Effect of High-Deductible Insurance on High-Acuity Outcomes in Diabetes: A Natural Experiment for Translation in Diabetes (NEXT-D) Study

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J. Frank Wharam,[1] Fang Zhang,[1] Emma M. Eggleston,[2] Christine Y. Lu,[1] Stephen B. Soumerai,[1] and Dennis Ross-Degnan[1]

OBJECTIVE

High-deductible health plans (HDHPs) are now the predominant commercial health insurance benefit in the U.S. We sought to determine the effects of HDHPs on emergency department and hospital care, adverse outcomes, and total health care expenditures among patients with diabetes.

RESEARCH DESIGN AND METHODS

We applied a controlled interrupted time–series design to study 23,493 HDHP members with diabetes, aged 12–64, insured through a large national health insurer from 2003 to 2012. HDHP members were enrolled for 1 year in a low-deductible (≤$500) plan, followed by 1 year in an HDHP (≥$1,000 deductible) after an employer-mandated switch. Patients transitioning to HDHPs were matched to 192,842 contemporaneous patients whose employers offered only low-deductible coverage. HDHP members from low-income neighborhoods (*n* = 8,453) were a subgroup of interest. Utilization measures included emergency department visits, hospitalizations, and total (health plan plus member out-of-pocket) health care expenditures. Proxy health outcome measures comprised high-severity emergency department visit expenditures and high-severity hospitalization days.

RESULTS

After the HDHP transition, emergency department visits declined by 4.0% (95% CI −7.8, −0.1), hospitalizations fell by 5.6% (−10.8, −0.5), direct (nonemergency department–based) hospitalizations declined by 11.1% (−16.6, −5.6), and total health care expenditures dropped by 3.8% (−4.3, −3.4). Adverse outcomes did not change in the overall HDHP cohort, but members from low-income neighborhoods experienced 23.5% higher (18.3, 28.7) high-severity emergency department visit expenditures and 27.4% higher (15.5, 39.2) high-severity hospitalization days.

CONCLUSIONS

After an HDHP switch, direct hospitalizations declined by 11.1% among patients with diabetes, likely driving 3.8% lower total health care expenditures. Proxy adverse outcomes were unchanged in the overall HDHP population with diabetes, but members from low-income neighborhoods experienced large, concerning increases in high-severity emergency department visit expenditures and hospitalization days.

[1]Department of Population Medicine, Harvard Medical School and Harvard Pilgrim Health Care Institute, Boston, MA
[2]Department of Medicine, West Virginia University Health Sciences Center, Morgantown, WV

Corresponding author: J. Frank Wharam, jwharam@post.harvard.edu.

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High-deductible health plans (HDHPs) have recently become the predominant commercial health insurance arrangement in the U.S., and enrollment is expected to further accelerate in coming years (1). In contrast to traditional plans with relatively low deductibles, HDHPs require potential annual out-of-pocket payments of ~\$1,000–\$6,000 for most nonpreventive services. In 2016, 51% of workers with employer-sponsored insurance in the U.S. had deductibles of \$1,000 or more, and 23% had deductibles of \$2,000 or more (1).

HDHPs are intended to encourage use of high-value, appropriate medical services while discouraging discretionary, low-value care, thus reducing health care spending and preserving or improving health outcomes. However, high cost sharing might create barriers that delay or reduce crucial care among chronically ill patients, leading to increased morbidity. Diabetes is the leading cause of end-stage renal disease, lower extremity amputation, and blindness in the U.S. and increases the risk of ischemic heart disease and stroke by 200–400% (2,3). Access to emergency department and hospital care is essential for managing complications of diabetes and its comorbidities (4–7).

Recent research has found that after an HDHP switch, patients with diabetes from low-income neighborhoods delay time-sensitive outpatient care and experience increased diabetes complication visits to the emergency department (8). However, no studies have assessed overall emergency department and hospital use among chronically ill HDHP members. In addition, although HDHPs have been shown to reduce low-severity emergency department visits among broadly defined populations (9–12), the effects on such low-value care among chronically ill patients is unknown. Our goal was therefore to determine whether HDHP enrollment among patients with diabetes affects emergency department use, hospitalizations, total expenditures, and proxy adverse high-acuity outcomes. Based on previous research (8,10,13), we hypothesized a priori that emergency department visits, hospitalizations, and total health care expenditures would decline and that low-income HDHP members would experience increased acuity of emergency department visits and hospitalizations. That is, low-income HDHP members with diabetes would be "sicker" by the time they reached the health system.

RESEARCH DESIGN AND METHODS

Study Population

Our study population included commercially insured members in the Optum database (Eden Prairie, MN) enrolled between 1 January 2003 and 31 December 2012. These data include enrollment information and all medical, pharmacy, and hospitalization claims from ~43 million commercially insured members of a large national health plan. We defined traditional and HDHP coverage as insurance plans with annual deductibles of ≤\$500 and ≥\$1,000, respectively (Supplementary Data). To determine employer annual deductibles, we used a benefits variable available for most smaller employers (~≤100 employees). For larger employers, we imputed deductible level categories of ≤\$500 and ≥\$1,000 using out-of-pocket spending among employees who used health services, an algorithm that had 96.2% sensitivity and 97.0% specificity (Supplementary Table 1). Of note, the \$1,000 threshold was the minimum deductible in the HDHP group, and the \$500 threshold was the maximum deductible in the control group. Actual mean deductible levels, although we are unable to calculate these over the entire population, would be higher and lower, respectively.

