 percent in San Diego.

# 6 Estimation Results and Discussion

## 6.1 Social Learning

Significant peer effects on physicians' HIV treatment practices are identified through the observed patient-sharing connections in these data. The relative magnitude and significance of these effects estimated among all physicians are displayed in Table 6 for Equations 1 – 4, which outlines important differences in the estimated effects across physician peers' clinical specialization and HIV treatment task complexity. The probability of performing the high- and low-complexity treatment tasks are transformed into percentage points, so the estimated peer effects parameters $\gamma_{\{H,L\}}$, $\gamma^{GEN}_{\{H,L\}}$, and $\gamma^{HIV}_{\{H,L\}}$ measure the impact of a one-percentage-point increase in peers' performance

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

on the percentage-point change in a physician's own performance of the recommended treatment tasks. Since these models specify both physician- and patient-level fixed effects, the main source of estimating variation comes from changes in treatment decisions for a given physician-patient pair $\{j,i\}$ over time. Thus, standard error estimates for $\gamma_{\{H,L\}}$, $\gamma^{GEN}_{\{H,L\}}$, and $\gamma^{HIV}_{\{H,L\}}$ are double-clustered at the physician and patient levels (Petersen, 2009).[15]

For the high-complexity treatment task, a ten-percentage-point increase in immediate peers' performance raises a physician's own performance by 0.6 percentage points across all physician types. However, when the peer group is separated into HIV specialist and generalist peers, the results show that generalist peers do not significantly impact physicians' performance of the high-complexity task, while a ten-percentage-point increase in HIV specialist peers' performance raises a physician's own performance by 0.7 percentage points. When the treatment behavior of intransitively connected peers is used to instrument for the behavior of all immediate peers (Equations 1 and 2), the estimated peer effect is reduced slightly to 0.4 percentage points. Similarly, the instrumental variable estimates find that generalist peers still do not exert a significant effect while the estimated peer effect of HIV specialist peers is 0.6 percentage points. These smaller instrumental variables estimates indicate that the OLS estimates are positively biased from a combination of simultaneity and network selection. Additionally, the estimate for $\beta_H$ in Equation 3 indicates that a one-standard-deviation increase in the average number of comorbidities in a physician's patient caseload – an increase from 0.52 to 1.41 comorbidities – decreases the physician's performance of the high-complexity task by 0.03 percentage points (not displayed in Table 6). The relatively small influence of patients' comorbidities on a physician's performance of the high-complexity task highlights the importance of physician peers in determining treatment practices.

The instrumental variables estimates of Equations 1 – 4 are generated under conditions of relevant and strong instruments for immediate peers' behavior. 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

[15] This procedure estimates heterogeneous errors for predictions of the same physician's treatment practices across patients, as well as nonzero covariance terms for residuals of the same physician's predicted behavior across different patients, and for residuals of the same patient's treatment across different physicians.

Yogo (2005), which indicates that the treatment decisions of physicians connected through three patient-sharing links is a strong predictor of immediate peers' treatment practices, and Hausman tests for endogeneity confirm that instrumental variables are necessary in this setting (Hausman, 1978). Additionally, the strength of the relationship between intransitively connected peers declines as the number of intransitive patient-sharing links increases. Specifically, the Kleibergen-Papp F statistic decreases from 26.8 to 8.61, 2.61, and 1.17 when using intransitive peers connected through three, four, five, and six patient-sharing links, respectively.

Table 6 also presents the OLS and IV peer effects estimates for physicians' performance of the low-complexity HIV treatment task. Among all physicians, a ten-percentage-point increase in immediate peers' performance raises a physician's own performance by 1.0 percentage points. When the peer group is separated into HIV specialist and generalist peers, the results show that both physician types exert similarly sized peer effects on the performance of this low-complexity task. The instrumental variable estimates for all effects are reduced slightly, where a ten-percentage-point increase in immediate peers' performance now raises a physician's own performance by 0.8 percentage points. This again is indicative of either simultaneity bias or network selection bias in the OLS estimates.

This identification strategy first employs a difference-in-differences framework by relating changes in a physician's treatment performance to changes in the past performance of their peers. To confirm the validity of this modeling approach, Figure 4 plots the average performance of the high-complexity task among all physicians and their HIV specialist peers during the four months before and after a large change the specialist peer's performance. For this analysis, the sample is restricted to cases where physicians treat a shared patient in the same month as an HIV specialist peer physician who demonstrates large changes in their performance of the high-complexity task for other patients in that month. The sample additionally excludes physicians that move within California during the sample period, but as in the full sample, the percent of physician movers is less than four percent and the results are unaffected by their exclusion. These plots confirm the stability of physicians' treatment performance before changes in specialist peers' performance of five percentage points or greater, where plots 4b and 4d show that physicians are responding to both positive and negative changes in specialist peers' performance of the high-complexity treatment task.

The difference in the peer effects the high- and low-complexity tasks are indicative of social learning among physicians in this setting. This is first evidenced by a significant heterogeneity in peer effects exists across peers' clinical specialization for the high-complexity task. Specifically, generalist peers exert no influence on physicians' performance of the high-complexity task, while a ten-percentage-point increase in HIV specialist peers' performance raises a physician's own performance by 0.4 percentage points. The medical literature has shown that HIV specialists perform better on the recommended HIV treatment task (Markson, Cosler, and Turner, 1994; Landon et al., 2005) and that generalists frequently seek advice from their specialist peers (Landon et al., 2005), so we would expect to only observe significant peer effects from specialist peers if the main mechanism for these effects is social learning. Since the high-complexity task requires disease-specific knowledge that a physician needs to tailor for their own patients' health status, simply mimicking peers' treatment choice or replicating local practice norms would not improve performance and would not explain the significant positive relationship between physicians' and peers' performance that results from both large increases and large decreases in peers' performance, as seen in Figure 4. Additionally, since the low-complexity task requires less disease-specific knowledge to implement, other mechanisms for influencing peers' behavior such peer pressure or mimicking peers' behavior can be equally exerted by both HIV specialist and generalist peers. Thus, we would expect to see similar physician peer effects for the low-complexity task, which are not the result of social learning.

To further determine whether social learning is influencing physicians' HIV treatment practices, Tables 7 and 8 examine how the peer effect estimates are heterogeneously experienced by generalist and HIV specialist physicians on the high- and low-complexity tasks, respectively. Table 7 presents the peer effects on physicians' performance of the high-complexity task, where both the OLS and IV estimates are again heterogeneously exerted by peers' clinical specialization. While generalist peers do not influence either generalist or HIV specialist physicians, HIV specialist peers significantly influence both groups, and the HIV specialist peer effects are larger for generalist physicians ($H_0 : \gamma_H^{HIV} = \gamma_H^{GEN}; p = 0.007$); generalists experience a 0.07 percent increase in performance of the high-complexity task from a one percent increase in the performance of their HIV specialist peers. An HIV specialist only increases their performance by 0.04 percent when their HIV specialist peers increase performance by one percent, which indicates that the marginal im-

pact of improved peers' performance diminishes for higher performing physicians. This suggests that HIV specialists are less likely to seek advice from and be informed by their physician peers. Conversely, the largest effect on the high-complexity task is experienced by generalist physicians from their HIV specialist peers, which is consistent again with the interpretation of social learning between generalists and specialists (low- and high-experienced workers).

## 6.2 Robustness of Model Estimates

The peer effect estimates in this paper are robust to alternative methods for constructing the peers' treatment performance measure, defining patient-sharing network links, and estimating the models using regional sub-samples. First, the peers' treatment performance measure computes the average performance of peers in the past twelve months. Instead of weighting previous treatment decisions by the reciprocal of the time gap between past and current prescriptions $\left(\frac{1}{d-d'}\right)$, Table 9 first shows estimates of Equation 3 under alternative temporal weighting procedures. Weighting peers' performance by the number of days since the past treatment decision (*linear temporal weighting*) or including only the previous five treatment observations does not diminish the size or significance of the heterogeneous peer effects estimates. Second, defining patient-sharing links between only those physicians who share at least five patients does not reduce the magnitude of the peer effect estimates. Instead, by eliminating physicians who are not as strongly connected with other physicians in this sample, the peer effect estimates increase slightly. This suggests that the number of shared patients may serve as a measure for the strength of physicians' professional connections, and further indicates that physicians are not copying the treatment choices of their peers which would be equally possible when sharing fewer patients. Finally, when peers are randomly assigned, creating an artificial physician network, parameter estimates for Equations 1 – 4 are not statistically different from zero. This is an important falsification test that is commonly used to verify the identification of peer effects through networked panel data (Rock, Aral, and Taylor, 2016).

Another possible concern with the estimation methods is that hospital referral region (HRR)-year fixed effects are unable to control for more localized contextual influences of treatment practices. For example, a policy called *Test and Treat* was introduced in 2009 in San Francsico, CA to promote the immediate initiation of HIV medications for all HIV-infected patients (Schwarcz, Hsu,

and Scheer, 2015), which could have also improved physicians' performance the high-complexity task by raising awareness of the HIV CPGs. The results in Table 9 show that the heterogeneous peer effect estimates maintain their significance and magnitude when either the San Francisco or the Los Angeles metropolitan areas are excluded from the estimation. These two regions represent roughly 19 percent and 30 percent of treatment observations in these data, respectively. The stability of the heterogeneous parameter estimates confirms that localized policy within the two most populous 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 – 4 if the true relationship between an individual physician's treatment performance and their peers' performance is nonlinear around the mean level of treatment task performance. Despite the documented bias in estimating panel non-linear models with many fixed effect parameters (Hahn and Newey, 2004), a panel probit functional form was also estimated for Equations 1 – 4. The parameter estimates identified through this method are not statistically different from those presented in Table 6 and are of the same significance, which supports the use of linear probability models for describing the marginal effect of changes in peers' performance local to the average performance in the sample. The policy simulations in Section 7 use the linear probability model estimates to describe the impact of physician network redesign based on small changes in peers' performance from the sample mean.

