



## Original Investigation | Health Policy

# Pharmacy Subscription Program and Medication Refills, Days' Supply, and Out-of-Pocket Costs

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## Abstract

**IMPORTANCE** Medication nonadherence imposes high morbidity, mortality, and costs but is challenging to address given its multiple causes. Subscription models are increasingly used in health care to encourage healthy behaviors; in January 2023, Amazon Pharmacy launched RxPass, a subscription program offering Amazon Prime members (hereafter, company members) in 45 states access to 60 common generic medications for a flat \$5 monthly fee.

**OBJECTIVE** To evaluate the associations of program enrollment with medication refills, days' supply, and out-of-pocket costs.

**DESIGN, SETTING, AND PARTICIPANTS** In this retrospective, population-based cohort study, a difference-in-differences approach with doubly robust estimation was used to assess outcomes 6 months before and after program enrollment, compared with a contemporaneous control group (study period included July 24, 2022, to January 24, 2024). Participants were younger than 65 years, company members, and not enrolled in Medicare or Medicaid. Exposure individuals were enrolled in the program in the first 6 months of program launch. Control individuals resided in the 5 states where the program was not available but who clicked on the enrollment webpage in the first 6 months of program launch.

**EXPOSURE** Subscription program enrollment.

**MAIN OUTCOMES AND MEASURES** The primary outcome was the number of days' supply of medications on the subscription program list per person per month (PPPM). Secondary outcomes were the number of prescription refills and out-of-pocket costs of medications on the program list, including program subscription costs, PPPM.

**RESULTS** After propensity score weighting, there were 5003 enrollees (mean [SD] age, 45.9 [11.1] years; 2076 female [41.5%]) and 5137 controls (mean [SD] age, 45.8 [11.1] years; 2116 female [41.2%]). The program was associated with an increase in days' supply of 10.39 days PPPM (95% CI, 10.29-10.48 days PPPM), a 27% increase, an increase in prescription refills of 0.19 PPPM (95% CI, 0.19-0.19 refills PPPM), a 29% increase, and a decrease in out-of-pocket spending by \$2.35 PPPM (95% CI, \$2.37-\$2.33 PPPM), a 30% decrease.

**CONCLUSIONS AND RELEVANCE** In this cohort study, program enrollment was associated with increased medication refills and total days' supply and reduced out-of-pocket costs. Future research should investigate the potential cognitive and/or behavioral mechanisms by which subscription programs encourage healthy behaviors and whether the results could be replicated among other pharmacies or cohorts.

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## Key Points

**Question** Is enrollment in a pharmacy subscription program that offers members access to 60 common generic prescription drugs for a \$5 monthly fee associated with medication refills, days' supply, and out-of-pocket costs?

**Findings** In this cohort study comparing 5003 enrollees with 5137 controls, before and after enrollment, subscription program enrollment was associated with statistically significantly increased medication refills and total days' supply of program medications and decreased out-of-pocket costs.

**Meaning** These findings suggest that the use of subscription models to access prescription drugs may be a promising way to improve days' supply.

## + Supplemental content

Author affiliations and article information are listed at the end of this article.

## Introduction

One-half of all US individuals who are prescribed medications do not take them as frequently as their prescriber intended.<sup>1</sup> This degree of nonadherence to medications causes an estimated 125 000 additional deaths and more than \$100 billion in additional health care costs annually.<sup>2</sup>

The challenge with improving medication refilling behavior arises from the multiple barriers that patients face, including financial, behavioral, and cognitive factors. High out-of-pocket costs are a barrier but reducing out-of-pocket costs alone only moderately improves adherence.<sup>3-5</sup> Cognitive and behavioral factors are also important.<sup>6,7</sup> One such factor is the lack of salience and/or transparency in benefit designs; patients often do not know the costs of their prescriptions until they pick up the medication from the pharmacy. Therefore, patients who need adherence improvements the most are the least aware of price reductions.<sup>4</sup> A second factor is present bias, which causes people to overweigh the immediate hassle of filling prescriptions relative to the downstream health benefit.<sup>8,9</sup> Finally, simple forgetfulness is a key factor to nonadherence.<sup>10</sup>