Traditional plans typically subject emergency department and hospital care to copayments, coinsurance, or low-level (≤\$500) deductibles (1). In contrast, HDHP members pay the full cost for these services until the annual high-deductible amount is reached. The study population comprised individuals whose employers did not offer choices between high- and low-deductible levels during the 2-year study period of interest; that is, the low-to-high switch among intervention group members and the low-to-low continuation among control group members was employer mandated, minimizing self-selection.

We required HDHP members to have 1 continuous year in a traditional plan, followed by 1 continuous year in an HDHP after their employer (with at least 10 enrollees) chose to switch to HDHP coverage (n = 711,180 overall members; i.e., not yet restricted to patients with diabetes). We defined the beginning of the month of the low-to-high deductible transition as the index date. We also identified all members whose employers offered only traditional plans over at least a 2-year period (n = 6,351,001 overall members; i.e., not yet restricted to patients with diabetes), and control subjects were selected from this pool.

We then identified patients with diabetes aged 12–64 as defined by having at least one inpatient or at least two outpatient diagnosis codes for diabetes or the dispensing of insulin or at least one oral hypoglycemic medication other than metformin alone (Supplementary Table 2), between 6 months before and 6 months after the beginning of the members' baseline period. This left a prematched sample of 24,137 HDHP and 200,995 control pool members (Table 1). Census-derived characteristics were missing for less than half a percent of members in the HDHP and control pool.

To further minimize potential selection effects, especially at the employer level, we used a coarsened exact match (14,15) on employer- and member-level propensity (16,17) to join HDHPs (Supplementary Data), baseline out-of-pocket expenditures, and members' baseline high- and low-severity emergency department visit and cost trends (Supplementary Data). Evidence suggests that matching on baseline trends of outcome measures and baseline covariates in interrupted time–series studies can substantially minimize bias (18,19). Our final group included 23,493 HDHP members with diabetes and 192,842 matched control subjects.

Based on previous research (12,13), including a recent study that detected delays in time-sensitive outpatient care (8), our primary HDHP diabetes subgroup of interest was low-income patients. We also conducted sensitivity analyses among high-morbidity members (subgroups defined below). To generate control groups for all subgroups, we used the same coarsened exact matching approach described above.

The Harvard Pilgrim Health Care Institutional Review Board (Boston, MA) approved this study.

Outcome Measures

We assessed health care utilization measures and proxy health outcomes measures. All measures were generated at the monthly level to allow assessment of trends in cumulative monthly outcomes that we generated by adding a given monthly value to the sum of all previous months' values over the baseline and

Table 1—Baseline characteristics of the HDHP group and the control group, before and after the coarsened exact match

	Before match			After match and weighting[1]		
Characteristics	HDHP group (n = 24,137)	Control group (n = 200,995)	Standardized difference*	HDHP group (n = 23,493)	Control group (n = 192,842)	Standardized difference*
Age >40 years on index date, n (%)	21,197 (87.8)	174,982 (87.1)	0.023	20,681 (88.0)	168,011.1 (87.1)	0.028
Age (years) on index date, mean (SD)	51.1 (9.4)	51.1 (9.7)	0.003	51.2 (9.3)	51.0 (9.6)	0.015
Female, n (%)	10,671 (44.2)	92,229 (45.9)	−0.034	10,319 (43.9)	84,076.3 (43.6)	0.007
N (%) living in neighborhoods with						
Below poverty levels of			0.043			0.017
<5%[2]	8,853 (36.7)	77,697 (38.7)		8,683 (37.0)	71,932.0 (37.3)	
5–9.9%[2]	6,420 (26.6)	52,714 (26.3)		6,240 (26.6)	51,803.4 (26.9)	
10–19.9%[3]	5,711 (23.7)	45,403 (22.6)		5,527 (23.5)	44,959.7 (23.3)	
≥20%[3]	3,135 (13.0)	24,932 (12.4)		3,025 (12.9)	23,894.3 (12.4)	
Below high school education levels of			0.053			0.028
<15%[4]	11,318 (46.9)	99,145 (49.4)		11,069 (47.2)	93,323.1 (48.5)	
15–24.9%[4]	6,437 (26.7)	51,317 (25.6)		6,253 (26.6)	49,510.4 (25.7)	
25–39.9%[5]	4,664 (19.3)	35,995 (17.9)		4,508 (19.2)	36,113.8 (18.8)	
≥40%[5]	1,700 (7.0)	14,289 (7.1)		1,645 (7.0)	13,642.2 (7.1)	
Race/ethnicity, n (%)[6]			0.114			0.038
Hispanic	2,738 (11.4)	24,906 (12.4)		2,671 (11.4)	21,872.7 (11.4)	
Asian	530 (2.2)	6,574 (3.3)		518 (2.2)	5,158.4 (2.7)	
Black neighborhood	776 (3.2)	8,490 (4.2)		747 (3.2)	6,540.6 (3.4)	
Mixed neighborhood	3,705 (15.4)	34,021 (17.0)		3,589 (15.3)	30,512.3 (15.9)	
White neighborhood	16,363 (67.9)	126,661 (63.1)		15,943 (67.9)	128,410.2 (66.7)	
ACG score, mean (SD)	3.1 (3.9)	3.2 (4.0)	−0.031	2.9 (3.7)	2.9 (3.6)	−0.001
U.S. region, n (%)			0.225			0.052
West	2,256 (9.3)	21,234 (10.6)		2,187 (9.3)	19,916.2 (10.3)	
Midwest	8,135 (33.7)	61,494 (30.6)		7,938 (33.8)	62,025.6 (32.2)	
South	12,277 (50.9)	93,574 (46.6)		11,926 (50.8)	100,167.5 (52.0)	
Northeast	1,461 (6.1)	24,592 (12.2)		1,434 (6.1)	10,622.3 (5.5)	
Outpatient copayment, mean $ (SD)	19.2 (7.0)	16.5 (6.9)	0.383	19.1 (7.0)	18.7 (6.3)	0.063
Employer size, mean n (SD)			1.214			0.068
0–99	9,179 (38.0)	24,589 (12.2)		8,845 (37.6)	78,799.3 (40.9)	
100–999	12,646 (52.4)	60,265 (30.0)		12,367 (52.6)	95,319.1 (49.4)	
≥1,000	2,312 (9.6)	116,141 (57.8)		2,281 (9.7)	18,723.6 (9.7)	

