Privacy at What Cost? Using Electronic Medical Records to Recover Lapsed Patients Into HIV Care

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Abstract

We show that Malawian healthcare staff save lives by tracking down HIV patients lapsed from care – even against their wishes – using data made accessible with the implementation of an electronic medical records (EMR) system. HIV patients in Malawi receive antiretroviral therapy (ART), a highly effective treatment that also prevents transmission, for free at clinics. Yet patients frequently lapse from care, resulting in increased community transmission and unnecessary deaths. The introduction of EMR allowed health providers to manage patient data, trace lapsed patients, and encourage lapsed patients to reinitiate treatment. We implement an event study analysis using data from 106 clinics that adopted EMR between 2007 and 2019 and find that the introduction of EMR leads to an immediate increase in the number of patients actively in care and to a decline in patient deaths. After five years of implementation, facilities with EMR have approximately 34 percent more patients in care and 41 percent fewer patient deaths than facilities without EMR. These effects are concentrated among patients under 50, and are larger among young children. Effects are also concentrated among patients who do not wish to be traced; these patients are in fact more likely to lapse from care and require tracing. Robust to additional specifications and supported by interview findings, the results demonstrate that an initial preference for privacy gives way to patient reinstatement in care when the health consequences are critical.

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1 Introduction

The AIDS epidemic is far from over, with more than 500,000 deaths per year in sub-Saharan Africa alone. The only viable route for ending the epidemic is to retain HIV patients actively in care and on treatment. Effective treatment is widely available in the form of antiretroviral therapy (ART), a combination of drugs that saves lives and prevents HIV transmission. At the community level, the availability of ART has improved mental health, and increased savings and human capital investment (Baranov, Bennett and Kohler, 2015; Baranov and Kohler, 2018). However, ART patients often lapse from care, some immediately after diagnosis. This leads to new infections and unnecessary deaths. Lapses pose a major challenge to healthcare providers and policymakers. Efforts to trace patients lapsed from care are hindered by the low staff-to-patient ratios often present in low income countries, by the large number of AIDS patients and by the high frequency of scheduled clinic visits.

In this paper, we show that the introduction of an electronic medical records (EMR) system in Malawi led to a decrease in AIDS deaths by facilitating access to patient records, but that this impact relies on the willingness of healthcare staff to circumvent patient privacy preferences. EMR systems enhance patient monitoring by providing easy access to patient records, but also raise questions about patient privacy. Privacy is a central concern for patients with a positive HIV diagnosis, who face trauma, ill health, mortality risk, relationship consequences, and stigmatization. Yet health information is crucial for healthcare staff to provide quality care. Public health policy often attaches low weight to individual privacy preferences in service of the social good, especially in an epidemic. We find that privacy preferences also come with health costs to the individual, including a greatly increased risk of death.

In Malawi, lapsed HIV patients are traced by clinic staff by telephone or at their home address – on foot and by consulting local community leaders if necessary – and encouraged to reinitiate treatment. At a patient's first appointment, the patient is asked for consent to be traced should a lapse occur, but the provision of care does not require the consent, and many do not provide it. Patients who visit the clinic without a support person are more likely to decline consent for tracing, suggesting that a lack of support from family or community

might contribute to a patient's preference for privacy. While HIV testing is discreet and confidential in Malawi, privacy is not prioritized when patients lapse from care because of the consequences for both the individual and the community. In particular, clinic staff often trace patients regardless of whether or not they consented to tracing. Once traced, lapsed patients regularly assent to return to care.

In clinics with an EMR system, as opposed to paper-based recordkeeping, the process for identifying and tracing lapsed patients is simpler. In clinics without EMR, clinic staff have to examine thousands of individual patient records to identify those with missed appointments. In contrast, the EMR system quickly generates a list of patients who missed appointments, and clinic staff use this list to trace lapsed patients. In practice, it is difficult for clinic staff to honor a patient's request for privacy, as their consent preference is not recorded on the tracing list. In addition to facilitating tracing, the EMR system provides staff with access to patient health records, even after an absence, and prompts staff to provide standardized care based on up-to-date guidelines.[1]

We use an event study design to identify the effect of the Malawian EMR system on health outcomes for HIV patients, and to explore the implications of ignoring patient preferences for privacy. We collected data on patient lapses in care and on deaths from 106 Malawian clinics that switched from paper records to EMR between 2007 and 2019. The data include information on health outcomes under both the paper-based and EMR systems. According to policy documents, the EMR rollout was dictated by clinic size, and we do not find evidence for pre-trends. We estimate time-varying impacts of the switch with clinic and year fixed effects, and confirm the results using several robust specifications, including estimators robust to hetergeneous treatment effects in event study designs (de Chaisemartin and D'Haultfœuille, 2020*a*; Borusyak, Jaravel and Spiess, 2021). The analysis of mechanisms is supplemented by rich data from qualitative interviews with clinic staff and other stakeholders.

The findings indicate that the introduction of EMR led to an immediate increase in the number of patients actively in care, and a gradual decrease in patient deaths. Five years after the EMR system was introduced, an EMR-enabled clinic had approximately 34 percent

[1] Using data from the US healthcare system, Abaluck et al. (2020) find that improving adherence to guidelines can have a meaningful impact on health outcomes.

more patients actively in care and 41 percent fewer patient deaths than a pre-EMR clinic. The increase in the number of patients in care is driven entirely by patients returning to care, as opposed to new patients. Effects are similar for men and women, and are concentrated in patients under the age of 50, with large impacts for young children, who are particularly vulnerable to lapses in care. Aggregated over time, our findings imply that the adoption of EMR has prevented over 15,000 AIDS deaths; this number is higher than the annual number of AIDS deaths in Malawi (UNAIDS, 2019).

We find that patients who declined consent for tracing in fact benefit more from the improved tracing process facilitated by EMR, as compared to those who assented. This is primarily due to selection: the patients who decline consent for tracing are more likely to lapse from care than those who assent, and are therefore, in fact, more likely to appear on the tracing list and to be traced. Indeed, clinic staff ignore privacy preferences when tracing patients.

Clinics appear to adapt to the increase in active patients after EMR implementation by spacing out patient visits slightly, which suggests that the increase in efficiency due to EMR is not sufficient to offset this influx of patients. We do not find strong evidence that EMR improves quality of care. There is no sustained increase in the diagnosis and treatment of tuberculosis (TB), a common comorbidity for AIDS patients, despite the existence of EMR prompts.

We make contributions to the literatures on privacy, selection on treatment effects, the impact of EMR and digitization more broadly, and demand for HIV care.

First, we show that honoring the data privacy preferences of patients can significantly hamper the effectiveness of an EMR system, and comes at the cost of disruptions in care and even deaths. A patient's decision to return to care despite a preference for privacy, and despite the violation of that preference by clinic staff, suggests a complex experience of privacy that has not been explored fully in the literature (Acquisti, Brandimarte and Loewenstein, 2015; Goldfarb and Tucker, 2012*b*; Kshetri, 2014). The policy implications are significant because, in many countries, privacy regulations are strictly enforced (Goldfarb and Tucker, 2011, 2012*a*). This can have serious consequences in the health sector. Studies show that hospitals in states with stronger privacy laws are less likely to adopt EMR, leading

to an increase in neonatal mortality (Miller and Tucker, 2009, 2011).

The finding that tracing primarily benefits patients who prefer privacy is a clear example of *negative selection on treatment effects*, a phenomenon that has been documented in other contexts. In contrast to the standard self-selection model (Roy, 1951), some policies appear to have larger impacts for the people who select out. For example, Einav et al. (2020) find that women who comply with breast cancer screening recommendations are in fact less likely to have cancer, and Oster (2020) finds that health recommendations are more likely to be followed by those in good health. This type of pattern has also been documented in context of migration; Chyn (2018) and Deryugina, Kawano and Levitt (2018) find that forced displacement can lead to positive economic outcomes.

The paper also contributes to a broader understanding of whether and how digital systems such as EMR improve patient outcomes. The findings reported here suggest that the impact of EMR can be quite large and even life saving in low-income countries where staff-to-patient ratios are low. In our setting, the mechanism is clear: EMR allows healthcare staff to easily query a large patient database according to particular criteria (missed appointments). This mechanism is likely at play in any context where follow-up is required for a subset of patients, for example, based on laboratory results or the date of a previous vaccine or procedure.[2] Prior studies on the impact of EMR – and more broadly, information technology (IT) – have focused on the United States health sector (Miller and Tucker, 2011; Bhargava and Mishra, 2014; Dranove et al., 2014; Hitt and Tambe, 2016) and have generally reported only minor impacts in quality improvement, staff productivity, and cost-effectiveness (Agha, 2014; Bhargava and Mishra, 2014; Dranove et al., 2014).[3] However, in some contexts, EMR adoption does appear to improve quality of care, and can impact patient health including mortality (McCullough et al., 2010; McCullough, Parente and Town, 2016; Miller and Tucker, 2011). Miller and Tucker (2011) show that EMR can facilitate access to patient records, and thus reduce neonatal mortality rates. Consistent with this result, we find that the impact of tracing on HIV patient outcomes after EMR implementation in Malawi is strongest among

[2] See Shadmi et al. (2020) for an example from the Israeli healthcare system, where machine learning was used to identify patients at risk of readmission.

[3] Douglas et al. (2010) present qualitative evidence on EMR implementation challenges in developing countries, and Driessen et al. (2013) estimates the cost savings associated with Malawi's EMR system.

children.

Finally, this study identifies an intervention that prevents AIDS deaths, and likely prevents the spread of HIV by returning lapsed patients into active care. Other electronic health interventions such as text message reminders have been found to slightly improve adherence to ART treatment (Pop-Eleches et al., 2011; Mbuagbaw et al., 2013; Wang et al., 2019). Related work has evaluated interventions that affect demand for HIV testing (Thornton, 2008; Banerjee, La Ferrara and Orozco-Olvera, 2019; Derksen, Muula and van Oosterhout, 2021). While testing is an important first step towards treatment, in this paper we directly observe and report on the impact of an electronic intervention – namely EMR – on important outcomes such as the continuity of HIV treatment and the reduction of patient deaths.

The remainder of the paper is organized as follows. Section 2 provides a description of the context. In Section 3, we discuss the data and the empirical approach. In Section 4, we discuss our findings, and in Section 5, we conclude.

2 Context

2.1 HIV Care in Malawi

Malawi, in southeastern Africa, is one of the most AIDS-affected countries in the world. With 9.5 percent of the population estimated to be HIV positive in 2019, the country ranks 9th worldwide in terms of HIV prevalence. Approximately 13 thousand Malawians died of AIDS in 2019 out of a population of near 20 million. In 2004, at the peak of the epidemic, more than 70 thousand AIDS deaths occurred.[4]

While the number of people living with HIV has increased over time, AIDS deaths have decreased dramatically due to the widespread availability of ART. ART is a combination of drugs, taken daily, that suppress the virus over the long term. ART alleviates the symptoms of AIDS and prolongs life by decades. ART also prevents HIV transmission between sexual

[4] Sources: USAID available at https://2012-2017.usaid.gov/malawi/fact-sheets/malawi-hivaids-fact-sheet and CIA The World Factbook available at https://www.cia.gov/the-world-factbook/field/hiv-aids-adult-prevalence-rate/country-comparison and https://www.cia.gov/the-world-factbook/field/hiv-aids-deaths/country-comparison. All accessed on March 24th, 2021.

partners (Cohen et al., 2011). For these reasons, scaling up treatment has become central to public health policy.

In Malawi, ART is available free to patients through more than three hundred urban and rural clinics. ART first became available in the early 2000's, with local accessibility improving over time. Eligibility for treatment has also expanded following changes in World Health Organization (WHO) guidelines. Initially, only those with advanced HIV (those with severe symptoms or a weak immune system as determined by a blood test) qualified for treatment. Since 2016, Malawi has adopted a universal test-and-treat policy: anyone diagnosed with HIV is encouraged to initiate treatment immediately. Patients must return to the clinic every few months for health assessments and to refill their prescriptions.

2.2 Electronic Medical Records

Early in the epidemic, ART clinics in Malawi used standardized paper records for patient data. The paper record included information on the patient's HIV status, initiation of ART, refill visits, and death. In 2005, the Malawian Ministry of Health (MoH) began the process of migrating Malawian clinics from paper-based patient records to EMR. EMR was first introduced in a large hospital in 2007, and was rolled out to 124 clinics by 2019.[5]

EMR is standardized across clinics in Malawi. In an EMR-enabled clinic, patient records are entered on a touchscreen device at the point-of-care (POC). A barcode on the patient's "health passport," a laminated card carried by the patient, allows staff to access the patient's record, which includes medical history. The health passport ensures the continuity of patient care by linking each reinstated patient with the patient's established EMR even if the patient returns to care after a long absence. During a patient visit, the EMR system alerts healthcare staff to medical issues, prompts the staff member to take measurements or conduct additional tests, and guides the dispensation of medication.[6]

[5] For a more detailed description of the EMR system and rollout see Douglas et al. (2010), as well as data from qualitative interviews in Appendix Table A5.

[6] A video explaning the development of the Malawian EMR system is available at `https://www.ted.com/talks/soyapi_mumba_medical_tech_designed_to_meet_africa_s_needs`, accessed on March 24th, 2021.

2.3 Lapse From Care and Patient Tracing

Approximately 79 percent of Malawians living with HIV are now enrolled in ART programs, but retaining ART patients in care is a challenge. Patients and their families may avoid care for reasons that include (i) fear of stigmatization or relationship consequences (ii) the need for frequent clinic visits, which impede fulfillment of work and family responsibilities, (iii) concerns by parents that children who are diagnosed as HIV-positive will die, be subjected to difficult treatments, or be burdensome to the family, and (iv) aversion to the side effects of treatment (Genberg et al., 2015; Hoffman et al., 2017). At the time of EMR implementation in a clinic, 49 percent of patients on average had lapsed from care. Clinic staff formally engage in patient "tracing:" they track patients down by telephone or at their home address if they miss an appointment. New ART patients are supposed to be asked whether they consent to being traced, and this preference is recorded in the health record. However, this preference is not always considered by staff because of the serious consequences of lapsed care, which include patient death and increased community spread of HIV.

Prior to EMR implementation, clinic staff could not easily trace lapses because patient appointment dates were not centrally listed or analyzed. Catching a missed appointment required searching through thousands of paper-based patient records; at the time of EMR implementation, the average clinic had over 3,000 patients enrolled. As a matter of routine, healthcare staff generally focused attention on patients that met appointments rather than tracking down those who lapsed.

The EMR system facilitates the tracing of lapsed patients by clinic staff. The system allows clinic staff to query patient records directly and automatically generates a list of patients at least two months late for an appointment. Clinic staff routinely engage in formal tracing by printing out a new tracing list approximately once every two weeks. This list contains patient contact information regardless of whether the patient expressed a preference for being contacted after a lapse. The tracing list does not include information on whether each patient on the list consented to the tracing. This makes it difficult for staff to honor a patient's preference even for those staff who may seek to do so.[7]

[7] For details on the perceived impact of EMR on tracing, see data from qualitative interviews with clinic staff in Appendix Table A5.

3 Data and Empirical Approach

3.1 Data Sources

The analysis relies on administrative data on ART patients in the Malawian healthcare system. We use a large proprietary dataset containing individual de-identified data on ART patients visiting the 124 clinics that implemented the EMR system between 2007 and 2019. The panel is unbalanced, as clinics began offering ART at various times between 2003 and 2012. After EMR implementation, data was entered at the point of care (POC) by clinic staff at every visit, including initiations, all prescription refill visits, and deaths. In 106 clinics, clerks also back-entered the paper-based files of all patients ever enrolled in ART at that clinic. This back-entered data includes all patient initiations and patient deaths recorded in paper records. However, only the most recent pre-EMR prescription refill visit was back-entered. The back-entered data enables us to estimate the impact of EMR on health outcomes. The dataset we use for analysis includes only the 106 clinics that back-entered data, and excludes the first and last year of data for each clinic, which are incomplete (see Table 1 for additional description of the sample used for analysis).

