Use of Routine Data in Evaluation: Technical Brief

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Impact of a District-Wide Health Center Strengthening Intervention on Healthcare Utilization in Rural Rwanda: Use of Interrupted Time Series Analysis

This document is part of a series that describes how routine data were used in research and evaluations of health programs and projects. Data for Impact (D4I) has compiled these examples from its own work and the work of others found through a literature review—and consultation with the original authors—to compare ways routine data can be appropriate for evaluations and to shed light on its benefits and shortcomings for evaluation.

A companion guidance document compiling these lessons is available at the D4I website. This suite of materials may be useful for others contemplating using available and routine data in their own work.

This brief describes an evaluation of an intervention to assess the effectiveness of a health system strengthening initiative that sought to increase utilization of healthcare services in Rwanda. Read the full report here.

Program Description

In 2009, a district-level health system strengthening (HSS) initiative was conducted in Rwanda by the Rwanda Population Health Implementation and Training (PHIT) partnership, a collaboration between the Government of Rwanda and Partners in Health, a US-based non-governmental organization. The intervention sought to improve health system utilization in rural primary care facilities by providing targeted financial, material, and technical support. The support included infrastructure renovation, salary support, medical equipment, referral network strengthening, and clinical training. In 2010, after completion of the first component of the program, researchers sought to use routine data to gauge the effectiveness of the intervention.

Rationale for the Use of Routine Data

Evaluations of public health policies and interventions are critical to understanding what works and what does not to improve health care service delivery. Planning and resource allocation are impaired and precious resources wasted when the effectiveness of interventions is unknown. However, the cost of collecting data to measure the effect of interventions presents a barrier to measuring impact and often results in inadequate evaluation.

Routine data from health management information systems (HMIS) can help inform policymakers on the effectiveness of public health policies and interventions. Evaluations using HMIS can save time and resources by using existing data already in use for routine management of the health system. Additionally, the use of HMIS for time series analysis allows for evaluation designs informed by principles of causal inference. In Rwanda, evidence of HMIS data quality further bolstered the case for its use in evaluation. For example, one study carried out in three rural districts in Rwanda showed that 73 percent of sampled facilities had concordance between facility registers and monthly reports of greater than or equal to 95 percent, and that 71 percent of facilities had concordance between facility registers and the electronic database of 95 percent or more (Karengera, et al., 2016)

Evaluation Questions

The study sought to determine the impact of the PHIT health information strengthening intervention on health service utilization rates by measuring the difference in health care utilization rates (outpatient visits), births in health facilities (institutional deliveries), and referrals for high-risk pregnancies between an intervention group of 14 primary care facilities, and a propensity-score matched group of 380 control facilities.

Data Description and Data Management

During the study period 2008–2012 (baseline and follow-up), Rwanda upgraded the electronic data management system for the HMIS from a legacy SQL database to the District Health Information Software, version 2 (DHIS2). Researchers had to merge the old database with the new one to compile continuous data throughout the study period. Monthly values for indicators of interest (e.g., outpatient visits, institutional deliveries, and referrals for high-risk pregnancies) were mapped and merged into a study dataset, and data used for matching (e.g., population density) were also gathered. Ministry of Health population estimates were used to convert these metrics to rates. Monthly rates were then aggregated by intervention group (PHIT versus propensity score-matched non-intervention series) for analysis. Population-based survey data (e.g., Demographic and Health Surveys [DHS] and health facility assessment survey data (e.g., Service Provision Assessment [SPA]) can be used to help match control facilities to intervention facilities. For example, area-level estimates of travel time to facilities can be found in DHS. The value of the survey estimate would then be applied to all facilities in the geographic area represented by the survey estimate.

Assessment of Usability and Quality of Data

Comparisons of HMIS data to population-based survey estimates also showed the quality of the Rwanda HMIS. Coverage for family planning and antenatal care from HMIS was compared to the DHS from 2010 and the results were found to be comparable (57% versus 69%).

Completeness of data was assessed for intervention and control facilities for the five-year study period. Facilities that had more than four missing HMIS reports during the baseline period were excluded (29 facilities from the control group were excluded under this criteria).

Data Analysis Methods Used

To estimate the district-level effect of the PHIT HSS intervention on delivery rates, outpatient visit rates, and referral rates for high-risk pregnancies, researchers used five years of monthly reproductive, maternal, newborn and child health (RMNCH) facility-level time series data to conduct a propensity score-matched controlled interrupted time series analysis. Barring cross-contamination from external events (e.g., other initiatives to increase service utilization, population movements, etc.), a controlled interrupted time series analysis permits unbiased estimation of population-level effects of an intervention.

The baseline period was established as the period from January 2008–April 2009, while the follow-up period was June 2009–July 2012 (the intervention date was set as May 2010). Time series models were fit to examine the significance of differences between intervention and control groups in the level and trend of the indicators of interest. Two main results were produced: (1) the difference in post-implementation change in level of mean outcome in the intervention relative to the control group, and (2) the difference in post-implementation trend in outcome in the intervention relative to the control group.

Limitations in Using Routine Data for Evaluation

A limitation of the study arose from the need to merge the HMIS datasets to produce a continuous stream of indicator values from baseline through the implementation period. Not all indicators (outcomes and potential confounders) could be mapped across the databases and so unmeasured confounding due to different population and facility characteristics is a risk. The evaluators can't be 100 percent convinced that the control series represents the counterfactual of our intervention facilities.

To mitigate any inadequacies in the HMIS data in controlling for confounders, researchers suggested using other available facility-level data sources, such as SPA, to improve the propensity score matching and make the intervention and control groups more similar.

What Worked Well?

Researchers cited as strengths of the analysis the use of propensity score matching on baseline trend and health center covariates, and the use of five years of monthly time series HMIS data to allow modeling of counterfactuals following the intervention. Systematic bias is unlikely to have been introduced in the analysis because control time series were included to account for external events that might influence utilization, and because the intervention start date was unambiguous.

Time series data permits researchers to use quasi-experimental designs using counterfactuals instead of pre-, post-, and cross-sectional evaluation designs. Such an analysis can provide useful information on program effectiveness and encourage the strengthening of information systems.

Conclusion

The savings in time and effort by using HMIS data collection definitely offset the disadvantages as processing the data and completing the analysis took several months, whereas a primary data collection effort would have led to a timeline of several years. This success was greatly aided because the routine HMIS data in Rwanda is of high quality. There were also no major concerns about differences in reporting between intervention and control districts. However, in settings where national data quality is poor (e.g., is incomplete or contains errors) and where there is reason to suspect differential reporting by intervention assignment, then the disadvantages of HMIS would overwhelm the costs-savings and speed, largely because the results would be invalid.

This evaluation showed the effectiveness of HSS interventions on increasing service utilization and demonstrated that combining HMIS time-series data with counterfactual-based methods would allow causal conclusions to be drawn.

References

Karengera, I., Onzima, R., Katongole, S., & Govule, P. (2016). Quality and Use of Routine Healthcare Data in Selected Districts of Eastern Province of Rwanda. *International Journal of Public Health Research*, 4 (2), 5–13.

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