An equally important source of bias in the parameter estimates of Equations 1 – 4 comes from the partial observation of physicians' true patient-sharing network. A complete census of Medicare insurance claims 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 (Pollack et al., 2013; Molitor, 2018), and the fact that better HIV treatment practices and patient outcomes are observed among privately insured patients (Bozette et al., 1998), this measurement error is likely depressing the peers' treatment performance measure for higher performing physicians.

The panel nature of this data helps to reduce the bias induced from partially observing peers' treatment performance. 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 to have higher treatment performance with a smaller variation in their performance, the correlation in measurement error over time is hypothesized to be larger than the serial correlation of true peers' performance. Estimates of the panel linear probability models specified by Equations 1 – 4 are therefore subject to a smaller measurement bias than if estimated in a static model. The estimated magnitude of the parameters on the low-complexity task support this hypothesis, since existing workplace peer effect estimates have a similar magnitude (Herbst and Mas, 2015). Specifically, previous research has found that physicians adopt roughly 11 percent of a productivity increase among their clinical peers in the emergency room (Silver, 2016) and the elasticity in work performance across occupations such as fruit pickers, scientists, and supermarket cashiers is equal to 0.12 (Herbst and Mas, 2015). Since the average of physician's own performance and the average peers' performance are nearly identical, the estimates for $\gamma_{\{H,L\}}$, $\gamma^{GEN}_{\{H,L\}}$, and $\gamma^{HIV}_{\{H,L\}}$ can alternatively be interpreted as an elasticity: a one-percent increase in peers' performance of the low-complexity task increases a physician's own performance by 0.08 percent, which is still lower than these previous estimates of peer effects on tasks that do not require learning from workplace peers.

# 7 Simulated Physician Network Redesign

This simulation exercise repositions the HIV specialists with above average performance on the high-complexity task to more central locations in their regional patient-sharing network in order to increase the region's overall performance. For each simulated policy, the observed pattern of patient-sharing links in a hospital referral region (HRR) are held constant. Repositioning in this context means that physicians would trade all existing patient-sharing links, so no new links are formed and no links are broken between any two network positions. After high performing HIV specialists are repositioned, the peers' average performance measure is recalculated separately among generalist and HIV specialist peers based on physicians' observed performance in 2010. The final impact of these policies through social learning between physicians is then determined based on the parameter estimates of Equation 3.

Two policy simulation exercises are performed within the largest clustered network in each

of the twenty-four HRRs in California in 2010.[16] The first simulation places high performing HIV specialists at the points with the greatest concentrations of generalists (highest generalist-weighted *degree*). The second simulation relocates specialists so they are better connected to remotely positioned generalists (minimizing network *distance*). I employ these methods as opposed to solving for the positions that maximize overall performance, because these two methods can more easily be approximated by organizational policies in an actual clinical setting.

Figure 5 shows that these two simulation methods produce opposite results for the largest clustered physician network in the Los Angeles area. Repositioning the above average HIV specialists by maximizing generalist connections reduces the region's overall performance by 0.5 percentage points, while the policy that minimizes network distance by serving remotely placed generalists increases the region's performance by 2.8 percentage points. By repositioning above average HIV specialists more evenly throughout the network, this second policy enables more generalists to benefit from the positive social learning that occurs between physician types. This conclusion mirrors other recommended policies that aim to leverage beneficial peer effects between worker types by increasing the diversity of workplace peers (Mas and Moretti, 2009; Chan, Li, and Pierce, 2014). Since network links represent patient-sharing relationships in these data, policies to optimize generalist and HIV specialist connections do not require large physical relocation costs. Instead, this network redesign could be facilitated through more HIV specialist consultations made via telemedicine technology or by other online physician chat services, such as *Lua* or *Doximity*.

The indiscriminate social learning between physician peers in this setting yields detrimental effects on overall performance and health outcomes from more naive policies that reposition HIV specialists without considering the specialists' relative performance. Specifically, relocated all HIV specialists reduces overall performance on the high-complexity tasks in the largest clustered network in the Los Angeles area by 2.5 percentage points when maximizing the number of generalist and specialist connections. Similarly, performance is reduced by 3.1 percentage points when all HIV specialists are evenly disbursed throughout the network. These significant declines in performance result from exposing more generalists to HIV specialists that improperly perform the high-complexity treatment task, and disseminate these practices to their less-experienced peers.

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

Based on the number of HIV-infected patients in the Los Angeles area, the results of the policy that successfully leverages only the beneficial social learning effects between generalist and HIV specialists to improve performance also corresponds to prescribing recommended HIV medication regimen for an additional 845 patients. After performing this exercise in each of the twenty-four HRRs in California, the aggregate impact is an additional $2,861$ patients receiving recommended HIV medication regimens. This increase would enable 17 percent of patients who were not previously virally suppressed through HIV treatment to achieve viral suppression.

In addition to improving patients' health, viral suppression reduces the risk of sexual transmission by 96 percent (Cohen et al., 2011). Back of the envelope calculations show that a 17 percent increase in virally suppressed patients could have reduced the annual number of new infections by 5 percent in California, 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.[17] Even after considering the cost of increasing HIV specialists' professional interactions and caseloads,[18] this represents a highly cost-effective policy for reducing the HIV epidemic in the U.S.

# 8 Conclusion

Social learning between workers is a significant determinant of performance in many workplace settings. When workers are able to diffuse task-specific knowledge to their peers, organizational policies can leverage these beneficial peer effects to improve aggregate performance and can use these channels of social learning to better disseminate new knowledge or protocols. This paper identifies the presence of social learning among physicians in regards to their HIV treatment task performance using a unique panel data set containing repeated observations of physician's HIV treatment practices and their time-varying professional networks. The identification strategy employs a difference-in-differences framework in combination with a novel instrumental variables technique that relies on the behavior of intransitively connected peers (Bramoullé, Djebbari, and Fortin, 2009). The results find significant heterogeneity in the peer effects exerted by HIV specialist and generalist peers for a high-complexity treatment task that requires a large degree of disease-

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

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

specific knowledge to successfully perform. These heterogeneous parameter estimates provide strong evidence for social learning in this workplace setting, indicating that physician networks may also be used to disseminate new medical knowledge or treatment practices.

However, social learning may be an unreliable method for improving performance in workplace settings where the outcome of tasks are not immediately observable. This is the case for the HIV treatment tasks examined by this paper which have significant long-term effects on patients' health outcomes that are not immediately visible.

To help quantify the impact of organizational policies that leverage these beneficial social learning effects to improve workers' performance, this paper performs two policy simulation exercises. Above-average specialists are repositioned by locating them in clusters of generalists or minimizing their distance to remotely-positioned generalist physicians. The policy that results in specialists being more evenly distributed throughout the regional network (i.e., the policy that minimizes distance) enables more generalists to learn from their more experienced peers and outlines a cost-effective mechanism for increasing regional performance. This finding has been documented in other workplace settings, but these existing workplace peer effects were not necessarily driven by social learning. By identifying the presence of social learning among physicians and quantifying the large policy impact of physician network redesign, this paper demonstrates how similar organizational policies could also be used to diffuse new medical information or practice styles through these same channels for knowledge transfer between physicians.

# References


Agha, Leila, Keith Ericson, Kimberley Geissler, and James Rebitzer. 2018. "Team Formation and Performance: Evidence from Healthcare Referral Networks." *NBER Working Paper No. 24338* .

Agha, Leila and Dan Zeltzer. 2018. "Drug Diffusion through Peer Networks: The Influence of Industry Payments." *Foerder Institute Discussion Paper* .

AIDSInfo. 2019a. "FDA-Approved HIV Medicines." U.S. Department of Health and Human Services. URL https://aidsinfo.nih.gov/understanding-hiv-aids/fact-sheets/21/58/fda-approved-hiv-medicines. Accessed March 2019.

———. 2019b. "What to Start: Initial Combination Regimens for the Antiretroviral-Naive Patient." U.S. Department of Health and Human Services. URL https://aidsinfo.nih.gov/guidelines/html/1/adult-and-adolescent-arv/11/what-to-start. Accessed March 2019.

Aral, Sinan. 2011. "Commentary—identifying social influence: A comment on opinion leadership and social contagion in new product diffusion." *Marketing Science* 30 (2):217–223.

Arrow, Kenneth J. 1994. "Methodological individualism and social knowledge." *The American Economic Review* 84 (2):1–9.

Azoulay, Pierre, Joshua Zivin, and Jialan Wang. 2010. "Superstar extinction." *The Quarterly Journal of Economics* 125 (2):549–589.

Baldwin, Laura-Mae, Walter Adamache, Carrie Klabunde, Kevin Kenward, Celia Dahlman, and Joan Warren. 2002. "Linking physician characteristics and Medicare claims data: Issues in data availability, quality, and measurement." *Medical Care* 40 (8):82–95.

Barnett, Michael, Nicholas Christakis, A. James O'Malley, Jukka-Pekka Onnela, Nancy Keating, and Bruce Landon. 2012. "Physician patient-sharing networks and the cost and intensity of care in US hospitals." *Medical Care* 50 (2):152.

Barnett, Michael, Bruce Landon, A. James O'Malley, Nancy Keating, and NicholaS Christakis. 2011. "Mapping physician networks with self-reported and administrative data." *Health Services Research* 46 (5):1592–1609.