To better understand the context and results, we complement our econometric analysis with qualitative interviews.[8] We interviewed clinic staff (nurses, physicians, data clerks, and coordinators), expert clients (responsible for monitoring, tracing, and encouraging patients to adhere to ART), MoH employees, non-governmental organization (NGO) collaborators, and local community leaders.[9]

3.2 Patients Actively In Care and Patient Deaths

In our sample, we observe a total of 755,175 patient initiations and 55,181 patient deaths. As of 2018, 358,843 patients were actively in care. Table 1 reports clinic-level averages including

[8] Recent literature in economics highlights the value of qualitative data (Blattman et al., 2016); see Bertrand et al. (2007) for an example of how qualitative data can be used to supplement analysis.

[9] Under the supervision of the authors, a local team conducted a total of 50 interviews. On average, each interview lasted for one hour and discussed topics related to the perceived effect of EMR on: clinic management, patient tracing, clinic quality, number of initiations, loss to care, and deaths. Appendix Table A5 includes a selection of quotes from the interviews further illustrating some of the mechanisms behind our results.

number of patients actively in care, new patients, returning patients, and patient deaths. Years prior to 2012 partially reflect selection into the panel because ART treatment was available at only a subset of the 106 clinics. In the database, ART initiations sometimes include previous patients who returned to care but were not linked to their previous record. Patient death dates are often reported to the clinic by a family member, but may also be discovered when a staff member attempts to trace the patient. The panel shows that, from 2012 to 2018, patient deaths fell steadily. Overall, 6 percent of patients died within two years of initiating ART.

Patients frequently miss appointments for ART refills and are lapsed from care. 17 percent of patients lapse immediately after initiating ART. On average, fully half of the patients within a clinic had lapsed from care at the time of EMR implementation. Children are particularly likely to lapse; 23 percent of children under age 10 lapse immediately after initiation, and 57 percent are lapsed at the time of EMR implementation (see Figure 1, which reports lapse rates by gender and age group). This suggests that parents make choices that reflect complex concerns about the consequences of HIV-positive diagnoses for the family. AIDS is fatal without treatment, and those who lapse from care often die. At the time of EMR implementation, one-fifth of lapsed patients had died.

3.3 Patient Consent for Tracing

Clinic staff are supposed to ask new ART patients whether they consent to tracing, i.e., whether they consent to being tracked down at home if they miss an appointment. In practice, 66 percent of patients are asked, and 91 percent of those who are asked provide consent. These rates do not vary substantially by patient gender or age group (see Figure 2, Panels A and B). However, patients who visit the clinic with a support person, as opposed to alone, are much more likely to consent to tracing (see Figure 2, Panel C). Among those who visit the clinic with a support person, 65 percent are asked for consent to tracing, and among those who are asked, 97 percent assent. In contrast, among those who visit the clinic alone, 60 percent are asked for consent to tracing, and 85 percent of those asked assent. This discrepancy suggests that local and family support networks may play a role in a patient's preference for privacy.

Patients with advanced disease are more likely to be asked for tracing consent, and those who give consent are less likely to miss an appointment, less likely to lapse care, and less likely to die. In Table 2, we report on these likelihoods by regressing each variable of interest on consent to tracing, where the reference category is those who were not asked. The regressions include clinic and year fixed effects. Those with advanced HIV (as defined by the WHO) are much more likely to be asked for tracing consent, perhaps because their continued care is so critical.[10] These patients are also given an earlier next appointment date.

Those who consent to tracing are less likely to miss their next appointment than those who refuse, and were seven times more likely to be actively in care at the time of EMR implementation. Before the implementation of an EMR system, patients asked for consent were more likely to die within two years than those who were not asked, likely due to their poorer health. However, among those who were asked, those who consented to tracing were more likely to survive than those who did not.

3.4 Empirical Approach

We focus on two outcomes at the clinic-year level: the number of patients actively in care and patient deaths. We define a patient as "in care" if they visit the clinic at least once during the year either to initiate ART or to obtain medication refills. We also separate this outcome into two subcategories: patients that visited the clinic to initiate ART and patients that visited only for prescription refills. We estimate heterogeneous treatment effects by examining subsets of patients based on gender, age, and preference for privacy, as defined by the consent to tracing response ("yes", "no" or "not asked").

To estimate the impact of EMR implementation on patient outcomes, we conduct an event study with year and clinic fixed effects. We allow for time-varying treatment effects to capture both the immediate and the long-run effect of EMR implementation on outcomes. The dependent variable is the logarithm of the outcome.[11] The estimation equation is:

[10] The WHO defines "advanced HIV" as having symptoms associated with Stage 3 or 4, or having a CD4 count below 200.

[11] We take the logarithm in order to address skew and estimate elasticities. We add one to each variable, to include clinics which are open but for whom the outcome is equal to zero. In Appendix Tables A2 and A3, we report results using the inverse hyperbolic sine transformation, an alternative way of incorporating zero values (Burbidge, Magee and Robb, 1988).

$$y_{ct} = \alpha_c + \lambda_t + \sum_{k=0}^{5} \tau_k \mathbf{1}\{t - E_c = k\} + \tau_6 \mathbf{1}\{t - E_c \geq 6\} + \varepsilon_{ct} \quad (1)$$

Here, y_{ct} is the dependent variable for clinic c and year t. α_c is a clinic fixed effect, and λ_t is a year fixed effect. k is the number of years since the event (EMR implementation), where the event occurs in clinic c at the beginning of year $t = E_c$ or $k = 0$. τ_k is the effect size k years after the event. Because all clinics adopt EMR at some point, and because of imbalance in our panel, we must exclude several time periods from the specification to avoid multicollinearity. We elected to exclude information on all pre-period years ($k < 0$) from the estimation, which allows data from these years to serve as a reference period and increases statistical power. We also assume a constant long-run effect, and estimate a single coefficient, τ_6, for all periods greater than or equal to 6 years post-event.[12] We investigate pre-trends separately by regressing outcomes on clinic and year fixed effects and on two lagged treatment indicators, including only pre-intervention data, following Borusyak, Jaravel and Spiess (2021).[13] We cluster standard errors at the clinic level (Cameron and Miller, 2015).

For the two-way fixed effects estimator to be causal, three assumptions must be satisfied: parallel trends, no pre-treatment effect, and treatment effect homogeneity by clinic (Abraham and Sun, 2020). The first assumption would fail if EMR adoption were endogenous, for example, to clinic performance. Policy documents show that the criterion for EMR implementation was primarily the total number of patients enrolled at the clinic (Douglas et al., 2010), independent of the number of lapsed patients. Table 1 shows a higher number of initiations among clinics that adopted earlier. We include a clinic fixed effect in our main analysis, which accounts for differences in clinic size, and confirm our results using various robustness tests. These include allowing for heterogeneous treatment effects by clinic size, and interacting time fixed effects with clinic size.[14]

[12] We have sufficient pre-intervention data to relax this assumption when estimating the effect on patient deaths. We plot the results of a two-way fixed effects estimation with fewer omitted periods in Appendix Figure A1.

[13] We include only two lagged treatment indicators in an effort to increase the statistical power of the F-test to detect pre-trends. This may be important given imbalance early in the panel.

[14] We cannot use the latter specification for outcomes measuring the number of patients actively in care, as we only have one period of pre-intervention data. We also note that because of panel imbalance, including clinic-specific time trends leads to perfect multicollinearity, which means that we cannot include these trends as controls.

Several recent papers have shown that, in staggered implementation designs, two-way fixed effects estimates, including estimates of pre-trends, may be biased due to heterogeneous treatment effects (de Chaisemartin and D'Haultfoeuille, 2020*b*; Goodman-Bacon, 2018; Abraham and Sun, 2020; Callaway and Sant'Anna, 2020; Baker, Larcker and Wang, 2021; Borusyak, Jaravel and Spiess, 2021). To address this, we estimate time-varying treatment effects, which partially alleviates this concern (Goodman-Bacon, 2018; Abraham and Sun, 2020). In order to further address this issue, we perform additional analyses using two estimators that are robust to heterogeneous effects across time and clinic, and which can be readily applied to an unbalanced panel. The first is the imputation estimator developed by Borusyak, Jaravel and Spiess (2021), which has attractive efficiency properties, and the second is a weighted sum of differences-in-differences as proposed by de Chaisemartin and D'Haultfœuille (2020*a*). These estimators confirm the effect on patient deaths. However, we cannot use these methods to estimate the effect on patients actively in care, as we only observe this outcome for one pre-intervention period. We are able to perform a different robustness test for this outcome because we expect EMR to improve patient tracing nearly immediately. We examine granular monthly data within a narrow time window around EMR implementation (one month before and twelve months after), and include only clinic fixed effects. This allows us to estimate a single coefficient for each month without assuming a constant long-run effect.

4 Results

4.1 Impact of EMR on Patient Outcomes

EMR implementation has an immediate and persistent positive impact on the number of patients actively in care, with larger impacts for younger patients (see Figure 3, Figure 4, and Table 3). We identify a significant ($p < 0.01$) 17 percent increase in the number of patients visiting a clinic in the year immediately following EMR implementation, and this increase grows over time after the implementation.[15] Five years after EMR implementation,

[15] We report estimated effect sizes by translating log points into elasticities, following Kennedy et al. (1981).

the number of patients actively in care is approximately 34 percent higher at an EMR clinics relative to a clinic that has not yet adopted EMR. This pattern arises for both men and women (see Figure 3). This effect is much larger for patients under the age of 50, and especially large for children and adolescents, who are more than 30 percent more likely to be in care in the year following EMR implementation ($p < 0.01$, see Figure 4 and Table 3).

We also observe a decline in deaths over time among patients enrolled in EMR clinics, and the effect is again concentrated among younger patients (see Figure 3, Figure 4, and Table 3). The decline is gradual, from a 7 percent decrease in the year immediately subsequent to EMR implementation to a significant 41 percent decrease ($p < 0.01$) after five years. While the impact on men appears as early as two years post-EMR, the effect is balanced across genders over the long run. The negative effect on deaths is concentrated among patients under the age of 50, and is particularly large for children under age 10 and for adults aged 18 to 49 (see Figure 4 and Table 4). The implementation of EMR decreases deaths among younger children by approximately 20 percent in the first year ($p < 0.05$), and by approximately 84 percent after five years ($p < 0.01$).

In a given year, each patient actively in care can be classified as either new (i.e., initiating ART) or returning (i.e., visiting only for prescription refills). Rerunning the analysis on each of these categories of patients shows that the increase in patients in care after EMR implementation is driven entirely by patients returning for prescription refills (see Table 6). The recorded number of returning patients in the year following EMR introduction is approximately 22 percent higher than in the year prior to EMR implementation, and this rises to 45 percent five years after EMR implementation. In contrast, ART initiations decrease slightly after the introduction of EMR, and this decrease is significant after five years of implementation. Recall that this variable includes reinitiations for patients who, against policy, received new identification numbers (IDs). The fact that EMR implementation is associated with fewer subsequent initiations likely arises because, prior to EMR implementation, many new identification numbers were applied erroneously to patients that should have been recording as previously lapsed and returning to care. Indeed, if we examine the pattern across age groups in Figure 4, we see that it mirrors the increase in returning patients, suggesting that, after EMR, returning patients are more likely to be assigned to their previous identifiers.

Therefore, this result partially reflects a change in the number of patient identifiers as opposed to a change in the number of patients. In contrast, the estimated impact of EMR on the number of patients actively in care (Table 3 Column 1) represents a true increase in the total number of patients; this outcome includes all patients regardless of whether they are classified as new or returning.

4.2 Heterogeneity by Privacy Preferences

Next, we investigate whether the impact of EMR is heterogeneous based on patient preferences for privacy.

The impact of the EMR system on the number of patients actively in care is concentrated among those who did not provide consent to being traced as well as among patients for whom a preference was not recorded (see Figure 5 and Table 7). The effect is immediate and persistent. Recall that these two categories of patients were more likely to be lapsed at the time of EMR implementation than patients who did consent to tracing (see Table 2), and were therefore more likely to actually require tracing. There is no impact among those who did consent to tracing. Because the EMR-generated tracing list does not include information on whether the patient consented to tracing, the likely explanation for this heterogeneity is that staff trace patients regardless of their preferences, and that patients who prefer privacy are more likely to lapse and therefore more likely to appear on the tracing list.

The impact on patient deaths is similarly concentrated among patients who did not consent to being traced or who were not asked to express a preference (see Figure 5 and Table 8). There is again no impact among those who consented to tracing.

4.3 Clinic Efficiency and Quality of Care

Finally, we investigate the impact of EMR on clinic efficiency and quality of care. At each visit, a patient is provided a particular number of doses of medication, which is used to determine their next appointment date. In Table 9, we estimate Equation 1, where the dependent variable is defined as the average number of days' worth of medication provided at the time of ART initiation, measured at the clinic-year level. We find that the introduction

of EMR quickly leads to a small increase in the amount of medication provided, suggesting an increase in the time between ART appointments as clinics reduce the frequency of patient visits to offset the increase in the number of patients in care.

To investigate the impact on quality of care, we examine the rate of treatment for TB, a common HIV comorbidity, among new patients. The EMR system prompts staff to diagnose and treat TB where indicated. We again estimate Equation 1, where the dependent variable is defined as the logarithm of the number of TB patients diagnosed and treated at the time of initiation. We find an 19 percent increase in TB diagnosis and treatment in the first year after EMR is introduced ($p < 0.1$, Table 9). This increase does not persist, however, which suggests that improvements in quality of care due to EMR may be limited.

4.4 Robustness

We perform several additional robustness tests.

First, we test for pre-trends using the robust method proposed by Borusyak, Jaravel and Spiess (2021), reporting F-statistics and p-values in all main tables. We do not find evidence of pre-trends for any outcomes. In Figures A1 and A2, we also plot these pre-trends, in addition to the pre-trends estimated by two-way fixed effects and by the de Chaisemartin and D'Haultfœuille (2020*a*) estimator.

Next, we show that our findings are robust to allowing for heterogeneous effects by clinic size, and we find no clear evidence of such heterogeneity (Table A1 and Figure A3). We also estimate the impact on patient deaths using time fixed effects interacted with standardized clinic size, and find similar impacts.[16]

Because of potential bias in the two-way fixed effects estimator, we confirm the results for deaths and initiations using the Borusyak, Jaravel and Spiess (2021) imputation estimator, as well as the de Chaisemartin and D'Haultfœuille (2020*a*) estimation procedure. We also estimate a version of Equation 1 which includes three pre-trends and does not assume a constant long-run effect.[17] These three sets of estimates are displayed in Figures A1 and A2.

[16] Recall we cannot estimate the impact on patients in care using this latter specification, as we only observe data for one pre-intervention period.

[17] Because we do not have a pure control group (all clinics are eventually treated), including many pre-trends results in highly imprecise estimates. To increase statistical power to detect pre-trends, we include

The results closely resemble our main findings in Figure 3.

We also report results of a model estimating a single average effect using two-way fixed effects, Borusyak, Jaravel and Spiess (2021) and de Chaisemartin and D'Haultfoeuille (2020*b*) estimators, in Appendix Table A4. Note that the two-way fixed effects estimator is likely to be biased for this specification, due to the presence of time varying effects (Goodman-Bacon, 2018). Again, the findings are robust, though the estimated average effect on deaths using the de Chaisemartin and D'Haultfoeuille (2020*b*) estimator, while negative and of a meaningful magnitude, is not significant.

