

Behavior-Based Diabetes Management: Impact on Care, Hospitalizations, and Costs

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D diabetes has a major adverse impact on productivity, disability, and health care costs.¹⁻⁴ The American Diabetes Association (ADA) recently updated estimates of the economic burden of diagnosed diabetes, reporting a total estimated cost in 2017 of \$327 billion, including \$237 billion in direct medical costs and \$90 billion in reduced productivity.⁵ For employers, the indirect costs of diagnosed diabetes include increased absenteeism (\$3.3 billion) and reduced productivity while at work (\$26.9 billion). Much of the medical cost of diabetes is related to comorbidities and complications arising from inadequate management of the disease. To help mitigate the adverse consequences of poor control of diabetes, the ADA provides evidence-based standards of care for persons with diabetes.⁶ Unfortunately, despite availability of these care standards and expanded therapeutic options, most people with diabetes demonstrate gaps in clinical care, low adherence to glucose monitoring, and inadequate management of cardiovascular risk factors.⁷⁻⁹ The proportion of patients meeting standards for diabetes care, such as glycated hemoglobin (A1C), blood pressure (BP), and low-density lipoprotein cholesterol levels, has not improved significantly between 2005 and 2016.¹⁰ Only 1 in 6 individuals with diabetes in the United States is achieving concomitant goals for A1C, BP, and cholesterol, as well as avoiding tobacco use.¹¹

Individuals with diabetes who are actively engaged in the management of their condition have fewer and less serious adverse health outcomes and avoid unnecessary hospitalizations compared with those who are not as engaged.^{12,13} Preventing unnecessary hospitalizations can significantly reduce overall health care spending.^{14,15} One promising approach harnesses the evidence base from behavioral science and behavioral medicine research.^{16,17} The use of structured incentives to engage individuals in health behaviors is an evidence-based behavioral science approach. Successful incentive-based interventions require careful attention to design and implementation.¹⁸ Incentives must be contingent, timely, and sufficiently large to both engage individuals and sustain the target health behaviors over time. This study examines the impact of the Diabetes Care Rewards (DCR) program, a behavioral science- and incentive-based care management program designed to increase

ABSTRACT

OBJECTIVES: To (1) examine the impact of the Diabetes Care Rewards (DCR) program on adherence to care standards and (2) evaluate the economic impact of adherence to care standards.

STUDY DESIGN: A retrospective observational cohort study design with propensity matching. Additional covariates adjustment was used to minimize residual imbalance.

METHODS: Utilization and cost data were compared between individuals enrolled vs individuals eligible for but not enrolled in the DCR program using a standard mean difference. Individuals were employees or their dependents from self-insured companies throughout the United States. Outcomes included adherence to the care standards, service utilization, and costs.

RESULTS: A total of 3318 propensity-matched participants were included. Primary analysis revealed that enrolled members increased adherence to semiannual glycated hemoglobin, annual lipid, and annual urine albumin-creatinine ratio testing. Additionally, enrolled members experienced less utilization of high-acuity services and increased rates of physician visits. In a secondary analysis, the enrolled group was associated with greater pharmaceutical costs.

CONCLUSIONS: A behavioral science- and incentive-based diabetes management program was associated with greater rates of adherence to recommended diabetes monitoring care standards, increased routine clinic visits, decreased hospital admissions, and decreased inpatient days. Results indicate the benefits of adherence to evidence-based standards for diabetes care.

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patient engagement in the management of their diabetes by rewarding timely completion of evidence-based standards of care.¹⁹ The DCR program was developed to address the increasing burden of unmanaged diabetes on employee health and productivity and to reduce costs to self-insured employers and their covered employees and dependents. The program was first implemented in 2007 for a financial services company with offices located across the United States. The program utilizes proven principles of behavioral science, is provider-centric, and incorporates ADA standards for diabetes education and self-management support using a structured diabetes health action plan (DHAP) care guide. It was hypothesized that the program would increase the proportion of persons with diabetes completing evidence-based diabetes screening evaluations in addition to reducing total medical costs and overall hospitalization rates.

METHODS

Design and Setting

We conducted a retrospective observational cohort study to compare utilization and cost data between individuals enrolled vs individuals eligible, but not enrolled, in the DCR program. Individuals were employees or their dependents (ie, members) from 26 self-insured companies throughout the United States. Self-insured companies cover the medical and pharmaceutical expenses of their employees and their beneficiaries, rather than outsourcing these costs to a third-party health insurance provider. The 26 companies were clients of Abacus Health Solutions that participated in the co-pay waiver incentive of the DCR program.

Study Cohort

The enrolled cohort was composed of members of any age or gender enrolled in the DCR program. Eligibility for enrollment required a diagnosis of diabetes, using claims-based *International Classification of Diseases, Ninth Revision (ICD-9)* or *Tenth Revision (ICD-10)* diagnosis codes, and presence of a 24-month block of continuous enrollment with at least 1 medical or pharmacy claim during that period. This 24-month block included 12 months of claims data prior to DCR program enrollment and 12 months of claims data following enrollment. The unenrolled group was composed of individuals with a diagnosis of diabetes, using claims-based *ICD-9* or *ICD-10* diagnosis codes or by identifying individuals taking 1 or more glucose-lowering medications, who were eligible for the DCR program but who did not enroll (see [eAppendix Table 1](#) [eAppendix available at [ajmc.com](#)]). Members in the control group were also required to have 24 months of continuous claims data. Both groups were engaged using multiple efforts in the forms of mailings to the home for employees and covered dependents,

TAKEAWAY POINTS

This study evaluated a commercially available diabetes care management program for members of self-insured health plans across the United States.

- ▶ Adherence to diabetes care standards can be improved significantly by deploying an approach to care management based on behavioral science and incentives.
- ▶ The pattern of health care service utilization improved with decreased hospital admissions and hospital days while outpatient physician visits increased for those members enrolled in the diabetes care management program.
- ▶ The study provides a business case for employers and health plans to promote patient engagement through use of contingent incentives, leading to better health outcomes and lower hospitalization costs.

and employees in both groups also received employer postal mail, employer email, and exposure to workplace posters and materials promoting program engagement.