*Lower standardized differences indicate greater similarity, and a standardized difference <0.2 indicates minimal differences between groups. [1]The coarsened exact match (see RESEARCH DESIGN AND METHODS) software creates weights for control group members to account for differing ratios of intervention: control group members within and across matching strata. [2]Defined as high income. [3]Defined as low income. [4]Defined as high education. [5]Defined as low education. [6]See RESEARCH DESIGN AND METHODS for definition of race/ethnicity categories.

follow-up periods. Utilization measures included total emergency department visits, low- and high-severity emergency department visits (10,20,21), total hospitalizations, hospital admissions not through the emergency department (termed "direct hospital admissions" for convenience), and total health care expenditures. We applied algorithms for detecting emergency department visits using a combination of place of service, revenue, and Current Procedural Terminology (CPT) evaluation and management codes. We used a validated (10,21) modification of the Billings (20) emergency department visit classification algorithm to categorize visits as low or high severity. The Billings algorithm assigns a percentage probability that a given visit is nonemergent, is emergent but primary care–treatable, or requires emergency department care. We defined visits as low or high severity when the probability that the primary diagnosis required emergency department care was <25 and ≥75%, respectively, thresholds shown to be proportional to hospitalization (10,21) and mortality (21) rates. Low-severity emergency department presentations are more likely to represent low-value care, given that these are defined as conditions, such as colds, low back pain, and ear infections, that do not require emergency department facilities or expertise (20). In contrast, high-severity presentations include conditions such as nephrolithiasis, cardiac arrhythmias, high-severity injuries, and asthma (20).

We identified total hospitalizations using a standard approach and excluded birth hospitalizations (ICD-9-CM diagnosis codes 650, normal delivery, or V27.×, outcome of delivery). Nonbirth hospitalizations not associated with same-day or prior-day emergency department visits were subclassified as nonemergency department–based admissions, likely to most often represent direct admissions by outpatient clinicians. To capture total health care expenditures (i.e., health insurer expenditures plus member out-of-pocket expenditures), we used a data vendor–provided field that includes claims-level and hospitalization-level cost estimates that are standardized across time (to 2012 dollars) and geography.

To assess intensity of and need for high-acuity diagnostic and therapeutic services, we measured high-severity emergency department visit (defined above) total expenditures and any hospitalization days that followed such high-severity visits. That is, we included these as proxy health outcome measures to indicate level of "sickness" at presentation to the emergency department and hospital for serious conditions. We focused on these measures rather than all emergency department visit expenditures or hospitalization days because some emergency department and hospital care can be appropriately shifted to lower-acuity settings. For example, reductions in all emergency department expenditures or hospitalization days among HDHP members might not indicate reduced acuity but rather a shifting of some lower-severity presentations to lower-acuity settings. To distinguish this potential shifting, we also measured the costs of more discretionary low-severity emergency department visit expenditures and hospitalization days that followed such visits.

To reduce the effect of extreme outliers on effect estimates, we tested winsorizing monthly hospitalization days and total expenditures that were in the top 1% then 2.5% of the nonzero distribution. The 1% winsorizing approach was associated with unstable trends and sudden month-to-month changes, which creates error in time-series analyses. In contrast, the 2.5% winsorizing approach reduced this instability. We therefore assigned any member in the top 2.5% to the 97.5% value of hospitalization days and total expenditures (19 days and $8,508.38, respectively). For example, a patient with a 42-day hospitalization would be reassigned to have a 19-day hospitalization, and a patient with $15,000 in monthly expenditures would be reassigned to $8,508.38.