Finally, we perform an additional robustness test for the outcomes that include patient visits for prescription refills. In a regression at the clinic-month level, with only clinic fixed effects, we observe a sudden drop in patients actively in care, and in returning patients, in the exact month of EMR implementation (see Figure A4). This drop is large and significant, and likely represents an attempt by clinics to avoid scheduling appointments during the implementation and training period. After four months of implementation, the number of patients in care, and the number of returning patients is significantly higher, compared to the month preceding EMR implementation. This increase in patients is sustained throughout the first year, and appears to reflect a level increase as opposed to a time trend.

4.5 Qualitative Data

In this section, we supplement our main analysis with qualitative insights obtained from interviews with clinic staff, MoH employees, NGO collaborators, and local community leaders.[18]

These interviews indicate that the EMR system facilitated patient tracing, which would explain the immediate increase in the number of patients in care after EMR implementation, and which could explain the eventual reduction in patient deaths. Staff describe an improved tracing system that identified lapsed patients early and that facilitated bringing lapsed patients back into care quickly. Rather than searching through handwritten patient records, staff describe using the EMR system to generate a list of patients to be traced.

only a small number of estimates.

[18] See Appendix Table A5 for full quotations from qualitative interviews.

Several staff members from different clinics and different hierarchical levels described this list as critical for effective patient tracing. According to the staff we interviewed, EMR also improved efficiency in clinic service provision. In particular, EMR optimized the flow of patients during clinic visits to obtain ART and other medication.

The qualitative data suggests that clinic staff face a tradeoff between ensuring patient privacy and averting death by returning patients into care. Often staff prioritize treatment over patient privacy given the consequences of lapsed care both for the patient and for the community. The staff do not verify whether a patient has consented prior to tracing, and this information is not included on the tracing list by default. Clinic staff and community leaders argue that, by prioritizing treatment over privacy, they are helping to save lives and prevent the spread of HIV in the community.

Despite this practice, staff express an awareness of patient privacy concerns and the risk of stigmatization. In fact, some clinic staff believe that patients do attend scheduled appointments partly to avoid being traced. When tracing a patient, staff often seek to avoid exposing patients to stigmatization. They prefer to start with a telephone call. If calls are not answered, or no number is listed, staff will follow up with an informal visit to the patient's home. If staff cannot find the patient, they will reach out to community leaders for help. Staff report that many patients have a positive reaction to the contact and return willingly to care. However, others are less willing, and may be cajoled or even coerced by community leaders to return to care. If other patients become aware of the use of aggressive tracing measures, they might provide false information to avoid being traced. In particular, staff complain about the time they spend attempting to trace patients who have provided false contact details. Community leaders generally support the tracing effort and cooperate fully with the goal of preventing HIV spread in their communities and of averting unnecessary deaths.

The interviews also reveal an explanation for the small decline in ART initiations we observe following EMR implementation. Before EMR implementation, staff report difficulties in reinstating lapsed patients by matching individuals after an absence with their prior health records. As a result, these patients were frequently misclassified as new initiations and assigned new patient IDs despite their prior histories. After implementing EMR, the system

allowed clinic staff to link existing patients to their original patient records rather than assigning new ones. This was because the patient's "health passport" (see Appendix A5 for illustration), which is presented by the patent upon reinstatement, includes a barcode that can be read by the EMR system. This barcode links the lapsed patient to their established health record. Even if the patient does not present a health passport, the EMR system can quickly recover a record based on the patient's name.

5 Discussion and Conclusion

This paper analyzes the impact of the implementation of an EMR system in Malawi, which improved access to patient records, and facilitated patient tracing by clinic staff. The findings indicate that the EMR system led to an immediate and persistent improvement in the recovery of lapsed patients into care, and a gradual decrease in patient deaths. These effects are more pronounced for patients under the age of 50, and are notably large for young children. Improved patient tracing appears to be the primary explanation for the decrease in deaths. The introduction of the EMR may also have increased clinic efficiency, and enabled clinic staff to perform better patient assessments. However, we do not see an improvement in TB treatment, a major comorbidity for AIDS patients. In interviews, clinic staff explain that the EMR system made patient tracing routinely feasible by facilitating access to patient records. Rather than sifting through thousands of paper records, clinic staff could use a system-generated list to trace patients, including those who had previously expressed a preference to not be traced.

In fact, our estimated effects are concentrated among patients with a preference for privacy; that is, a preference to not be traced. Patients with a preference for privacy are more likely to visit the clinic alone, as opposed to with a support person. Prior to EMR implementation, patients with such a preference were significantly more likely than those who did consent to tracing to miss an appointment, to lapse from care, and to die. This could reflect selection; people who consent to tracing may be more committed to their treatment than those who do not. Or, as suggested in interviews with clinic staff, patients might view the threat of tracing as a commitment device: after consenting to tracing, patients might

prefer to attend their appointments on time to avoid being visited at home.[19]

These results suggest a complex evolution in the preferences and experiences of those who initially express a preference for privacy, subsequently lapse, are traced, and then return to care. Expressing a preference for privacy may be tantamount to expressing a preference not to be stigmatized or even a preference not to be labeled as HIV-positive. Yet patients that are traced – even against their initial expression of preferences for privacy – are more likely to survive than those who are not traced. Understanding this process is important because it suggests for many patients the cost of privacy may be death – both personally and through transmission of disease in the community.

Tracing benefits society by preventing the spread of HIV and preventing AIDS deaths. It likely also benefits individual patients directly since it lowers the risk of death. The effectiveness of tracing implies that social pressure is often sufficient to offset a patient's perceived cost to returning to care. Patients might be unaware initially that delaying HIV treatment significantly increases the risk of mortality (Insight Start Study Group, 2015). Social pressure may also help patients overcome problems of limited self-control; indeed, procrastination has been identified as a significant barrier to HIV testing (Derksen et al., 2021). Tracing children, in particular, is immensely beneficial. Young children are particularly vulnerable to lapses in care. They therefore benefit most from an improved patient tracing process, which greatly reduces their risk of death. Several factors likely contribute to this important yet alarming result. Parents might find it difficult to accept a child's diagnosis, and having an HIV-infected child may carry additional stigma. Moreover, caring for an HIV-positive child is a great burden for families, and many HIV-positive children are orphans. Children cannot typically visit a clinic on their own, nor keep track of appointments themselves, and therefore rely on the attention of caregivers who are often busy with other work and family responsibilities.

We observe fewer new patient initiations after the implementation of EMR. Both quantitative and qualitative results suggest that the decrease in ART initiations following EMR implementation likely represents a decrease in redundant initiations, as lapsed patients return to care under their original patient ID instead of receiving a new ID. This result is an

[19] This explanation implies that patients (incorrectly) expect their privacy preferences to be honored.

indication that EMR improves continuity of patient care. This finding is related to a second explanation for the reduction in new initiations. We see that retention in care is accompanied by a reduction in "new" initiations. If a patient is not lost to care, then the patient cannot be recorded later as a "new" patient. Alternatively, a decrease in initiations could arise due to capacity constraints, especially given the increase in the number of patients in care, or due to a decrease in new HIV infections. However, the criteria for ART initiation are set by the MoH, and Malawi has never had a shortage of ART medication relative to the MoH treatment guidelines. Clinic capacity can easily be managed by extending the time between visits, rather, than delaying ART initiation. Indeed, we see that clinics do manage capacity in this way after the introduction of EMR. However, even after EMR implementation, clinics do not seem stretched to capacity in terms of patient visits: among clinics in our sample, the median time between initiation and the first scheduled visit is rarely more than one month.[20] Moreover, neither capacity constraints nor a decrease in new infections would not explain the fact that the decrease is sharper among the age groups who are more likely to remain alive and in care post-EMR implementation.

The fact that our measure of patient initiations includes some returning patients means that we cannot accurately calculate the total number of patients ever enrolled at a given clinic. This type of measurement error is likely widespread, and raises the possibility that country- and region-level reports overestimate ART coverage.

The primary limitation of this study is that we have only limited information on the economic, social and psychological processes that lead patients to express preferences for privacy. Similarly, we have little information on the economic, social and psychological processes that lead lapsed patients to respond favorably to tracing despite prior expressed preferences for privacy. We conjecture that these patients initially express a preference for privacy for fear of stigmatization, reputational concerns, and other social consequences. To the extent that these concerns are stronger among younger adults, our results support this conjecture. Moreover, we find that patients who visit the clinic with a support person are more accepting of tracing practices; this suggests that the existence of a local or family support network may influence a patient's preference for privacy. However, more research

[20] In 99 percent of clinic-years, the median time between visits is one month or less.

on these challenges is warranted.

Our study has other limitations. We are limited in our choice of alternative estimators due to imbalance in the sample, and the fact that all clinics are treated at some point in time. We only observe the number of actively in care patients for one period prior to EMR implementation, further limiting potential specifications for that outcome. Moreover, deaths are reported to clinics by family members or are discovered by staff when tracing a patient. For this reason, deaths might be underreported especially prior to EMR implementation. This suggests that our estimate of the impact of the EMR system in reducing patient deaths may be an underestimate.

Our findings indicate that the benefits of using electronic medical records to trace lapsed HIV patients, even against their expression of preferences at the onset of care, can have lifesaving benefits. This has nuanced implications for policy. While the EMR system sharply increases the total number of patients actively in care, it is possible that tracing patients, especially against their original wishes, has other negative consequences. For example, the prospect of tracing may encourage patients to give false names and addresses, and may even discourage pursuing care among some subpopulations. This is a worthy topic of future research.

One set of potential policy responses addresses behavioral and informational barriers to tracing while respecting patient privacy preferences. This approach includes using an opt-out approach to tracing, providing patients with additional opportunities beyond the first visit to consent to tracing, giving patients options to be traced by phone vs. at home, and providing additional information to patients about the benefits and importance of tracing, at the time consent is sought. This approach might also include ensuring that patients are aware of the risks of lapsing from care, by providing precise information about the mortality risk of delaying treatment, or about the risk of infecting others.[21]

The second set of potential policy responses involves deepening the social and psychological resources available both in clinics and through community outreach to support patients and healthcare staff throughout the processes of diagnosis, treatment, and comprehensive

[21] Derksen, Muula and van Oosterhout (2021) find that providing information about transmission risk increases HIV testing.

care, and to foster community-level acceptance and support for people living with HIV. The consequences of an HIV diagnosis for patients are profound. The positive implications of provision of care subsequent to tracing even against a patient's wishes suggests that both patients and staff undergo transformations that may benefit from specialized social care and psychological support. While individual counselling is a critical component of HIV care, patient privacy preferences likely depend on stigmatization and other community level attitudes towards HIV. A carefully designed community outreach campaign could address the root causes of stigma, and cultivate a supportive local environment for ART patients, which might in turn increase patients' engagement with the healthcare system.[22]

The third policy implication is that the adoption of EMR can deliver life-saving benefits even when these benefits are not appreciated, understood, or pursued by patients. Even when patients equivocate regarding the receipt of care, the EMR system enables effective intervention by healthcare staff. Indeed, the introduction of EMR can dramatically increase efficiency among healthcare staff, while reducing costs (Driessen et al., 2013). This is particularly important in low income countries with poor staffing ratios and overburdened healthcare systems. The efficiency improvements associated with EMR can affect critical health outcomes, including deaths among both adults and children. The ethical considerations related to patient privacy and consent become considerably more complicated when a parent answers on behalf of a child.

Many questions arise from this analysis for further research. Chief among them is the economic, social and psychological processes challenges that lead patients to express a preference for privacy in the face of an HIV diagnosis. More study is required on the stigmatization of the ill, and of the consequences of this stigmatization for privacy preferences. Privacy, it turns out, is not so simple. Many express a preference for privacy that is deeply motivated by fear of stigmatization, loss of work, loss of family life, and loss of social relationships. When stigmatization has life-threatening consequences, understanding how expressions of preferences for privacy are motivated is critical. When healthcare providers understand the fear, social challenges, and psychological impact of a positive diagnosis, then they can de-

[22] Derksen, Muula and van Oosterhout (2021) find that providing information on "treatement-as-prevention" reduces stigma towards ART users. On the other hand, some campaigns designed to reduce stigma have been found to in fact exacerbate it (Yang et al., 2021).

liver treatment that includes not only the scheduled administration of medicines, but also the social contact that keeps patients in care and that averts premature death.

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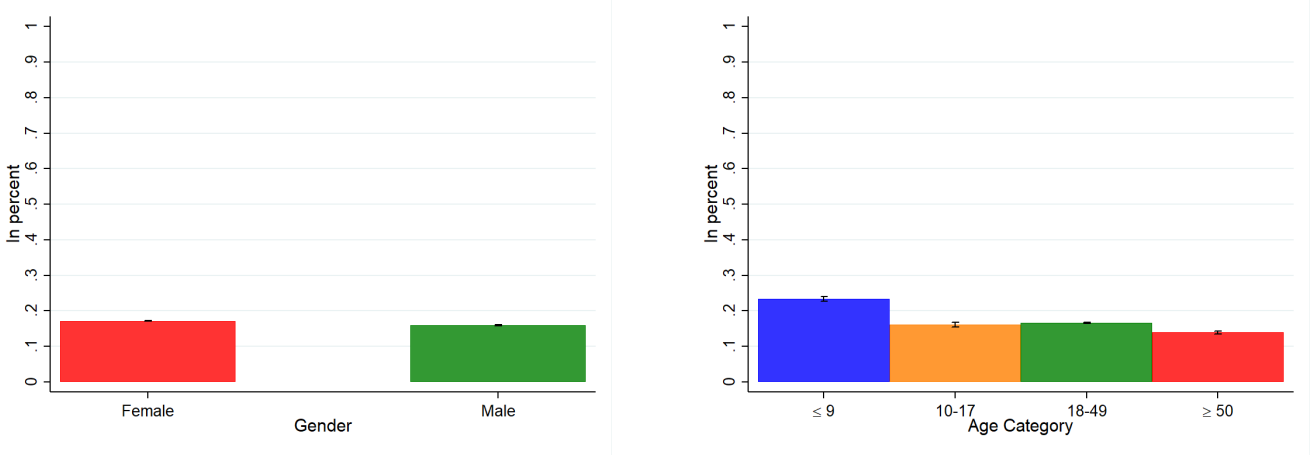
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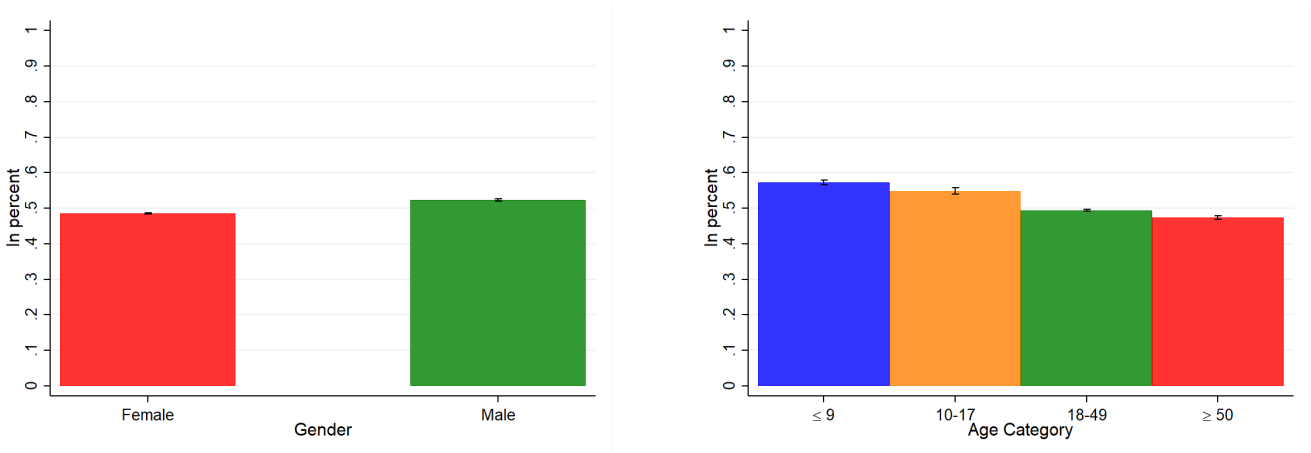
Figures

