NBER WORKING PAPER SERIES

PRICE ELASTICITIES OF PHARMACEUTICALS IN A VALUE-BASED-FORMULARY SETTING

Kai Yeung
Anirban Basu
Ryan N. Hansen
Sean D. Sullivan

Working Paper 22308
http://www.nber.org/papers/w22308

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
June 2016

The authors would like to acknowledge the many contributions of the Pharmacy and Actuary staff at Premera Blue Cross, including John Watkins, Dan Danielson, Carol Vogeler, Chad Murphy and Kathryn Brown. They acknowledge helpful comments from Surrey Walton, Jim Burgess and participants of the Will Manning Memorial Conference at the University of Chicago. The views expressed herein are those of the authors and do not necessarily reflect the views of the University of Washington, Premera Blue Cross or its affiliates, or the National Bureau of Economic Research.

Price Elasticities of Pharmaceuticals in a Value-Based-Formulary Setting
Kai Yeung, Anirban Basu, Ryan N. Hansen, and Sean D. Sullivan
NBER Working Paper No. 22308
June 2016
JEL No. C10,D61,I13,I18

ABSTRACT

Ever since the seminal RAND Health insurance experiment (HIE) was conducted, most health care services, including pharmaceuticals, are deemed to be price inelastic with price elasticities of demand (PED) close to -0.20. However, most studies of PED exploit natural experiments that change demand prices for multiple components of health care. Consequently, these experiments usually do not produce estimates for the true own-price elasticities of demand but rather composite own-price elasticities that are driven by concomitant price changes to their substitutes and complements. Hence, an estimate of price elasticity is expected to vary based on the setting in which it was estimated, and likely not be applicable to other settings. In this work, exploiting a natural experiment of exogenous policy implementation of a value-based formulary (VBF) that was designed based on drug-specific incremental cost-effectiveness ratios, we estimate price elasticities of pharmaceuticals within a VBF design, formally accounting for the nature of composite elasticities that such a setting would generate. We also calculate welfare effects of such a policy using a consumer surplus approach. We show theoretically that VBF designs can increase dispersion of price elasticities of demand among pharmaceutical products compared to their true own-price elasticities and affect their magnitude based on direction of price change. Aligning these PEDs with value VBF is also likely to produce positive welfare effects. We estimate an overall PED for pharmaceuticals to be -0.16, close to the estimate of RAND HIE. However, we see substantial dispersion of PED across the VBF tiers ranging from -0.09 to -0.87 with trends aligned with the levels of value as reflected by the cost-effectiveness ratio ($p<0.001$). The net welfare increase was $147,000 for the cohort or $28 per member over the post-policy year. Further experimentations of VBF designs with alternative cost-effectiveness thresholds, copayment levels and value-definitions could be quite promising for improving welfare.

Kai Yeung
Pharmaceutical Outcomes Research and Policy Program
Department of Pharmacy
1959 Pacific St NE
Box 357631
Seattle, WA 98195
kaiy@uw.edu

Ryan N. Hansen
Pharmaceutical Outcomes Research and Policy Program
Department of Pharmacy
1959 Pacific St NE
Box 357631
Seattle, WA 98195
rhansen@uw.edu

Anirban Basu
Departments of Health Services, Pharmacy and Economics
University of Washington
1959 NE Pacific St
Box - 357660
Seattle WA 98195
and NBER
basua@uw.edu

Sean D. Sullivan
Pharmaceutical Outcomes Research and Policy Program
Department of Pharmacy
1959 Pacific St NE
Box 357631
Seattle, WA 98195
sdsull@uw.edu

1. INTRODUCTION

Price (own) elasticity of demand reflects the responsiveness in demand for a product with respect to its price, *ceteris paribus*. There is a large literature that has tried to estimate price elasticities of health care products, including pharmaceuticals. The RAND Health Insurance Experiment (HIE) was the first to study these effects in a randomized context (Keeler and Rolph 1988; Manning et al. 1987). These estimates are used for a variety of purposes such as setting optimal coinsurance rates and calculating welfare implications for policies.

Here we will focus on the price elasticity of demand for pharmaceuticals. Typically, when estimating price elasticity of demand, pharmaceutical products are thought of as one monolithic product. Analysts then exploit some natural experiments, such as changes in cost-sharing that applies across all pharmaceutical products, to estimate the responsiveness of pharmaceutical demand with respect to changes in such cost-sharing. However, within the same setting, when one tries to look at the price responsiveness of specific classes of pharmaceuticals, one is no longer able to estimate the true own-price elasticity of demand for that class. This is because, this class of pharmaceuticals may have substitutes and complements whose demand prices are also affected by the same natural experiment. Therefore, the *ceteris paribus* argument no longer applies. To our knowledge, this limitation of interpreting estimated price elasticities for specific classes of drugs, when the entire pharmaceutical demand is affected via price changes, has not been discussed adequately in the literature. It is expected that estimates of total elasticity of demand for pharmaceuticals would vary considerably depending on how their substitutes' and complements' demand prices were also changing. More importantly, price responsiveness estimated in one setting may not be generalizable to other settings.

We exploit a similar natural experiment, but in the context of transitioning a cost-based formulary to a value-based formulary. Typically, pharmaceuticals are groups into tiers within a health plan's formulary. These tiers are cost-based, which indicates that drugs with lower acquisition costs are placed on a lower tier with lower co-insurance rate or copayment High costs drugs are placed on higher tiers. Such a cost-based formulary incentivizes patients to use low-cost drugs by offering lower cost-sharing (demand price) for them. Researchers have exploited natural policy experiments that have changed co-insurance rates of co-payments, either by increasing or decreasing these amounts within the existing tiers or by adding a new tier for some of the drugs with a new co-payment level, to calculate the price-elasticity of pharmaceuticals. Since in most of these experiments, direction of change of demand price is unilateral, estimates of elasticities from these settings may not be informative about the price responsiveness of pharmaceuticals within a value-based formulary (VBF) context. A VBF tries to incentivize patients to use drugs that are likely to produce better value (in terms of patient

health net of costs) by assigning drugs to tiers using some notion of value (rather than acquisition costs) and then simultaneously aligning cost-sharing levels based on value (Chernew et al. 2008, 2010). VBF can also, at the same time, increase cost-sharing for those drugs that are likely to produce low value. Two forces drive price responsiveness to a pharmaceutical product within this setting: 1) Signaling of value to the consumer (physician or patient or both),[1] which could shift the market demand curve outward or inwards depending on the value signal, and 2) the own demand price changes and relative demand price changes between the various substitutes and complements. A VBF may signal information about the value of a drug to the consumer although it is not clear how much new information it provides beyond what the prescriber already knows and what she advises the patients on.

In this paper, we assume that the effect of such value signals on the movement of market demand (among the population studied) is minimal. The primary effect of VBF is realized as it manipulates the own-demand price and the demand prices for the substitutes and complements to affect demand behavior along a drug-specific fixed demand curve. We develop a simple intuitive formulation for the overall price elasticity of demand within a VBF design and provide empirical estimates of these elasticities through a recent natural experiment of VBF implementation. Moreover, we provide evidence of how the overall price elasticity of demand varies by VBF tiers that hinges on some notion of value. We discuss the implication for own price elasticities within these tiers. We also provide estimates of price elasticities by therapeutic class, and by brand-generic status. Finally, we provide a framework for welfare calculation for VBF implementation and provide estimates from the natural experiment.

In the next section (Section 2), we start with a short review of the literature on price elasticities of demand for pharmaceuticals. Throughout we will use the term "pharmaceutical", "drug" and "medication" interchangeably. We start with the RAND HIE and only focus on those that have exploited a natural experiment to solve the endogeneity problem of price change. In Section 3, we lay out the price responsiveness of a pharmaceutical product as a function of own prices and also prices of its substitutes and/or complements and then translate these expressions to the context of VBF. Finally, we describe how we use these elasticities to calculate welfare effects of VBF. In Section 4, we describe our data that comes from an exogenous change in pharmacy benefit in a Preferred Provider Organization employer-sponsored plan in the Pacific Northwest that, in 2010, implemented a VBF benefit among their own employees and dependents that explicitly used cost-effectiveness analysis (CEA) to determine medication copayments. We also describe the methods that we use to estimate the price elasticities of demand. Section 5 presents the results and some robustness checks for our

[1] The consumer could also be thought of as the patient-prescriber-pharmacist triad making a joint decision.

findings. The paper concludes with a discussion of our findings and policy implications in Section 6.

2. LITERATURE REVIEW

Overall price responsiveness for pharmaceuticals

The RAND HIE, conducted from 1974 to 1981, is the only randomized study to produce estimates for price elasticities of demand for pharmaceuticals (Manning et al. 1987). 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 (Keeler and Rolph 1988).

