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The Impact of Private Sector Pricing Policy on Health Care: Evidence from Wal-Mart's $4 Prescription Program

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I. INTRODUCTION

Prescription drugs are vital to preventing and treating illness and in helping to avoid more costly medical problems. Rising drug costs, implementation of the Medicare Part D drug benefit in 2006, and the expansion of both the number of people covered by health insurance and the breadth of their benefits from the passage of health reform legislation in March 2010 have all highlighted the pressing need for a better understanding of the pharmaceutical market and the cost efficiency of prescription drug expenditures.

Although prescription drug spending has been a relatively small proportion of national health care spending, it is one of the fastest growing components. Spending on prescription drug was $234.1 billion in 2008, about 3.57 times the $40.3 billion spent in 1990[1]. The annual prescription spending growth slowed down from 18% in 1999 to 6% in 2005[2]. The increased use of generic drugs which, to some degree, replace the more expensive name-brand drugs is one of the major reasons for the slowing down from 1999 to 2005. Although the growth of costs seemed to slow down, after Medicare Part D, a federal program that subsidizes Medicare beneficiaries for prescription drugs, was introduced in 2006, the annual growth in drug spending in 2006 increased to 9% again. Furthermore, the United States Department of Health and Human Services projects that the US prescription drug spending will double from $234.1 billion in 2008 to $457.8

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[1] Kaiser Family Foundation Calculations using National Health Expenditure historical data from Centers for Medicare & Medicaid Services. <http://www.cmc.hhs.gov/NationalHealthExpendData/>.
Note: To adjust for inflation, the real growth rate uses historical annual inflation rate of Consumer Price Index published by the Bureau of Labor Statistics.

[2] Kaiser Family Foundation, *Kaiser Family Foundation Prescription Drug May 2010 Fact Sheet*. < http://www.kff.org/rxdrugs/upload/3057-08.pdf>.

billion in 2019[3]. The Affordable Care Act (ACA), passed by Congress and then signed into law by the President on March 23, 2010, is also extending health insurance to people who are currently uninsured and is providing copayment subsidies for low-income people, which can potentially cause an increase in the prescription drug utilization.

Rising drug costs and the expansion of both the number of people covered by health insurance and the breadth of their benefits should all raise the awareness of policy makers on the cost efficiency of prescription drug expenditures. The impact of increased usage of prescription drugs on the utilization of other types of medical care and the impact on patients' health status should be carefully studied. My thesis uses Wal-Mart's prescription drug program to examine the impact of a prescription drug pricing policy by private firms on health spending behavior and health outcomes. This program, started in 2006, cut prices of nearly 300 generic prescription drugs to $4 per prescription for a month's supply and includes generics that treat allergies, high cholesterol, hypertension and diabetes, etc. Due to Wal-Mart's large purchasing bargaining power and the high profit margin in generic drugs, there should be no significant difference in the quality of generic prescription drugs before and after the program.

After Wal-Mart introduced this pricing policy to lower the cost of prescription drugs, patients should be able to afford more prescription drugs. However, health policy makers should also seek to understand the strength and the extent of substitution and complementarity between prescription drugs and other medical services, such as hospital visits and emergency room usage, in order to understand the impact of the change in price of prescription drugs on utilization of other medical care. In addition, if patients use other

[3] Kaiser Family Foundation, *Kaiser Family Foundation Prescription Drug May 2010 Fact Sheet*. < http://www.kff.org/rxdrugs/upload/3057-08.pdf>. Note: Data is not adjusted for inflation.

types of medical care more after the pricing policy, health policy makers may expect improvement in health outcomes as a result of the increased utilization of medical care.

Since incentive levels are different for the uninsured and the insured, I expect to see a disproportional impact from the pricing policy in these two groups on health spending and health outcomes. The uninsured are more likely to be affected by the price decline in prescription drugs since they pay mostly on their own, while the insured people may not respond to the price change as much as the uninsured people do because their insurance company can subsidize them a lot through low insurance copayment. Therefore, in my research, I make the uninsured my treatment group and the insured my control group. I use a differences-in-differences model to measure the impact of the pricing policy on average drug prices, the usage of prescription drugs, utilization of other types of medical care and health improvement for the uninsured.

From my results, I find that overall, prescription drug usage increases and other health care services usage decreases among the uninsured as a result of the $4 program. The decreased utilization of other types of medical services can be a result from a substitution effect from other medical services to prescription drugs, or from improved health outcomes of patients. From my research, however, I could not find any statistically significant improvement on health outcomes. Additionally, I find that the price elasticity of demand for prescription drugs among the uninsured group to be -1.0, comparing to the traditionally accepted RAND price elasticity -0.2. This shows that the uninsured people are more price-sensitive than the general population. The price sensitivity of medical care decisions among the uninsured can help us in designing health insurance products for them accordingly. For instance, if the uninsured are not price sensitive, then copayments don't matter; if they are very price sensitive, there is a lot of value in incorporating copayments. Since the Affordable Care Act (ACA) is extending health insurance to people who are currently uninsured and is including copayment subsidies for low-income people, the knowledge of uninsured people's price sensitivity might be able to give some suggestions to the ACA.

II. WALMART'S $4 PRESCRIPTION PROGRAM

In 2006, Wal-Mart launched a program cutting prices of nearly 300 generic prescription drugs to $4 per prescription for a month's supply. Initially, this program was launched only in the Tampa Bay area in Florida in September. The company claimed that this program was designed to "help consumers manage health costs," which can be achieved not only by a direct price decline, but also by "introducing competition to an area where there hasn't been enough of it", and to help consumers, especially working families, "treat illness, manage conditions and stay well."[4] Just in two months after the program started, Wal-Mart quickly made this program available in all Wal-Mart stores all over the United States including Neighborhood Market and Sam's Club. In order to ensure more patients take advantage of the program, regardless of whether or not they live close to a pharmacy, in 2009 the program further expanded its access by providing a nationwide free prescription mail delivery program. In addition to the geographical expansion, to further lower customers' spending and to create more benefits, Wal-Mart has expanded the drug types from 291 to around 350 generic prescriptions. The program covers a variety of drug types including medicines for diabetes, cardiovascular disease,

[4] "Wal-Mart cuts generic prescription medicines to $4." *Wal-Mart.com.* News Archive, 21 Sep. 2006. Web. 5 Apr. 2013.

asthma, colds and infections. This program is available to people with or without health insurance and requires no membership.[5]

When the program started in Florida, the company claimed that this program could provide a solution for the nearly 2.7 million uninsured Floridians and could potentially save Florida's Medicaid program hundreds of thousands of dollars annually[6]. They calculated savings by comparing $4 to the price of the comparable name brand medicine. Wal-Mart then concluded that drugs in this program can save its customers a large amount of money each year. For example, Lisinopril for $4 could save customers around $100. Moreover, in one of its 2008 news announcements, Wal-Mart reported that, by March 2008, the program had saved Americans more than $1 billion[7]. They certainly overstated the saving effect of the program, since they did not compare the new price to the old price of generic drugs; instead they compared it to the price of name brand drugs that have always been more expensive.

Although generic drugs are less-expensive drugs compared to brand name drugs and the saving effect could not be as much as Wal-Mart has stated, the $4 program still makes a big difference in many consumers' medical costs. Based on data from the National Association of Chain Drug Stores, a prescription drug trends report in 2010 found that the average price to fill a prescription for a generic drug was $35.22[8]. In addition, the US Food and Drug Administration (FDA) concluded that, on average, the cost of a generic drug is 80 to 85 percent lower than the brand name ones. The FDA also

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[5] "Complete list of $4 Prescriptions". *Wal-Mart.com.* $4 Prescriptions. Web. 5 Apr. 2013. <http://www.walmart.com/cp/PI-4-Prescriptions>.
[6] "Wal-Mart cuts generic prescription medicines to $4." *Wal-Mart.com.* News Archive, 21 Sep. 2006. Web. 5 Apr. 2013.
[7] "Wal-Mart Saves Customers More than $1 Billion." *Wal-Mart.com.* News Archive, 14 Mar. 2008. Web. 5 Apr. 2013.
[8] Kaiser Family Foundation, *Prescription Drug Trends*, Page 3, May 2010.

reported that generic drugs and name brand drugs have similar quality[9]. The generic drugs are much cheaper because they are not required to repeat the costly clinical trials of new drugs and generally do not pay for costly advertising, marketing, and promotion. In addition, multiple generic companies approved to market a single product can create competition in the market place, often resulting in lower prices.

Wal-Mart's contribution to lowering prices was not limited to its own stores; rather, this program further lowered the market price by creating stronger competition in the generic prescription drug market. Now, Kroger, Target and Hy-Vee all have $4 generic drugs programs for a 30-day supply and $10 programs for a 90-day supply. CVS does not have a $4 program, but it has started to sell generic drugs at $9.99 for a 90-day supply. Moreover, the program has been successfully attracting the uninsured since it was reported in the same 2008 news announcement that nearly 30 percent of $4 prescriptions were filled without insurance, significantly higher than the 10 percent industry average in the same year.