Intervention

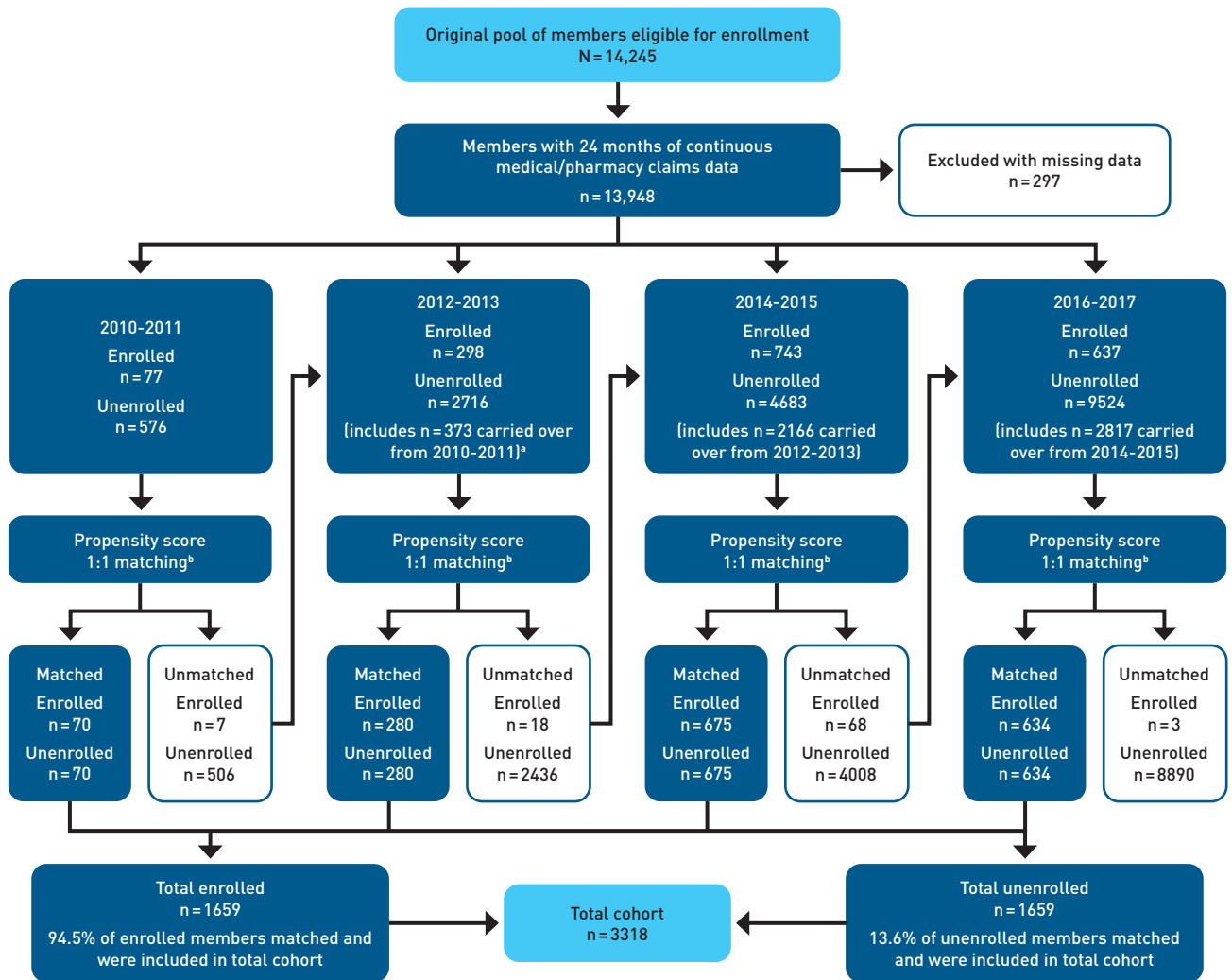
The DCR program provides incentives in the form of pharmacy co-pay waivers to cover out-of-pocket expenses for diabetes medications and supplies. Pharmacy co-pay waivers were contingent on members having an active relationship with their primary care physician or endocrinologist and documenting completion of recommended diabetes care processes: (1) semiannual testing of A1C, (2) annual lipid panel, (3) annual urine albumin-creatinine ratio (ACR), (4) annual eye exam, and (5) annual foot exam. The DCR program utilizes a patented system grounded in behavioral science for contingent activation and deactivation of incentives. Through integration with each member's pharmacy benefit, co-payments for diabetes medications and supplies were waived at the point of sale if the member was actively adherent to all program criteria; otherwise, co-payments were required. Pharmacies were provided a data feed of information regarding each participant's adherence status, which was updated daily.

To receive the co-pay waiver incentive, members were required to complete an annual 30- to 45-minute telephonic assessment by a trained certified diabetes nurse educator or clinical pharmacist to develop a written DHAP that is shared with and signed off by their diabetes treatment provider. Using motivational interviewing, these trained clinical staff completed the DHAP as a structured interview using guidelines for diabetes self-management education and support as promoted by the ADA.²⁰ The DHAP addresses core aspects of diabetes self-management, identifies barriers and challenges to health-related goals, and provides training on stimulus-control techniques. Telephonic follow-up was scheduled for 3 months but adjusted by the nurse or pharmacist according to participant needs.

Data Analysis

The exposure was defined as enrolled vs not enrolled. This exposure was self-selected by the member and possibly confounded by variables such as demographics and comorbidities. Covariates included in the propensity score matching model were calendar

FIGURE. STROBE Diagram of Cohort Construction



*Beginning with the 2012-2013 time block, members who were unmatched and unenrolled after propensity score matching in the previous 2010-2011 time block and who also had 24 months of continuous claims data within the 2012-2013 time block were carried into that time block. This process was applied to the subsequent 2014-2015 and 2016-2017 time blocks.