Mirroring the 4-fold growth of subscription programs in e-commerce in the past decade, there has been rapid growth in the number of digital health companies offering subscription-based models providing access to prescription medications.<sup>10-13</sup> These programs leverage a number of cognitive and behavioral factors, including transparent pricing, automatic subscription renewal, bundling of goods or services, and enhancing customer-company identification through loyalty programs.<sup>14,15</sup> One study<sup>16</sup> of an e-commerce subscription program found that two-thirds of the program's effect on repeated purchases was through cognitive and behavioral mechanisms. Despite the growth of subscription programs and their potential to improve medication refilling behavior, to our knowledge, there are no studies measuring such effects. In this study, we evaluate the association of a pharmaceutical subscription program with medication refills, days' supply, and out-of-pocket medication spending.

## Methods

This cohort study was approved by the WCG institutional review board<sup>17</sup> for a waiver of the Health Insurance Portability and Accountability Act authorization requirement and the need for informed consent due to the minimal risk this study posed to study individuals, in accordance with 45 CFR §46. This study was also approved by the subscription company's data privacy board. This article follows the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) reporting guidelines for cohort studies.

## Program Description

On January 24, 2023, Amazon Pharmacy launched RxPass, a program that provides 60 common generic prescription medications for a \$5 monthly subscription; only Amazon Prime members living in 45 states are eligible for the program. The subscription program covers a diverse set of medications, with the 3 most common therapeutic classes being statins, antihypertensives, and antidepressants (eTable 1 in [Supplement 1](#)). These medications can generally be filled as a 90 days' supply, with or without program enrollment. During the study period, the program was not available to Medicare or Medicaid beneficiaries or to individuals with shipping addresses in California, Minnesota, New Hampshire, Texas, and Washington. Outside the subscription program, the pharmacy serves customers in all 50 states.

The launch of the program was communicated on the company's website in every state and through a onetime email at program launch to existing customers who had medications on the program list and resided in the eligible states. Once enrolled, the program renews each month unless the customer chooses to cancel the subscription, which the customer can do at any time. Although subscription payment renews monthly, patients still need to choose to refill their prescriptions. Customers receive a monthly emailed receipt that serves to remind them of their participation in the

program. There were no other differences in program communications between members and nonmembers during the study period.

### Data Source

We constructed a patient-month-level dataset using pharmacy data, including patient demographics, enrollment in the subscription program, company membership, prescription fills, prescription out-of-pocket spending in the program, and clicks on the subscription program enrollment webpage. Consistent with its privacy policy, the program collects program enrollment website browsing and click-through data to provide and improve its products and services. For this study, we also obtained area-level socioeconomic status measures at the 5-digit zip code level from the 2021 American Community Survey.<sup>18</sup>

Analyses were performed in Python version 3.10.8 (Python Software Foundation). The analytic environment was certified to securely handle the company's most sensitive data types.

### Study Design

We compared outcomes 6 months before and after program enrollment in the exposure group with a contemporaneous control group. Individuals were required to be younger than 65 years, not enrolled in Medicare or Medicaid, and be a company member before their index date. Individuals in the exposure group were defined as those who enrolled in the program for any duration in the first 6 months of program launch. Individuals in the control group were defined as those who never enrolled in the program during the period of study, but did click on the program enrollment webpage at least once within the first 6 months of program launch, and who resided in a state in which the program was not available during the period of study. For individuals in the control group, the index date was defined as the date on which individuals clicked on the program enrollment webpage, or the median click date, if there were multiple click dates. The study period encompassed July 24, 2022, to January 24, 2024—that is, 6 months before the earliest program enrollment date (January 24, 2023) and 6 months after the latest included program enrollment date (July 24, 2023).

The pharmacy's data do not include information on prescription fills at other pharmacies. Yet, we are interested in estimating medication refills as a clinical outcome rather than changes in prescription transfers into or out of the pharmacy. Therefore, we restrict our dataset in the postenrollment period to include only prescription fills for medications on the subscription program list that the same individual had filled in the pre-enrollment period. This minimizes the effect of new prescription transfers into the pharmacy. To reduce the effect of prescription transfers out of the pharmacy, we identified individuals who were stable users of the pharmacy by requiring individuals to have at least 2 prescription fills for medications that were on the program list in the pre-enrollment period.

