

Does Cost-Effectiveness Analysis Have a Role in US Managed Care Drug Formularies?

An Empirical Study of Utilization, Costs, Outcomes, and Elasticity of Demand of a

Value-Based Formulary

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Abstract

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Chair of the Supervisory Committee:

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The standard economic model for health insurance posits that in order to account for moral hazard in a population for which there is varying marginal benefit of treatment that is unknown to the insurer, cost-sharing should be proportional to the price elasticity of demand.¹ Yet, many have observed that when faced with cost-sharing, consumers may reduce utilization to suboptimal levels due to underestimation of the marginal benefit of treatment. Hence, optimal health insurance design requires consideration of both insurer and consumer information asymmetries regarding the marginal benefits of treatment. This dissertation investigates whether cost-effectiveness analysis (CEA) may be useful for optimizing insurance in the face of insurer and consumer information asymmetries.

In 2010, Premera Blue Cross, a large non-profit health plan in the Pacific Northwest implemented a value based formulary (VBF) benefit among their own employees and dependents that explicitly uses CEA to inform medication placement within copayment tiers. We exploit this natural experiment to empirically assess the impact of the VBF on medication utilization and other health services utilization and the impact of the VBF on medication costs and non-medication costs from the member, health plan, and overall perspectives. We also estimate price elasticities of demand for pharmaceuticals overall, by therapeutic class, by brand-generic status, and finally by the copayment tiers informed by CEA.

In the first paper, we use individual-level data from July 2006 to June 2013 drawn from the employees of Premera and their dependents as well as data from employees and dependents of 5 employer sponsored plans administrated by Premera and chosen based on similarity to the intervention group in industry classification. After controlling for member demographics and plan characteristics and secular trends using an interrupted time series design with concurrent control, we find that the VBF shifted member medication utilization towards drugs placed in lower copayment tiers. The VBF also was associated with increased member medication costs and decreased health plan medication costs, leading to a net medication savings of \$8 per member per month (PMPM) (95% confidence interval [CI], -\$15, -\$2). Over the 3 year period of the study, the medication cost savings totaled over \$1.1 million USD. The findings regarding non-medication costs were comparatively small and not statistically significant. Total costs decreased by \$9 PMPM (95% CI, -\$49, \$30) but was not statistically significant. We did not detect any changes in the probability or the number of emergency department visits, hospitalizations, or office visits. This evaluation suggests that the VBF may have reduced overall

medication costs without negatively impacting utilization of other health services – a proxy for adverse outcomes.

In the second paper, we use data from July 2009 to June 2011 drawn from the employees of Premera and their dependents to construct a medication level dataset of 284 unique medications. These medications accounted for 79.3% of the prescription medication volume over the period of observation. After controlling for member demographics and using a pre-post design, we find that our elasticity estimates of -0.14 for the probability of filling a medication were similar to the overall elasticity estimates of -0.17 from the RAND Health Insurance Experiment.^{2,3} We also find that the estimates by therapeutic class and brand-generic status also were generally similar to published studies. Finally, we estimate of price elasticity of demand by copayment tiers informed by CEA. We found that elasticity estimates for the probability of fill and days' supply of medication respectively were -0.07 and -0.06 for the preventive tier, -0.09 and 0.08 for tier 1, -0.26 and -0.26 for tier 2, -0.27 and -0.32 for tier 3, and -0.45 and -0.55 for tier 4. Thus we observed a general trend of increasing elasticity with increasing copayment tiers. These results suggest that a cost sharing strategy based on elasticity estimates may be similar to a cost sharing strategy informed by CEA. Furthermore, since in the first paper we observed that the VBF was associated with decreased medication costs without negatively impacting health services utilization, we suggest that the use of CEA to inform medication copayment tiers may have a role in optimizing insurance benefit design.

Contemporaneous with the implementation of the VBF on July 2010, the US health insurance market has experienced many changes. The passage of the Patient Protection and Affordable Care Act (PPACA) in March 2010 and the progressive implementation of many provisions in that law have fundamentally altered the insurance and provider markets.⁴ One provision in

PPACA explicitly supports the development of value-based insurance design. This provision has led to the promulgation of federal regulations that have focused on eliminating cost-sharing for certain preventive services.^{a 5} The PPACA also has mandated coverage of preventive services recommended by Advisory Committee on Immunization Practices and the US Preventive Services Task Force. Due to the direct influence these national advisory bodies now have on the coverage of preventive services, others have advocated use of CEA by these bodies to inform the relative costs and benefits of their decisions.⁶ Our research suggests that the application of CEA to explicitly inform cost-sharing may allow the expansion of value-based principles beyond waivers of cost-sharing for specific “high value” services. Another important provision of PPACA is the formation of Accountable Care Organizations (ACOs) by health care providers that are accountable for the quality, cost, and overall care of Medicare beneficiaries. Under this provision, the ACOs enter into payment contracts that share both financial risk and savings for the care of beneficiaries. This shift in financial risk may cause ACOs to become more aware of the cost of health care. Further, since providers can greatly influence medications utilization behavior, ACOs may become an important lever for the introduction of value-based principles in integrated delivery system models. Finally, PPACA and the Health Information Technology for Economic and Clinical Health Act of 2009 have financially incentivized the use of electronic health records (EHR).⁷ It is possible that future iterations of VBFs could utilize patient-level information from EHRs to more accurately triangulate levels of cost-sharing with better estimates of treatment benefit. Further, the adoption of electronic health records may allow for future evaluations of VBFs that are able to assess true health outcomes. In sum, changes in the

^a A joint regulation issued by the Department of Health and Human Services, the Internal Revenue Service and the Department of Labor, regarding the elimination copayments for certain preventive services states “The Departments recognize the important role that value-based insurance design can play in promoting the use of appropriate preventive services.”

health insurance market present many opportunities and challenges for the adoption and evaluation of value-based principles in health insurance design. Policymakers and researchers should carefully assess such dynamics when considering the role of value-based insurance in health insurance markets in the future.

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PAPER 1: IMPACT OF A VALUE-BASED FORMULARY ON HEALTHCARE COSTS,
MEDICATION UTILIZATION, AND OTHER HEALTH SERVICES UTILIZATION

ABSTRACT

Context

Increases in cost sharing in prescription drug plans in the past decade may have reduced medication utilization according to cost and not value.

Objectives

To determine the impact of a novel drug benefit, the value-base formulary (VBF) that explicitly uses cost-effectiveness analysis to inform drug copayment on medication and other health services utilization and healthcare expenditures.

Design and Setting

Interrupted time-series analysis of claims data from 48 months before and 36 months after implementation of the VBF on July 2010.

Participants

Intervention group was composed of 5,235 beneficiaries aged 0-64 in an employer sponsored plan where the VBF was implemented. Control group was composed of 11,171 beneficiaries aged 0-64 in employer sponsored plans where the VBF was not implemented.

Main Outcome Measures

Medication utilization, emergency department (ED) visits, hospitalizations, and office visits. Medication and non-medication expenditures by member health plan, and overall.

Results

After the implementation of the VBF, only drugs moved into the lowest copayment tiers had a statistically significant increase in medication utilization, although there is a general trend of decreased utilization in higher copayment tiers. Other health services utilization did not statistically differ. Member medication costs increased by \$2 per member per month (PMPM) (95% confidence interval [CI], \$1, \$3), while health plan medication costs decreased by -\$10 PMPM (95% CI, -\$18, -\$2) resulting in a net decrease of -\$8 PMPM (95% CI, -\$15, -\$2). Non-medication expenditures did not statistically differ.

Conclusions

This evaluation suggests that it is possible to cost share in a way that reduces overall medication expenditures without negatively impacting the utilization of other health services or non-medication expenditures. Future studies should investigate whether the VBF would have similar impacts in other populations and ascertain the impact of the VBF on true health outcomes such as mortality and quality of life.

INTRODUCTION

Employer-sponsored health plans cover about 149 million Americans and the majority of these plans utilize copayment tiers for prescription drugs.^{1,2} In the past decade, these plans have increased both the number of higher copayment tiers and the copayment amounts within each tier in order to slow prescription expenditures.² However, increasing copayments without considering the value provided by the drugs may incentivize utilization according to cost and not value.

Some employer groups have attempted to align utilization with value by implementing value-based insurance design (VBID) plans. These plans have waived or reduced copayments for maintenance medications used to treat chronic conditions.³⁻¹⁵ Although these plans have achieved modest (1.5%-9.4%) increases in medication adherence, the impact on medication and medical costs depends on perspective. Studies have found that waiving or reducing medication copayments, is associated with lower both member medication expenditures and member non-medication expenditures and therefore lower overall member healthcare expenditures.^{5,7,15-19} However, from the health plan perspective, waiving or reducing copayments increases medication expenditures and is only sometimes associated with lower medical expenditures, resulting in either no change or increased overall health plan expenditures. Combining expenditures from both perspectives, VBID policies were associated with increased medication expenditures, while medical expenditures and overall healthcare expenditures did not change.