^bThe same propensity score matching algorithm and tolerance used in the 2010-2011 block was used in each of the 3 remaining time blocks.

time, age, region, sex, comorbidities (preprogram insulin use status and Elixhauser Comorbidity Index score²¹), and preprogram total medical costs capped at \$200,000 parameterized as quartiles.¹⁵ All costs were adjusted to 2018 US\$ using the Consumer Price Index inflation calculator for health care services from the US Department of Labor.

To adjust for these baseline (initial 12-month, pre-index date) possible confounders, control members were matched by propensity scores with match tolerance set at 0.10 (0, exact match; 1.0, any control would match any intervention member) using a nearest neighbor approach, and analysis was conducted on the resultant matched sample. Enrolled members were assigned to 2-year time

blocks based on the calendar year at the onset of their 24-month claims interval. Unenrolled members were allocated to the earliest 2-year time block for which they had 24 months of continuous claims data and underwent 1:1 propensity score matching with the enrolled members. Those who remained unmatched and unenrolled after propensity score matching and had 24 months of continuous claims data in the next 2-year time block were carried forward into the next 2-year time block. The process of carrying forward those unmatched and unenrolled members was applied to the 2012-2013, 2014-2015, and 2016-2017-time blocks (Figure and eAppendix Figure). Those who were unmatched and unenrolled after propensity score matching in the 2016-2017 time block were excluded from

the study (n = 8890); however, no members were excluded due to nonoverlapping propensity scores between the 2 groups.

For the intervention group, the index date was the date of enrollment into the DCR program. The outcomes were ascertained during the 12 months following the index date and baseline information was ascertained from the 12 months preceding the index date. For the control group, each member had the same index date for data inclusion as their matched intervention group member. The outcomes of interest and for which data were available were (1) receipt of medical care (semi-annual A1C, annual lipid, and annual urine microalbumin test), (2) service utilization (hospital admission [yes vs no; counts], hospital days [counts, truncated to 60 days], and outpatient office visits [yes vs no; counts]), and (3) costs (pharmacy and medical [pharmacy and medical measured as per member per month, capped at \$200,000 for medical costs]). Capping medical costs is a conventional approach used by health plans to attenuate the impact of catastrophic claim costs and has been used in recent studies of diabetes.¹⁵

Characteristics between the intervention and control groups were compared and differences between the groups were assessed using a standardized mean difference (SMD). Analyses were further adjusted for covariates that had an |SMD| greater than 0.10 to adjust for residual imbalances in the matched sample.^{22,23} In the analysis for each of the primary outcomes—namely, medical care, services and costs—we employed outcome models in the matched sample (ie, adjusted for some covariates included in the propensity score) to allow for further adjustment of possible residual confounding by total preenrollment costs and region.^{23,24} Pharmacy and medical costs for the year were divided by 12 to obtain the per-member-per-month costs. To allow the model to be more flexible, we included total preprogram cost as a continuous variable with quadratic splines and centered this variable on its mean.²⁵ We presented the model results for the receipt of medical care and service outcomes adjusted for preenrollment total costs and region, as well as those for cost outcomes adjusted for the preprogram total costs, region, and the estimated propensity score. For comparison, we also presented the matched, unadjusted analyses. Results that further adjusted for other imbalances in preprogram variables were comparable (see eAppendix). Binary outcomes were modeled using a log-binomial or logistic regression, count outcomes were modeled using negative binomial regression or a zero-inflated Poisson or negative binomial regression, and costs were modeled using gamma regression. When log-binomial models did not converge, log-Poisson models were used to estimate risk ratios.²⁶ Analyses were performed using SPSS version 25 (IBM) and R version 4.0.5 with RStudio version 1.2.5033 (R Project for Statistical Computing).

RESULTS

Study Cohort

A total of 14,245 members with diabetes were eligible for enrollment into the DCR program between August 1, 2010, through December 27,

TABLE 1. Preintervention Baseline Characteristics in a Matched Sample of Enrollees and Nonenrollees in the Diabetes Care Rewards Program From 26 Self-insured Companies in the United States, 2012-2017 (N=3318)

Characteristic	Enrolled n = 1659	Unenrolled n = 1659	SMD
Age in years, mean (SD) ^a	53.4 (14.2)	54.7 (14.7)	0.09
Gender, n (%) ^a			0.02
Female	706 (42.5)	691 (41.7)	
Male	953 (57.4)	968 (58.3)	
Region, n (%) ^a			0.17
Northeast	975 (58.7)	1062 (64.0)	
Midwest	123 (7.4)	97 (5.9)	
South	408 (24.6)	413 (24.9)	
West	153 (9.2)	87 (5.2)	
Insulin status, n (%) ^a			0.01
Insulin independent	1167 (70.3)	1175 (70.8)	
Insulin dependent	492 (29.7)	484 (29.2)	
Preintervention total cost quartiles, n (%) ^{a, b}			0.36
\$0-<\$2585	278 (16.8)	552 (33.3)	
\$2585-<\$5966	389 (23.4)	440 (26.5)	
\$5966-<\$14,126	471 (28.4)	358 (21.6)	
≥\$14,126	521 (31.4)	309 (18.6)	
Elixhauser Comorbidity Index score, ^a mean (SD)	11.54 (10.87)	13.39 (13.01)	0.07

SMD, standardized mean difference.

^aCharacteristics that were incorporated into the 1:1 propensity score matching.

^bAmounts greater than \$200,000 were truncated to \$200,000.

