Can Walmart make us healthier?

The effect of market forces on health care utilization *

JOB MARKET PAPER

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Abstract

This paper analyzes how market forces in the retail market for pharmaceuticals affect utilization of health care. Specifically, I study the impact of Walmart's $4 Prescription Drug Program on utilization of blood pressure medication and hospitalizations for conditions amenable to drug therapy for the state of Florida. The empirical strategy relies on the change in the availability of cheap generic drugs introduced by the launch of Walmart's program in 2006, exploiting differences in the distance to the nearest Walmart store across ZIP codes in a difference-in-differences framework. I find that living close to a source of cheap generic drugs increases adherence to antihypertensive medications by 16 percent and decreases the probability of an avoidable hospitalization by 6.5 percent, saving over $50.5 million annually in inpatient costs. These findings shed some light on the potential of market forces to have a significant impact on utilization and overall costs in the health care system.

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(1) Introduction

Rising health care costs have been the subject of extensive debate in the United States in recent years, with national health expenditures reaching $2.6 trillion or 17.9 percent of GDP in 2010.[1,2] Chronic diseases such as heart disease, stroke, lung cancer, diabetes, and arthritis are among the most common, costly, and preventable of all health problems in the U.S.[3] Patients with chronic conditions are the heaviest users of health care services, accounting for almost 80 percent of all health care spending.[4] For chronic conditions, pharmacological treatments can substantially delay or even prevent costly medical complications, but high out-of-pocket cost of drugs can lead to underutilization: patients recurrently underuse medications because of cost, either by taking less than their prescribed doses, or not taking them continuously (Goldman et al. 2004). The failure to treat chronic conditions with medications may have adverse consequences both for individual health outcomes and for the sustainability of the health care system, as non-compliance eventually necessitates more costly medical interventions.

Theoretically, there are two approaches to increase adherence to pharmacological treatments through a cost reduction. One is a public health approach: the provision of public insurance or subsidies to provide incentives to increase the utilization of prescription drugs by making patients' demand less sensitive to price. However, public health interventions can be very costly and not always effective. The RAND Health Insurance Experiment showed that providing free care increased health care utilization but presented modest effects on health outcomes. A second approach is a market based one. Theoretically, one way to increase utilization is to foster competition in the retail market for pharmaceuticals thereby reducing prices. However, the impact of competition on health outcomes is ambiguous. If cost is a barrier to sustained drug adherence, reducing the price of prescription drugs might increase utilization of medications and

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[1] Centers for Medicare and Medicaid Services, Office of the Actuary, National Health Statistics Group,*National Health Care Expenditures Data*, January 2012.
[2] Martin, A.B. et al. (2012). Growth in US health spending remained slow in 2010; Health share of gross domestic product was unchanged from 2009. *Health Affairs* 31(1): 208-219.
[3]. The CDC reports that 70 percent of deaths among Americans each year are from chronic diseases and, in particular, heart disease, cancer and stroke account for more than 50% of all deaths. In 2005, almost 1 out of every 2 adults had at least one chronic illness, while 1 in 5 Americans have multiple chronic conditions. Source: http://www.cdc.gov/chronicdisease/overview/index.htm#ref1
[4] .(Anderson, Partnership for Solutions, 2002)

presumably lead to improvements in health, and, in turn, lower downstream costs in the form of reductions in avoidable hospitalizations.[5] On the other hand, if demand is sensitive to prices on a margin where health is relatively insensitive to utilization, health outcomes would not necessarily respond to price changes.[6] In this paper I consider changes in health care utilization that arise from increased market pressures in the retail market for pharmaceuticals: Walmart's aggressive pricing of generic drugs.

I exploit Walmart's $4 Prescription Drug Program in order to study the effect of a reduction in prices of generic drugs on utilization of medicines and avoidable hospitalizations.[7] The $4 Prescription Program is a prescription drug discount program created in 2006 which offers generic drugs for $4 per prescription and covers the most common therapeutic categories, including conditions such as allergies, cholesterol, high blood pressure and diabetes.
At $4 for a 30-day supply of drugs, this program offers prescription drugs at a price that is substantially lower than the price that an uninsured patient would face. Even for workers with health insurance that includes prescription drug cost sharing, Walmart's price of $4 is less than half the average copayment for generics and about one fifth of the average copayment for preferred drugs. [8]

I estimate the magnitude of the effect of a reduction in the price of generic drugs on health using a difference-in-differences regression approach that compares prescription drug utilization and avoidable hospitalizations for individuals living close to a Walmart store, before and after the launch of the program. My estimates are based on the identifying assumption that the $4 prescription program is more likely to affect those living close to a Walmart store.

Even though there is a literature on the relation between cost and health care utilization, most

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[5] On the other hand, an overabundance of prescription drugs could potentially be harmful. See, for example, Bennett et. al (2011) for an analysis of drug resistance and antibiotics.
[6] This would be the case if only relatively healthy people show the greatest sensitivity to price changes.
[7] Avoidable hospitalizations are defined as "diagnoses for which timely and effective ambulatory care can help to reduce the risks of hospitalization by either preventing the onset of an illness or condition, or controlling an acute episodic disease or condition". (Billings and Teicholz 1990)
[8] Workers with prescription drug coverage face average copayments of $11 for generic drugs and $25 for preferred (branded) drugs. Source: Kaiser Family Foundation, "Prescription Drug Trends 2008" (available from: http://www.kff.org/rxdrugs/upload/3057_07.pdf) and Employer Health Benefits Annual Survey 2009.

papers do no refer to drugs specifically. The RAND Health Insurance Experiment, of the mid 1970s remains the most-cited evidence on the relationship between cost and health care. Manning et al. (1987) and Newhouse (1993) report a small and significant response of medical care utilization to the cost changes, but no increase in the demand for hospital care associated with reduced primary care. More recent work has relied on quasi-experimental settings to provide evidence that health care utilization decreases as a result of an increase in out-of-pocket costs (Chandra, Gruber, and McKnight 2010; Chandra, Gruber, and Mcknight 2012; Encinosa, Bernard, and Dor 2010; Goldman et al. 2004; Goldman, Joyce, and Karaca-Mandic 2006). With the exception of Goldman (2006), these papers analyze changes in the scheme of out of pocket costs for patients, and are not able to isolate the effect of a change in the cost of prescription drugs separately. More recently, Finkelstein et al. (2012) found a significant increase in health care utilization among the treatment group who won the lottery and could apply for health insurance in the Oregon Health Study. However, the analyses are restricted to a single insurance scheme, or rely empirically on a set of changes in cost that occur simultaneously, and, moreover, most papers focus on elderly populations or on privately insured patients.

This paper makes a contribution to the literature by providing an estimate of the impact on health care utilization of a market forces-driven change in the cost of prescription drugs for the non elderly population. While there is some evidence that (and every reason to think theoretically that) prescription drug utilization is sensitive to price, it is not clear whether these responses are large enough –and whether the diseases affected are such that– the change in demand has important effects on hospitalizations. There is some evidence in the literature for particular insurance schemes in particular areas, but not for the broader population that I analyze, and not for the heterogeneous effects across insurance schemes, including the uninsured population.

Based on hospital discharge data from Florida, the results suggest that the price reduction of generic drugs caused by Walmart's $4 program is associated with an increase in the utilization of antihypertensive medications of 16 percent, and a 6.5 percent decrease in the probability of an avoidable hospitalization.[9] This translates into 1320 fewer hospitalizations per year after the

[9] In this paper I focus on antihypertensive medications because of data availability. Walmart's program reduced the price across a wide variety of drugs and utilization most likely increased for many of them, but I am able to show

launch of the $4 generic prescription drug program in Florida alone, which is equivalent to over $50.5 million annual savings in hospitalization costs.[10]

I find the largest effects of availability of cheap generics on nonwhites, consistent with the literature that suggest that blacks are less likely to comply with their medication regimes because of cost and are also more likely to be poor and shop at Walmart.[11] I find an effect for the uninsured living under one mile to the nearest Walmart, who have to face the full cost of prescriptions. Consistent with the incentives provided by prescription drug coverage from health insurance, I find no effect for patients with Medicaid, who, while poor, do not face copayments for prescription drugs in Florida and thus are unaffected by Walmart's price reduction. Moreover, the effect seems to be driven by those aged 45 to 64 (as opposed to younger adults), as this is the population with a higher incidence of chronic diseases.

The paper proceeds as follows. Section 2 provides some background on prescription drugs, Walmart's $4 program and related literature on Walmart. Section 3 describes the data. Section 4 presents evidence that Walmart's program reduced the price consumers paid for prescription drugs in areas close to a Walmart store but not for areas further away; and that utilization of prescription drugs and adherence to drug regimes increased. Section 5 outlines the empirical strategy and presents the difference-in-differences estimates of the impact of the $4 program on avoidable hospitalizations. Section 6 concludes.

(2) Background

a. Prescription Drugs and Health

Chronic diseases are the leading cause of death and disability in the US. Almost one out of every two adults suffers from at least one chronic condition, and these are the heaviest users of health care services in all major categories: hospitalizations, office visits, home care and prescription

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evidence on antihypertensives, which is the only drug category included in the Behavioral Risk Factor Surveillance System for Florida in the relevant period of analysis.

[10] Using an average cost of hospitalization for AHCs of $32936 from the sample for the years 2007 to 2009. The effect amounts to 5.7 percent of total hospitalizations charges for AHCs in 2008, and 39 percent of total hospitalizations charges for AHCs in 2008 for uninsured patient discharges.

[11] Sources: Kaiser Family Foundation, The Uninsured, a primer. 2009 and BRFSS.

drugs. In addition, more than 75 percent of the national health care spending is on people with chronic conditions. For instance, the CDC estimates that in 2009, medical expenditures on cardiovascular disease and stroke were $313.8 billion, and in 2007, medical expenditures on diabetes and cancer were $116 billion and $89 billion, respectively.[12]

Pharmacological treatments can substantially delay or even prevent the costly medical complications that can arise from conditions such as high blood pressure, high cholesterol and diabetes. Despite the ability to effectively manage chronic conditions with prescription drugs, an estimated one third to one half of all patients fails to take medications as prescribed by their providers. This often results in preventable worsening of disease and, in turn, excess hospitalizations.[13,14] The treatment of many chronic conditions requires compliance with a drug regimen prescribed by a physician, for example in the form of a daily intake.[15,16]
Several papers have tried to find explanations for the lack of adherence to pharmaceutical treatments. Interventions aimed at improving adherence often include nurse outreach, reminders to patients, automatic medication refills, and educational newsletters.

A major component of compliance is out-of-pocket cost. Gibson et at. (2005) show that reducing drug copayments increases drug adherence. Further, many studies show that a reduction in drug copayment improves outcomes and reduces costs.[17] Chandra et al., 2010 show that an increase in patient cost sharing decreased physician visits and prescription drug usage while increasing

[12] CDC The Power of Prevention 2009
[13] (Osterberg and Blaschke 2005)
[14] According to Kaiser Family Foundation, ("Prescription Drug Trends May 2010"), an April 2009 survey found that uninsured nonelderly adults (ages 18-64) are more than twice as likely as insured nonelderly adults to say that they or a family member did not fill a prescription (45% vs. 22%) or cut pills or skipped doses of medicine (38% vs.18%) in the past year because of the cost. Among nonelderly adults in 2008, 27% of the uninsured could not afford a prescription drug in the past 12 months, compared to 13% of those with Medicaid or other public coverage, and 5% of those with employer or other private coverage. A September 2009 survey found that during the past 12 months, 26% of American adults did not fill a prescription, and 21% cut pills in half or skipped doses of medicine, because of cost.
[15] (Encinosa et al. 2010) (Hughes et al, 2001; Dezii, 2000)
[16] Further, many of these conditions require a combination of drugs to be taken simultaneously, which increases the out-of-pocket cost faced by patients. The average non-elderly American consumes twelve prescription drugs per year, and about 58 percent of the non-elderly population reports an expense in prescription drugs. Total RX expenses amounted to over $170 million in 2009, with almost 21 percent of this being represented by out-of-pocket payments.
[17] (Hsu et al, 2006; Rice and Matsuoka, 2004; Goldman et al, 2007), (Gaynor et al, 2007; Shang and Goldman, 2007; Zhang et al 2009; and Deb et al 2009)

hospital utilization, among retired public employees in California. Analyzing low-income enrollees in the Massachusetts' Commonwealth Care program, Chandra et al. (2012) report a decline in utilization as a response to higher copayments, but no offsetting increases in hospitalizations or ER visits. Encinosa et al. (2010) analyze the impact of diabetic drug adherence on hospitalizations and find that for this population, drug adherence reduced hospitalization rates and ER visits, reducing overall costs.