It is important to note that that this estimate should only be interpreted as the own-price elasticity of pharmaceuticals if other health care services are not substitutes or complements for pharmaceuticals. This is because the experiment changed cost-sharing for not only pharmaceuticals but also other health care services simultaneously. To the extent any of these services serve as a substitute or complement to pharmaceuticals, the total elasticity would be the sum of the own price elasticity and other components. We study this more formally in Section 3.

More recent observational studies have produced overall elasticity of demand estimates on total drug costs ranging from -0.33 to -0.12 (Joyce et al. 2002; Contoyannis et al. 2005; Gilman and Kautter 2008; Chandra et al. 2010, 2014). Chernew et al. (2008) found the elasticity of demand on drug adherence to range from -0.18 to -1.2. Other studies have estimated elasticities by medication class. Goldman et al. (2004) looked at elasticities with respect to drug days and found slightly higher elasticities for NSAIDs (-0.45), antihistamines (-0.44), anti-hyperlipidimics (-0.34), anti-asthmatics (-0.32), anti-hypertensives (-0.26), antidepressants (-0.26) and antidiabetics (-0.25). Landsman et al. (2005) estimated elasticities with respect to number of prescriptions and surprisingly found lower elasticities for drugs used in asymptomatic conditions (-0.10 to -0.16 for ACE inhibitors, statins etc.) and higher elasticities for drugs used in symptomatic conditions (-0.24 to -0.60 for Cox-e inhibitors, NSAIDs, SSRIs etc.). Finally, Gatwood et al. (2014) looked at medication fills and found elasticities ranging from -0.02 to -0.16 across eight medication classes. _ENREF_13Based on these estimates, it is usually inferred that pharmaceuticals are price-inelastic in nature and there is not much variability in the price-

elasticity of demand across drug classes. However, an argument can be made that these total elasticities estimated through these natural experiments underestimate of the own-price elasticity. This is because of three reasons: pharmaceuticals are likely to have more substitutes than complements, relative changes to prices across these substitutes are positive (i.e. price changes are in the same direction), and that the cross–price elasticity for substitutes are expected to be positive. Hence, the estimated total price elasticity of demand for a drug is likely to be biased towards zero due to the addition of these positive effects. In essence, pharmaceutical demand could be quite elastic if demand prices for specific drugs are targeted instead of an overall group that includes many of its substitutes. This notion aligns with the rationale for a VBF design.

Moreover, estimating price responsiveness at the drug level rather than at the group level may be more suitable to unmask variations of total elasticities for specific medications, which can then be grouped in many different ways. For example, when estimating elasticity, many studies utilize panel data from natural experiments in which prescription drug cost-sharing was increased.[4,8,9,11,15,16] This increase in cost-sharing may occur differentially, with cost-sharing increases being greater for branded medications than for generic medications.[15] Cost-sharing increases may also be greater for non-preferred branded medications than for preferred branded medications.[8,9,16] The studies deal with these differential increases in cost-sharing by constructing plan level or medication class level cost-sharing indexes and then comparing medication utilization across plans and time.[10,12-14] These studies implicitly only capture changes in mean cost-sharing at the plan (or medication class) level and do not account for differential changes in cost-sharing within a plan or medication class in order to estimate elasticities at the individual drug level. In this study, we empirically estimate the composite or total price elasticity of demand at the drug level (taking into account own and cross price elasticities) and aggregate them to estimate the overall elasticity of pharmaceuticals, and by medication copayment tier and a few prevalent drug classes.

3. THEORY

Demand as a Function of Own and Cross Price Effects

The level of demand for a particular (index) medication depends on both the price of the medication and the prices of its substitutes/complements. Since there are fewer examples of complement pharmaceutical pairs as compared to substitutes, we will focus the discussion on substitutes. However, the same framework can be used for complements and a mix of substitutes and complements. In the context of price changes for both the medication and its substitutes, as is typical when the overall benefit design for pharmaceuticals change, even

exogenously, the demand for the index medication will depend on its own and cross price elasticities of demand and the relative changes in prices of the medications. We first illustrate this with an example involving only two medications, then we extend our example to multiple medications and then to an example involving value-based cost-sharing.

For two medications, the demand for medication 1 (D_1) is a function of the (demand) price of both medication 1 (P_1) and medication 2 (P_2).

$$D_1(P_1, P_2) \tag{1}$$

The total change in demand for medication 1 (dD_1) is a function of the changes in prices, dP_1 and dP_2, and the effect of the changes in prices on the demand for medication 1:

$$dD_1(P_1, P_2) = \frac{\partial D_1(P_1,P_2)}{\partial P_1} \cdot dP_1 + \frac{\partial D_1(P_1,P_2)}{\partial P_2} \cdot dP_2 \tag{2}$$

Note that in (2), the cross-price effect $\frac{\partial D_1(P_1,P_2)}{\partial P_2}$, can also be written as the product of the marginal rate of substitution between the two drugs and the own price elasticity of medication 2, i.e. $\frac{\partial D_1(P_1,P_2)}{\partial D_2} \cdot \frac{\partial D_2}{\partial P_2}$. If $\frac{\partial D_1(P_1,P_2)}{\partial D_2} < 0$, which implies that $\frac{\partial D_1(P_1,P_2)}{\partial P_2} > 0$, it indicates that medications 1 and 2 are substitutes.

Multiplying both sides on (2) with $\frac{\bar{P}_1}{\bar{D}_1} \cdot \frac{1}{dP_1}$, where $\bar{P}_1$ and $\bar{D}_1$ represent the mean price and demand, we have:

$$\frac{\bar{P}_1}{\bar{D}_1} \cdot \frac{dD_1(P_1,P_2)}{dP_1} = \frac{\partial D_1(P_1,P_2)}{\partial P_1} \cdot \frac{\bar{P}_1}{\bar{D}_1} + \frac{\bar{P}_2}{\bar{P}_2} \cdot \frac{\partial D_1(P_1,P_2)}{\partial P_2} \cdot \frac{dP_2}{dP_1} \cdot \frac{\bar{P}_1}{\bar{D}_1} \tag{3}$$

Therefore, the "overall" elasticity of demand for the index medication with respect to its own price, denoted by $\theta_{11} = \frac{\bar{P}_1}{\bar{D}_1} \cdot \frac{dD_1(P_1,P_2)}{dP_1}$, is comprised of: 1) the true own price elasticity of demand of medication 1 (η_{11}) and 2) a second term represents the product of the true cross price elasticity of medication 1 with respect to medication 2 prices (η_{12}) and the elasticity of price of medication 2 relative to medication 1 prices (ε_{21}).

$$\theta_{11} = \eta_{11} + \eta_{12} \cdot \frac{dP_2}{dP_1} \cdot \frac{\bar{P}_1}{\bar{P}_2} \tag{4a}$$

$$\theta_{11} = \eta_{11} + \eta_{12} \cdot \varepsilon_{21} \tag{4b}$$

This shows that the overall elasticity of demand for medication 1 will depend on whether medication 1 and 2 are substitutes ($\eta_{12} > 0$) or complements ($\eta_{12} < 0$) and on the relative change in the price of medication 2 with respect to medication 1. For example, if medications 1 and 2 are substitutes ($\eta_{12} > 0$) and the relative change in the price of medication 2 is large ($\varepsilon_{21} >> 1$), then it is possible that overall elasticity of demand for medication 1 is positive despite the own price elasticity of demand for medication 1 being negative ($\eta_{11} < 0$).

Generalizing our model to J medications, we see that the overall elasticity of demand for medication 1, θ_{11}, is the sum of η_{11} plus the sum of the product of the cross price elasticity of demand for medication 1 with respect to medication j prices (η_{1j}) and the elasticity of prices for medication j with respect to medication 1 (ε_{j1}):

$$\theta_{11} = \eta_{11} + \sum_{j=2}^{J} \eta_{1j} \cdot \varepsilon_{j1} \quad (5)$$

Note that, these elasticities can also be interpreted as the elasticities with respect to the demand prices, where the patient only faces a fraction (co-payment) of the overall price for each drug. We will interpret price elasticities as demand price elasticities throughout the paper.

