THE EFFECTS OF GLOBAL BUDGET PAYMENTS ON HOSPITAL UTILIZATION AND QUALITY IN RURAL MARYLAND

by

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Abstract

Background/Purpose: Hospital spending comprises the largest share of health care expenditures in the United States, and is projected to continue to grow rapidly. To align payment incentives with high quality, efficient care, Maryland piloted an innovative payment model called the Total Patient Revenue (TPR) program starting in 2010. Eight rural acute care hospitals voluntarily agreed to revenue caps covering inpatient and outpatient services starting in 2010. In 2014, the program was slightly modified and expanded to all hospitals in the state as the Global Budget Revenue (GBR) program. This study assesses the impact of TPR on population-level rates of total and preventable utilization.

Methods: We use data on all discharge abstracts in Maryland hospitals from the state's Health Services Cost Review Commission (HSCRC) for years 2008-2013, linked to ZIP Code Tabulation Area (ZCTA) level data from Claritas Demographic Reports and county-level data from various sources. We analyze ZCTA-level rates of inpatient and outpatient utilization per capita, including total admissions, inpatient days, outpatient encounters, observation stays, and Emergency Department (ED) visits. We also distinguish between preventable vs. non-preventable and deferrable vs. non-deferrable utilization. Preventable inpatient utilization includes readmissions and admissions due to ambulatory care sensitive conditions as defined using the Agency for Healthcare Research and Quality (AHRQ)'s methodology for Prevention Quality Indicators (PQIs). Preventable outpatient utilization includes emergent preventable and primary-care treatable ED visits as defined by the validated Billings algorithm. To empirically examine the effect of TPR's implementation on changes in utilization over time, we compare changes in utilization rates pre- and post-intervention using a difference-in-differences (DD) approach with ZCTA and year fixed effects. We estimate different models using four different control groups, starting with the service areas of three rural non-participating hospitals and expanding to the entire state.

Results: We observe a statistically significant 8.19 percent reduction in total outpatient visits. In contrast, total hospital admissions decreased only slightly in areas affected by the TPR reform by 1.77 percent relative to control areas, but the effect is not statistically significant. The TPR program, however, led to a statistically significant decrease of 5.09 percent in total inpatient days. The rates of preventable hospitalizations showed statistically insignificant reductions, driven mostly by chronic ACSCs (composite indicator PQI #92) including asthma, diabetes, and heart failure. These results are generally robust to a number of sensitivity analyses. We also find little effect on preventable and primary care treatable ED visits.

ABSTRACT

Conclusion/Implications: Hospital global budgets are a promising policy for decreasing preventable hospitalizations in rural hospitals, but may be difficult to implement for hospitals competing in overlapping service areas. Moreover, they may have to be adapted to other states lacking hospital rate-setting authority across all payers.

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Dedication

This dissertation is dedicated to my grandfather Nicolae Done, Sr., my childhood hero, who instilled in me the value of constant self-improvement, dignity, and resilience in the face of adversity.

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Chapter 1

Introduction

Policy makers throughout the world are seeking to improve the allocation of limited health care resources to achieve better population health and long-term financial sustainability (OECD 2010; WHO 2014). Faced with aging populations and a steady shift in disease burden towards chronic conditions, governments are under pressure to strike an elusive balance between prevention and curative care (Hirshon et al. 2013). Moreover, evolving patient preferences, the introduction of new and expensive medical technologies and the spread of health insurance coverage create new dilemmas for those concerned about both equity and economic efficiency.

The United States, despite spending more per capita than any other country in the world, still lags behind other industrialized nations in many measures of population health (Squires and Anderson 2015). Its complex health care system has some of the highest prices in the world for many basic services (Anderson et al. 2003; Squires 2012), yet still leaves a significant share of the US population without health insurance coverage and therefore exposed to high medical expenses. There is widespread recognition that a major cause for this state of affairs is the fragmentation of health care financing and delivery (Reinhardt 2012; Sutherland, Fisher, et al. 2009), both enabled and exacerbated by fee-for-service payment systems that reward more, but not necessarily better care (Baicker et al. 2009; Fisher and et al. 2009).

As researchers have begun to recognize the limitations of demand-side incentives induced through benefits package and insurance cost-sharing design (Manning et al. 1987), the focus has shifted markedly towards the methods of reimbursement used by insurance funds, both public and private, and how they can be used to promote the development of the health care system and to achieve policy objectives (Ellis et al. 1993). Part of this approach has been tried before, even though with a different twist. Most prominently, the managed care revolution, which started gaining traction in 1973 with the passage, of the Health Maintenance Organization (HMO) Act, passed in 1973, focused on developing networks of providers that could deliver integrated care. This movement ultimately led to the creation of Medicare Advantage and popularized managed care plans throughout the US. However, in the late 1990s, provider push-back and the backlash to what the public saw as unacceptable limits on access led to a scale-down and dilution of this form of care delivery.

The current wave of care transformation is based on the principle that payment reform should create the incentive environment that rewards what society considers valuable in health care, while providers should be allowed to evolve naturally into integrated organizations. A prominent strategy of the federal and state governments in the quest for higher value in health care over the past several years has therefore been to transform health care delivery by reforming provider payment (Obama 2016). The goal has been to gradually shift provider incentives from a focus on service volume to rewarding higher quality and reductions in wasteful care.

There are at least three reasons for this strategy. First, payment is a readily available policy lever, since government financing still accounts for a large portion of health care expenses via Medicare and Medicaid. Moreover, private plans often follow the lead taken by public payers on reimbursement methods. Second, altering payment models is more likely to be viewed as less intrusive by providers and other stakeholders in the system than other top-down approaches. Third, altering the system's incentives could likely draw change organically, therefore improving the prospects of long-term success.

Even after deciding that payment was the right intervention point, policy makers have been largely agnostic about the specifics. They avoided being too prescriptive and have instead enabled a wide array of pilot programs and demonstrations. For instance, the Center for Medicare and Medicaid Innovation (CMMI) was created within the Centers for Medicare and Medicaid Services (CMS) to test different payment models and to draw lessons for policy using a ”rapid-cycle evaluation” approach (Shrank 2013). The fundamental operating premise has been that in a market of ideas, those ideas that actually work in practice would eventually ”rise to the top”. The hope was that over time enough evidence would be accumulated to permit informed decision making while also allowing enough local flexibility in the absence of a general consensus on specific delivery models.

The alternative payment models currently tested within Medicare include the formation of risk-taking Accountable Care Organizations (ACOs), bundled payments, primary care transformation initiatives, and pay-for-performance (P4P) programs (Center for Medicare and Medicaid Innovation 2017a). Most likely, the shift to value-based payment is only set to accelerate, as CMS has set a goal of tying 50 percent of Medicare payments to quality or value (as opposed to volume) by the end of 2018, up from around 30 percent currently (Burwell 2015).

Hospitals have been the target of many of these payment initiatives, either directly or indirectly. Hospital expenditures comprise nearly one trillion dollars, thus making up for the largest component of total US health spending (Martin et al. 2016). Traditionally, hospitals have been the bedrock of health care provision in most industrialized countries, as most medical services used to be provided for acute episodes of illness or injury during inpatient stays (Cylus et al. 2010). The transition to case-based payments began in the 1980s with Medicare's Inpatient Prospective Payment System (IPPS) and was a major improvement in efficiency compared to the highly inflationary retrospective cost-based reimbursement system used previously. But while the IPPS decreased lengths of stay and led to a reduction in admissions (contrary to initial expectations) (Rosenberg et al. 2001), the system was not conducive to care coordination and population health management. The growing recognition that this system has become less and less tenable is at the core of the new push for hospital incentive realignment.

Alongside Medicare initiatives, alternative payment models have also been developed by commercial payers and Medicaid programs (Muhlestein et al. 2016). For example, the Alternative Quality Contract (AQC) in Massachusetts, launched by Blue Cross Blue Shield of Massachusetts, the state's largest commercial payer, pays providers risk-adjusted global budgets (Chernew et al. 2011). The program seems to have produced substantial savings, ranging from 7 to 9 percent of medical spending, both through price and utilization reduction (Song et al. 2014). Another example, this time in Medicaid, is Colorado's Accountable Care Collaborative (ACC) program. Under ACC, the state's Medicaid agency contracts with seven Regional Care Collaborative Organizations (RCCOs) to create primary care networks which ensure coordination of care for Medicaid enrollees with hospitals, specialist physicians, and social services (Rodin et al. 2013). As of 2016, the 38 awardees of the CMS State Innovation Models (SIM) Initiative included 34 states, three territories, and the District of Columbia, across the different phases of the program.

In this climate of state innovation models, the State of Maryland implemented Total Patient Revenue (TPR), a global budget payment program, in eight rural hospitals in 2010 (Patel et al. 2015). The program, described in detail in Chapter 2, leverages Maryland's unique hospital rate-setting system, in place since the late 1970s. TPR essentially achieves a system of global budgets by allowing the state rate-setting agency to set hospital-specific revenue constraints based on projections of utilization in each hospital's service area. If a hospital's revenue falls below that target, it is allowed to keep the difference as a reward. Alternatively, if the hospital's revenue exceeds the target, it is subject to penalties to the following year's budget, thus achieving a two-sided risk sharing model. Although the model was expanded to suburban and urban Maryland hospitals in 2014 and now serves as one of the critical components of the state's revised CMS waiver (Rajkumar et al. 2014), the impact of global hospital budgets on population-level metrics has not been comprehensively evaluated. Mortensen et al. (2013) analyzed the early effects of the program on 30-day readmissions, but their study's limited outcomes and lack of a population-based approach leave many questions unanswered. Specifically, can global budgets limit overall hospital use in an entire hospital service area? With budget constraints covering both inpatient and outpatient revenues, are both types of utilization targeted by the hospitals? Importantly, beyond a focus on total hospital care use, can the program limit the use of preventable utilization, or low-value care?