Most of these papers rely empirically on a change in the cost sharing schedule of individuals within a particular health insurance scheme. In this paper, I will broaden the scope of prior research by focusing on a decrease in the cost of pharmaceuticals that is widespread and available to any patient regardless of their insurance coverage.

I analyze the effect of a price reduction of prescription drugs on avoidable hospitalizations, defined as "diagnoses for which timely and effective ambulatory care can help to reduce the risks of hospitalization by either preventing the onset of an illness or condition, or controlling an acute episodic disease or condition,"[18] are believed to be a good measure of access to health care (see, among others, Dafny and Gruber (2005) and Aizer (2007)).

Examples of avoidable hospitalization conditions (AHCs) include malignant hypertension, and diabetes. Several of these chronic conditions can be treated with maintenance drugs, giving prescription drugs an important role in ambulatory care. I will focus my analysis on the most common chronic avoidable hospitalization conditions for which pharmaceutical treatments exist and that are major drivers of drug spending, namely hypertension, diabetes, congestive heart failure and asthma.[19]

[18] (Billings and Teicholz, 1990) (Weissman et al. 1992)

[19] From the most commonly used definition I exclude conditions that only reflect a lack of adequate ambulatory care (but are not necessarily susceptible to treatment with maintenance prescription drugs) from my outcome variable, such as gangrene, ruptured appendix, bleeding ulcer and immunizable conditions. Hospitalizations for hypertension, diabetes, congestive heart failure and asthma account to over forty percent of discharges for all conditions in the broaer definition.

b. Local markets

As in many other markets, consumers value proximity in their consumption of health care. Kessler and McClellan (2000) report that the average patient will travel approximately 5 miles for inpatient care.[20] Retail pharmacy markets are typically local markets, since consumers tend not to travel long distances to purchase prescription drugs (Sorensen 2001).[21]

Why focus on Walmart? Walmart is the largest retailer in the United States with over 4000 stores spread across the country. According to Zook and Graham (2006), about 60 percent of the U.S. population lives within 5 miles of a Walmart store and 96 percent live within 20 miles.[22] About 120 million customers per week visit Walmart stores in the US, and 84% of Americans shopped at Walmart at least once during 2005 (Emek Basker 2007). Furthermore, Walmart's regular customers are typically low income families.[23] Maps 1 and 2 in the Appendix show the distribution of Walmart stores across the US, from Zook and Graham (2005).[24] In particular, they show that the distribution of stores in Florida is not different from those in other states in the South, Northeast and Midwest. Appendix Table 1 shows summary statistics on the distribution of Walmart stores across ZIP codes in Florida.

Despite its size in retail, in terms of total prescription revenues in 2010, Walmart's market share in the retail pharmaceutical market is 6.2 percent, whereas CVS and Walgreens are the biggest players, with shares of 14 and 16 percent respectively. However, given Walmart's extensive presence in the US and the local nature of health care consumption, it can plausibly be argued that the $4 prescription plan represents a price reduction of prescription drugs for those individuals living close a store.

c. $4 Prescription Drug Program

[20] See also McClellan (1994)

[21]The rise of mail-order pharmacies has somewhat decreased the localness of pharmacy markets, although they still account for a relatively small proportion of total prescription sales (17 percent in 2010).

[22] Walmart or associated store (Sam's club, Neighborhood market, etc).

[23] According to a 2005 Pew Research Center survey, 53% of those with incomes below $30,000 shop there regularly, compared to 33% of those with incomes above $50,000.

[24] Matthew Zook and Mark Graham (http://www.zook.info/Wal-Mart/)

Walmart launched the generic drug program in September 2006 in Florida, and quickly introduced the program across the country. By the end of 2006, Walmart pharmacies in all states were offering $4 generics.[25,26]

Walmart's "$4 Prescription Drug Program" allows a customer to purchase selected generic medications for $4 per prescription for a 30-day supply. [27] The majority of the most frequently prescribed generic medications in the United States are part of the $4 program, including treatments for chronic conditions such as hypertension, diabetes and asthma. The list, which is advertised as including over 300 drugs, actually includes multiple dosages of the same products, totaling approximately 130 different drugs. Many of the drugs included in the program are older and relatively inexpensive generics, and some of the newer blockbuster generics are excluded.[28,29] See Appendix Table 2 for more details on the types of drugs included in the program.[30]

At $4 for a 30-day supply, this program offers prescription drugs at a fraction of the cash price that a patient without any prescription drug coverage would pay. Furthermore, among covered workers with prescription drug cost sharing, $4 represents less than half of the average copayment for generics and about one fifth of the average for preferred drugs, so there is a substantial drop in the out-of-pocket expense per prescription.[31]

The exact magnitude of the price drop due to the $4 prescription program depends on each particular drug. For example a 30 day supply of the hypertension controlling drug lisinopril went

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[25] With the exception of North Dakota, where Walmart does not operate pharmacies.

[26] Target quickly imitated the program, offering the same list of products at the same price. Starting in 2008, the largest retail pharmacy chains introduced their versions of low-cost generic programs at varying prices and membership fees.

[27] Throughout the paper I will refer to the program as "$4 program" or "$4 prescription drug program" interchangeably.

[28] For example, the generic versions of Zocor (simvastatin) and Zoloft (sertraline) are not included in the program as of July 2012.

[29] It has been claimed that Walmart's $4 program is a "bait-and-switch loss leader". There are two reasons why this is not necessarily the case. First, the Average Manufacturer Price (AMP) of generics is very low. The Center for Medicare and Medicaid Services (CMS) provides data on AMPs, which shows that about one-quarter of the AMPs are less than 5 cents per unit (pill, capsule, etc.) and over half of them are under 15 cents per unit. Source: http://www.drugchannels.net/2011/09/hello-transparency-cms-publishes-its.html Second, Walmart buys generics directly from the manufacturer (instead of through a wholesaler).

[30] The current list of drugs included in the program can be found in http://www.walmart.com/cp/1078664.

[31] Kaiser Family Foundation and Health Research and Educational Trust. Employer health benefits: 2009 Annual Survey. (available from: http://ehbs.kff.org/pdf/2009/7936.pdf.) and Kaiser Family Foundation, "Prescription Drug Trends 2008". Available from: http://www.kff.org/rxdrugs/upload/3057_07.pdf

from $26 to $4, while a 30 day supply of the diabetes treating drug metformin went from $47 to $4 for a cash paying customer.[32] These two drugs are among the medications most frequently prescribed for chronic conditions (Choudhry and Shrank 2010). Section 4 presents a detailed analysis of the price changes.

d. The effect of Walmart on other outcomes

There is a growing body of literature that has been studying the case of Walmart in recent years. The diffusion of Walmart Supercenters have been associated with lower average prices for food items (E Basker 2005; Emek Basker and Noel 2009; Hausman and Leibtag 2007) and an increase in consumer surplus (Hausman and Leibtag 2007).

The evidence on the effect of Walmart on local labor markets is mixed, as Basker (2005) and Hicks (2007) find positive effects on employment and/or wages, while Neumark et al. (2008) find the opposite. More recently, Pope and Pope (2012) associate the opening of a Walmart store with an increase in nearby housing prices. [33]

Courtemanche and Carden (2011) analyze the effect of a Walmart Supercenter store opening to obesity. Using county level data from the Behavioral Risk Factor Surveillance System for the period 1996-2005, and instrumenting for store openings, they find that an additional Supercenter per 100000 residents is raises an individual's probability of being obese by 2.3% points. These results are at the county level, relating the density of stores to obesity rates. There is no mention of distance between consumers and stores, and so there is no reason to think that there are higher obesity rates (or worse health conditions) closer to Walmart stores.[34]

[32] The cost of these drugs in Walmart was on average $18 and $28 before the launch of the program. Note that some of the drugs increased their price as a result of this program (for example some versions of amoxicillin and hydrochlorothiazide), but this is the exception rather than the rule.

[33] Holmes (2011) and Jia (2008) analyze the spatial expansion of Walmart stores. Others have analyzed a variety of outcomes in relation to Walmart: (Goetz and Swaminathan, 2006) study poverty rates, (Goetz and Rupasingha, 2006; Carden et al., 2009a) and (Carden et al., 2009b) focus on social capital and traditional values respectively, (Sobel and Dean, 2008) analyze small business activity, (Carden and Courtemanche, 2009) study leisure activities , while (Hicks, 2007b) and (Vandegrift , Loyer, and Kababik (2011) analyze property tax collections and commercial properties respectively.

[34] Figure 1 shows that this is not a concern in my setting, as there are no differential trends in health conditions by distance to a Walmart store before the $4 generic drugs program was launched in 2006

Most of these papers need to deal with the endogeneity of the timing and/or location of opening of a new store, for which they use a variety of instrumental variables. As the $4 prescription program was launched throughout the country in all Walmart stores, there is no reason to suppose that Walmart introduced the program in ZIP codes with worse health conditions.

(3) Data description

I rely on pricing information for prescription drugs utilized by Medicaid patients in Florida and medicine utilization data from the Behavioral Risk Factors Surveillance Survey. The main empirical analysis uses hospital patient discharge data from the state of Florida for the years 2002 to 2009. Other data sources include the location of each Walmart store, Census 2000 and 2010 ZIP code level statistics.

Data on prices of prescription drugs comes from the Florida Agency for Health Care Administration (AHCA), which collects pricing information on prescription drugs purchased by Medicaid patients in the state of Florida. This information is then published in a website (www.myfloridarx.com), with the aim of providing consumers with the lowest price of prescription drugs in their area. The prices are the "usual and customary prices" (the price that an uninsured consumer would normally pay) for the 150 most commonly used prescription drugs in Florida. The unit of observation is at the drug-pharmacy-month level for the years 2005-2010, but not consistently for all products/pharmacies. This information is collected for a list of top selling drugs.[35] For the prescriptions filled by Medicaid patients, the sample provides information on the pharmacy where the transaction took place and the price that would have been paid by an uninsured customer for that same prescription.

Walmart does not provide information on the number of scripts filled, the composition of its pharmacy customers, nor on the costs associated with running the pharmacies.[36] I therefore rely

[35] See http://myfloridarx.com/rx.nsf/finder.
[36] Walmart provides some data through their news releases, but without enough information to be able to estimate the level or the growth rate of scripts filled, as noted in http://www.drugchannels.net/2007/09/wal-mart-adds-some-4-generics-yawn.html

on data on the consumption of medicines at the county level from the Behavioral Risk Factor Surveillance System (BRFSS). The BRFSS consists of annual telephone surveys of persons ages 18 and older conducted by state health departments in collaboration with the Centers for Disease Control and Prevention (CDC). I use repeated cross sections for the years 2002, 2007 and 2010.