Implications of VBF on price responsiveness

A VBF design offers lower cost-sharing for drugs that are of high value and high cost sharing for drugs that are of low value. Therefore, a VBF affects the overall price responsiveness of a medication through two ways. First, it signals the value of that medication, more explicitly, by assigning the drug to a high (low value) versus low (high value) tier. This information alone can shift the market demand curve outward or inward depending on the overall value signal of a prescription and its substitutes. However, it does not provide any new information on effectiveness that does not already exist in the medical community. Hence we assume that the effect of such signaling mechanism is minimal is shifting market demand curve. The second way in which VBF affects overall price responsiveness is through demand prices and is perhaps the most direct and the strongest way. The VBF structurally influences the elasticity of relative (demand) prices (ε_{j1}) so that low value drugs experience large positive price changes and high value drugs experiences small positive or even negative price changes. This mechanism, we believe, is driving price responsiveness in this setting. Therefore, a high value drug that has low own price elasticity (i.e. is inelastic) can be made even more price inelastic in a VBF setting by increasing the relative prices of its low valued substitutes. In fact, if the increases in prices of the low value drugs were large enough, it if possible that increase in price of the high value drug would still lead to increase in consumption of the drug leading to welfare gains. These dynamics are fundamental to understanding the welfare effects of a VBF policy and are described below.

Following our stylized example above, let's consider two drugs that are substitutes. Also, let's assume for simplicity that $\bar{P}_1 = \bar{P}_2$. Then under a traditional unidirectional and similar shift in costs sharing, $\varepsilon_{j1} = 1$, and the overall price elasticity of demand for drug 1 is given as,

$$\theta_{11,Tr} = \eta_{11} + \eta_{12}.$$

Certainly, $\theta_{11,Tr} > \eta_{11}$ since $\eta_{12} > 0$, indicating that in traditional setting demand price shifts for all drugs in the same direction would produce more inelastic demand estimates than the true own-price elasticity.

Under a VBF setting, suppose drug 2 is of lower value. So a VBF would separate the demand price for the two drugs making drug 2 more expensive than drug 1. There are two ways a VBF can enforce price changes: 1) $dP_1>0$ & $dP_2>>0$, or 2) $dP_1<0$ & $dP_2>0$. Note however,

If $dP_1>0$ & $dP_2>>0$: $\eta_{11} < 0$, $\eta_{12} > 0$, $\varepsilon_{21} > 1$ ➔ $\theta_{11} > \theta_{11,Tr} > \eta_{11}$

Thus, if higher value drug 1 experiences a price increase, VBF makes its demand more inelastic by changing the price of its low value substitutes even higher. Thus, not many people are deterred from using this high value drug 1 despite of an increase in price. In fact, it is possible that overall elasticity for a good value drug could even be positive under the VBF setting. In contrast,

If $dP_1<0$ & $dP_2>0$: $\eta_{11} < 0$, $\eta_{12} > 0$, $\varepsilon_{21} < 0$ ➔ $\theta_{11} < \eta_{11} < \theta_{11,Tr}$

Thus if the high value drug experiences a decrease in price, VBF makes its demand more elastic to allow more people to take up the drug.

One can also look at the effect of VBF on the price elasticities of the low-value drugs. We reverse order that consider drug 1 to be the low-valued drug and drug 2 to be the high valued drug. In that case,

If $dP_1>>0$ & $dP_2>0$: $\eta_{11} < 0$, $\eta_{12} > 0$, $\varepsilon_{21} < 1$ ➔ $\theta_{11,Tr} > \theta_{11} > \eta_{11}$

Similarly,

If $dP_1>0$ & $dP_2 < 0$: $\eta_{11} < 0$, $\eta_{12} > 0$, $\varepsilon_{21} < 0$ ➔ $\theta_{11} < \eta_{11} < \theta_{11,Tr}$

With a price increase for the low value drug, the VBF makes the demand for the low value drug more elastic than in the traditional setting thus encouraging patient to reduce use of this drug.

Welfare Effects of the VBF

Following traditional economic theory, the true own price elasticity of demand is assumed to be negative, implying that as demand price falls, consumption increases *ceteris paribus*. Under a traditional insurance design, patients pay a fraction of the price of a drug. It is expected that there is an inherent welfare loss due to moral hazard, as patients would consume the drug even when its marginal value is lower than its marginal price. If the demand is price elastic

(inelastic), as would be expected with a low(high)-value drug, the moral hazard would be large (small).[17]

The elasticity of a drug also is driven by the availability of substitutes and their prices. For example, demand price responsiveness for a low-value drug can be low if this drug has no available substitutes or if the available substitutes are themselves of low value and/or high price. In this case, despite being low value, the true own price elasticity of the original drug can be low (inelastic). Indeed the literature has shown that, on average, generic medications (which are likely to have more expensive branded substitutes) have lower price elasticities compared to branded medication (which are likely to have more low cost generic substitutes).[15]

In the VBF setting, there are bidirectional changes to demand prices to different drugs. For drugs whose demand prices increase, we expect that there will be welfare gains due to the decrease in moral hazard. Alternatively, for drugs whose demand prices decrease, moral hazard increases along with decline in welfare. However, aligning these price changes with the underlying value of drugs, a VBF design can increase the dispersion in price elasticities, compared to those present based on true own price elasticity. Therefore, a VBF design is likely to make a high-value drug more inelastic and a low value drug more elastic than its own true price elasticity would suggest. Consequently, we expect that, on average, the change in welfare loss brought about by a VBF design that is able to align demand with value will be positive.

One challenge in welfare calculations is to understand the marginal costs of the drugs. For example, for a branded drug, the total reimbursed plus out-of pocket costs amount to the market price of the drug (sans discount that the insurer may receive from the manufacturer). However, this market price should not be used to estimate welfare since it does not reflect the marginal costs of the drug due to the monopoly mark-up. The long-run marginal costs of the drug should also account for the R&D costs of developing and commercializing the drug. The Second Panel for Cost-Effectiveness recommends using the Federal Supply Schedule (FSS) prices for the long-run marginal costs of drugs from a societal perspective, since prevailing transaction prices with a social insurer will usually act as a serviceable way to reflect the production costs of the drugs from a societal perspective (Basu, 2016). In our case, we were unable to obtain the FSS prices for every drug in our sample. Instead, we use 40% and 100% of the observed market prices to reflect FSS prices for all branded and generic drugs respectively.[18]

Consider that copayments (demand price) levels changed from level P_1 to P_1^* for a drug and the long-run marginal costs be denoted by SMC. The associated change in welfare loss will depend on the following conditions: 1) if $P_1^* >$ or $< P_1$; and 2) if SMC $> P_1$ and SMC $> P_1^*$; OR

3) if P_1^* > SMC > P_1 or if P_1^* < SMC < P_1; OR 4) if SMC < P_1 and SMC < P_1^*. It is expected that for generic drugs 1) and 2) always holds. However, for branded drugs, any of the conditions may hold. Consequently, the welfare calculations for each combination of these conditions are illustrated in Figure 1.

Assuming that high-value drugs would be, on average, less price elastic than low-value drugs, the welfare losses from price decreases from high value drugs could be more than offset by the welfare gains from price increases of low-value drugs within a VBF. To the extent that these high value and low-value drugs are substitutes for each other, the total price responsiveness would be tempered for high value drugs while they would be made more sensitive for low-value drugs within a VBF. For example, the overall price responsiveness (say, θ_{11}) for the high value drug with a decrease in its demand prices could be much lower than its own price elasticity (η_{11}) would suggest since it is reinforced positively by η_{12} and ε_{21} since both would be positive under a VBF design and $\varepsilon_{21} > 1$. Therefore, the welfare loss associated with the decrease in demand price for this drug within a VBF will be smaller than what would be expected if that demand price would have changed *ceteris paribus*. In essence, a VBF is likely to increase dispersion in price responsiveness of drugs. To what extent a specific VBF design can affect total welfare will require empirical estimation. This will be driven by not only the own price-elasticity of each medication but also the number of medications with increases in copayment, the number of medications with decreases in copayment, the substitutability between these medications and the magnitudes of the copayment changes. More importantly, it will depend on the specific operationalization of "value" used to design the VBF.

Our empirical exercise presented below exploits a natural experiment where cost-effectiveness results are used to proxy value and thereby demand price changes correlate with the drug-specific incremental cost-effectiveness ratios. This is an important operationalization of "value" due to the use of CEA across the world to make value arguments. However, perception of value may be different for prescribers and patients, and therefore, these demand price changes may not systematically correlated with elasticity. To understand this correlation, we study the price-responsiveness of demand to the cost-effectiveness-based tiers used in the VBF setting. We will produce nuanced price elasticities and welfare effects in this setting that can be used to project welfare effects under other VBF designs.

4. EMPIRICAL EXAMPLE

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 employees and dependents, which explicitly used CEA to inform medication copayments. The design and implementation of the VBF has been described in detail elsewhere.[2] 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. The ICER estimate using the comparator representing the standard of care for the clinical indication with the highest expected prescription volume was considered. 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 for the intervention and control groups. In the contrast, the medical benefits did not change for either the intervention and control groups over the period of observation.