2017. Of this initial pool, 13,948 had 24 months of continuous claims data. The Figure shows the STROBE diagram of the construction of the cohort. After the process of 1:1 propensity score matching, 3318 members were matched: 1659 in the enrolled cohort and 1659 in the unenrolled cohort. Descriptive statistics regarding the preintervention cohort are provided in **Table 1**. Members were mostly male, middle-aged, from the Northeast, and not prescribed insulin. When comparing baseline characteristics in the matched sample using an SMD, there were differences by region (SMD, 0.17) and preintervention total cost (SMD, 0.36). The enrolled group was more likely to be from the Midwest (7.4% vs 5.8%) and West (9.2% vs 5.2%) compared with the unenrolled group. The enrolled group had slightly higher preenrollment total costs (mean [SD] = \$16,137.46 [\$26,496.79] vs \$12,830.95 [\$28,087.70]).

Table 2 displays the estimated effects of enrollment in the DCR program on each of the medical care and service outcomes in the matched sample, both unadjusted and adjusted for preenrollment total costs. After adjustment for preenrollment total costs (with a spline) and region, enrolled members had an increased likelihood of adherence to the semiannual A1C test (risk ratio [RiR], 1.55; 95% CI, 1.45-1.67), annual lipid test (RiR, 1.20; 95% CI, 1.14-1.26), and annual urine microalbumin test (RiR, 1.54; 95% CI, 1.42-1.66). Enrolled members had a lower estimated risk of

TABLE 2. Estimated Effects of Diabetes Care Rewards Program on Medical Care and Service Outcomes in a Matched Sample of Enrollees and Nonenrollees From 26 Self-insured Companies in the United States, 2012-2017 (N=3318)^a

Outcome	Unadjusted	Adjusted for region and preintervention total cost (continuous)	Adjusted for region and preintervention total cost (continuous with quadratic spline)
	Risk ratio (95% CI)	Risk ratio (95% CI)	Risk ratio (95% CI)
Receipt of medical care (yes vs no)			
A1C test	1.73 (1.61-1.86)	1.72 (1.60-1.85) ^b	1.55 (1.45-1.67) ^b
Lipid panel	1.24 (1.18-1.30)	1.24 (1.18-1.30) ^b	1.20 (1.14-1.26) ^b
Urine ACR test	1.66 (1.54-1.79)	1.66 (1.54-1.79) ^b	1.54 (1.42-1.66) ^b
Service			
Odds ratio (95% CI)			
Hospital admission (yes vs no)	0.82 (0.67-1.01)	0.82 (0.67-1.01) ^b	0.72 (0.59-0.89) ^b
Physician visit (yes vs no)	1.16 (1.12-1.21)	1.17 (1.12-1.21) ^b	1.15 (1.11-1.20) ^b
Rate ratio (95% CI)			
Hospital admission (yes vs no)	0.80 (0.64-1.01)	0.78 (0.62-0.99)	0.68 (0.53-0.86)
Physician visit (yes vs no)	1.86 (1.58-2.19)	1.89 (1.60-2.22)	1.80 (1.52-2.13)
Rate ratio (95% CI)			
Hospital stay length ^c (days per 12 months)	0.80 (0.54-1.20)	0.82 (0.53-1.26)	0.76 (0.50-1.16)
Hospital admission ^d (admits per 12 months)	0.76 (0.60-0.98)	0.78 (0.62-1.00)	0.69 (0.54-0.89)
Physician visits ^e (per 12 months)	1.26 (1.15-1.39)	1.29 (1.17-1.41)	1.16 (1.06-1.27)

A1C, glycated hemoglobin; ACR, albumin-creatinine ratio.

^aAll comparisons are enrolled vs nonenrolled. Effect estimates are displayed as risk ratios or odds ratios for binary outcomes and rate ratios for count outcomes with corresponding 95% CIs.

^bThese log-binomial models did not converge and log-Poisson models, which provide consistent but not fully efficient estimates of the risk ratio, were used.

^cDue to the large number of participants with no hospital admissions (and 0 days for length of hospital stay), this model was fit using a zero-inflated negative binomial regression and corresponding 95% CIs were obtained using a bootstrap resampling procedure.

^dDue to the large number of patients with no hospital admissions, this model was fit using a negative binomial generalized linear model and corresponding 95% CIs were obtained using model-based standard error.

^eDue to the large number of participants with no physician visits, this model was fit using a zero-inflated negative binomial regression and corresponding 95% CIs were obtained using a bootstrap resampling procedure.

hospital admissions (RiR, 0.72; 95% CI, 0.59-0.89), lower rate of hospital admits per calendar year (rate ratio [RaR], 0.69; 95% CI, 0.54-0.89), and lower rate of inpatient days per calendar year (RaR, 0.76; 95% CI, 0.50-1.16). Enrolled members also had a 16% increase in the rate of physician visits per calendar year (RaR, 1.16; 95% CI, 1.06-1.27). Results for the medical care and service outcomes were comparable after further adjustment in the outcome model for preenrollment total costs, age, and Elixhauser Comorbidity Index score (see eAppendix Table 1).

The unadjusted and adjusted estimated effects of enrollment in the DCR program on cost outcomes are presented in [Table 3](#).

Adjusting for the propensity score, region, and preenrollment total cost (spline), the enrolled group demonstrated greater pharmaceutical costs (per-member per-month cost difference of \$62.12; 95% CI, \$38.77-\$85.47). Results for the cost outcomes were comparable after adjustment for age and Elixhauser Comorbidity Index score (see [eAppendix Tables 2 and 3](#)).

DISCUSSION

In this real-world study, individuals with diabetes who were enrolled in an incentive-based care management program demonstrated increased adherence to recommended diabetes care standards, increased provider outpatient visits, decreased hospital admissions, and decreased inpatient hospital days. The program was associated with greater pharmaceutical expenditures. These findings confirm the hypothesis that a behavioral science- and incentive-based approach to diabetes, incorporating contingent and meaningful rewards to promote engagement with diabetes care teams, can improve adherence to diabetes care while significantly reducing the use of high-acuity health services.²⁷

The DCR program was designed and evaluated specifically with health plans and employers—especially those that are self-insured, for which both productivity and cost benefits are priorities—and provides a health plan-based incentive for initial and continued engagement in completing ADA care standards. Members are provided an enhanced plan benefit (ie, co-pay reductions) for being actively engaged in the program, with this incentive contingent upon the member’s adherence to the standards of diabetes care, which could be completed only through collaboration between the member and their health care provider(s).