The Agency for Health Care Administration collects inpatient discharge data from acute, psychiatric, psychiatric and comprehensive rehabilitation hospitals in Florida, each observation corresponds to an individual inpatient hospital stay. Patient level information include patient demographics (gender, age, race and ethnicity) ZIP code of residence, diagnosis codes, procedure codes, discharge status, cost, and principal payer. The main advantage of using these data is that they contain the universe of patient discharges from licensed hospitals in Florida. I make several sampling restrictions for both datasets. First, I exclude patients discharges from psychiatric and rehabilitation hospitals, and discharges due to childbirth. Second, I restrict the sample to non-elderly adults. In particular, I exclude patients over 65 years of age from my analysis because Medicare Part D went into effect in January 2006, the same year that the $4 prescription program was launched. For the same reason, I exclude patients under the age of 65 who are covered by Medicare because of disability. ZIP codes are the smallest level of geographical aggregation.[37] The final sample consists of adults aged 20 to 64, discharged from a hospital in Florida in the period 2002 to 2009, with over 800,000 observations each year. In Table 1, I describe the characteristics of the patients in my sample. The average non-elderly patient is 46.5 years old, while over half of the discharges are for females and 36 percent are for nonwhites. Over half of the hospitalizations correspond to individuals with private insurance, 18 percent for patients with Medicaid, 13 percent are uninsured and the rest have other types of insurance, such as local government programs or worker’s compensation. The average distance from the patient’s ZIP code of residence to the nearest Walmart is 4.5 miles. The rate of avoidable hospitalizations is 3.3 percent. Among discharges for avoidable hospitalizations, over half are for females; almost 52 percent correspond to nonwhites, 15.75 percent to uninsured, and 70 percent to individuals over 45 years of age.

[37] In order to match discharge data with Census data, I restrict the sample to ZIP codes that can be matched to ZIP Code Tabulation Areas (ZCTA) as constructed by the Census Bureau. The final number of ZCTAs in the sample is 1484. Throughout the paper I will refer to ZCTAs and ZIP codes interchangeably.

Data on the location of each Walmart store is from Zook and Graham (2006), who collected information on the type of store (Walmart, Walmart Supercenter, Sam's Club or Neighborhood Market), the address, and a geo-reference to the location (latitude and longitude). I updated this dataset to include store openings and in-store pharmacy locations using the store locator in Walmart's website and the Rand McNally Road Atlas Walmart Edition. By the end of 2006 there are 3791 stores in the U.S., including 222 stores in Florida. Appendix Table 2 shows ZIP code level characteristics from Census 2000 by presence of a Walmart store. Compared to ZIP codes without Walmart stores, ZIP codes with Walmart stores are more populated, but have a similar share of people who are black, Hispanic, over 65, poor or recipients of Medicaid.

Finally, using data from the Missouri Census Data Center (MCDC), I calculate the linear distance from each ZIP code to the nearest Walmart store. I use two measures of distance: the distance from the geographical centroid of each ZIP code and the distance from the population weighted centroid of the ZIP code.[38] I merge this to the patient discharge databases to have a measure of the distance from each patient's ZIP code of residence to the nearest Walmart store. The distance measure is constructed using the stock of Walmart stores by the end of 2006. I follow this rationale in my analysis since there is related literature (see Section 2) that describes ambiguous effects of Walmart store openings on several outcomes. By excluding store openings, I am able to isolate the effect of the program (which is launched on existing stores) from the effect of a new store. Note that the exclusion of store openings after 2007 will cause my estimates to be downward-biased as any positive health effect will not be attributed to the program.

(4) Prices and Utilization

a. Average Price of Prescription Drugs

As discussed in Section 2, Walmart's aggressive pricing policy had a differential impact: for some drugs in the $4 program the decrease in price was in the order of 300 percent while for others it was much smaller. Details are given in Appendix Table 2. In this section, using data

[38] Using block level population estimates from the Census, the MCDC calculates a weighted version of the centroid of each ZIP code.

collected from Florida's Medicaid patient pharmacy claims, I present evidence that there was a reduction in average prices of prescription drugs after the launch of the $4 program. The estimating equation is:

$$\Delta\log\,(price)_{dqz} = \alpha_0 + \alpha_1 post \times belongs_{dq} + brandname_d + \delta_z + \gamma_q + \varepsilon_{dqz} \qquad (1)$$

where the outcome variable is the log of the price for each drug, in each ZIP code and quarter. The variable $brandname$ is a dummy variable indicating whether the drug is a brand name, and the variable of interest is $\text{post} \times \text{belongs}$, which is the interaction between an indicator that is one after the start of the program and another indicator of whether the drug is included in the program (and therefore costs $4). The regression includes year and quarter dummies and ZIP code fixed effects. I estimate this model separately for two samples. The first one corresponds to observations for the years 2006 to 2008, where there is information for 18 drugs, while the second one extends the time frame to 2005 to 2009, but has information on a smaller number of drugs. Appendix Table 3 lists the drugs included in each sample.

Table 2 shows the results of this analysis. Specifically, column (1) shows the regression of log prices across all pharmacies in the sample, and the difference-in-difference coefficient implies a reduction in average prices of 0.2 percent for drugs that are included in Walmart's program across all pharmacies, but this coefficient is not statistically significant. Column (2) restricts the sample to Walmart pharmacies, to show that the drop in price for drugs in the program is over 90 percent. Finally, column (3) excludes the sales from Walmart pharmacies from the sample to show that the average prices for other pharmacies even increases 5 percent. Table 2b presents similar results when I include observations for the years 2005 and 2009 in the analysis. Average prices across all pharmacies decrease by less than 2 percent (column (1)), while prices for all pharmacies excluding Walmart increase 4.2 percent. The drop in prices for Walmart pharmacies for drugs in the $4 program is over 80 percent. These results support the use of distance to the nearest Walmart store as a measure of treatment intensity, since if all pharmacies had reduced their prices, distance to Walmart would not necessarily be a relevant measure of the likelihood of patients accessing cheap generic drugs.

The average price increase for the other pharmacies may seem counterintuitive at first, as one would expect a price reduction for all pharmacies under perfect competition in the retail pharmacy market. This result is mainly driven by independent pharmacies, whose strategy seems to be to focus on non-price sensitive customers, in particular those with government insurance. Furthermore, this is consistent with evidence that when Walmart enters the grocery market, it has prices that are on average 10 percent lower than its competitors, but that incumbent supermarkets respond by dropping their prices as little as one percent in response (Basker and Noel, 2009).

b. Utilization of Prescription Drugs

In this section I provide evidence that the decrease in the price of prescription drugs led to an increase in the adherence to pharmaceutical treatments. To the best of my knowledge there are no comprehensive datasets that include information on the consumption of prescription medicines at the ZIP code level and insurance status. Even pharmacy claims data, which are largely used to analyze the access to pharmaceutical care, are not necessarily the best source for my analysis for two reasons: first, they focus on insured populations, and second, many pharmacies fail to submit claims to insurers when the customers pay cash, as they lack incentives to do so (Choudhry and Shrank 2010). As noted previously, Walmart does not provide any information on the number of prescriptions filled. I therefore rely on a survey that is available at the county level, the Behavioral Risk Factor Surveillance System (BRFSS). The BRFSS provides data on the consumption of medicines for the years 2002, 2007, and 2010 among those above 45 years of age. I exclude individuals over 65 years old, so that the final sample corresponds to individuals aged 45 to 64.[39] The exclusion of young consumers is not a limitation to the analysis, as this is the (non-elderly) population where chronic conditions are most relevant. For example, the incidence of hypertension among adults aged 18 to 44 is only11.6 percent, whereas among those aged 45 to 64 it is 33.9 percent.[40]

The empirical strategy relies on the change in the availability of cheap generic drugs introduced by the launch of Walmart's $4 Prescription Drug Program in 2006, exploiting differences in the

[39] Note that this sample is consistent with the one presented in Table 3.
[40] Source: Florida BRFSS 2007.

average distance to the nearest Walmart store across counties, in a difference-in-differences framework.

I construct the average distance to the nearest Walmart store in each county, by calculating a weighted average of the distance from each ZIP code using the ZIP code level population as weights. I estimate the following model, using as an outcome the percentage of individuals in each county who take a medicine to treat their hypertension condition.[41] The estimating equation is:

$$sharemeds_{\mathrm{tc}} = \beta_0 + \beta_1 post \times distcat_{tc} + \beta_2 \mathrm{X}_{\mathrm{tc}} + \delta_{\mathrm{t}} + \gamma_{\mathrm{c}} + \epsilon_{\mathrm{tc}} \qquad (2)$$

where t indexes year and c counties. The outcome variable in the above equation is the percentage of individuals that are currently taking medicines to treat their hypertension conditional on having high blood pressure. The variable of interest is $\mathrm{post} \times \mathrm{distcat}$, which represents the weighted average of the distance to the nearest Walmart across all ZIP codes in a county, interacted with a dummy that indicates the years after the prescription drug program was launched. The distance variable groups counties in the following categories: 2 to 4 miles, 4 to 6 and more than 6 miles to the nearest Walmart. The latter is omitted in the regression. Note that because of the aggregation, there are no counties in the "under 2 miles" category.

Table 3 shows an increase in the probability of pharmaceutical treatment in those counties where the average distance to a Walmart store is smaller. The coefficient on the interaction between *post* and the distance category "between 2 and 4 miles" implies that there is a rise in the utilization of antihypertensive medications (among individuals with a diagnosis of high blood pressure) of 5.5 percentage points in counties that are closer to Walmart, which is represents over 16 percent of the mean of this variable.

Even though antihypertensives are only one among all the drugs in the $4 program, this example makes the point that the mechanism linking the reduction in the price of prescription drugs and hospitalizations is indeed utilization.

[41] The exact variable as provided by the BRFSS is "Percentage of Adults with hypertension who currently take high blood pressure medicine".

(5) Walmart's $4 Program and Avoidable Hospitalizations

a. Main Results

The empirical strategy relies on the change in the availability of cheap generic drugs introduced by the launch of Walmart's $4 Prescription Drug Program in 2006, exploiting differences in the distance to the nearest Walmart store across ZIP codes in a difference-in-differences framework.

Several factors allow me to identify the relationship between the prescription program and hospitalizations. First, I can exploit the variation across ZIP codes in the distance to the nearest Walmart store. As retail pharmacy markets are local, customers are more likely to buy from stores closer to them. Second, there is a clear launch date for the program in each state, which is the same for all stores.[42] Finally, since some health conditions may be more sensitive to a better adherence to pharmaceutical treatment than others I can use non-sensitive conditions as falsification tests.

The main health outcome variables are conditions that result in hospitalization but are sensitive to being treated with prescription drugs: hypertension, congestive heart failure, diabetes and asthma. I will refer to these as "avoidable hospitalizations" or AHCs interchangeably. The variable AHC is constructed by matching the diagnosis code for each patient discharge to the diagnosis codes in Billings and Teicholz (1990).

The underlying assumption is that the treatment of these avoidable-hospitalization-conditions becomes cheaper in ZIP codes closer to a Walmart store after the launch of the $4 prescription program. If more people treat their conditions, or if they start treating them more effectively than before, then we should observe a differential decrease in the number of hospitalizations for these conditions.

[42] There is only one exception: the pilot program was launched in late September 2006 in pharmacies located in Tampa Bay, less than two weeks before the roll out for the rest of Florida on October 6.
By the end of October 2006, the roll-out was complete in all of Walmart's Florida pharmacies. Since the patient discharge data only allows me to identify quarters (and not months) I assume a unique start date for the program in my regressions, namely October 1st 2006.

As the $4 prescription program was launched throughout the country in all Walmart stores, there is no possibility that Walmart introduced the program particularly in ZIP codes where people have worse health, or that people moved near a Walmart store in order to be close to the pharmacy. Figure 1 confirms this. There are no differential trends in health conditions by distance to a Walmart store before the program was launched in 2006.