Study Design

We applied a controlled interrupted time–series design, a rigorous quasi-experimental approach that has the ability to generate causal inference (22). Our matching approach aligned the HDHP and control groups at their defined index dates.

Covariates

We applied the Johns Hopkins Adjusted Clinical Groups system comorbidity score (ACG, version 10) algorithm, a validated measure that predicts mortality (23,24), to members' baseline year to estimate comorbidity and defined high- and low-morbidity as ACG scores of ≥3.0 and <2.0, respectively. Using 2000 U.S. Census block data (25,26), we created validated income- and education-level categories (Supplementary Data) (25–27) and defined low- and high-income as residence in neighborhoods with below-poverty levels of ≥10% and <10%, respectively. We classified members as white, black, Hispanic, Asian, or other based on a combination of geocoding and surname analysis (Supplementary Data) (28,29). Other covariates included age category (12–25, 26–45, ≥40–64 years), sex, and U.S. region (West, Midwest, South, Northeast).

Analysis

We used a standardized differences approach to compare baseline characteristics of our study groups (30). We aligned relative time for all cohort members at their index dates and used generalized estimating equations (31,32) with a Poisson distribution to model monthly visit rates and costs in both study groups, adjusting for baseline age, sex, race/ethnicity, education level, poverty level, U.S. region, ACG score, employer size, and calendar month/year of the index date, and accounting for clustering at the person level (33). We applied marginal effects methods (34) to calculate monthly rates in both groups that were fully adjusted for the preceding covariates. We then generated cumulative monthly rates (35,36) from these adjusted monthly rates and plotted the cumulative control group and HDHP group rates before and after the index date. This approach allows visualization of changes in rare outcomes that gradually accrue over time and prediction of cumulative rates at a given follow-up time based on the baseline trend in the monthly cumulative points. We modeled cumulative HDHP and control group trends using aggregate-level segmented regression (37), adjusting standard errors for autocorrelation. The regression models included intercept, baseline trend, trend change, and quadratic trend change terms for the HDHP and control groups and were included in final models using backward elimination with a threshold of $P < 0.20$. Using marginal effects methods (34), we estimated absolute and relative changes in the HDHP group compared with the control group at the end of follow-up versus the end of baseline using the above segmented regression terms.

We conducted sensitivity analyses among the key subgroups described above using the same methods and outcomes.

RESULTS

After matching and applying match-generated weights, all standardized differences between HDHP and control group characteristics were well below 0.2 (Table 1), indicating minimal differences (30). The average age of HDHP and control members was ~51 years, and 44% in each group were female. Approximately 36% lived in low-income neighborhoods, 26% lived in low-education neighborhoods, 11% were Hispanic, and the mean ACG morbidity score was 2.9 (SD 3.6–3.7). Slightly more HDHP members (52.6%) than control group members (49.4%) were enrolled through midsized employers with 100–999 enrollees.

In adjusted regression analyses, the overall HDHP group experienced total out-of-pocket medical costs that were 30.6% (95% CI 24.5, 36.7) higher on average than the control group at follow-up compared with baseline (absolute change: $256.0 [214.7, 297.2]). Corresponding increases among the low-income and high-income groups were 36.4% (29.0, 43.9; absolute $296.4 [249.4, 343.3]) and 29.4% (23.0, 35.7; absolute $244.3 [201.3, 287.4]), respectively (data not shown).

Utilization Measures

By the end of the follow-up period compared with the end of baseline, HDHP members had estimated changes in cumulative overall emergency department visits of −4.0% (95% CI −7.8, −0.1) and changes in low-severity emergency department visits of −4.3% (−7.3, −1.4) relative to the control group (Table 2). Effects on high-severity emergency department visits were not detectable. Overall and direct hospital admissions declined by 5.6% (−10.8, −0.5) and 11.1% (−16.6, −5.6), respectively, and total expenditures fell by 3.8% (−4.3, −3.4) among HDHP members relative to control members.

HDHP members from low-income neighborhoods experienced reduced low-severity (−8.8% [95% CI −11.8, −5.8]) but increased high-severity emergency department visits (10.5% [8.1, 12.9]), and overall emergency department visits were unchanged (−2.2% [−5.0, 0.7]). Direct hospital admissions and total expenditures declined by 10.0% (−14.8, −5.3) and 2.7% (−3.6, −1.9), respectively.

High-income HDHP members had a similar pattern of high acuity utilization as the overall cohort, demonstrating statistically significant reductions only in direct hospital admissions (−7.7% [95%

Table 2—Emergency department visits, hospitalizations, and total health care expenditures, overall and among key HDHP subgroups, 1 year before and after an HDHP switch compared with contemporaneous control group members