Bozette, Samuel, Sandra Berry, Naihua Duan, Martin Frankel, and Arleen Leibowitz. 1998. "The care of HIV-infected adults in the United States." *New England Journal of Medicine* 339 (26):1897–1904.

Bramoullé, Yann, Habiba Djebbari, and Bernard Fortin. 2009. "Identification of peer effects through social networks." *Journal of Econometrics* 150 (1):41–55.

Brown, Marie, Jennifer Bussell, Suparna Dutta, Katherine Davis, Shelby Strong, and Suja Mathew. 2016. "Medication adherence: truth and consequences." *The American Journal of the Medical Sciences* 351 (4):387–399.

Burke, Mary, Gary Fournier, and Kislaya Prasad. 2007. "The diffusion of a medical innovation: is success in the stars?" *Southern Economic Journal* :588–603.

Buscher, April, Christine Hartman, Michael Kallen, and Thomas Giordano. 2012. "Impact of antiretroviral dosing frequency and pill burden on adherence among newly diagnosed, antiretroviral-naive HIV patients." *International Journal of STD & AIDS* 23 (5):351–355.

Card, David, Jörg Heining, and Patrick Kline. 2013. "Workplace heterogeneity and the rise of West German wage inequality." *The Quarterly Journal of Economics* 128 (3):967–1015.

CDC. 2012. "HIV in the United States: The Stages of Care." Centers for Disease Control and Prevention. URL https://www.cdc.gov/hiv/pdf/research_mmp_stagesofcare.pdf. Accessed January 2019.

———. 2016. "Today's HIV/AIDS Epidemic." Centers for Disease Control and Prevention. URL https://www.cdc.gov/nchhstp/newsroom/docs/factsheets/todaysepidemic-508.pdf. Accessed September 2016.

Chaillet, Nils, Eric Dubé, Marylène Dugas, François Audibert, Caroline Tourigny, William Fraser, and Alexandre Dumont. 2006. "Evidence-based strategies for implementing guidelines in obstetrics: a systematic review." *Obstetrics & Gynecology* 108 (5):1234–1245.

Chan, David. 2016. "Teamwork and moral hazard: Evidence from the emergency department." *Journal of Political Economy* 124 (3):734–770.

Chan, Tat, Jia Li, and Lamar Pierce. 2014. "Learning from peers: Knowledge transfer and sales force productivity growth." *Marketing Science* 33 (4):463–484.

Charlson, Mary, Peter Pompei, Kathy Ales, and C Ronald MacKenzie. 1987. "A new method of classifying prognostic comorbidity in longitudinal studies: Development and validation." *Journal of Chronic Diseases* 40 (5):373–383.

Clauset, Aaron, Mark Newman, and Cristopher Moore. 2004. "Finding community structure in very large networks." *Physical Review E* 70 (6):066111.

Cohen, Myron, Ying Chen, Marybeth McCauley, Theresa Gamble, Mina Hosseinipour, Nagalingeswaran Kumarasamy, James Hakim, Johnstone Kumwenda, Beatriz Grinsztejn, Jose Pilotto et al. 2011. "Prevention of HIV-1 infection with early antiretroviral therapy." *New England Journal of Medicine* 365 (6):493–505.

Coleman, James, Elihu Katz, and Herbert Menzel. 1957. "The diffusion of an innovation among physicians." *Sociometry* 20 (4):253–270.

Cornelissen, Thomas, Christian Dustmann, and Uta Schönberg. 2017. "Peer effects in the workplace." *American Economic Review* 107 (2):425–56.

Cutler, David, Jonathan Skinner, Ariel Stern, and David Wennberg. 2019. "Physician beliefs and patient preferences: a new look at regional variation in health care spending." *American Economic Journal: Economic Policy* 11 (1):192–221.

Duffus, W.A., M. Barragan, L. Metsch, C.S. Krawczyk, A.M. Loughlin, L.I. Gardner, P. Anderson Mahoney, Gordon Dickinson, and C del Rio. 2003. "Effect of Physician Specialty on Counseling Practices and Medical Referral Patterns among Physicians Caring for Disadvantaged Human Immunodeficiency Virus—Infected Populations." *Clinical Infectious Diseases* 36 (12):1577–1584.

Elliott, Daniel, Robert Young, Joanne Brice, Ruth Aguiar, and Paul Kolm. 2014. "Effect of hospitalist workload on the quality and efficiency of care." *JAMA Internal Medicine* 174 (5):786–793.

Epstein, Andrew and Sean Nicholson. 2009. "The formation and evolution of physician treatment styles: An application to cesarean sections." *Journal of Health Economics* 28 (6):1126–1140.

Escarce, José. 1996. "Externalities in hospitals and physician adoption of a new surgical technology: an exploratory analysis." *Journal of Health Economics* 15 (6):715–734.

Flagg, Elaine and Hillard Weinstock. 2011. "Incidence of neonatal herpes simplex virus infections in the United States, 2006." *Pediatrics* 127 (1):1–8.

Fruchterman, Thomas and Edward Reingold. 1991. "Graph drawing by force-directed placement." *Software: Practice and Experience* 21 (11):1129–1164.

Gabbay, John and Andrée le May. 2004. "Evidence based guidelines or collectively constructed 'mindlines?' Ethnographic study of knowledge management in primary care." *British Medical Journal* 329 (7473):1013.

Hahn, Jinyong and Whitney Newey. 2004. "Jackknife and analytical bias reduction for nonlinear panel models." *Econometrica* 72 (4):1295–1319.

Handford, Curtis, Julia Rackal, Anne-Marie Tynan, Damian Rzeznikiewiz, and Richard Glazier. 2012. "The association of hospital, clinic and provider volume with HIV/AIDS care and mortality: Systematic review and meta-analysis." *AIDS Care* 24 (3):267–282.

Hausman, Jerry. 1978. "Specification tests in econometrics." *Econometrica: Journal of the Econometric Society* 46 (6):1251–1271.

Healthcare Cost and Utilization Project. 2016. "Clinical Classifications Software (CCS) for ICD-9-CM." U.S. Agency for Healthcare Research and Quality. URL http://www.hcup-us.ahrq.gov/toolssoftware/ccs/ccs.jsp. Accessed August 2016.

Herbst, Daniel and Alexandre Mas. 2015. "Peer effects on worker output in the laboratory generalize to the field." *Science* 350 (6260):545–549.

Jackson, CK and Elias Bruegmann. 2009. "Teaching students and teaching each other: The importance of peer learning for teachers." *American Economic Journal: Applied Economics* 1 (4):85–108.

KC, Diwas, Bradley Staats, and F. Gino. 2013. "Learning from my success and from others' failure: Evidence from minimally invasive cardiac surgery." *Management Science* 59 (11):2435–2449.

Keating, Nancy, John Ayanian, Paul Cleary, and Peter Marsden. 2007. "Factors affecting influential discussions among physicians: a social network analysis of a primary care practice." *Journal of General Internal Medicine* 22 (6):794–798.

Keating, Nancy, Alan Zaslavsky, and John Ayanian. 1998. "Physicians' experiences and beliefs regarding informal consultation." *Journal of the American Medical Association* 280 (10):900–904.

Kitahata, Mari, Thomas Koepsell, Richard Deyo, Clare Maxwell, Wayne Dodge, and Edward Wagner. 1996. "Physicians' experience with the acquired immunodeficiency syndrome as a factor in patients' survival." *New England Journal of Medicine* 334 (11):701–707.

Kitahata, Mari, Stephen Rompaey, Peter Dillingham, Thomas Koepsell, Richard Deyo, Wayne Dodge, and Edward Wagner. 2003. "Primary care delivery is associated with greater physician experience and improved survival among persons with AIDS." *Journal of General Internal Medicine* 18 (2):95–103.

Kitahata, Mari, Stephen Van Rompaey, and Anne Shields. 2000. "Physician experience in the care of HIV-infected persons is associated with earlier adoption of new antiretroviral therapy." *JAIDS Journal of Acquired Immune Deficiency Syndromes* 24 (2):106–114.

Kleibergen, Frank and Richard Paap. 2006. "Generalized reduced rank tests using the singular value decomposition." *Journal of Econometrics* 133 (1):97–126.

Landon, Bruce, Nancy Keating, Michael Barnett, Jukka-Pekka Onnela, Sudeshna Paul, A. James O'Malley, Thomas Keegan, and Nicholas Christakis. 2012. "Variation in patient-sharing networks of physicians across the United States." *Journal of the American Medical Association* 308 (3):265–273.

Landon, Bruce, Ira Wilson, Keith McInnes, Mary Landrum, Lisa Hirschhorn, Peter Marsden, and Paul Cleary. 2005. "Physician specialization and the quality of care for human immunodeficiency virus infection." *Archives of Internal Medicine* 165 (10):1133–1139.

Landon, Bruce, Ira Wilson, Neil Wenger, Susan Cohn, Carl Fichtenbaum, Samuel Bozzette, Martin Shapiro, and Paul Cleary. 2002. "Specialty training and specialization among physicians who treat HIV/AIDS in the United States." *Journal of General Internal Medicine* 17 (1):12–22.

Landovitz, Raphael, Katherine Desmond, and Arleen Leibowitz. 2017. "Antiretroviral therapy: racial disparities among publicly insured Californians with HIV." *Journal of Health Care for the Poor and Underserved* 28 (1):406–429.

Leibowitz, Arleen and Katherine Desmond. 2015. "Identifying a sample of HIV-positive beneficiaries from medicaid claims data and estimating their treatment costs." *American Journal of Public Health* 105 (3):567–574.