The basic specification relates the probability of being hospitalized for a preventable condition to the distance to the nearest Walmart from the patient's ZIP code of residence in a difference-in-differences framework, using individual level hospitalization data:

$$AHC_{tqz} = \beta_0 + \beta_1 post \times dist[i, i+1]_{tqz} + \varphi X_{tqz} + \delta_t + \gamma_q + \theta_z + \varepsilon_{tqz} \quad (3)$$

where *t* indexes year, *q* quarter, and *z* ZIP codes. *AHC* in the above equation is a dummy equal to 1 if the discharge observed at time t in ZIP code z is for an avoidable hospitalization condition and 0 otherwise. The variable $dist[i, i+1]$ is a dummy equal to one if the distance from the patient's ZIP code of residence and the nearest Walmart is between [*i*,*i*+1] miles, for *i* in [0,6]. The variable of interest is $\mathrm{post} \times \mathrm{dist}[\mathrm{i}, \mathrm{i}+1]$, which represents the distance to Walmart after the prescription drug program was launched. The vector X_{tqz} includes the individual level controls for gender, age, race, ethnicity, and type of insurance (Medicaid, uninsured and other types of insurance hospitalizations, with private insurance as the omitted category). All regressions include year, quarter and ZIP code fixed effects.

Table 4 shows the estimates of the effect of distance to Walmart on an avoidable hospitalization dummy from equation (2) using patient discharge data described in Section (3) for the years 2002-2009. Column (1) shows that there is a significant decrease in the probability that an avoidable hospitalization is observed for individuals living under one mile the nearest Walmart store after the introduction of the program compared to those living further away (over 1 mile).
Column (2) includes all distance categories ([0,1], [1,2] … [6,7]) and shows that the relevant distance is one mile. Further distances are not significant as revealed by an F-test. While the coefficients in Table 4 appear somewhat small, note that on a baseline of 3.3 percent for avoidable hospitalization conditions that can be treated with prescription drugs, this implies that

closeness to a source of cheap generic drugs leads to a 6.5 percent decrease in avoidable hospitalizations. In particular, these estimates imply that for patients living less than one mile to the nearest Walmart store there is decrease of 6.5 percent in the probability that we observe a preventable hospitalization in the years after the program was launched. Note that these likely under-estimate of the total effect, since people who live further away from Walmart are likely to benefit as well.

Once that I established that the relevant distance is under one mile, I proceed to test whether the there is any effect of distance to the nearest Walmart before the launch of the $4 program. The estimating equation is :

$$AHC_{tqz} = \beta_0 + \beta_1 dist[0{,}1] \times yearD_{tqz} + \varphi X_{tqz} + \delta_t + \gamma_q + \theta_z + \varepsilon_{tqz} \qquad (4)$$

where *t* indexes year, *q* quarter, and *z* ZIP codes. *AHC* in the above equation is a dummy equal to 1 if the discharge observed at time t in ZIP code z is for an avoidable hospitalization condition and 0 otherwise. The variable $dist[0{,}1]$ is a dummy equal to one if the distance from the patient's ZIP code of residence and the nearest Walmart is under one mile, and the variable of interest is the interaction between this distance and the year dummies. As in equation (3), the vector $\mathrm{X}_{\mathrm{tqz}}$ includes the individual level controls for gender, age, race, ethnicity, and type of insurance (Medicaid, uninsured and other types of insurance hospitalizations, with private insurance as the omitted category). All regressions include year, quarter and ZIP code fixed effects.

Table (5) shows the estimates of the interaction between the "under 1 mile to Walmart" dummy and year dummies, and confirms that distance to Walmart is not relevant prior to 2006. Figure (2) graphs the coefficients from this regression for my main outcome variable, avoidable hospitalizations, and also for the falsification conditions that will be described below. This figure shows that distance to the nearest Walmart store can be interpreted as a measure of intensity of treatment after the launch of the $4 program for the avoidable hospitalization conditions, while it does not affect the other conditions.

b. Heterogeneity of the effect on hospitalizations

The results so far have shown a negative and statistically significant relationship between closeness to a Walmart store and avoidable hospitalizations after the four dollar program was launched. I explore whether there is any heterogeneity of the effect by race, age and type of insurance.

In particular, I estimate equation (2) stratifying the sample by race. Table 6 shows that the effect is larger for nonwhites, consistent with the fact that nonwhites are more likely to fail to comply with their medication treatment.[43] The coefficient implies a reduction of over 13 percent in the probability of an avoidable hospitalization for this group.

Table 7 stratifies the sample by age, from 20 to 44, and from 45 to 64 years old. As expected, the effect is driven by older adults since the incidence of chronic diseases is higher for this age group (Martinson, Teitler, and Reichman 2011). The coefficient is larger than in the baseline specification, implying that for individuals aged 45 to 64, living closer than one mile to the nearest Walmart store is associated with a decrease of 9 percent in the probability that we observe a preventable hospitalization after the $4 program was launched.

Finally, Table 8 breaks the analysis by insurance coverage. Presumably, individuals with less generous coverage are more likely to be affected, since their average copayment for prescription drugs is higher than $4, and individuals covered with Medicaid should not be affected, since their copayment is zero.[44]

Columns (1) and (2) show that the point estimate is not statistically significant when the sample is restricted to Medicaid patients. This is to be expected, Medicaid patients do not seem to be affected by the program as they face no copayments for pharmaceuticals. Column (3) shows an effect for the uninsured patients living within one mile of the nearest Walmart that is larger than the average. The coefficient implies an 11 percent reduction in the probability of observing an

[43] According to the 2005 BRFSS (http://apps.nccd.cdc.gov/s_broker/WEATSQL.exe/weat/index.hsql), 84.5 percent of whites diagnosed with hypertension take their blood pressure medications, while this percentage is 83.4 for nonwhites. Also see Kaiser Family Foundation, The Uninsured, a primer. 2009

[44] There are no copayments for prescription drugs for Medicaid patients in Florida. http://portal.flmmis.com/FLPublic/Portals/0/StaticContent/Public/Public%20Misc%20Files/FLORIDA%20MCD%20COPAYMENTS%20and%20COINSURANCE%20-%202010.pdf

avoidable hospitalization in relation for this group. However, the significance of this effect disappears once the rest of the distance categories are included in column (4), even though the point estimate remains similar in magnitude. Columns (5) and (6) imply that there is a decrease in avoidable hospitalizations for by individuals with private coverage, which is similar in magnitude to the average effect. The results for privately insured patients are consistent with the fact that they face average copayments of $11 for generic drugs and $25 for preferred (branded) drugs so that proximity to Walmart decreases prices.[45] Finally, columns (7) and (8) show no effect for patients in the other insurance category (local government programs, worker's compensation, etc.).

c. <u>Robustness Checks</u>

i. <u>Number of Avoidable Hospitalizations</u>

Another natural specification is to look at the raw number of avoidable hospitalizations. In the equation below, I relate the change in the number of avoidable hospitalizations in a given ZIP code to the distance from the centroid of that ZIP code to the nearest Walmart. The estimating equation is:

$$\log(numberAHC + 1)_{tz} = \alpha_0 + \alpha_1 post \times dist[i, i + 1]_{tz} + \varphi X_{tz} + \delta_t + \theta_z + \varepsilon_{tz} \qquad (5)$$

Where $\log(\mathrm{numberAHC} + 1)$ is the log of the number of avoidable hospitalizations (plus one) in ZIP code *z* in year *t*. The variable $dist[i, i + 1]$ is a dummy equal to one if the distance from the patient's ZIP code of residence and the nearest Walmart is between [*i*,*i*+1] miles, for *i* in [0,6]. The variable of interest is $\mathrm{post} \times \mathrm{dist}[\mathrm{i}, \mathrm{i} + 1]$, which represents the how close (in miles) a patient's ZIP code of residence is to the nearest Walmart store after the prescription drug program was launched. The vector X_{tz} includes the log of the number of hospitalizations for females, nonwhites, Hispanics, Medicaid, uninsured and other types of insurance[46] (the omitted

[45] Source: Kaiser- Employer Health Benefits Annual Survey 2009
[46] This category includes worker's compensation, local government programs, CHAMPUS and VA.

category is private insurance), and the ZIP code level population.[47] Indicators for each year are included to control for time varying factors at the state level, and ZIP code fixed effects control for any time-invariant ZIP code level. Note that the main effects of the distance categories are subsumed by the ZIP fixed effects.

Table 9 presents ZIP code fixed effects estimates of equation (5) using patient discharge data collapsed at the ZIP code-year level. Column (1) reports a regression of the log of the number of avoidable hospitalizations[48] on individual level characteristics (number of hospitalizations for females, nonwhites, and for each insurance category (Medicaid, Uninsured, and other insurance[49] , with private insurance as the excluded category), year dummies,ZIP code level fixed effects, and the "under 1 mile to Walmart" dummy. Column (2) further includes the rest of the distance categories interactions. Consistent with the findings above, and conditional on the individual level controls in the model, there is a statistically significant decrease in the number of avoidable hospitalizations for ZIP codes very close to a Walmart store (less than one mile) after the launch of the program. The coefficients imply a 5.4 (4.6 in column (2)) percent drop in the number of avoidable hospitalizations, consistent with the previous results.

ii. Falsification Tests

There are a number of conditions that are used in the literature (see Currie and Tekin, 2011; Billings and Teicholz, 1990; Weissman et al., 1992 among others) that can be used as control conditions or falsification tests, since they should not be immediately affected by an increase in the adherence to a pharmaceutical treatment: cancer, appendicitis and gastrointestinal obstruction.[50]

[47] ZIP code level population is calculated by interpolating Census 2000 with Census 2010.
[48] As mentioned above, the outcome variable is actually log(AHC+1), since there 2806 ZIP-year cells with 0 discharges (24 percent of the sample).
[49] "Other insurance" includes worker's compensation, local government programs, CHAMPUS and VA.
[50] A potentially negative effect could arise from the overdose of prescription drugs. The most common pharmaceuticals used as narcotics are painkillers (in particular hydrocodone and oxycodone, see NYTIMES articles: http://www.nytimes.com/2012/04/09/health/opioid-painkiller-prescriptions-pose-danger-without-oversight.html?pagewanted=all and http://www.nytimes.com/2011/10/04/health/policy/04medicare.html). However, these drugs are not included in the $4 prescription drug list, and are therefore not part of my analysis.

I conduct falsification tests and show the results in Table 10. We expect no effects of an increase in the availability of cheap generics for conditions that are not susceptible of treatment with prescription drugs. I run regressions analogous to those in equation (3), replacing the outcome variable by the falsification conditions: cancer, appendicitis and gastrointestinal obstruction. Table 10 shows that there are no statistically significant effects of the Walmart program by distance on hospital discharges for these conditions. Further, in Table 11 I estimate regressions analogous to those in equation (4) with the falsification conditions as outcome variables in order to show that the distance to the nearest Walmart is irrelevant for these conditions throughout the years covered by the sample. Figure 2 shows these coefficients together with the avoidable hospitalization condition outcome.

iii. An alternative measure of distance

The measure of distance from the geographic centroid of each ZIP code is arguably noisy. I construct and alternative measure, where I use a population weighted centroid of the ZIP code to the nearest Walmart store, as described in Section 3. Table 12 shows that my results are not sensitive to using a different measure of distance.[51]

(6) Conclusion

In the context of the current health care debate, understanding the effect of the affordability of prescription drugs has become particularly relevant. This paper adds to the existing literature by examining the effect of a reduction in price brought about an increase in market pressure in the retail market for pharmaceuticals on utilization of prescription drugs and hospitalizations.

[51] Note that both these distances are linear, "as the crow flies" distances, as opposed to distances utilizing actual roads and highways. A future version of this paper will include the actual distance from the centroid of each ZIP code to the nearest Walmart store using roads and highways.

The results suggest that the price reduction of generic drugs caused by Walmart's $4 program is associated with an increase in the utilization of antihypertensive medications of sixteen percent for individuals living near a Walmart store. Due to data availability I can provide evidence on this particular class of drugs, even though it is likely that the utilization of other medicines increased. Using Florida's patient discharge data, I find that there is a sizable effect on hospitalizations due to a decrease in the price of prescription drugs. Results imply a 6.5 percent reduction in avoidable hospitalizations after the launch of the $4 program for individuals living near a store. This effect is equivalent to over $50.5 million annual savings in hospitalization costs, or 39 percent of total hospitalizations charges for avoidable conditions in 2008 for uninsured patient discharges. Moreover, this effect is among those with the highest out-of-pocket cost for medicines.