These results suggest that there may be some limitations to current VBID plans. One limitation is that these plans have only lowered copayments for high value drugs and have never increased copayments for low value drugs. It has been suggested that in order for VBIDs to be financially sustainable and accessible to a wider patient population, copayment decreases for

high value medications may need to be paired with copayment increases for low value medications.^{20,21} Furthermore, current VBIDs have uniformly reduced copayments for drugs within a therapeutic area despite the fact that not all medications within a therapeutic area have the same value. Aligning each individual medication's copayment to reflect its value may incentivize use of higher value medications.

In 2010, Premera Blue Cross, a large non-profit health plan in the Pacific Northwest implemented a value based formulary (VBF) benefit among their own employees and dependents that explicitly uses cost-effectiveness analysis (CEA) to determine drug copayments. The design and implementation of the VBF has been described in detail elsewhere.²² Briefly, Premera pharmacists trained in economic evaluation gather available CEA estimates and when necessary, produce *de novo* estimates. An external panel of clinical, economic and bioethical experts and lay members uses the incremental cost-effectiveness ratio (ICER) estimates along with information on additional social or ethical values to assign the drug to the appropriate copayment tier. Drugs with high ICERs are placed on high copayment tiers to disincentivize use and drugs with low ICERs are placed on low copayment tiers to incentivize use. On the policy implementation date of July 2010, the 25 highest volume drug classes used by Premera members in the previous year (representing approximately three-fourths of the total drug utilization within the plan) had been assigned to their VBF tiers. The remainder of the drugs were kept in the pre-policy tiers (but with the copayment levels of the post-policy tiers). These drugs, along with new drugs that have gained regulatory marketing approval were assigned to their VBF copayment tiers in ongoing quarterly reviews.

Although promising, the impact of the VBF policy as implemented by Premera is unknown beyond the first year impact on medication costs from the health plan's previously reported.²²

First, it is unclear whether the available CEA evidence was sufficient to appropriately determine the value of drugs. Second, it is also unclear whether the process for assignment of the drugs to their corresponding copayment tiers appropriately reflects their value. Third, whereas copayment tiers are based on average cost-effectiveness estimates for a drug, actual cost-effectiveness is patient-specific due to heterogeneous treatment effects.^{23,24} Finally, even if the VBF achieves its intended effect of shifting medication utilization towards higher value medications, total healthcare costs may still rise if the increased use is for medications that are higher value, but are not cost-saving. To understand the impact of a VBF on healthcare utilization and healthcare costs, we exploit the natural experiment arising from the implementation of the VBF in the Premera cohort. Our analyses investigate the impact of the VBF on medication and health services utilization and the impact of the VBF on medication and non-medication costs from member, plan and overall perspectives.

METHODS

Sample, Data Source and Measurements

The initial sample was composed of the entire population of employees and dependents aged 0-64 who were covered under Preferred Provider Organization employer sponsored plans administrated by Premera Blue Cross, the largest private health plan in Washington State. The sample was restricted to include only individuals continuously enrolled at least 1 year prior to VBF implementation. The intervention group was composed of employees and dependents of Premera who were exposed to the VBID formulary on July 2010. The control group was composed of employees and dependents of 5 employer sponsored plans administrated by Premera where the VBF was not implemented and chosen based on similarity to the intervention

group in industry classification and member geography of residence and without any changes in pharmacy benefits over the entire study period.

For each member in our sample, we obtained monthly measures on demographics (age, sex, ZIP code of residence, relationship to employee), prescriptions fills (National Drug Code, hierarchical ingredient code, therapeutic class, brand-generic status, number of days' supply, date dispensed, place of purchase (retail or mail order pharmacy)), non-medication services (date of service, place of service, length of hospitalization, procedure, diagnosis, and revenue codes), expenditures (amount paid out of pocket, amount paid by employer), and plan characteristics (benefit renewal month, medical benefit relativity value and industry classification).

We used data on individual's ZIP code of residence to link to zip code level demographics using the 2009-2013 American Community Surveys and 2010 US Census, including information on median household income, proportion of urban residents, proportion of African American persons, proportion with bachelor's degree.^{25,26}

Outcomes

We first assessed overall average monthly drug utilization per member, as measured by the probability of filling any drug and the total days' supply of drug. We next assessed health services utilization per member per month, as measured by the probability of incurring emergency department (ED) visits, the number of ED visits, the probability of hospitalization, the number of days spent hospitalized, and the probability of incurring office visits and the number of visits. We finally assessed member, health plan, and overall medication and non-medication costs per member per month. Based on our sample size, we will have 80% power to detect a 2.5% change in overall medication costs at $p = 0.05$.

We conducted secondary analyses in which we assessed drug utilization based on 2 categorization methods: 1) whether the VBF moved a drug into a lower copayment tier, higher copayment tier, or no change in tier and 2) whether the VBF moved a drug into the preventive tier or into tiers 1-4. As a falsification test, we assessed the costs for vision services (a category of costs which is unlikely to be impacted by the VBF policy) from the overall perspective.

Time Frame and Intervention

We divided our analysis into 3 periods, 3 years before to 1 year before VBF implementation (early pre-VBF period: July 2006 to June 2009), 1 year before VBF implementation (late pre-VBF period: July 2009 to June 2010) and immediately after VBF implementation to 3 years after (post-VBF period: July 2010 to June 2013). In July 2009 (early pre-VBF period), the intervention group had an increase of \$5 in pharmacy copayment in 2 copayment tiers, an increase in the medical deductible from \$400 to \$500, an increase of \$25 in the emergency department copayment and an increase in the out of pocket maximum by \$200. The pharmacy benefits in the early pre-VBF, late pre-VBF, and post-VBF periods for the intervention group are described in detail in Table 1. In contrast, there were no changes in the pharmacy benefits for the control group over the entire period. We control for all benefit changes other than the implementation of the VBF policy in our statistical analyses as described below.

Analytic and Estimation Techniques

Since we aimed to estimate the effect of the VBF, we sought to compare the observed healthcare costs and utilization among VBF members with the expected (counterfactual) outcomes for the same group of VBF members had VBF not been implemented. We obtained the counterfactual estimate by using the contemporaneous observed outcomes in the 5 control plans

that were not exposed to the VBF in our regression models, after adjusting for the covariate distributions in both the groups. We confirmed the similarity of the control group to the intervention group by examining both the statistical significance and magnitude of the coefficients in our regression models that represented the differential trends in the groups prior to VBF implementation.

We estimated trends and generated predictions by using generalized estimating equations (GEEs). We adjusted for: individual-level characteristics (sex, age, total healthcare expenditure greater than \$100,000 in any 12 month period in the pre-VBF period), ZIP code-level characteristics (bachelor's degree, household income, urban residence, African American race, Washington state residence), plan-level characteristics (medical benefits relativity value, benefit renewal month), fixed effects for calendar months (January to December), and study period (early pre-VBF period, late pre-VBF period and post-VBF periods).²⁷

For medication and other health services utilization, we used two-part models with binomial distribution with logit link to model probabilities and poisson distribution with log link to model counts. For medication and non-medication costs, we used binomial distribution and logit link to model the probability of incurring costs and gamma distribution with log link to model costs among those who have incurred costs. We modeled correlations between monthly observations within members using a first-order autoregressive correlation structure for probabilities and using robust estimators for all other models.²⁸ The results were generally robust to correlational assumptions. We assessed overall model fit by using a variety of goodness-of-fit criteria. We validated the sample data extraction coding, data management, data definitions and analytic coding by multiple independent peer review by Premera subject matter experts as well as by the

authors. Further details regarding the validation process are described in appendix A1. This study was approved by the institutional review board at University of Washington.

RESULTS

Population Characteristics

The intervention group and control group totaled 5,235 and 11,171 members respectively. The two groups were similar in demographic and socioeconomic characteristics in the pre-policy period although many differences are statistically significant, principally due to sample size (Table 2). As specified *a priori*, we control for various demographic and socioeconomic characteristics. Rates of enrollment or attrition (results not shown) did not differ between VBF and control groups in the pre- and post- policy periods.

Changes in Utilization and Expenditures after Accounting for Secular Trends

The VBF policy had no statistically significant overall impact on medication utilization. However, secondary analyses revealed that the VBF generally shifted medication utilization as expected based on copayment. Medications subject to lower copayment had increased utilization and medications subject to higher copayments had decreased utilization, although not all measures were statistically significant. We found that only the drugs that were moved into lower tiers had a statistically significant change in utilization (Table 3b). These drugs had a 0.02 PMPM (11%, $P < 0.001$) increase in the probability of fill and a 1.95 day PMPM (17%, $P < 0.001$) increase in days' supply. Only drugs that were moved into the preventive tier had a statistically significant change in utilization. These drugs had a 0.02 PMPM (11%, $P < 0.001$) increase in the probability of fill and 1.68 day PMPM (16%, $P < 0.001$) increase in days' supply (Table 3c).