Figure 1
Missed Appointments and Lapse from Care by Gender and Age

Panel A: Missed First Appointment



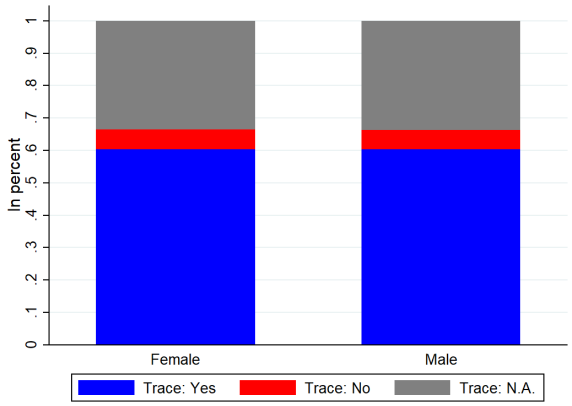
Panel B: Lapsed at Time of EMR



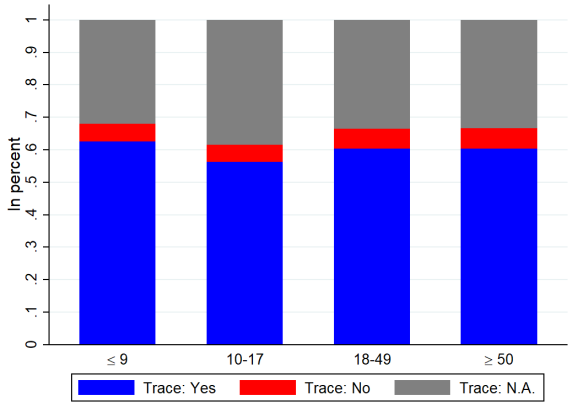
Notes: *Missed First Appointment* is an indicator for more than 60 days late to first appointment after initiation. Excludes patients who initiate more than 90 days before EMR implementation due to missing visit data. *Lapse of Care* is an indicator for no clinic visit in the year immediately preceding EMR implementation. Includes only patients who initiate at least 1 year prior to EMR implementation.

Figure 2
Trace Consent Response Rates

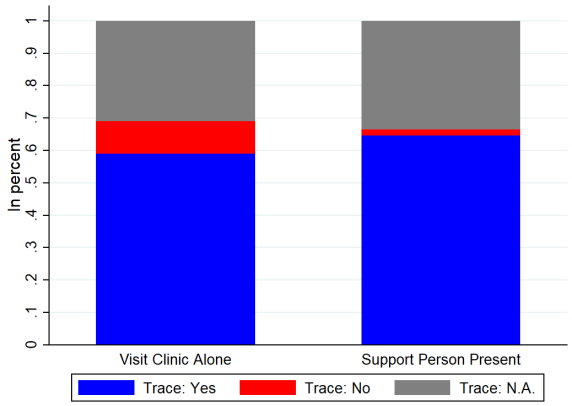
Panel A: Gender



Panel B: Age



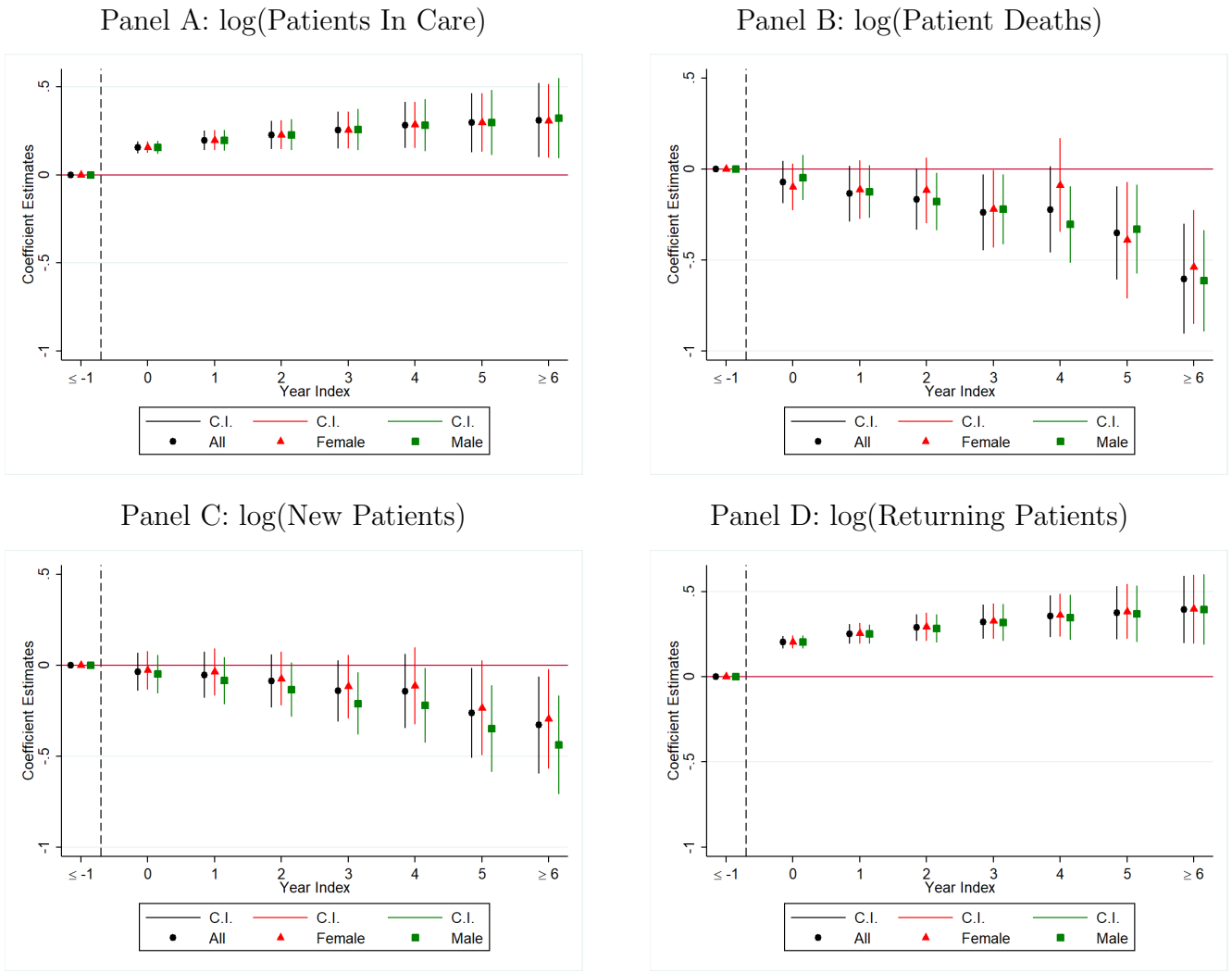
Panel C: Support During Clinic Visit



Notes: Response to question "Do you consent to being traced by clinic staff if you miss an appointment?" at time of ART initiation. 755,175 observations. *Trace Consent = N.A.* if the patient was not asked for consent.

Figure 3

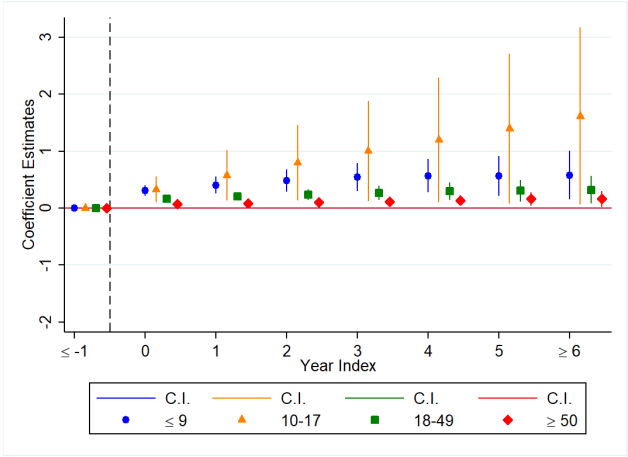
Effect of EMR on Patient Outcomes, Overall and by Gender



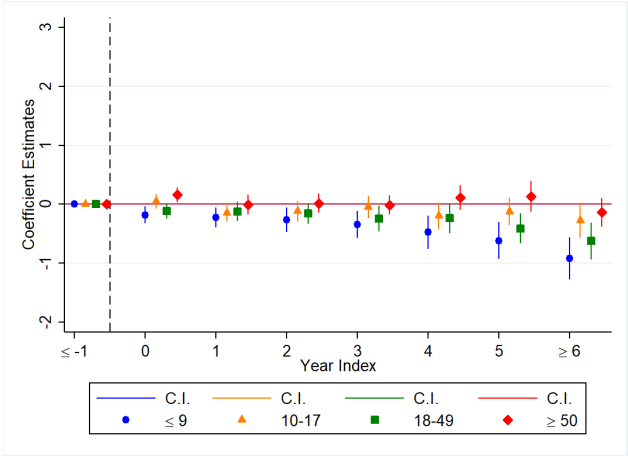
Notes: Outcomes measured at clinic-year level. Panel A: number of ART patients visiting the clinic at least once for ART initiation and/or prescription refill. Panel B: number of ART patient deaths. Panel C: the number of patients who visit the clinic for ART initiation. Panel D: number of patients who visit the clinic only for prescription refill. We add 1 to all outcome measures. $k = 0$ is the year immediately following EMR implementation, $k \leq -1$ serves as the reference period. Regressions include year and clinic fixed effects. 95% C.I. based on heteroskedasticity-robust standard errors clustered at the clinic level.

Figure 4
Effect of EMR on Patient Outcomes by Age

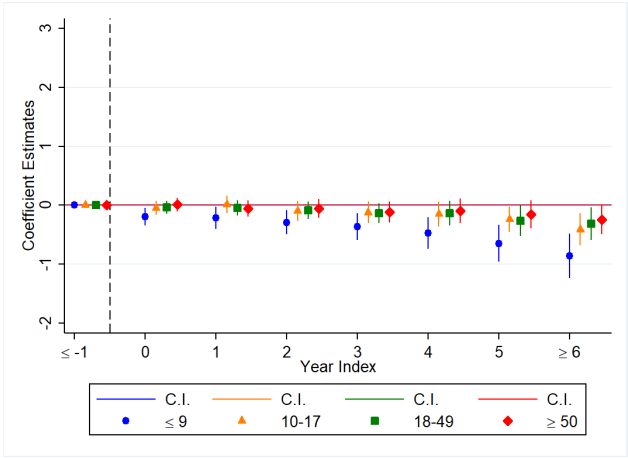
Panel A: log(Patients In Care)



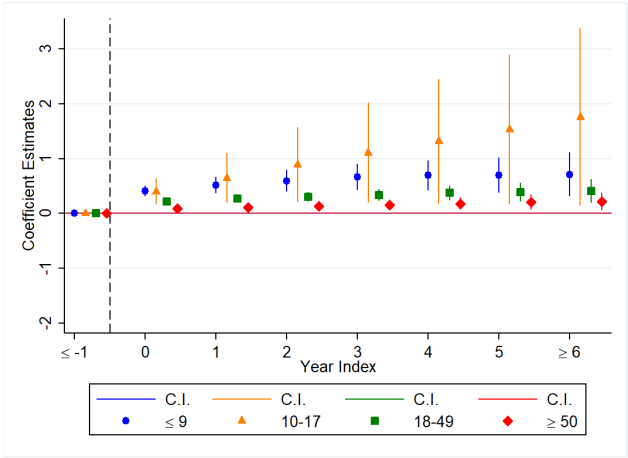
Panel B: log(Patient Deaths)



Panel C: log(New Patients)



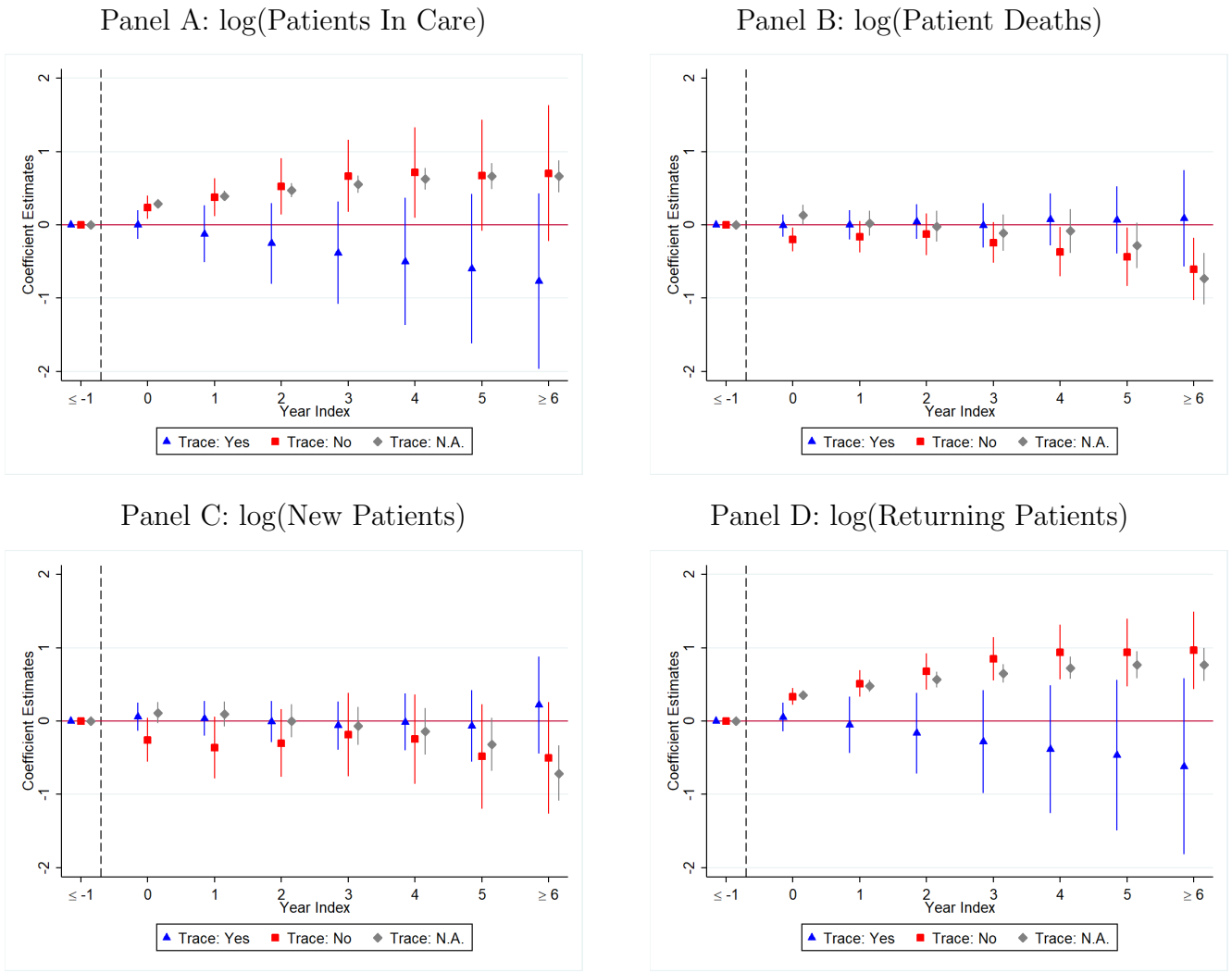
Panel D: log(Returning Patients)



Notes: Outcomes measured at clinic-year level. Panel A: number of ART patients visiting the clinic at least once for ART initiation and/or prescription refill. Panel B: number of ART patient deaths. Panel C: the number of patients who visit the clinic for ART initiation. Panel D: number of patients who visit the clinic only for prescription refill. We add 1 to all outcome measures. $k = 0$ is the year immediately following EMR implementation, $k \leq -1$ serves as the reference period. Regressions include year and clinic fixed effects. 95% C.I. based on heteroskedasticity-robust standard errors clustered at the clinic level.