These results have two important policy implications. First, they highlight the positive effect of market forces on health care utilization. In particular, lower prices in the retail market of generic drugs leads to an increase in adherence to treatment and a reduction in hospitalizations. Second, the finding that there is an increase in compliance that leads to an improvement in health highlights the importance of early treatment of chronic conditions to reduce overall health care costs.

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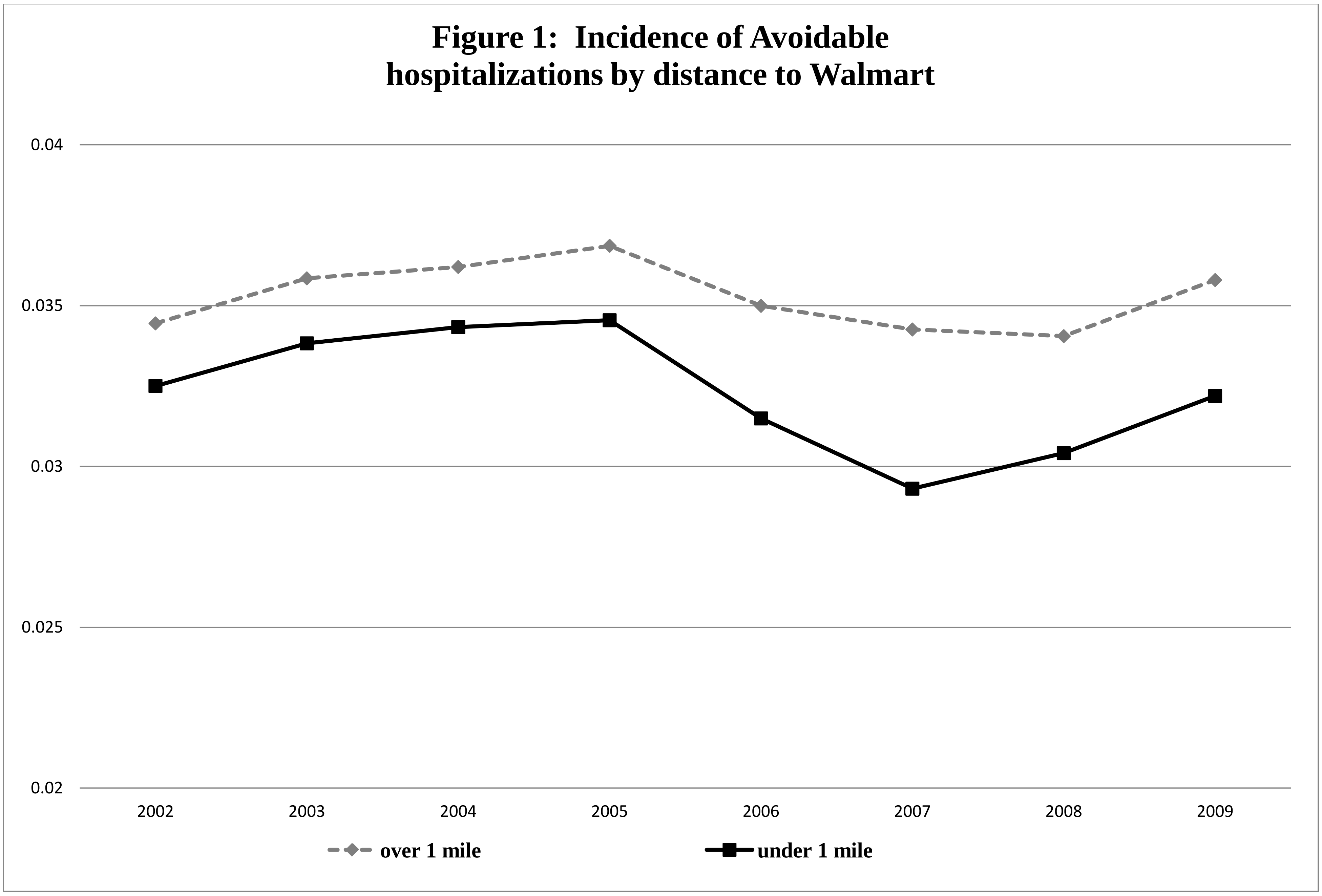
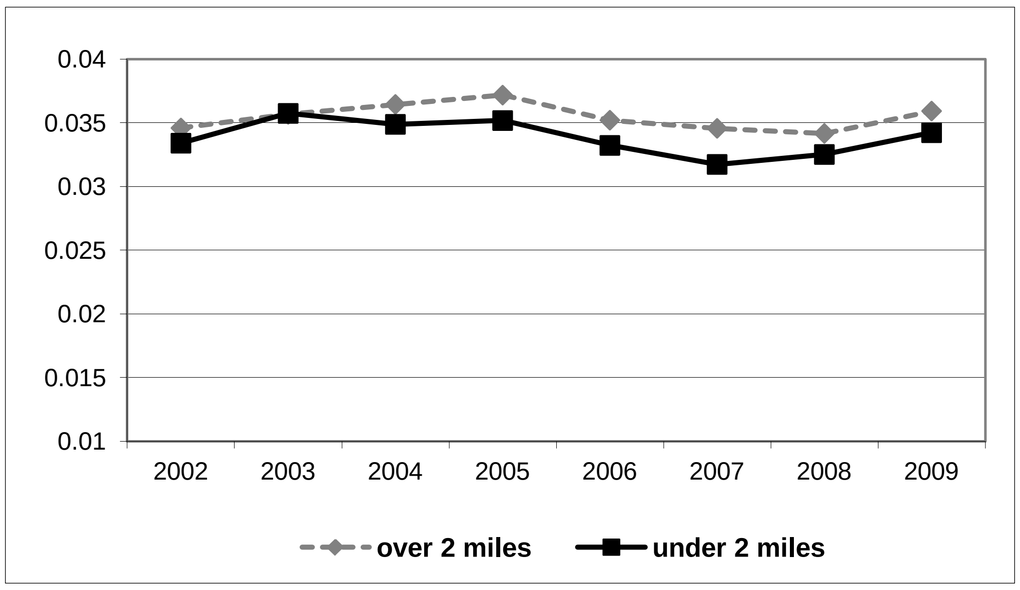
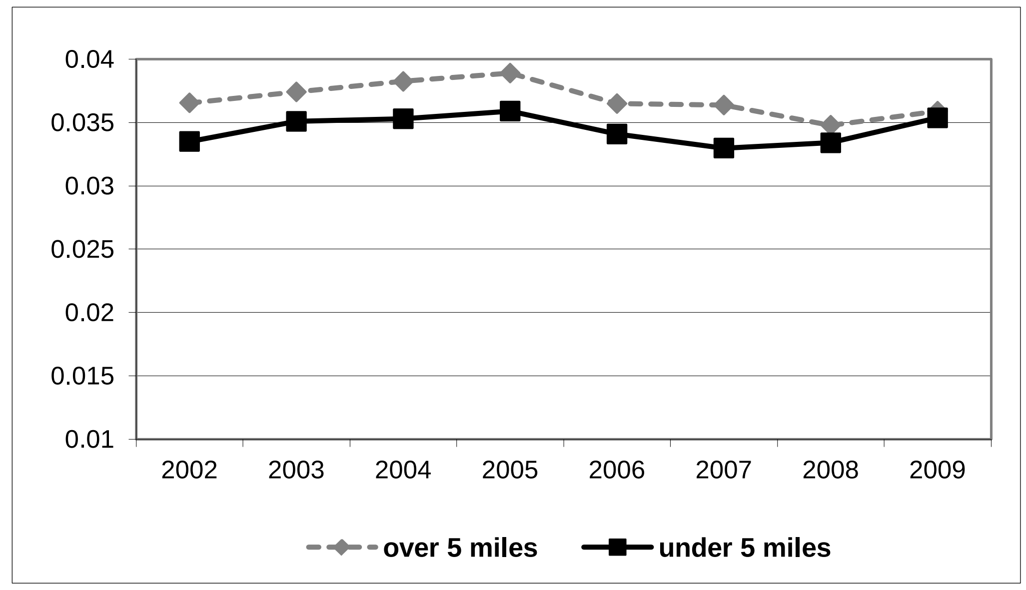
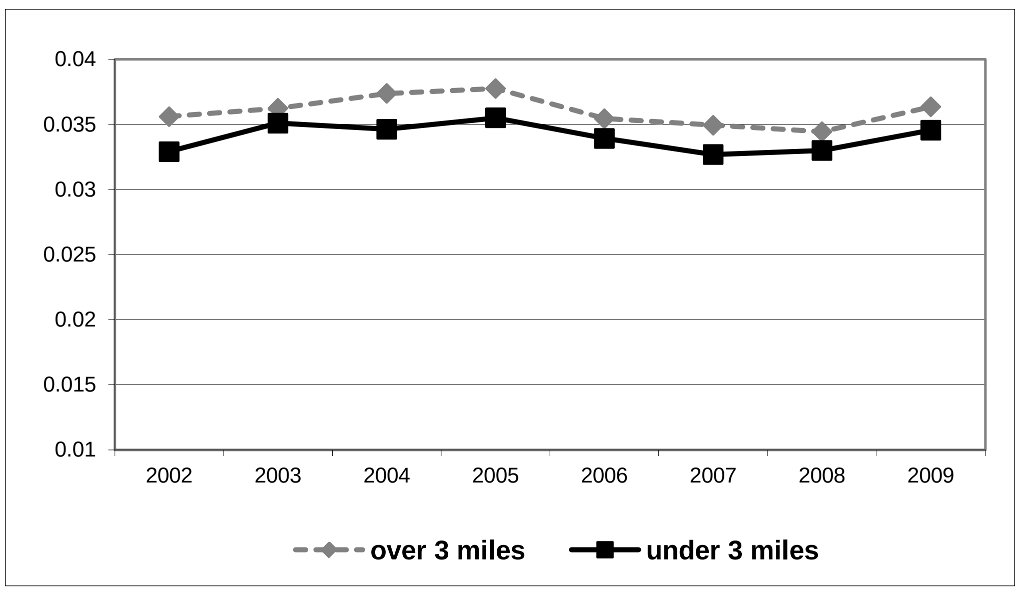


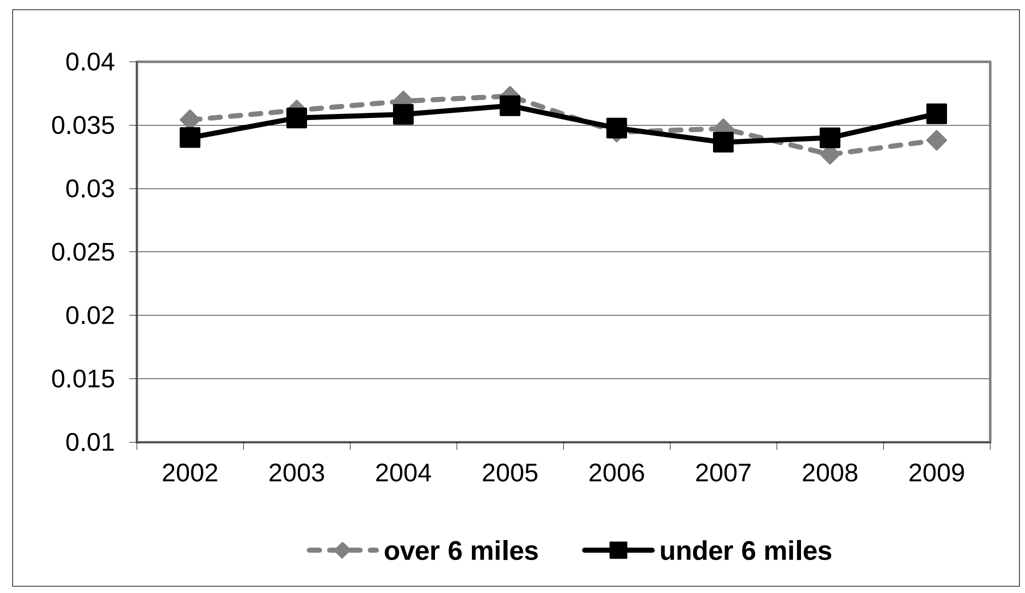
Figure 1: Incidence of Avoidable
hospitalizations by distance to Walmart
0.04
0.035
0.03
0.025
0.02
2002
2003
2004
2005
2006
2007
2008
2009
over 1 mile
under 1 mile