The policy effect on health services utilization was generally small. We find no statistically significant changes in probability or quantity of use for ED visits, hospitalization or office visits (Table 4).

Expenditures in the pre-policy period in the intervention group did not differ statistically in both level and trend from the expenditures in the control group (Figures 1a-c). In the post-policy period, medication and total expenditures in the intervention group seemed to have a decrease in level and trend whereas there was no apparent change in the level or trend of expenditures in the control group. Figures 1a-c also compares the observed (factual) expenditures in the intervention group with the expected counterfactual expenditures in the intervention group had the VBF policy not been implemented, as estimated using GEE.

Member medication expenditures increased significantly by \$2 PMPM ($P = 0.004$) while health plan and total medication expenditures decreased significantly by -\$10 PMPM ($P = 0.018$) and -\$8 PMPM ($P = 0.013$) respectively. Member non-medication expenditures decreased non-significantly by \$3 PMPM ($P = 0.204$). Health plan expenditures increased non-significantly by \$2 PMPM ($P = 0.911$) while total non-medication expenditures decreased non-significantly by -\$1 PMPM ($P = 0.945$). Overall total medication and non-medication expenditures decreased non-significantly by -\$9 PMPM ($P = 0.632$). There was no change in overall vision expenditures.

COMMENT

Efforts to implement VBID policies have been hindered by an inability to assess the value of individual medications and to adjust copayments based on the individual value estimates. Hence, previous VBID policies have been limited to reducing copayments for specific drug categories.³⁻

¹⁵ Consequently, empirical evaluations of VBID policies alone have found that overall healthcare

spending does not change and may actually increase from the health plan perspective.¹⁵⁻¹⁹ This study presents an evaluation of the impact of a VBF policy that explicitly used cost-effectiveness evidence to inform formulary copayment tiers.^{20,22} We found that the VBF shifted member medication utilization towards drugs placed in lower copayment tiers. Although the other findings on medication utilization were not statistically significant, we note a trend towards decrease in utilization with increases in copayment tier, consistent with expectation. Health plan medication costs in the intervention group also decreased over a three year post-policy time frame. These results are consistent with our preliminary first-year findings that indicated health plan medication savings.²² This study adds a more complete analysis by including member and overall cost perspectives, non-medication costs, longer duration of follow up, and measures of medication and other healthcare utilization. The additional medication cost perspectives indicated that some costs were shifted from the health plan to the member; however there was a net savings in overall medication expenditures.

The larger literature of the impact of the cost sharing for prescription drugs on the use of other health services is mixed. Studies assessing the impact of increases in cost sharing for prescription drugs for a broad population of insured members find no impact on utilization of health services such as office visits, ED visits, hospitalizations.²⁹⁻³² Other studies, focusing on the chronically ill found that increased prescription drug cost sharing is associated with an increase use of other health services.³²⁻³⁵ Conversely, decreasing cost-sharing for the chronically ill is associated with decrease use of other health services.^{17,19,36,37} As an intervention that attempts to align utilization with estimated value by both increases and decreases in copayments, it is important to assess the impact of the VBF on health outcomes. Our findings on the impact of

the VBF on health services utilization no significant impact on the utilization of services in the ED, hospital or physician office settings.

This study has several limitations. First, our sample was drawn from a working-age population and their dependents and thus our results are not necessarily generalizable to other populations such as the poor or the elderly. Second, the intervention group was composed of employees of a health insurance and their dependents. Hence, although we observed similar pre-policy outcome trends in the VBF and control groups, our estimates of counterfactual trends may be biased if some unobserved confounder affects these trends differentially during the post-policy period. However, a secondary analysis restricting the control group to the one plan that was composed of employees and dependents of an actuarial firm revealed similar results. Furthermore, after controlling for pharmacy and medical benefits, measureable demographic and socioeconomic factors, there is no likely confounder that could account for the marked changes in the post-policy period, particularly in medication costs. We also assume that the absence of a claim for an individual represents no healthcare utilization and no costs rather than the use of an alternative method of payment. A secondary analysis including amounts paid by other health plans (coordination of benefits) when Premera was the secondary insurance revealed similar results. Nevertheless, our results may still underestimate true total healthcare costs incurred particularly when Premera is the primary insurance and members have an additional insurance. Finally, although we find no negative changes in health services utilization, we do not know the impact of the VBF on actual health outcomes. Few studies assessing the impact of health insurance include direct measures of health outcomes. Yet this is an important aspect of understanding the true impact of the health policy changes.^{38,39}

The rise of cost sharing in prescription drug plans has shifted a larger proportion of costs onto plan members. VBID has largely resulted in shifting costs back to the health plan. This evaluation of a novel VBF suggests that it is possible to shift costs in a way that reduces overall medication costs without negatively impacting the utilization of other health services or non-medication costs. Future studies should investigate whether the VBF would have similar impact in other populations and ascertain the impact of the VBF on true health outcomes such as mortality and quality of life.

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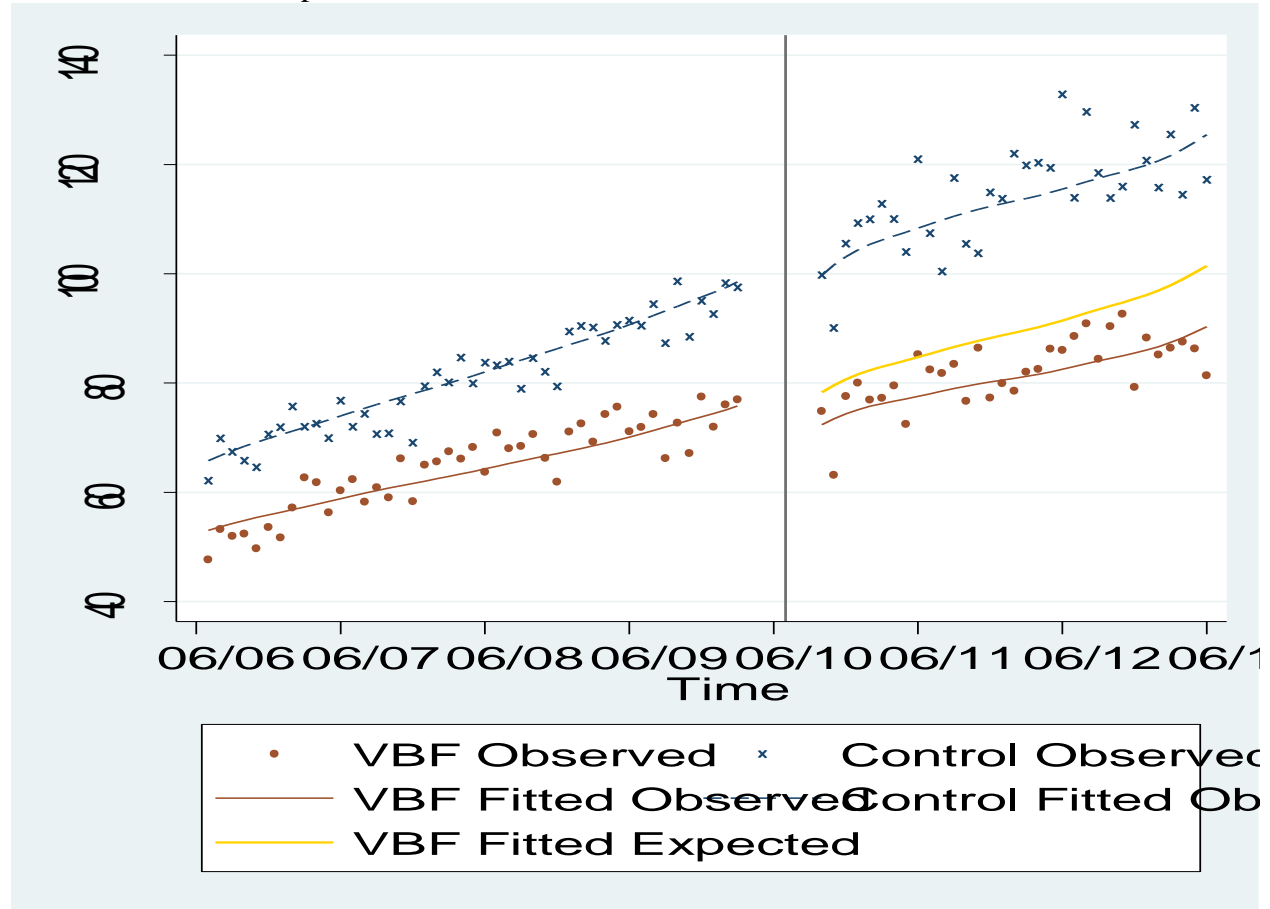
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FIGURES AND TABLES