When Wal-Mart announced this program, they made it sound like this program was an act of charity, mainly to help the working class save money and live a healthier life. Charity may be one of the reasons why Wal-Mart started the program, but this company definitely did not plan to give its money away or directly transfer to people in need. Instead, Wal-Mart uses its mass distribution strategy to lower prices in its stores so that the company will not be selling the drugs at a loss. One potential reason for Wal-Mart to run this program is to attract more customers who will spend money elsewhere in the store. Another possibility is that the drugs in the $4 program were unpopular, so Wal-

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[9] U.S. Food and Drug Administration, *Facts about Generic Drugs*. <http://www.fda.gov/>.

Mart reduced their prices in order to get rid of them. The true reason why the program was built may be a combination of all.

III. LITERATURE REVIEW

A. Wal-Mart

Wal-Mart is usually considered to be a non-traditional outlet, a supercenter because it is a chain of extremely large stores that sell a wide variety of products at a low price. Differentiated from more traditional shopping outlets that often specialize in a specific category of goods, Wal-Mart sells food, clothing, prescription drugs, home office supplies and electronic equipment, etc. In order to reduce transportation costs, Wal-Mart stores tend to locate close to distribution centers. In addition, because one of Wal-Mart's major business strategies is its competitively low prices, the company is more likely to locate its stores in lower income areas. When a Wal-Mart enters a new area, it often encounters significant opposition from competing outlets and from labor unions: competing outlets often have to respond by lowering their price, and Wal-Mart is often accused of giving workers low wages and long hours.

Basker (2007) reports that Wal-Mart's comparative advantage comes from a combination of technological prowess and economies of scale, scope, and density. With the comparative advantages from its advanced technological system and strong buying power, Wal-Mart is able to lower its price to a competitive price level. She also points out that the suppliers' market is not perfectly competitive because if it were, the market would already be at the zero economic profit equilibrium. In that case, Wal-Mart could not force prices down. Basker also reports that the company brings consumers lower prices and increased convenience and its entry usually lowers the prices of other incumbent competitors. As a result, consumers who shop elsewhere also indirectly benefit from its lower price.

Although workers may complain about their low wages and long hours, past studies show that Wal-Mart actually makes consumers better off. Hausman et al (2007) use household-level consumer food-at-home expenditure data to test the effect of the introduction of Wal-Mart on consumers' welfare level. They find that consumers substantially benefit from Wal-Mart's entry and expansion into markets for food by direct price decreases and by indirect price effects. They report that Wal-Mart offers many identical food items at an average price 20.2% lower than traditional supermarkets and the average indirect price effect that arises from the increased competition is about 4.8%. As a result, they find an average total effect to be 25% of food expenditure and this increases consumers' welfare. If the impact of Wal-Mart's entry in the food market can be applied to the pharmaceutical market, one should be able to find that after Wal-Mart lowers its prescription drugs' price down directly followed by an indirect price effect in the market, consumers should be better off.

B. Price Elasticity

When health care is cheaper, economic theory predicts that utilization of health care should be at a higher level. The magnitude of this effect is measured by the price elasticity of demand. The price elasticity of demand for health care has already been studied widely, especially after the RAND Health Insurance Experiment. The most famous and widely accepted result is the RAND result by Manning et al (1987), which suggests that the price elasticity of demand for medical care is -0.2. The -0.2 price elasticity of demand for health care implies that, if the price decreases by 10%, then quantity will increase by 2%.

Aron-Dine et al's (2012) working paper reexamines the RAND experiment and tests the effect of health insurance generosity on health care utilization. They find that the RAND data reject the null hypothesis of no utilization response to cost sharing. In particular, "when the outcome is total spending, our ability to reject the null that utilization does not respond to consumer cost sharing survives all of our adjustments in two of the three specifications, any spending and log spending", indicating that the health utilization changes when price changes.

Besides the RAND experiment, the previous literature measures the price elasticity of medical care using other methods as well, and different methodologies will lead to different results. Finkelstein (2005) uses the introduction of Medicare in 1965 to estimate the change in aggregate demand and her estimate is much larger than the RAND result, due to the spillover effect of Medicare on non-beneficiaries. She explains that since her investigation uses the introduction of Medicare instead of RAND experiment, a much larger population is affected compared to RAND and the macro environment is changed. The introduction of Medicare, lowering the out-of-pocket medical cost and increasing utilization of medical care for a huge population, further changed the medical treatment practice through advances in medical technology. Therefore, Medicare beneficiaries were not the only people who are affected by the introduction of Medicare, but non-beneficiaries were affected indirectly as well. Because both Medicare beneficiaries and non-beneficiaries increased their health care utilization after Medicare was introduced, it is not surprising that the overall increase in per capita health utilization after the introduction of Medicare is higher than the increase in per capita health utilization for people assigned to low coinsurance plans in the RAND experiment. Kowalski (2010) also finds that her estimate of price elasticity of demand for medical care is larger than the RAND result. She uses an estimator called Censored Quantile Instrumental Variable (CQIV) in her working paper and finds the price elasticity to be -2.3 "across the .65 to .95 quantiles of the expenditure distribution." Her instrumental variable is an indicator for a family member having an injury. A crucial assumption in her paper is that being in a family with an injured family member only lowers one's marginal price of medical care, not directly affecting one's medical spending. To create the instrument, Kowalski includes only specific injury categories. These injury categories are unexpected enough that treatment for an injury in these categories should not be related to an underlying family-level propensity to seek treatment, and severe enough to meet the household medical spending threshold that makes its family members' marginal prices different from families without an injured member due to exceeding a stop-loss. Her results show that the price elasticity of expenditure on medical care is "-2.3 across the .65 to .95 quantiles of the expenditure distribution, with a point-wise 95% confidence interval at the .80 quantile of -2.5 to -2.0."

From the literatures on the price elasticity of demand for medical care, one can conclude that the impact of a price change on health utilization under different situations targeting different groups can be very different. This may indicate that my study of prescription drug spending responding to the $4 prescription drug program might get very different results compared to results from the previous literatures. I will not be surprised since my study targets different groups (the uninsured) and different type of medical services (prescription drugs instead of general medical care).

C. Impact of price change on health care utilization and health outcomes

Since my research focuses on pricing policy for prescription drugs instead of general medical care, I am also interested in the impact of price changes for prescription drugs on utilization of other types of medical care. Economic theory suggests that there may be two types of effect here, the income effect and substitution effect. The income effect says that since prescription drugs are cheaper, patients have a better affordability and utilization of other types of health care should be higher. But substitution effect says that because prescription drugs are cheaper now, patients might want to spend more on prescription drugs and reduce their spending on other types of medical care. If the income effect is bigger, the price change in prescription drugs has a positive impact on utilization of other medical care. If the substitution effect is larger, the impact is negative. Prescription drugs might also be complements of other forms of medical care, which could lead to more use of those types of care when prescription drug use increases. The past literature finds empirically that the impact on utilization of other medical services can be both positive and negative.

Gaynor et al. (2007) find a positive overall effect on utilization of other medical services. They use individual health insurance claims and benefits data from 1997 to 2003 to study the impact of changes in co-payments for prescription drugs on use of and expenditure on prescription drugs, inpatient care, and outpatient care. They find that the substitution between outpatient care and prescription drug expenditures is about 35%

which implies that about 35% of the expenditure reductions on prescription drugs are offset by increases in other medical expenditures.

Similarly, Tamblyn et al (2001) find that the increased cost-sharing for prescription drugs is followed by reductions in use of essential drugs but increased Emergency Department visits associated with these reductions for elderly and welfare recipients. Encinosa et al. (2010) report that increasing diabetic drug adherence from 50% to 100% reduced the annual hospitalization rate by 23.3% from 15% to 11.5%. ER visits are reduced by 46.2% from 17.3% to 9.3%.

Some research shows that income level matters when measuring the substitution between prescription drugs and other types of medical care. For example, Shang and Goldman (2007) find that lowering the price of prescription drugs does affect utilization of other health care, but the strength of the substitution is associated with consumers' income level. They use the Medicare Current Beneficiary Survey (MCBS) panel data to examine spending of Medicare beneficiaries with and without supplemental drug coverage and find that a $1 increase in prescription drug spending is associated with a $2.06 reduction in Medicare spending on other types of care. Furthermore, they find that the substitution effect decreases as income rises, indicating that low-income targeted programs affect other health utilization in a larger extent.