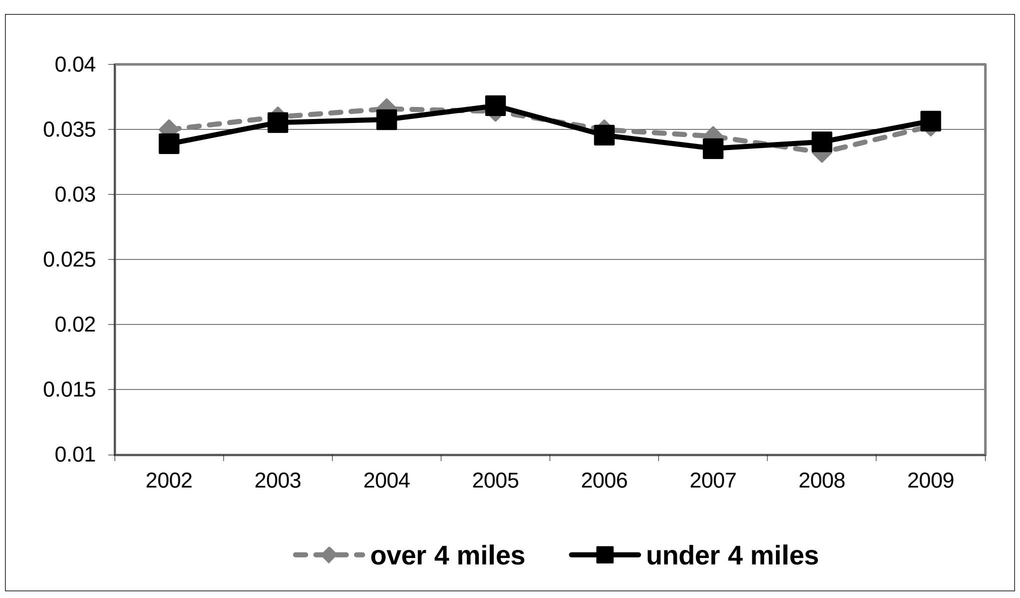
Figure 1 (cont)

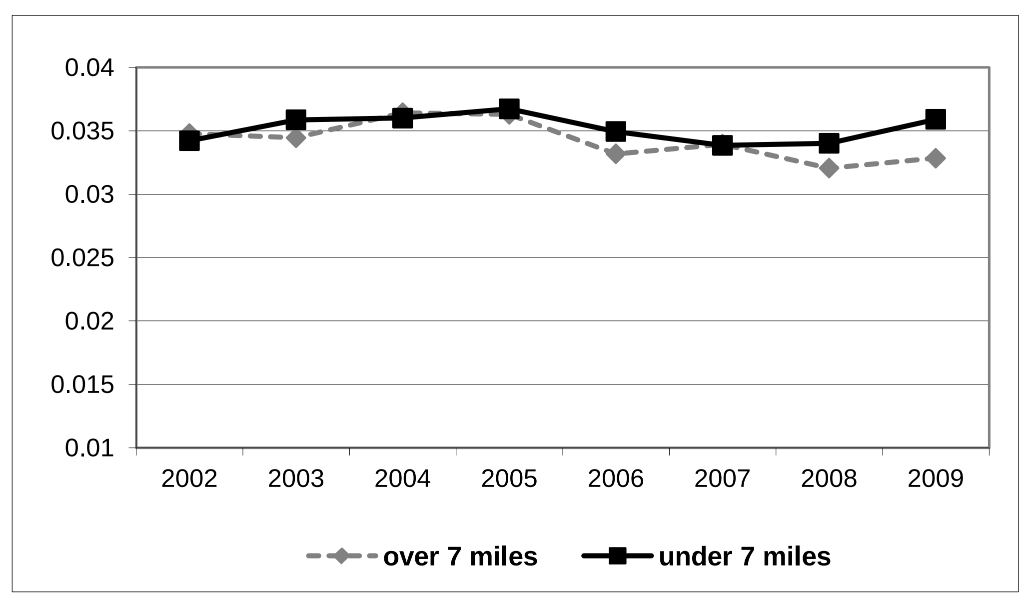












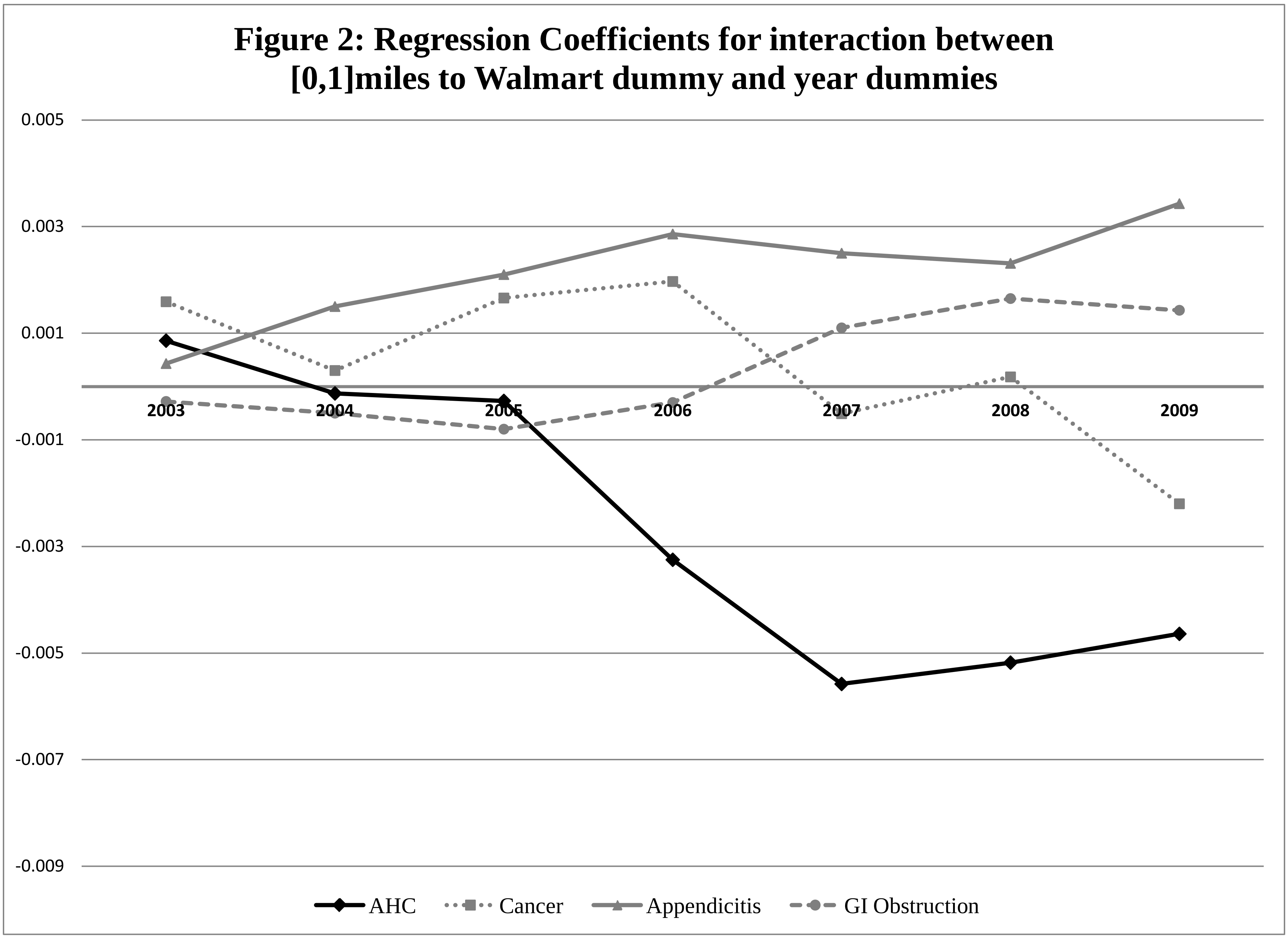


Figure 2: Regression Coefficients for interaction between
[0,1]miles to Walmart dummy and year dummies
0.005
0.003
0.001
-0.001
-0.003
-0.005
-0.007
-0.009
2003
2004
2005
2006
2007
2008
2009
AHC
Cancer
Appendicitis
GI Obstruction

Table 1

Patient Characteristics	mean	sd
Female	0.524	0.499
Nonwhite	0.357	0.479
Age	46.5	11.7
Medicaid	0.183	0.386
Uninsured	0.133	0.340
Private	0.555	0.497
Other insured*	0.129	0.335
Distance to the nearest Walmart from ZIP centroid (miles)	4.49	7.11
(miles)	4.36	7.14
Avoidable hospitalizations	0.033	0.179
Cancer hospitalizations	0.043	0.203
Appendicitis hosp.	0.015	0.122
Gastrointestinal obstruction hosp.	0.009	0.093
Total charges per hospitalization	$ 32,638	$ 52,654
Total charges per hospitalization for Avoidable conditions	$ 28,221	$ 51,248
N	5655466	

Notes: Sample corresponds to discharges of individuals aged 20 to 64 in Florida Patient Discharge Data, for the period 2002-2009. Sample excludes: births, psychiatric and rehabilitation hospitals and Medicare patients. "Other insured " includes worker’s compensation, local government programs, CHAMPUS and VA.

Table 2 - sample 2006-2008

Dependent Variable: log (price)

VARIABLES	(1) all pharmacies	(2) only Walmart	(3) excluding Walmart
post X dummy drug belongs to $4 program	-0.002	-0.943***	0.055***
	[0.007]	[0.010]	[0.004]
dummy drug belongs to $4 program	-1.018***	-1.136***	-1.005***
	[0.006]	[0.016]	[0.007]
branded drug	0.996***	1.189***	0.987***
	[0.008]	[0.013]	[0.008]
year and quarter dummies	y	y	y
ZIP code fixed effects	y	y	y
Observations	1,391,352	79,609	1,311,743
R-squared	0.659	0.892	0.673

Robust standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

Table 2b - sample 2005-2009

Dependent Variable: log (price)

VARIABLES	(1) all pharmacies	(2) only Walmart	(3) excluding Walmart
post X dummy drug belongs to $4 program	-0.017***	-0.838***	0.042***
	[0.006]	[0.010]	[0.003]
dummy drug belongs to $4 program	-1.278***	-1.158***	-1.286***
	[0.008]	[0.009]	[0.008]
branded drug	0.984***	1.329***	0.962***
	[0.007]	[0.008]	[0.007]
year and quarter dummies	y	y	y
ZIP code fixed effects	y	y	y
Observations	1,142,879	71,600	1,071,279
R-squared	0.838	0.932	0.854

Robust standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

Table 3

Dependent Variable: Percentage of Adults with hypertension who currently take high blood pressure medicine

VARIABLES	(1)
post X avg distance between 2 and 4 miles	5.499**
	[2.680]
post X avg distance between 4 and 6 miles	4.727
	[3.027]
post X avg distance between 6 and 8 miles	1.128
	[2.457]
Observations	2,522
R-squared	0.263
Number of counties	66

Robust standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

Notes: Ommited category is over 8 miles. Because of aggregation, there are no counties in the 0 to 2 miles category.