With respect to improving recommended diabetes care standards, participation in the DCR was associated with greater adherence to A1C and urine ACR testing compared with lipid panel testing. This finding likely reflects the additional requirement for 12-hour fasting and venous blood draw for a lipid exam as opposed to obtaining an A1C level, which does not require fasting and can be obtained by point-of-care testing.

Regarding provider engagement, those members enrolled in the DCR program experienced a 16% increase in the number of primary care provider visits, suggesting more active and effective management of their diabetes, resulting in less need for hospital-based services.

TABLE 3. Estimated Effects of Diabetes Care Rewards Program on Cost Outcomes in the Matched Sample of Enrollees and Nonenrollees From 26 Self-insured Companies in the United States, 2012-2017 (N=3318)^a

Outcome	Unadjusted	Adjusted for propensity score	Adjusted for propensity score, region, and preintervention total cost (continuous)	Adjusted for propensity score, region, and preintervention total cost (continuous with quadratic spline)
Cost (per member per month)	Cost ratio (95% CI)	Cost ratio (95% CI)	Cost ratio (95% CI)	Cost ratio (95% CI)
Pharmacy	1.73 (1.52-2.00)	1.73 (1.50-2.01)	1.77 (1.55-2.02)	1.49 (1.31-1.70)
Medical	1.01 (0.86-1.18)	1.01 (0.86-1.18)	1.10 (0.95-1.29)	0.99 (0.84-1.18)
Cost (per member per month)	Cost difference in US\$ (95% CI)	Cost difference in US\$ (95% CI)	Cost difference in US\$ (95% CI)	Cost difference in US\$ (95% CI)
Pharmacy	252.44 (183.31-321.57)	249.69 (178.73-320.66)	70.07 (45.6-94.54) ^b	62.12 (38.77-85.47) ^c
Medical	6.97 (-135.92 to 149.86)	12.05 (-130.58 to 154.67)	48.19 (-41.11 to 137.49) ^b	45.23 (-44.13 to 134.59) ^c

^aAll comparisons are enrolled vs nonenrolled. Effect estimates are displayed as cost ratios and average cost differences with corresponding 95% CIs.

^bThe model adjusted for propensity score, preintervention total costs, and region did not converge for the gamma regression with an identity link, so this model excluded the propensity score.

^cThe model adjusted for propensity score, preintervention total costs (spline), and region did not converge for the gamma regression with an identity link, so this model excluded the propensity score and included a quadratic term for preintervention total costs (instead of the spline).

This is reflected by the reduction in hospital admissions and total inpatient days. These results are consistent with recently published findings by Zhang et al that showed a positive association between the frequency of contact with a patient's primary care provider and both a decrease in A1C level and lower rates of 10-year occurrence of cardiovascular events.²⁸

Being enrolled in the DCR program was associated with greater medication use and pharmaceutical expenses. Interestingly, the estimated cost difference indicated a higher pharmacy cost among those enrolled in both unadjusted and adjusted analyses. We anticipated an increase in pharmacy costs, as the DCR program was aimed at increasing engagement in care. Although pharmacy costs were higher for enrolled members than for unenrolled members, this study was unable to capture pharmacy rebates from manufacturers and pharmacy benefit managers to self-insurers. The cost-benefit analysis of this program weighs pharmaceutical expenses against the costs of hospitalizations and other high-acuity services. Rebates decrease the final costs of pharmacy expenditures and, if available, could result in a favorable cost-benefit ratio of the DCR program.

Strengths and Limitations

Strengths of this study include matching enrolled members to eligible unenrolled members using propensity score matching.^{22,23} Matching on patient characteristics such as age, sex, Elixhauser Comorbidity Index score, geographic region, and insulin use offers some protection against comparing heterogeneous cohorts by ensuring that both study cohorts contained members with certain similar baseline characteristics. Additional strengths include a novel but practical and feasible incentive structure that scaled

across multiple diverse self-insured employers.

As an observational study that utilized administrative claims data, this analysis is subject to inherent limitations, including selection bias. Members who enrolled are likely different from those who did not enroll, which is unavoidable in retrospective studies of voluntary programs. To address this limitation, members were propensity score matched in the analysis, which is a valid approach to control for measured confounders, including insulin dependence, to compare members whose disease state has or has not advanced to the point of requiring insulin therapy. When adjusting for covariates in an outcome model to control for residual imbalance between the groups, the outcome model needs to be correctly specified. To address this concern, we flexibly modeled covariate functional forms and conducted sensitivity analyses for covariates included in the outcome model. Because this study was reliant on administrative claims data alone, comparisons between clinically reported and laboratory values of enrolled vs unenrolled members could not be made. Additionally, identifying those with diabetes could be done only by using *ICD-9* and *ICD-10* codes (see eAppendix) or by identifying individuals taking 1 or more glucose-lowering medications.

