Health care hotspotting and outpatient care: a randomized controlled trial of the Camden Coalition superutilizer model

October 2020

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Background:

Rapidly rising health care costs in the United States are putting increasing pressure on patients, employers, and federal and state budgets.[1] At the same time, there is widespread interest in improving the delivery of health care.[2] The goals of reducing costs and improving health and patient experience are closely related, because health care spending is heavily concentrated. Five percent of the population accounts for 50 percent of health care expenditures.[3] This has led to particular interest in interventions that aim to reduce cost and improve care by targeting "superutilizers" of the health care system.

The Camden Coalition of Healthcare Providers' (CCHP) Camden Core Model is an exemplar of this approach, and it has received national attention and served as a model for superutilizer programs elsewhere.[4–7] The Camden Core Model targets individuals with medically and socially complex needs, who have frequent hospital admissions. Despite representing 0.5% of the Camden population, the eligible population accounted for 11% of the city's hospital expenditures.[8] The Camden Core Model engages this high-utilizer population using a team of nurses, social workers, and community health workers to visit participants in their homes. They provide initial clinical assessments and assure appropriate follow-up with primary care and specialty providers, connection with social services, and support for self-care.[8,9]

Between 2014 and 2017, several of the authors collaborated with the Camden Coalition to conduct a randomized controlled trial of the Camden Core Model's impact on hospital readmissions. The results of this study, published in *NEJM* in January 2020, showed that the program had no effect on the primary outcome: the 180-day hospital readmission rate. As we wrote in the paper, "the 180-day readmission rate was 62.3% in the intervention group and 61.7% in the control group. The adjusted between-group difference was not significant (0.82 percentage points; 95% confidence interval, −5.97 to 7.61)."[8]

Proposed study:

In this extension study, we turn our attention to analyzing the effect of the Camden Core Model on outpatient utilization. We had hoped to measure these outcomes from the start of the randomized controlled trial, as we noted in our previous pre-analysis plan, both to provide a broader picture of the costs of the program as well as potential mechanisms by which the program may or may not reduce re-hospitalization.[10] To date we have been unable to investigate these outcomes because we lacked access to data on outpatient utilization for both treatment and control groups.

In light of our findings on hospital readmissions, our primary motivation in this extension study is to distinguish between two broad classes of explanations for the null results. The Camden Core Model is designed to improve care coordination after hospital discharge. Care teams scheduled and accompanied participants to visits, coordinated follow-up care, managed medication, and connected participants to additional services. Did we not find a significant effect on readmission rates because the program did not achieve its coordination goals, or because improved care coordination did not translate to reduced hospitalization (either because care coordination is the wrong approach or because the level of care coordination proved insufficient)?

Both explanations are plausible. In our previous work we noted that while engagement with the program was high, two stated program goals – a home visit from the Coalition within 5 days and a provider visit within 7 days – were met only 30 percent of the time. Program staff cited lack of stable housing, phones, and transportation, behavioral health, and few available appointments as impediments to successful care coordination. At the same time, the program treats a particularly high use and complex patient population with persistently high medical needs, making it possible that few hospital re-admissions are in fact preventable through better coordination of existing resources.[a]

This new study will assess the Camden Core Model's theory of change by examining additional utilization outcomes available in the Medicaid population. Estimates from our hospital admissions data suggest that about 500 patients in our 800-patient study population are covered by Medicaid and thus will be available for analysis.

We note several limitations to our analysis. First, the investigation of the care coordination mechanism will provide only suggestive evidence, not a definitive explanation, for the null readmission results. If the program did not achieve its coordination goals, this does not necessarily mean that readmissions would have improved had the coordination goals been met. Similarly, if the program achieved its coordination goals, we cannot distinguish whether care coordination cannot affect readmissions or whether the level of care coordination achieved was insufficient to have an effect.