No matter what the direction of the effect on other health care utilization is, after prescription drugs become cheaper, utilization of prescription drug use in general should increase. With an increased utilization of prescription drugs, policy makers might expect to see an overall health improvement. However, very little of prior literature suggests that there is any significant impact on health outcomes after health care becomes more affordable. Manning et al (1988) use RAND experiment data and conclude that there is no significant health improvement after coinsurance is lowered. Finkelstein and McKnight (2005) examine the effect of the introduction of Medicare on health outcomes and find that there is no significant health improvement, either. But economic theory predicts that health outcomes associated with health reform might be related to beneficiaries' income level. Usually we cannot see significant improvements on high-income individuals because they are on the so-called "flat of the curve", meaning that their marginal health improvement from additional health expenditure is very low since they are already receiving sufficient care. However, one could expect to see the low-income group have some level of health improvement, since they are often in the status of under-care, and some additional care can bring higher marginal benefit. In my research, since uninsured people tend to be less wealthy people, I would expect to see an improvement in health outcomes following an increased utilization of health care in general.

IV. DATA & EMPRICAL DESIGN

To examine the effects of prescription drug pricing policy on the prescription drug usage, cost, health utilization and health outcomes, I use a quasi-experimental empirical approach, the differences-in-differences model, exploiting the disproportionate impact of Wal-Mart's pricing policy on the uninsured. In my setting, the uninsured are the treatment group and the insured are the control group, under the assumption that this $4 prescription program, although open to both groups, provides a higher incentive for the uninsured to participate in the program. Therefore, this pricing policy should have a much larger impact on the uninsured people. Another assumption for the differences-in-differences to be valid is the parallel trend assumption, which in this case is that, in the absence of the program, the trend for the uninsured over time would have shown the same pattern as the trend for the insured. The treatment effect in differences-in-differences represents the difference in an outcome variable after the policy change relative to before the policy change for the treatment group compared to the control group, i.e. the difference in the changes in outcomes for the uninsured and the insured after the introduction of the program.

Since the Wal-Mart program affects the pharmaceutical market directly, my data should include information on drug usage, drug spending, and the payment sources. Health utilization information such as inpatient and outpatient expenditures and health outcome status should also be part of my data for use as dependent variables. As a result, the data used in my analysis are aggregated from two different data sources, the Medical Expenditure Panel Survey (MEPS) and the Integrated Health Interview Series (IHIS), both from 2003 to 2010.

The MEPS data, my major data, have been collected since 1996. They are a set of large-scale surveys of families and individuals, their medical providers and employers across the United States. In my research, I mainly use two sub data files of MEPS, the Full-Year Consolidated Data file and the Prescribed Medicines file. The Full-Year Consolidated Data file collects individual level data on a variety of different health services that Americans use, how frequently they use these services, the cost, and how these services are paid for, as well as data on the characteristics of the individuals and their households. The Prescribed Medicine file compiles drug-level information on the price of each drug, its payment sources, its quantity sold and the MEPS ID number of the individual who purchased the drug, etc.

The IHIS is an annual data file from the 1960s to the present. It asks individuals a wide range of questions including their health conditions, health behaviors and health care access. Similar to the MEPS household sub data file, it is an individual-level data set. Data about health conditions include self-reported health status, body mass index (BMI), work loss days in the past 12 months and so on. The health behavior section asks people questions about the average number of hours of sleep per day, smoking habits and drinking habits, etc. Similar to the MEPS data, the IHIS data also have information on insurance status, along with individuals' demographic and socioeconomic information.

The Wal-Mart program was initiated in 2006; therefore I use data from 2003 to 2010. The Medicare beneficiaries started to receive more subsidies on prescription drugs from the federal government after the introduction of the Medicare Part D program in 2006. Since the Medicare Part D program largely reduces the out of pocket price of prescription drugs for the population over 65 years old, I eliminate every individual who is over 65 years old in my data.

Table 1 and Table 8 are the summary statistics for the MEPS and the IHIS after dropping individuals over 65 years old, respectively. The MEPS data have information for around 300,000 individuals, while the IHIS has twice as many observations. By comparing Table 1 to Table 8, we can see that the samples in two data sets have similar characteristics in many ways. The average age for MEPS is 34.30 and for IHIS is 30.37. The percentage male in MEPS is 48%, while in IHIS it is 49%. Individuals in the first data set on average have 11 years of education when they first entered, while in the second data set individuals have attained an average of 12 years of education. Twenty-two percent of the MEPS sample report being uninsured, and 18% of the IHIS sample are uninsured. From the data (not shown in the tables), I find that the geographical and racial compositions of the two data sets are very close to each other, too. Note that, since most of my research questions can be answered by using MEPS data, if not otherwise mentioned, the data I discuss in my paper is MEPS data.

A. The difference between the uninsured and the insured

Table 1 shows summary statistics for the individual-level data that include around 300,000 individuals. Among all individuals in my data, 22.1% are uninsured. The uninsured are on average 31.8 years old, about 3 years younger than the insured. More than half of the uninsured are male, while only 46.6% of the insured are male. The insured group also has a slightly higher educational level (0.3 more years of education) than the uninsured. The uninsured are generally poorer; the personal income of the uninsured is on average 36.8% lower than that of the insured. Utilization of health treatment by the uninsured is much lower than the insured for all types of medical care. For example, the number of outpatient visits for the uninsured is only 1/3 of the usage of the insured, total outpatient expenditures 40%, inpatient visits 41% and inpatient expenditures 37%. For prescription drugs, specifically, the uninsured individuals fill only 3.7 prescriptions per person per year, while the insured fill 10.9. The total expenditures on drug are $214.2 for the uninsured, while the insured spend about $790.4, almost four times more than the uninsured. The out of pocket cost of drugs is $137.3 on average for the uninsured, and $219.1 for the insured. Note that for the uninsured, out of pocket costs do not equal total expenditures. From my data, I find that the uninsured, besides out-of-pocket health payment, also receive assistance from state and local government or from unknown private sources to pay their prescription drugs' bills.

B. The impact on drug cost, usage and expenditure

Table 2 shows summary statistics for the drug-level data, separately by years. We can see that filling a prescription for any prescription drug on average costs between $60 and $80. If the National Association of Chain Drug Stores is correct and the average price to fill a prescription for a generic drug is indeed around $35, it is easy for us to see that generic drugs are much cheaper compared with non-generic drugs.

After Wal-Mart started the $4 program, the fraction of drugs purchased for exactly $4 drugs in the market increased rapidly, from an average of 0.03% before 2006 to 6.01% in 2010. Specifically, the uninsured group consumes substantially more $4 drugs in proportion of their total drug usage (12.52% in 2010) comparing to the insured group (5.34% in 2010). These patterns are also shown in Figure 1.

The average cost of a single prescription drug increased over time for the insured. Although the average cost of a single prescription drug for the uninsured also increased between 2003 and 2006, it started decreasing after 2006. Figure 2 shows that the trends for the average number of drugs purchased per person for the insured and the uninsured are very similar before 2006. However, after 2006 the average number of drugs purchased started to decrease for the insured, but remained pretty stable for the uninsured. Figure 3 shows that similar trend patterns follow for the average annual spending on prescription drug per person. These patterns suggest a differential decline in prices per drug for the uninsured after 2006 and a differential increase in drug purchases by the uninsured after 2006.

I show these patterns more formally in my differences-in-differences regression analysis. Specifically, I estimate:

$$Drug_{it} = \alpha + \beta *1(Uninsured_i) + \sum_{t=2003}^{2010} \sigma_t *1(Year_t) + \delta *1(Uninsured_i) * 1(Post_t) + \gamma * X_{it} + \varepsilon_{i,t} \quad (1)$$

A collection of dependent variables relevant to drug usage and cost can replace $Drug_{it}$ in the regression, including price per drug, out of pocket cost per drug, a dummy variable for \$4 prescription drugs, a dummy variable for drugs cheaper than \$5, total number of drugs purchased per person, total expenditure on drugs per person and total out of pocket expenditure on drugs per person. I choose to use $Drug_{it}$ instead of $\log(Drug_{it})$ because there are many observations with no drug purchases.

In equation (1), the dummy variable $1(Uninsured_i)$ indicates the insurance status for an individual. The variable is 1 if the associated individual is uninsured and is 0 otherwise. The dummy variable $1(Post_t)$ is 1 if year is later than 2006 and is 0 otherwise. I also include a series of year fixed effects $1(Year_t)$ and a vector of characteristics X_{it} that controls for age, race, region, family income level, etc. Note that the MEPS data only include four major regions (northeast, mid-west, south and west) and do not have state-level information.