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 one year prior to VBF implementation. The intervention group was composed of employees and dependents of Premera in an employer sponsored plan that implemented the VBF on July 2010. The control group was composed of employees and dependents of two employer sponsored plans administrated by Premera that did not implement the VBF. These plans were chosen based on similarity to the intervention group prior to VBF implementation in industry classification, member geography of residence, medication copayment tiers and without any changes in pharmacy benefits over the entire study period.

From July 2009 through June 2011, we obtained quarterly 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)) for each member in our sample. 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.[19,20]

Our focus on health plans that had pharmacy benefit structures consisting of fixed dollar copays with no deductibles, no co-insurance provisions, no maximum expenditure limits and no coverage for out-of-network pharmacies results in a linear price schedule for cost-sharing. Since the copays were changed exogenously with the VBF implementation in our intervention arm, it allows for allow for a clean medication level analysis. The unique combinations of active ingredient (hierarchical ingredient code), dosage form and brand-generic status defined every medication in our data. Every member in our sample had a choice to fill any of these medications in any month. This is the basic unit by which copayment tiers, including VBF tiers, were assigned. Therefore copayments are homogenous within a unique combination at a given time (after taking into account mail order status).

Empirical Approach

Demand Price or Copayment

Our primary explanatory variable was the expected copayment amount for each medication faced by a member in a given quarter. Unfortunately, the tier status of each of these medications, both before and after VBF implementation in the intervention group was not observed in the dataset. However, because of the linear price schedule and the homogenous copays for each medication, we are able to infer the tiers for each drug based on the observed copayments. Naturally, this approach restricted us to use only those medications that were filled in every quarter of observation by at least one person in the intervention group. In contrast, the tier status and their corresponding copayments, which did not change over the duration of our study period for the control group, were observed in the dataset. This limited our analysis to 269 unique medications, which accounted for 79.3% of the prescription medication volume over the period of observation.

We infer these marginal medication-specific copayments for each quarter by calculating the mean copayment observed for retail and mail order claims separately. VBF copayment tier assignments were applied in the same manner for both retail and mail order benefits. However, mail order copayment amounts are 2.5 times the copayment amount for a retail claim but provide three times the quantity of medication (this multiple was not impacted by the VBF). We calculate the weighted mean copayment for every medication in a given quarter by weighting the mean retail and mail copayments in that quarter with the proportion of retail and mail claims for that medication during the pre-policy year. Therefore, the post-policy quantities do not affect the weighted mean copayment levels and changes in these demand prices were only driven by the implementation of the VBF formulary, considered to be exogenous in nature. These weighted co-payment levels are denoted as *factual* copayment levels, which represent

the mean prices a consumer truly faced for a given medication in a given quarter. The factual copayments were calculated separately for the intervention and control groups. For the intervention group, we also derived the counterfactual copayment for each medication in the post-policy period for the VBF cohort, reflecting the price a consumer would have faced for a given medication in the post-policy period for the VBF cohort had the price of the medication not been changed by the VBF policy. These counterfactual copayment levels were based on calculating the average copayment for each medication during the pre-policy period and then multiplying by pre-policy period mail and retail weights. The control group was used to adjust for any temporal changes during this time period.

Econometric estimation-utilization

We modeled the probability of filling each medication in a given quarter as well as the number of fills of the medication using two-part models. For each part, we utilized a difference-in-differences estimator to account for unobserved time-varying and non-time-varying confounders. 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[2] to estimate the number of days' supply, given a fill (Eq. 2). We combined the first and second part regressions to obtain an overall estimate of the effect of copayment changes on number of fills of a medication per quarter. The two-part model has the following specification:

$$\text{Part 1: } \Phi^{-1}[E(filled_{idt})|\cdot] = \beta_0 + \beta_1\, copay_{idt} + \beta_{2d}\, rx_d + \beta_{3d} copay_{idt} * rx_d + \alpha_n covariates_{nidt} + quarter_t + season_{idt} \quad (6)$$

$$\text{Part 2: } log\, E\,[number\ of\ fills_{idt}|\ Any\ filled\,] = \beta_0 + \beta_1\, copay_{idt} + \beta_2 rx_d + \beta_3 copay_{idt} * rx_d + \alpha_n covariates_{nidt} + quarter_t + season_{idt} \quad (7)$$

Here, filled and number of fills are subscripted for individual *i*, medication *d* and quarter *t*. *Copay* is the mean copayment in the VBF or control groups for drug *d* at quarter *t*. The rx_d is a fixed effect for drug *d*. Regression covariates in both models include age, sex, Washington state residence, zip-code median household income, proportion of urban residents, proportion of African-American persons, and proportion of individuals with bachelor's degrees,. *Quarter*

[2] A negative binomial distribution was considered for the second part regression. However, the outcome (count of fills conditional on having a fill) was not overdispersed (variance = 1.0, mean = 1.8) and the Pearson's correlation test, and modified Hosmer-Lemeshow test indicated similar goodness of fit for both poisson and negative binomial distribution models.

indexes tri-monthly periods centered on VBF policy implementation (July 2010), and *season* are fixed effects for calendar month to account for seasonal effects.

Using the above models, we estimate the relationship between the observed medication utilization and the observed copayment. Then, based on the estimated model, we utilize the observed (factual) copayment to predict the factual medication utilization in the VBF group. We then utilized the counterfactual copayments (i.e. the copayment faced by a consumer in the VBF group had the copayment not changed) to predict the counterfactual medication utilization. The factual and counterfactual copayments and medication utilization estimates are used to calculate elasticities and welfare changes as described in the following sections.

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.[21,22] We generated standard errors and confidence intervals by 1000 bootstrap replications.

Econometric estimation-price elasticity of demand

We computed elasticities for the total number of fills of a medication using the combined results of the two-part models. We first estimated the overall elasticity for the entire set of medications included in the analysis. We next estimated elasticities for medications in each of the five VBF copayment tiers, then for medications in five therapeutic classes as defined by the American Hospital Formulary Service (AHFS) Pharmacologic-Therapeutic Classification: Statins, Beta2 Receptor-Blockers, Proton Pump Inhibitors, ACE-Inhibitors, and Biguanides. We select these classes because of the high prevalence in their use. Finally, we estimated elasticities for brand versus generic medications. For each group-level elasticity estimate, we weight the drug-specific estimates within that group by the number of fills for each medication in the VBF group in the pre-policy period. We use a non-parametric trend test to assess whether there is a trend in elasticity estimates based on VBF copayment tier placement.[23]

Econometric estimation-welfare effects

We approximate the welfare effects using our regression-based model predictions. We predicted quantity demanded given the factual and counterfactual copayment levels and the quantity demanded given the marginal cost of the medication. Using the predicted quantities and the copayments and the social marginal costs approximated using principles laid out earlier, we calculate these welfare effects as shown in Figure 1 and as follows using the area of a right trapezoid or a triangle. If marginal cost is greater than both copayment levels (Figure 1a;

SMC> P_1^*>P1 or SMC>P1> P_1^*) or if marginal cost is less than both copayment levels (Figure 1c; P1> P_1^*>SMC or P_1^*>P1>SMC) then the welfare change is:

$$\Delta welfare_{idt} = (0.5 \cdot ((SMC_{idt} - P^*_{1,idt}) + (SMC_{idt} - P_{1,idt})) \cdot (Q_{1,idt} - Q^*_{1,idt})) \quad (8)$$

where "P_1^*" is the factual copayment and "Q_1^*" is the factual estimate of demand (i.e. with VBF policy) while "P_1" is the counterfactual copayment and "Q_1" is the counterfactual estimate of demand (i.e. if there was no VBF policy). "S*MC*" is the social marginal cost. We calculate the welfare change (Δ*welfare*) for each enrollee (*i*), medication (*d*), and quarter (*t*) in the VBF group in the post-policy period. Under Figure 1a scenario, if factual demand (under VBF) is less than counterfactual demand (under old regime), welfare increases and vice versa. The opposite is true for the Figure 1c scenario.

If the social marginal cost is between the old and new copayment levels (Figure 2b) then the welfare change is:

$$\Delta welfare_{idt} = ((0.5 \cdot (SMC_{idt} - P^*_{1,idt}) \cdot (MQ_{idt} - Q^*_{1,idt})) - ((0.5 \cdot (SMC_{idt} - P_{1,idt}) \cdot (MQ_{idt} - Q_{1,idt})) \quad (9)$$

"*MQ*" is the quantity demanded when price is at marginal cost and is predicted using our estimated models.