To fill these gaps in the literature, this dissertation examines the impact of TPR on hospital care utilization and preventable quality indicators in rural Maryland. We focus on utilization rates since payment rates are fixed and total hospital revenues are capped. Our study combines all-payer administrative data on inpatient and outpatient episodes from all hospitals in the state with population estimates of state residents. We use a well-established difference-in-differences (DD) econometric technique on data aggregated at the ZIP Code Tabulation Area (ZCTA) level and use several different sets of control groups for the rural areas participating in TPR. We use a baseline of two years (2008-2009) and focus on the first four years of the program (2010-2013), which covers the program's first contract cycle (Maryland Health Services Cost Review Commission 2010).

We find a modest and statistically insignificant reduction in the rate of overall inpatient admissions but a significant reduction in outpatient visits, on top of the strong downward trend in utilization present in the state prior to the reform. This suggests that the TPR revenue constraint acts as a slightly stronger incentive to limit hospital use compared to the payment tapering mechanisms already enforced by the state's hospital regulating agency, the Health Services Cost Review Commission (HSCRC) (Kalman et al. 2013).

One of the critical policy questions is whether TPR can induce hospitals to increase quality by limiting the use of low-value care, as opposed to indiscriminately reducing all forms of care. Our follow-on analysis finds that no significant reduction in potentially preventable hospitalizations due to chronic Ambulatory Care Sensitive Conditions (ACSCs) in TPR areas compared to Maryland control areas. Although the effects are small in magnitude, they indicate that global budgets can potentially be an effective tool for improving population health.

Our analysis also reveals no significant effect on preventable Emergency Department (ED) visits–including those that are non-emergent, treatable in primary care settings, or potentially avoidable, although these results are more sensitive to model specification and the particular control group used. This suggests the implausibility that some of the patients may have ended up seeking care in the Emergency Room, as opposed to being admitted to the hospital. Our findings also highlight the importance of examining the program's impacts on a wide range of measures, and the need for continuous monitoring to test *a priori* assumptions and the program's architects' hopes about how it would affect the use of hospital care.

Although the results are specific to the particular setting of all-payer rate setting in Maryland, they suggest that the TPR program can potentially serve as a basis for Medicare reimbursement for hospitals that serve beneficiaries in a relatively well-defined geographic area, such as rural hospitals. Around the US, rural hospitals in particular are showing signs of great distress. More than eighty have closed since 2010 (North Carolina Rural Health Service Program 2017) and many others are struggling to remain financially sound (Kaufman et al. 2016). While approaches that do not fundamentally change the financial incentives for these hospitals in the face of decreasing demand and growing economic distress in rural America are likely bound to fail, global budgets may provide a long-term, feasible solution (Sharfstein 2016).

In fact, other states are following Maryland's lead and in some cases going even farther. Pennsylvania recently entered an agreement with the Centers for Medicare and Medicaid Services (CMS) to test an all-payer global budget model for its rural hospitals over the next seven years (Center for Medicare and Medicaid Innovation 2017b). Under this agreement, the state commits to achieving at least \$35 million in Medicare hospital savings over the course of the model, while keeping the model budget-neutral overall for Medicare. Across all participating payers, Pennsylvania also agrees to keep the annual all-payer *hospital spending* growth rate below 3.38 percent, which is the average annual growth rate for Pennsylvania's gross state product from 1997 to 2015. If successful, the program would demonstrate that having an underlying rate-setting system like the one in Maryland is not indispensable to the implementation of global budgets, as Pennsylvania's model has all payers agree to pay specific shares of the hospitals' budgets, based on their enrollee populations.

Similarly, Vermont entered a new agreement with CMS (Green Mountain Care Board 2016). Vermont's model goes even farther than Maryland's or Pennsylvania's, by introducing a system of global budgets for all health care spending, not just spending on hospital care. Vermont's experience could show what is possible for Maryland if it decides to take the next natural step of expanding global budgets beyond hospital care when its agreement with CMS is up for renewal in 2019.

This dissertation is organized as follows. Chapter 2 provides the context in which the TPR global budget policy intervention was introduced and outlines its critical components. Chapter 3 reviews the conceptual frameworks for understanding payment system incentives and summarizes the empirical evidence regarding the effects of hospital global budgets, both in the US and internationally. Chapter 4 outlines an economic theoretical model of hospital behavior under a change in payment incentives and then specifies testable assumptions regarding the effects of TPR.

Chapter 5 describes the data, the study design, and the analytical approach of the study. Chapter 6 presents our estimates of the reform's effects on total and preventable inpatient hospital utilization and Chapter 7 presents effect estimates on total and preventable outpatient utilization. Finally, Chapter 8 interprets the study results, discusses its limitations, and suggests future directions for research and policy.

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Chapter 2

Policy Context and Reform

This chapter provides the institutional background of Maryland's health care regulatory environment and describes the most salient features of the Total Patient Revenue hospital payment reform. Understanding Maryland's system and its evolution over time is helpful to put the findings of our analysis into the proper perspective and distinguish what is generalizable from what is context-specific. Moreover, this background information assists with the development of the study hypotheses and the empirical design by better focusing on policy relevant questions and allowing for proper empirical identification of the reform's impacts.

2.1 Health financing and delivery in Maryland

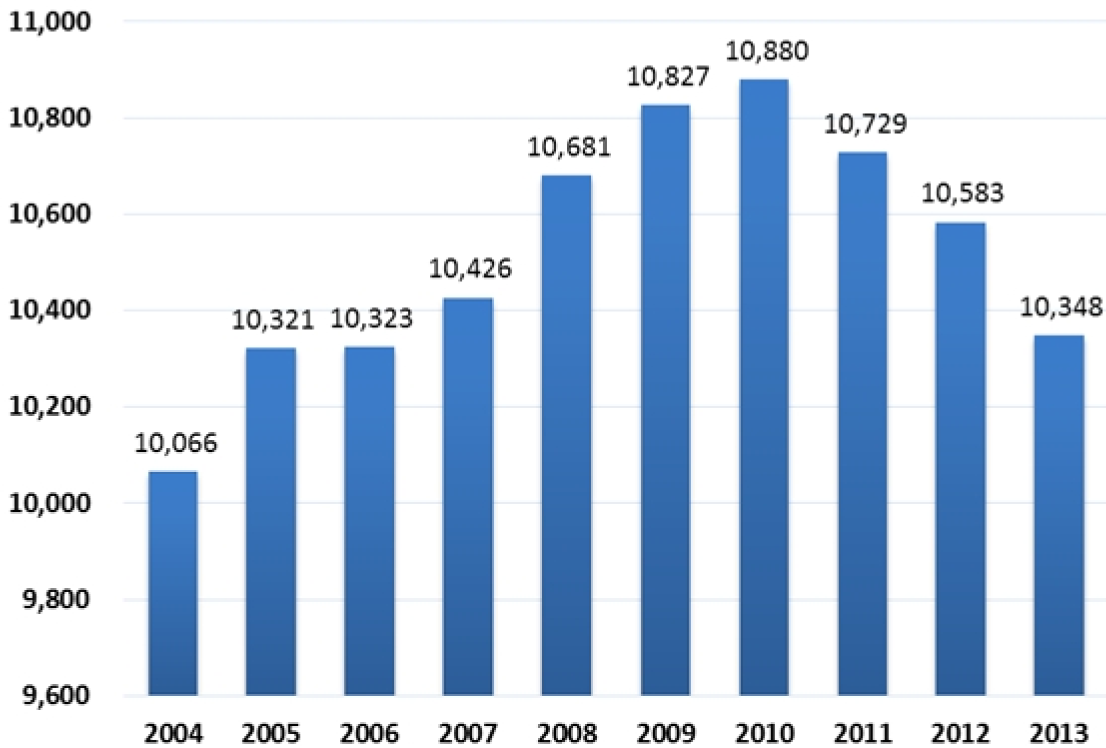
In 2010, health care spending in Maryland totaled $7,698 per resident, including expenditures on hospital care, professional services, prescription drugs, and long-term care. This level was 8.9 percent higher than the national average (Maryland Health Care Commission 2012), with Maryland ranking 14^{th} among the 50 US states. The growth rate of per capita health care spending in Maryland had been declining steadily over the previous ten years, from 8.6 percent in 2001 to 2.5 percent in 2010, but these growth rates were slightly higher than the US as a whole. Of this amount, 37.3 percent was spent on hospital care, while physician and clinical services made up 23.6 percent of the total.

There were 46 acute care hospitals in Maryland in 2013, totaling 10,348 licensed acute care beds (Maryland Health Care Commission 2013). The number of beds grew by 8.1 percent from 2004 to 2010 but then declined by 4.9 percent between 2010 and 2013 (Figure 2.1). The State of Maryland is unique in that it is the only state that still operates an all-payer rate-setting system for hospitals[1]. This rate-setting system and the Medicare waivers that facilitate it have a long history in Maryland, elements of which are depicted schematically on the timeline in Figure 2.2.

Rate-setting for Maryland hospitals originated in the early 1970s, when rapid hospital cost inflation was putting tremendous pressure on health care budgets. In Maryland, the mean cost per hospital admission was at the time more than 25 percent above the US average (Murray and Berenson 2015).

[1]Although several states operated similar all-payer systems in the 1980s and 1990s, these states have all gradually eliminated the rate-setting regulations. The West Virginia Health Care Authority was established in 1983 to set rates for inpatient admissions to commercial payers, thus excluding government payers like Medicare, Medicaid, and the Public Employees Insurance Agency (PEIA). However, beginning in July 2016, the ability of the Authority to regulate hospital rates was eliminated (West Virginia Legislature 2016).