Figure 5

Effect of EMR on Patient Outcomes by Privacy Preference



Notes: Outcomes measured at clinic-year level. Panel A: number of ART patients visiting the clinic at least once for ART initiation and/or prescription refill. Panel B: number of ART patient deaths. Panel C: the number of patients who visit the clinic for ART initiation. Panel D: number of patients who visit the clinic only for prescription refill. We add 1 to all outcome measures. Privacy preference is response to question "Do you consent to being traced by clinic staff if you miss an appointment?" at time of ART initiation. *Trace Consent = N.A.* if the patient was not asked for consent. $k = 0$ is the year immediately following EMR implementation, $k \leq -1$ serves as the reference period. Regressions include year and clinic fixed effects. 95% C.I. based on heteroskedasticity-robust standard errors clustered at the clinic level.

Tables

Table 1
Descriptive Statistics

Year	Number of Clinics in the Database	Number of Clinics that Adopted EMR	Average Number of Deaths (all clinics)	Average Number of New Patients (all clinics)	Average Number of Deaths among EMR Clinics	Average Number of Patients In Care among EMR Clinics	Average Number of New Patients among EMR Clinics	Average Number of Returning Patients among EMR Clinics
2003	4	0	14.3	60.5	N/A	N/A	N/A	N/A
2004	12	0	72.8	338.9	N/A	N/A	N/A	N/A
2005	33	0	92.3	448.1	N/A	N/A	N/A	N/A
2006	51	0	105.1	505.6	N/A	N/A	N/A	N/A
2007	57	1	114.5	667.2	304.0	4829.0	1885.0	4449.0
2008	67	2	105.0	677.8	387.5	5923.5	1876.0	5669.0
2009	75	3	91.2	701.6	307.3	5637.7	1987.0	5264.7
2010	83	9	91.0	656.8	300.6	5161.8	1654.3	4935.3
2011	97	17	90.9	702.0	269.1	4776.3	1365.1	4494.3
2012	106	24	81.0	641.1	251.8	5142.1	1338.1	4906.9
2013	106	32	74.8	554.6	193.5	4971.5	1070.4	4736.8
2014	106	41	72.6	571.0	154.2	4783.9	947.5	4594.8
2015	106	51	68.5	548.3	125.2	4643.3	827.4	4467.6
2016	106	55	57.1	662.7	96.4	4881.1	930.4	4687.5
2017	106	79	44.1	694.8	56.6	4354.6	817.5	4159.7
2018	106	82	22.5	543.1	27.8	4235.1	609.0	4048.0
2019	106	106	N/A	N/A	N/A	N/A	N/A	N/A

Notes: This table describes the dataset used for analysis. Averages measured at the clinic level.

Table 2

Privacy Preferences, Patient Health and Patient Care

	(1) Advanced HIV Stage	(2) Average Time to Appointment (in Days)	(3) Missed First Appointment	(4) Lapsed at Time of EMR	(5) Death Within Two Years (pre-EMR)
Trace Consent: "Yes"	0.260***	-15.44***	0.0378***	-0.0399**	0.0391***
	(0.0287)	(1.669)	(0.00577)	(0.0163)	(0.00416)
Trace Consent: "No"	0.261***	-12.53***	0.0566***	-0.00579	0.0458***
	(0.0258)	(1.449)	(0.00880)	(0.0157)	(0.00456)
Year FE	Y	Y	Y	Y	Y
Clinic FE	Y	Y	Y	Y	Y
Constant	0.251***	39.55***	0.143***	0.524***	0.0563***
	(0.0188)	(1.096)	(0.00352)	(0.0113)	(0.00292)
Trace Yes = No F-test	0.01	8.35	7.10	10.99	4.07
p-value of F-test	0.944	0.005	0.009	0.001	0.046
Observations	755,175	732,962	349,745	350,692	284,593
R-squared	0.270	0.262	0.023	0.076	0.035

Notes: *Trace Consent*: response to question "Do you consent to being traced by clinic staff if you miss an appointment?" at time of ART initiation. Reference category is patients who are not asked for tracing consent. (1): indicator for HIV Stage 3 or 4, or CD4 count < 200 (WHO definition). (2): average time to first appointment after initiation. (3): indicator for more than 60 days late to first appointment after initiation. Excludes patients who initiate more than 90 days before EMR implementation. (4): indicator for no clinic visit in the year immediately preceding EMR implementation. Includes only patients who initiate at least 1 year prior to EMR implementation. (5): indicator for patient death within two years of initiation. Includes only patients who initiate at least 2 years prior to EMR implementation. Each regression includes year and clinic fixed effects. Heteroskedasticity-robust standard errors clustered at the clinic level, in parentheses: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 3

Effect of EMR on Number of Patients In Care

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	log(Patients In Care)						
	All	Gender		Age			
Event Year		Female	Male	≤ 9	10 to 17	18 to 49	≥ 50
k ≤ -1	0	0	0	0	0	0	0
k = 0	0.155***	0.157***	0.156***	0.307***	0.331***	0.166***	0.0680***
	(0.0167)	(0.0168)	(0.0184)	(0.0454)	(0.113)	(0.0188)	(0.0134)
k = 1	0.195***	0.197***	0.195***	0.404***	0.571**	0.208***	0.0809***
	(0.0274)	(0.0281)	(0.0294)	(0.0752)	(0.221)	(0.0307)	(0.0239)
k = 2	0.227***	0.227***	0.227***	0.480***	0.797**	0.238***	0.0993***
	(0.0404)	(0.0407)	(0.0441)	(0.0971)	(0.331)	(0.0455)	(0.0325)
k = 3	0.254***	0.255***	0.256***	0.544***	1.001**	0.266***	0.114***
	(0.0527)	(0.0523)	(0.0588)	(0.122)	(0.440)	(0.0601)	(0.0390)
k = 4	0.282***	0.284***	0.282***	0.566***	1.197**	0.296***	0.136***
	(0.0660)	(0.0655)	(0.0738)	(0.146)	(0.551)	(0.0758)	(0.0471)
k = 5	0.296***	0.296***	0.298***	0.562***	1.397**	0.305***	0.159***
	(0.0839)	(0.0837)	(0.0928)	(0.175)	(0.659)	(0.0966)	(0.0587)
k ≥ 6	0.311***	0.306***	0.321***	0.580***	1.613**	0.320**	0.163**
	(0.105)	(0.105)	(0.114)	(0.212)	(0.782)	(0.122)	(0.0695)
Year FE	Y	Y	Y	Y	Y	Y	Y
Clinic FE	Y	Y	Y	Y	Y	Y	Y
Constant	7.962***	7.519***	6.924***	4.455***	4.167***	7.689***	6.141***
	(0.0368)	(0.0368)	(0.0404)	(0.0836)	(0.300)	(0.0422)	(0.0268)
F-test on pre-trends	N/A	N/A	N/A	N/A	N/A	N/A	N/A
p-value of F-test	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Observations	411	411	411	411	411	411	411
R-squared	0.987	0.987	0.986	0.954	0.970	0.986	0.989

Notes: Outcome measured at clinic-year level, defined as the number of ART patients visiting the clinic at least once for either ART initiation or prescription refill. We add 1 to all outcome measures. $k = 0$ is the year immediately following EMR implementation, $k = -1$ serves as the reference period. Each regression includes year and clinic fixed effects. Heteroskedasticity-robust standard errors clustered at the clinic level, in parentheses: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 4
Effect of EMR on Number of Patient Deaths

	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	log(Patient Deaths)						
	All	Gender		Age			
Event Year		Female	Male	≤ 9	10 to 17	18 to 49	≥ 50
k ≤ -1	0	0	0	0	0	0	0
k = 0	-0.0713	-0.0970	-0.0460	-0.183**	0.0526	-0.116*	0.159**
	(0.0589)	(0.0644)	(0.0625)	(0.0734)	(0.0625)	(0.0650)	(0.0635)
k = 1	-0.135*	-0.113	-0.123*	-0.229***	-0.144*	-0.123	-0.00705
	(0.0777)	(0.0811)	(0.0724)	(0.0849)	(0.0739)	(0.0819)	(0.0863)
k = 2	-0.167*	-0.117	-0.177**	-0.266**	-0.118	-0.157*	0.0183
	(0.0847)	(0.0911)	(0.0798)	(0.106)	(0.0881)	(0.0877)	(0.0807)
k = 3	-0.239**	-0.219**	-0.221**	-0.346***	-0.0488	-0.242**	-0.0128
	(0.105)	(0.108)	(0.0966)	(0.116)	(0.0959)	(0.111)	(0.0833)
k = 4	-0.222*	-0.0878	-0.305***	-0.476***	-0.199*	-0.239*	0.114
	(0.119)	(0.130)	(0.106)	(0.144)	(0.112)	(0.126)	(0.106)
k = 5	-0.351***	-0.391**	-0.329***	-0.622***	-0.121	-0.409***	0.135
	(0.130)	(0.161)	(0.123)	(0.158)	(0.117)	(0.128)	(0.130)
k ≥ 6	-0.604***	-0.540***	-0.615***	-0.919***	-0.278*	-0.624***	-0.140
	(0.153)	(0.157)	(0.141)	(0.179)	(0.150)	(0.157)	(0.123)
Year FE	Y	Y	Y	Y	Y	Y	Y
Clinic FE	Y	Y	Y	Y	Y	Y	Y
Constant	3.485***	2.795***	2.835***	1.076***	0.677***	3.180***	1.796***
	(0.0231)	(0.0239)	(0.0210)	(0.0239)	(0.0175)	(0.0235)	(0.0198)
F-test on pre-trends	0.09	0.08	0.19	1.30	1.12	0.11	1.52
p-value of F-test	0.914	0.924	0.825	0.278	0.329	0.893	0.225
Observations	1,166	1,166	1,166	1,166	1,166	1,166	1,166
R-squared	0.795	0.771	0.785	0.571	0.536	0.784	0.722

Notes: Outcomes measured at clinic-year level, defined as the number of ART patient deaths. We add 1 to all outcome measures. $k = 0$ is the year immediately following EMR implementation, $k \leq -1$ serves as the reference period. Each regression includes year and clinic fixed effects. Heteroskedasticity-robust standard errors clustered at the clinic level, in parentheses: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 5
Effect of EMR on Number of New Patients

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	log(New Patients)						
	All	Gender		Age			
Event Year		Female	Male	≤ 9	10 to 17	18 to 49	≥ 50
k ≤ -1	0	0	0	0	0	0	0
k = 0	-0.0349	-0.0274	-0.0485	-0.195**	-0.0475	-0.0337	0.0130
	(0.0524)	(0.0536)	(0.0532)	(0.0743)	(0.0592)	(0.0540)	(0.0577)
k = 1	-0.0520	-0.0363	-0.0844	-0.210**	0.0119	-0.0490	-0.0560
	(0.0643)	(0.0657)	(0.0651)	(0.0953)	(0.0761)	(0.0653)	(0.0719)
k = 2	-0.0862	-0.0729	-0.133*	-0.291***	-0.0947	-0.0831	-0.0543
	(0.0731)	(0.0749)	(0.0751)	(0.101)	(0.0853)	(0.0747)	(0.0792)
k = 3	-0.140	-0.116	-0.210**	-0.365***	-0.123	-0.135	-0.117
	(0.0849)	(0.0880)	(0.0860)	(0.115)	(0.0924)	(0.0870)	(0.0902)
k = 4	-0.141	-0.114	-0.220**	-0.475***	-0.150	-0.135	-0.0982
	(0.103)	(0.107)	(0.104)	(0.136)	(0.107)	(0.106)	(0.104)
k = 5	-0.262**	-0.234*	-0.349***	-0.647***	-0.239**	-0.263**	-0.155
	(0.124)	(0.131)	(0.120)	(0.157)	(0.108)	(0.130)	(0.118)
k ≥ 6	-0.328**	-0.295**	-0.438***	-0.860***	-0.410***	-0.316**	-0.242*
	(0.135)	(0.139)	(0.137)	(0.188)	(0.136)	(0.139)	(0.126)
Year FE	Y	Y	Y	Y	Y	Y	Y
Clinic FE	Y	Y	Y	Y	Y	Y	Y
Constant	6.162***	5.698***	5.158***	3.342***	2.757***	5.950***	3.783***
	(0.0215)	(0.0222)	(0.0211)	(0.0294)	(0.0220)	(0.0220)	(0.0218)
F-test on pre-trends	0.04	0.01	0.21	0.95	0.91	0.13	0.03
p-value of F-test	0.958	0.988	0.813	0.392	0.405	0.874	0.972
Observations	1,166	1,166	1,166	1,166	1,166	1,166	1,166
R-squared	0.852	0.842	0.835	0.731	0.764	0.850	0.797

Notes: Outcomes measured at clinic-year level, defined as the number of patients who visit the clinic for ART initiation. We add 1 to all outcome measures. $k = 0$ is the year immediately following EMR implementation, $k \leq -1$ serves as the reference period. Each regression includes year and clinic fixed effects. Heteroskedasticity-robust standard errors clustered at the clinic level, in parentheses: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 6

Effect of EMR on Number of Returning Patients

	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	log(Returning Patients)						
	All	Gender		Age			
Event Year		Female	Male	≤ 9	10 to 17	18 to 49	≥ 50
k ≤ -1	0	0	0	0	0	0	0
k = 0	0.202***	0.204***	0.202***	0.407***	0.399***	0.215***	0.0949***
	(0.0184)	(0.0189)	(0.0193)	(0.0476)	(0.119)	(0.0197)	(0.0177)
k = 1	0.252***	0.254***	0.250***	0.512***	0.650***	0.268***	0.116***
	(0.0286)	(0.0305)	(0.0285)	(0.0754)	(0.230)	(0.0303)	(0.0309)
k = 2	0.288***	0.291***	0.284***	0.597***	0.889**	0.303***	0.134***
	(0.0397)	(0.0415)	(0.0413)	(0.0969)	(0.345)	(0.0426)	(0.0393)
k = 3	0.322***	0.326***	0.317***	0.667***	1.106**	0.338***	0.153***
	(0.0505)	(0.0521)	(0.0539)	(0.119)	(0.458)	(0.0551)	(0.0469)
k = 4	0.354***	0.361***	0.347***	0.694***	1.315**	0.373***	0.178***
	(0.0615)	(0.0635)	(0.0663)	(0.137)	(0.571)	(0.0679)	(0.0561)
k = 5	0.376***	0.382***	0.368***	0.698***	1.530**	0.391***	0.208***
	(0.0780)	(0.0809)	(0.0830)	(0.163)	(0.684)	(0.0869)	(0.0689)
k ≥ 6	0.394***	0.396***	0.394***	0.711***	1.759**	0.410***	0.214***
	(0.0983)	(0.101)	(0.103)	(0.201)	(0.812)	(0.110)	(0.0810)
Year FE	Y	Y	Y	Y	Y	Y	Y
Clinic FE	Y	Y	Y	Y	Y	Y	Y
Constant	7.855***	7.411***	6.820***	4.261***	4.031***	7.576***	6.079***
	(0.0352)	(0.0367)	(0.0370)	(0.0799)	(0.312)	(0.0386)	(0.0328)
F-test on pre-trends	N/A	N/A	N/A	N/A	N/A	N/A	N/A
p-value of F-test	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Observations	411	411	411	411	411	411	411
R-squared	0.986	0.985	0.985	0.945	0.967	0.984	0.987