### Covariate Measures

We adjusted for sex, age at index date, calendar month indicators (January to December), US Census geographic regions (West, Midwest, Northeast, and South), and the most common payment type in the 6 months before individuals' index dates (commercial, Prime Rx [a prescription discount program that is included with membership], and without insurance). Finally, we included the following zip code-level measures: population size, percentage of the population that was self-reported White, percentage of the population aged 25 years or older with any college education, and median household income. Race was included as a covariate since it was expected to be associated with medication fills.

### Outcome Measures

Our primary outcome was the total days' supply of program medications that patients had on hand, per person per month (PPPM). We computed this for each individual by taking the sum of total days'

supply of all program medications an individual filled in that month. Secondary outcomes were the number of prescriptions and out-of-pocket costs for program medications PPPM.

## Statistical Analysis

We used a doubly robust estimator, which combines a propensity of program enrollment model and a regression adjustment model to estimate associations, using the aforementioned covariates.<sup>19</sup> Thus, our model estimates adjusted outcomes by comparing exposed individuals (ie, those who clicked on the program enrollment webpage and enrolled, in the exposure states) to control individuals (ie, those who clicked on the program enrollment webpage in the control states) with propensity score weighting to balance on propensity to enroll. Our parameter of interest is the association of program enrollment with mean outcomes in the exposure group PPPM. This parameter combines the coefficients representing the impact of program enrollment with the level and slope of the outcomes of interest (eMethods in [Supplement 1](#)). We generated 95% CIs using 1000 bootstrap replicates with replacement and clustering on the individual member. Statistical significance was defined as a 95% CI that did not cross the null value of zero.

## Sensitivity Analyses

To further minimize the effect of prescription transfers out of the pharmacy, we conducted sensitivity analyses that further restricted our sample to individuals who had at least 3 or at least 4 prescription fills for medications that are covered by the program formulary in the pre-enrollment period, in 2 sensitivity analyses. To evaluate the effect of anticipatory prescription-filling behavior resulting from individual-level selection into the program, we censored observations in the month before and after the index date. To evaluate whether exposure-control state differences confounded our analyses, we conducted a sensitivity analysis in which we used an alternative control group composed of individuals who resided in the same state as the exposure group, met all previously described inclusion criteria, and clicked on the program enrollment page during the period of interest but did not enroll. To further account for exposure and control state differences, we used a difference-in-difference-in-differences model. This model adds the alternative control individuals to the primary analytic sample and adds an indicator of residence in exposure state that is fully interacted with our main effect terms.

## Subgroup Analyses

We evaluated the association of the program with our outcomes of interest among the 3 therapeutic classes with the greatest number of medications included in the program: statins, antihypertensives, and antidepressants. For each of these analyses, individuals were required to have at least 2 fills for program medications in the therapeutic class of interest in the pre-enrollment period. We also included only the program medications in the respective therapeutic class in our outcomes measurement.

## Results

The final sample included 5003 enrollees (mean [SD] age, 45.9 [11.1] years; 2076 female [41.5%]) and 5137 controls (mean [SD] age, 45.8 [11.1] years; 2116 female [41.2%]) (**Table 1**). Exposed individuals were enrolled in the program for a mean (SD) of 153 (47) days during the 6-month follow up. Exposed individuals constituted 26.8% of all individuals in the exposure states who met inclusion criteria and who clicked on the program enrollment page in the 6 months after program launch. Before program enrollment, 65% of individuals did not use insurance or paid using a discount program.

Before inverse probability weighting, exposed and control individuals were similar in terms of age, sex, and payment type but differed by geographic region and zip code-level characteristics, likely because control individuals were limited to specific states (eTable 2 in [Supplement 1](#)). After inverse probability weighting, all characteristics were well balanced across the 2 groups (Table 1).

Both exposure and control groups had the same average index date (March 8, 2023). The propensity scores in the control group were generally lower than those in the exposure group; however, there was common support across the large majority of propensity score values (eFigure in Supplement 1). On the basis of zip code-level characteristics, the demographics of enrollees were also similar to those of the US general population.<sup>20</sup> Pre-enrollment period prescription fills in the exposure and control groups exhibited similar trends (Figure and eTable 3 in Supplement 1). Between 92.5% and 98.3% of included individuals were observed (ie, filled at least 1 prescription in the pharmacy) in the postenrollment period (eTable 4 in Supplement 1). We observe that days' supply and medication refills declined in the control group in the postenrollment period. Medication refills are known to decline over time for most patients, in the absence of intervention.<sup>21-24</sup>