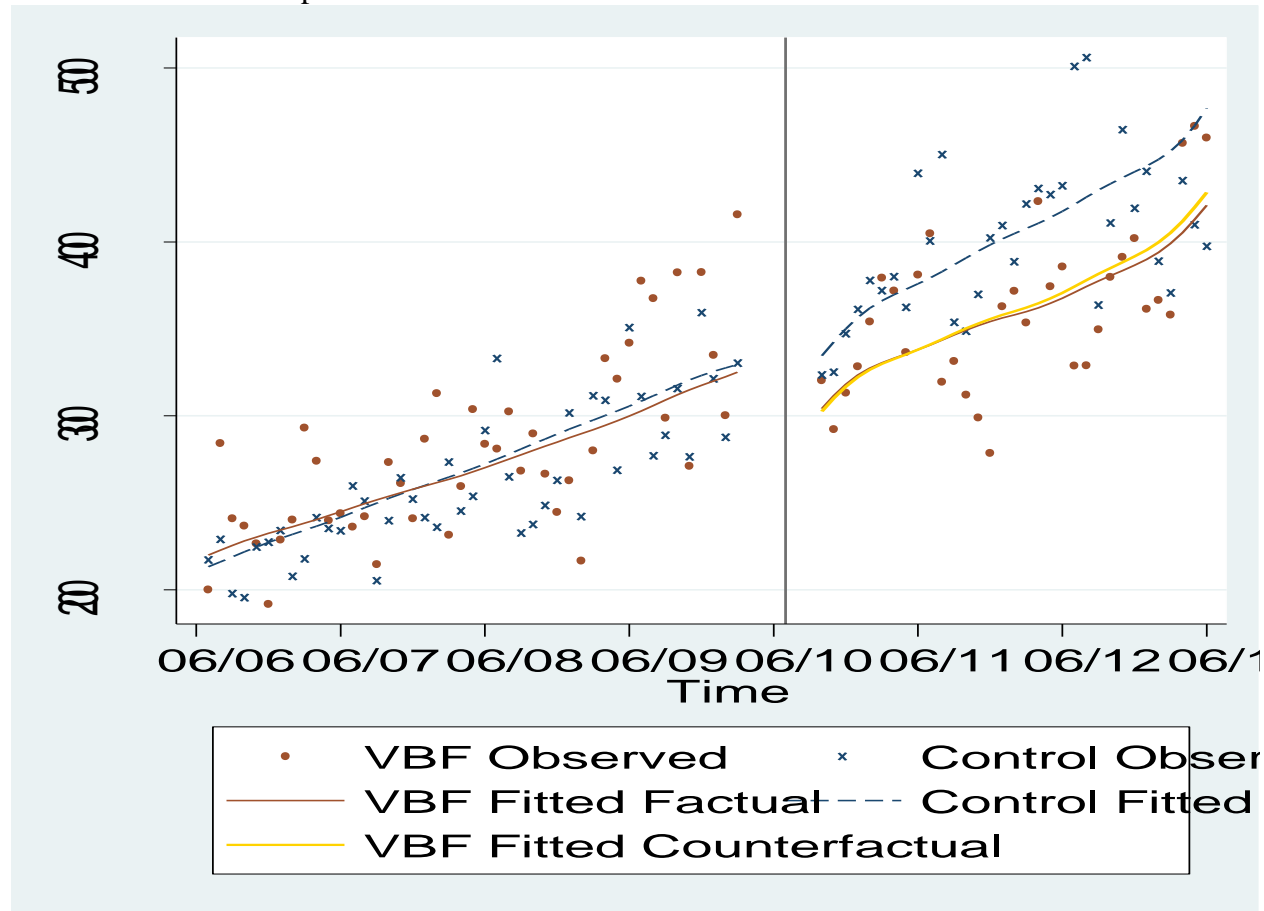
Figure 1a. Observed, Fitted Factual and Fitted Counterfactual Medication Expenditures Per Member Per Month (PMPM) in VBF and Control Groups Combining Expenditures from Member and Plan Perspectives



Factual: predicted expenditure trends if the VBF had been implemented

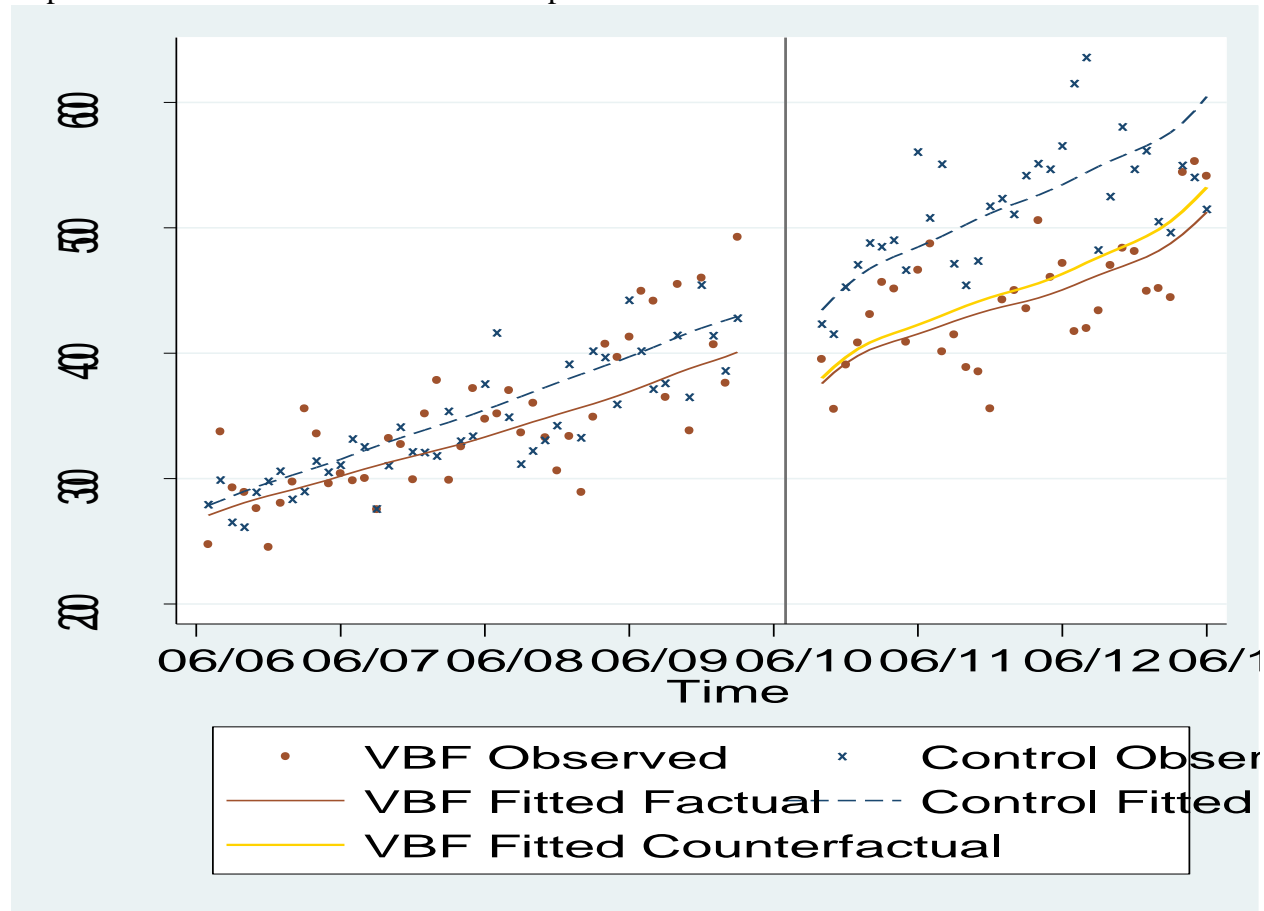
Counterfactual: predicted expenditure trend if the VBF had not been implemented

Figure 1b. Observed, Fitted Factual and Fitted Counterfactual Non-Medication Expenditures Per Member Per Month (PMPM) in VBF and Control Groups Combining Expenditures from Member and Plan Perspectives



Factual: predicted expenditure trends if the VBF had been implemented
 Counterfactual: predicted expenditure trend if the VBF had not been implemented

Figure 1c. Observed, Fitted Factual and Fitted Counterfactual Total Expenditures (Medication and Non-medication) Per Member Per Month (PMPM) in VBF and Control Groups Combining Expenditures from Member and Plan Perspectives