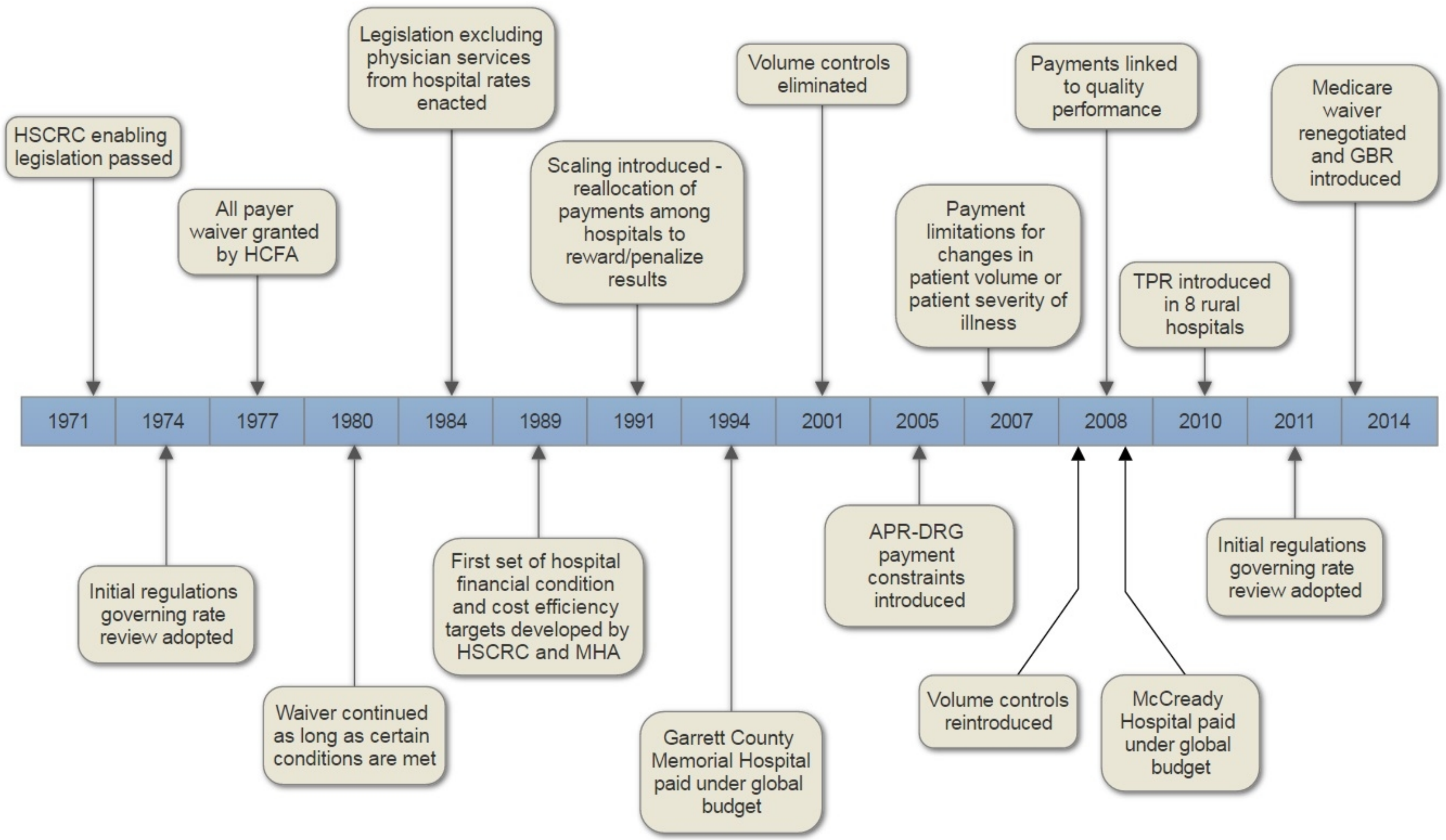
Figure 2.1: Total Licensed Acute Care Beds in Maryland Hospitals, 2008-2013



Note: Data is shown by Fiscal Year. *Source:* Maryland Health Care Commission 2013.

Health care regulation was at the height of its popularity during this decade both nationally and in the state. Regulation was seen as a powerful tool not just for constraining spending, but also for improving equity among payers and supporting hospitals by reducing the levels of uncompensated care. Throughout the 1970s, both the American Hospital Association (AHA) and the Health Insurance Association of America (HIAA, now AHIP) supported state rate-setting (Crozier 1982). Spurred by the federal National Health Planning and Resources Development Act of 1974, many states instituted health planning agencies and Certificate-of-Need (CON) programs in an attempt to constrain the perceived surplus in the supply of health care facilities.

Figure 2.2: Timeline of Important Changes in Maryland's Hospital Payment System, 1971-2014



Consistent with this national trend, Maryland established the Health Services Cost Review Commission (HSCRC) in 1971 as an independent state agency responsible for hospital rate setting within its Department of Mental Health and Hygiene (DHMH). The Commission gained regulatory authority to set hospital payment rates and publicly disclose hospital operating performance data beginning on July 1, 1974, but started rate regulation for some hospitals in 1975 and then for all hospitals in 1977 (Biles et al. 1980).

The Commission initially had authority over *private* commercial payers only. Its all-payer rate setting authority was established as a result of a waiver granted by the Health Care Financing Administration (HCFA), now Centers for Medicare and Medicaid Services (CMS). At the time, given HCFA's interest to experiment with new forms of hospital payment, Maryland and a few other states (New York, New Jersey, Massachusetts, West Virginia, and Washington) applied for waivers granting them the ability to devise different systems to cover Medicare and Medicaid beneficiaries. Maryland's waiver, described in more detail below, was the first to be approved in 1977 as a "demonstration" waiver. It became permanent in 1980 when it was incorporated into section 1814(b) of the Social Security Act, being the only waiver ingrained into Federal statute (Murray and Berenson 2015).

Structure and operation of HSCRC

HSCRC's mandate has been to promote cost containment, access to services, equity, financial stability, and accountability to the public (Colmers et al. 2010). In doing so, it acknowledged certain failures of the health care market and the need for robust, but not overreaching, government intervention to correct them.

By statute, the services covered under HSCRC's jurisdiction include hospital inpatient services and hospital outpatient services provided "at the hospital," but exclude physician and professional fees, other operating revenue, non-operating revenue, and other services like those provided by skilled nursing facilities, home health, and outpatient renal dialysis centers. Initially, the Commission had the authority to regulate the fees of hospital-based physicians. This authority ended in 1981, when the Court of Appeals of Montgomery County ruled that the professional fees of physicians were not costs of the hospital and were thus beyond the Commission's jurisdiction (Murray and Berenson 2015).

Because the establishing law was broadly worded, the HSCRC was able to adapt its regulations over time to the changing forces in the health care market (Murray 2009). Unlike the other states using hospital rate setting, Maryland's statute did not specify the details of the rate setting methods to be used. It did stipulate that the system must be prospective, but left considerable discretion to the regulators (Murray and Berenson 2015). Moreover, the HSCRC has sustained a more cooperative relationship with the hospital industry, which allowed it to largely avoid the abrupt changes displayed by other state programs (McDonough 1997).

Maryland funds the Commission's activities through an assessment on hospital rates. This funding method means that its budget is outside of the state's general fund, thus protecting the political independence of the Commission (Murray and Berenson 2015). But in contrast to states like West Virginia and Massachusetts, which appointed and paid full-time commissioners, Maryland's seven commissioners are part-time, unpaid experts appointed by the governor. This voluntary commission model is based on the belief that the state's salary scale would not attract sufficiently qualified individuals. However, it has the disadvantage that part-time commissioners often do not have the time to fully understand the rate-setting system or changes proposed by the professional staff (Murray and Berenson 2015).

Several broad features of Maryland's rate-setting scheme have remained relatively constant since its inception. But, as described below, the system has also evolved considerably over time, as specific elements were introduced or phased out in response to trends in health care costs or changes in the State's economic conditions. One essential aspect is the structure of the waiver negotiated with the Federal Government, including the constraints placed on the State regarding the funding for its Medicare and Medicaid populations. These constraints affected the ability of Maryland's HSCRC to influence the behavior of hospitals in the state through regulatory policies.

2.2 The hospital payment system prior to global budget reform

This section focuses on the hospital payment system in effect before the use of global budgets in both the 2010 rural TPR pilot program and the 2014 statewide GBR program. It describes the prior payment system's most salient features, many of which were actually maintained under the TPR (and GBR) system, with the addition of the hospital revenue constraints, as described below, which essentially create the new global budget constraint. Where appropriate, we also provide evidence regarding the impact of specific payment elements on pre-reform trends in utilization and spending.

Maryland's prior hospital payment system can be characterized as a "hybrid" between fee-for-service and case-based reimbursement. The fee-for-service part of the rate-setting process stems from its micro-costing process for determining payment rates for each service specific to each hospital. The case-based part of the rate-setting process consists of constraints to how much each hospital could charge per admission, set using Diagnostic-Related Groups (DRGs).

The unit rates

Under the first part of the rate setting process, the HSCRC first calculates allowed unit rates per cost item for each hospital. Cost items are the types of services provided under each of 65 revenue centers and classified into three categories: inpatient, outpatient, and ancillary. Inpatient revenue centers include, for example, the medical surgical acute unit, the pediatric intensive care unit, and the burn care unit. The units of service for these revenue centers are simply patient days. Outpatient revenue centers are paid based on different units depending on the specific services they provide. For example, Relative Value Units (RVUs) are used for clinic services, hours for the observation unit, and visits for the psychiatry day and night care units. Similarly, units for ancillary revenue centers range from minutes for anesthesiology to Maryland RVUs (a state-specific unit) for occupational therapy.

The unit rates are hospital-specific and are determined from detailed data collected by the HSCRC on costs based on hospital activity. This data is supplied by hospitals through a detailed accounting system as a condition of eligibility for Medicare reimbursement. The HSCRC allocates direct and indirect costs to each revenue item and calculates unit costs for each revenue center. The unit rates are then obtained by applying markups to unit costs and are subsequently adjusted to reflect the patient demographic mix and local labor market conditions for each hospital, resulting in prospective rates for a base period that could differ substantially across different hospitals. The rates also differ among the hospitals depending on the amount of uncompensated care they provide (Kastor et al. 2011).

The unit rates are also updated each year by applying an update factor composed of several elements. First, the update factor reflects price inflation in the underlying health service production input factors (Brown 2009). Second, the HSCRC has the discretion to use the update factor as a policy tool for achieving certain objectives, such as encouraging capital investment. Third, the factor could include further adjustments based on hospital specific programs endorsed by the Commission.