Adjusted Association of Program Enrollment With Medication Refills, Days' Supply, and Out-of-Pocket Costs

Enrollment was associated with an increase in the days' supply of program medications by 10.39 days PPPM (95% CI, 10.29-10.48 days PPPM) compared with the days' supply had these same members not enrolled in the program, a 27% increase (Table 2). Similarly, enrollment was associated with an increase in prescription refills of 0.19 PPPM (95% CI, 0.19-0.19 refills PPPM) for program medications, a 29% increase. Enrollment was associated with a decrease in out-of-pocket spending, including program subscription costs, of \$2.35 PPPM (95% CI, \$2.33-\$2.37 PPPM), a 30% decrease.

Sensitivity Analyses

The results from the analyses without inverse probability weighting were similar to the results with inverse probability weighting (eTable 5 in Supplement 1). In all sensitivity analyses, the association of program enrollment with days' supply of medication and prescription refills were larger than our primary analyses, with the largest estimates being from restricting the sample to individuals with 4 or more fills of program medications in the pre-enrollment period (16.27 days PPPM [95% CI, 16.11-16.43 days PPPM]; 0.29 refills PPPM [95% CI, 0.29-0.29 refills PPPM]) (Table 3). In all sensitivity

Table 1. Characteristics of Exposure and Control Group Members in the 6 Months Before Index Date With Inverse Probability Weighting

Characteristic	Participants, No. (%)		Cohen <i>d</i> or Cohen <i>h</i> <sup>a</sup>
	Exposure (n = 5003)	Control (n = 5137)	
Individual-level characteristics			
Age, mean (SD), y	45.9 (11.1)	45.8 (11.1)	0.01
Sex			
Male	2927 (58.5)	3021 (58.8)	0.00
Female	2076 (41.5)	2116 (41.2)	0.00
Payment type			
Commercial insurance	1801 (36.0)	1777 (34.6)	0.01
Cash	620 (12.4)	637 (12.4)	0.00
PrimeRx	2582 (51.6)	2723 (53.0)	−0.01
Geographic region			
Midwest	798 (16.0)	735 (14.3)	0.02
Northeast	525 (10.5)	848 (16.5)	−0.09
South	2066 (41.3)	1783 (34.7)	0.07
West	1614 (32.3)	1771 (34.5)	−0.02
Index date minus program launch date, mean (SD), d	43.2 (46.6)	43.2 (44.9)	0.00
Zip code-level characteristics			
Population size, mean (SD)	31 322 (18 744)	29 860 (20 378)	0.08
Household income in prior 12 mo, mean (SD), \$US <sup>b</sup>	84 254 (34 844)	86 098 (32 848)	−0.05
Aged ≥25 y with any college attendance, mean (SD) <sup>b</sup>	68.2 (14.3)	68.9 (14.6)	−0.04
White residents, mean (SD), % <sup>b</sup>	72.7 (18.8)	73.7 (17.6)	−0.06

<sup>a</sup> Cohen d are computed for continuous measures and Cohen h for categorical measures.