Table 4

Dependent Variable: AVOIDABLE HOSPITALIZATION DUMMY

	(1)	(2)
post X distance to nearest Walmart ϵ [0,1] miles	-0.00205***	-0.00215***
	[0.00065]	[0.00073]
post X distance to nearest Walmart ϵ [1,2] miles		-0.00048
		[0.00068]
post X distance to nearest Walmart ϵ [2,3] miles		0.00045
		[0.00061]
post X distance to nearest Walmart ϵ [3,4] miles		-0.00047
		[0.00064]
post X distance to nearest Walmart ϵ [4,5] miles		0.00008
		[0.00086]
post X distance to nearest Walmart ϵ [5,6] miles		0.00030
		[0.00113]
post X distance to nearest Walmart ϵ [6,7] miles		-0.00105
		[0.00095]
individual level controls	y	y
year and quarter dummies	y	y
ZIP code fixed effects	y	y
Constant	-0.02517***	-0.02516***
	[0.00132]	[0.00131]
Observations	5,655,251	5,655,251
R-squared	0.009	0.009
Number of zip	1,482	1,482

Robust standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

Notes: The ommitted category: 7+ miles. Individual level controls for gender, age, race, ethnicity, and type of insurance (Medicaid, uninsured and other types of insurance hospitalizations, with private insurance as the omitted category). All regressions include year, quarter and ZIP code fixed effects.

Table 5

Dependent Variable: AVOIDABLE HOSPITALIZATION DUMMY

distance to nearest Walmart ϵ [0,1] miles X dummy year	2003	0.00004
		[0.00118]
distance to nearest Walmart ϵ [0,1] miles X dummy year	2004	-0.00065
		[0.00123]
distance to nearest Walmart ϵ [0,1] miles X dummy year	2005	-0.00123
		[0.00133]
distance to nearest Walmart ϵ [0,1] miles X dummy year	2006	-0.00236*
		[0.00134]
distance to nearest Walmart ϵ [0,1] miles X dummy year	2007	-0.00355***
		[0.00125]
distance to nearest Walmart ϵ [0,1] miles X dummy year	2008	-0.00212*
		[0.00115]
distance to nearest Walmart ϵ [0,1] miles X dummy year	2009	-0.00227*
		[0.00130]
individual level controls		y
year and quarter dummies		y
ZIP code fixed effects		y
Constant		-0.02519***
		[0.00132]
Observations		5,655,251
R-squared		0.009
Number of zip		1,482

Robust standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

Notes: Individual level controls for gender, age, race, ethnicity, and type of insurance (Medicaid, uninsured and other types of insurance hospitalizations, with private insurance as the omitted category). All regressions include year, quarter and ZIP code fixed effects.

Table 6

Dependent Variable: AVOIDABLE HOSPITALIZATION DUMMY

Sample	NONWHITES		WHITES	
	(1)	(2)	(3)	(4)
post X distance to nearest Walmart ϵ [0,1] miles	-0.00425***	-0.00504***	-0.00118*	-0.00096
	[0.00135]	[0.00156]	[0.00070]	[0.00078]
post X distance to nearest Walmart ϵ [1,2] miles		-0.00136		-0.00011
		[0.00139]		[0.00067]
post X distance to nearest Walmart ϵ [2,3] miles		0.00078		0.00016
		[0.00120]		[0.00061]
post X distance to nearest Walmart ϵ [3,4] miles		-0.00210		0.00035
		[0.00133]		[0.00068]
post X distance to nearest Walmart ϵ [4,5] miles		0.00030		0.00002
		[0.00180]		[0.00079]
post X distance to nearest Walmart ϵ [5,6] miles		-0.00142		0.00138
		[0.00247]		[0.00100]
post X distance to nearest Walmart ϵ [6,7] miles		-0.00361**		0.00124
		[0.00159]		[0.00106]
individual level controls	y	y	y	y
year and quarter dummies	y	y	y	y
ZIP code fixed effects	y	y	y	y
Constant	-0.02172***	-0.02164***	-0.01201***	-0.01204***
	[0.00198]	[0.00198]	[0.00071]	[0.00071]
Observations	2,020,671	2,020,671	3,634,580	3,634,580
R-squared	0.010	0.010	0.004	0.004
Number of zip	1,466	1,466	1,480	1,480

Robust standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

Notes: The ommitted category: 7+ miles. Individual level controls for gender, age, ethnicity, and type of insurance (Medicaid, uninsured and other types of insurance hospitalizations, with private insurance as the omitted category). All regressions include year, quarter and ZIP code fixed effects.

Table 7

Dependent Variable: AVOIDABLE HOSPITALIZATION DUMMY

Sample	AGE 45-64		AGE 20-44	
	(1)	(2)	(3)	(4)
post X distance to nearest Walmart ϵ [0,1] miles	-0.00288***	-0.00299***	-0.00055	-0.00064
	[0.00092]	[0.00104]	[0.00103]	[0.00112]
post X distance to nearest Walmart ϵ [1,2] miles		-0.00018		-0.00088
		[0.00093]		[0.00089]
post X distance to nearest Walmart ϵ [2,3] miles		0.00021		0.00081
		[0.00085]		[0.00088]
post X distance to nearest Walmart ϵ [3,4] miles		-0.00040		-0.00068
		[0.00088]		[0.00092]
post X distance to nearest Walmart ϵ [4,5] miles		0.00029		0.00012
		[0.00116]		[0.00116]
post X distance to nearest Walmart ϵ [5,6] miles		0.00043		-0.00011
		[0.00174]		[0.00103]
post X distance to nearest Walmart ϵ [6,7] miles		-0.00203		0.00003
		[0.00144]		[0.00141]
individual level controls	y	y	y	y
year and quarter dummies	y	y	y	y
ZIP code fixed effects	y	y	y	y
Constant	-0.03344***	-0.03342***	-0.01127***	-0.01127***
	[0.00210]	[0.00209]	[0.00133]	[0.00133]
Observations	3,393,811	3,393,811	2,261,440	2,261,440
R-squared	0.008	0.008	0.005	0.005
Number of zip	1,478	1,478	1,479	1,479

Robust standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

Notes: The ommitted category: 7+ miles. Individual level controls for gender, race, ethnicity, and type of insurance (Medicaid, uninsured and other types of insurance hospitalizations, with private insurance as the omitted category). All regressions include year, quarter and ZIP code fixed effects.

Table 8

Dependent Variable: AVOIDABLE HOSPITALIZATION DUMMY

Sample	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Medicaid		Uninsured		Private		Other insured	
post X dist to Walmart ϵ [0,1] miles	-0.00279	-0.00234	-0.00360**	-0.00280	-0.00213***	-0.00277***	0.00116	0.00114
	[0.00194]	[0.00228]	[0.00169]	[0.00186]	[0.00073]	[0.00081]	[0.00193]	[0.00209]
post X dist to Walmart ϵ [1,2] miles		0.00023		0.00089		-0.00114		-0.00009
		[0.00194]		[0.00169]		[0.00070]		[0.00174]
post X dist to Walmart ϵ [2,3] miles		0.00371*		0.00007		-0.00086		0.00048
		[0.00193]		[0.00150]		[0.00063]		[0.00163]
post X dist to Walmart ϵ [3,4] miles		-0.00201		0.00339**		-0.00100		-0.00020
		[0.00209]		[0.00171]		[0.00068]		[0.00184]
post X dist to Walmart ϵ [4,5] miles		0.00090		0.00136		-0.00063		0.00012
		[0.00323]		[0.00244]		[0.00090]		[0.00192]
post X dist to Walmart ϵ [5,6] miles		-0.00027		-0.00040		0.00078		-0.00059
		[0.00303]		[0.00210]		[0.00104]		[0.00234]
post X dist to Walmart ϵ [6,7] miles		-0.00118		-0.00074		-0.00101		-0.00082
		[0.00267]		[0.00300]		[0.00108]		[0.00289]
individual level controls	y	y	y	y	y	y	y	y
year and quarter dummies	y	y	y	y	y	y	y	y
ZIP code fixed effects	y	y	y	y	y	y	y	y
Constant	-0.03869***	-0.03874***	-0.01758***	-0.01766***	-0.00584***	-0.00577***	-0.02279***	-0.02279***
	[0.00252]	[0.00251]	[0.00173]	[0.00172]	[0.00081]	[0.00081]	[0.00205]	[0.00206]
Observations	1,032,452	1,032,452	754,126	754,126	3,138,637	3,138,637	730,036	730,036
R-squared	0.011	0.011	0.009	0.009	0.003	0.003	0.007	0.007
Number of zip	1,453	1,453	1,463	1,463	1,476	1,476	1,460	1,460

Robust standard errors in brackets, *** p<0.01, ** p<0.05, * p<0.1

Notes: "Other insurance " includes worker’s compensation, local government programs, CHAMPUS and VA. The ommitted category: 7+ miles. Individual level controls for gender, age, race, and ethnicity. All regressions include year, quarter and ZIP code fixed effects.

Table 9

Dependent Variable: LOG(NUMBER OF AVOIDABLE HOSPITALIZATIONS)

	(1)	(2)
post X distance to nearest Walmart ϵ [0,1] miles	-0.05366***	-0.04635**
	[0.01875]	[0.01984]
post X distance to nearest Walmart ϵ [1,2] miles		0.00778
		[0.01537]
post X distance to nearest Walmart ϵ [2,3] miles		0.00643
		[0.01369]
post X distance to nearest Walmart ϵ [3,4] miles		0.01560
		[0.01485]
post X distance to nearest Walmart ϵ [4,5] miles		0.01540
		[0.01841]
post X distance to nearest Walmart ϵ [5,6] miles		0.01552
		[0.01952]
post X distance to nearest Walmart ϵ [6,7] miles		0.00894
		[0.02021]
individual level controls	y	y
year and quarter dummies	y	y
ZIP code fixed effects	y	y
Constant	0.15506***	0.15571***
	[0.02861]	[0.02857]
Observations	44,472	44,472
R-squared	0.069	0.069
Number of zip	1,482	1,482

Robust standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

Notes: The ommitted category: 7+ miles. Full sample collapsed at the ZIP code-year level. Individual level controls for gender, age, race, ethnicity, and type of insurance (Medicaid, uninsured and other types of insurance hospitalizations, with private insurance as the omitted category). All regressions include year and ZIP code fixed effects.

Table 10

Dependent Variable: Falsification condition hospitalization dummy

	(1)	(2)	(3)	(4)	(5)	(6)
	CANCER		APPENDICITIS		GI OBSTRUCTION	
post X dist to Walmart ϵ [0,1] miles	-0.00069	-0.00105	-0.00024	-0.00009	0.00036	0.00061*
	[0.00091]	[0.00097]	[0.00033]	[0.00040]	[0.00030]	[0.00035]
post X dist to Walmart ϵ [1,2] miles		-0.00019		-0.00006		0.00007
		[0.00071]		[0.00039]		[0.00031]
post X dist to Walmart ϵ [2,3] miles		-0.00106		0.00013		0.00052*
		[0.00068]		[0.00037]		[0.00028]
post X dist to Walmart ϵ [3,4] miles		0.00011		0.00038		0.00007
		[0.00075]		[0.00040]		[0.00031]
post X dist to Walmart ϵ [4,5] miles		-0.00086		0.00051		0.00035
		[0.00084]		[0.00054]		[0.00037]
post X dist to Walmart ϵ [5,6] miles		-0.00022		0.00014		0.00072
		[0.00090]		[0.00051]		[0.00049]
post X dist to Walmart ϵ [6,7] miles		-0.00025		0.00026		0.00048
		[0.00146]		[0.00051]		[0.00036]
individual level controls	y	y	y	y	y	y
year and quarter dummies	y	y	y	y	y	y
ZIP code fixed effects	y	y	y	y	y	y
Constant	-0.03438***	-0.03434***	0.06255***	0.06253***	0.00240***	0.00237***
	[0.00089]	[0.00089]	[0.00073]	[0.00073]	[0.00026]	[0.00026]
Observations	5,655,251	5,655,251	5,655,251	5,655,251	5,655,251	5,655,251
R-squared	0.012	0.012	0.010	0.010	0.001	0.001
Number of zip	1,482	1,482	1,482	1,482	1,482	1,482

Robust standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

Notes: The ommitted category: 7+ miles. Individual level controls for gender, age, race, ethnicity, and type of insurance (Medicaid, uninsured and other types of insurance hospitalizations, with private insurance as the omitted category). All regressions include year, quarter and ZIP code fixed effects.