CONCLUSIONS

By creating behavioral activation with a contingent financial incentive and promoting ongoing participant-provider interactions, the DCR program reported here reduced rates of gaps in care and high-cost health care utilization from the perspective of health plans and self-insured employers. Consequently, a business case exists for health plans to promote patient engagement through use

of contingent incentives, with the goal of leading to better health outcomes and lower rates of hospitalizations. ■

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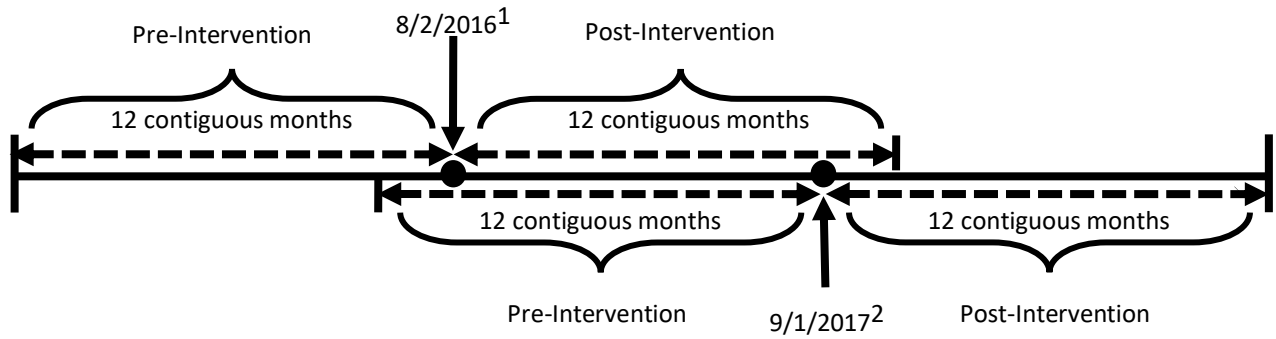
Identification of Control Cohort

Using claims data, unenrolled members were identified by the logic below:

- A review of pharmacy claims was used to identify any members who filled a diabetes-related prescription.
- A review of medical claims was used to further identify any members who received medical care coded with a diabetes-related diagnosis code per below:
 - For claims coded with ICD9 codes, the following codes/wildcards were used:
 - 250*
 - 2714*
 - 3620*
 - V5867
 - 36641
 - 3572*
 - For claims coded with ICD10 codes, the following codes/wildcards were used:
 - E10*
 - E11*
 - E13*
 - O241*
 - O243*
 - O248*
 - O249*
 - Z794*

eAppendix Figure. Time block representing an enrolled subject and matched, unenrolled counterpart

2016-2017 Time Block



¹Date that the matched member enrolled in DCR program.

² Index date for the matched, unenrolled counterpart (where 24 months of continuous data were available in this time block).

Adjusted Outcome Models

Statistical Methods

In the adjusted analysis, we employed outcome models in the matched sample (i.e., adjusted for the propensity score) to allow for further adjustment of possible residual confounding by total pre-enrollment costs and region, and possibly age and Elixhauser Index (Austin, 2017; Nguyen, 2017). As determined by the standardized mean difference, there were imbalances in the matched sample for both total pre-enrollment costs and region. To allow the model to be more flexible, we included total pre-enrollment cost as a continuous variable centered on its mean with quadratic splines, while we included continuous terms for age and Elixhauser Index and categorical terms for region (Northeast vs. elsewhere). Binary outcomes were modeled using a log-binomial regression to obtain risk ratios, count outcomes were modeled using zero-inflated negative binomial regression or negative binomial regression to obtain rate ratios, and costs were modeled using gamma regression with both log and identity links to obtain both cost ratios and differences, respectively. In a few instances, the models for the risk ratios did not converge and log-Poisson models, which provide consistent but not fully efficient estimates of the risk ratio, were used (Spiegelman and Hertzmark, 2005). For binary outcomes, odds ratios based on logistic regression models were also reported.

For the receipt of medical care outcomes and hospital admission, we checked for collinearity between the predictors enrollment status, total pre-enrollment cost, age, Elixhauser Index, and region and no evidence of collinearity was found (i.e., the variance inflation factor was < 2 for each variable). We also confirmed through visual inspection that there was a log-linear relationship between each of the medical care outcomes and total pre-enrollment costs.

For the outcome number of hospital days outcome, there was overdispersion; that is, the variance was larger than the mean (mean = 0.87, variance = 22.99), due in part, to the large number of observations with a hospital length stay of zero days (2987/3318, 90%). We fit this model using a zero-inflated negative binomial regression and compared this model to a log-poisson model using the Vuong z-statistic ($p < 0.001$), indicating that the zero-inflated negative binomial model is a better fit. For the zero-inflated model, we obtained standard errors using a bootstrap (using 200 bootstrap resamples) to compute corresponding confidence intervals.

For the outcome number of hospital admits, there was also overdispersion; that is, the variance was much larger than the mean (mean = 0.15, variance = 0.34), due in part, to the large number of observations with zero hospital admits (2987/3318, 90%). We attempted to fit a zero-inflated negative binomial regression, as well as a zero-inflated Poisson regression; however, neither model converged. We instead fit a negative binomial regression, which was a better fit than the Poisson model (P value < 0.001). For the negative binomial regression, the Pearson residuals from this model indicated a possible lack of fit (Chi-square statistic = 3,900.02; P value < 0.001); however, the deviance did not indicate a possible lack of fit (Chi-square statistic = 1,075.64; P value = 1).

For the outcome number of physician visits, there was also overdispersion; that is, the variance was much larger than the mean (mean = 7.20, variance = 98.29), due in part, to the large number of observations with zero physician visits (819/3318, 25%). We fit this model using a zero-inflated negative binomial regression and compared this model to a log-poisson model using the Vuong z-statistic ($p < 0.001$), indicating that the zero-inflated negative binomial model is a better fit. For the zero-inflated model, we obtained standard errors using a bootstrap (using 200 bootstrap resamples) to compute corresponding confidence intervals.

For the cost outcomes, we employed gamma regression models, which assumed a constant coefficient of variation and that the variance is proportional to the square of the mean. We fit this model using both identity and log links to obtain estimated cost ratios and cost differences, respectively. For pharmacy costs adjusted for pre-enrollment total cost (centered on its mean) and the propensity score, an identity link with the gamma distribution fit better than the log link (log-link AIC= 45,316, identity link AIC= 44,346). For medical costs adjusted for pre-enrollment total cost (centered on its mean) and the propensity score, an identity link with the gamma distribution fit better than the log link (log-link AIC= 49,745, identity link AIC= 49,475).