We calculate welfare effects at the individual- drug combination level so that we can aggregate the net welfare effects across any drug class or subgroups. Pooling across our two-part models, we estimate net welfare change induced by VBF copayment changes at the individual-drug combination level. We calculate the aggregated welfare effects separately for medications with decreases in copayment and those with increases. We next obtain the overall welfare change across enrollees, medications, and quarter by calculating the sum of the welfare changes:

$$\Delta welfare = \sum_{i=1}^{n} \sum_{d=1}^{n} \sum_{t=1}^{n} welfare\Delta_{idt} \quad (9)$$

Results

The intervention group and control group were composed of 5,235 and 4,357 individuals, respectively (Table 2). Since our unit of analysis is at the individual-quarter-drug level, we have over 20 million observations (=9592X8X269). The intervention group did differ from the control group in some demographic and socioeconomic characteristics. Notably, the intervention group had slightly higher median household income ($68,900, sd=$18,500 vs $66,100 sd=$24,300)

and were slightly younger (32.9 yrs. sd=17.6 yrs. vs 33.9 yrs. sd=18.2 yrs.). As specified *a priori*, we controlled for these and other demographic and socioeconomic characteristics. The unadjusted percentage of prescriptions filled by the mail order pharmacy benefit did not differ in the pre-policy and post-policy periods for the intervention (8.76% vs. 8.54%) or control group (7.95% vs. 7.32%). Before applying the study requirement of continuous enrollment in the pre-policy period, the rates of attrition (results not shown) did not differ between VBF and control groups in the pre-policy periods. After applying the study requirement of continuous enrollment in the pre-policy period, the rates of attrition (results not shown) also did not differ between VBF and control groups in the post-policy period.

In a previous study (Kai et al. 2016), we evaluated the impact of this VBF policy on medication expenditures from member, health plan, and member plus health plan (overall) perspectives. We also measured as secondary outcomes, medication utilization, emergency department visits, hospitalizations, office visits, and non-medication expenditures using these data over a slightly longer period of time. We assessed changes using an interrupted trends analysis with generalized estimating equations. In the intervention group after VBF implementation, member medication expenditures increased by $2 per member per month (PMPM) (95% CI, $1 to $3) or 9%, while health plan medication expenditures decreased by $10 PMPM (95% CI, $18 to $2) or 16%, resulting in a net decrease of $8 PMPM (95% CI, $15 to $2) or 10%, which translates to a net savings of $1.1 million. Utilization of medications moved into lower copayment tiers increased by 1.95 days' supply (95% CI, 1.29 to 2.62) or 17%. Total medication utilization, health services utilization and non-medication expenditures did not change. There were no differences in pre-period trends between the intervention and control group and the effect of VBF was found to be an intercept shift in the post period with no effect on the differential trends. This makes our difference-in-difference strategy for this analysis valid.

For the current analysis, Figure 2 shows the regression-based predictions of a $1 increase in copayment on the quarterly probability of fill per member (i.e. first part of the two part model, Figure 2a) and the number fills per member for each drug conditional on having a fill (i.e. second part of the two part model, Figure 2b) as well as the total number of fills per member (i.e. combination of the two part model, Figure 2b). As suggested by our composite elasticity formulation, some medications had predicted increases in quantity demanded despite copayment increases. However, for each measure of quantity, there were more medications with predicted decreases than increases in quantity demanded. It is also important to note that the effect of the price change manifest mostly on the intensive margin rather than the extensive margin of fills.

We find that overall price elasticity of demand was -0.16 (95% CI: -0.23, -0.09) (Table 2). Hence, a doubling of copayment faced by the enrollees in this study is expected to reduce the number of fills of a medication by 16%.

Our elasticity estimates by VBF copayment tier were -0.09 (95% CI, -0.11 to -0.07) for medications placed in the preventive tier, -0.06 (95% CI, -0.18 to 0.05) for medications placed in tier 1, -0.60 (95% CI, -0.7 to -0.49) for medications placed in tier 2, -0.77 (95% CI to -0.93, -0.6) for medications placed in tier 3, and -0.87 (95% CI, -1.16 to -0.58) for medications placed in tier 4. Based on the trend test, we reject the null hypothesis that there is no trend in elasticities comparing copayment tiers ($p < 0.01$). This suggests that 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 given the VBF design.

More importantly, as expected based on the theoretical discussions in the previous section, we find that for VBF Tier 1 drugs, which represent good value, price elasticity was larger for those that experienced price decreases but smaller for those that experienced price increases. Similarly, for drugs placed in higher VBF tiers, which represent lower value, price increases were associated with much higher price elasticities.

The elasticity estimates for statins, beta blockers, PPIs, ACE inhibitors, and biguanides were -0.41 (95% CI, -0.47 to -0.35), -0.09 (95% CI, -0.15 to -0.03),-0.69 (95% CI, -0.88 to -0.5), -0.04 (95% CI, -0.08 to 0.01), and -0.17 (95% CI, -0.24 to -0.11), respectively. The branded PPI are expected to show higher elasticity to price due to the availability of non-prescription substitutes (generic PPI and H2-blockers). More importantly, within a drug class, where each drug can be considered to be substitute for each other, PEDs align with the theoretical predictions. For example, within the statins group, statins that increased in price (indicating low value) have substantially high PED than their high value counterparts.

Our estimates for branded and generic medications were -0.76 (95% CI, -0.86 to -0.65) and -0.03 (95% CI, -0.09 to 0.04), respectively.

Overall, we find that the welfare increases due to copayment increases more than offset the welfare loss from copayment decreases. We find that for medications with copayment increases, total welfare gain was $210,000 for the cohort in the post-policy period or $40 per member while for medications with copayment decreases, welfare loss was -$63,000 or -$12 per member, therefore the net welfare gain was $147,000 for the cohort or $28 per member. Assessing welfare changes by copayment tiers, we find that there was net welfare loss in the preventive tier (-$62,000), primarily due to decreases of demand prices, and net welfare gains in tiers one ($97,000), two ($89,000), three ($18,000) and four ($4,000).

5. ROBUSTNESS CHECKS

We examined whether our findings were affected by our inclusion criteria: individuals were not required to be continuously enrolled in the post-policy period. We assessed an alternative specification in which we required individuals to be enrolled for the entire period of study. This reduced our sample size to 4,252 members and 3,789 members in the intervention and control groups, respectively. The results are similar to the findings of our primary analysis (Table 5).

6. DISCUSSION AND IMPLICATIONS

In this study, we present a formal framework to explain consumer medication utilization behavior in the context of differential changes in copayments that incorporates cross price elasticity and own price elasticity effects into a model of observed composite elasticity. Specifically, our model predicts that when copayments decrease for a (high value) medication and increase for its (low value) substitutes, we would find greater price elasticity than would be expected had either the medication or its substitute been subject to a copayment change (but not both). We further extend our model to predict welfare effects. All else being equal, our model predicts that welfare loss due to copayment decreases for high value medications (which we expect to have inelastic demand) will be smaller than welfare gains from copayment increases for low value medications (which we expect to have elastic demand). We empirically estimated the composite price elasticity of demand and welfare changes in a VBF that had differential changes in copayments.

Our overall elasticity estimate of -0.16 is similar to the estimate from the RAND HIE and the estimates from observation studies using instrumental variable methods. This indicates that pharmaceutical drugs are less likely to be substitutes or complements with other medical services. This does not mean that certain drugs cannot offset other medical expenditures in the long-term, but it implies that other medical services are not considered substitutes or compliments at the point of demand for pharmaceuticals. For the elasticity estimates by copayment tiers, we observed a trend of increasing elasticity with increasing copayment tiers. That is, consumers seemed to be more price sensitive to medications placed into higher copayment tiers. This may be a direct consequence of the VBF policy: to cause substitution of medications in higher copayment tiers for medications in lower copayment tiers. Further, for medications placed in the same VBF copayment tier, medications with decreases in copayment were more elastic than medications with increases in copayment. This is most clearly observed for medications in copayment tier one. Medications with decreases in copayment had an

elasticity estimate of -0.52 and medications with increases in copayment had an elasticity estimate of -0.02. This may also be a direct consequence of the VBF to differentially increase utilization of medications in lower copayment tiers relative medications in higher copayment tiers. For example, this difference in elasticity estimates is greater in medications in tier one than tier two likely because the substitution effect is stronger in tier one than in tier two.

We found that the net effect of the VBF on welfare was positive. That is, the welfare loss decreases due to copayment increases more than offset the welfare loss increases due to copayment increases. This finding suggests that despite copayment decreases for some medications, the VBF can increase overall welfare by copayment increases. There may be multiple reasons for this finding. It may be that there were more medications with copayment increases, the magnitude of the copayment increases were larger than the copayment decreases, and the overall utilization of medications with copayment increases were greater. Indeed, we find evidence for these factors since the overall mean utilization-weighted copayment across all medications increased comparing the post VBF period to the pre VBF period. Finally, the substitution effect may also contribute to the finding. The bidirectional changes in copayments resulted in greater composite elasticity for medications with larger copayment increases (low value) because their high-valued substitutes may be experiencing lower copayment increases or copayment decreases. Similarly, the VBF generates lower composite elasticity for medications with smaller copayment increases or copayment decreases (high value) since their low-valued substitutes are experiencing larger increases in co-payments.