The key variable of interest is the post dummy variable interacted with the uninsured dummy variable ($1(Uninsured_i) * 1(Post_t)$). The coefficient δ shows the disproportional impact on the uninsured of the program. To see whether the change in $Drug_{it}$ occurred at the times that coincide with the \$4 prescription drug policy change, or if they started before the \$4 prescription drug change, I add a falsification test as follows:

$Drug_{it} = \alpha + \beta * 1(Uninsured_i) + \sum_{t=2003}^{2010} \sigma_t * 1(Year_t) + \sum_{t=2003}^{2010} \delta_t * 1(Uninsured_i) * 1(Year_t) + \gamma * X_{it} + \varepsilon_{i,t}$ (2)

$Drug_{it}$ again can be the number of purchased drugs, drug price, out of pocket cost, etc. The definitions of dummy variables 1($Uninsured_i$), the year fixed effect 1($Year_t$) and the characteristic variable X_{it} remain the same. The key variables here are the pattern of coefficients on these variables (the δ_t's). By plotting all the δ_t's across years, I am able to find the estimated change in $Drug_{it}$ in each year for the uninsured relative to the insured.

C. Utilization of other types of health care

Table 1 shows that the total outpatient department expenditure is on average \$56.00, with the insured spending about \$64 on average and the uninsured only \$26.31. The Emergency Room Facility Expenditure is on average \$146.78; the insured spend about \$163.65 and the uninsured again spend much lower, only around \$85.17. The inpatient expenditure for the full sample is \$792.82 on average; the insured spend \$868.01 and the uninsured only about \$320.296. These summary statistics show that the uninsured people utilize significantly less than the insured for all types of medical services.

I use the same regression framework as equation (1) by changing the dependent variable to analyze the impact of this pricing policy on utilization of other health treatments. Specifically, I estimate:

$Utilization_{it} = \alpha + \beta * 1(Uninsured_i) + \sum_{t=2003}^{2010} \sigma_t * 1(Year_t) + \delta * 1(Uninsured_i) * 1(Post_t) + \gamma_{it} * X_{it} + \varepsilon_{i,t}$ (3)

The definitions of the dummy variable 1($Uninsured_i$), 1($Year_t$), 1($Uninsured_i$) * 1($Post_t$) and X_{it} are exactly the same as those in equation (1). The only difference is the dependent variable $Utilization_{it}$, which is a collection of dependent variables related to health utilization, including inpatient cost, number of inpatient stays, the outpatient cost, etc. I choose to use $Utilization_{it}$ instead of log ($Utilization_{it}$) because some individuals do not use certain medical services at all and $Utilization_{it}$ is zero.

The key variable of interest here is again the post dummy variable interacted with the uninsured dummy variable ($1(Uninsured_i) * 1(Post_t)$), and its coefficient δ shows the disproportional impact on the uninsured by the program. Again, I include a falsification test as below:

$$Utilization_{it} = \alpha + \beta * 1(Uninsured) + \sum_{t=2003}^{2010} \sigma_t * 1(Year_t) + \sum_{t=2003}^{2010} \delta_t * 1(Uninsured_i) * 1(Year_t) + \gamma_{it} * X_{it} + \varepsilon_{i,t} \quad (4)$$

The key coefficients of interest are the interactions between year dummies and the uninsured dummy (the δ_t's). By plotting all the δ_t's across years, I am able to find the estimated change in $Utilization_{it}$ in each year for the uninsured relative to the insured.

D. Health outcomes

After measuring the impact of the price change of prescription drugs on health spending and health utilization using the MEPS data, I switch to use the IHIS data for health outcomes analysis. Table 8 shows the summary statistics for the IHIS data and includes about 600,000 observations. In addition to investigating the difference between the insured and the uninsured, in order to show changes more clearly, I also break the data down to the pre-program period, 2003-2005, and post-program period, 2006-2010, included in Table 8.

As mentioned before, by comparing Table 1 and Table 8, we see that the IHIS population has similar characteristics compared to the MEPS population. Table 8 shows that the IHIS data have only18% of people uninsured, smaller than the percentage in the MEPS data. Overall, the uninsured in the IHIS are also more likely to be male and receive slightly fewer years of education than the insured. Interestingly, the uninsured in the IHIS are on average 1 years older than the insured. Out of 100 people, about 68 people will report themselves to be in very good health. The percentage in the insured is 71%, slightly higher than the average, but only 59 out of 100 uninsured people will report being in very good health. The probability to be in poor health is very close for both uninsured and insured people: only about 2 people out of 100, whether they are insured or not, will report that they are in poor health. Normally there are two reasons for a person to not enroll in an insurance plan: the uninsured choose not to or they simply cannot afford it. If an individual has a very good health, he is less likely to buy insurance because even without insurance, his health care cost can be lower than the insurance cost. In the data, the probability of being in very good health is much lower for the uninsured than the insured, implying that most uninsured people do not buy insurance because they cannot afford it. This is shown in the data too, that on average the uninsured earn 20%-40% less than the insured[10].

Table 8 also shows that the uninsured are more likely to be obese but less likely to take diabetic pills. Compared to the insured, a bigger proportion of the uninsured report that they constantly feel nervous, hopeless or sad, indicating that on average they have worse mental health. Although the uninsured seem to have worse health in general, they report fewer work loss days and bed disability days than the insured people do. This might again result from the difference in income level between the insured and the

[10] Note: The personal income level in IHIS is reported in bins. Due to the difficulty of showing it in a table, I am not presenting the data to show the difference of income between the insured and the uninsured in this paper.

uninsured. The probability for a person to be limited in activities due to arthritis and the probability to be ever told that he has hypertension on the past 2+ visits are similar for both the insured and the uninsured. I use whether a person sleeps less than 6 hours per day and whether a person ever smoked in the past year as measures of a person's health behavior. Although economic theory suggests that there may be moral hazard issue associated with insurance, my data show that the insured actually behave better than the uninsured.

By comparing the post-2006 period with the pre-2006 period, we can see that the self-reported health status does not change much over time for the general population. The likelihood of being obese, the mental health outcomes, the number of bed disability days and the number of work loss days do not change much over time, either. It seems like more people are sleeping less than 6 hours after 2006, but the percentage of people who smoke remains the same too.

I use the same regression as equation (1) but change the dependent variable $Drug_{\mathrm{it}}$ to $HealthOutcome_{it}$. The regression is the following:

$$HealthOutcome_{it} = \alpha + \beta * 1(Uninsured_i) + \sum_{t=2003}^{2010} \sigma_t * 1(Year_t) + \delta * 1(Uninsured_i) * 1(Post_t) + \gamma_{it} * X_{it} + \varepsilon_{i,t} \quad (4)$$

Definitions are all the same except for the dependent variable, which this time covers self-reported health, obesity level and mental health status. I do not use a falsification test for the health outcomes regression, since I can barely find statistically significant impacts of the pricing policy on health outcomes.

E. Affected Drugs vs. Unaffected Drugs

Since the total number of drugs purchased each year is a sum of the number of drugs affected by the program and the number of drugs unaffected by the program, I construct a slightly different regression model by breaking the dependent variable in equation (1), the number of prescription medicine purchased by an individual, into two variables, $Affecteddrug_{it}$ and $Unaffecteddrug_{it}$, representing the number of affected drugs and the number of unaffected drugs purchased by individual i in year t respectively. $Affecteddrug_{it}$ includes drugs that have ever been priced at $4 from 2003 to 2010. $Unaffecteddrug_{it}$, includes drugs that have never been priced at $4 from 2003 to 2010.

In addition to equation (1), the model contains two new regressions:

$Affecteddrug_{it} = \alpha + \beta * 1(Uninsured_i) + \sum_{t=2003}^{2010} \sigma_t * 1(Year_t) + \delta * 1(Uninsured_i) * 1(Post_t) + \gamma_{it} * X + \varepsilon_{i,t}$ (5)

$Unaffecteddrug_{it} = \alpha + \beta * 1(Uninsured_i) + \sum_{t=2003}^{2010} \sigma_t * 1(Year_t) + \delta * 1(Uninsured_i) * 1(Post_t) + \gamma * X_{it} + \varepsilon_{i,t}$ (6)

The variables on the right hand side are defined exactly the same as in equation (1) but the dependent variables are different. The key variable in each of the three regressions is still $1(Uninsured) * 1(Post_t)$, the interaction term between post dummy variable and the uninsured dummy variable. By comparing δ in (1) to δ's in (5) and (6), we can estimate whether or not the results are mainly driven by drugs affected by the $4 prescription drug program. These regressions will allow me to confirm if any increase in drug utilization is indeed driven by increases in affected drugs, verifying the validity of my empirical strategy. In addition, they will allow me to observe whether the increase in affected drugs is a result of substitution away from unaffected drugs.

RESULTS

A. Impact on Drugs

Table 3 presents the results of a series of regressions with the key independent variable (1(*Uninsured*) * 1($Post_t$)) on all drug-related variables ($Drug_{it}$), measured with the full sample less than 65 years old. Each row represents a group of regressions with a different $Drug_{it}$ variable. Column 1 includes the results with time fixed effects and column 2 adds observable individual controls. None of the standard errors are clustered.