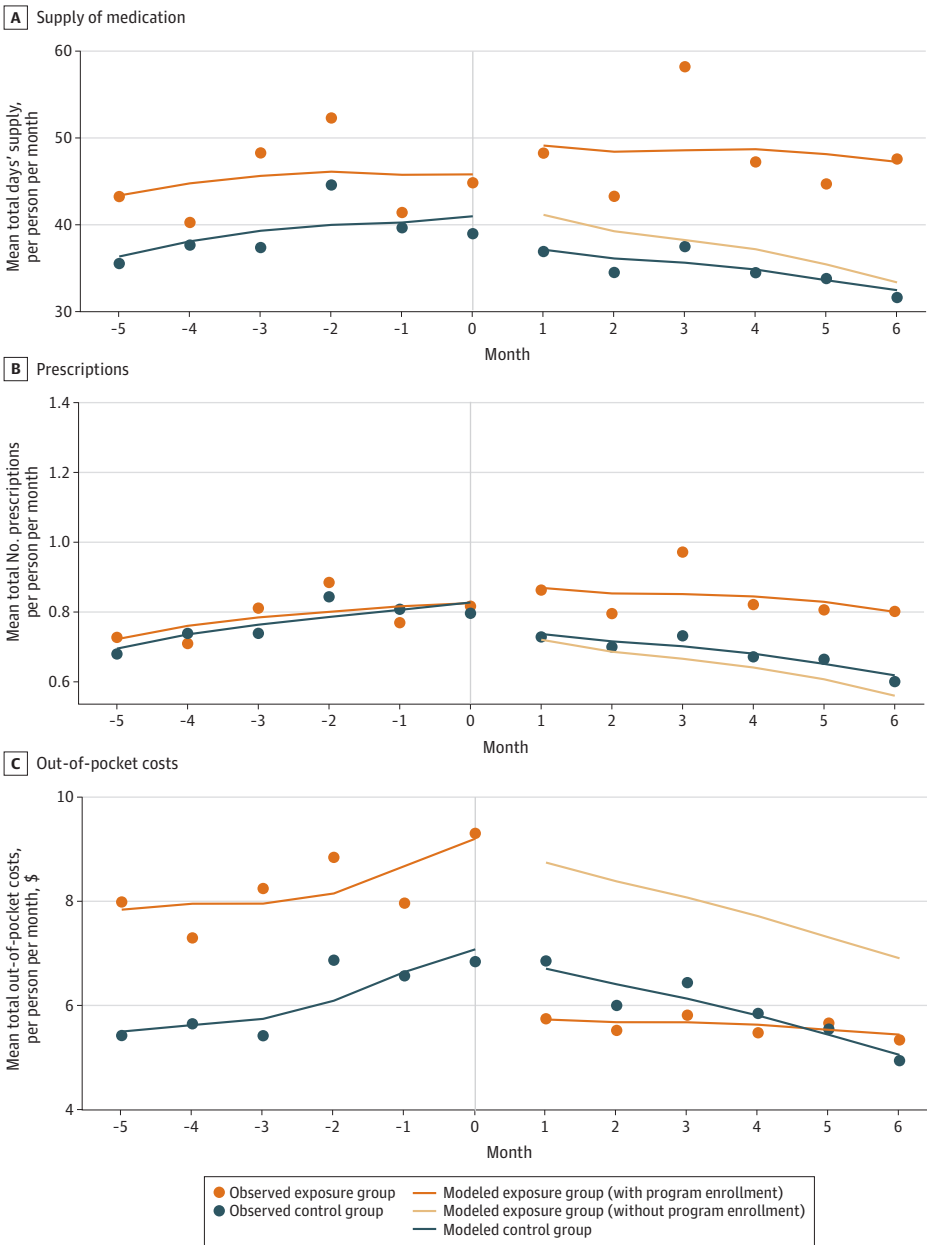
<sup>b</sup> Computed as the mean (SD) of the percentage in each zip code.

analyses, the association of enrollment on out-of-pocket costs was smaller than our primary analyses, with the smallest estimates being from censoring the month before and after the index date (\$1.21 PPPM [95% CI, \$1.24-\$1.17 PPPM]).

Subgroup Analyses

For the statin cohort, there were 1291 individuals in the treatment group and 1354 individuals in the control group; for the antihypertensive cohort, there were 1180 individuals in the treatment group and 1133 individuals in the control group; and for the antidepressant cohort, there were 1783 individuals in the treatment group and 1705 individuals in the control group. Enrollment was associated with an increase in the days' supply of medication of 8.56 days PPPM (95% CI, 8.43-8.69

Figure. Modeled vs Observed Days' Supply, Number of Prescription Refills, and Out-of-Pocket Costs Per Person Per Month for Drugs on the Program List Before and After the Index Date in the Exposure and Control Groups



Graphs show mean total days' supply of medication (A), mean total number of prescription refills (B), and mean total out-of-pocket costs (C).

days PPPM) for the statin cohort, 3.70 days PPPM (95% CI, 3.60-3.81 days PPPM) for the antihypertensive cohort, and 5.29 days PPPM (95% CI, 5.16-5.42 days PPPM) for the antidepressant cohort (**Table 4**). Enrollment was also associated with increased prescription refills of 0.15 refills PPPM (95% CI, 0.15-0.15 refills PPPM) for the statin cohort, 0.06 refills PPPM (95% CI, 0.06-0.06 refills PPPM) for the antihypertensive cohort, and 0.10 refills PPPM (95% CI, 0.10-0.10 refills PPPM) for the antidepressant cohort. Enrollment was associated with decreased out-of-pocket costs of \$1.47 PPPM (95% CI, \$1.45-\$1.50 PPPM) for the statin cohort, \$0.73 PPPM (95% CI, \$0.72-\$0.75 PPPM) for the antihypertensive cohort, and \$3.59 PPPM (95% CI, \$3.56-\$3.63 PPPM) for the antidepressant cohort.