The additional adjustment variables were correlated in the following way in this data set: pre-enrollment total cost and Elixhauser ($\rho = 0.48$), age and Elixhauser ($\rho = 0.27$), age and propensity score ($\rho = 0.23$), Elixhauser and propensity score ($\rho = 0.20$), pre-enrollment total cost and propensity score ($\rho = -0.05$), and pre-enrollment total cost and age ($\rho = 0.003$). In some models, these correlations lead to numerical instability, so continuous variables were redefined to binary (e.g., dichotomized at median) or categorical variables were redefined to binary (e.g., 1 vs. 2, 3, or 4).

Results

eAppendix Table 1 displays the estimated effects of enrollment in the program on medical care and service outcomes in the matched sample. eAppendix Table 2 displays the estimated effects of enrollment in the program on cost outcomes in the matched sample adjusted for additional variables as continuous covariates. eAppendix Table 3 displays the estimated effects of enrollment in the program on cost outcomes in the matched sample adjusted for pre-enrollment total cost with a spline and additional variables as continuous covariates. For example, after adjusting for pre-enrollment total costs (spline) and region in the matched sample, enrollees had an estimated 55% increase in the likelihood of receiving an HBA1C test, as compare to non-enrollees (95% confidence interval (CI): 1.45, 1.67). After adjusting for pre-enrollment total costs, the propensity score, and region in the matched sample, enrollees had 10% increase in medical costs (95% CI: 0.95, 1.29), which corresponds to an absolute estimated average increase of \$48 per member per month, as compared to non-enrollees (95% CI = -41.11, 137.49).

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eAppendix Table 1. Estimated effects of Diabetes Care Program on Medical Care and Service Outcomes in the Matched Sample of Enrollees and Non-Enrollees (n = 3,318). All comparisons are enrolled vs. non-enrolled.¹

Outcome	Unadjusted	Adjusted for Region, Pre-Enrollment Total Cost (continuous)	Adjusted for Region, Pre-Enrollment Total Cost (continuous with quadratic spline)	Adjusted for Region, Age, Elixhauser (continuous) and Pre-Enrollment Total Cost (continuous)	Adjusted for Region, Age and Elixhauser (continuous), and Pre-Enrollment Total Cost (continuous with quadratic spline)
<i>Receipt of Medical Care (Yes vs. No)</i>	<i>Risk Ratio (95% CI)</i>	<i>Risk Ratio (95% CI)</i>	<i>Risk Ratio (95% CI)</i>	<i>Risk Ratio (95% CI)</i>	<i>Risk Ratio (95% CI)</i>
HBA1C Test	1.73 (1.61, 1.86)	1.72 (1.60, 1.85) ²	1.55 (1.45, 1.67) ²	1.72 (1.60, 1.85) ²	1.54 (1.43, 1.65) ²
Lipid Test	1.24 (1.18, 1.30)	1.24 (1.18, 1.30) ²	1.20 (1.14, 1.26) ²	1.23 (1.17, 1.29) ²	1.19 (1.13, 1.25) ²
Albumin Test	1.66 (1.54, 1.79)	1.66 (1.54, 1.79) ²	1.54 (1.42, 1.66) ²	1.66 (1.54, 1.79) ²	1.52 (1.41, 1.64) ²
<i>Service</i>	<i>Risk Ratio (95% CI)</i>	<i>Risk Ratio (95% CI)</i>	<i>Risk Ratio (95% CI)</i>	<i>Risk Ratio (95% CI)</i>	<i>Risk Ratio (95% CI)</i>
Hospital Admission (Yes vs. No)	0.82 (0.67, 1.01)	0.82 (0.67, 1.01) ²	0.72 (0.59, 0.89) ²	0.91 (0.74, 1.11) ²	0.84 (0.68, 1.03) ²
Physician Visit (Yes vs. No)	1.16 (1.12, 1.21)	1.17 (1.12, 1.21) ²	1.15 (1.11, 1.20) ²	1.16 (1.12, 1.21) ²	1.15 (1.10, 1.19) ²
	<i>Odds Ratio (95% CI)</i>	<i>Odds Ratio (95% CI)</i>	<i>Odds Ratio (95% CI)</i>	<i>Odds Ratio (95% CI)</i>	<i>Odds Ratio (95% CI)</i>
Hospital Admission (Yes vs. No)	0.80 (0.64, 1.01)	0.78 (0.62, 0.99)	0.68 (0.53, 0.86)	0.87 (0.69, 1.12)	0.80 (0.62, 1.02)
Physician Visit (Yes vs. No)	1.86 (1.58, 2.19)	1.89 (1.60, 2.22)	1.80 (1.52, 2.13)	1.88 (1.59, 2.21)	1.78 (1.50, 2.11)
	<i>Rate Ratio (95% CI)</i>	<i>Rate Ratio (95% CI)</i>	<i>Rate Ratio (95% CI)</i>	<i>Rate Ratio (95% CI)</i>	<i>Rate Ratio (95% CI)</i>
Hospital Stay Length ³ (Days per 12 months)	0.80 (0.54, 1.20)	0.82 (0.53, 1.26)	0.76 (0.50, 1.16)	0.89 (0.60, 1.33) ⁴	0.89 (0.61, 1.29)
Hospital Admission ⁵ (Admits per 12 months)	0.76 (0.60, 0.98)	0.78 (0.62, 1.00)	0.69 (0.54, 0.89)	0.86 (0.68, 1.09)	0.80 (0.63, 1.01)
Physician Visits ⁶ (per 12 months)	1.26 (1.15, 1.39)	1.29 (1.17, 1.41)	1.16 (1.06, 1.27)	1.33 (1.20, 1.46) ⁷	1.22(1.11, 1.34)

¹ Effect estimates are displayed as risk ratios or odds ratios for binary outcomes and rate ratios for count outcomes with corresponding 95% confidence intervals (CI).