In general, I find that these dependent variables are affected by the introduction of Wal-Mart's program for uninsured individuals; most coefficients are significant at the level of 1%. As expected, after $4 drugs were introduced in 2006, the probability of consuming $4 drugs and cheap drugs (drugs cheaper than $5) increase more for the uninsured compared to the insured. The consumption of all prescription medicine increases more for the uninsured as well. However, the total expenditures decline more by about $76 more for the uninsured. The differential decline in total expenditures for the uninsured reflects the differentially lowered per-drug price. The average prescription price drops more for the uninsured after 2006, but as the total number of drugs consumed increases, the out of pocket expenditure for all drugs actually increases more for the uninsured.

In Column 1, the results show that without control variables, the introduction of the $4 prescription program in 2006 lowers the average price of prescriptions for the uninsured $13.38 more compared to the insured after controlling for year fixed effects, indicating a 9.7% decline in total out of pocket expenditures of prescription drugs for the uninsured. The out-of-pocket cost per drug on average decreases by $4.41 more for the uninsured. The percentages of $4 drugs and of cheaper-than-$5 drugs out of all drugs increase by 3.6% and 3.3%, respectively, more for the uninsured than the insured. Uninsured individuals on average increase 0.43 more prescription drug purchases and increase out-of-pocket spending by $21.84 more. According to Table 1, the uninsured on average buy 3.6 drugs at the price of about $58 per drug. The uninsured now buy 0.43 more prescription drugs and the additional prescription drug consumed should cost between $4 and $58 per drug because the major change in prescription drug consumption is driven by the increased consumption in cheaper drugs. From Table 1, we can expect that the out-of-pocket cost increases by between $1.7 and $25 for the uninsured, and the data shows that the increase in out-of-pocket cost is $21.84. The difference of increases in out-of-pocket cost between the uninsured and the insured indeed lies in the expected range.

When it comes to total expenditure that adds up all types of payments including copayments, uninsured individual on average increase their total spending by $76.13 less. This is reasonable because the program increases the number of prescription drug purchases from 3.6 to about 4 drugs. We can see that each prescription drug is on average $13.38 cheaper for the uninsured. This means the total expenditures on prescription drug should be about $188. Compared to $214, the total spending fell by about $30. Though the decline in total spending is not quite the same as the regression coefficient, $76, at least the direction of the change in total spending is the same.

Column 2 presents coefficients from a series of regressions that include characteristics controls. From 2006 to 2010, after the $4 program was launched, the average price of prescription drugs decreases by $13.75 more for the uninsured than the insured, and out-of-pocket cost decreases by 4.55 more. The likelihood of consuming $4 drugs among all drugs increases 3.7% more for the uninsured. For using cheaper-than-$5 drugs, it also increases by around 3.5% more for the uninsured. The uninsured individuals on average increase their purchase of prescription drugs by 0.025 more, but the result is statistically insignificant. The uninsured also increase their spending by $17.00 more than the insured, which is statistically significant at the level of 1%. Total expenditure on prescription drugs per person per year decreases on average $120.12 more for the uninsured compared to the insured. The regression coefficient for total prescription expenditure with year fixed effect and characteristic controls, compared to $75.13 from the uncontrolled regression, is largely different. This difference mainly comes from controlling for age and education level. More specifically, the coefficient jumps from -75 to about -100 after adding the control variables years of education and age to the regression. In other words, within the same age and education level, the increase in the spending for the uninsured declines more.

Table 4 and Figure 4 both show the δ_t 's from estimating equation (2). Table 4 shows that for number of prescription drugs and total prescription expenditures, the coefficients before Wal-Mart's $4 program are not statistically significant, but several coefficients after 2006 are statistically significant. It also shows that that increase in out-of-pocket expenditures on prescription drugs for the uninsured are driven largely by a large negative coefficient in 2003. This may imply that the estimated increase in out-of-pocket expenditures for the uninsured from equation (1) in Table 3 may be spurious. Figure 4 shows that, prior to the start of the $4 program, for individuals of age under 65, prescription drug expenditures were increasing for the uninsured relative to the insured.

For four years around the time that the program was launched in 2006, the coefficient is very close to zero, indicating that the insured and the uninsured were on the parallel trends during this time. After 2008, however, when the Wal-Mart program really expanded, the trends diverge and the expenditures on prescription drugs increase less for the uninsured compared to the insured.

B. Price elasticity

Table 5 breaks down the change in prescription drug use into changes in affected and unaffected drugs. It is not hard to see that holding the insured as the control group, the uninsured have most of their relative change coming from the affected drugs. The average change in total drug consumption among the uninsured after the program was introduced is 0.43 more than the change for the insured people. The increase in the number of affected drugs is 0.69 units more for the uninsured after 2006, while the number of unaffected drugs increases only 0.18 units more, a statistically insignificantly increase.

The coefficients of the key interaction term on the number of all prescription drugs and the number of affected drugs are statistically significant, but the key coefficient for unaffected drugs is insignificant. One of our main results from equation (1) is that with the introduction of the $4 program the number of all prescription drugs increased more for the uninsured. Table 4 further shows that drugs that have ever been priced at $4, as expected, drive this result, suggesting that the pricing policy of $4 drug actually did bring about a net increase in prescription drug purchases, instead of there being a pure substitution effect from unaffected drugs to affected drugs.

Combining results from Table 1, Table 3 and Table 5, I derive the price elasticity of demand for prescription drugs among the uninsured. By dividing the key coefficient for number of prescription drugs consumed, 0.43 from the regression without individual controls, by the average number of prescription drugs consumed by the uninsured, 3.65, I find the differential percentage change in quantity for the uninsured, to be 11.78%. Similarly, by dividing the key coefficient for out of pocket cost per drug, -4.41, by the average out of pocket cost per drug for the uninsured, $37.65, I find the differential percentage change in price for the uninsured, to be 11.71%. Dividing the percentage change in quantity by the percentage change in price gives me -1.00, my estimated price elasticity of demand for prescription drugs among the uninsured. Note that the widely accepted price elasticity from the RAND experiment is an estimate of -0.2. The deviation from -0.2 to -1.00 might be explained by differences between the uninsured group and the insured group. Specifically, RAND measures the price sensitivity for a group of people already covered under insurance by changing the copayment rates, while my research estimates price elasticity of demand for the uninsured. Because the uninsured are more likely to have lower income than the insured, it may be that the uninsured people are more price-sensitive. Another possibility is that uninsured people are more price-sensitive; thus they choose to not buy insurance.

C. Health utilization

Coefficients in Table 6 show the impact of the key independent variable ($1(Uninsured) * 1(Post_t)$) on all utilization-related variables ($Utilization_{it}$). Again, the data exclude everyone over 65 years old. Each row represents a distinct set of regressions for a single dependent variable. Column 1 is a regression including time fixed effects and Column 2 adds observable individual controls.

Overall, outpatient, inpatient and ER facility expenditures are all negatively correlated with the introduction of the Wal-Mart's program for the uninsured individual, with coefficients that are significant at the 1% level. The total home health agency expenditure is also negatively correlated with the key interaction term, but only significant at the 10% level. These coefficients suggest that, as expected, after the program was launched in 2006, the expenditures on other types of health care services decline disproportionately for the uninsured compared to the insured, with the inflation across years adjusted.

Column 1 represents the results without control variables. Compared to the insured, uninsured people increased their spending by $34.61 less on outpatient physician department after the introduction of the program. On average, they also increased by $68.15 less on emergency room facility and by $203.13 less on hospital inpatient facility.

I show the falsification test results in Table 7 from estimating equation (4). It is not hard to notice that almost no δ_t's are statistically significant. In addition, by plotting the coefficients, I see that most of the patterns have big noises. I noticed that the estimated effects on ER and inpatient care, both statistically significant from equation (3), appear to be driven by data anomalies in 2009 and 2005, respectively. Therefore, I can no longer claim that the pricing policy has any impact on utilizations of ER and of inpatient care. I am only left with the conclusion that drug policy may be related to a small increase in outpatient spending and a small decline in home health care spending.

D. Health outcome

Table 9 show the impact of the key independent variable (1(*Uninsured*) * 1($Post_t$)) on all health outcome related variables using the IHIS from year 2003 to 2010 with population under 65 years old. Again, each row represents a distinct set of regressions for a single dependent variable. Column 1 is a regression including time fixed effects and Column 2 adds observable individual controls.