The case-based constraints

Under the second part of the rate setting process, the HSCRC layered a set of hospital specific per-case revenue constraints. This process had the role of controlling aggregate resource use per case while still reflecting each hospital's specific cost structure described above. The constraints were calculated differently for inpatient and outpatient services.

Inpatient admissions were categorized into one of 320 All Patient Refined Diagnosis Related Groups (APR-DRG). APR-DRGs classify cases into clinically cohesive categories based on their medical condition, and each APR-DRG is then further separated into four "severity of illness" levels. Severity is assigned in terms of predicted impact on the patient's intensity of treatment. In 2005, Maryland became the first state to introduce the use of severity-adjusted DRGs. Its adoption of this system likely influenced the decision by CMS to also transition the Medicare Inpatient Prospective Payment System (IPPS) to Medicare Severity DRG (MS-DRG) (Atkinson et al. 2008).

Outpatient cases are classified using the Enhanced Ambulatory Patient Group (EAPG) system, introduced in Maryland in 2008. The EAPG classification groups outpatient visits based on resource use according to patients' clinical characteristics (using ICD-9-CM codes), treatments, and procedures (using HCPCS codes) (3M Health Information Systems 2016). There are a total of 505 EAPGs classified into 13 different types, including 229 based on significant procedures, 183 based on medical groups, 12 based on drugs (e.g., for chemotherapy), and 66 based on ancillary services.

With the underlying unit rates set for each hospital (as described in the prior subsection), allowed charges were then assigned to each APR-DRG and EAPG by aggregating the specific unit rates across cost centers (Atkinson et al. 2008). Then, the HSCRC calculated hospital-specific revenue targets per DRG and EAPG category. The targets aggregated allowed charges for all the cases within a DRG and EAPG over the course of a year, and hospitals faced a modest penalty if their actual revenues surpass these targets. The implication of these targets was that even though each hospital could charge for each case an amount closer to the actual resource used (as opposed to the DRG or EAPG allowed rate), it would generally monitor its aggregated charges relative to these targets and perhaps adjust charges over the course of the year to ultimately meet those targets or pay the penalties. Specifically, at the end of the year, the hospital would be required to invoice insurers for the total authorized amount equal to the product of the fixed charge per episode and the case mix. Any penalties would be aggregated and applied through adjustments to overall hospital-approved revenue each year (Murray 2009). Hospitals could thus offset overbilling by either invoicing a lower price per cost center (within ± 5

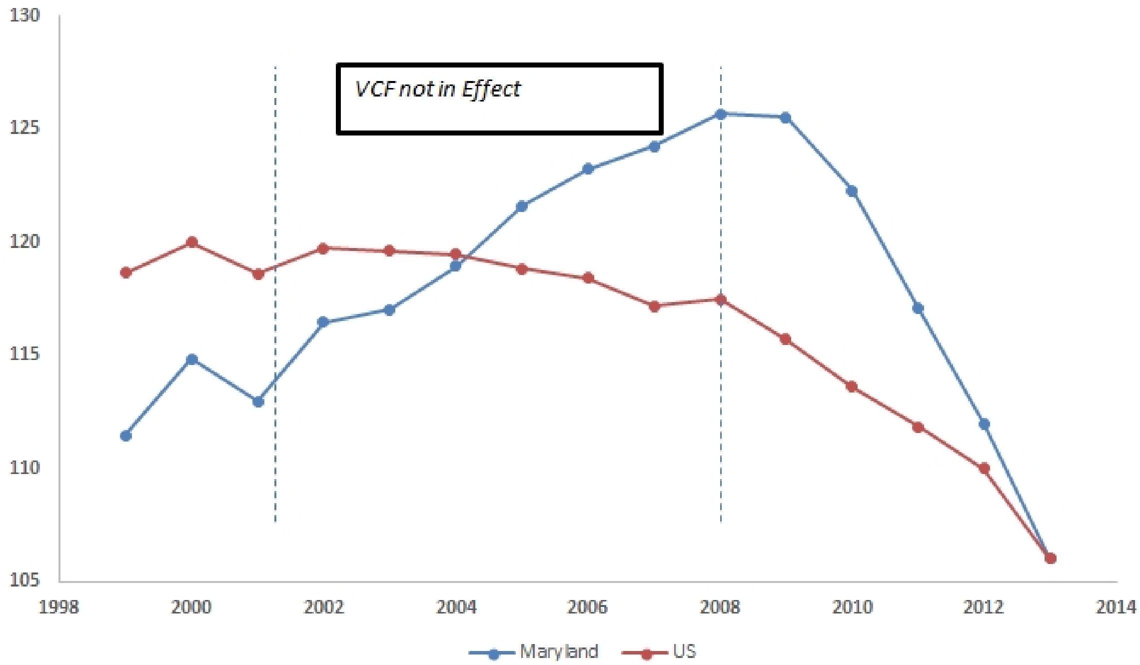
percent of the unit rates set by the HSCRC) or by lowering the resources used.

The volume constraints

The HSCRC also employed several other important mechanisms to control utilization pre-TPR, but these mechanisms varied over time. In particular, the Commission was concerned that hospitals' cost structure displays considerable economies of scale, leading marginal costs to be substantially lower than average costs for large hospitals. Because payments in the DRG-based system reimburse for average costs, hospitals are incentivized to invest in expensive technology and induce demand for services, thereby driving up costs.

Therefore, the HSCRC implemented a mechanism for attenuating payments called the Variable Cost Factor (VCF). Any increase in activity beyond the revenue budgets was billed at 50 percent of the allowed charge. This allowed the HSCRC to capture marginal revenues that result from an increase in volume. However, the VCF was temporarily eliminated in 2001 at the hospitals' request. This apparently minor and relatively obscure change in policy was strongly associated with a dramatic change in utilization, with inpatient admission rates increasing significantly, as shown in Figure 2.3. In 2008, HSCRC decided to reintroduce the VCF in the rate-setting process at a higher rate of 85% for volume growth above baseline and changed its charge-per-case constraints. The result was that the growth in admission rates first leveled off and subsequently began to decrease quickly across Maryland hospitals (Kalman et

Figure 2.3: Hospital Inpatient Admissions per 1,000 capita in Maryland vs. the United States, 1999-2013



Source: Kaiser Family Foundation, State Health Facts 2015.

al. 2013).

In addition, two further constraints were imposed on hospital activity. The first one was called the *volume governor* and restricted the growth in hospital volumes to 2 percent per year. The second one was *case-mix governor* and restricted growth in hospital case mix to 0.5 percent per year. As hospitals monitored their own activity, they would adjust their intensity of treatment to stay within the authorized revenue after accounting for the rate attenuation mechanism. Any differences would be applied upwards or downwards in the next year.

Although allowed charges calculated by the HSCRC are mandatory for both public and private payers, including for out-of-state patients admitted to Maryland hospitals (Brown 2009), revenue for non-Maryland residents was excluded from maximum revenue calculations and volume policies.

Other rate setting elements

The above description of Maryland's rate-setting mechanisms makes it clear that the system has never imposed the same rate paid for each service to a given hospital by all payers and patients. In reality, Maryland's rate regulation system establishes systematic methods to determine *how much rates may vary*. Notably, Medicare and Medicaid receive a 6 percent discount on charges, intended to recognize their role in reducing uncompensated care, while commercial plans face higher rates to offset these differentials. Similarly, the Blue Cross plan CareFirst has received discounts for its perceived role in increasing access and reducing uncompensated care by offering open enrollment throughout the year (Murray and Berenson 2015).

Moreover, since 2002 the State has used an assessment on hospital rates to subsidize the premiums for those in the "high-risk pool" insurance plan to, in turn, decrease uncompensated care. In 2008 these mark-ups were equalized across hospitals to increase the fairness of the system (Murray 2009).

Maryland's old waiver test

As mentioned above, Maryland's waiver was innovative at the time of its adoption and allowed the state to effectively operate an all-payer rate-setting system. In exchange for this flexibility, the state has had to pass a Medicare-specific ”waiver test”. Specifically, until 2014, this test relied purely on the rate of growth in Medicare Part A inpatient reimbursement per discharge. Under this methodology, Maryland’s rate of increase had to remain below the national average rate of increase in Medicare Part A payments per discharge, with the base period set to calendar year 1980.

Over time, Maryland had managed to stay under this level, partly because its baseline hospital cost per case in the 1970s exceeded the national average by about 25 percent (Intner et al. 2014). However, since then, the “cushion” available for growth shrank steadily, as a result of Maryland’s inability to reduce costs per admission, though perhaps linked to the state’s successful attempts to reduce lower-cost admissions. By the end of FY 2012, the waiver margin had declined to 1.7 percent, putting Maryland close to the brink of losing its Medicare waiver. This explains Maryland’s negotiation of a new waiver with CMS, the features of which are described below.

Other incentive programs

Other innovative payment initiatives were also introduced in Maryland over time, often with the goal of targeting specific types of hospital utilization or more comprehensive care transformation programs. These programs are similar to those implemented nationally, but often were introduced earlier and had critical Maryland-specific differences. This section provides a brief overview of these programs in order to better understand the policy context in Maryland before and during the implementation of TPR.

The Quality-Based Reimbursement (QBR) Program, introduced in 2008, focused initially on a set of clinical process measures in four domains related to heart attack, heart failure, pneumonia, and surgical prevention. The measures are updated annually to reflect changes from CMS and the Joint Commission on Accreditation of Healthcare Organizations (JCAHO) recommendations. Patient experience measures based on Consumer Assessment of Health Plans and Systems (CAHPS) survey scores were incorporated in 2012, and mortality was added as an outcome measure in 2015. The HSCRC calculates hospital-specific scores and places a portion of hospital all-payer revenue at risk based on these scores in a revenue-neutral manner. QBR is similar to Medicare's Value-Based Payment (VBP) program, but the latter also includes certain efficiency measures which the HSCRC considers are already addressed by its rate-setting methodology.