These results should be considered while acknowledging several 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 characteristics 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 spillovers and therefore the elasticity estimates may not necessarily generalize to a social insurance plan. Practically, the availability of cost-effectiveness evidence from a true societal perspective is limited. Third, practical limitations of pharmacy claims adjudication systems result in imprecision in matching value to copayments. Typically, the clinical indication for a medication is unknown to the health plan (or pharmacy claims adjudicator) at the time of fill. Therefore the health plan assigns the same copayment to a medication regardless of indication. However, ICER estimates may vary across indications for a single medication. Practically, the VBF assigns medications to

copayment tiers based on the ICER estimate for the indication with the highest prescription volume. This imprecision does not bias our mean elasticity estimates (since the analysis was performed at the medication level) but does impact the welfare change estimates. More precise matching of value to copayments is expected to increase the estimated effect of the VBF on welfare loss reduction. 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.

Our work suggests that by changing copayments bidirectionally, the substitution effect may be used to either amplify or dampen medication utilization. This in turn may be used to optimize welfare loss changes. Drug-specific overall elasticities that we estimated could be used to forecast welfare effects of alternative cost-effectiveness thresholds. We hope that our results presented in this paper presents a more clear picture of the effects of VBF designs on welfare and provide a more intuitive description of price elasticities obtained through such natural experiments.

References

Basu A. *Estimating Costs and Valuations of Non-Health Benefits in Cost-Effectiveness Analysis*. In. Chapter 8, Second Panel on Cost-effectiveness Analysis in Health and Medicine (ed. TBA) forthcoming 2016.

Chandra A, Gruber J, McKnight R. Patient Cost-Sharing and Hospitalization Offsets in the Elderly. *The American Economic Review.* Mar 1 2010;100(1):193-213.

Chandra A, Gruber J, McKnight R. The impact of patient cost-sharing on low-income populations: evidence from Massachusetts. *Journal of Health Economics.* Jan 2014;33:57-66.

Chernew M, Gibson TB, Yu-Isenberg K, Sokol MC, Rosen AB, Fendrick AM. Effects of increased patient cost sharing on socioeconomic disparities in health care. *Journal of General Internal Medicine.* Aug 2008;23(8):1131-1136.

Contoyannis P, Hurley J, Grootendorst P, Jeon SH, Tamblyn R. Estimating the price elasticity of expenditure for prescription drugs in the presence of non-linear price schedules: an illustration from Quebec, Canada. *Health Economics.* Sep 2005;14(9):909-923.

Cuzick J. A Wilcoxon-type test for trend. *Statistics in medicine.* Jan-Mar 1985;4(1):87-90.

Danzon P. *Price comparison of pharmaceuticals: A review of the US and cross national studies* Washington DC: AEI Press; 1999.

Gatwood J, Gibson TB, Chernew ME, Farr AM, Vogtmann E, Fendrick AM. Price elasticity and medication use: cost sharing across multiple clinical conditions. *Journal of managed care & specialty pharmacy.* Nov 2014;20(11):1102-1107.

Gaynor M, Li J, Vogt W. Substitution, spending offsets, and prescription drug benefit design. *Forum for Health Economics & Policy.* 2007;10(2).

Gibson TB, McLaughlin CG, Smith DG. A copayment increase for prescription drugs: the long-term and short-term effects on use and expenditures. *Inquiry : a journal of medical care organization, provision and financing.* Fall 2005;42(3):293-310.

Gilman BH, Kautter J. Impact of multitiered copayments on the use and cost of prescription drugs among Medicare beneficiaries. *Health Services Research.* Apr 2008;43(2):478-495.

Goldman DP, Joyce GF, Escarce JJ, et al. Pharmacy benefits and the use of drugs by the chronically ill. *JAMA.* May 19 2004;291(19):2344-2350.

Goldman DP, Joyce GF, Zheng Y. Prescription drug cost sharing: associations with medication and medical utilization and spending and health. *JAMA.* Jul 4 2007;298(1):61-69.

Hosmer DW, Lemeshow S. *Applied logistic regression.* 2nd ed. New York: Wiley; 2000.

Joyce GF, Escarce JJ, Solomon MD, Goldman DP. Employer drug benefit plans and spending on prescription drugs. *JAMA.* Oct 9 2002;288(14):1733-1739.

Keeler Emmett B, Rolph John E. The Demand for Episodes of Treatment in the Health Insurance Experiment. *Journal of Health Economics.* 1988; 7:337–367.

Landsman PB, Yu W, Liu X, Teutsch SM, Berger ML. Impact of 3-tier pharmacy benefit design and increased consumer cost-sharing on drug utilization. *The American Journal of Managed Care.* Oct 2005;11(10):621-628.

Manning WG, Newhouse JP, Duan N, Keeler EB, Leibowitz A, Marquis MS. Health insurance and the demand for medical care: evidence from a randomized experiment. *The American economic review.* Jun 1987;77(3):251-277.

Newhouse JP. *Free for All?: Lessons from the RAND Health Insurance Experiment.* Cambridge, MA.: Harvard University Press; 1993.

Pregibon D. Goodness of Link Tests for Generalized Linear Models. *Applied Statistics.*

Figure 1. Effect of copayment change on welfare. (a) if P_1^* >, < P_1 and SMC > P_1 and SMC > P_1^*; (b) if P_1^* >, < P_1 AND (P_1^* > SMC > P_1 or if P_1^* < SMC < P_1) (c) if P_1^* >, < P_1 AND SMC < P_1 and MC < P_1^*.