Notes: Outcomes measured at clinic-year level, defined as the number of patients who visit the clinic only for prescription refill. We add 1 to all outcome measures. $k = 0$ is the year immediately following EMR implementation, $k = -1$ serves as the reference period. Each regression includes year and clinic fixed effects. Heteroskedasticity-robust standard errors clustered at the clinic level, in parentheses: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 7

Effects of EMR by Patient Privacy Preferences (Patients In Care and Deaths)

	(1)	(2)	(3)	(4)	(5)	(6)
	log(Patients In Care)			log(Patient Deaths)		
Trace Consent:	Yes	No	N.A.	Yes	No	N.A.
k ≤ -1	0	0	0	0	0	0
k = 0	0.00238	0.239***	0.290***	-0.0102	-0.202**	0.135*
	(0.0982)	(0.0807)	(0.0236)	(0.0771)	(0.0813)	(0.0682)
k = 1	-0.123	0.377***	0.394***	0.00240	-0.162	0.0218
	(0.194)	(0.131)	(0.0345)	(0.100)	(0.108)	(0.0853)
k = 2	-0.255	0.524***	0.474***	0.0437	-0.129	-0.0202
	(0.276)	(0.192)	(0.0477)	(0.120)	(0.144)	(0.107)
k = 3	-0.384	0.666***	0.553***	-0.00874	-0.241*	-0.108
	(0.351)	(0.247)	(0.0593)	(0.153)	(0.138)	(0.123)
k = 4	-0.502	0.715**	0.626***	0.0734	-0.369**	-0.0852
	(0.436)	(0.310)	(0.0736)	(0.180)	(0.169)	(0.149)
k = 5	-0.600	0.673*	0.665***	0.0657	-0.437**	-0.281*
	(0.513)	(0.380)	(0.0901)	(0.231)	(0.203)	(0.155)
k ≥ 6	-0.768	0.704	0.661***	0.0890	-0.604***	-0.734***
	(0.602)	(0.466)	(0.111)	(0.332)	(0.215)	(0.178)
Year FE	Y	Y	Y	Y	Y	Y
Clinic FE	Y	Y	Y	Y	Y	Y
Constant	7.618***	3.902***	6.237***	2.914***	1.019***	1.661***
	(0.242)	(0.171)	(0.0406)	(0.0386)	(0.0326)	(0.0270)
F-test on pre-trends	N/A	N/A	N/A	0.26	0.97	0.55
p-value of F-test	N/A	N/A	N/A	0.770	0.384	0.577
Observations	411	411	411	1,166	1,166	1,166
R-squared	0.987	0.950	0.989	0.785	0.608	0.790

Notes: Outcomes measured at clinic-year level. We add 1 to all outcome measures. *Trace Consent*: response to question "Do you consent to being traced by clinic staff if you miss an appointment?" at time of ART initiation. *Trace Consent = N.A.* if the patient was not asked for consent. $k = 0$ is the year immediately following EMR implementation, $k \leq -1$ serves as the reference period. Each regression includes year and clinic fixed effects. Heteroskedasticity-robust standard errors clustered at the clinic level, in parentheses: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 8

Effects of EMR by Patient Privacy Preferences (New and Returning Patients)

	(1)	(2)	(3)	(4)	(5)	(6)
	log(New Patients)			log(Returning Patients)		
Trace Consent:	Yes	No	N.A.	Yes	No	N.A.
k ≤ -1	0	0	0	0	0	0
k = 0	0.0578	-0.256*	0.114	0.0531	0.335***	0.356***
	(0.0964)	(0.152)	(0.0722)	(0.0982)	(0.0588)	(0.0305)
k = 1	0.0330	-0.363*	0.0943	-0.0523	0.510***	0.479***
	(0.119)	(0.211)	(0.0859)	(0.194)	(0.0911)	(0.0408)
k = 2	-0.00657	-0.300	0.00268	-0.166	0.676***	0.565***
	(0.141)	(0.234)	(0.112)	(0.277)	(0.124)	(0.0527)
k = 3	-0.0619	-0.186	-0.0650	-0.281	0.848***	0.648***
	(0.166)	(0.286)	(0.131)	(0.352)	(0.149)	(0.0631)
k = 4	-0.0145	-0.247	-0.141	-0.385	0.938***	0.726***
	(0.196)	(0.308)	(0.161)	(0.437)	(0.187)	(0.0757)
k = 5	-0.0659	-0.484	-0.320*	-0.465	0.935***	0.768***
	(0.246)	(0.361)	(0.182)	(0.516)	(0.231)	(0.0921)
k ≥ 6	0.220	-0.501	-0.714***	-0.618	0.965***	0.768***
	(0.334)	(0.384)	(0.190)	(0.603)	(0.267)	(0.113)
Year FE	Y	Y	Y	Y	Y	Y
Clinic FE	Y	Y	Y	Y	Y	Y
Constant	5.498***	2.848***	4.405***	7.486***	3.690***	6.097***
	(0.0441)	(0.0594)	(0.0314)	(0.243)	(0.102)	(0.0437)
F-test on pre-trends	0.29	0.16	0.46	N/A	N/A	N/A
p-value of F-test	0.753	0.853	0.632	N/A	N/A	N/A
Observations	1,166	1,166	1,166	411	411	411
R-squared	0.817	0.555	0.824	0.986	0.953	0.986

Notes: Outcomes measured at clinic-year level. We add 1 to all outcome measures. *Trace Consent*: response to question "Do you consent to being traced by clinic staff if you miss an appointment?" at time of ART initiation. *Trace Consent = N.A.* if the patient was not asked for consent. $k = 0$ is the year immediately following EMR implementation, $k \leq -1$ serves as the reference period. Each regression includes year and clinic fixed effects. Heteroskedasticity-robust standard errors clustered at the clinic level, in parentheses: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 9
Effect of EMR on Clinic Efficiency and Quality of Care

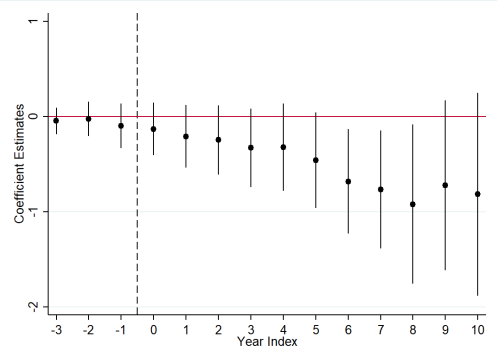
Event Year	(1) Average Time to Appointment (in Days)	(2) log(Patients Diagnosed and Treated for Tuberculosis)
k ≤ -1	0	0
k = 0	4.845***	0.179*
	(1.220)	(0.0987)
k = 1	6.313***	0.176
	(1.256)	(0.113)
k = 2	7.610***	0.126
	(2.127)	(0.181)
k = 3	8.010***	-0.0143
	(2.578)	(0.216)
k = 4	8.821***	-0.261
	(3.016)	(0.274)
k = 5	10.32***	-0.421
	(3.565)	(0.352)
k ≥ 6	5.749	-0.236
	(6.706)	(0.565)
Year FE	Y	Y
Clinic FE	Y	Y
Constant	28.34***	1.342***
	(0.686)	(0.0529)
F-test on pre-trends	1.34	0.12
p-value of F-test	0.267	0.892
Observations	1,166	1,166
R-squared	0.572	0.704

Notes: (1): average number of days between initiation and first scheduled appointment, at the clinic level. (2): number of patients diagnosed and treated for tuberculosis. We add 1 to this outcome. $k = 0$ is the year immediately following EMR implementation, $k \leq -1$ serves as the reference period. Each regression includes year and clinic fixed effects. Heteroskedasticity-robust standard errors clustered at the clinic level, in parentheses: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

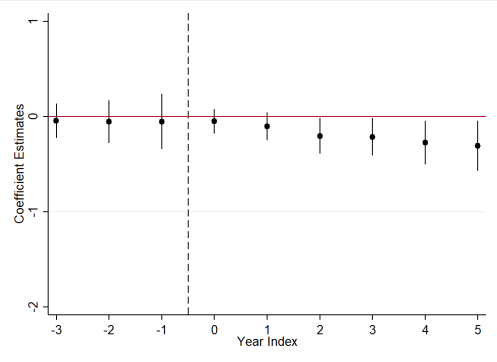
Appendix – For Online Publication

Appendix Figure A1
Effect of EMR on log(Patient Deaths), Alternative Estimators

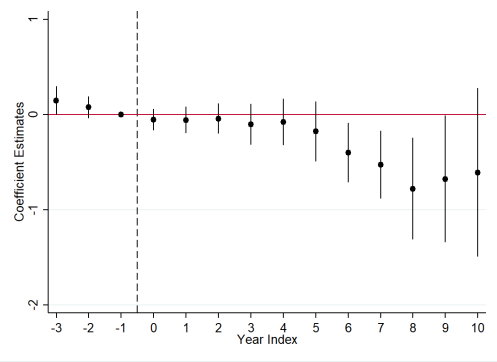
Panel A: Two-Way Fixed Effects



Panel B: Borusyak, Jaravel and Spiess (2021)



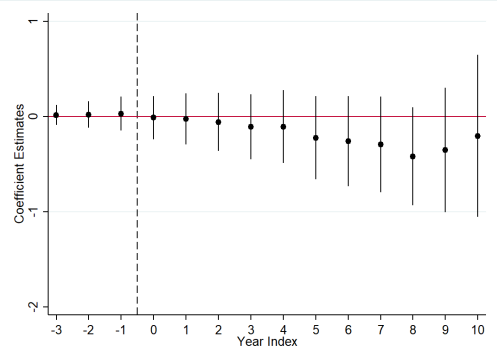
Panel C: de Chaisemartin and D'Haultfœuille (2020*a*)



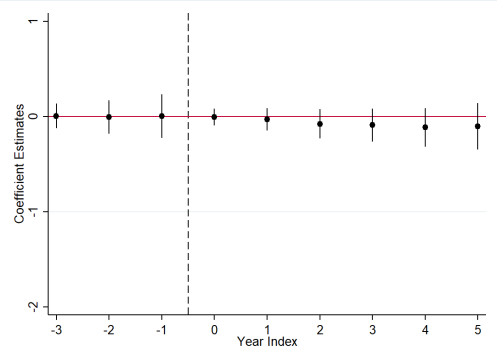
Notes: Outcome (number of patient deaths) measured at clinic-year level. We add 1 to the outcome measure. de Chaisemartin and D'Haultfœuille (2020*a*) standard errors estimated using 1,000 bootstrap replications. $k = 0$ is the year immediately following EMR implementation. 95% C.I. based on heteroskedasticity-robust standard errors clustered at the clinic level.

Appendix Figure A2
Effect of EMR on New Patients, Alternative Estimators

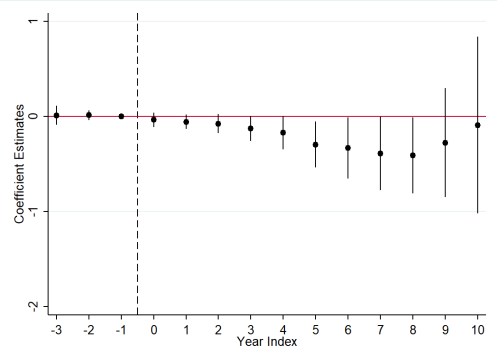
Panel A: Two-Way Fixed Effects



Panel B: Borusyak, Jaravel and Spiess (2021)



Panel C: de Chaisemartin and D'Haultfœuille (2020*a*)

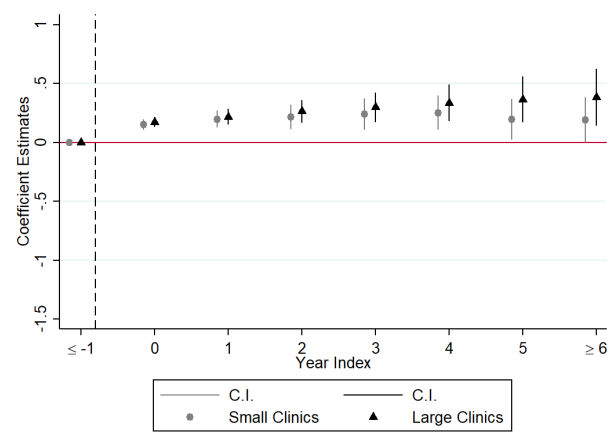


Notes: Outcome (number of new patient ART initiations) measured at clinic-year level. We add 1 to the outcome measure. de Chaisemartin and D'Haultfœuille (2020*a*) estimated using 1,000 bootstrap replications. $k = 0$ is the year immediately following EMR implementation. 95% C.I. based on heteroskedasticity-robust standard errors clustered at the clinic level.

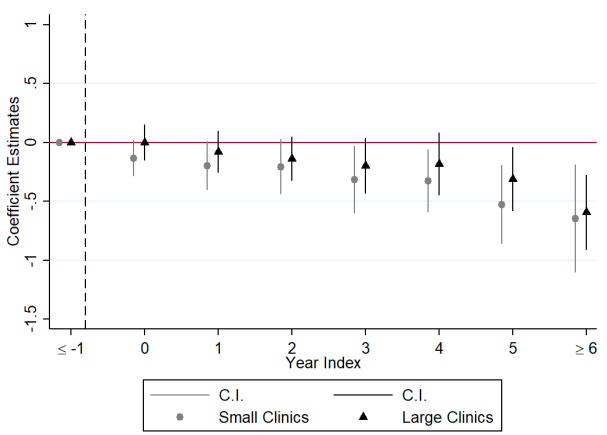
Appendix Figure A3

Effect of EMR on Patient Outcomes by Clinic Size

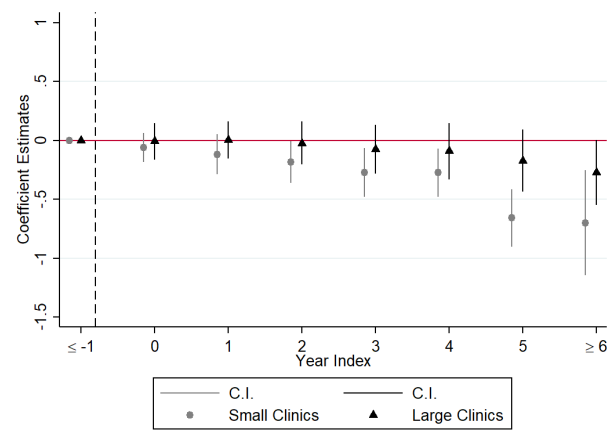
Panel A: log(Patients In Care)



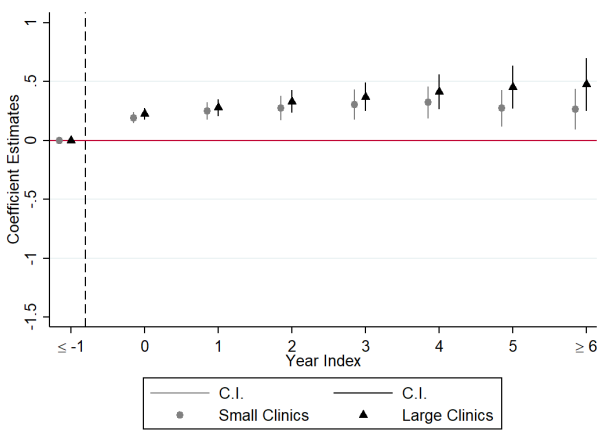
Panel B: log(Patient Deaths)



Panel C: log(New Patients)