The Maryland Hospital-Acquired Conditions (MHAC) Program was introduced in 2009 with the goal of reducing hospital-acquired conditions. But in contrast to the similar program implemented by CMS nationally, MHAC was based on a more expansive set of conditions included in the 3M Health Information Systems' list of Potentially Preventable Complications (PPCs). Under MHAC, the HSCRC compares the risk-adjusted rates of these complications to the state average, with the conditions weighted based on their estimated cost or resource use. Hospitals are then ranked based on these rates, and a percentage of hospitals' revenue is placed at risk for their performance. An evaluation of the program's early experience found that it had reduced included PPCs by more than 18 percent in the first two years, while the rates of excluded complications increased modestly by almost 3 percent (Calikoglu et al. 2012).

The Admission-Readmission Revenue (ARR) Program, implemented in 2011, was a voluntary program incentivizing hospitals to reduce 30-day readmissions by making bundled payments for an episode of an index admission and its subsequent readmissions. This program, ultimately implemented in 27 hospitals, was deemed necessary considering the higher readmission rates among Maryland's Medicare beneficiaries compared to the national rate.

The Maryland Multi-Payor Patient Centered Medical Home Program (MMPP) started as a three-year pilot program introduced in 2011 with the goal of testing the Patient Centered Medical Homes (PCMH) model in Maryland. Distinguishing this program from other national initiatives was the broad diversity of participating health plans, including the five largest private payers in Maryland and other state and federal government payers. An early evaluation of the program found some cost savings and some improvements in the utilization of physician services and hospital admissions due to asthma (IMPAQ International 2014).

2.3 The 2010 TPR reform

The experience with the rate-setting system's admissions-based payments convinced Maryland regulators that total hospital utilization and total spending per capita, not spending per admission, was a much more meaningful target for policy. In addition, the HSCRC had experimented with global budgeting for a long time, as one hospital (Garrett County Memorial Hospital) had been paid using a guaranteed revenue methodology resembling a global budget since 1994 and another (Edward McCready Memorial Hospital) since 2008.

Thus, the HSCRC decided to move towards global revenue constraints for the other rural hospitals in Maryland. Rural hospitals were targeted first because they were either sole community provider hospitals or hospitals without highly overlapping service areas. The expectation was that setting their budgets would therefore be less complicated by patient choice among multiple hospitals. The TPR reform was also viewed more like a pilot from which lessons could be drawn for potential statewide implementation of hospital global budgets. The eligibility criteria resulted in a total of 11 hospitals operating as sole community providers in rural Maryland counties. Of these, eight hospitals enrolled in the program and three hospitals declined participation (Table 2.1). The TPR reform established a revenue target for each hospital, covering the care for the entire population in the hospital's service area. The program's stated objective was to provide hospitals with a financial incentive to manage their resources efficiently in order to slow the rate of increase in the cost of

Table 2.1: Characteristics of Non-Federal Short-Term Acute Care Hospitals in Maryland, by TPR Eligibility and Participation, 2010

Hospital name	Beds	Discharges	Revenue
TPR participating hospitals			
Chester River Hospital Center	42	2,227	$66,359,390
Dorchester General Hospital in Cambridge	66	16,645	$38,690,745
Calvert Memorial Hospital	113	8,140	$148,025,790
Union Hospital	141	5,762	$153,372,942
Carroll Hospital Center	158	12,637	$259,282,620
Shore Medical Center at Easton	178	10,697	$299,959,579
Western Maryland Regional Medical Center	247	14,052	$367,301,120
Meritus Medical Center	265	17,792	$357,561,605
Average	***151***	***10,994***	***$211,319,224***
Eligible but declined participation (rural control hospitals)			
Charles Regional Medical Center (Civista)	110	8,522	$137,800,705
Upper Chesapeake Medical Center	181	14,000	$290,000,785
Frederick Medical Hospital	298	17,585	$435,664,988
Average	***196***	***13,369***	***$287,822,159***
Ineligible (urban and suburban hospitals)			
Fort Washington Medical Center	31	2,185	$46,372,500
UMD Harford Memorial Hospital	89	4,731	$103,630,000
MedStar Saint Mary's Hospital	90	8,591	$166,187,036
Bon Secours Hospital	115	5,994	$159,912,960
Laurel Regional Hospital	123	6,757	$126,786,366
MedStar Montgomery General Hospital	138	9,291	$175,573,519
UMD Rehabilitation and Orthopaedic Institute	153	4,453	$115,271,846
Maryland General Hospital	155	8,084	$223,477,540
MedStar Harbor Hospital	187	11,637	$277,723,132
Doctors Community Hospital	207	10,875	$217,638,601
Suburban Hospital	229	13,283	$286,000,879
Union Memorial Hospital	236	14,073	$550,116,063
Howard County General Hospital	249	19,454	$278,901,588
Northwest Hospital	250	13,355	$258,860,391
Washington Adventist Hospital	252	11,671	$245,940,174
Prince George's Hospital Center	262	12,465	$296,427,996
MedStar Southern Maryland Hospital	263	16,195	$281,257,689
UMD Saint Joseph Medical Center	267	21,209	$469,947,731
Mercy Medical Center	288	19,496	$480,065,775
Baltimore Washington Medical Center	307	19,722	$405,338,803
Saint Agnes Hospital	311	17,902	$561,353,599
Medstar Good Samaritan Hospital	335	14,207	$440,388,976
Shady Grove Medical Center	353	21,202	$404,330,170
MedStar Franklin Square Medical Center	369	24,366	$619,232,829
Anne Arundel Medical Center	380	33,573	$550,363,683
Greater Baltimore Medical Center	421	17,845	$433,342,307
Holy Cross Hospital	442	36,026	$489,771,326
Sinai Hospital of Baltimore	447	27,921	$873,087,556
Johns Hopkins Bayview Medical Center	483	20,810	$602,351,377
UMD Medical Center	688	36,054	$1,441,356,346
The Johns Hopkins Hospital	978	49,484	$2,137,134,183
Average	***293***	***17,191***	***$442,520,740***

Source: Discharge data from the American Hospital Directory. Financial data from Medicare cost reports for period ending 06/30/2013 (HCRIS 524939 - 2010).
Notes: Beds include all staffed beds. Discharges refers to total inpatient discharges. Revenue refers to gross patient revenue.

health care. The underlying goal, acknowledged by Maryland regulators, was to determine hospitals to maximize the value of care they provide to their communities (Rajkumar et al. 2014).

The target budget for each TPR hospital was calculated prospectively using a model based on four key elements (Maryland Health Services Cost Review Commission 2010). First, the population in the hospital's service area was determined, with two types of areas defined for each hospital: the primary service area, which consists of ZIP codes in which at least 75 percent of the patient volume is treated by the hospital; and the secondary service area, which consists of ZIP codes in which between 25 and 75 percent of the patient volume is treated by the hospital. Second, the base year budget was set as the most recent Fiscal Year before program implementation, i.e. FY2010. Third, the regulated services subject to state-approved rates were determined to include all the inpatient and outpatient services provided at the hospital campus. Non-regulated services include services provided off-campus or to non-Maryland residents. Fourth, adjustments were allowed based on projected changes in patient volume, payer mix, and variation in service prices from the state-approved rates.

Accounting for these four factors, the HSCRC calculated a budget called the *approved combined total revenue*. DRG-based constraints were removed and hospitals were allowed to continue to charge payers based on the unit rates set by HSCRC, but could adjust their prices within a ± 5 percent corridor (or, if approved with justification by the HSCRC, within a ± 10 percent corridor).

At the end of the fiscal year the budget was compared to the charged revenue, and any amount in excess of the revenue constraint simply became a one-time penalty in the revenue constraint for the subsequent year. Similarly, a shortfall became a one-time addition to the subsequent year's revenue constraint.

The budget for each of the subsequent years was calculated similarly starting with the approved combined total revenue as a base and applying an annual update factor that combined adjustments for volume variations, changes to payer mix, and any one-time adjustments from the previous year's budget. Each hospital was also eligible to receive an agreed-upon transitional revenue as a lump sum for specific hospital investments in the first two years of the program's operation. These revenues were intended to aid the hospitals in changing their service delivery process towards improved care coordination, chronic disease management, and resource utilization (Rajkumar et al. 2014).

Importantly, because the program was implemented with yearly targets established over a three-year time frame, there was little scope for a more dynamic recalculation of targets to account for decreased utilization during the course of the program. In other words, the HSCRC aimed to maintain the credibility that targets would not be decreased further on a yearly basis as the program would potentially reduce utilization, leading to a downward spiral whereby hospitals would get penalized in the long term for responding in a beneficial way by containing utilization in the short term.

The TPR program also relied on continuous monitoring of activity and quality over the course of its implementation. Hospitals have been required to submit monthly reports to the HSCRC detailing their activity, and the HSCRC also monitored several indicators of performance, including patient satisfaction. Clinical quality indicators that are monitored include rates of preventable admissions as measured by AHRQs Preventable Quality Indicators, preventable readmissions, hospital risk-adjusted mortality, and hospital-acquired conditions. Hospitals were eligible to receive additional “scaling revenue” if they performed well on the Consumer Assessment of Health Plans and Systems (CAHPS) and clinical process of care results as measured by the state’s Quality-Based Reimbursement (described below), which added a pay-for-performance dimension to the global budget program (Maryland Health Services Cost Review Commission 2010). The intention was to counteract any potential incentives hospital may have to decrease service quality under the revenue constraint.

2.4 The 2014 GBR reform

As noted above, the growth rate in statewide hospital cost per case had accelerated in the late 2000s into the early 2010s, placing the state close to failing the Medicare waiver test. Losing the waiver would have resulted in an estimated $1.5 billion loss in additional Medicare payments to Maryland hospitals–an artifact of the higher Maryland rates established back in 1980, the waiver’s baseline year. Therefore, the state had a strong incentive to revise its waiver arrangement to maintain its all-payer rate-setting mechanism (Murray and

Berenson 2015).