Factual: predicted expenditure trends if the VBF had been implemented

Counterfactual: predicted expenditure trend if the VBF had not been implemented

Table 1. Pharmacy benefits in the early pre-Value based formulary (VBF), late pre-VBF, and post-VBF periods for the intervention group

Tier	Early Pre-VBF Copayment	Late Pre-VBF Copayment	Post-VBF Copayment
Preventive	—	—	\$0
Tier 1	\$10	\$10	\$20
Tier 2	\$25	\$30	\$40
Tier 3	\$45	\$50	\$65
Tier 4	—	—	\$100

Table 2. Sample Characteristics for Intervention and Control Members prior to Value-based formulary (VBF) implementation

Characteristic	VBF Members (n = 5,235)	Control Members (n = 11,171)	P Value
Individual characteristics			
Age, yrs, n (SD)	31.6 (17.5)	35.8 (18.5)	<0.001
Charlson score=0, N (%)	4,422 (84.5)	9325 (83.5)	0.084
Charlson score=1 , N (%)	582 (11.1)	1266 (11.3)	0.084
Charlson score \geq 2, N (%)	231 (4.4)	580 (5.2)	0.084
Enrollees per family unit, n (SD)	3.13 (1.5)	2.85 (1.6)	<0.001
Female, N (%)	2,960 (56.5)	6,378 (57.1)	0.099
ZIP code characteristics			
African American, % (SD)	2.9 (3.5)	4.0 (6.1)	<0.001
Bachelor's degree or higher, % (SD)	34 (13.6)	40.8 (17.7)	<0.001
Median household income, \$1000 % (SD)	68.9 (18.5)	65.1 (20.7)	<0.001
Urban residence, % (SD)	91.7 (17.0)	89.8 (21.7)	<0.001
Washington state residence, N (%)	4,638 (88.6)	9,533 (85.3)	<0.001
Utilization Characteristics per month			
Number of prescription users, N (%)	1,785 (34.1)	4,289 (38.4)	<0.001
Number of prescriptions per member, n (SD)	0.83 (1.36)	0.92 (1.34)	<0.001
Number of emergency department visits per member, n (SD)	0.02 (0.04)	0.02 (0.03)	0.260
Number of office visits per member, n (SD)	0.27 (0.31)	0.26 (0.27)	0.062
Number of days in hospital, n (SD)	0.03 (0.14)	0.02 (0.10)	0.003

Table 3a. Overall impact of the Value-Based Formulary on the probability of filling a drug and the days' supply of drug per member per month

Tier Movement	Factual Estimate	Counterfactual Estimate	Absolute Change	P Value
Probability of fill (95% C.I.)	0.38 (0.36, 0.39)	0.37 (0.35, 0.38)	0.01 (0.00, 0.02)	0.153
Days' supply (95% C.I.)	30.34 (28.83, 31.86)	29.47 (27.78, 31.16)	0.87 (-0.43, 2.17)	0.186

Table 3b. Impact of the Value-Based Formulary on the probability of filling a drug and the days' supply of drug per member per month for drugs moved into higher copayment tiers, lower copayment tiers or no change in copayment tiers

Tier Movement	Factual Estimate	Counterfactual Estimate	Absolute Change	P Value
No Change in Tier				
Probability of fill (95% C.I.)	0.29 (0.28, 0.30)	0.29 (0.28, 0.30)	0.00 (-0.01, 0.01)	0.683
Days' supply (95% C.I.)	15.77 (14.90, 16.65)	16.01 (15.00, 17.02)	-0.24 (-1.04, 0.57)	0.555
Placed in lower Tier				
Probability of fill (95% C.I.)	0.18 (0.17, 0.19)	0.16 (0.15, 0.17)	0.02 (0.01, 0.03)	<0.001
Days' supply (95% C.I.)	11.69 (10.91, 12.48)	9.74 (8.98, 10.50)	1.95 (1.29, 2.62)	<0.001
Placed in higher Tier				
Probability of fill (95% C.I.)	0.02 (0.02, 0.03)	0.03 (0.02, 0.03)	0.00 (-0.01, 0.00)	0.142
Days' supply (95% C.I.)	0.93 (0.79, 1.08)	1.12 (0.91, 1.32)	-0.18 (-0.37, 0.01)	0.058

Table 3c. Impact of the Value-Based Formulary (VBF) on the probability of filling a drug and the days' supply of drug per member per month for drugs moved into the preventive tier or tiers 0 through 4

VBF Tier Placement	Factual Estimate	Counterfactual Estimate	Absolute Change	P Value
Preventive Tier				
Probability of fill (95% C.I.)	0.16 (0.15, 0.17)	0.15 (0.13, 0.16)	0.02 (0.01, 0.03)	<0.001
Days' supply (95% C.I.)	10.36 (9.63, 11.1)	8.68 (7.95, 9.41)	1.68 (1.05, 2.32)	<0.001
Tier 1				
Probability of fill (95% C.I.)	0.27 (0.26, 0.28)	0.27 (0.26, 0.29)	0.00 (-0.01, 0.01)	0.906
Days' supply (95% C.I.)	13.62 (12.83, 14.41)	13.99 (13.07, 14.92)	-0.37 (-1.15, 0.40)	0.338
Tier 2				
Probability of fill (95% C.I.)	0.06 (0.05, 0.06)	0.06 (0.06, 0.07)	0.00 (-0.01, 0.00)	0.404
Days' supply (95% C.I.)	2.58 (2.34, 2.83)	2.66 (2.36, 2.96)	-0.08 (-0.32, 0.17)	0.534
Tier 3				
Probability of fill (95% C.I.)	0.04 (0.03, 0.04)	0.04 (0.03, 0.04)	0.00 (-0.01, 0.00)	0.182
Days' supply (95% C.I.)	1.37 (1.2, 1.54)	1.48 (1.27, 1.69)	-0.11 (-0.31, 0.09)	0.273
Tier 4				
Probability of fill (95% C.I.)	0.01 (0.01, 0.01)	0.01 (0.01, 0.02)	0.00 (-0.01, 0.00)	0.086
Days' supply (95% C.I.)	0.39 (0.29, 0.49)	0.5 (0.38, 0.63)	-0.12 (-0.23, 0.00)	0.051

Table 4. Impact of the Value-based Formulary on Health Services Utilization per member per month

Outcome	Factual Estimate	Counterfactual Estimate	Absolute Change	P Value
Probability of ED Visits, p	0.01 (0.01, 0.02)	0.01 (0.01, 0.01)	0.00 (0.00, 0.00)	0.283
Number of ED Visits, n	0.02 (0.01, 0.02)	0.01 (0.01, 0.02)	0.00 (0.00, 0.00)	0.329
Probability of hospitalization, p	0.00 (0.00, 0.01)	0.00 (0.00, 0.01)	0.00 (0.00, 0.00)	0.791
Days in hospital, days	0.03 (0.02, 0.04)	0.03 (0.01, 0.04)	0.00 (-0.01, 0.02)	0.641
Probability of Office Visit, p	0.22 (0.21, 0.23)	0.21 (0.20, 0.23)	0.00 (-0.01, 0.02)	0.361
Number of Office Visits, n	0.30 (0.29, 0.31)	0.30 (0.28, 0.32)	0.00 (-0.02, 0.02)	0.757

Table 5. Impact of the Value-based Formulary on medication and non-medication expenditures per member per month

(US \$)	Factual Estimate	Counterfactual Estimate	Absolute Change	P Value
Medication Costs				
Member (95% C.I.)	17 (16, 18)	15 (14, 16)	2 (1, 3)	0.004
Health Plan (95% C.I.)	64 (56, 72)	74 (63, 84)	-10 (-18, -2)	0.018
Total (95% C.I.)	80 (72, 89)	89 (79, 99)	-8 (-15, -2)	0.013
Non-Medication Costs				
Member (95% C.I.)	61 (60, 64)	64 (60, 68)	-3 (-6, 1)	0.204
Health Plan (95% C.I.)	293 (267, 320)	292 (257, 327)	2 (-35, 38)	0.911
Total (95% C.I.)	355 (327, 383)	356 (318, 393)	-1 (-39, 38)	0.945
Grand Total	436 (406, 465)	445 (406, 483)	-9 (-49, 30)	0.632

APPENDIX A1. Detailed Description of Data Validation Process

1. Data extraction code was applied correctly: Independent peer review by 2 Premera supervisory analysts
2. Data management code and data analysis code were applied correctly: Independent peer review by 2 economists
3. No changes in pharmacy and medical benefit as indicated by claims-based variable descriptions (including no changes in pharmacy and medical prior authorization process and criteria): Review by team of Premera underwriters who specifically underwrite the plans used in this analysis
4. Group choices, inclusion/exclusion criteria and variable definitions were applied correctly: Independent peer review by 3 different Premera analysts in 3 different departments.
5. A small number of influential observations did not drive the majority of the result: Cook's distance statistic using different thresholds of influence (statistic greater than 1, statistic greater than $4/n$ where n is the number of members in the sample, and statistic greater than $4/n$ where n is the number of members-months in the sample) revealed that the impact of the VBF on overall medical costs were not driven by a small number of influential points.