	Cumulative annual rate at the end of[1]				Change in HDHP vs. control group, end of follow-up vs. end of baseline[1]	
	HDHP group		Control group		Absolute estimate (95% CI)	Relative estimate, % (95% CI)
	Baseline	Follow-up	Baseline	Follow-up		
Overall (*n* = 23,493 HDHP and 192,842 control)						
Emergency department visits, per 1,000 members	258.0	285.1	253.7	292.6	−11.8 (−23.5, 0.0)	**−4.0 (−7.8, −0.1)**
Low severity[2]	73.0	87.7	73.0	91.7	**−4.0 (−6.7, −1.2)**	**−4.3 (−7.3, −1.4)**
High severity[2]	28.5	38.2	28.5	38.2	ND	ND
Hospitalizations, per 1,000 members	137.2	140.2	129.8	141.2	**−8.4 (−16.4, −0.4)**	**−5.6 (−10.8, −0.5)**
Direct admissions	81.3	74.9	75.3	78.2	**−9.4 (−14.3, −4.4)**	**−11.1 (−16.6, −5.6)**
Total expenditures, $ per member	8,550.4	8,759.3	8,518.1	9,076.9	**−349.9 (−392.0, −307.8)**	**−3.8 (−4.3, −3.4)**
Low income (*n* = 8,453 HDHP and 65,468 control)[3]						
Emergency department visits, per 1,000 members	280.5	321.3	270.8	324.1	−7.2 (−16.7, 2.4)	−2.2 (−5.0, 0.7)
Low severity[2]	80.8	97.4	78.9	104.9	**−9.4 (−12.8, −5.9)**	**−8.8 (−11.8, −5.8)**
High severity[2]	25.3	43.7	25.3	39.5	**4.1 (3.3, 5.0)**	**10.5 (8.1, 12.9)**
Hospitalizations, per 1,000 members	140.2	149.9	131.2	149.9	**−9.0 (−15.9, −2.1)**	**−5.7 (−9.9, −1.5)**
Direct admissions	82.4	78.2	77.5	82.0	**−8.7 (−13.2, −4.3)**	**−10.0 (−14.8, −5.3)**
Total expenditures, $ per member	7,893.5	8,272.8	7,920.4	8,532.6	**−232.8 (−305.7, −160.0)**	**−2.7 (−3.6, −1.9)**
High income (*n* = 14,841 HDHP and 124,479 control)[4]						
Emergency department visits, per 1,000 members	231.0	261.0	2,31.0	264.8	**−3.7 (−10.4, 2.9)**	−1.4 (−3.9, 1.1)
Low severity[2]	62.7	80.0	62.7	81.6	**−1.5 (−4.6, 1.5)**	−1.9 (−5.6, 1.8)
High severity[2]	25.5	34.4	25.5	35.7	**−1.3 (−2.5, −0.1)**	**−3.5 (−6.8, −0.2)**
Hospitalizations, per 1,000 members	130.3	132.9	123.7	133.9	−7.7 (−17.3, 2.0)	−5.4 (−12.1, 1.2)
Direct admissions	78.4	73.1	72.7	73.4	**−6.1 (−11.5, −0.7)**	**−7.7 (−14.2, −1.2)**
Total expenditures, $ per member	8,793.3	8,962.8	8,778.0	9,304.7	**−341.9 (−362.6, −321.2)**	**−3.7 (−3.9, −3.5)**

ND, not detected. Bold values indicate significant difference. [1]All rates and changes account for differing baseline trends between HDHP and control group members and are estimated with marginal effects methods using parameters from aggregate-level segmented regression analysis of cumulative interrupted time–series data that were adjusted for age, sex, race/ethnicity, education level, poverty level, U.S. region, ACG score, employer size, and calendar month of the index date. [2]See RESEARCH DESIGN AND METHODS for definition of low- and high-severity emergency department visits. [3]Living in a neighborhood with below-poverty levels of ≥10%. [4]Living in neighborhoods with below-poverty levels of <10%.

CI −14.2, −1.2]) and total expenditures (−3.7% [−3.9, −3.5]).

Proxy Health Outcomes and Comparison Low-Severity Measures

By the end of the follow-up period versus the end of the baseline period, HDHP members from low-income neighborhoods experienced increases in high-severity emergency department visit total expenditures and hospitalization days of 23.5% (95% CI 18.3, 28.7) and 27.4% (15.5, 39.2), respectively, relative to low-income control members (Fig. 1 and Table 3). These HDHP members from low-income neighborhoods experienced a 5.5% (−8.0, −3.0) reduction in low-severity emergency department visit expenditures.

High-income HDHP members experienced an 8.0% (95% CI 0.3, 15.7) increase in high-severity emergency department visit expenditures, a 10.7% (−18.8, −2.6) reduction in high-severity hospitalization days and no detectible changes in low-severity emergency department visit expenditures and hospitalization days.

In secondary analyses, high-morbidity HDHP members with diabetes experienced changes in high-acuity utilization and proxy outcomes similar to the overall cohort, and low-morbidity HDHP members experienced ∼5–7% reductions in overall and low-severity emergency department visits as well as low-severity hospitalization days (Supplementary Data).

CONCLUSIONS

After an HDHP switch, emergency department visits declined by 4.0% among patients with diabetes, and direct hospital admissions fell by 11.1%, likely driving 3.8% lower total health care expenditures. Proxy adverse outcomes were unchanged in the overall HDHP population with diabetes, but HDHP members from low-income neighborhoods experienced large increases in high-severity emergency department visit expenditures and hospitalization days. These are concerning findings that warrant further study and close attention by clinicians, policy makers, and employers.