Linnemayr, Sebastian, Chad Stecher, and Barbara Mukasa. 2017. "Behavioral economic incentives to improve adherence to antiretroviral medication." *AIDS* 31 (5):719–726.

Manski, Charles. 1993. "Identification of endogenous social effects: The reflection problem." *The Review of Economic Studies* 60 (3):531–542.

Markson, Leona, Leon Cosler, and Barbara Turner. 1994. "Implications of generalists' slow adoption of zidovudine in clinical practice." *Archives of Internal Medicine* 154 (13):1497–1504.

Mas, Alexandre and Enrico Moretti. 2009. "Peers at work." *American Economic Review* 99 (1):112–145.

Molitor, David. 2018. "The evolution of physician practice styles: evidence from cardiologist migration." *American Economic Journal: Economic Policy* 10 (1):326–56.

Nair, Harikesh, Puneet Manchanda, and Tulikaa Bhatia. 2010. "Asymmetric social interactions in physician prescription behavior: The role of opinion leaders." *Journal of Marketing Research* 47 (5):883–895.

Office of AIDS. 2010. "The Continuum of HIV Care – California, 2010." California Department of Public Health. URL https://www.cdph.ca.gov/Programs/CID/DOA/CDPH/20Document/20Library/HIVCareContinuum-2010_ADACompliant.pdf. Access August 2016.

———. 2012. "HIV/AIDS Surveillance Section." California Department of Public Health. URL http://www.cdph.ca.gov/programs/aids/Pages/TOASurv.aspx. Access August 2016.

———. 2016. "Laying a Foundation for Getting to Zero: California's Integrated HIV Surveillance, Prevention and Care Plan." California Department of Public Health. URL http://www.cdph.ca.gov/programs/aids/Documents/IP_2016_Final.pdf. Access October 2016.

Peabody, John, Jeff Luck, Sharad Jain, Dan Bertenthal, and Peter Glassman. 2004. "Assessing the accuracy of administrative data in health information systems." *Medical Care* 42 (11):1066–1072.

Petersen, Mitchell. 2009. "Estimating standard errors in finance panel data sets: Comparing approaches." *Review of Financial Studies* 22 (1):435–480.

Pollack, Craig, Hao Wang, Justin Bekelman, Gary Weissman, Andrew Epstein, Kaijun Liao, Eva Dugoff, and Katrina Armstrong. 2014. "Physician social networks and variation in rates of complications after radical prostatectomy." *Value in Health* 17 (5):611–618.

Pollack, Craig, Gary Weissman, Justin Bekelman, Kaijun Liao, and Katrina Armstrong. 2012. "Physician social networks and variation in prostate cancer treatment in three cities." *Health Services Research* 47 (1 pt 2):380–403.

Pollack, Craig, Gary Weissman, Klaus Lemke, Peter Hussey, and Jonathan Weiner. 2013. "Patient sharing among physicians and costs of care: A network analytic approach to care coordination using claims data." *Journal of General Internal Medicine* 28 (3):459–465.

Rock, Daniel, Sinan Aral, and Sean Taylor. 2016. "Identification of peer effects in networked panel data." *In: Thirty Seventh International Conference on Information Systems* .

Schackman, Bruce, John Fleishman, Amanda Su, Bethany Berkowitz, Richard Moore, Rochelle Walensky, Jessica Becker, Cindy Voss, David Paltiel, Milton Weinstein et al. 2015. "The lifetime medical cost savings from preventing HIV in the United States." *Medical Care* 53 (4):293–301.

Schectman, Joel, W. Scott Schroth, Dante Verme, and John Voss. 2003. "Randomized controlled trial of education and feedback for implementation of guidelines for acute low back pain." *Journal of General Internal Medicine* 18 (10):773–780.

Schwarcz, Sandra, Ling Hsu, and Susan Scheer. 2015. "Disparities and trends in viral suppression during a transition to a "test and treat" approach to the HIV epidemic, San Francisco, 2008–2012." *JAIDS Journal of Acquired Immune Deficiency Syndromes* 70 (5):529–537.

Silver, David. 2016. "Haste or Waste?" *Job Market Paper* .

Skinner, Jonathan. 2011. "Causes and consequences of regional variations in health care." In *Handbook of Health Economics*, vol. 2. Elsevier, 45–93.

Stock, James and Motohiro Yogo. 2005. "Testing for weak instruments in linear IV regression." *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg* :80–108.

United Nations Joint Programme on HIV/AIDS. 2016. "The Gap Report." (UNAIDS). URL http://www.unaids.org/en/resources/documents/2016/prevention-gap. Access October 2016.

United States Census Bureau. 2013. "Summary File. 2007 – 2011 American Community Survey." URL http://ftp2.census.gov/. Accessed August 2016.

Weissman, Sharon, Wayne Duffus, Medha Iyer, Hrishikesh Chakraborty, Ashok Samantapudi, and Helmut Albrecht. 2015. "Rural-urban differences in HIV viral loads and progression to AIDS among new HIV cases." *Southern Medical Journal* 108 (3):180–188.

Wennberg, John and Megan Cooper. 1996. "The Dartmouth Aalas of health care." *The Center for the Evaluative Clinical Sciences, Dartmouth Medical School, American Hospital Publishing* :15–20.

WHO. 1980. *International Classification of Diseases, Ninth Revision*. World Health Organization. Geneva, Switzerland.

Yehia, Baligh, John Fleishman, Allison Agwu, Joshua Metlay, Stephen Berry, and K. A. Gebo. 2014. "Health insurance coverage for persons in HIV care, 2006–2012." *Journal of Acquired Immune Deficiency Syndromes* 67 (1):102–106.

**Table 1:** Commonly Prescribed, FDA Approved HIV Medications by Drugs' Class

| | (1) **NRTIs** | (2) **NNRTIs** | (3) **PIs** | (4) **FIs** | (5) **INSTIs** | (6) **CCR5s** |
|---|---|---|---|---|---|---|
| **FDA approved drugs:** *(single compound)* | abacavir<br>didanosine<br>emtricitabine<br>lamivudine<br>stavudine<br>tenofovir<br>zidovudine | delavirdine<br>efavirenz<br>etravirine<br>nevirapine | amprenavir<br>atazanavir<br>darunavir<br>fosamprenavir<br>indinavir<br>nelfinavir<br>ritonavir<br>saquinavir<br>tipranavir | enfuvirtide | bictegravir<br>dolutegravir<br>elvitegravir<br>raltegravir | maraviroc |
| **Combination drugs:** | | | | | | |
| *Atripla* | emtricitabine<br>tenofovir | efavirenz | | | | |
| *Epzicom* | abacavir<br>lamivudine | | | | | |
| *Truvada* | emtricitabine<br>tenofovir | | | | | |

*Note:* This table presents a list of commonly prescribed HIV drugs in the U.S. during the sample period (2007-2010). Columns (1-6) separate each drug according to the following six drug classes: Nucleoside Reverse Transcriptase Inhibitors (NRTIs), Non-nucleoside reverse transcriptase inhibitors (NNRTIs), Protease inhibitors (PIs), Fusion inhibitors (FIs), Integrase inhibitors (INSTIs), and Chemokine receptor antagonists (CCR5s). This is not intended to be an exhaustive list of all available FDA approved drugs, but does contain the most frequently prescribed medications observed in the Medicare claims data used by this paper. A recommended HIV medication regimen contains *three* different HIV drugs that come from at least *two* different drug classes.

*Source:* Information published by the U.S. Department of Health and Human Services AIDSInfo (AIDSInfo, 2019a).

**Table 2:** ARV Considerations for Several Clinical Scenarios

| (1) **Clinical Scenario** | (2) **Condition(s)** | (3) **Consideration(s)** | (4) **Rational/Comments** |
|---|---|---|---|
| **Pre-ART** | HIV RNA >100,000 copies/mL | Do Not Use the Following Regimens: · RPV-based regimens · ABC/3TC w/ EFV or ATV · DRV/r plus RAL | Higher rates of virologic failure have been observed in in those with high pretreatment HIV RNA levels. |
| | HLA-B*5701 positive or result unknown | Do not use ABC-containing regimens | ABC hypersensitivity, a potentially fatal reaction, is highly associated with the presence of the HLA-B*5701 allele. |
| **Comorbidities** | Chronic kidney disease | Avoid TDF unless the patient has ESRD. Use ABC or TAF. | TDF has been associated with proximal renal tubulopathy. |
| | Osteoporosis | Avoid TDF. Use ABC or TAF. | TDF is associated with decreases in BMD along with renal tubulopathy, urine phosphate wasting, and resultant osteomalacia. |
| | Psychiatric illnesses | Avoid EFV- and RPV-based regimens. | EFV and RPV can exacerbate psychiatric symptoms and may be associated with suicidality. |

*Note:* This table outlines specific considerations that a physician should make when selecting an ARV drug regimen that is suitable for the clinical scenarios categorized by column (1). For each specific condition described in column (2), the appropriate medical considerations are identified in column (3), and a brief rational is provided in column (4). The medical acronyms are: 3TC = lamivudine; ABC = abacavir; ART = antiretroviral therapy; ATV = atazanavir; ATV/c = atazanavir/cobicistat; ATV/r = atazanavir/ritonavir; BMD = bone mineral density; DRV/r = darunavir/ritonavir; EFV = efavirenz; ESRD = end stage renal disease; EVG/c = elvitegravir/cobicistat; HLA = human leukocyte antigen; RAL = raltegravir; RNA = ribonucleic acid; RPV = rilpivirine; TAF = tenofovir alafenamide; TDF = tenofovir disoproxil fumarate.