In 2013, Maryland applied for a new five-year waiver from CMS, which was approved and began functioning in January 2014. Under this revised waiver, Maryland expanded a slightly modified version of the global budget constraint under TPR to all general, acute care hospitals in the state. It also committed to containing inpatient and outpatient expenditure growth within 3.58 percent for the first three years, with the possibility of adjusting the rate in the fourth and fifth years based on more recent data. This ceiling was based on the state's 10-year Gross State Product (GSP) per capita growth rate (Centers for Medicare and Medicaid Services 2014).

The waiver includes a separate Medicare cost growth benchmark guaranteed by Maryland, totaling $330 million in savings to Medicare over the 5-year period. This savings is calculated based on the difference in the Medicare per-beneficiary hospital cost growth in Maryland and the national growth rate.

With the new waiver, Maryland also committed to meeting two quality targets. The first is a reduction of its all-cause 30-day hospital readmission rate to the unadjusted national Medicare average. Given the already higher rate of readmissions among Maryland's Medicare beneficiaries, this requires Maryland to outperform the national rate by at least 2 percentage points over 5 years. The second quality target is a reduction in the rate of Potentially Preventable Complications (PPCs) by nearly 30 percent over 5 years.

The new CMS waiver relies on a more flexible version of the TPR program for non-rural hospitals and has been renamed Global Budget Revenue (GBR).

The GBR methodology adapts the TPR framework to suburban and urban hospitals, which have much more competition in their markets, as well as to academic centers providing highly specialized tertiary care services, often to a large number of out-of-state patients (e.g., The Johns Hopkins Hospital and the University of Maryland Medical Center). The main difference between the TPR and GBR models is the determination of hospitals' geographic market boundaries. While participation in the GBR system is voluntary, it has been adopted by all the hospitals in the state, which makes the evaluation of the TPR pilot even more important and timely.

Finally, Maryland agreed to monitor and report progress on a range of population health measures developed by quality measurement groups such as the National Committee for Quality Assurance (NCQA) and National Quality Forum (NQF), some of which are being used in other initiatives implemented by the CMS. These include mammography, colorectal cancer screening, optimal diabetes care, blood pressure control, influenza immunization, and others (Centers for Medicare and Medicaid Services 2014).

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Chapter 3

Literature Review

Provider payment policies are powerful instruments for affecting the quantity and the quality of medical services as well as the level of integration in the provision of care (Cutler et al. 2000; Fisher, McClellan, et al. 2009). Designing and implementing effective payment systems, however, is not an easy task, particularly in a complex health care system (Langenbrunner et al. 2009). Multiple and often conflicting policy objectives must be balanced, including cost containment, patient-centeredness, quality improvement, coordination of care, and equitable access to services. The priority given to these objectives depends on economic, political, and cultural factors specific to the relevant setting and its historical background.

Capital-intensive, institutionally complex, and politically powerful providers like hospitals pose especially difficult challenges to government regulators. Organizational elements such as leadership capacity and non-pecuniary incentives play an important role in how hospitals respond to payment system changes. In a complex institution with multiple economic agents, financial incentives can get diluted or distorted depending on the organizational hierarchy and interactions between constituents. These distortions may lead to unintended consequences which must be weighed carefully against any benefits caused by the payment reform.

Moreover, regulators have limited capacity to measure outcomes and enforce payment policies through legal contracts (Chalkley et al. 2000). Despite significant progress made in the measurement of quality of care in recent decades, this field still suffers from an insufficient ability to collect, analyze, and report data on meaningful indicators as care processes and technologies evolve. If the measures tied to reimbursement are not perceived as valid or relevant by hospital staff, reforms could be easily undermined. For example, the measurement movement is currently facing a backlash, as providers report confusion and increased administrative burden as they face different measures, incentives, and reporting systems (Stempniak 2015). Given the limited ability for enforcement, the shift of financial risk onto hospitals may lead them to improve efficiency, but it may also cause them to skimp on care, stop offering unprofitable services in favor of elective but risky surgeries, or even select against unfavorable risks. All of these limitations need to be ultimately addressed by the structure of a payment system.

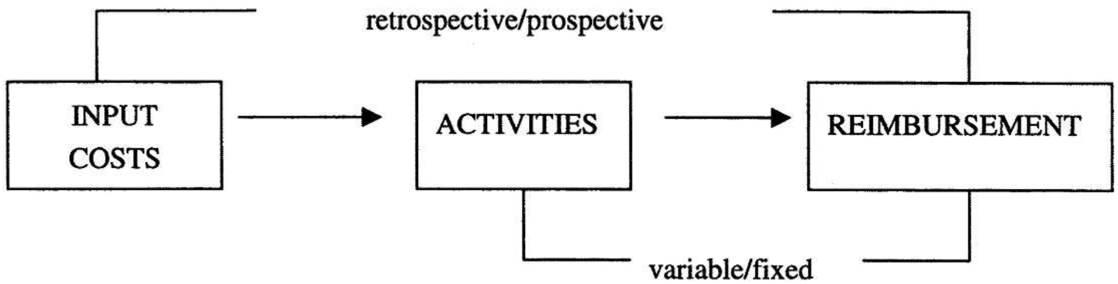
This chapter reviews two main groups of literature. The first summarizes a set of papers describing the key technical design elements of hospital payment mechanisms utilized in modern health care systems. While this literature summarizes the incentives providers face under different payment mechanisms, a more formal neoclassical economic model of hospital behavior is presented in Chapter 4 to examine the likely effects of switching from case-based reimbursement to global budgets. The second part of this chapter summarizing the relevant literature then reviews the empirical evidence for the impact of global budgets of hospitals internationally and in the United States (a systematic review of the related literature of the effects of capitation and other payment reforms on physician behavior is outside the scope of this dissertation chapter).

3.1 Payment design elements

Provider payment *methods* have been defined as mechanisms used to transfer funds from the purchaser of health care services, while payment *systems* encompass the payment methods in combination with its supporting mechanisms, such as contracting, information, and accountability systems (Langenbrunner et al. 2009).

A useful typology of payment systems developed by Jegers et al. (2002) distinguishes three main dimensions for classification. First, the *retrospective vs. prospective* dimension refers to the link between input costs and reimbursement; see the left side of Figure 3.1. In a retrospective system, a provider's costs are fully reimbursed *ex post*, thus providing little motivation to increase efficiency. In contrast, in prospective payment systems rates or budgets are set in advance of service provision, and are therefore disconnected from the costs

Figure 3.1: Dimensions for Classifying Provider Payment Systems



Source: Adapted from Jegers et al. (2002).

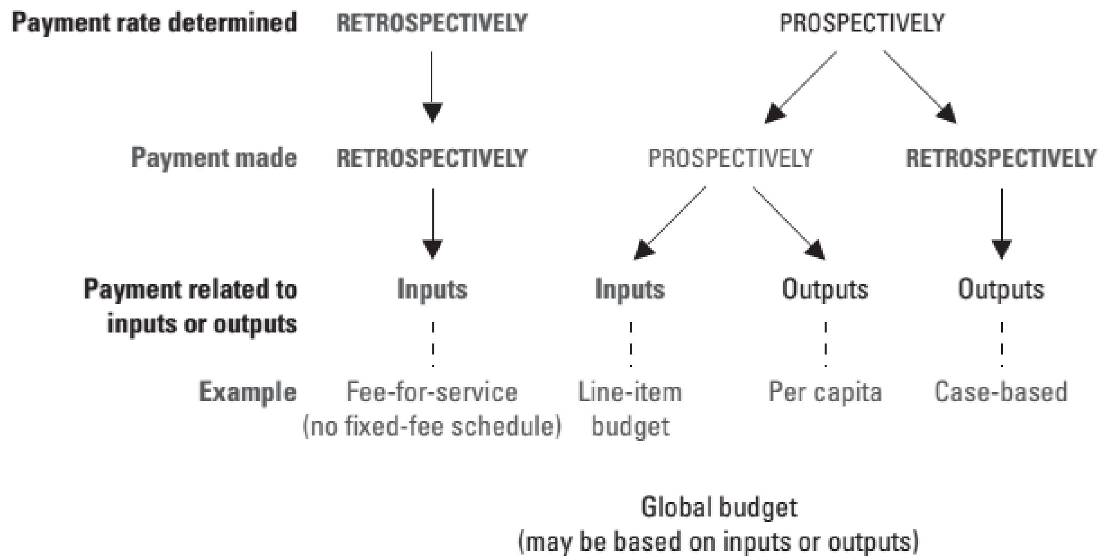
of the provider.

Second, the *fixed vs. variable* dimension refers to the link between the service activities and reimbursement. A payment system which reimburses for each additional unit of activity is considered *variable*, whereas one that reimburses a constant sum regardless of the provider's activity is considered *fixed*; see the right side of Figure 3.1.

The third dimension concerns whether payments are set based on inputs (e.g., hospital beds) or outputs (e.g., cases treated, surgeries provided, etc.) (Langenbrunner et al. 2009); see Figure 3.2. This dimension can fundamentally alter the economic incentives of a payment system, in particular by determining the levels of staff productivity.

In addition to these three dimensions, payment systems fundamentally differ based on whether their expenditures are capped at the macro level. These *closed-end* systems can have either total budget caps, or partial budget caps which restrict certain types of health care expenditures. And although prospectively setting a budget cap does not guarantee that it will not be exceeded, hard

Figure 3.2: Characterization of Provider Payment Methods Based on Timing of Reimbursement and Relation to Inputs or Outputs



Source: Adapted from Langenbrunner et al. (2009).

caps tend to perform better at cost containment than soft caps, whereby adjustments are applied to budgets if they are overrun (Schwartz et al. 1997). A combination of budget constraints can be imposed at both the micro and macro levels.