Our results should be interpreted in light of recent findings that low-income but not high-income HDHP members with diabetes delay outpatient visits for time-sensitive conditions such as cellulitis, urinary tract infection, and pneumonia (8). HDHP members from low-income neighborhoods might be attempting to minimize health expenditures by avoiding important care, causing missed opportunities for prevention and treatment and thus more severe emergency department and hospital presentations.

Moderate reductions in direct hospital admissions among HDHP members might imply that these patients and their outpatient clinicians were aware of the out-of-pocket implications of inpatient stays. Providers might have attempted to shift care to an ambulatory setting to manage certain conditions.

We expected that emergency department visits and hospitalizations would decline to a greater degree. Reductions in total health care expenditures were also smaller than expected but comparable to previous studies that included overall HDHP

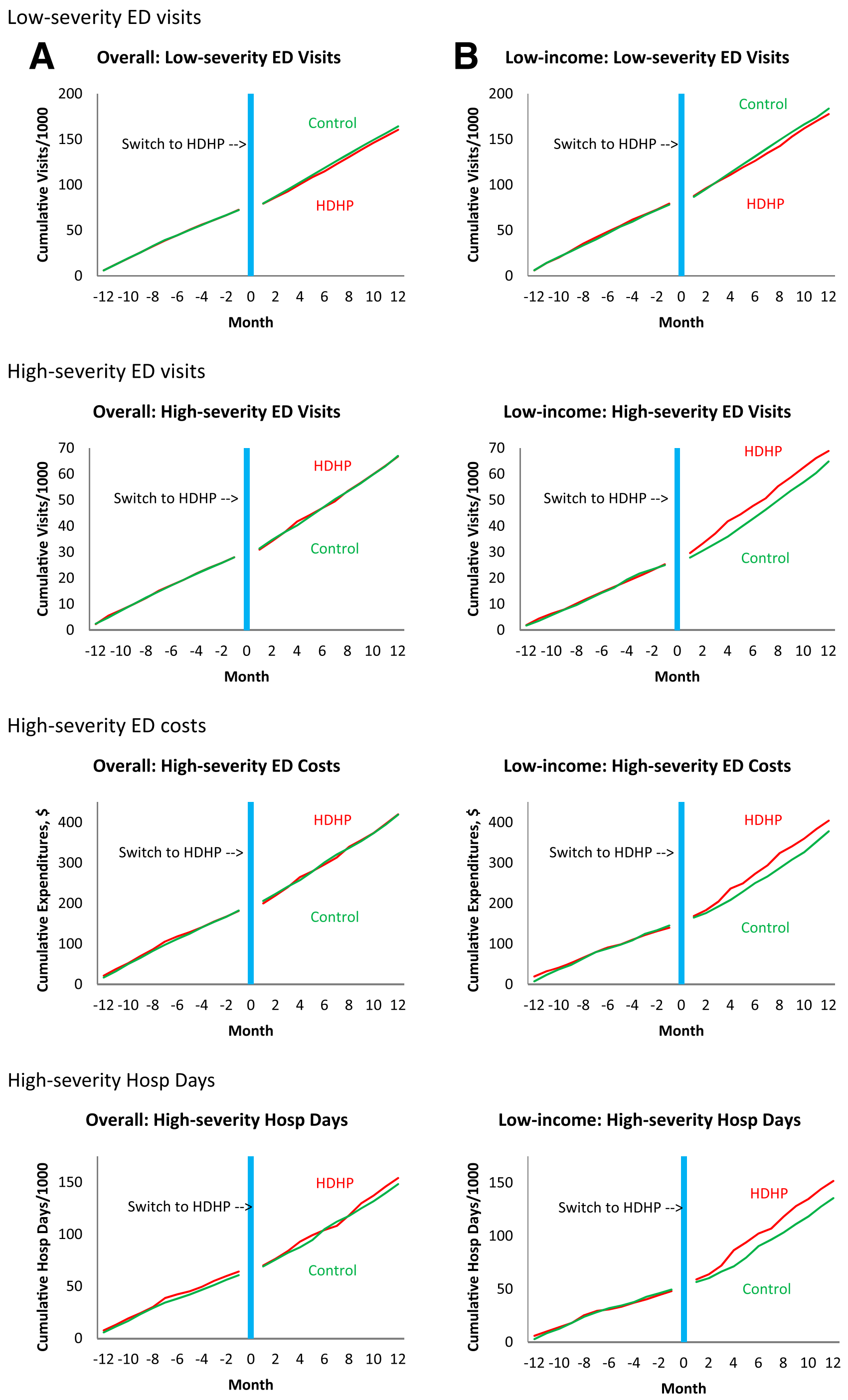

Figure 1—Cumulative plots of low-severity ED visits, high-severity ED visits, high-severity ED total (out-of-pocket plus health plan) expenditures, and high-severity hospitalization days in the overall (*A*) and low-income (*B*) cohort (low-income defined as living in a neighborhood with below-poverty levels of ≥10%). ED, emergency department; Hosp, hospitalization.

populations (38–40). A potential explanation for these modest changes is that they reflect reductions in discretionary utilization offset by increased utilization due to greater illness or acuity, as seen in the low-income HDHP population we examined. It is also possible that some HDHP members with diabetes anticipate exceeding their annual deductible, providing less incentive to cut back on services.