PAPER 2: THE IMPACT OF COST-SHARING ON MEDICATION UTILIZATION IN A
VALUE-BASED FORMULARY: EMPIRICAL ESTIMATES OF PRICE ELASTICITY OF
DEMAND

ABSTRACT

In 2010, a large employer-sponsored health insurance plan reconfigured their pharmacy benefit design explicitly using cost-effectiveness analysis (CEA) to inform medication copayment tiers. We exploit this exogenous change in pharmaceutical cost sharing to estimate the price elasticity of demand for pharmaceuticals, overall, by therapeutic class, by brand-generic status, and by copayment tiers informed by CEA. Our overall elasticity estimate was -0.14 for the probability of filling a medication and -0.06 for the days' supply of medications. Our elasticity estimates for HMG-CoA Reductase Inhibitors, Angiotensin-Converting-Enzyme Inhibitors, and Proton Pump Inhibitors were -0.29, -0.02, and -0.20 respectively for the probability of fill, and -0.26, -0.04, and -0.29 respectively for days' supply of medication. Our elasticity estimates for single-source brand drugs and generic drugs were -0.24 and -0.09 respectively for the probability of fill, and -0.26 and 0.03 respectively for days' supply of medications. These estimates are generally similar to elasticity estimates from previous studies. Finally, our elasticity estimates for copayment tiers informed by CEA for the probability of fill and days' supply of medication respectively were -0.07 and -0.06 for the preventive tier, -0.09 and 0.08 for tier 1, -0.26 and -0.26 for tier 2, -0.27 and -0.32 for tier 3, and -0.45 and -0.55 for tier 4. Thus, we observed a general trend of increasing elasticity with increasing copayment tiers. These results suggest that a cost sharing strategy based on elasticity estimates may be similar to a cost sharing strategy informed by CEA.

INTRODUCTION

The standard economic model for health insurance dictates that optimal insurance accounting for moral hazard should set cost-sharing levels proportional to the price elasticity of demand; all things being equal, treatments that are more price elastic ought to have a higher level of cost-sharing.¹ Yet, many have observed that when faced with cost-sharing, patients may underuse beneficial treatments due to underestimation of the marginal benefit of treatment.²⁻⁴ Based on these observations, other researchers have argued that optimal insurance should take into account both welfare loss due to moral hazard and welfare loss due to incorrect estimation of marginal benefit. We previously demonstrated that a cost-sharing strategy informed by population average cost-effectiveness can reduce medication costs without negative impact on non-medication costs or health outcomes (paper 1). Yet it is unknown whether a CEA-driven cost-sharing strategy would be similar to a strategy based on elasticity estimates. In a market where consumers have full information on the marginal benefits of treatment, the two strategies would set cost-sharing in the same way.⁵ However, if consumers have imperfect information about the marginal benefits of treatment, the strategies may differ in cost-sharing levels.

In order to investigate optimal insurance design, we exploit an exogenous change in pharmacy benefit in a Preferred Provider Organization employer-sponsored plan in the Pacific Northwest that, in 2010, implemented a value based formulary (VBF) benefit among their own employees and dependents that explicitly used cost-effectiveness analysis (CEA) to determine medication copayments. Specifically, we assess the price elasticity of demand for pharmaceuticals, overall, by therapeutic class, by brand-generic status, and finally by copayment tiers informed by CEA.

This paper is organized as follows. Section 2 presents a brief literature review, and Section 3 describes the institutional setting of the pharmacy benefit change and the sample dataset. Section 4 describes the econometric approach and Section 5 presents the results. Section 6 outlines robustness checks for our findings, and the paper concludes with a discussion of our findings and policy implications in Section 7.

LITERATURE REVIEW

Overall price responsiveness for pharmaceuticals

The RAND Health Insurance Experiment (HIE), conducted from 1974 to 1981, is the only randomized study to produce estimates for own-price elasticities of demand for pharmaceuticals.^{6,7} The results of the HIE are still held as a standard by which other studies are compared. This study, which randomized 5,809 non-elderly individuals to four different levels of coinsurance and three levels of maximum out of pocket expenditures, found an overall elasticity estimate for pharmaceuticals of -0.17, which means that a 10% increase in cost-sharing results in a 1.7% reduction in utilization of pharmaceuticals.

Observational studies have produced overall elasticity of demand estimates ranging from -0.04 to -0.60.⁸⁻¹² These studies have generally exploited an exogenous change in price due to a change in pharmacy benefit structure. A potential concern with observational studies is that cost-sharing may be endogenous in a model of pharmaceutical demand, particularly in cases where there are non-linear price schedules as a result of deductibles, out of pocket maximums, and benefit caps.¹³ Indeed, studies using instrumental variable methods to correct for the endogeneity of price found elasticity estimates between -0.12 to -0.16.^{4,9} Additional discounts offered for mail order or in-network pharmacies further complicate the prediction of the marginal copayment

faced by a member even when the pharmacy benefit structure is known. Most studies estimating elasticity of demand calculate an index of plan generosity based on the mean observed cost-sharing amount usually weighed by a measure of utilization.^{11,14-19} This is done for each plan and for each unit of time. A concern acknowledged by some authors is that the price index represents the *average* price paid for a medication rather than the *marginal* price faced by each person.¹⁴ Hence the elasticities of demand estimates for these studies are for average changes in price, which may differ from marginal changes in price.

Relationship between price responsiveness and treatment effectiveness

The RAND HIE produced a surprising finding: individuals subject to greater cost-sharing reduced their use of ineffective medical care by about as much as they reduced their use of effective care.^{7,20-22} The HIE researchers classified diagnostic conditions listed on medical claims forms based on whether there were any effective medical treatments for the condition. They found that when faced with cost sharing, individuals were just as likely to reduce medical care for conditions in which there were effective treatments as medical care for conditions in which there were no effective treatments. Further, the researchers found that for antibiotics, cost-sharing reduced antibiotic use for viral conditions (conditions where there were no strong indications for use) just as much as it reduced antibiotic use for bacterial conditions.

Regarding price responsiveness by medication effectiveness for other conditions, some observational studies suggest an ability to distinguish between effective treatments while others do not. Tamblyn *et al* found that the introduction of a prescription coinsurance and deductible cost-sharing policy in Quebec reduced the use of essential medications by 9.12% and 14.42% and non-essential medications by 15.14% and 22.39% for elderly and welfare recipients,

respectively.²³ Further, investigators of a study comparing price responsiveness among individuals receiving treatment for a specific condition (antidepressants, antihypertensives, antihyperlipidemics, antiulcerants, and antiasthmatics) found that they reduced their use of disease-specific medications less than to those not receiving treatment for the condition.²⁴ The investigators also found differences in overall elasticity estimates by therapeutic class, for example the elasticity of demand for antihypertensives (-0.26) was less than for antihyperlipidemics (-0.34) or antiulcerants (-0.33). Similarly, authors of another study found that the elasticity of demand for medications used to treat asymptomatic conditions was lower (-0.16 to -0.10) than for medications used to treat symptomatic conditions (-0.60 to -0.24).¹⁵ If marginal benefit differs by therapeutic class or by symptoms, then this evidence would also be suggestive of an ability to discriminate between treatments.

In contrast, other studies found similar decreases in utilization regardless of potential benefit. A study assessed utilization changes due to a shift from a two tier formulary structure to a three tier formulary structure and an increase in copayments for branded medications among retired public employees in California.¹⁴ This study found that medications used for acute conditions, chronic conditions, and medications used solely for symptomatic relief all were subject to substantial utilization reduction. Another study modeled the change in percent of individuals fully compliant to cholesterol lowering medications due to a doubling of copayment (from \$10 to \$20). This study found similar decreases in utilization for individuals classified as low, medium and high risk of coronary heart disease.²⁵

These empirical findings suggest that patients do discriminate between treatments. However, it is unclear whether such discrimination is based on optimal information regarding marginal benefit. Here we use CEA, a commonly used extra-welfarist metric for assessing the value of

interventions in healthcare to assess explicitly whether elasticities differ by cost-effectiveness.²⁶⁻

²⁸ Specifically, we exploit an exogenous change in pharmacy benefit in a single plan that implemented a VBF to assess the price elasticity of demand for pharmaceuticals, overall, by therapeutic class, by brand-generic status, by VBF copayment tier, and finally by pairs of medications that were in the same pre-policy tier but one set of medications changed tiers in the post-policy period.