Overall, the coefficients for heath outcome variables are not as statistically significant as the coefficients for drug-related and utilization-related variables. Even without falsification test, we couldn't see statistically significant improvements on self-reported health status and indirectly indicators of one's health status such as number of work loss days. However, after 2006, we can see that the likelihood to be obese decreases by -0.45 more percentage point for the uninsured than the insured. The percentage of people who felt hopeless and the percentage who felt sad most of the time also decreased more for the uninsured than the insured, although these results are only marginally significant. Since there are many factors affecting one's weight, it is hard to say that the improvement in obesity simply comes from the program. Mental health problem has the same issue, too. Nonetheless, the results may give us some suggestions that the program might be able to help people treat obesity problems and improve their mental health even though we do not have strong evidence. From the MEPS data, I see that, after 2006, the top 20 $4 drugs consumed are mainly drugs that treat blood pressure, diabetes and mental problems; this finding is in accordance with the health outcomes improvement.

V. CONCLUSION

In 2006, when Wal-Mart launched the $4 prescription program, the goal, according to Wal-Mart, was to help consumers save on health care costs. This program cut the price of more than 300 types of generic prescription drugs to 4 dollars and increased its access to all U.S. consumers by making this program available in all its physical stores and by providing delivery services to every state. Although the program only lowers the price of generic drugs, which are less-expensive comparing to brand name drugs, it still makes a big difference in many consumers' medical costs. Wal-Mart contributes to lowering costs not only by cutting the price in its stores, but by generating stronger competition in the generic prescription drug market in competing stores such as Kroger and Target. In my paper, I use this program to measure the impact of a price decline on health care costs, health care utilization, and health outcomes. My paper relies on the insured as the control group and the uninsured as the treatment group. I use a differences-in-differences model and my results mainly measure the disproportionate change among the uninsured after the introduction of the program.

In this paper, I demonstrate empirically that drug usage and costs are affected by the introduction of the Wal-Mart's program for the uninsured individuals. By analyzing MEPS data, I find that the introduction of the $4 prescription program in 2006 lowers the average price of prescriptions for the uninsured about $13.5 more compared to the insured. It also decreases the out-of-pocket cost per drug by $4.41 more for the uninsured. The probability of consuming $4 drugs and drugs cheaper than $5 increases more for the uninsured. The total number of prescription drugs consumed increases more as well.

As expected, after the program was launched in 2006, the expenditures on other types of health care services decline disproportionately for the uninsured compared to the insured, with the inflation across years adjusted. Regression results show that the uninsured increase their utilization of other types (outpatient, inpatient and ER facility expenditures) by less if we compare them to the insured and the relationship is highly statistically significant. Compared to the insured, uninsured people increase their outpatient expenditure by $5.92 more after the introduction of the program, but the estimated effects on inpatient and ER care appear to be driven by data anomalies. I then look at the impact on health outcome using a different data set, the IHIS, and find out that there is no strong eviden to show that the Wal-Mart program does improve people's health outcomes. I also find that the price elasticity for the uninsured is -1.00. Compared to -0.2, the widely accepted price elasticity from RAND experiment, -1.00 shows that the uninsured is more sensitive to price changes, suggesting that there might be some value in incorporating copayments if a health policy targets the uninsured.

VI. REFERENCE

Aron-Dine, A., Einav, L., & Finkelstein, A. (2012). "The RAND Health Insurance Experiment, Three Decades Later." *National Bureau of Economic Research*, No. w18642.

Basker, E. (2007). "The Causes and Consequences of Wal-Mart's Growth." *The Journal of Economic Perspectives*, 21.3, 177-198.

Encinosa, W., Bernard, D., & Dor, A. (2010). "Does Prescription Drug Adherence Reduce Hospitalizations and Costs?" *National Bureau of Economic Research*, No. w15691.

Finkelstein, A. (2005). "The aggregate effects of health insurance: Evidence from the introduction of Medicare". *National Bureau of Economic Research*, No. w11619.

Finkelstein, A., McKnight, R. (2005). "What Did Medicare Do (And Was It Worth It)?" *National Bureau of Economic Research*. No. w11609.

Hausman, J., Leibtag E. (2007). "Consumer benefits from increased competition in shopping outlets: Measuring the effect of Wal-Mart." *Journal of Applied Econometrics*, 22.7. 1157-1177.

Gaynor, M., Li, J., and Vogt, W.B. (2007). "Substitution, Spending Offsets, and Prescription Drug Benefit Design". *Forum for Health Economics and Policy*, 10, 1-31.

Kowalski, A. (2010), "Censored Quantile Instrumental Variable Estimates of the Price Elasticity of Expenditure on Medical Care", *National Bureau of Economic Research Working Paper*.

Manning, W. G., Newhouse, J. P., Duan, N., Keeler, E. B., & Leibowitz, A. (1987). "Health insurance and the demand for medical care: evidence from a randomized experiment." *The American Economic Review*, 251-277.

Shang, B. and Goldman, D.P. (2007). "Prescription Drug Coverage and Elderly Medicare Spending." *National Bureau of Economic Research Working Paper*, No. 13358.

Tamblyn, R., Laprise, R., Hanley, J. A., Abrahamowicz, M., Scott, S., Mayo, N., ... & Mallet, L. (2001). "Adverse events associated with prescription drug cost-sharing among poor and elderly persons." *JAMA: the journal of the American Medical Association*, *285*(4), 421-429.

VII. TABLES

Table 1: Summary Statistics

Definition	Full Sample	Uninsured	Insured
Uninsured	0.22 (0.42)	1	0
Age	34.20 (22.41)	31.81 (15.87)	34.88 (23.90)
Male	0.48 (0.50)	0.51 (0.50)	0.47 (0.50)
Married	0.37 (0.48)	0.36 (0.48)	0.38 (0.49)
Years of education when first entered MEPS	11 (5)	10 (4)	11 (5)
Person's total income	19270 (27825)	13299 (18632)	21046 (29784)
Number of prescription medicine including refills	9.28 (19.79)	3.65 (10.82)	10.89 (21.42)
Total prescription medicine expenditure	662 (2629)	214 (967)	790 (2925)
Total out of pocket expenditure on medicine expenditure (self/family)	201 (719)	137 (703)	219 (717)
Number of outpatient department physician visits	0.16 (1.50)	0.068 (0.70)	0.19 (1.66)
Total outpatient physician department expenditure	56 (972)	26 (782)	64 (1013)
Total Emergency Room Facility Expenditure	147 (1154)	85 (864)	164 (1221)
Total hospital inpatient facility expenditure	793 (6366)	320 (4139)	868 (6590)
Total hospital stays doctor expenditure	129 (953)	57 (637)	142 (990)
Number of nights in hospital for discharges	0.52 (4.12)	0.22 (2.07)	0.54 (4.15)
Sample size	268,297	59,279	209,018

Notes: Standard errors are in parentheses.

Table 2: Impact of price change on health spending

	2003	2004	2005	2006	2007	2008	2009	2010
Mean cost of unit prescription	62.62	64.40	68.40	69.04	74.01	75.49	77.26	80.29
For uninsured	56.54	60.12	60.07	62.90	60.35	64.53	52.44	52.60
For insured	63.22	64.84	69.26	69.57	75.02	76.61	79.83	83.14
Percentage of $4 drugs out of all drugs purchased in the market	0.05	0.03	0.03	0.14	1.52	2.17	4.91	6.01
For uninsured	0.09	0.06	0.03	0.17	2.49	4.23	11.89	12.52
For insured	0.04	0.02	0.03	0.13	1.43	1.95	4.21	5.34
Percentage of drugs purchased by uninsured people	9.16	8.73	9.45	9.54	9.14	9.66	9.21	9.35
Number of prescription drug purchases (N)	304,324	317,065	317,587	341,994	300,099	293,379	333,629	301,032

Notes: Standard errors are in parentheses.

Table 3: Impact of key variable on drug-related variables

Dependent Variables	Uninsured*Post (Without controls)	Uninsured*Post (With controls)
Price (per drug)	-13.38***	-13.75***
	(1.31)	(1.34)
Out of pocket cost (per drug)	-4.41***	-4.55***
	(0.31)	(0.32)
$4 Drug (dummy)	0.036***	0.037***
	(0.001)	(0.001)
Drug cheaper than $5 (dummy)	0.033***	0.035***
	(0.001)	(0.001)
Number of prescriptions including refills	0.43***	0.025
	(0.16)	(0.16)
Total prescription expenditure	-76.13***	-120.12***
	(24.68)	(26.95)
Total out of pocket expenditure on prescription expenditure (self/family)	21.84***	17.007***
	(6.078)	(6.60)

Notes: statistical significance at the 1% level is denoted by ***. Standard errors are in parentheses.