Nevertheless, in the current environment of continuously increasing health care costs, the ~4% reduction in total costs among HDHP members with diabetes is notable. For example, such cost savings among higher-income members could be used to offset cost burdens (41), such as insulin expenses, among lower-income members. The ~6% reduction in inpatient admissions is also important given that hospitalizations are a major driver of health care expenditures (42) and can cause iatrogenic harm.

Our finding that some members experienced increases in care subject to high deductibles is relatively unique in the HDHP literature, where a standard hypothesis is that deductibles are a “blunt instrument” that reduces all forms of care (43,44). Such results might therefore be surprising, but the isolation of this increased utilization to an at-risk group and to care classified as high severity (and not low severity) lends credence to the hypothesis that HDHPs caused adverse effects in a vulnerable population.

Recent national efforts, such as the Choosing Wisely campaign (45), have focused on reducing low-value care. We found that HDHP members from low-income neighborhoods reduced low-value (low-severity) emergency department visits by almost 9%. However, given concomitant adverse outcomes, the HDHP types we studied do not appear to be a viable tool for reducing low-value care among patients with diabetes.

Our study adds several unique findings to the cost-sharing and diabetes literature. The RAND Health Insurance Experiment (HIE) from 40 years ago did not measure adverse high-acuity outcomes but predicted that low-income and high-morbidity patients would have increased long-term mortality under high-level cost sharing due to reduced antihypertensive medication adherence (13). Our study and another that focused on diabetes outpatient care (8) are the first to demonstrate (rather than predict) adverse proxy health outcomes after HDHP transition. The latter study (8) found that HDHP members from low-income neighborhoods delayed outpatient visits for acute diabetes complications and experienced major increases in emergency department visits for diabetes complications. The proxy health outcomes in that study were defined narrowly as diabetes-specific complications deemed sensitive to the timing of outpatient care. In contrast, the current study examined all emergency department visits, and the proxy health outcomes comprised costs for emergency department visits classified as high-severity

Table 3—Proxy adverse health outcomes comprising high-severity emergency department visit expenditures and high-severity hospitalization days (and low-severity outcomes for comparison), overall and among key HDHP subgroups, 1 year before and after an HDHP switch compared with contemporaneous control group members

	Cumulative annual rate at the end of[1]				Change in HDHP vs. control group, end of follow-up vs. end of baseline[1]	
	HDHP group		Control group		Absolute	Relative, %
	Baseline	Follow-up	Baseline	Follow-up	Estimate (95% CI)	Estimate (95% CI)
Overall (*n* = 23,493 HDHP and 192,842 control)						
ED visit expenditures, $ per member						
High severity[2]	185.0	233.6	185.0	233.6	ND	ND
Low severity[2]	170.3	213.0	165.5	212.3	−10.6 (−29.3, 8.0)	−4.8 (−12.8, 3.3)
Hospitalization days, per 1,000 members						
High severity[2]	64.9	89.0	62.7	85.8	3.2 (−1.1, 7.4)	3.7 (−1.4, 8.8)
Low severity[2]	41.3	55.3	41.3	53.7	1.6 (−1.6, 4.7)	2.9 (−3.1, 8.9)
Low income (*n* = 8,453 HDHP and 65,468 control)[3]						
ED visit expenditures, $ per member						
High severity[2]	143.1	262.7	148.1	228.4	**50.0 (40.6, 59.4)**	**23.5 (18.3, 28.7)**
Low severity[2]	158.2	230.3	166.8	243.6	**−13.3 (−19.5, −7.1)**	**−5.5 (−8.0, −3.0)**
Hospitalization days, per 1,000 members						
High severity[2]	48.8	103.3	50.7	85.7	**22.2 (14.3, 30.1)**	**27.4 (15.5, 39.2)**
Low severity[2]	38.4	62.6	40.8	58.7	3.9 (0.0, 7.7)	6.6 (−0.2, 13.4)
High income (*n* = 14,841 HDHP and 124,479 control)[4]						
ED visit expenditures, $ per member						
High severity[2]	181.7	217.3	199.1	218.6	**16.1 (1.3, 30.8)**	**8.0**
Low severity[2]	162.5	199.8	148.8	186.2	ND	ND
Hospitalization days, per 1,000 members						
High severity[2]	64.8	78.1	58.4	81.0	**−9.4 (−17.0, −1.7)**	**−10.7 (−18.8, −2.6)**
Low severity[2]	39.9	51.4	37.8	45.5	3.8 (−3.8, 11.4)	8.0 (−8.8, 24.8)

ED, emergency department; ND, not detected. Bold values indicate statistical significance. [1]All rates and changes account for differing baseline trends between HDHP and control group members and are estimated with marginal effects methods using parameters from aggregate-level segmented regression analysis of cumulative interrupted time–series data that were adjusted for age, sex, race/ethnicity, education level, poverty level, U.S. region, ACG score, employer size, and calendar month of the index date. [2]See RESEARCH DESIGN AND METHODS for definition of low- and high-severity emergency department visit expenditures and hospitalization days. [3]Living in a neighborhood with below-poverty levels of ≥10%. [4]Living in neighborhoods with below-poverty levels of <10%.

and hospitalization days after such visits. Thus, the high-severity outcomes in the current study were not diabetes-specific, providing a broad picture of high-acuity health care use and outcomes under HDHPs. The current study also adds the key finding that concerning utilization patterns begin as early as the first year after an HDHP switch among vulnerable populations. A potentially important finding for the design of future HDHP studies is that the larger tide of decreasing utilization due to HDHPs might mask increases in less common but concerning outcomes (e.g., high-severity hospitalization days) unless such measures are carefully defined. Finally, our study remains one of the few that has examined nonmedication measures among chronically ill HDHP members.