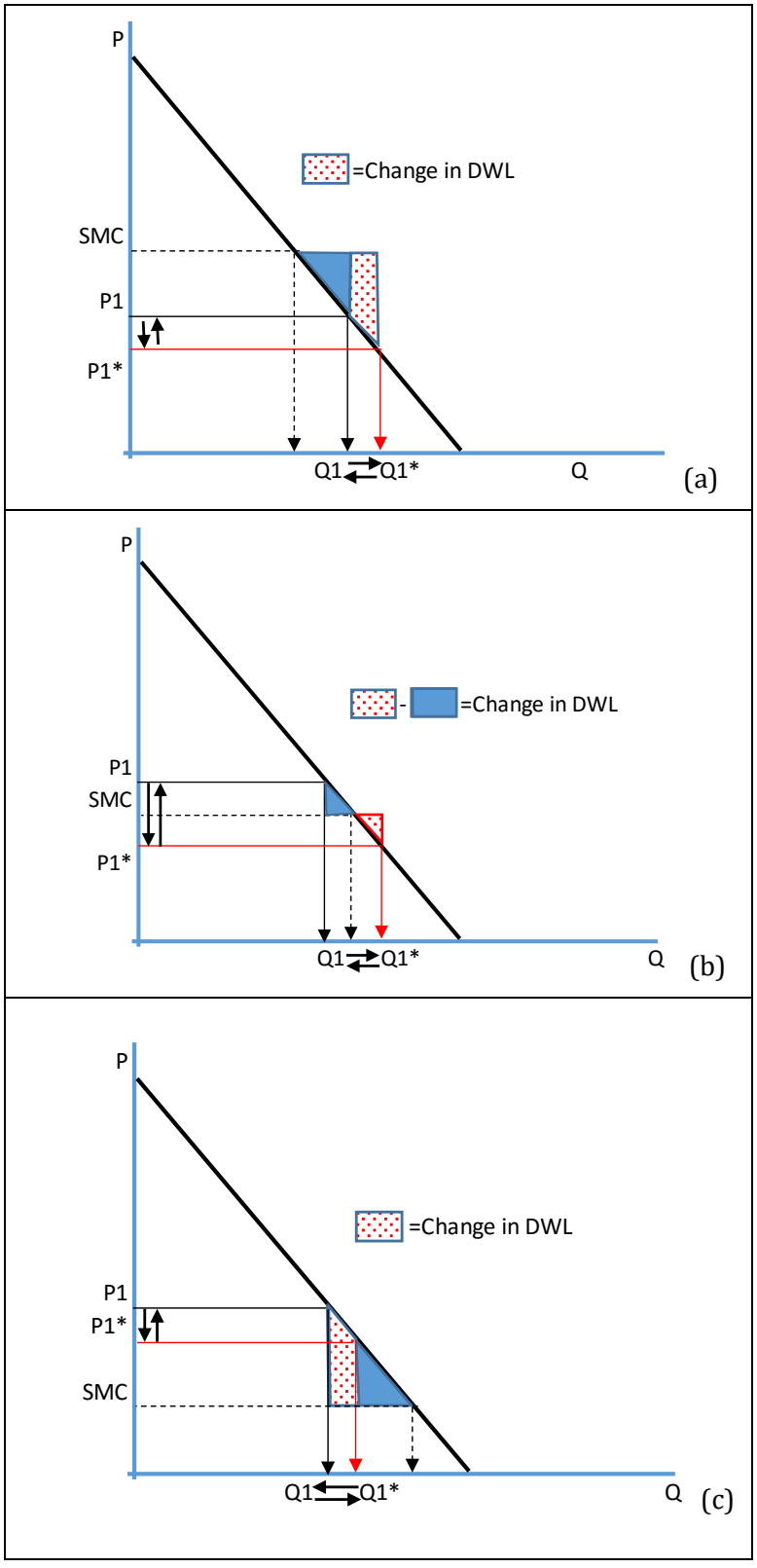
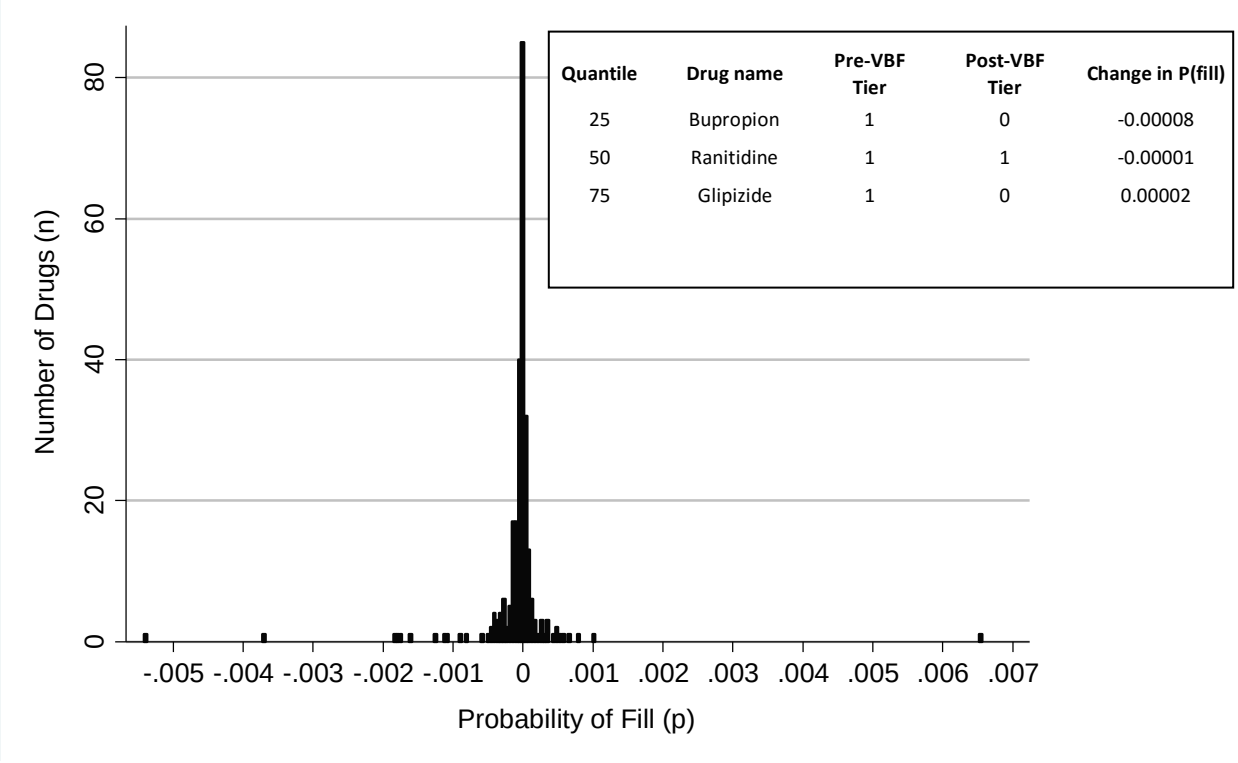
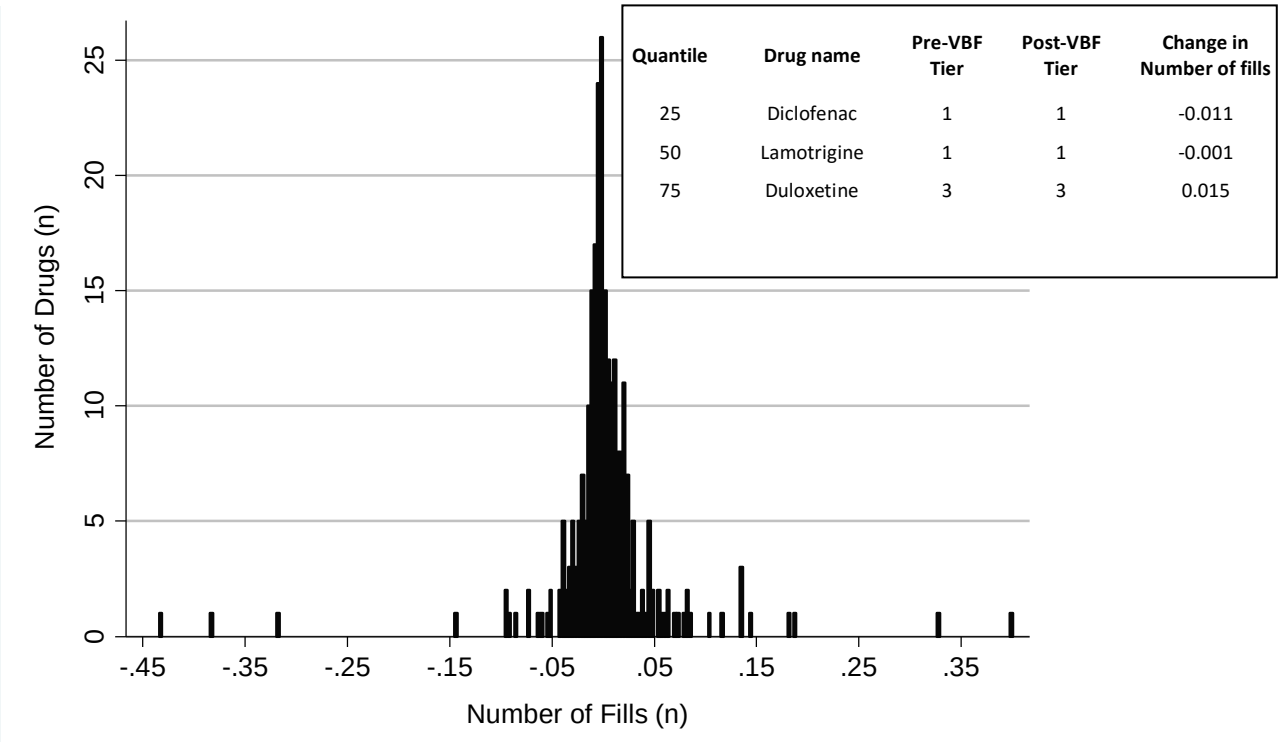


Figure 2a. Predicted effect of $1 increase in copayment on the quarterly probability of fill per member for each drug



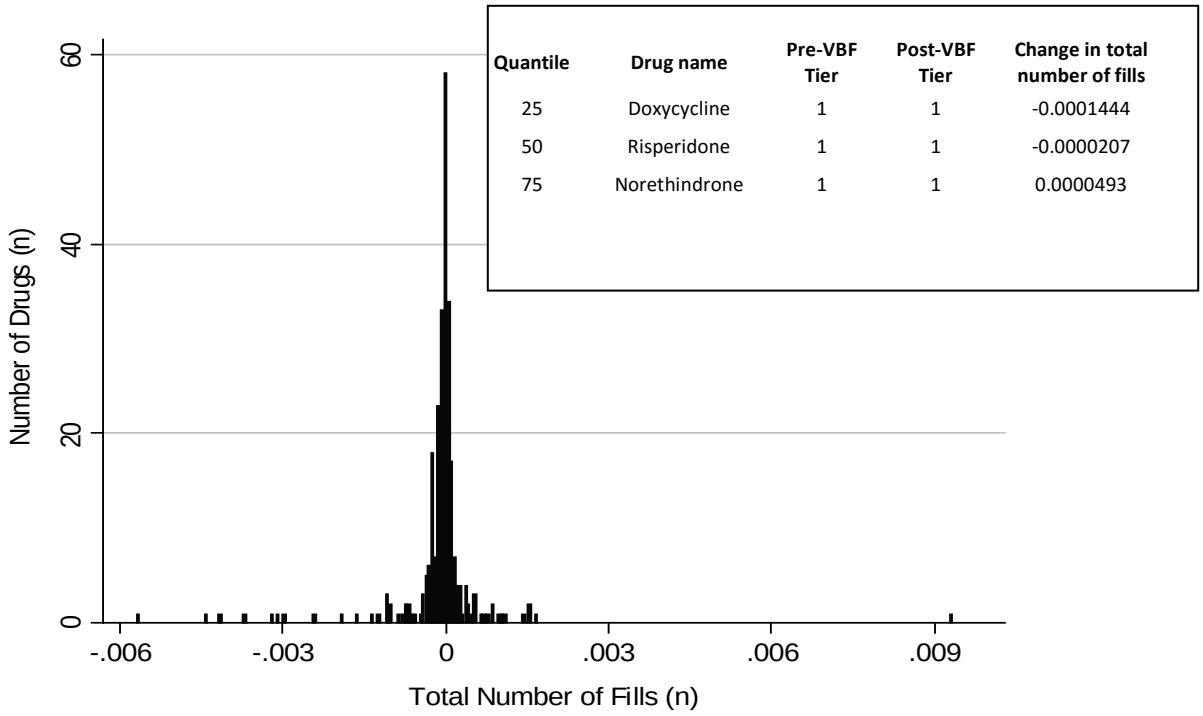
Quantile	Drug name	Pre-VBF Tier	Post-VBF Tier	Change in P(fill)
25	Bupropion	1	0	-0.00008
50	Ranitidine	1	1	-0.00001
75	Glipizide	1	0	0.00002