The characteristics and incentives of the five main types of hospital payment methods are presented in Table 3.1. The cost-based reimbursement utilized by Medicare (and most other payers) before 1983 was retrospective. Under this system, Medicare made interim payments to hospitals throughout the year, and then reconciled those payments with allowable costs defined by regulations based on cost reports submitted by hospitals (Office of Inspector General 2001). Beginning in 1983, the IPPS introduced case-based payments which classified all admissions into DRGs. Subsequently, similar systems were

Table 3.1: Hospital Payment Methods, Characteristics, and Incentives

Payment method	Characteristics			Provider incentives
	Payment rate set	Payment made to providers	Payment basis	
Line-item budget	Prospectively	Prospectively	Inputs	Underprovide services; refer to other providers; increase inputs; neglect efficiency of input mix; spend all remaining funds by end of the year
Fee-for-service (fixed fee schedule)	Prospectively	Retrospectively	Outputs	Increase the number of services including above the necessary level; reduce inputs per service
Fee-for-service (no fixed fee schedule)	Retrospectively	Retrospectively	Inputs	Increase number of services; increase inputs
Per diem	Prospectively	Retrospectively	Outputs	Increase number of days (admissions and length of stay); reduce inputs per hospital day; increase bed capacity
Case-based	Prospectively	Retrospectively	Outputs	Increase number of cases, including preventable admissions; reduce inputs per case; improve the efficiency of the input mix; reduce length of stay; shift rehabilitation care to the outpatient setting
Global budget	Prospectively	Prospectively	Inputs or outputs	Underprovide services; refer to other providers; increase inputs; improve efficiency of the input mix

Source: Adapted from Kutzin (2001) and Maceira (1998).

adopted by private payers and other countries.

A case-based system can induce profound changes to the delivery of hospital services, incentivizing providers to reexamine the way in which they motivate and supervise staff and utilize resources (Eichler et al. 2001) but may also have some unintended consequences (Langenbrunner et al. 2009). Table 3.2 summarizes these intended and unintended consequences. In particular, the process for defining and differentiating cases based on underlying costs determine the incentives created and the complexity of the support systems needed. Moreover, differences in input costs across hospitals are addressed by having allowable variation depend on policy objectives like increased access in rural areas or an emphasis on efficiency of resource use.

Global budgets, on the other hand, are prospectively agreed-upon sums within which hospital operating expenses must be constrained. Further constraints may be imposed on the use of the budget, such as certain inputs or outputs (Dredge 2009). However, in general, global budgets offer hospital managers considerable flexibility to reallocate resources as they deem necessary, but under the expectation that they will be held accountable for their performance (Barnum et al. 1995). Moreover, global budgets are generally administratively simple and relatively inexpensive to operate compared to other hospital funding approaches. One very important aspect is that they provide a large degree of predictability and stability for both hospitals and governments (Marini et al. 2007; Sharfstein 2016).

Table 3.2: Possible Consequences of Case-Based Hospital Payment Systems

Possible intended consequences	Possible unintended consequences	Design features to reduce unintended consequences
Shorter hospital stays	Increase in hospital admissions Increase in readmissions	Instruments for the purchaser to monitor and control volume and quality of care
More efficient use of hospital inputs	Excessive reduction in intensity of care and poor quality Increase in use of outpatient and community care for follow-up	Adequate capacity to increase outpatient and community care for follow-up
More efficient and effective mix of hospital services	Avoidance of high resource-intensity (severe) cases or cases with a low profit margin	Cross-subsidization across case payment rates to favor priority diagnoses and services
Higher quality hospital data	Gaming of the system through upcoding	Instrument for the purchaser to monitor coding patterns and identify upcoding trends
Closure of hospital beds, departments, and facilities	Inadequate access to hospital services in some geographic areas	A combination of planning and payment incentives to achieve the desired size and location of hospital infrastructure

Source: Adapted from Langenbrunner et al. (2009).

There are three main ways of determining global budgets, although there can be mixed models combining these three ways (Dredge 2009). First, under an *historical approach*, spending for each hospital is analyzed by purchaser, and patient flows are categorized by specialty and degree of complexity. Then the patient flows from each purchaser are costed, total costs are reconciled to current spending, and projections are made for the prorated share of each purchaser in the global budget of the hospital. This method continues existing resource flows, thus providing stability and assuring providers and patients that current services will be maintained.

Second, under a more complex *capitation approach*, there is first an agreement on the services that need to be covered and the main characteristics that drive service use at the population level. Budgets are then allocated to eligible providers based on the population they cover and the characteristics of that population in terms of service use drivers. This method requires a significant degree of sophistication from the budget-setting agency, but it can rectify certain historical inefficiencies and inequities if the right data and expertise are available.

Third, under a *normative approach*, external rate-setting mechanisms determine unit rates for services, which are then applied to the volume of services required by the purchaser. This approach, while potentially simpler and more transparent, also allows purchasers to apply a cost benchmark they deem appropriate, inducing efficiency on providers (Dredge 2009).

Finally, under a *mixed model*, multiple elements from the first three approaches can be combined, with budgets calculated on the basis of historical budgets, capitation shares, and benchmark costs. Moreover, performance elements can be set, either as relative or absolute targets, and certain shares of the budget can be tied to the achievement of these targets.

In conclusion, the above description allows us to better characterize Maryland's 2010 TPR reform. It can best be thought of as the introduction of a fixed, prospective budget constraint calculated based on outputs using a mixed method, with hospital cash flow driven by case-based payments from multiple public and private payers. This makes TPR a relatively complex global budget system. The complexity of TPR also resides in the fact that some of the other mechanisms of case-based reimbursement and rate-setting were kept in place in order to facilitate the continued interactions between the payers and the hospitals using the existing system architecture. Moreover, the pre-TPR system made use of constraints on hospital case volume, which made the transition to global budgets complex in its own right. In other words, TPR was not introduced as block payments made in advance to hospitals previously paid purely on a DRG system.

3.2 Evidence on hospital global budgets

From a normative standpoint, there is a debate among policy-oriented researchers as to whether global budgets are necessary. Proponents of this approach often do not favor the use of market mechanisms based on ability to pay to ration services, and instead support a more top-down regulatory allocation of resources (Gottret et al. 2006). Others instead argue that global budgets impede market efficiency through an artificially imposed spending constraint (Ham 2003). It is therefore important to examine the empirical evidence on the impact of global budgets. This section summarizes the most relevant literature from the US and from international settings.

In the US the most informative case is the experience with hospitals in Rochester, New York in the 1980s. Rochester implemented individual and aggregate caps on hospital income between 1980 and 1988 as a voluntary program ultimately including seven Rochester hospitals and one outlying hospital (Griner 1994). Budgets were comprised by inpatient and outpatient revenue from all payers and were calculated from costs prior to implementation with allowable growth rates set based on a combination of local and state wage trends. Hospitals agreed to report clinical and administrative data to a community-wide database. Hospitals were allowed to keep any surplus but were also at risk for losses. Throughout the period, New York also operated a hospital rate-setting system for all payers (McDonough 1997). Outpatient payments were set generously in order to discourage hospital stays, while a fund was set up for capital investments approved through the state's Certificate-of-Need (CON) process. In the last three years the community-wide cap was also extended to capital costs (Griner 1994).

During the program operation, spending in participating hospitals grew at rates below the state and national averages. Hospital spending growth also slowed compared to hospitals in Boston and Minneapolis, adjusted for sex, age, and wage levels (Block et al. 1987). The financial performance of the Rochester hospitals, measured by operating margins, improved compared to the rest of the hospitals in New York (Block et al. 1987; Griner 1994). Moreover, the hospital component of the community's total health care spending decreased from 55 percent in 1978 to 38 percent in 1990. In the first five years of the program, admission rates in Rochester hospitals decreased by 11 per 1,000 capita, while remaining relatively constant in New England and New York state hospitals (Block et al. 1987). The program also led to some modest improvements in clinical quality of services, as well as an increase in public satisfaction with care from 79 percent in 1980 to 96 percent in 1985 (Block et al. 1987). Despite these promising results, the program ended when the HCFA terminated the state's Medicare waiver, leading many to feel like they "threw the baby out with the bathwater" (Griner 1994).

The Rochester experiment, while generally successful, also had several limitations. In particular, with the fee-for-service physician payment system still in place, the program provided insufficient incentives to substitute expensive utilization for more cost-effective services. Moreover, the program's limits on capital investments seem to have fallen short of the community's demand for new technologies (Griner 1994). These limitations highlight the difficulty of establishing systems which contain costs by allocating resources towards effective services while also investing sufficiently in often-unproven innovations demanded by patients.

Several countries also have experience with various global budget schemes for hospital care. These countries include Canada, France, Italy, the Netherlands, Denmark, Sweden, Australia, New Zealand, India, China, and Hong Kong. Some of these countries now use a mix of global budgets and other payment methods for their hospitals (i.e., the Nordic countries, Singapore), while others use global budgets for some types of hospitals but not for others (e.g., public hospitals in India, rural hospitals in Australia) (Mossialos et al. 2016).

In Canada, provincial governments acting as single payers allocate annual budgets to each hospital, while also negotiating physician fee schedules with medical associations. Ontario, for instance, was the first to shift in 1969 from a line-item budgeting system to a prospective global budget with a formula for calculating allowed rates of increase. Between 1968 and 1981, hospital expenditures in Ontario increased by only 16 percent in terms of real inputs, while in the same period US hospital costs grew by 101 percent (Detsky et al. 1983). At the same time, average real inputs per patient-day grew at an average annual rate of only 0.68 percent, compared to 5.19 percent in the US (Detsky et al. 1983).

Gradually, all Canadian provinces have adopted some form of global budgets for hospitals (Wolfe et al. 1993). But while Canada's global budgets have succeeded in limiting hospital expenditures by constraining their budgets quite drastically during the 1990s, some data suggest that they have extended beyond the initial incentives towards efficiency and have rationed valuable care. Wait times for certain elective surgical procedures were the highest in Canada among 11 OECD countries (Schoen et al. 2010), despite government efforts to reduce wait time by increasing allocated budgets (Sutherland, Barer, et al. 2011).