*Source:* Information published by the U.S. Department of Health and Human Services AIDSInfo (AIDSInfo, 2019b).

**Table 3:** Data Sources and Variables

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

*Note:* This table identifies the source of information for the variables constructed at the insurance claims-level and the county-level. 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 4:** Regional Variation in Physicians' HIV Treatment Task Performance

| | (1) Northern CA | (2) San Francisco | (3) Central CA | (4) Los Angeles | (5) Southern CA | (6) Total |
|---|---|---|---|---|---|---|
| High-complexity task | | | | | | |
| Mean | 93.3 | 90.9 | 88.1 | 84.3 | 90.1 | 88.8 |
| Std. deviation | (14.51) | (17.12) | (17.67) | (23.19) | (19.33) | (19.72) |
| Median | 98.5 | 97.6 | 94.3 | 90.9 | 97.1 | 95.3 |
| $25^{th}$ pctl. | 90.1 | 86.7 | 84.8 | 79.1 | 83.8 | 84.8 |
| N | 119 | 289 | 186 | 271 | 165 | 1030 |
| Low-complexity task | | | | | | |
| Mean | 57.1 | 57.8 | 54.3 | 52.3 | 57.8 | 56.4 |
| Std. deviation | (33.32) | (32.89) | (28.03) | (30.11) | (32.59) | (31.76) |
| Median | 57.0 | 56.7 | 56.4 | 53.4 | 55.3 | 56.1 |
| $25^{th}$ pctl. | 29.1 | 30.1 | 31.3 | 28.0 | 30.6 | 29.9 |
| N | 119 | 289 | 186 | 271 | 165 | 1030 |

*Note:* This table outlines the regional variation in physicians' performance of both the high- and low-complexity tasks recommended by all HIV clinical practice guidelines. The high-complexity task identifies whether individual prescriptions contain a recommended HIV medication combination. The low-complexity task identifies whether a physician prescribes any combined ARV drug. These five regions are defined by aggregating the twenty-four hospital referral regions identified in California by Wennberg and Cooper (1996).

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

**Table 5:** Physician Network Characteristics

| | (1)<br>2008 | (2)<br>2009 | (3)<br>2010 |
|---|---|---|---|
| *Population* | | | |
| # of patients | 8,287 | 9,145 | 9,167 |
| # of physicians | 789 | 936 | 915 |
| # of HIV Specialists | 154 | 194 | 196 |
| *Network Dimensions* | | | |
| Physicians per patient | 1.4 | 1.4 | 1.4 |
| | (0.6) | (0.7) | (0.7) |
| Patients per physician | 13.5 | 12.7 | 13.1 |
| | (18.2) | (17.7) | (19.6) |
| # of patient + physician pairs | 10,763 | 11,856 | 12,086 |
| Observations of same patient + phys. pair | 3.2 | 3.1 | 3.1 |
| | (2.4) | (2.6) | (2.5) |
| *Network Link Characteristics* | | | |
| Physician links per prescription | 8.5 | 8.6 | 8.4 |
| | (6.1) | (5.7) | (6.2) |
| HIV Specialist links per prescription | 2.8 | 2.8 | 2.7 |
| | (2.1) | (2.3) | (2.1) |
| % of all links with an HIV Specialist | 27.1 | 28.8 | 28.2 |
| | (41.5) | (43.7) | (44.8) |
| % of all links within same county | 71.3 | 71.0 | 71.2 |
| | (14.2) | (14.8) | (14.7) |
| *Generalists' Link Characteristics* | | | |
| % Generalists with any HIV Specialist links | 65.6 | 66.7 | 63.3 |
| | (46.8) | (47.2) | (47.4) |

*Note:* This table outlines several dimensions of the annual patient-sharing networks constructed from the analytic sample, where patient-sharing links are recorded between physicians who share one or more patient in the calendar year.

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

**Table 6:** Physician Peer Effects on HIV Treatment Decisions

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| **High-complexity task** | **OLS** | | **IV** | |
| Mean 88.74 (SD 19.72) | | | | |
| All physician peers | 0.06** | | 0.04* | |
| | (0.021) | | (0.019) | |
| Generalists | | 0.01 | | 0.02 |
| | | (0.031) | | (0.034) |
| HIV Specialists | | 0.07** | | 0.06* |
| | | (0.028) | | (0.026) |
| **Low-complexity task** | | | | |
| Mean 56.41 (SD 31.76) | | | | |
| All physician peers | 0.10** | | 0.08** | |
| | (0.042) | | (0.039) | |
| Generalists | | 0.11** | | 0.09** |
| | | (0.051) | | (0.041) |
| HIV Specialists | | 0.09** | | 0.08* |
| | | (0.045) | | (0.044) |
| 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 – 4, where coefficient estimates measure the percentage-point change in physicians' performance of the high-complexity and low-complexity HIV clinical practice guidelines that results from a one-percentage-point increase in peers' average performance. The high-complexity task identifies whether individual prescriptions contain a recommended HIV medication combination. The low-complexity task identifies whether a physician prescribes any combined ARV drug. The measure of peers' average performance of these recommendations is calculated as a weighted average over the past twelve months among the physicians who share one or more HIV-infected patients, where weights are the reciprocal of the time gap between the current observation and past prescriptions. These measures of peers' average performance are instrumented for by the average performance among intransitively connected peers.

*Source:* Medicare Part D drug claims for HIV-infected patients in California (2007-2010).

**Table 7:** Physician Peer Effects on the High-Complexity Task

| **High-complexity Task** | | (1) | (2) | (3) | (4) |
|---|---|---|---|---|---|
| | | **OLS** | | **IV** | |
| *Panel A: Generalists only* | Mean 87.55 (SD 19.33) | | | | |
| All physician peers | | 0.07*** | | 0.06** | |
| | | (0.025) | | (0.024) | |
| Generalists | | | 0.00 | | 0.02 |
| | | | (0.031) | | (0.035) |
| HIV Specialists | | | 0.09** | | 0.07** |
| | | | (0.042) | | (0.038) |
| *Panel B: HIV Specialists only* | Mean 89.94 (SD 19.43) | | | | |
| All physician peers | | 0.04* | | 0.03* | |
| | | (0.021) | | (0.018) | |
| Generalists | | | 0.00 | | 0.01 |
| | | | (0.017) | | (0.026) |
| HIV Specialists | | | 0.06* | | 0.04* |
| | | | (0.026) | | (0.028) |
| 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 – 4, where coefficient estimates measure the percentage-point change in physicians' performance of the high-complexity HIV clinical practice guideline that results from a one-percentage-point increase in peers' average performance. The high-complexity task identifies whether individual prescriptions contain a recommended HIV medication combination. The measure of peers' average performance of this recommendation is calculated as a weighted average over the past twelve months among the physicians who share one or more HIV-infected patients, where weights are the reciprocal of the time gap between the current observation and past prescriptions. This measure of peers' average performance is instrumented for by the average performance among intransitively connected peers.

*Source:* Medicare Part D drug claims for HIV-infected patients in California (2007-2010).

**Table 8:** Physician Peer Effects on the Low-Complexity Task

| **Low-complexity Task** | | (1) | (2) | (3) | (4) |
|---|---|---|---|---|---|
| | | **OLS** | | **IV** | |
| *Panel A: Generalists only* | Mean 54.13 (SD 32.64) | | | | |
| All physician peers | | 0.11** | | 0.09** | |
| | | (0.049) | | (0.046) | |
| Generalists | | | 0.12** | | 0.10* |
| | | | (0.051) | | (0.041) |
| HIV Specialists | | | 0.10* | | 0.08* |
| | | | (0.035) | | (0.037) |
| *Panel B: HIV Specialists only* | Mean 58.90 (SD 30.03) | | | | |
| All physician peers | | 0.09* | | 0.07* | |
| | | (0.041) | | (0.038) | |
| Generalists | | | 0.09* | | 0.08** |
| | | | (0.044) | | (0.035) |
| HIV Specialists | | | 0.08* | | 0.07* |
| | | | (0.040) | | (0.0391) |
| 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 – 4, where coefficient estimates measure the percentage-point change in physicians' performance of the low-complexity HIV clinical practice guideline that results from a one-percentage-point increase in peers' average performance. The low-complexity task identifies whether a physician prescribes any combined ARV drug. The measure of peers' average performance of this recommendation is calculated as a weighted average over the past twelve months among the physicians who share one or more HIV-infected patients, where weights are the reciprocal of the time gap between the current observation and past prescriptions. This measure of peers' average performance is instrumented for by the average performance among intransitively connected peers.

*Source:* Medicare Part D drug claims for HIV-infected patients in California (2007-2010).