Table 4: Results of falsification test of equation (1)

Dependent Variables		2003	2004	2005	2006	2007	2008	2009	2010
Number of prescriptions including refills	(1)	0.07 (0.15)	-0.29 (0.30)	-0.11 (0.30)	0.00	-0.06 (0.31)	0.65** (0.31)	0.38 (0.29)	0.55* (0.31)
	(2)	0.36 (0.31)	-0.07 (0.31)	-0.12 (0.31)	0.00	0.17 (0.32)	0.36 (0.31)	-0.12 (0.31)	0.04 (0.31)
Total prescription expenditure	(1)	55.74 (47.82)	29.30 (47.81)	-5.15 (47.81)	0.00	-47.40 (49.15)	8.08 (47.81)	-92.77** (46.63)	-111.90** (48.12)
	(2)	83.16 (52.22)	51.38 (52.15)	-6.10 (52.18)	0.00	-36.28 (53.67)	-17.78 (52.26)	-149.39*** (50.85)	-171.88*** (50.85)
Total out of pocket expenditure on prescription expenditure (self/family)	(1)	-45.80*** (11.78)	-18.91 (11.76)	-22.05* (11.78)	0.00	-4.79 (12.10)	5.23 (11.78)	-12.95 (11.48)	-22.25* (11.85)
	(2)	-43.72*** (12.79)	-14.68 (12.78)	-23.33* (12.78)	0.00	1.80 (13.15)	1.18 (12.80)	-20.33 (12.45)	-31.59** (12.83)

Notes: statistical significance at the 1% level is denoted by ***; statistical significance at the 5% level is denoted by **; statistical significance at the 10% level is denoted by *. (1) indicates that results are from regression without characteristic controls and (2) is with controls. Standard errors are in parentheses.

Table 5: Impact of key variable on usage of affected and unaffected drugs

Independent Variable	Number of prescription medicine (including refills)	Number of affected drugs	Number of unaffected drugs
Uninsured	-4.41***	-0.87***	-2.95***
	(0.12)	(0.097)	(0.18)
Uninsured*post	0.43***	0.69***	0.18
	(0.16)	(0.12)	(0.23)

Notes: statistical significance at the 1% level is denoted by ***. Standard errors are in parentheses.

Table 6: Impact of key variable on utilization-related variables

Dependent Variables	Uninsured*Post (Without controls)	Uninsured*Post (With controls)
Number of outpatient department physician visits	0.018	0.014
	(0.013)	(0.014)
Total outpatient physician department expenditure	5.92**	4.25
	(2.74)	(3.00)
Total Emergency Room Facility Expenditure (Note: 2009 is coded wrongly)	-76.29***	-95.17***
	(11.07)	(12.19)
Total hospital inpatient facility expenditure	-203.13***	-207.70***
	(54.89)	(55.63)
Total hospital stays doctor expenditure	2.02	3.53
	(8.52)	(8.57)
Number of nights in hospital for discharges	0.032	0.023
	(0.023)	(0.029)
Total Home health agency expenditure	-29.84*	-35.12*
	(17.47)	(18.30)
Home health agency provider days	-0.049	-0.108
	(0.10)	(0.11)

Notes: statistical significance at the 1% level is denoted by ***; statistical significance at the 10% level is denoted by *. Standard errors are in parentheses.

Table 7: Results of falsification test of equation (4)

		2003	2004	2005	2006	2007	2008	2009	2010
Number of outpatient department physician visits	(1)	-0.0023	-0.027	-0.011	0.00	0.014	-0.009	0.002	0.015
	(2)	-0.0027	-0.025	-0.014	0.00	0.018	-0.018	-0.007	0.010
Total outpatient physician department expenditure	(1)	-2.14	0.18	-3.32	0.00	2.51	2.82	4.71	10.73**
	(2)	-2.46	96.80	-4.34	0.00	-63.71	0.05	2.04	7.91
Total Emergency Room facility expenditure	(1)	15.74	8.78	0.50	0.00	11.99	-7.29	-334.73[11]	30.16
	(2)	19.15	7.74	-1.56	0.00	14.20	32.94	-408.07	24.26
Total hospital inpatient facility expenditure	(1)	69.04	67.96	393.43[12]	0.00	39.75	-95.76	-23.29	-47.07
	(2)	32.58	17.90	370.75	0.00	-3.69	-101.34	-98.74	-123.57
Total hospital stays doctor expenditure	(1)	-5.92	-8.44	-4.19***	0.00	-13.88	-22.69	18.98	-6.81
	(2)	-7.74	-13.02	-9.60	0.00	-16.63	-17.91	14.21	-16.23
Number of nights in hospital for discharges	(1)	-0.06	-0.033	-0.060	0.00	-0.021	-0.023	-0.019	-0.027
	(2)	-0.05	-0.059	-0.065	0.00	-0.032	-0.034	-0.048	-0.060
Total Home health agency expenditure	(1)	15.16	-2.85	-10.44	0.00	-36.91	-27.71	-61.99*	-16.35
	(2)	21.84	-2.68	-11.62	0.00	-22.71	-27.35	-77.83	-28.96
Home health agency provider days	(1)	0.12	0.016	0.00	0.00	-0.019	-0.002	-0.027	0.035
	(2)	0.23	0.008	-0.001	0.00	0.058	-0.029	-0.102	-0.051

Notes: statistical significance at the 1% level is denoted by ***; statistical significance at the 5% level is denoted by **; statistical significance at the 10% level is denoted by *. (1) indicates that results are from regression without characteristic controls and (2) is with controls. Standard errors are in parentheses.

[11] Note: Total Emergency Room facility expenditure of 2009 in MEPS is clearly off but MEPS did not explain why the number in year 2009 is so different from other years. It is highly likely that there is a coding error in the original data file.

[12] Note: It is likely that there is a coding error in the original data file for total hospital inpatient facility expenditure in 2006.

Table 8: Summary statistics (IHIS data)

Definition	Full Sample	Uninsured	Insured	2003-2005	2006-2010
Uninsured	0.19 (0.39)	1	0	0.18 (0.39)	0.19 (0.39)
Age	30.37 (18.29)	31.13 (15.30)	30.17 (18.92)	30.19 (18.15)	30.49 (18.38)
Male (dummy)	0.49 (0.50)	0.53 (0.50)	0.48 (0.50)	0.49 (0.50)	0.49 (0.50)
Married (dummy)	0.40 (0.49)	0.35 (0.48)	0.41 (0.49)	0.40 (0.49)	0.39 (0.49)
Years of education attained	11.85 (4.85)	11.12 (4.30)	11.99 (4.95)	11.80 (4.85)	11.88 (4.84)
Very good health (self-reported, dummy)	0.68 (0.47)	0.59 (0.49)	0.71 (0.46)	0.69 (0.46)	0.68 (0.47)
Poor health (self-reported, dummy)	0.017 (0.13)	0.018 (0.13)	0.017 (0.13)	0.017 (0.13)	0.017 (0.13)
Obese (bmi ≥30, dummy)	0.087 (0.28)	0.097 (0.30)	0.085 (0.28)	0.086 (0.29)	0.087 (0.28)
Now taking diabetic pills (dummy)	0.25 (0.43)	0.18 (0.39)	0.26 (0.44)	0.69 (0.46)	0.51* (0.50)
Felt hopeless most of the time (dummy)	0.025 (0.16)	0.036 (0.19)	0.022 (0.15)	0.025 (0.15)	0.024 (01.15)
Felt nervous most of the time (dummy)	0.29 (0.67)	0.30 (0.67)	0.29 (0.67)	0.28 (0.66)	0.28 (0.66)
Felt sad most of the time (dummy)	0.038 (0.19)	0.053 (0.22)	0.034 (0.18)	0.039 (0.19)	0.036 (0.19)
Number of bed disability days	4.69 (24.92)	3.70 (21.10)	4.96 (25.84)	4.56 (24.01)	4.78 (25.59)
Number of work loss days	4.15 (18.00)	3.64 (17.71)	4.29 (18.10)	4.21 (17.85)	4.10 (18.11)
Ever told had arthritis (dummy)	0.05 (0.22)	0.06 (0.23)	0.05 (0.22)	0.0010 (0.032)	0.083 (0.28)
Limited in activities due to arthritis	0.32 (0.47)	0.33 (0.47)	0.32 (0.46)	0.31 (0.46)	0.32 (0.47)

(dummy)					
Ever told had hypertension on 2+ visits	0.84 (0.37)	0.79 (0.41)	0.85 (0.36)	0.84 (0.37)	0.84 (0.37)
Sleep less than 6 hours per day (dummy)	0.021 (0.14)	0.025 (0.16)	0.020 (0.14)	0.017 (0.13)	0.023 (0.15)
Ever smoke in the past year (dummy)	0.13 (0.11)	0.21 (0.14)	0.12 (0.12)	0.13 (0.11)	0.13 (0.11)
Sample size	611,269	113,857	491,253	252,996	358,273

Note*: Drinking behavior is not recorded here since IHIS uses different universe for 2003, 2004-2007, and 2008-2011. Standard errors are in parentheses.