Table 11

Dependent Variable: Falsification condition hospitalization dummy

	(1)	(2)	(3)
	CANCER	APPENDICITIS	GI OBSTRUCTION
distance to nearest Walmart ϵ [0,1] miles X dummy year 2003	0.00162	-0.00043	-0.00059
	[0.00141]	[0.00074]	[0.00063]
distance to nearest Walmart ϵ [0,1] miles X dummy year 2004	0.00065	0.00011	-0.00089
	[0.00144]	[0.00074]	[0.00058]
distance to nearest Walmart ϵ [0,1] miles X dummy year 2005	0.00229	0.00009	-0.00111**
	[0.00149]	[0.00061]	[0.00054]
distance to nearest Walmart ϵ [0,1] miles X dummy year 2006	0.00218	0.00022	-0.00082
	[0.00155]	[0.00071]	[0.00059]
distance to nearest Walmart ϵ [0,1] miles X dummy year 2007	0.00003	-0.00056	-0.00008
	[0.00156]	[0.00069]	[0.00050]
distance to nearest Walmart ϵ [0,1] miles X dummy year 2008	0.00103	-0.00114	-0.00005
	[0.00173]	[0.00087]	[0.00061]
distance to nearest Walmart ϵ [0,1] miles X dummy year 2009	0.00122	-0.00010	-0.00065
	[0.00139]	[0.00067]	[0.00060]
individual level controls	y	y	y
year and quarter dummies	y	y	y
ZIP code fixed effects	y	y	y
Constant	-0.03439***	0.06254***	0.00240***
	[0.00089]	[0.00073]	[0.00026]
Observations	5,655,251	5,655,251	5,655,251
R-squared	0.012	0.010	0.001
Number of zip	1,482	1,482	1,482

Robust standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

Notes: The ommitted category: 7+ miles. Individual level controls for gender, age, race, ethnicity, and type of insurance (Medicaid, uninsured and other types of insurance hospitalizations, with private insurance as the omitted category). All regressions include year, quarter and ZIP code fixed effects.

Table 12

Dependent Variable: AVOIDABLE HOSPITALIZATION DUMMY

	(1)	(2)
post X distance to nearest Walmart ϵ [0,1] miles	-0.00157**	-0.00165**
	[0.00065]	[0.00074]
post X distance to nearest Walmart ϵ [1,2] miles		-0.00133*
		[0.00068]
post X distance to nearest Walmart ϵ [2,3] miles		0.00118*
		[0.00061]
post X distance to nearest Walmart ϵ [3,4] miles		-0.00024
		[0.00066]
post X distance to nearest Walmart ϵ [4,5] miles		-0.00029
		[0.00098]
post X distance to nearest Walmart ϵ [5,6] miles		0.00059
		[0.00113]
post X distance to nearest Walmart ϵ [6,7] miles		-0.00148
		[0.00096]
individual level controls	y	y
year and quarter dummies	y	y
ZIP code fixed effects	y	y
Constant	-0.02541***	-0.02540***
	[0.00136]	[0.00136]
Observations	5,434,481	5,434,481
R-squared	0.009	0.009
Number of zip	922	922

Robust standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

Notes: This table uses and alternative measure of distance to the nearest Walmart store: instead of using the distance from the geographic centroid of each ZIP code, it uses a population weighted centroid. The ommitted category: 7+ miles. Individual level controls for gender, age, race, ethnicity, and type of insurance (Medicaid, uninsured and other types of insurance hospitalizations, with private insurance as the omitted category). All regressions include year, quarter and ZIP code fixed effects.

Appendix Table 1:Florida ZIP code level characteristics

	ALL	No Walmart in ZIP code	One + Walmart in ZIP code
Average population	17238	14914.21	26433.76
Average land area (sq miles)	49.99	47.73	58.91
Total population	15979631	11036517	4943114
Total land area (sq miles)	46335.86	35319.13	11016.73
Population Density	344.87	312.48	448.69
Average distance from centroid of ZIP to nearest Walmart	6.97	8.12	2.09
Median distance from centroid of ZIP to nearest Walmart	4.39	5.45	1.67
Number of ZIP codes	1003	812	191

* unit of observations ZCTA

Appendix Table 2: Medications most frequently prescribed in the US for chronic conditions

Generic drug name	Number of Prescriptions in 2009 (millions)*	Available through $4 program	Average price before $4 program**
Simvastatin	83.0	no	139.31
Lisinopril	81.3	yes	26.12
Levothyroxine	66.0	yes	14.34
Metformin	52.0	yes	46.58
Atorvastatin	51.5	no	-
Amlodipine	50.9	no	-
Hydrocholorthiazide	47.1	yes	12.69
Omeprazole	45.4	no	-
Furosemide	42.8	yes	10.25
Metoprolol	40.5	yes	19.97
Atenolol	38.6	yes	17.19

*Source: Choudhry and Shrank (2010)

** from the Florida RX price data set, no information from the drugs atorvastatin, amlodipine and omeprazole.

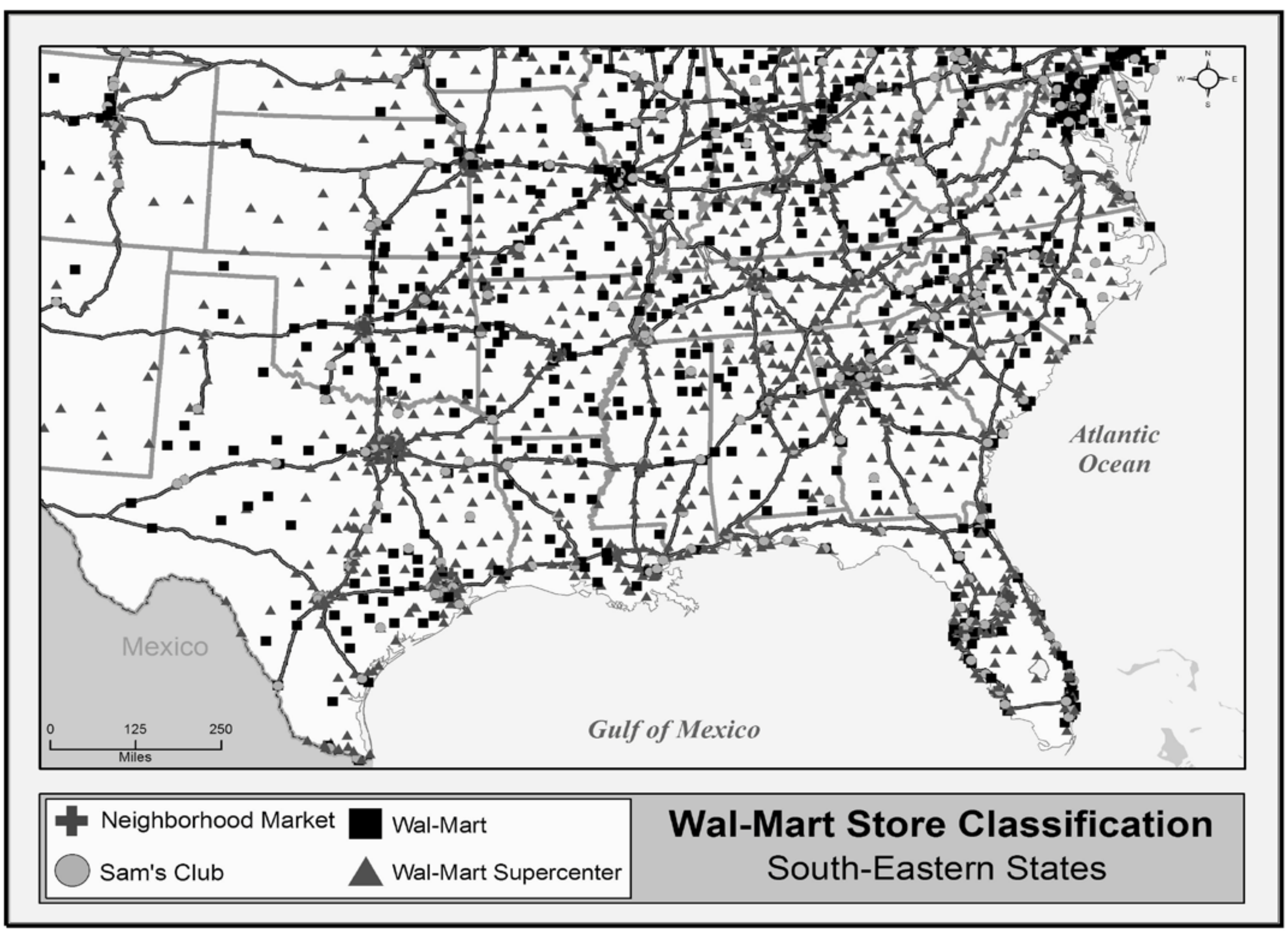
Appendix Table 3: Drugs included in Price Regressions

Drug name	Sample 1 2006 - 2008	Sample 2 2005 - 2009	Belongs to $4 program
ALPRAZOLAM	x		no
AMOXICILLIN	x	x	yes
ATENOLOL	x		yes
AZITHROMYCIN	x	x	no
CITALOPRAM	x		yes
FUROSEMIDE	x	x	yes
GABAPENTIN	x		no
HYDROCHLOROTHIAZIDE	x		yes
IBUPROFEN	x		yes
LEVOTHYROXINE	x	x	yes
LIPITOR	x		no
LISINOPRIL	x		yes
METFORMIN	x		yes
METOPROLOL	x	x	yes
PLAVIX	x	x	no
SERTRALINE	x		no
SIMVASTATIN		x	no
SINGULAIR	x	x	no
WARFARIN	x		yes

Appendix Table 4: Link between $4 prescription drugs and Avoidable Hospitalization Conditions

$4 Prescription Drugs		*Condition*	*Avoidable*
Amiloride-HCTZ	Hydrochlorothiazide	**Heart Health and High Blood Pressure**	Malignant Hypertension (IC9-CM codes: 401.0 402.0 403.0 404.0 405.0 437.2) Congestive Heart Failure (IC9-CM codes: 428 402.01 402.11 402.91)
Atenolol-Chlorthalidone	Indapamide		
Atenolol	Isosorbide Mononitrate		
Benazepril	Lisinopril-HCTZ		
Bisoprolol-HCTZ	Lisinopril		
Bumetanide	Methyldopa		
Captopril	Metoprolol Tartrate		
Carvedilol	Nadolol		
Chlorthalidone	Pindolol		
Clonidine	Prazosin HCL		
Digitek	Propranolol		
Diltiazem	Sotalol		
Doxazosin	Spironolactone		
Enalapril-HCTZ	Terazosin		
Enalapril	Triamterene-HCTZ		
Furosemide	Verapamil		
Guanfacine	Warfarin		
Hydralazine			
Chlorpropamide		**Diabetes**	Diabetes (IC9-CM codes: 250.1 250.2 250.3 251.0)
Glimepiride			
Glipizide			
Glyburide			
Metformin			
Albuterol		**Asthma**	Asthma (IC9-CM codes: 493)
Ipratropium			

Maps 1 and 2



Source: Matthew Zook and Mark Graham (http://www.zook.info/Wal-Mart/)