INSTITUTIONAL SETTING AND DATA

In 2010, Premera Blue Cross, a large non-profit health plan in the Pacific Northwest implemented a VBF benefit among their own employees and dependents which explicitly used CEA to inform medication copayments. The design and implementation of the VBF has been described in detail elsewhere.²⁹ Briefly, Premera pharmacists who are trained in economic evaluation gather available CEA estimates and, when necessary, produce *de novo* estimates. An external panel of clinical, economic, and public experts uses the ICER estimates along with information on additional social or ethical values to assign the medication to the appropriate copayment tier. Medications with high ICERs are placed on high copayment tiers to disincentivize use and medications with low ICERs are placed on low copayment tiers to incentivize use. Table 1 shows the pharmacy benefits in the pre-policy and post-policy periods.

We obtained de-identified enrollment and claims data for the entire population of Premera employees and dependents aged 0-64 who were covered under a Preferred Provider Organization employer-sponsored plan 1 year before and after the date of policy change on July 1st 2010. We excluded 19,151 (14%) member-months (2,311 members) from our sample by requiring individuals in the sample to be continuously enrolled in the year prior to policy change. After

making these adjustments, our sample includes 116,886 member-months (5,235 members) of observation.

For each member in our sample, we obtained monthly measures on demographics (age, sex, ZIP code of residence, relationship to employee), and prescription fills (National Drug Code, hierarchical ingredient code, therapeutic class, brand-generic status, number of days' supply, date dispensed, place of purchase (retail or mail order pharmacy)). We used data on individual's ZIP code of residence to link to ZIP code level measures from the 2009-2013 American Community Surveys and 2010 US Census, including information on median household income, proportion of urban residents, proportion of African-American persons, and proportion of individuals with bachelor's degree.^{30,31}

Table 2 shows the characteristics of the Premera group before and after policy implementation. The cohort was highly similar in demographic and socioeconomic characteristics before and after policy implementation, although age was statistically significant since one year had elapsed in the post-policy period. As specified *a priori*, we control for various demographic and socioeconomic characteristics.

Our focus on a single health plan that had a pharmacy benefit structure consisting of fixed dollar copays with no deductibles, co-insurance provisions, maximum expenditure limits and no coverage for out-of-network pharmacies results in a linear price schedule for cost-sharing. This means that prices are not endogenous (a function of medication consumption) and allow for a medication level analysis. In accordance with a medication level analysis, every member in every month faced the choice of filling every medication. Medications were defined by unique combinations of active ingredient (hierarchical ingredient code), dosage form and brand-generic

status. This is the basic unit by which VBF copayment tiers are assigned, and therefore copayments are homogenous within a unique combination at a given time (after taking into account mail order status). Since the tier assignments were unobserved, we included only those medications that were filled in every month of observation in order to infer a copayment tier for these medications. This limited our analysis to 284 medications, which accounted for 79.3% of the prescription medication volume over the period of observation.

EMPIRICAL APPROACH

Copayment amount

Our primary explanatory variable was the copayment amount for each medication faced by a member in a given month. We infer these medication-specific copayments for each month by calculating the mean copayment observed for retail and mail claims separately. Mail order copayment amounts are 2.5 times the copayment amount for a retail claim but provide three times the quantity of medication. We calculate the weighted mean retail-mail copayment by multiplying the mean retail and mail copayments with the proportion of retail and mail claims during the pre-policy year.

Econometric estimation

We modeled the probability of filling a medication as well as the days' supply of the medication using a two-part model. For the first part, we used probit regression to estimate the probability of fill (Eq. 1). For the second part, we used a generalized linear model with a logarithmic link function and a poisson distribution to estimate the number of days' supply, given a fill. We combined the first and second part regressions to obtain an overall estimate of

the effect of copayment changes on days' supply of medication (Eq. 2). The two-part model has the following specification:

$$\text{probit}[\text{filled}_{idt} | \text{time}_{idt}, \text{copayment}_{idt}, \text{rx}_{idt}, \text{covariates}_{idt}] = \beta_0 + \beta_1 \text{copayment}_{idt} + \beta_2 \text{rx}_d + \beta_3 \text{copayment}_{idt} * \text{rx}_d + \alpha_n \text{covariates}_{nidt} + \text{month}_t + u_i + e_{idt} \quad (1)$$

$$\log E [\text{days' supply}_{idt} | \text{time}_{idt}, \text{copayment}_{idt}, \text{rx}_{idt}, \text{covariates}_{idt}] = \beta_0 + \beta_1 \text{copayment}_{idt} + \beta_2 \text{rx}_d + \beta_3 \text{copayment}_{idt} * \text{rx}_d + \alpha_n \text{covariates}_{nidt} + \text{month}_t + u_i + e_{idt} \quad (2)$$

Here, filled and days' supply are the probability of fill and the days' supply of medication for individual i and drug d at month t . Copayment is the weighted mean copayment for drug d at month t and rx is a fixed effect for drug d . Covariates are a set of potentially endogenous observed variables (age, sex, median household income, proportion of urban residents, proportion of African-American persons, proportion of individuals with bachelor's degrees, Washington state residence), and month are fixed effects for calendar month to account for seasonal effects. We accounted for repeated observations by clustering our regressions by member. We assessed overall model fit using the following goodness-of-fit tests: Pearson's correlation test, Pregibon link test, and a modified Hosmer-Lemeshow test.^{32,33}

We computed overall elasticities for the probability of fill and days' supply of medication using estimated coefficients from the models. We also estimated elasticities for medications in three therapeutic classes (HMG-CoA Reductase Inhibitors (Statins), Proton Pump Inhibitors (PPIs), Angiotensin-Converting-Enzyme (ACE) Inhibitors), for brand versus generic medications, and for medications in each of the five VBF copayment tiers.

RESULTS

We find that overall price elasticity of demand was -0.14 (95% confidence interval [CI], -0.21, -0.07) and -0.06 (95% CI, -0.13, 0.02) for the probability of fill and days' supply of medication. Hence, a 10% increase in copayment faced by the patients in this study is expected to reduce the probability of fill and the number of days' supply of medication by 1.40% and 0.06%, respectively, although the elasticity estimate for days' supply of medication did not differ statistically from zero. These estimates are in the lower range of published estimates for overall elasticity estimates for pharmaceuticals ranging from -0.04 to -0.60.⁷⁻¹² However, all but one of these studies are observational and in the one randomized trial, the RAND HIE, the overall elasticity estimate for pharmaceuticals of -0.17 was closer to our own estimates. Indeed, studies using instrumental variable methods to correct for the endogeneity of price found elasticity estimates between -0.12 and -0.16.^{4,9}

The elasticity estimates for statins, PPIs and ACE inhibitors were -0.29 (95% CI, -0.38, -0.19), -0.02 (95% CI, -0.10, 0.06), and -0.20 (95% CI, -0.49, 0.09) respectively for the probability of fill, and -0.26 (95% CI, -0.37, -0.14), -0.04 (95% CI, -0.11, 0.04), and -0.29 (95% CI, -0.61, 0.04) respectively for days' supply of medication. Other study researchers also found that elasticity of demand is higher for PPIs than for ACE inhibitors and statins^{18,19,24} Some of these researchers also found higher elasticity for ACE inhibitors than for statins while others found the opposite.^{15,19,24}

Our estimates for branded and generic medications were -0.24 (95% CI, -0.41, -0.07) and -0.09 (95% CI, -0.16, -0.03) respectively for the probability of fill, and -0.26 (95% CI, -0.45, -0.08) and 0.03 (95% CI, -0.04, 0.10) respectively for days' supply of medication. These estimates are also consistent with published studies.^{24,34}

Finally, our estimates for the probability of fill and days' supply of medication respectively by value-based tier assignment were -0.07 (95% CI,-0.10, -0.03) and -0.06 (95% CI,-0.10, -0.03) for the preventive tier, -0.09 (95% CI,-0.18, -0.01) and 0.08 (95% CI,-0.02, 0.17) for tier 1, -0.26 (95% CI,-0.49, -0.03) and -0.26 (95% CI,-0.51, -0.00) for tier 2, -0.27 (95% CI,-0.58, 0.04) and -0.32 (95% CI,-0.65, 0.01) for tier 3, and -0.45 (95% CI,-1.15, 0.24) and -0.55 (95% CI,-1.27, 0.16) for tier 4. In summary, we see a general trend of increasing elasticity with increasing copayment tiers. That is, patients seem to be more price sensitive to drugs placed in higher ICER-informed copayment tiers than drugs placed in lower ICER-informed copayment tiers.