Second, we note that our analysis will be limited to only those care coordination efforts and outcomes measurable in our data. The Camden Core Model had only limited explicit care coordination goals: a PCP visit within 7 or 14 days and home visit within 5. In an effort to characterize more fully the effects of the program on outpatient utilization, we will evaluate a larger set of related outcomes. These efforts constitute a bundle of related services, and it is not a priori clear that there is a single "most important measure." We acknowledge that the interpretation of some outcomes is unclear. For example, although the program endeavored to connect patients to primary care and address medication needs, it is not clear that an increase in the number of primary care visits or unique prescription drugs beyond a certain point constitutes a positive outcome. We will be cautious in tying changes in utilization to conclusions about the quality of care or program success.

Our outcomes fall into four main categories. First, our primary outcome is whether a participant has any physician visit with 14 days of discharge. We chose this as our primary outcome because getting patients to have a physician visit shortly after discharge was one of the key ways in which the Camden Core Model tried to improve care coordination and because (as discussed in more detail below) our statistical power to detect impacts on this outcome appears reasonable (at least relative to alternatives). Second, for secondary outcomes we will examine the impact on the use of other forms

[a] The inclusion criteria for the study were at least one hospital admission at any of four Camden-area hospital systems in the 6 months before the index admission, when patients were enrolled; at least two chronic conditions; and at least two of the following traits or conditions: use of at least five active outpatient medications, difficulty accessing services, lack of social support, a coexisting mental health condition, an active drug habit, and homelessness.

of outpatient care, such as specialty care, home healthcare, prescription drugs, and care quality as secondary outcomes. Third, we will also explore the effects of the Camden Core Model on the stability of Medicaid enrollment. We will do this for two distinct reasons: it is an outcome that is potentially affected by the intervention, and if it is affected by the intervention, it is a potential confounder for interpreting all other outcomes measured in the Medicaid data.[b] Finally, we will use the Medicaid claims data to validate previous analysis on the effect of the intervention on inpatient care and emergency department visits using hospital discharge data. These analyses will help us paint a much more comprehensive picture of the effect of the program than the analyses we could conduct using only data collected from the hospitals during the initial RCT.

Analysis:

<u>Outcomes</u>

We will analyze the following outcomes:

Primary outcome:

- Any physician visit within 14 days of discharge (PCP or specialist)

Secondary outcomes:

- *Quantity of Non-Institutional Care*
    - Primary outcome at other time horizons (7/90/180 days)
    - Any/# of unique prescription drugs (180 days)
    - Any/# of PCP visits (14/90/180 days)
    - Any/# of specialists visits (14/90/180 days)
    - Any/# of home health care visits, not including Camden Coalition visits (7/14/90/180 days)
    - Any/# of durable medical equipment
- *Quality of Care*
    - Medication adherence for chronic conditions (cholesterol, hypertension, and diabetes) (180 days)
        - Proportion of Days Covered and Medication Possession Ratio.[c]
    - Measures of care fragmentation (180 days)
        - Bice-Boxerman Continuity of Care Index[12]
        - Herfindahl concentration index of all primary care visits
- *Medicaid enrollment*
    - # of days enrolled in Medicaid in the 180 days post discharge
    - # enrolled in Medicaid 180 days post discharge

[b] We have not prespecified how we will address possible confounding. Exploratory work using inpatient data suggests that treatment status has no effect on Medicaid enrollment or attrition. If we do find this confounding to be a concern, we will exercise discretion post hoc and implement an approach based on the severity of the problem, for example bounding exercises or using a more restricted sample that does not suffer from this bias.
[c] Medication Possession Ratio (MPR) is defined as total Rx days of supply divided by Rx period. Proportion of Days Covered is defined as total Rx days a patient is "covered" by a drug class divided by the number of days in the measurement period. For the PDC measures, we follow the method used by the CMS Medicare-Medicaid Plan Performance Data Technical Guide (https://www.cms.gov/Medicare-Medicaid-Coordination/Medicare-and-Medicaid-Coordination/Medicare-Medicaid-Coordination-Office/FinancialAlignmentInitiative/Downloads/MMPPerformanceDataTechNotesCY2018_04252018.pdf) . We measure average MPR and PDC across drugs for multiple chronic conditions taken by a recipient. See Leslie et. al (2008) for a discussion of methods for calculating medication adherence.[11]