Table 9: Impact of key variable on health outcome related variables

Dependent Variables	Uninsured*Post (Without controls)	Uninsured*Post (With controls)
Obese (bmi ≥30, dummy)	-0.0045** (0.019)	-0.0076*** (0.020)
Very good health (self-reported, dummy)	0.00095 (0.003)	0.0032 (0.0031)
Poor health (self-reported, dummy)	-0.00024 (0.00087)	-0.00053 (0.00092)
Number of bed disability days	-0.19 (0.30)	-0.20 (0.30)
Number of work loss days	-0.36 (0.24)	-0.36 (0.24)
Felt hopeless most of the time (dummy)	-0.0034* (0.0019)	-0.0031* (0.0019)
Felt sad most of the time (dummy)	-0.0043* (0.0022)	-0.0039* (0.0022)
Limited in activities due to arthritis (dummy)	-0.013 (0.010)	-0.010 (0.010)

Notes: statistical significance at the 1% level is denoted by ***; statistical significance at the 5% level is denoted by **; statistical significance at the 10% level is denoted by *. Standard errors are in parentheses.

VIII. FIGURES

Figure 1: Percentage of $4 drug in total unit drug consumption per person

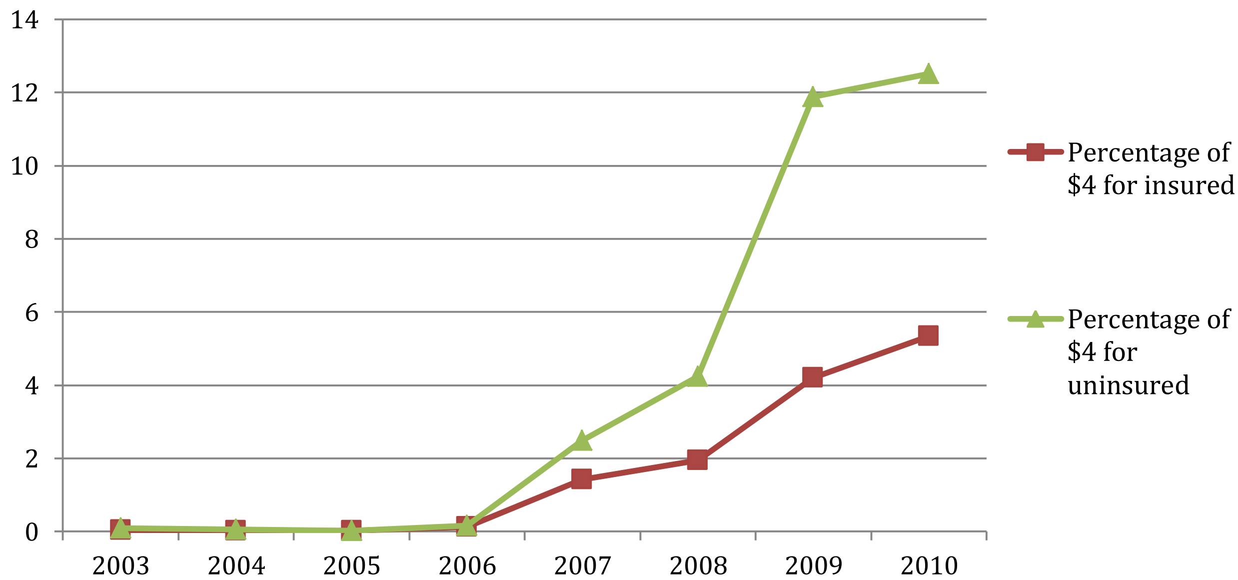

Figure 2: Average number of drugs purchased per person

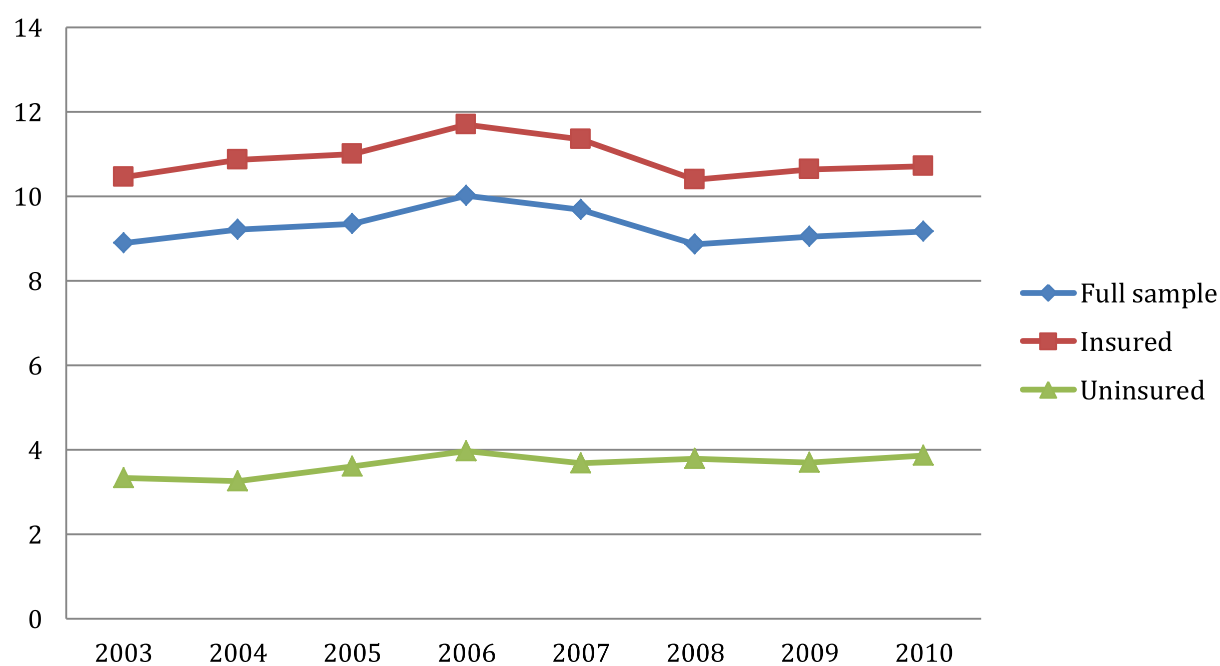

Figure 3: Average annual spending on prescription drugs per person

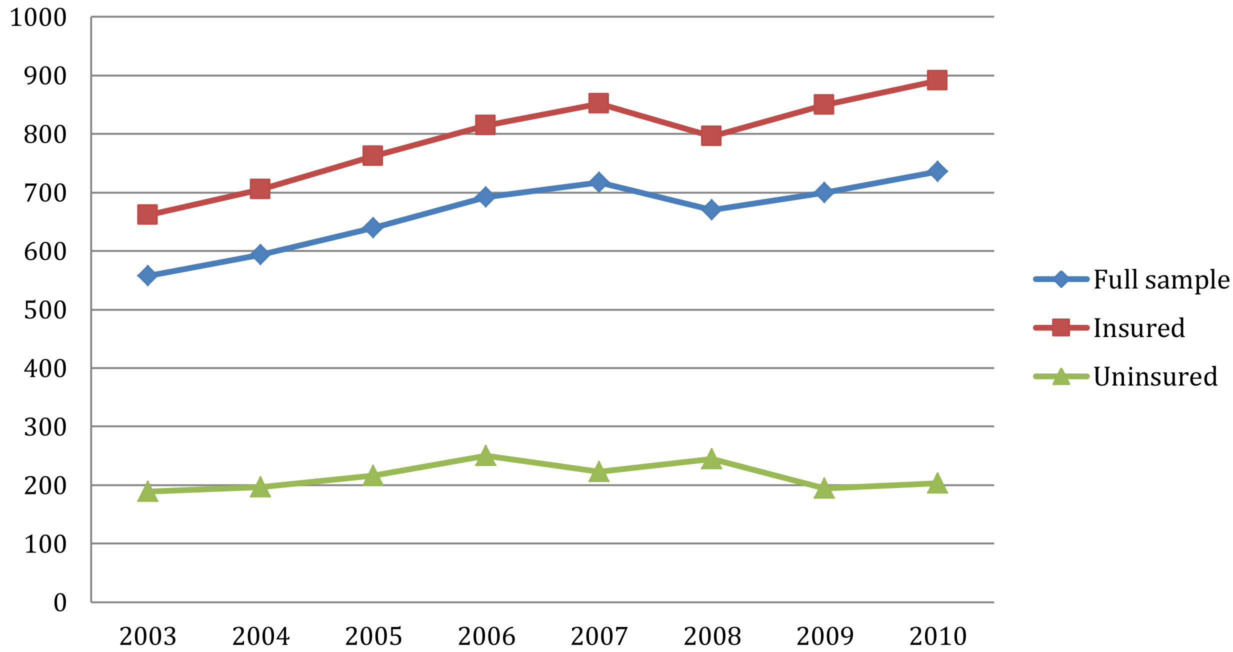

Figure 4: Estimates of equation (2), the falsification test of the impact of Wal-Mart's program on prescription drug expenditures