ROBUSTNESS CHECKS

We examined whether our findings were affected by our enrollment criteria: individuals were not required to be continuously enrolled in the post-policy period. We assessed an alternative enrollment criteria in which we required individuals to be enrolled for the entire period of study. This reduced our sample size to 74,450 member-months (3,219 members). The results are similar to the findings of our primary analysis (Table 5). Further, in this full sample we found that rates of enrollment, attrition, or mail order pharmacy use (results not shown) did not differ between the pre- and post- policy periods. Together, these results suggest that our elasticity estimates were not subject to overt identification biases.

DISCUSSION AND IMPLICATIONS

The standard economic model for insurance indicates that in order to account for moral hazard, elasticity should vary with cost-sharing. However, empirical observations (most notably from the RAND HIE) suggest that patients may have imperfect information and may be making sub-optimal choices. This has given rise to value-based insurance designs that attempt to correct for this non-optimality by aligning cost-sharing with average estimates of effectiveness. Yet, due

to heterogeneity of treatment effects, information on average treatment effectiveness may be insufficient to optimize insurance.^{35,36} Hence, there is ambiguity regarding whether cost-sharing based on elasticity estimates would be similar to cost-sharing based on population average cost-effectiveness estimates.

We investigated this issue by exploiting an exogenous change in pharmacy benefit that began using CEA to inform copayments.²⁹ We found that drugs with greater elasticity of demand were also drugs that were placed in higher copayment tiers informed by CEA. This suggests that a cost-sharing strategy based on elasticity and a strategy based on cost-effectiveness in this case would set copayments in the same direction. Both strategies would place drugs with higher elasticity and estimated ICERs into higher copayment tiers relative to drugs that are less elastic and have lower estimated ICERs.

Hence this study suggests that a strategy in which copayment tiers are informed by CEA can be similar to a strategy in which copayment tiers are informed by elasticity estimates. However, in order to further optimize insurance, there needs to be information regarding the risk premium (and the amount of welfare loss associated with cost-sharing) as well as further information on the magnitude of consumer information imperfection.³⁵ Future work should empirically assess the magnitude of welfare loss and the magnitude of information imperfection by estimating the socially optimal marginal benefit curve.

The results are subject to a number of limitations. First, this was a natural experiment performed without randomization. Although we performed robustness checks to assess for identification biases and our elasticity estimates overall, by therapeutic class and by brand-generic status are in accordance with the published literature, it still is possible that unobserved

covariates may confound our findings. Second, Premera is a health plan and the ICER estimates are largely drawn from the health plan perspective instead of a societal perspective. Hence this policy may optimize insurance based on the payer perspective ignoring costs and benefits accrued to care givers and other spill overs and therefore the elasticity estimates may not necessarily generalize to a policy based on ICER estimates drawn from the societal perspective. Practically, the use of a true societal perspective in CEA modeling is limited, therefore ICER estimates for a true societal perspective is uncommon.

Finally, the study population is comprised of employees and dependents of a health insurance firm. To the extent that these individuals are better informed about the marginal benefits of treatment and are better aligned to their optimal therapy, they are less likely to reduce utilization. Alternately, it is also possible that this population may be more aware of changes in insurance benefits and this may make them more price sensitive.

Optimal insurance design requires accounting for price elasticity of demand and consumer information imperfection. Our work suggests that insurance based on elasticity and insurance based on CEA are not necessarily different. Future research should assess whether this observation can be generalized to other populations and whether additional information regarding the magnitude of consumer imperfect information can further optimize insurance.

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FIGURES AND TABLES

Table 1. Pharmacy benefits for Premera Blue Cross during the pre-policy and post-policy periods

Tier	Pre-policy Copayment (\$)	Post-policy Copayment (\$)
Preventive	—	0
Tier 1	10	20
Tier 2	30	40
Tier 3	50	65
Tier 4	—	100

Table 2. Sample Characteristics for Intervention and Control Members prior to Value-based formulary (VBF) implementation

Characteristic	Pre-Policy (n = 5,235)	Post-Policy (n = 4,813)	P Value
Individual characteristics			
Age, yrs, n (SD)	32.9 (17.6)	34.2 (17.6)	<0.001
Charlson score=0, N (%)	4,422 (84.5)	4,041 (84.0)	0.78
Charlson score=1 , N (%)	582 (11.1)	552 (11.5)	0.78
Charlson score>=2, N (%)	231 (4.4)	220 (4.6)	0.78
Enrollees per family unit, n (SD)	3.1 (1.5)	3.1 (1.5)	0.76
Female, N (%)	2,960 (56.5)	2,743 (57.0)	0.65
ZIP code characteristics			
African American, % (SD)	2.9 (3.5)	2.9 (3.5)	0.95
Bachelor's degree or higher, % (SD)	34 (13.6)	33.8 (13.5)	0.61
Median household income, \$1000, (SD)	68.9 (18.5)	68.6 (18.0)	0.44
Urban residence, % (SD)	91.7 (17.0)	91.6 (17.3)	0.97
Washington state residence, N (%)	4,638 (88.6%)	4,265 (88.6%)	0.98
Utilization Characteristics			
Number of prescription users per month, N (%)	1,863 (35.6)	1,809 (37.6)	0.036
Number of prescriptions per month, n (SD)	0.903 (1.53)	0.981 (1.63)	0.14

Table 3. Measurements of changes in medication utilization and copayments and elasticity of estimates (overall, by therapeutic class, and by brand-generic status) for the probability of fill and days' supply of medication

	Mean Change Monthly Days' Supply per Medication per Member Given Doubling of Copayment, n (95% CI)	Mean Copayment per Medication Pre- Period, \$ (SD)	Mean Copayment per Medication Post- Period, \$ (SD)	Elasticity Estimate Probability of Fill, (95% CI)	Elasticity Estimate Days' Supply, (95% CI)
Overall	-1.8 (-3.07, -0.56)	16.46 (13.35)	21.59 (21.31)	-0.14 (-0.21, -0.07)	-0.06 (-0.13, 0.02)
HMG-CoA Reductase Inhibitors	-19.37 (-25.76, - 12.99)	13.00 (7.18)	18.34 (23.76)	-0.29 (-0.38, -0.19)	-0.26 (-0.37, -0.14)
ACE inhibitors	-1.90 (-3.78, -0.03)	8.96 (1.12)	0.01 (0.06)	-0.02 (-0.10, 0.06)	-0.04 (-0.11, 0.04)
PPI	-8.04 (-20.36, 4.27)	23.37 (14.59)	42.15 (30.73)	-0.20 (-0.49, 0.09)	-0.29 (-0.61, 0.04)
Single- Source Branded Drugs	-4.19 (-6.34, -2.05)	33.85 (11.00)	46.86 (18.56)	-0.24 (-0.41, -0.07)	-0.26 (-0.45, -0.08)
Generic Drugs	-0.83 (-2.35, 0.68)	8.70 (2.19)	10.22 (8.16)	-0.09 (-0.16, -0.03)	0.03 (-0.04, 0.10)

Table 4. Measurements of changes in medication utilization and copayments and elasticity of estimates (by value-based tier assignment) for the probability of fill and days' supply of medication

	Mean Change Monthly Days' Supply per Medication per Member Given Doubling of Copayment, n (95% CI)	Mean Copayment per Medication Pre-Period, \$ (SD)	Mean Copayment per Medication Post-Period, \$ (SD)	Elasticity Estimate Probability of Fill (95% CI)	Elasticity Estimate Days' Supply (95% CI)
0	-2.62 (-3.45, -1.80)	8.98 (3.1)	0.48 (2.26)	-0.07 (-0.10, -0.03)	-0.06 (-0.10, -0.03)
1	-0.16 (-2.23, 1.91)	9.24 (3.82)	14.37 (5.92)	-0.09 (-0.18, -0.01)	0.08 (-0.02, 0.17)
2	-4.22 (-7.31, -1.12)	30.07 (6.29)	38.87 (3.61)	-0.26 (-0.49, -0.03)	-0.26 (-0.51, -0.00)
3	-4.59 (-8.11, -1.08)	42.00 (9.74)	62.72 (3.44)	-0.27 (-0.58, 0.04)	-0.32 (-0.65, 0.01)
4	-2.54 (-5.53, 0.44)	48.39 (2.24)	97.32 (4.55)	-0.45 (-1.15, 0.24)	-0.55 (-1.27, 0.16)

Table 5. Robustness check: estimating elasticities by requiring continuous enrollment for the entire 2 years of observation

Dataset Restriction	Mean Change Monthly Days' Supply per Medication per Member Given Doubling of Copayment, n (95% CI)	Mean Copayment per Medication Pre- Period, \$ (SD)	Mean Copayment per Medication Post-Period, \$ (SD)	Elasticity Estimate Probability of Fill (95% CI)	Elasticity Estimate Days' Supply (95% CI)
Continuous enrollment	-0.02 (-0.03, -0.01)	16.46 (13.35)	21.59 (21.31)	-1.67 (-0.23, -0.10)	-0.07 (-0.16, -0.01)