Our results have implications for clinicians, patients with diabetes, and policy makers. HDHP enrollment is expected to dramatically increase during the coming decade. Clinicians should be aware that low-income HDHP members with diabetes might have a substantially increased risk of adverse outcomes. Reductions in direct hospitalizations that we detected might imply that clinicians will increasingly face value-related questions about plannable, high-cost health events. Population-based management teams should be especially attentive to care patterns among vulnerable HDHP members with expensive chronic illnesses.

Patients with diabetes in HDHPs should consider the relatively high likelihood that they will have an expensive health event. If affordable, they should consider maximizing medical savings (including through health savings accounts). They might also benefit from learning the nuances of navigating HDHPs through educational materials, health care planning calculators, and value-shopping tools. However, opting for lower out-of-pocket insurance benefit designs, if available, might be advisable for vulnerable patients.

Policy makers and employers hoping that HDHPs will substantially reduce total health expenditures among chronically ill patients might be disappointed, given the relatively small reductions we detected. On one hand, modest cost reductions and no evidence of harm among higher-income patients might be welcomed by firms that have higher socioeconomic status employees. On the other hand, policy makers and employers should consider adopting protections for patients with diabetes who are of lower socioeconomic status. These stakeholders might view our results as motivation to develop and encourage evidence-based, population-specific health insurance designs (8,41,46–48) targeted to maintain or improve outcomes among vulnerable populations. Employers could purchase such health plans, target education about HDHPs to vulnerable enrollees, encourage medical savings, or consider increasing health savings account or health reimbursement arrangement contributions for at-risk families.

This study has several limitations. We monitored patients with diabetes for only 1 year after the HDHP transition. The abilities of patients from low-income neighborhoods to navigate HDHPs might improve after longer exposure, but the early adverse outcomes we detected, combined with expected large increases in HDHP enrollment, suggest that our findings have significant implications for the health of patients with diabetes from low-income neighborhoods.

Although we knew exact deductible amounts for small employers, we did not have benefit coverage details for large employers. We therefore categorized their deductible levels using an imputation algorithm (Supplementary Data), the high sensitivity and specificity of which was increased by using broad deductible categories, namely, ≤$500 and ≥$1,000. Our analyses of out-of-pocket expenditures showed that at the population level, the HDHP group experienced an increase in out-of-pocket medical expenditures of ~30% (Supplementary Data), further indicating the validity of our plan type classification. Our need to impute broad deductible categories and the relative infrequency of higher deductibles during 2003–2012 (49) meant we were unable to analyze effects of higher levels such as ≥$2,000 or ≥$3,000. We did not have access to health insurance premiums and therefore could not estimate total member expenditures (premiums plus out-of-pocket). By including in our sample only members offered no choice in health plan selection in the baseline or follow-up periods (exogenous insurance choice), we minimize individual-level selection bias, the major threat to internal validity. Employer selection could still bias effect estimates, but we minimized this by removing very small employers and including in our match employers' propensity to switch to HDHPs based on multiple employer characteristics.

We used U.S. Census 2000 data to categorize members' neighborhood poverty levels rather than more updated American Community Survey values due to recognized problems with American Community Survey estimates of income (50,51). Misclassification of members' neighborhood income and poverty levels could arise if neighborhood characteristics change substantially over time or if members do not live in neighborhoods with the characteristics assigned to them during the baseline and follow-up periods. However, these phenomena are unlikely to differ by study group and thus should not bias effect estimates. U.S. Census 2000 poverty variables have been reliable indicators of health care disparities in previous studies in this data set (8,52–54). These measures are not intended to be proxy individual-level measures of socioeconomic status; rather, they are intended to capture a mix of individual-level and neighborhood socioeconomic effects (55).

We did not include medication outcomes in this report given their substantial complexity that require, for example, detailed descriptions of measure construction and analytic approaches. Such ongoing work is crucial to understanding effects of HDHPs given that patients with diabetes generally rely heavily on access to medications to control their disease.

Finally, our study may not be representative of very low socioeconomic status patients, newly insured people, or patients newly diagnosed with diabetes.

HDHPs had a modest effect on high-acuity utilization and outcomes in the overall diabetes cohort, but the low-income subgroup experienced substantial and concerning increases in adverse outcomes. Policy makers and employers should consider approaches for protecting such vulnerable populations, including providing health plans tailored to reduce barriers to care, facilitating medical savings, and educating members about HDHPs.

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