Discussion

In this cohort study, we found that program enrollment was associated with a 30% reduction in out-of-pocket costs and a 27% increase in days' supply. Estimates of price elasticity of pharmaceuticals from prior studies would have projected an increase in days' supply between 6% and 18%, on the basis of our reduction in out-of-pocket costs.<sup>25</sup> Our results are similar to the results

Table 2. Association of Subscription Program Enrollment With Total Days' Supply, Number of Prescription Refills, and Out-of-Pocket Costs for Drugs on the Program List Per Person Per Month in the 6 Months After Program Enrollment, Using Doubly Robust Estimation

Outcome	Mean (95% CI)		
	Enrolled in program	Not enrolled in program	Estimated difference
Total days' supply	48.24 (48.22 to 48.27)	37.86 (37.77 to 37.95)	10.39 (10.29 to 10.48)
No. of prescription refills	0.84 (0.84 to 0.84)	0.65 (0.65 to 0.66)	0.19 (0.19 to 0.19)
Out-of-pocket costs, \$ <sup>a</sup>	5.43 (5.43 to 5.43)	7.78 (7.76 to 7.80)	-2.35 (-2.37 to -2.33)

<sup>a</sup> Includes program subscription costs.

Table 3. Sensitivity Analyses Estimating the Association of Program Enrollment With Total Days' Supply, Number of Prescription Refills, and Out-of-Pocket Costs for Drugs on the Program List Per Person Per Month in the 6 Months After Program Enrollment With Doubly Robust Estimation

Outcome	Mean (95% CI)		
	Enrolled in program	Not enrolled in program	Estimated difference
Restricted to individuals with ≥3 fills of drugs on the program list in the pre-enrollment period			
Total days' supply	51.88 (51.86 to 51.91)	35.89 (35.76 to 36.01)	16.00 (15.87 to 16.13)
No. of prescription refills	0.93 (0.93 to 0.93)	0.65 (0.64 to 0.65)	0.28 (0.28 to 0.28)
Patient out-of-pocket costs, \$ <sup>a</sup>	5.57 (5.56 to 5.57)	7.25 (7.23 to 7.28)	-1.69 (-1.72 to -1.66)
Restricted to individuals with ≥4 fills of drugs on the program list in the pre-period			
Total days' supply	56.20 (56.17 to 56.23)	39.93 (39.78 to 40.08)	16.27 (16.11 to 16.43)
No. of prescription refills	1.02 (1.02 to 1.02)	0.73 (0.72 to 0.73)	0.29 (0.29 to 0.29)
Patient out-of-pocket costs, \$ <sup>a</sup>	5.69 (5.68 to 5.69)	7.97 (7.93 to 8.00)	-2.28 (-2.31 to -2.25)
Censored the month before and after program enrollment			
Total days' supply	48.36 (48.33 to 48.38)	33.79 (33.62 to 33.95)	14.57 (14.40 to 14.74)
No. of prescription refills	0.84 (0.84 to 0.84)	0.59 (0.58 to 0.59)	0.25 (0.25 to 0.26)
Patient out-of-pocket costs, \$ <sup>a</sup>	5.44 (5.44 to 5.44)	6.65 (6.61 to 6.68)	-1.21 (-1.24 to -1.17)
Alternative control group: individuals in the exposure states who did not enroll in the program			
Total days' supply	48.35 (48.33 to 48.38)	32.13 (32.04 to 32.23)	16.22 (16.12 to 16.31)
No. of prescription refills	0.84 (0.84 to 0.85)	0.63 (0.63 to 0.63)	0.22 (0.22 to 0.22)
Patient out-of-pocket costs, \$ <sup>a</sup>	5.44 (5.43 to 5.44)	7.14 (7.11 to 7.17)	-1.71 (-1.73 to -1.68)
Difference-in-differences-in-differences			
Total days' supply	48.27 (48.24 to 48.29)	32.24 (32.14 to 32.33)	16.03 (15.93 to 16.13)
No. of prescription refills	0.84 (0.84 to 0.84)	0.63 (0.63 to 0.63)	0.21 (0.21 to 0.22)
Patient out-of-pocket costs, \$ <sup>a</sup>	5.44 (5.43 to 5.44)	7.16 (7.14 to 7.19)	-1.73 (-1.75 to -1.70)