**Table 9:** Robustness: Physician Peer Effects on the High-complexity Task

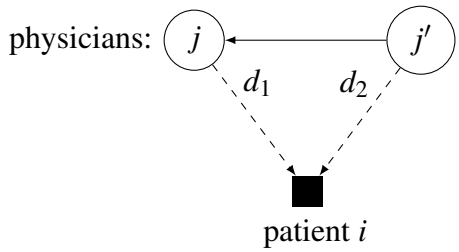
| **Re-weighting Past Performance** | | (1) **OLS** | (2) **IV** |
|---|---|---|---|
| *Linear temporal weighting* | Mean 87.44 (SD 31.31) | | |
| Generalists | | 0.01 | 0.02 |
| | | (0.017) | (0.026) |
| HIV Specialists | | 0.08* | 0.07* |
| | | (0.031) | (0.027) |
| *Past five observations only* | | | |
| Generalists | | 0.02 | 0.02 |
| | | (0.012) | (0.016) |
| HIV Specialists | | 0.10** | 0.08** |
| | | (0.033) | (0.029) |
| **Patient-sharing Link Strength** | | | |
| *Five or more shared patients only* | Mean 89.08 (SD 33.26) | | |
| Generalists | | −0.01 | 0.01 |
| | | (0.011) | (0.017) |
| HIV Specialists | | 0.12** | 0.10** |
| | | (0.058) | (0.051) |
| **Regional Subsamples** | | | |
| *Without San Francisco* | Mean 84.86 (SD 32.14) | | |
| Generalists | | 0.02 | 0.03 |
| | | (0.026) | (0.034) |
| HIV Specialists | | 0.09* | 0.07** |
| | | (0.035) | (0.029) |
| *Without Los Angeles* | Mean 89.12 (SD 31.62) | | |
| Generalists | | 0.01 | 0.02 |
| | | (0.018) | (0.022) |
| HIV Specialists | | 0.10** | 0.09** |
| | | (0.042) | (0.038) |
| 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 3 that predicts physicians' performance of the high-complexity task recommended by all HIV clinical practice guidelines under alternative temporal weighting procedures for the calculation of peers' average performance, a stronger cutoff for recording patient-sharing links, and regional subsamples. Specifically, estimates are generated when separately excluding the Los Angeles and San Francisco metropolitan areas, which represent roughly 29.6 percent and 19.1 percent of prescriptions, respectively. These estimates are generated for generalist physicians across both generalist and HIV specialist peers.

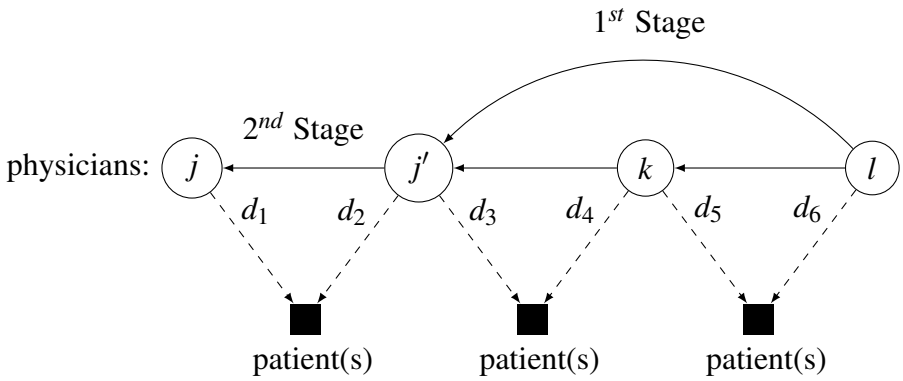
*Source:* Medicare Part D drug claims for HIV-infected patients in California (2007-2010).

**Constructing Physicians' Patient-Sharing Links**




**(a)** Physicians $j$ and $j'$ are immediate peers, connected by one patient-sharing link. Since physician $j$ treats patient $i$ on day $d_1$ and physician $j'$ treats patient $i$ on day $d_2 < d_1$, the treatment performance of physician $j'$ on days $d < d_2$ for other patients not shared with physician $j$ would be included in the peers' treatment performance measures.

**Instrumental Variables Approach: Intransitive Physician Peers**




**(b)** Physicians $j$ and $l$ do not share patients, but are connected by three patient-sharing links. Since physician $l$ does not share patients with ether physicians $j$ or $j'$, there is not a shorter patient-sharing network path between physicians $j$ and $l$. Similarly, since physicians $k$ and $j$ do not share patients, the shortest connection between physicians $j$ and $k$ is two patient-sharing links. Physicians $k$ and $l$ are both considered intransitively connected peers' of physician $j$, and the performance of physician $l$ is used as an instrument for the performance of physician $j'$. The timing of physicians treatment decisions are also used to direct the peer effect estimates, where only the treatment performance of physician $l$ on days $d_6 < d_5 < d_4 < d_3$ is used to predict the performance of physician $j'$.

**Figure 1:** Figure 1a describes the patient-sharing connections used to construct the measure of immediate peers' HIV treatment task performance. Figure 1b outlines the definition of intransitively connected peers, which is used to perform instrumental variables estimation. Specifically, the treatment performance of physician $l$ are used to predict the performance of physician $j'$ in the first stage, and this prediction is used to describe changes in the treatment performance of physician $j$ in the second stage.

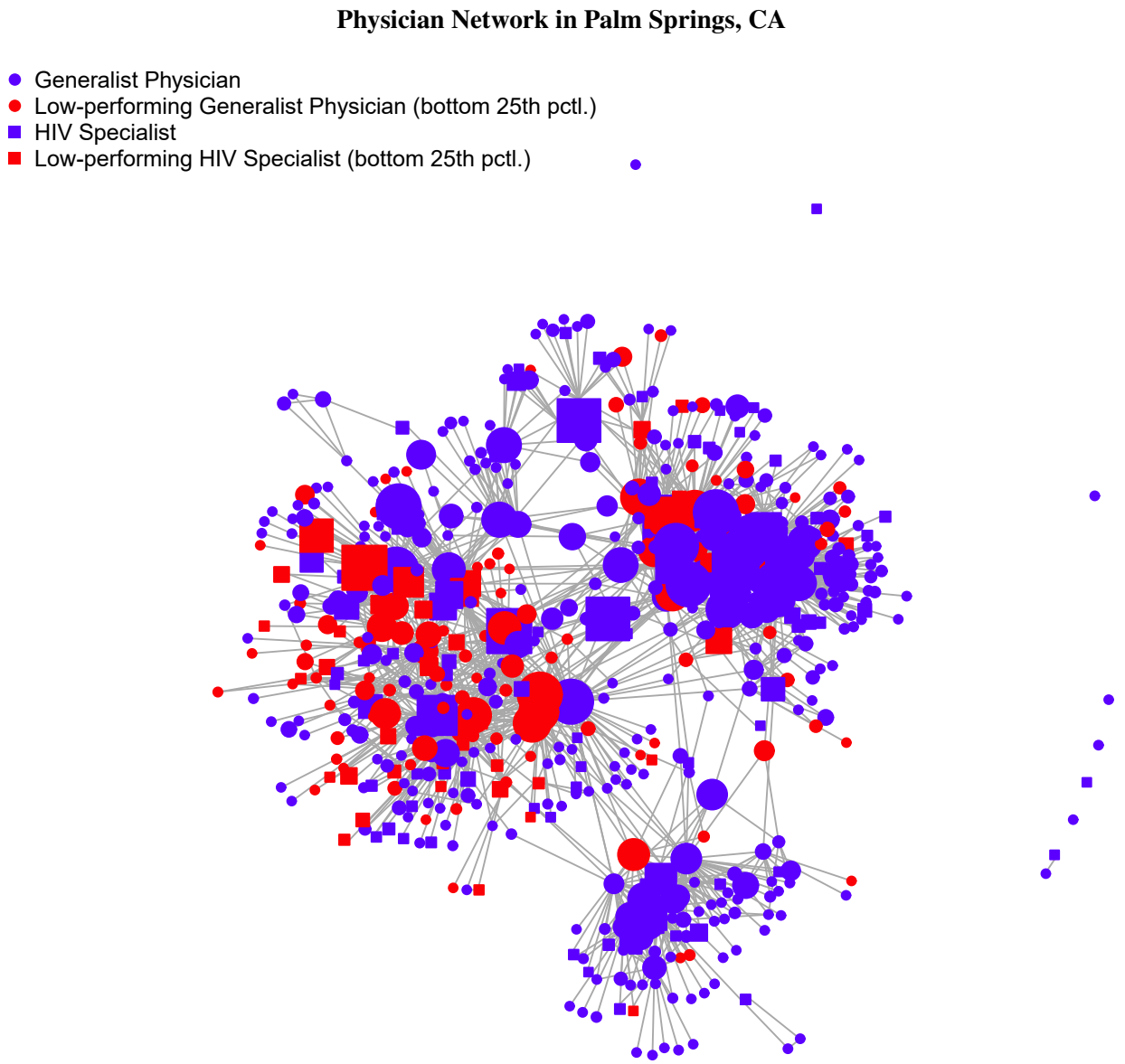



**Figure 2:** This figure plots the patient-sharing in Palm Springs, CA. Shapes distinguish physician specialty, size indicates the physician's relative HIV-infected patient caseload, and color identifies a physician's relative performance of the high-complexity HIV treatment task in 2010. The average performance of the high-complexity treatment task was 88.6 percent in Palm Springs, which is slightly lower than the statewide average of 88.8 percent.