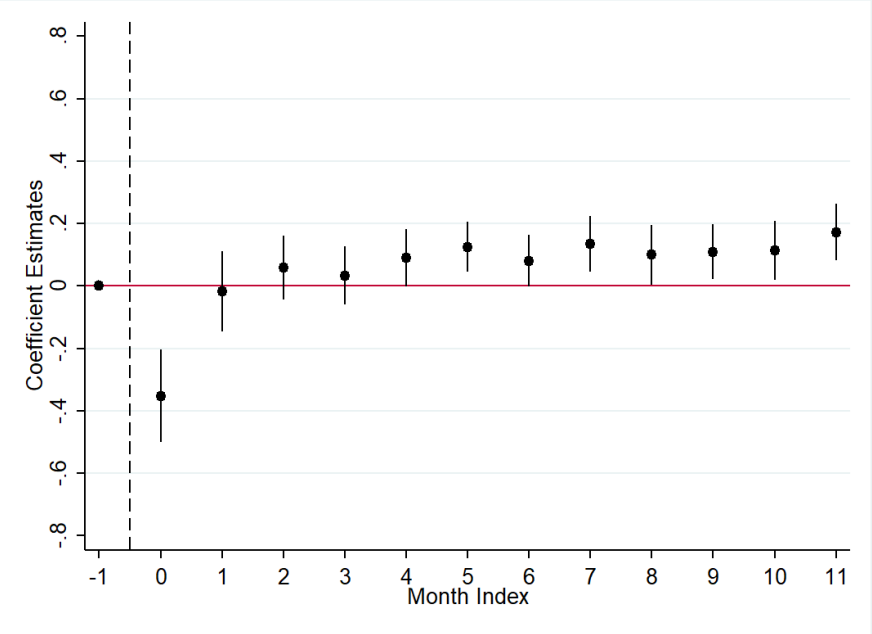
Panel D: log(Returning Patients)



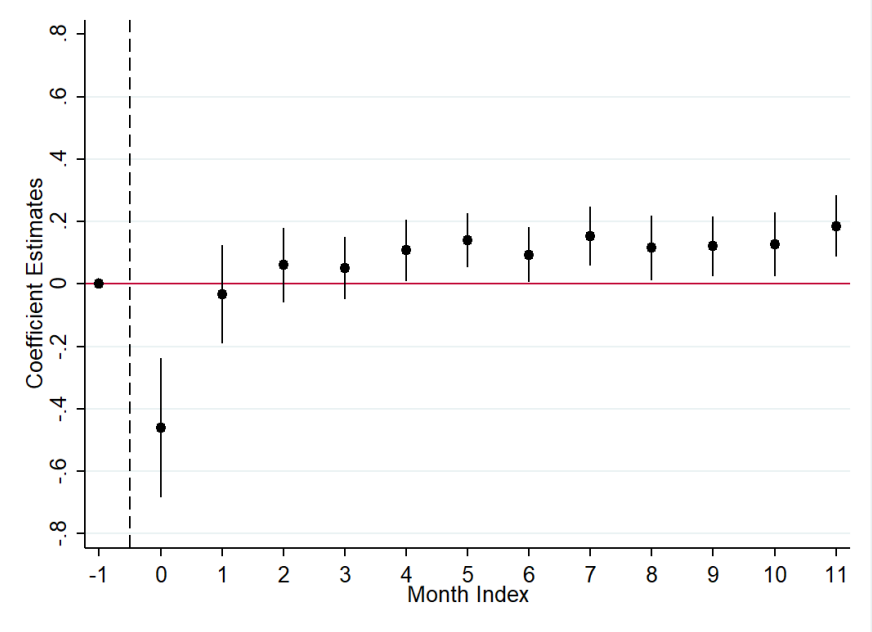
Notes: Outcomes measured at clinic-year level. Panel A: number of ART patients visiting the clinic at least once for ART initiation and/or prescription refill. Panel B: number of ART patient deaths. Panel C: the number of patients who visit the clinic for ART initiation. Panel D: number of patients who visit the clinic only for prescription refill. Clinic size defined as above or below mean number of new patients in 2013. We add 1 to all outcome measures. $k = 0$ is the year immediately following EMR implementation, $k \leq -1$ serves as the reference period. Regressions include year and clinic fixed effects. 95% C.I. based on heteroskedasticity-robust standard errors clustered at the clinic level.

Appendix Figure A4
Monthly Effect of EMR on Patients In Care

Panel A: log(Patients In Care)



Panel B: log(Returning Patients)



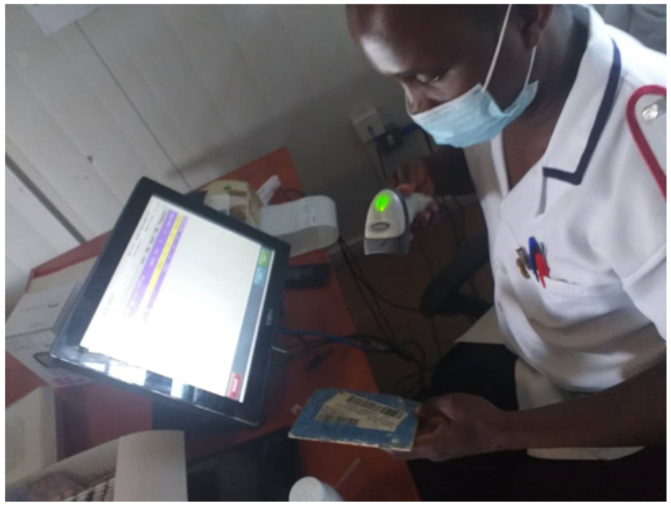
Notes: Outcomes measured at clinic-month level. Panel A: number of ART patients visiting the clinic at least once for ART initiation and/or prescription refill. Panel B: number of patients who visit the clinic only for prescription refill. We add 1 to all outcome measures. $k = 0$ is the month immediately following EMR implementation, $k = -1$ serves as the reference period. Regressions include only clinic fixed effects. 95% C.I. based on heteroskedasticity-robust standard errors clustered at the clinic level.

Appendix Figure A5
Photos of EMR System in Malawi

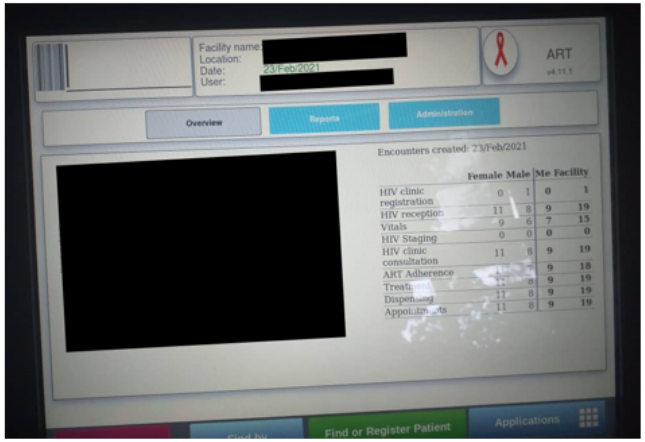
Panel A: Clinic Staff with ART Refills



Panel B: Clinic Staff Scanning a Patient Health Passport.



Panel C: EMR Screen with Clinic Overview Statistics



Panel D: Patient Health Passport with Bar Code



Notes: Names and locations deidentified.

Appendix Table A1

Robustness: Heterogeneity by Clinic Size and Interacted FE

	(1)	(2)	(3)	(4)	(5)	(6)
Event Year	log(Patients In Care)	log(Patient Deaths)		log(New Patients)		log(Returning Patients)
k ≤ -1	0	0	0	0	0	0
k = 0	0.153***	-0.0830	-0.0807	-0.0452	-0.0641	0.200***
	(0.0171)	(0.0595)	(0.0579)	(0.0529)	(0.0509)	(0.0186)
k = 1	0.191***	-0.151*	-0.141*	-0.0659	-0.0899	0.248***
	(0.0281)	(0.0801)	(0.0761)	(0.0658)	(0.0611)	(0.0290)
k = 2	0.221***	-0.173*	-0.168*	-0.111	-0.135*	0.283***
	(0.0410)	(0.0887)	(0.0867)	(0.0740)	(0.0709)	(0.0404)
k = 3	0.247***	-0.235**	-0.233**	-0.169*	-0.198**	0.315***
	(0.0537)	(0.111)	(0.108)	(0.0872)	(0.0845)	(0.0514)
k = 4	0.272***	-0.185	-0.194	-0.168	-0.214**	0.346***
	(0.0665)	(0.124)	(0.124)	(0.107)	(0.102)	(0.0618)
k = 5	0.283***	-0.295**	-0.301**	-0.297**	-0.343**	0.364***
	(0.0854)	(0.134)	(0.134)	(0.134)	(0.132)	(0.0790)
k ≥ 6	0.306***	-0.583***	-0.511***	-0.350**	-0.423***	0.391***
	(0.107)	(0.156)	(0.158)	(0.147)	(0.143)	(0.101)
k ≤ -1 × Clinic Size	0	0		0		0
k = 0 × Clinic Size	0.00718	0.0566*		0.0433		0.00866
	(0.00781)	(0.0295)		(0.0288)		(0.0114)
k = 1 × Clinic Size	0.00597	0.0463		0.0386		0.00553
	(0.00883)	(0.0317)		(0.0327)		(0.0115)
k = 2 × Clinic Size	0.00733	0.0144		0.0558*		0.00624
	(0.0106)	(0.0298)		(0.0301)		(0.0126)
k = 3 × Clinic Size	0.00787	-0.00647		0.0535*		0.00670
	(0.0115)	(0.0343)		(0.0300)		(0.0131)
k = 4 × Clinic Size	0.00938	-0.0497*		0.0395		0.00755
	(0.0108)	(0.0299)		(0.0277)		(0.0120)
k = 5 × Clinic Size	0.0108	-0.0609*		0.0442		0.0101
	(0.0125)	(0.0366)		(0.0318)		(0.0141)
k ≥ 6 × Clinic Size	0.000293	-0.0178		0.0250		7.45e-05
	(0.0146)	(0.0406)		(0.0358)		(0.0163)
Year FE	Y	Y	Y	Y	Y	Y
Clinic FE	Y	Y	Y	Y	Y	Y
Year FE X Clinic Size	N	N	Y	N	Y	N
Constant	7.964***	3.485***	3.475***	6.162***	6.181***	7.857***
	(0.0365)	(0.0232)	(0.0248)	(0.0215)	(0.0225)	(0.0347)
Observations	411	1,166	1,166	1,166	1,166	411
R-squared	0.987	0.796	0.797	0.852	0.854	0.986

Notes: Outcomes measured at clinic-year level. (1): number of ART patients visiting the clinic at least once for ART initiation and/or prescription refill. (2-3): number of ART patient deaths. (4-5): number of patients who visit the clinic for ART initiation. (6): number of patients who visit the clinic only for prescription refill. We add 1 to all outcome measures. $k = 0$ is the year immediately following EMR implementation, $k \leq -1$ serves as the reference period. Clinic size defined as the standardized number of new patients in 2013. Regressions include year and clinic fixed effects. Heteroskedasticity-robust standard errors clustered at the clinic level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Appendix Table A2

Effect of EMR on Patients In Care, Inverse Hyperbolic Sine Transformation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	arcsinh(Patients In Care)						
	All	Gender		Age			
Event Year		Female	Male	≤ 9	10 to 17	18 to 49	≥ 50
k ≤ -1	0	0	0	0	0	0	0
k = 0	0.156***	0.157***	0.156***	0.318***	0.334***	0.167***	0.0687***
	(0.0168)	(0.0168)	(0.0184)	(0.0504)	(0.114)	(0.0188)	(0.0135)
k = 1	0.196***	0.197***	0.195***	0.420***	0.578**	0.208***	0.0820***
	(0.0274)	(0.0281)	(0.0294)	(0.0825)	(0.222)	(0.0307)	(0.0240)
k = 2	0.227***	0.227***	0.228***	0.496***	0.805**	0.238***	0.101***
	(0.0404)	(0.0407)	(0.0441)	(0.103)	(0.333)	(0.0455)	(0.0326)
k = 3	0.255***	0.255***	0.257***	0.560***	1.011**	0.266***	0.116***
	(0.0528)	(0.0524)	(0.0589)	(0.129)	(0.442)	(0.0601)	(0.0391)
k = 4	0.283***	0.284***	0.283***	0.581***	1.208**	0.296***	0.137***
	(0.0660)	(0.0655)	(0.0738)	(0.153)	(0.553)	(0.0758)	(0.0472)
k = 5	0.296***	0.297***	0.298***	0.578***	1.409**	0.305***	0.162***
	(0.0840)	(0.0837)	(0.0928)	(0.183)	(0.662)	(0.0967)	(0.0589)
k ≥ 6	0.311***	0.306***	0.321***	0.594***	1.626**	0.321**	0.165**
	(0.106)	(0.105)	(0.114)	(0.220)	(0.785)	(0.122)	(0.0696)
Year FE	Y	Y	Y	Y	Y	Y	Y
Clinic FE	Y	Y	Y	Y	Y	Y	Y
Constant	8.654***	8.211***	7.616***	5.122***	4.842***	8.381***	6.830***
	(0.0368)	(0.0369)	(0.0404)	(0.0885)	(0.302)	(0.0422)	(0.0268)
Observations	411	411	411	411	411	411	411
R-squared	0.987	0.987	0.986	0.948	0.970	0.986	0.989

Notes: Outcome measured at clinic-year level, defined as the number of ART patients visiting the clinic at least once for ART initiation and/or prescription refill. $k = 0$ is the year immediately following EMR implementation, $k = -1$ serves as the reference period. Regressions include year and clinic fixed effects. Heteroskedasticity-robust standard errors clustered at the clinic level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Appendix Table A3

Effect of EMR on Patient Deaths, Inverse Hyperbolic Sine Transformation

	(8)	(9)	(10)	(11)	(12)	(13)	(14)
	arcsinh(Patient Deaths)						
		Gender		Age			
Event Year	All	Female	Male	≤ 9	10 to 17	18 to 49	≥ 50
k ≤ -1	0	0	0	0	0	0	0
k = 0	-0.0856	-0.117	-0.0651	-0.237**	0.0672	-0.136*	0.171**
	(0.0642)	(0.0726)	(0.0704)	(0.0935)	(0.0807)	(0.0729)	(0.0762)
k = 1	-0.156*	-0.125	-0.154*	-0.288***	-0.182*	-0.142	-0.0334
	(0.0851)	(0.0911)	(0.0818)	(0.108)	(0.0954)	(0.0907)	(0.106)
k = 2	-0.193**	-0.126	-0.217**	-0.319**	-0.146	-0.181*	0.00354
	(0.0934)	(0.103)	(0.0906)	(0.134)	(0.113)	(0.0975)	(0.0981)
k = 3	-0.271**	-0.242*	-0.264**	-0.412***	-0.0611	-0.276**	-0.0326
	(0.115)	(0.122)	(0.109)	(0.146)	(0.124)	(0.122)	(0.101)
k = 4	-0.256*	-0.0998	-0.359***	-0.568***	-0.250*	-0.272*	0.106
	(0.130)	(0.144)	(0.120)	(0.182)	(0.144)	(0.139)	(0.125)
k = 5	-0.392***	-0.437**	-0.389***	-0.739***	-0.152	-0.451***	0.131
	(0.141)	(0.188)	(0.138)	(0.199)	(0.150)	(0.141)	(0.153)
k ≥ 6	-0.657***	-0.576***	-0.698***	-1.122***	-0.355*	-0.676***	-0.197
	(0.166)	(0.172)	(0.157)	(0.229)	(0.192)	(0.171)	(0.148)
Year FE	Y	Y	Y	Y	Y	Y	Y
Clinic FE	Y	Y	Y	Y	Y	Y	Y
Constant	4.130***	3.390***	3.438***	1.372***	0.873***	3.805***	2.266***
	(0.0256)	(0.0270)	(0.0240)	(0.0303)	(0.0225)	(0.0262)	(0.0241)
Observations	1,166	1,166	1,166	1,166	1,166	1,166	1,166
R-squared	0.780	0.756	0.771	0.561	0.535	0.769	0.706