<sup>a</sup> Includes program subscription costs.



of an e-commerce subscription program that reported a 3-fold higher effect than would be expected by price reductions alone.<sup>16</sup>

There are a number of potential explanations for the higher medication refill and days' supply increase. Before program enrollment, 65% of individuals did not use insurance or paid using a discount program. These individuals are more likely to be more price sensitive than well-insured individuals.<sup>26,27</sup> The majority of prior studies relied on pharmacy claims data, which typically only include pharmacy purchases involving insurance. Furthermore, our sample was limited to relatively engaged individuals (ie, those who had 2 fills for medications of interest in the pre-enrollment period), who may be more attentive to price changes than the average individual. In addition, some of the medications on the program medication list, such as biotin, folic acid, or naproxen, are for low-acuity or asymptomatic conditions or conditions for which there are over-the-counter treatment substitutes. Patients may be more price responsive to such medications.

There may also be a number of cognitive or behavioral factors by which the program may be associated with increased medication refills and days' supply. First, as a result of information salience,<sup>28</sup> enrollees are likely to be aware of their reduced prescription costs at the point of purchase owing to the program's upfront pricing. Second, the subscription program renews monthly with an emailed receipt, which serves as a reminder of their participation in the program. Customers, therefore, continue to participate in the program unless they choose to cancel, which they can do at any time.<sup>29</sup> Third, subscription programs may act as a commitment device<sup>30</sup>; by paying an upfront fee, individuals may be subsequently more motivated to refill their prescriptions to get their money's worth. Finally, in nonhealth contexts, bundling of multiple complementary products at discounted prices are known to increase their use.<sup>31</sup>

This program may also support medication refills and days' supply since it includes many first-line and second-line therapeutic options for several common chronic conditions, such as hypertension, hyperlipidemia, and depression. Patients taking medications to manage 1 or more of these disease states can fill most of their medications through the program, avoiding the need to fill prescriptions outside this program. This one-stop-shopping approach to medication management for chronic diseases may reduce cognitive burden of separate prescription fills.

Limitations

One major limitation that may also increase the estimated medication refill and days' supply impact is individual-level selection into the program. It is possible that individuals who choose to enroll in the program are more likely than control individuals to refill their prescriptions for unobserved reasons, since control individuals are a mixture of those who would and those who would not have enrolled in

Table 4. Subgroup Analyses: Association of Program Enrollment With Total Days' Supply, Number of Prescription Refills, and Out-of-Pocket Costs for Drugs on the Program List Per Person Per Month in the 6 Months After Program Enrollment in 3 Chronic Disease Cohorts With Doubly Robust Estimation

Outcome	Mean (95% CI)		
	Enrolled in program	Not enrolled in program	Estimated difference
Statins			
Total days' supply	26.01 (25.99 to 26.04)	17.46 (17.33 to 17.58)	8.56 (8.43 to 8.69)
No. of prescription refills	0.44 (0.44 to 0.44)	0.28 (0.28 to 0.28)	0.15 (0.15 to 0.15)
Out-of-pocket costs, \$ <sup>a</sup>	1.73 (1.73 to 1.73)	3.20 (3.18 to 3.23)	-1.47 (-1.50 to -1.45)
Antihypertensives			
Total days' supply	12.21 (12.19 to 12.23)	8.51 (8.41 to 8.61)	3.70 (3.60 to 3.81)
No. of prescription refills	0.20 (0.20 to 0.20)	0.14 (0.14 to 0.14)	0.06 (0.06 to 0.06)
Out-of-pocket costs, \$ <sup>a</sup>	0.67 (0.66 to 0.67)	1.40 (1.38 to 1.41)	-0.73 (-0.75 to -0.72)
Antidepressants			
Total days' supply	29.10 (29.08 to 29.13)	23.81 (23.68 to 23.94)	5.29 (5.16 to 5.42)
No. of prescription refills	0.54 (0.54 to 0.54)	0.44 (0.44 to 0.44)	0.10 (0.10 to 0.10)
Out-of-pocket costs, \$ <sup>a</sup>	2.64 (2.64 to 2.65)	6.24 (6.20 to 6.27)	-3.59 (-3.63 to -3.56)