    - # of starts and stops to enrollment in the 180 days post discharge
    - # enrolled in Medicaid during the 180 days post discharge (for the full RCT population)
- *Institutional Care and Replication of Prior Results* (all measured within 180 days post-discharge)
    - Any/#/LOS of hospital readmissions
        - All readmissions
        - Readmissions from the ED
        - Readmissions not from the ED
    - Any/# of ED visits
        - All ED visits
        - Outpatient ED visits (i.e., "treat and release" visits)
    - Any/# of hospital trips requiring EMS transport
    - Any/#/LOS of SNF/nursing home care admission

Empirical Model

The main analysis will compare outcomes for those who were randomized to receive the Camden Core Model intervention compared to those who were randomized to the control group.

Consider an outcome, Y, such as an indicator that the participant was readmitted to a hospital within 180 days after discharge from the hospital. For subject i, the estimating equation is:

$$Y_i = \beta_0 + \beta_1 1(\text{Treatment})_i + \beta_2 X_i + \varepsilon_i$$

where $1(\text{Treatment})_i$ is an indicator variable equal to one if the subject was randomized to the treatment group and zero if the subject was randomized to the control group. $\beta_1$is the parameter of interest and measures the causal effect of being randomized into the treatment group. X_i is a vector of control variables.[d] These control variables will be uncorrelated with the treatment indicator, but they can aid in the precision of the estimate. We will adjust for the set of demographic and prior utilization controls that we have pre-specified in the previous analysis of this RCT: age (5-year age bins), sex (indicator that the patient is male), race/ethnicity (indicators for African American and Hispanic), as well as lags of the dependent variable (if feasible) in the 0-6 months and 7-12 months prior to the enrollment admission; these are analogous to the controls we used in our prior analysis. In addition, we will include controls for prior Medicaid enrollment and chronic condition indicators, covariates that were not previously available to us but that we believe will be in the Medicaid data.

Multiple Inference Adjustment

We have a plurality of outcomes in two domains of outcomes: the quantity of non-institutional care and the quality of care received. To account for the multiple inference problem, we will also compute and report the family-wise p-values within each domain (as well as the per-comparison p-values). Since we are looking at multiple outcome measures within a domain, the per-comparison p-values will be lower than when each outcome is viewed as part of a "family of hypotheses" that the Camden Core Model has no effect on this domain. We will therefore also calculate and report the family-wise error rate adjusted p-values. This adjusted p-value corresponds to the probability of rejecting the null hypothesis of no effect on a given outcome under the null family of hypotheses of no effect on any

[d] We estimate linear models even though a number of our outcomes are binary. This approach is appropriate when examining causal treatment effects and is standard practice in economics.[13] We will check robustness to model specification.

outcomes in this domain. We will calculate these family-wise error rate adjusted p-values based on 10,000 iterations of the free step-down resampling method of Westfall and Young (1993).[14]

Data

Sample Size & Match

We anticipate that approximately 500 of our 800 study participants can be linked to Medicaid administrative records. To identify our Medicaid subsample, the Camden Coalition will provide a "finder file" with identifiers along with a de-identified subject ID to New Jersey Medicaid. The identifiers will include first name, middle name/initial, last name, date of birth, sex, Social Security number, and address, as recorded at the time of the baseline survey (pre-randomization). NJ Medicaid (or its contractor Optum) will then identify these participants in the state's data and return a "crosswalk file" without the personal identifiers but with the de-identified subject ID matched to an encrypted Rutgers Medicaid ID. The Rutgers Canter for State Health Policy has an existing research relationship with NJ Medicaid and manages a Medicaid limited data set for research. The crosswalk file will be used to create an extract of this limited data set for the RCT's Medicaid population.