Notes: Outcome measured at clinic-year level, defined as the number of ART patient deaths. $k = 0$ is the year immediately following EMR implementation, $k \leq -1$ serves as the reference period. Regression include year and clinic fixed effects. Heteroskedasticity-robust standard errors clustered at the clinic level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Appendix Table A4

Average Treatment Effect of EMR

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	log(Patients In Care)	log(Patient Deaths)			log(New Patients)			log(Returning Patients)
Post-EMR	0.146***	-0.111*	-0.218**	-0.123	-0.0548	-0.0977	-0.126	0.190***
	(0.0155)	(0.0655)	(0.0876)	(0.069)	(0.0596)	(0.0774)	(0.056)	(0.0183)
95% C.I.				[-0.26, 0.01]			[-0.24, -0.02]	
Two-Way Fixed Effects	Y	Y	N	N	Y	N	N	Y
Borusyak, Jaravel & Spiess	N	N	Y	N	N	Y	N	N
de Chaisemartin & D'Haultfoeuille	N	N	N	Y	N	N	Y	N
Constant	8.028***	3.455***			6.143***			7.937***
	(0.0126)	(0.0187)			(0.0170)			(0.0149)
Switchers				333			333	
Observations	411	1,166	1,114	3,083	1,166	1,114	3,083	411
R-squared	0.987	0.790			0.849			0.985

Notes: Outcomes measured at clinic-year level. (1): number of ART patients visiting the clinic at least once for ART initiation and/or prescription refill. (2-4): number of ART patient deaths. (5-7): number of patients who visit the clinic for ART initiation. (8): number of patients who visit the clinic only for prescription refill. *Post-EMR*= 1 for all years after EMR implementation. We add 1 to all outcome measures. de Chaisemartin and D'Haultfoeuille (2020*b*) standard errors estimated using 1,000 bootstrap replications. Heteroskedasticity-robust standard errors clustered at the clinic level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Appendix Table A5
Qualitative Data from Interviews

Theme	Qualitative Evidence
EMR Facilitates Patient Tracing	"J2 [EMR computer] has helped to increase the numbers [of patients in care] because it has revealed a correct number of people who were skipped or missed. J2 doesn't miss numbers. Sometimes we get tired and miss the count, but J2 has all the details. (...) J2 produces good reports. The detailed report of missed appointments is also reported by J2. (...) It helps for the work to go faster, especially when stamping drugs instead of manual. Respondents compliant of delayed when using manual." **-- Tracing Staff #2**
	"I am saying it [EMR] changed patient care in a good way, for instance, the way it traces defaulters; they can easily be traced through EMR than manually. Because with manual, if we take a facility with a cohort of 7000-9000 for you to check from 7000 to 9000 to check how many defaulters are there is almost impossible." **-- NGO Strategic Information and Evaluation Officer**
	"For example, I can come with a list of those that have defaulted from 1st December up to 8th December. So the EMR will generate the list on its own and show me that these are the people that have defaulted, and I will get the list and trace them. So the outcomes that we get from the process of tracing are the ones that we feed. So to a large extent, I would say that EMR helps to identify defaulting clients. Without EMR, we cannot easily know the next appointments and defaulters." **-- Clinic Coordinator**
	"The EMR brings the list with all the demographics, such as where they live. Sometimes when we are lucky, it gives us the phone numbers because when a person starts treatment, we take his/her details, including the phone number. So if we see that the client has failed to come and get drugs, we call them and ask why they failed to show up. They give a number of reasons, for instance, saying they were away. If the phone numbers are not reachable, we use the geographical map that we have to get on the EMR and trace the person's physical location." **-- Clinic Coordinator**
	"There is an improvement (...) because we are able to trace the defaulters easily and we are able to know who are meeting their appointments, but before it was difficult to identify them." **-- EMR Data Statistician**
	"EMR has helped to identify the defaulters because we just run a list of defaulters (...) when the list of the defaulters has been run (...) we have the expert clients [tracing staff] who work under 'Mother to Mothers' [local NGO] as adherence support officers who help us in tracing the defaulters. These people are given a list of names to share amongst themselves; we have five expert clients [tracing staff], so they share the list and start tracing. The outcomes from the tracing are updated in the system" **-- Nurse #1**
	"When we have found a defaulter, we start with counseling, assuming we followed this person to his or her home village, and we called them and they come to the clinic we start a conversation, and they agree to start taking medicine again, then we go back to the EMR since it indicated that the person defaulted, then we update in the EMR that the person has started taking medicines again." **– Clinician #1**
	"(...) when there are defaulters, it is right away to spot them and generate a list of defaulters. Right away they are followed in the communities, and they are brought back into the system." **-- ART Clerk**
	"[EMR] has been helping the department a lot comparing to working without the EMR.(...) of course, using the paper-based file is not difficult, but if you want to identify the defaulters, identify the missing appointments, it is hectic because there is a need to check individual file at a time, let's take for example at the facility has over six thousand patients so it means on that particular day one has to check six [thousand] files to get what you want, while J2 you just click and select, you can use years or month and date, you can just use the month of the defaulters at the same time the machine will run and produce the information that the J2 has given you." **-- Tracing Staff #3**

Theme	Qualitative Evidence
EMR Features, Linking Data to Patient IDs, Back-Entry	"Client's health passport is where we paste the client's visits, all the vitals, and also next appointment so that the client should know when she/he supposed to go to the facility to get drugs. The information we paste in the book is the same information we paste on the master card. [When a patient loses her/his health passport] It's very easy for us. We just search his name in the system, and the system brings out the information of the client." **-- ART Clerk**
	"Sometimes the master cards can be missing and makes it difficult to access certain information and when a client has come to the clinic with no information and it becomes difficult to start searching the master card with no enough information. These clients come to the clinic and they will only tell you their name but when you asks them the number which is in the master card they will say that they have forgotten and you begin searching by looking individual cards which is very difficult. Sometimes they leave the health passport home, while on the EMR you can just punch a button and it brings all the information." **-- Nurse #1**
	"Currently, the system is localized. The fact that I am on ART it's only Naisi system that knows that. It has not yet migrated, but plans are there that if a client upon scanning of his barcode whether he was getting drugs from Lilongwe and now he is in Zomba when you scan the barcode, it will be able to show you where he is getting drugs from and all that." **-- Clinician #2**
	"EMR reminds you things that you are supposed to do to a client. Even a patient who has a high viral load, once you enter the Respondent ID, it indicates to you that this person has a high viral load. It blinks because of the counseling sessions, and it assists on how to assist every patient coming to the clinic." **-- Nurse #1**
	"(...) the coming of EMR reduced time taken to treat a patient. There is some information on the vitals from the patients which the health provider forgets to collect from a patient, and the EMR reminds the provider to collect such information (...)" **-- EMR Data Statistician**
	"[When asked which data has been back entered in EMR] We were entering all the data the facility had. For instance, if the facility had a cohort of more than 2000, we would enter data from patient one up to patient 2000. We were doing back data entry. (...) we were entering data in chronological order. (...) You were guided by the card to enter everything that was on the card until everything has entered." **-- NGO Strategic Information and Evaluation Officer**
	When which data back-entered into EMR] "I can say it was all the data; let us say; if the clinic started its operations in 2008; that means we will register all the patients from our patient number one. So we need to enter all the information of the patients and their outcomes whether they died or they transferred" **-- Clinician #4**

Theme	Qualitative Evidence
Improvements in Efficiency, Quality of Care and Outcomes due to EMR (Part 1)	"[EMR was introduced] mainly it was to ease the burden of data management especially in the terms of reporting but later on it was embedded with decision making abilities to help the clinicians with their work; for example, if they want to decide which regimen they should give the clients and also it should remind them when to take the viral load and other things. So the main reasons were one; the report writing and decision making ability. (...) right now the goals [of EMR] have been met and the cohort has grown in number of patients alive on ART. It is a very huge number and cannot be managed on paper " **– Government Monitoring and Evaluation Officer**
	"Yeah, in a way, because in EMR, there are things such as signs and symptoms of other diseases are opportunistic infections, or to say infections that get advantage because of low immunity, such as Tuberculosis. Because when clients come, the system reminds you to ask if the client is coughing or if the client has a fever. So in such a way, the client is detected early, also starts treatment early, and the outcomes come out good that we prevent deaths. So the system has really helped. Even things like weight, the system already calculates that this one is going into severe malnutrition, and it alerts you to do something. So adult malnutrition is dangerous and can cause death. So the system helps us to detect malnutrition in people." **-- Physician and Hospital Manager**
	"EMR helps in doing your work very fast, and it is consistent; instead of searching through the master cards and the files, you just use the EMR, and it brings whatever you want. Sometimes the master cards can be missing and make it difficult to access certain information, and when a client has come to the clinic with no information, and it becomes difficult to start searching the master card with no enough information. These clients come to the clinic, and they will only tell you their name, but when you ask them the number which is in the master card, they will say that they have forgotten, and you begin searching by looking at individual cards, which is very difficult. Sometimes they leave the health passport home, while on the EMR you can just punch a button, and it brings all the information" **-- Nurse #1**
	"The system is able to flag out the people that need to check viral load. (...) when you are entering the data into the EMR, the system is able to remind you to get the viral load from the client. Another way is that the system is able to show you the type of drug the client is supposed to get according to the weight of the client. You don't have to go to the pharmacy to ask because the system is able to show you which is helping patients in care." **-- NGO Strategic Information and Evaluation Officer**

Theme	Qualitative Evidence
Improvements in Efficiency, Quality of Care and Outcomes due to EMR (Part 2)	"Indirectly [EMR contributed to reducing deaths] in the sense that first, as I said that, it created a systematic review of the client. So since we are following the client systematically, the issues such as malnutrition can be elicited fast, issues of TB can be diagnosed fast, issues of high viral load can be elicited fast, issues of drug combinations that you cannot mix such kind of drugs the EMR is able to let you know. So in that direction, I would say that it has helped to improve the quality of life for clients. Secondly, by giving us the number of defaulters, it helps us to trace those people, and in the long-run, we put those people back in care. (...) So it did not help prevent deaths directly, but indirectly it has improved the quality of life for these clients and thereby prevents other deaths." **-- Clinic Coordinator**
	"Another advantage [of EMR] is that data is safe because, with the hard copies, you could find that pages have been torn and some data has been lost, and it was very difficult for us to trace when the client started drugs. (...) when we are at the consultation for us to give the client drugs, the time we are taking is very little. Because the system already calculates. The drugs, time, next appointment, everything is already calculated in the system. So a patient does not take long to get drugs at a facility. (...) in the past, we were having trouble with calculating. In those days, we lacked calendars, so we had to get calculators and do mathematics until we help the client. But now it's straight forward. When we are at the consultation, we are having a wonderful time with the clients." **-- ART Clerk**
	"Now, when you want to generate a report, you don't bother to get the master cards and the register; you just go into the system and click buttons, and you download a report. So within 30 minutes, you are able to finish the report, unlike in the past with the paper-based system, it could take three days, including nights, to write a report. Similarly, when you are attending a client, you spend less time with him. You don't bother to write anything because things are already in the system. So clients are being helped faster." **-- NGO District Technical Officer**
	"More clients are coming because as of now our cohort reached 5000 from 4000. (...) in general even the clients themselves are happy with the system because what they cite include; the speed of service delivery, and secondly their heath passports are preserved. This is so because the print outs that we paste in the passport saves space than the manual way of writing using a pen. But so far what I can say is that most people are coming to ART" **-- Nurse #2**
	"I would say more clients came because we started doing things a little faster than the way we used to because writing in the cards was time-consuming. So since some clients would be in a hurry to work, to school, they were opting not to come because they would feel that they will be late. That's just an opinion. But now, with the EMR, we are a bit faster, and I would say more clients have come. Secondly, with the EMR, it's easy to elicit those clients who have defaulted treatment, so it's easy to trace them. So basically, I would say more clients have come because of the EMR." **-- Clinic Coordinator**

Theme	Qualitative Evidence
Tracing Practices (Part 1)	"When a client has started the ART we follow them up for the first six months and every time they come to the clinic we monitor them we want them to have good retention and when the clients are missing the appointment we make sure that we follow them immediately; our aim is to have good retention for the first six months after starting the ART." -- **Tracing Staff #1**
	"(...) if the person is difficult [person that does not want to be traced and go back to treatment] we engage the chief to assist us; so the chief can call the person and tell him that you are refusing to get treatment so in that case I will banish you from my village and you will be telling the people why you have been banished from the village so you will have yourself to blame for letting people know about your status and in that way people comply to come to the clinic. (...) I have one client from Mphyuphu and other girls they were giving us problems and we had to involve the chiefs to assist us in bringing these people to the clinic." – **Tracing Staff #5**
	"[When asked why most people agree to be traced] They have confidence that they will not default on their treatment, because we tell them if you default and we come to follow you people will know that you are taking the drugs. (...) [light laugh] there is no client who refused to agree to follow up." – **Tracing Staff #4**
	"There is a check box on the master card; where we tick agreed to follow up; or not. So we have Yes or No; so if we have No as the option then we take the phone number for the client. (...) If he doesn't come or the phone is not available we do make a follow up using our 'techniques'. (...) when you click on the J2 and request for the master card; when the master card comes up it will show if the client agreed to follow up or not." – **Tracing Staff #5**
	"Our main worry is that client give us wrong information about their names; phone numbers and physical address so it makes our work much harder and we have poor outcomes. We can go to the client follow up to trace five clients and we come back without finding anyone and this happens because people give us wrong addresses and we do the follow up for nothing." – **Tracing Staff #6**

Theme	Qualitative Evidence
Tracing Practices (Part 2)	"First, we look in the defaulters' record book. Then we look at the village of the defaulters. We look for special features lose or near the home of the defaulter. So, we travel to the village and look for the features, and we find the defaulter. Then we ask them to come for a chat. We chat with them nicely so that they shouldn't be afraid to get shouted at or reprimanded when they return to the hospital. Some say: 'I have been absent for too long, and I can't go back.' But we encourage them to go to the hospital, and you see them coming and saying: 'I am back.' So we welcome them nicely." **-- Tracing Staff #2**
	"(...) when we found out that they defaulted because they are afraid of being seen by people or friend from work we give them a special day to come to the clinic for example Wednesday or Friday, most people are shy, if the patient did not show up at the clinic again the issue is reported to the chief, but after telling the patient that we have visited you for more than enough and you are not helping us we are reporting this matter to the chief. The main reason for reporting you is because we are afraid that you will infect other people because you haven't stop having sex with someone, if the patient hears you saying you will report to the matter to the chief they become afraid. (...) the chief called the person and ask if the patient knows me and also they ask the patient what kind of the matter has been brought to him or her, therefore the chief tells the patient that if he or she doesn't show up to the clinic next time the patient will be banished from the village." **-- Tracing Staff #3**
	"It depends on Expert client's approach; but as for me I go straight to the client's house without first approaching anyone; it is only when the client is missing and people have said they don't know him that is when I go and meet the village chief. (...)Most of the chiefs in my area know us and we don't hide anything because they are also the members of HACC (Health Centre Advisory Committee) so they know that when we are looking for a client it means it has to do with the clinic." **-- Tracing Staff #7**
	"(...) they [Expert Clients] do come and ask us to assist them locating the house of the person and when we have done that they meet the person and when the person comes back from the hospital they tell us (...) When the person is refusing to go to the hospital; we talk to his relatives and as chiefs we also tell him that if he is refusing to go to the hospital and something happens it means we will give a penalty. (...) if this fails we take the matter to the Group Village Headman (GVH) we do this because we want to prevent deaths and also if the person is not taking the drugs it is easy for him to spread the HIV to other people. We don't want to have children who are orphaned when we could have prevented this from happening." **-- Community Leader**