<sup>a</sup> Includes program subscription costs.



the program had they resided in a program-eligible state. A few considerations minimize this possibility. First, our inverse probability weighting approach appeared to achieve good balance between exposure and control in observable characteristics.<sup>19</sup> Second, our doubly robust model reduces bias by specifying that only 1 of the 2 models need be correctly specified to obtain an unbiased estimate of the impact of the program. Third, the similarity of our results in sensitivity analyses, in which we minimize anticipatory filling behavior, and state-level differences provide additional confidence in our results. Specifically, the difference-in-difference-in-differences model controls for unobserved non-time-varying factors, unobserved time-varying state-specific factors, and observed time-varying individual-specific factors (ie, age), but there may still be other unmeasured time-varying factor that may confound the analysis.

A second limitation that may also contribute to the higher impact estimate in this study is our inability to observe prescription refills at other pharmacies. Control individuals may be differentially more likely to transfer their prescriptions out of the pharmacy. We reduced the effect of transfer out of the pharmacy by including relatively engaged patients in our primary analyses and further increased the stability of our control group in sensitivity analyses.

A third limitation is that the program is not paid through insurance. Therefore, patients will not receive a drug interaction check from their pharmacy benefit manager when ordering their program medications. Such drug interaction checks performed by the pharmacy benefit manager would typically include medications that were filled by the patient at other pharmacies. Like other pharmacies, however, the subscription program requests medication lists from patients to further enhance its own drug interaction checks.

Fifth, we required participants to be company members as part of our inclusion criteria for exposure and control groups. This limits the generalizability of our results to the 180 million US shoppers who are members.<sup>32</sup> Sixth, the program does not include branded medications. Despite the increasing use of branded medications for certain chronic conditions, medication refills for generic medications are critical because they still represent over 90% of all prescription fills in the US.<sup>33</sup> Seventh, we are only able to observe medication fills, not actual medication use by patients. Although studies<sup>34-37</sup> have consistently demonstrated positive associations between medication fills and patient-reported medication use, the true association of program enrollment with medication use in this study is unknown.

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## Conclusions

To our knowledge, this is the first study to evaluate a subscription model to access prescription medications, and we found that the program was associated with increased medication refills, days' supply, and reduced out-of-pocket costs. Future work should decompose the elements of the program that underlie the results.

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## ARTICLE INFORMATION

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**Author Contributions:** Dr Yeung had full access to all of the data in the study and takes responsibility for the integrity of the data and the accuracy of the data analysis.

**Concept and design:** All authors.

**Acquisition, analysis, or interpretation of data:** Yeung, Wilden, Matlin.

**Drafting of the manuscript:** Yeung, Gupta.

**Critical review of the manuscript for important intellectual content:** All authors.

**Statistical analysis:** Yeung, Wilden, Gupta.

**Administrative, technical, or material support:** All authors.

**Supervision:** Yeung, Gupta, Matlin.

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**Data Sharing Statement:** See [Supplement 2](#).

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#### SUPPLEMENT 1.

**eFigure.** Histogram of propensity scores for exposure and control groups

**eTable 1.** Medications available through the subscription program

**eTable 2.** Characteristics of exposure and control group members in the 6 months before index date without inverse probability weighting

**eTable 3.** Coefficients and 95% confidence intervals for the association of program enrollment with days' supply of medications on the program list per person per month (primary analysis)

**eTable 4.** Percent of distinct individuals who are observed in the pre-period but not in the post-period for analyses with the inclusion criteria of requiring 2 (primary analysis), 3, or 4 fills in the pre-period.

**eTable 5.** Association of program enrollment with total days' supply, number of prescription refills and out-of-pocket costs for drugs on the program list per person per month in the 6 months after program enrollment, without inverse probability weighting  
**eMethods.** Analytic Model Specification

**SUPPLEMENT 2.**  
**Data Sharing Statement**