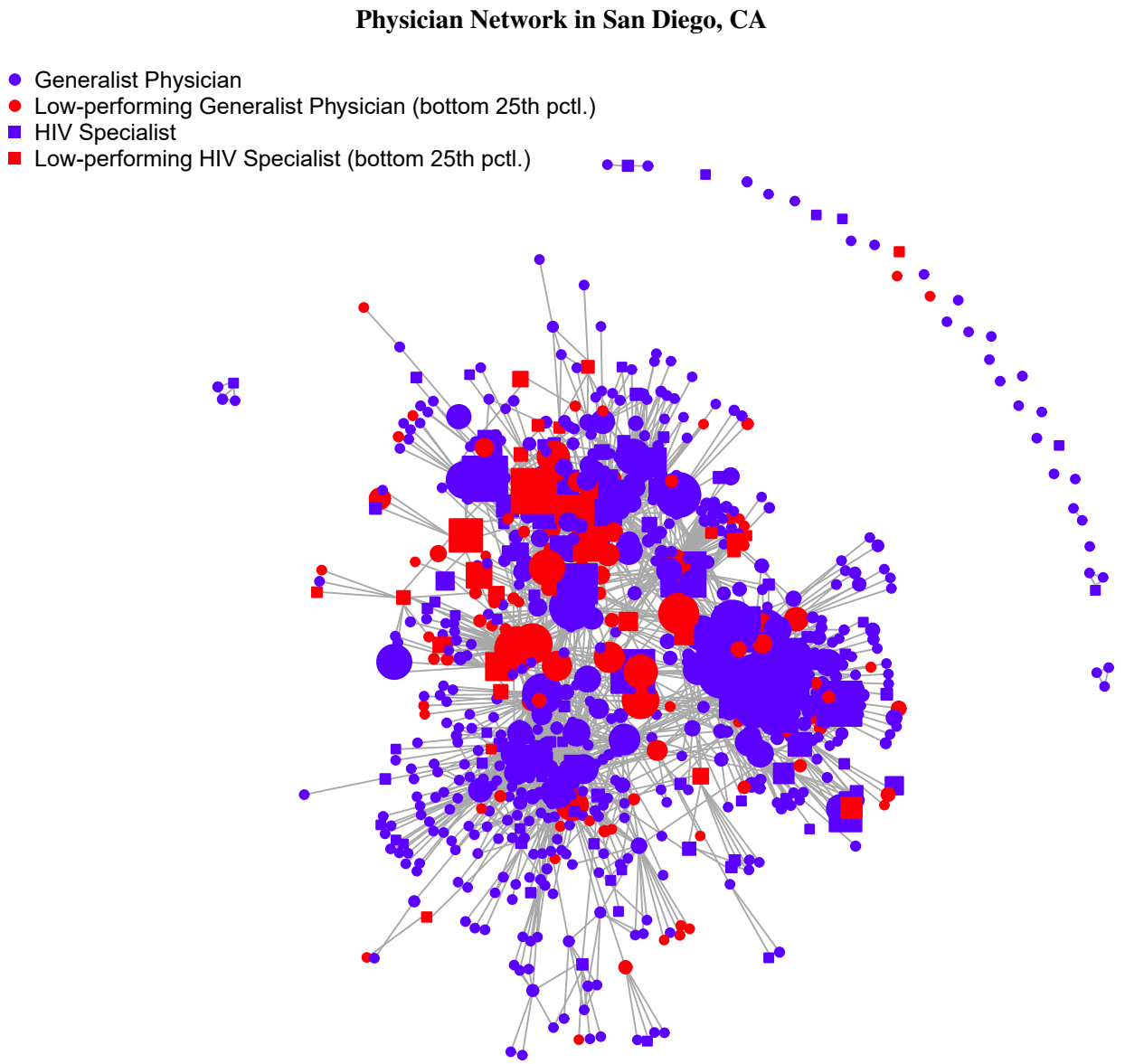



**Figure 3:** This figure plots the patient-sharing network in San Diego, CA. Shapes distinguish physician specialty, size indicates the physician's relative HIV-infected patient caseload, and color identifies a physician's relative performance of the high-complexity HIV treatment task in 2010. The average performance of the high-complexity treatment task was 95.0 percent in San Diego, which is significantly higher than the statewide average of 88.8 percent.

**Variation in Physicians' Performance of the High-complexity Task by Changes in Specialist Peers' Performance**

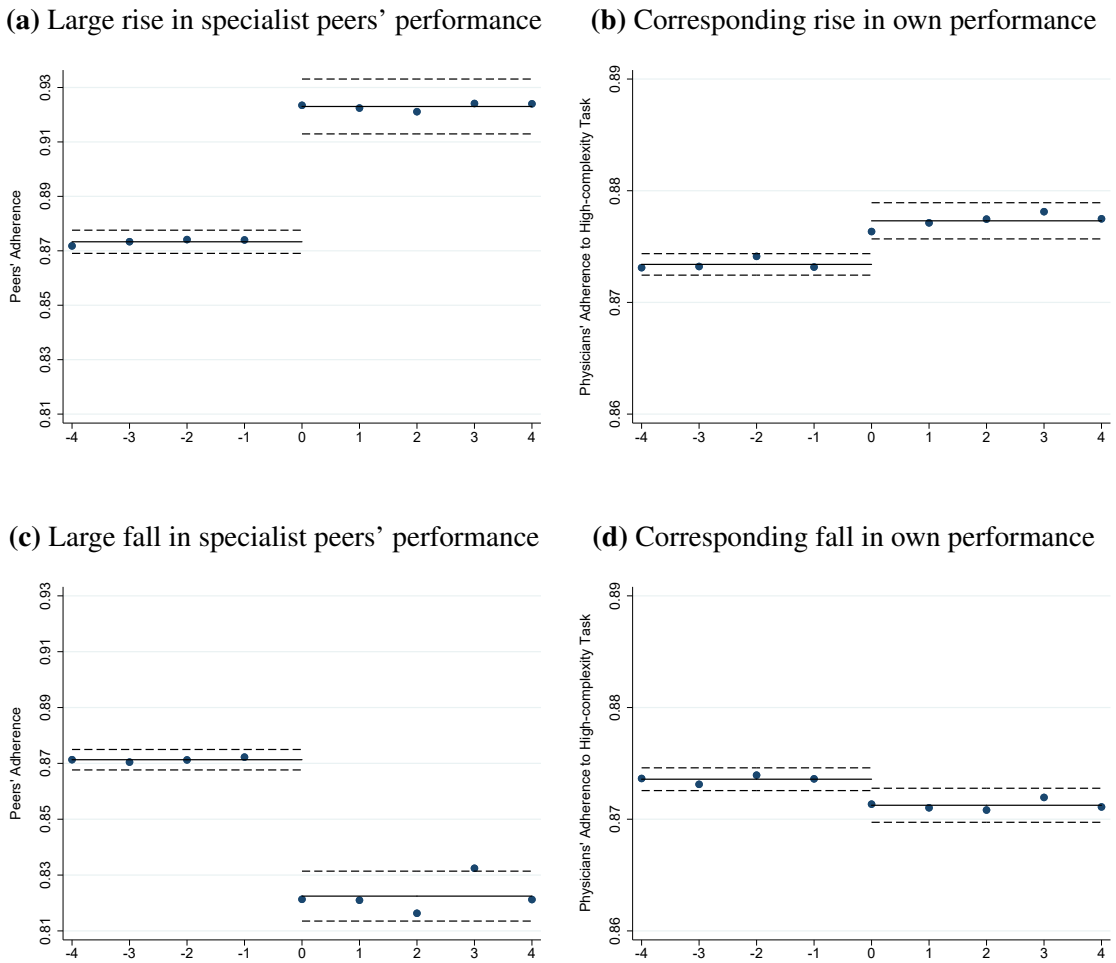
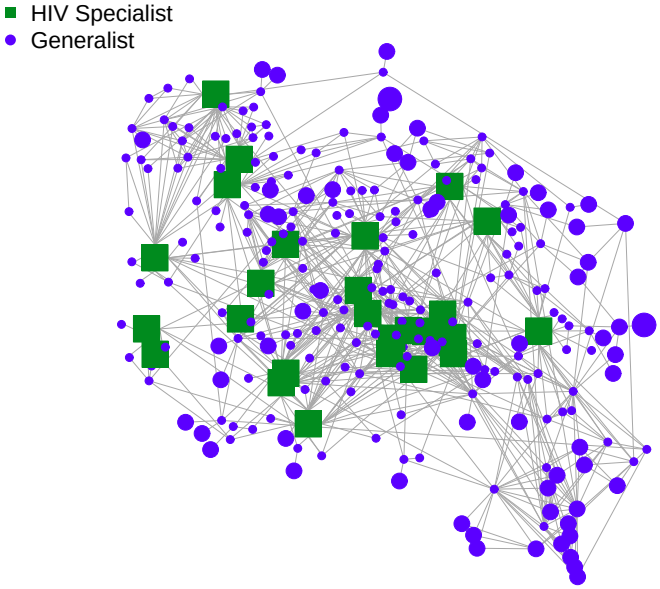


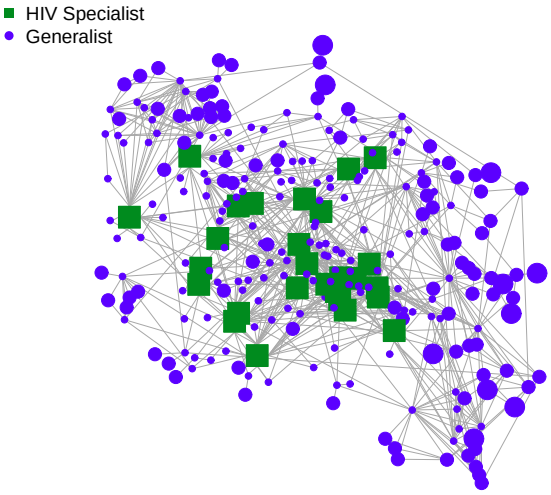

**Figure 4:** Plots 4a and 4c display HIV specialist peers' performance of the high-complexity treatment task during the four months before and four months after a large rise and fall in their performance (greater than 5 percentage points from month -1 to 0), respectively. Corresponding changes in a physician's own performance of the high-complexity task are displayed in plots 4b and 4d. The sample is restricted to cases where physicians treat a shared patient who was previously treated in the same month by an HIV specialist peer physician who made a large change to their performance of the high-complexity treatment task that month. The sample sizes for the large increase and decrease in peer's performance are 142 and 86 physicians, roughly 13 and 8 percent of the full sample population.

*Source:* Medicare Part D drug claims for HIV-infected patients in California (2007-2010).