Inclusion Criteria

To account the possibility that the Camden Core Model may have increased Medicaid enrollment for those in the treatment group, we will limit our analysis to only participants who were enrolled in Medicaid at baseline. Separately, we are interested in the effect of the Camden Core Model on enrollment in Medicaid and will measure this in the full RCT sample.

Power calculation

We conducted a preliminary power calculation for our primary outcome using hospital discharge data. We first subset our participants to those who have a Medicaid claim in the hospital discharge data (n = 522). Using program data, we see that 60.2% of study participants in the treatment group visit a doctor within 14 days of discharge, with a standard deviation of 48.76%. With a sample size of 522, of which 260 are in the control group and a two-sided test with $\alpha = 0.05$, we have 80% power to detect an effect size that is equal to or greater than 11.98 percentage points. This calculation does not control for any covariates. As explained above, we plan to include lagged measures of the outcome as well as other participant demographics in our analysis, which should hopefully improve power.

References

1. Centers for Medicare and Medicaid Services. National Health Expenditures: 2012 Highlights [Internet]. 2012 [cited 2014 Jun 30]. Available from: http://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-andReports/NationalHealthExpendData/downloads/highlights.pdf

2. Berwick DM, Nolan TW, Whittington J. The Triple Aim: Care, Health, and Cost. Health Aff (Millwood) 2008;27(3):759–69.

3. Cohen S. The Concentration of Health Care Expenditures and Related Expenses for Costly Medical Conditions, 2012. Agency for Healthcare Research and Quality; 2014.

4. Gawande A. The Hot Spotters. New Yorker [Internet] 2011 [cited 2018 Sep 28];Available from: https://www.newyorker.com/magazine/2011/01/24/the-hot-spotters

5. Gorenstein D. Setting up shop where the sick are [Internet]. MarketPlace. 2013 [cited 2018 Sep 28];Available from: https://www.marketplace.org/2013/08/02/health-care/diagnosis-data/setting-shop-where-sick-are

6. Mann C. Targetting Medicaid Super-Utilizers to Decrease Costs and Improve Quality [Internet]. Baltimore, Maryland: Centers for Medicare & Medicaid Services; 2013 [cited 2018 Sep 28]. Available from: https://www.medicaid.gov/federal-policy-guidance/downloads/cib-07-24-2013.pdf

7. Robert Wood Johnson Foundation. Expanding “Hot Spotting" to new Communities [Internet]. Robert Wood Johnson Foundation; 2012 [cited 2017 Sep 28]. Available from: http://forces4quality.org/node/5182.html

8. Finkelstein AN, Zhou A, Taubman S, Doyle J. Health Care Hotspotting — A Randomized, Controlled Trial. N Engl J Med 2020;382:152–62.

9. Camden Core Model [Internet]. Camden Coalit. [cited 2020 Sep 2];Available from: https://camdenhealth.org/care-interventions/camden-core-model/

10. Brenner J, Finkelstein A, Doyle J, Taubman S, Zhou R. Health Care Hotspotting: A Randomized Controlled Trial Analysis Plan. AEA RCT Regist 2014;

11. Leslie SR, Gwadry-Sridhar F, Thiebaud P, Patel BV. Calculating medication compliance, adherence and persistence in administrative pharmacy claims databases. Pharm Program [Internet] 2013 [cited 2020 Sep 9];Available from: https://www.tandfonline.com/doi/pdf/10.1179/175709208X334614?needAccess=true

12. Pollack CE, Hussey PS, Rudin RS, Fox DS, Lai J, Schneider EC. Measuring Care Continuity: A Comparison of Claims-Based Methods. Med Care 2016;54(5):e30–4.

13. Angrist JD, Pischke J-S. Mostly harmless econometrics: An empiricist’s companion. Princeton University Press; 2009.

14. Westfall PH, Young SS. Resampling-Based Multiple Testing: Examples and Methods for p-Value Adjustment. Wiley; 1993.