² These log-Binomial models did not converge and log-Poisson models, which provide consistent but not fully efficient estimates of the risk ratio, were used.

³ Due to the large number of patients with no hospital admissions (and zero days for length of hospital stay), this model was fit using a zero-inflated negative binomial regression and corresponding 95% confidence intervals (CI) were obtained using a bootstrap resampling procedure.

⁴ For the bootstrap standard error for the confidence intervals of the rate ratios for the outcome hospital stay length, the bootstrap standard error is based on those at least 200 samples for which the model converged. The model adjusted for pre-enrollment total costs (continuous), region, age and Elixhauser status did not converge for the zero-inflated negative binomial model, so this model excludes the Elixhauser status and included binary terms for age (≤ 55.5 years vs. 55.5 years) and region (Northeast vs. elsewhere).

⁵ Due to the large number of patients with no hospital admissions, this model was fit using a negative binomial generalized linear model and corresponding 95% confidence intervals (CI) were obtained using model-based standard error.

⁶ Due to the large number of patients with no physician visits, this model was fit using a zero-inflated negative binomial regression and corresponding 95% confidence intervals (CI) were obtained using a bootstrap resampling procedure.

⁷ The model adjusted for region, pre-enrollment total costs (continuous), age, and Elixhauser Status did not converge, so this model included binary terms for age (≤ 55.5 years vs. 55.5 years) and region (Northeast vs. elsewhere).

eAppendix Table 2. Estimated effects of Diabetes Care Program on Cost Outcomes in the Matched Sample of Enrollees and non-Enrollees (n = 3,318). All comparisons are enrolled vs. non-enrolled. Additional variables adjusted for as continuous covariate.¹

Outcome	Unadjusted	Adjusted for Propensity Score	Adjusted for Propensity Score, Region and Pre-Enrollment Total Cost (continuous)	Adjusted for Propensity Score, Region, Age, Elixhauser (continuous), and Pre-Enrollment Total Cost (continuous)
<i>Cost (per member per month)</i>	<i>Cost Ratio (95% CI)</i>	<i>Cost Ratio (95% CI)</i>	<i>Cost Ratio (95% CI)</i>	<i>Cost Ratio (95% CI)</i>
Pharmacy	1.73 (1.52, 2.00)	1.73 (1.50, 2.01)	1.77 (1.55, 2.02)	1.79 (1.58, 2.04)
Medical	1.01 (0.86, 1.18)	1.01 (0.86, 1.18)	1.10 (0.95,1.29)	1.14 (0.98, 1.32)
	<i>Cost Difference (95% CI)</i>	<i>Cost Difference (95% CI)</i>	<i>Cost Difference (95% CI)</i>	<i>Cost Difference (95% CI)</i>
Pharmacy	252.44 (183.31, 321.57)	249.69 (178.73, 320.66)	70.07 (45.6, 94.54) ²	69.80 (45.41, 94.19) ³
Medical	6.97 (-135.92, 149.86)	12.05 (-130.58, 154.67)	48.19 (-41.11,137.49) ²	39.19 (-44.79, 123.16) ⁴

¹All comparisons are enrolled vs nonenrolled. Effect estimates are displayed as cost ratios and average cost differences with corresponding 95% CIs.

²The model adjusted for propensity score, preintervention total costs, and region did not converge for the gamma regression with an identity link, so this model excluded the propensity score.

³The model adjusted for propensity score, pre-enrollment total costs (continuous), region, age and Elixhauser status did not converge for the Gamma regression with an identity link, so this model excludes the propensity score and age.

⁴The model adjusted for propensity score, pre-enrollment total costs (continuous), region, age and Elixhauser status did not converge for the Gamma regression with an identity link, so this model excludes the propensity score.

eAppendix Table 3. Estimated effects of Diabetes Care Program on Cost Outcomes in the Matched Sample of Enrollees and non-Enrollees (n = 3,318). All comparisons are enrolled vs. non-enrolled. Pre-enrollment cost included with a quadratic spline and additional variables adjusted for as continuous covariates.¹

Outcome	Adjusted for Propensity Score, Region and Pre-Enrollment Total Cost (continuous with quadratic spline)	Adjusted for Propensity Score, Region, Age and Elixhauser (continuous), and Pre-Enrollment Total Cost (continuous with quadratic spline)
<i>Cost (per member per month)</i>	<i>Cost Ratio (95% CI)</i>	<i>Cost Ratio (95% CI)</i>
Pharmacy	1.49 (1.31, 1.70)	1.49 (1.31, 1.69)
Medical	0.99 (0.84, 1.18)	1.02 (0.86, 1.20)
	<i>Cost Difference (95% CI)</i>	<i>Cost Difference (95% CI)</i>
Pharmacy	62.12 (38.77, 85.47) ²	64.74 (40.84, 88.63) ³
Medical	45.23 (-44.13, 134.59) ²	24.29 (-60.44, 109.03) ⁴

¹ Effect estimates are displayed as cost ratios and cost differences with corresponding 95% confidence intervals (CI).

² The model adjusted for propensity score, preintervention total costs (spline), and region did not converge for the Gamma regression with an identity link, so this model excludes the propensity score and included a quadratic term for preintervention total costs (instead of the spline).

³ The model adjusted for propensity score, pre-enrollment total costs (spline), age, and Elixhauser Status did not converge for the Gamma regression with an identity link, so this model excludes the propensity score and Elixhauser Status and included a quadratic term for pre-enrollment total costs (instead of the spline) and binary terms for age (≤ 55.5 years vs. 55.5 years) and region (Northeast vs. elsewhere).

⁴ The model adjusted for propensity score, pre-enrollment total costs (spline), age, and Elixhauser Status did not converge for the Gamma regression with an identity link, so this model excludes the propensity score and included a quadratic term for pre-enrollment total costs (instead of the spline) and binary terms for age (≤ 55.5 years vs. 55.5 years) and region (Northeast vs. elsewhere).