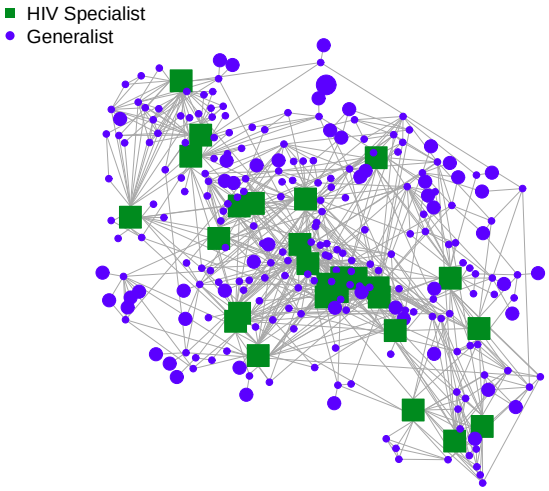
**Simulated Network Redesign in Los Angeles, CA**




**(a) Original network:** 86.8% of physicians correctly perform the high-complexity task.




**(b) Simulated** by maximizing degree: 86.3% network performance.




**(c) Simulated** by minimizing distance: 89.6% network performance.

**Figure 5:** Figure 5a plots the largest clustered physician network in the Los Angeles hospital referral region in 2010, where HIV specialists with above average performance of the high-complexity treatment task are represented by green squares and generalist physicians are blue circles sized by the number of patient-sharing links to the nearest above average HIV specialist. Figures 5b and 5c plot the simulated networks where these specialists are repositioned to maximize their generalist-weighted degree (5b) and minimizing the number of patient-sharing links to as many generalists as possible in the region (5c), respectively.

# Appendix A

## A Data Selection Procedures

This research utilizes the complete set of Medicare insurance claims for HIV-infected patients filed between 2007 and 2010 in California. To identify insurance claims for this target population, the Centers for Medicare & Medicaid Services (CMS) initially compiled all claims for Medicare enrollees with any antiretroviral (ARV) prescription or any claim containing an International Classification of Diseases, Ninth Revision (ICD-9) diagnosis code for HIV during this time period (WHO, 1980). Among this broad set of potential HIV/AIDS patients, an algorithm developed by Leibowitz and Desmond (2015) was used to isolate the final analytic sample of verifiable HIV-infected adults. This algorithm is needed because medical research has found that only 57 percent of administrative records have the correct primary diagnosis coded (Peabody et al., 2004), and it has been documented that "rule-out" diagnoses remain on claims even after a condition has officially been ruled out (Flagg and Weinstock, 2011). Additionally, ARV medication can also be prescribed to treat the hepatitis B virus. Leibowitz and Desmond (2015) detail the specific algorithm used for selecting verifiable HIV-infect patients, which is broadly based on the procedural codes associated with an insurance claim containing an HIV diagnosis and the frequency of HIV diagnoses for a given enrollee.

All available insurance claims for every Medicare enrollee identified by this algorithm was compiled for this research, including the outpatient, inpatient, hospice, and Part D drug event files. This information includes all ICD-9 diagnosis codes, ICD-9-CM procedural codes, and National Drug Codes (NDC) associated with an enrollee's entire health care usage between 2007 and 2010. To measure an individual's overall health status, common comorbidities were then classified according to the Charlson Comorbidity Index (Charlson et al., 1987). Additional identifiers for anxiety disorders, mood disorders, schizophrenia or other psychotic disorders, or other mental health disorders were recorded using the Mental Health and Substance Abuse Clinical Classifications Software (Healthcare Cost and Utilization Project, 2016).

In addition to diagnostic and procedural codes, insurance claims include enrollees' age, gender, race, ethnicity, and residential zip code at the time each claim is filed. Based on an enrollee's county of residence, additional contextual information was included in the analysis. The annual

median household income for all counties in California between 2007 and 2010 was obtained from 3-year estimates generated by the American Community Survey (United States Census Bureau, 2013). Additionally, county-level HIV prevalence statistics were recorded annually by the California Department of Public Health, Office of AIDS (Office of AIDS, 2012).

Finally, physician characteristics compiled by the American Medical Association (AMA) are linked to each insurance claim based on physicians' unique National Provider Identifier (NPI). The AMA Masterfile includes physicians' age, gender, country of birth, and a detailed summary of their medical training (Baldwin et al., 2002). Medical training data include the name, location, year of graduation, and if applicable, specialty, for all completed (or ongoing) medical school, residency, and fellowship training programs. Additionally, historical clinical practice information measured annually between 2007 and 2010 describes the location and type (e.g. solo private practice, group private practice, hospital appointment, or other practice type) of each physician's practice.

The final combined data set allows this research to detail the health care experience of the HIV-infected patient population covered by Medicare in California between 2007 and 2010. Between 2007 and 2010, this population contained $11,219$ individuals, representing roughly 11.1 percent of the total HIV population in California. The clinical information provided by CMS was approved for use in this study by the University of California, Los Angeles Institutional Review Board (UCLA IRB #: 10-000823), and the additional AMA data merge was approved under (UCLA IRB #: 16-000736).

## B Physician Selection

As is common in HIV care, patients are seen by a wide range of physicians and other health care providers. Corresponding health insurance claims can be filed for clinical visits to manage comorbidities, treat psychological symptoms such as stress and depression, or other holistic treatments, in addition to the recommended HIV treatments. The physician sample for this research is composed of only the physicians who are directly involved in a patient's main HIV treatments. Unique physician identifiers for the "performing," "prescribing," or "servicing" physician indicated on each insurance claim issued for an HIV evaluation and monitoring visit are used to construct this sample.

HIV evaluation and monitoring visits are identified based on the place and type of services

provided, which includes all the claims for procedures measured by the high- and low-complexity tasks. Between 2007 and 2010, there are approximately 5,000,000 Medicare insurance claim records for the verified HIV-infected patient population. Among these 5 million claims, roughly 750,000 Medicare claims correspond to specific HIV-related evaluation and monitoring (E&M) services, representing 15 percent of total Medicaid insurance claims.

Up to three physicians are listed on each HIV evaluation and monitoring insurance claim. The main analysis includes only physicians listed as the "performing," "prescribing," or "servicing" physician, as these are the physicians directly involved in HIV care. Network measurements are also estimated between all listed physicians (including "referring," "attending," "billing," and "other") on the HIV E&M claims, and the results derived from these broader networks are qualitatively very similar although effect sizes are smaller under the presence of these additional network connections.

## Appendix Tables

- Table A1 presents the demographic characteristics of all HIV-infected patients in the analytic sample.
- Table A2 presents the demographic characteristics of all treating physicians in the analytic sample.

**Table A1:** HIV-infected Patients' Characteristics

| | Share of Patients |
|---|---|
| Female | 10.0 |
| *Age* | |
| Age <30 | 1.1 |
| Age 30-39 | 7.5 |
| Age 40-49 | 33.1 |
| Age 50+ | 58.4 |
| *Race* | |
| White | 57.0 |
| African American | 19.2 |
| Hispanic | 19.7 |
| Asian/PI | 2.7 |
| Other races | 1.4 |
| *Mental Health* | |
| Any adjustment/anxiety diagnosed | 5.0 |
| Any mood disorders diagnosed | 16.2 |
| Any schizophrenia diagnosed | 3.5 |
| *Total Comorbidities* | |
| No comorbidities | 61.4 |
| 1 comorbidity | 26.4 |
| 2 comorbidities | 7.8 |
| 3 comorbidities | 2.1 |
| 4+ comorbidities | 2.3 |
| *Region* | |
| Northern CA | 10.6 |
| San Francisco Area | 27.2 |
| Central CA | 12.9 |
| Los Angeles Area | 28.7 |
| Southern CA | 19.1 |
| *County-level Covariates* | |
| County HIV/AIDS Prevalence | 0.59 |
| Median county household income ($10,000) | 6.12 |
| Observations | 11,219 |

*Note:* This table presents the demographic characteristics of HIV-infected patients included in the analytical sample of Medicare Part D drug claims, where demographics are presented as the share of patients in each category.

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

**Table A2:** Treating Physicians' Characteristics

| | Share of Physicians |
|---|---|
| Female | 26.5 |
| *Age* | |
| <30 yo. | 0.0 |
| 30-39 yo. | 2.2 |
| 40-49 yo. | 26.7 |
| 50-59 yo. | 33.0 |
| 60+ yo. | 38.0 |
| *Clinical Specialty* | |
| GP/Internist/Family Pratice | 54.7 |
| Surgeon | 3.2 |
| Cardiologist | 1.0 |
| Psychiatrist | 0.8 |
| Other specialty | 16.4 |
| *HIV Specialists* | |
| Specialize in Infectious Disease | 23.9 |
| Experienced HIV Physician | 5.0 |
| HIV Specialist (Experience + ID Training) | 26.7 |
| *Region* | |
| Northern CA | 6.0 |
| San Francisco Area | 14.9 |
| Central CA | 11.6 |
| Los Angeles Area | 24.9 |
| Southern CA | 14.4 |
| Urban | 94.9 |
| *Practice Type* | |
| Small (1-5 phys.) private practice | 26.0 |
| Group (>5 phys.) private practice | 52.2 |
| Hospital appointment | 16.2 |
| Foreign Born | 34.4 |
| *Clinical Experience* | |
| Experince since med graduation (yrs.) | 28.6 |
| (sd) | (10.2) |
| Observations | 1,105 |

*Note:* This table presents the American Medical Association (AMA) background information for all physicians in the analytical sample of Medicare Part D drug claims. Demographics are presented as the share of physicians in each category, and standard deviations are in parentheses.

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