Figure 2b. Predicted effect of $1 increase in copayment on the quarterly number of fills (given any fill) per member for each drug



Quantile	Drug name	Pre-VBF Tier	Post-VBF Tier	Change in Number of fills
25	Diclofenac	1	1	-0.011
50	Lamotrigine	1	1	-0.001
75	Duloxetine	3	3	0.015

Figure 2c. Predicted effect of $1 increase in copayment on the quarterly total number of fills per member for each drug



Quantile	Drug name	Pre-VBF Tier	Post-VBF Tier	Change in total number of fills
25	Doxycycline	1	1	-0.0001444
50	Risperidone	1	1	-0.0000207
75	Norethindrone	1	1	0.0000493

Table 1. Pharmacy benefits for intervention and control groups during the pre-policy and post-policy periods

Intervention		
Tier	Pre-policy Copayment ($)	Post-policy Copayment ($)
Preventive	—	0
Tier 1	10	20
Tier 2	30	40
Tier 3	50	65
Tier 4	—	100
Control		
Tier	Pre-policy Copayment ($)	Post-policy Copayment ($)
Tier 1	20	20
Tier 2	40	40
Tier 3	80	80

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

Characteristic	Intervention (n = 5,235)	Control (n = 4,357)	P Value
Individual characteristics			
Age, yrs, n (SD)	32.9 (17.6)	33.9 (18.2)	0.007
Charlson score=0, N (%)	4,422 (84.5)	3,727 (84.0)	0.33
Charlson score=1, N (%)	582 (11.1)	447 (11.5)	0.33
Charlson score>=2, N (%)	231 (4.4)	183 (4.6)	0.33
Enrollees per family unit, n (SD)	3.1 (1.5)	3.31 (1.64)	0.76
Female, N (%)	2,960 (56.5)	2,217 (57.0)	0.65
ZIP code characteristics			
African American, % (SD)	2.9 (3.5)	3.64 (6.76)	<0.001
Bachelor's degree or higher, % (SD)	34 (13.6)	37.3 (16.7)	<0.001
Median household income, $1000, (SD)	68.9 (18.5)	66.1(24.3)	<0.001
Urban residence, % (SD)	91.7 (17.0)	84.7 (25.9)	<0.001
Utilization Characteristics			
Use of prescription, N (%)	3,784 (35.6)	3,195 (36.9)	0.084
Total monthly prescriptions, n (SD)	0.903 (1.53)	.879 (1.42)	0.43

Table 3. Mean co-payments and quantities demanded in the year before and after policy change and associated elasticity and welfare estimates overall and by Value-based Formulary (VBF) copayment tier

Drug Category	Copay change Direction	Unique drugs, n	Mean copayment Per medication		Mean Quarterly Fills per Medication per 100 Members		Elasticity Estimates (95% CI)		Welfare Effect per Member (95% CI), $	
			Counter-factual Estimate, $	Factual Estimate, $	Counter-factual Estimate, n	Factual Estimate, n	By copay change direction	Overall	By copay change direction	Overall
Overall	Decrease	72	13	3	2.60	3.20	-0.17 (-0.24, -0.1)	-0.16 (-0.23, -0.09)	-12 (-14, -10)	28 (20, 36)
	Increase	197	16	25	2.68	2.65	-0.15 (-0.25, -0.05)		40 (33, 47)	
Value-based Copayment Tier										
Preventive	Decrease	56	11	0	2.70	3.40	-0.09 (-0.11, -0.07)	-0.09 (-0.11, -0.07)	-12 (-14, -10)	-12 (-14, -10)
	Increase	0	N/A	N/A	N/A	N/A	N/A		N/A	
1	Decrease	12	18	13	2.14	2.15	-0.52 (-1.04, -0.01)	-0.06 (-0.18, 0.05)	0 (-1, 0)	19 (14, 23)
	Increase	120	9	15	3.10	3.20	-0.02 (-0.13, 0.09)		19 (14, 23)	
2	Decrease	4	51	44	1.20	1.40	-.79 (-1.35, -.24)	-0.6 (-0.7, -0.49)	0 (0, 0)	17 (13, 21)
	Increase	38	33	47	1.10	0.80	-0.57 (-0.68, -0.46)		17 (13, 21)	
3	Decrease	0	N/A	N/A	N/A	N/A	N/A	-0.77 (-0.93, -0.6)	N/A	3 (2, 5)
	Increase	29	47	74	0.78	0.60	-0.77 (-0.93, -0.6)		3 (2, 5)	
4	Decrease	0	N/A	N/A	N/A	N/A	N/A	-0.87 (-1.16, -0.58)	N/A	1 (0, 1)
	Increase	10	50	117	0.39	0.14	-0.87 (-1.16, -0.58)		1 (0, 1)	

Table 4. Mean co-payments and quantities demanded in the year before and after policy change and associated elasticity and welfare estimates by therapeutic class, and by brand-generic status

Drug Category	Copay change Direction	Unique drugs, n	Mean copayment Per medication		Mean Quarterly Fills per Medication per 100 Members		Elasticity Estimates (95% CI)		Welfare Effect per Member (95% CI), $	
			Counter-factual Estimate, $	Factual Estimate, $	Counter-factual Estimate, n	Factual Estimate, n	By copay change direction	Overall	By copay change direction	Overall
Therapeutic Class										
Statins	Decrease	3	10	0	4.10	5.30	-0.13 (-0.17, -0.09)	-0.41 (-0.47, -0.35)	-3 (-4, -2)	-2 (-3, -1)
	Increase	2	25	51	3.40	1.80	-1.08 (-1.26, -0.9)		1 (1, 2)	
Beta Blockers	Decrease	8	11	0	1.80	2.20	-0.08 (-0.13, -0.02)	-0.09 (-0.15, -0.03)	-1 (-1, 0)	-1 (-1, 0)
	Increase	1	50	57	0.27	0.25	-0.63 (-2.45, 1.19)		0 (0, 0)	
Proton-pump Inhibitors	Decrease	0	N/A	N/A	N/A	N/A	N/A	-0.69 (-0.88, -0.5)	N/A	1 (1, 2)
	Increase	3	27	41	1.30	1.00	-0.69 (-0.88, -0.5)		1 (1, 2)	
ACE Inhibitors	Decrease	7	11	0	4.70	5.40	-0.04 (-0.08, 0.01)	-0.04 (-0.08, 0.01)	-1 (-2, -1)	-1 (-2, -1)
	Increase	0	N/A	N/A	N/A	N/A	N/A		N/A	
Biguanides	Decrease	2	11	0	2.70	3.90	-0.17 (-0.24, -0.11)	-0.17 (-0.24, -0.11)	-1 (-2, -1)	-1 (-2, -1)
	Increase	0	N/A	N/A	N/A	N/A	N/A		N/A	
Branded or Generic Drugs										
Generic Drugs	Decrease	65	10	0	2.70	3.20	-0.16 (-0.24, -0.09)	-0.03 (-0.09, 0.04)	-11 (-13, -9)	8 (3, 14)
	Increase	118	9	15	3.10	3.20	0.06 (-0.04, 0.17)		19 (15, 24)	

Branded Drugs	Decrease	7	38	24	2.30	2.50	-0.2 (-0.4, 0)	-0.76 (-0.86, -0.65)	-1 (-2, -1)	20 (14, 25)
	Increase	79	38	59	1.00	0.69	-0.93 (-1.05, -0.8)		21 (16, 26)	