More recently, Canadian provinces started moving in the opposite direction by introducing case-based payments, termed Activity-Based Funding (ABF). British Columbia was the first one to make the transition, in 2010, while Ontario and Quebec introduced partial reforms more recently (Sutherland, Hellsten, et al. 2016). Only the province's largest hospitals implemented the reform, though, as the small and rural hospitals were excluded. Furthermore, only 20 percent of the hospitals' revenues were changed to case-based payments, and the budgets excluded physician costs. An evaluation of reform experience after three years found the intended increase in the trend for inpatient and outpatient surgeries (Sutherland, Liu, et al. 2016). At the same time, the volume of medical inpatients decreased, and average length of stay increased, likely as a result of a disproportionate reduction in shorter stays. The reform did not seem to have observable effects on a limited set of quality measures examined.

The Canadian experience with global budgets is useful for several reasons. First, it suggests that over time, under fiscal pressures hospital budgets can become targets for governments, causing a reduction in service volume and thus potentially worsening access to services like elective surgeries (Deber et al. 2008; Street et al. 1996). In the US, this is likely to be a significant political issue. Canadian hospitals also tend to limit services earlier in the year to minimize the risk of incurring a deficit at year end. Service reductions can lead to delays or cancellations for elective procedures and result in longer emergency department wait times for non-elective admissions (Deber et al. 2008). Second, global budgets lack incentives to improve productivity, since there is no opportunity to generate more revenue by increasing patient throughput. Third, the basis for the budget updating factors can be an important factor determining the performance of global budgets. Payments updated based on historical growth tend to disincentivize hospitals to focus on shortening lengths of stay and shifting less acute activities to less costly settings such as outpatient or home-based care (Sutherland 2011).

However, while the private provision of care and the dual role of the federal and provincial governments in financing care make the Canadian experience instructive, its single-payer system with strong government regulation and predominantly tax-based financing warrant caution when drawing lessons from its experience for global budgets for the United States.

In France, a payment system with sector-wide expenditure targets and hospital-specific global budgets was introduced in 1984 to replace the existing per-diem payment system. This system seems to have been successful in slowing national health expenditure growth by limiting the flow of real resources into the hospital sector. The effect on spending seems to have been achieved by decreasing the quantity of services provided, while the relative prices of hospital services remained constant (Redmon et al. 1995). Although the new system decreased service utilization, including total inpatient days, it is unclear whether it lowered access to services or simply represented a reduction in excess supply. Thus, the experience of France reinforces the important question of whether the decline in the quantity of hospital services actually leads to better care.

In Hong Kong, the experience also shows that while global budgets may be effective at controlling costs, access may suffer. There, a strictly limited budget for hospital care led to regional disparities in the adoption of advanced technologies (Chu 1992).

In the Netherlands, budgets were introduced in 1983 for all 176 short-term hospitals, 90 percent of which were private. Budgets replaced the previous cost-based reimbursement system using unit rates negotiated between sickness funds and hospitals. Targets were calculated to each hospital based on historical inpatient and outpatient utilization, and starting in 1985 were defined based on capacity (i.e., number of beds and ambulatory units) and output parameters (i.e., number of admissions and total inpatient days). Output parameters were negotiated between hospitals and sickness funds, and if expenses exceeded the target by more than 5 percent they would be adjusted downward the following year (Maarse 1989). Similarly, if a hospital's spending fell below the target, it would be allowed to add the difference to its reserves (Maarse et al. 1993).

In the years after the Dutch policy was enacted, admission rates decreased at an accelerated pace in all age groups except for the elderly (Casparie et al. 1991). In patients aged 65 and older, admission rates continued to rise, suggesting that there might have been a shift in utilization across age groups. Surgery rates for non-elderly patients have decreased similarly to admission rates, while increasing for the elderly. But despite the increase in intensity of care for the elderly, mortality rates in the country and the percentage of patients discharged to nursing homes continued to decline the after the introduction of the program (Casparie et al. 1991). Hospital capacity was also lowered from 4.5 to 4.2 beds per 1,000 population post-implementation, despite a growing and aging population. The program did not change total hospital spending (11.0 vs. 11.2 billion Dutch guilders in 1982 and 1988, respectively), although counterfactual spending without the program is likely to have grown more. There is no reliable evidence on how the program impacted other services, such as diagnostic tests or other outpatient procedures.

Italy is an example of a country that moved in the opposite direction, from global budgets to case-based payments. An observational study of Italy's reform based on regional utilization data found a decrease of 17.3 percent in hospital admissions and a decrease in the average length of stay from 9.1 days to 8.8 days (Louis et al. 1999). However, day hospital use increased sevenfold, suggesting that the hospitals adapted to the new payment mechanism by attempting to maximize revenue from high-margin services.

In a rare cross-country study, Leonard et al. (2003) compared the incentives on length of stay induced by the Austrian case-based payment system with the Canadian global budgeting. In six major clinical categories which are comparable between the two countries, they found significantly higher length of stay for Austrian patients compared to Canadian patients, suggesting potential reductions in intensity of care associated with a shift to global budgets.

In conclusion, global budgets are not a uniform payment system. The incentives induced by global budgets depend on how the budgets are calculated, what services and populations they cover, and how performance is defined and monitored. The structure of the payment schemes implemented, as well as the larger health care policy and regulatory environments in these settings, differ widely (Kent 1993). And despite the experience with global budgets being quite rich internationally, the literature is relatively descriptive in nature and limited in rigorous empirical assessments of global budgeting schemes. A relatively rigorous evaluation of the effectiveness of the TPR reform in Maryland hospitals would therefore make an important contribution to this literature.

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Chapter 4

Theoretical Model

This chapter presents a simple theoretical model of hospital behavior to illustrate the economic incentives resulting from the reform to switch to global budget payments from case-based reimbursement. As with any theoretical model, our model makes a set of simplifying assumptions for tractability. Where possible, we comment on how and to what extent these assumptions apply to the circumstances of Maryland's specific case of revenue constraints applied to case-based hospital reimbursement. We believe that, in many instances, a richer model allowing for a more realistic treatment of hospital interactions with payers and patients would still yield similar conclusions. In the second section of this chapter, we derive a set of predictions about hospital behavior under the new payment system which follow from this theoretical framework. Finally, we examine how the model's predictions may be tempered or difficult to measure in reality.

4.1 An economic model of hospital behavior

We consider a single hospital servicing a delineated geographic area with a stable population within a given year. Although this situation rarely applies in urban hospital markets in the United States, it rather accurately reflects the situation of rural areas in Maryland subject to the TPR reform. This assumption could also be relaxed to account for multiple hospitals competing in a market as long as underlying patient populations are clearly defined; this would be a situation applicable to the GBR program implemented statewide in 2014.

We assume that the hospital interacts with one purchaser paying for health care services for that population. This assumption is appropriate for single-payer systems like those found in some European and Asian countries, but may first seem too strong in our case, as the HSCRC is not a single payer entity. However, because the Commission has rate-regulating authority over all hospitals and payers in the state, the model is more consistent with fixed rates as if set by a single payer. This model could also be easily extended to account for multiple payers engaged in different contracts with the hospitals.

Let q be the number of hospital visits in a given year. For simplicity in this model, we do not distinguish between inpatient stays (in which a patient is hospitalized for at least one night) or outpatient visits (in which a patient generally visit a hospital-affiliated outpatient department during the day). We assume that the hospital chooses the quantity q to maximize an objective function of the following form:

$$\max_{q} \Pi = R(q) - C(q) + \alpha \cdot U(q) \tag{4.1}$$

The first term in equation (4.1) represents the total revenues of the hospital, and its form is dependent on the payment system in effect (to be examined below). The second term is the total monetary cost incurred by the hospital, which includes both a fixed component (i.e., cost of capital, medical equipment, etc.) and a variable component depending on the number of hospital visits per year. While a large literature seeks to estimate the specific form of hospital cost functions, we assume that $C'(\cdot) > 0$ and $C''(\cdot) > 0$. The third term represents the altruism (or benevolence) of hospital activity, which is assumed to equal the product of an altruism parameter α times patient utility (expressed in monetary terms) from receiving care at the hospital $U(q)$ (Chalkley et al. 2000). A hospital that is completely self-interested has $\alpha = 0$, while greater values of α represent increasing amounts of altruism. The patient utility function is assumed to $U'(\cdot) > 0$ and $U''(\cdot) < 0$.

Intuitively, Π therefore represents a linear combination of the hospital's financial surplus and the welfare from providing medical care to the patients. We believe that this setup is suitable for either for-profit or nonprofit hospitals. Because the TPR hospitals, as most hospitals in the US and all hospitals in Maryland, are nonprofit institutions, the surplus cannot be simply posted as profits but instead consists of either additions to reserves or expenditures that can be directed towards managerial perquisites (Chalkley et al. 2000).

We now consider the effect of the TPR reform to switch from using DRGs for reimbursement to using of global budgets. To do so, we first characterize the quantity of services under DRGs, q^*_{DRG}, and the quantity of services under global budgets, s, q^*_{TPR}, and then compare the two. As described in Chapter 2, pre-TPR inpatient services are paid per case, with payments constrained on the basis of DRGs determined by the patient's main diagnosis. Similarly, outpatient payments are calibrated based on EAPGs. For simplicity in the model, we assume a constant rate paid per case p.

When revenues are based on DRGs, the first-order conditions for the hospital's maximization problem above becomes:[1]

$$\frac{\partial \Pi(q^*_{DRG})}{\partial q} = p - \frac{\partial C(q)}{\partial q} + \alpha \frac{\partial U}{\partial q} = 0 \tag{4.2}$$

When revenues are instead based on global budgets through TPR, the hospital maximizes the objective function:

$$\max_{q} \Pi(q_{TPR}) = R(q_{TPR}) - C(q_{TPR}) + \alpha \cdot U(q_{TPR}) \tag{4.3}$$

subject to the budget constraint:

$$q_{TPR} \cdot p = B \tag{4.4}$$

Thus, each hospital solves a constrained maximization problem of the form:

$$\max_{q,\lambda} \mathcal{L} = q_{TPR} \cdot p - C(q_{TPR}) + \alpha U_{TPR} + \lambda(B - q_{TPR} \cdot p) \tag{4.5}$$

[1] As described in Chapter 2, the HSCRC incorporated volume constraints on hospital activity through the VCF and other policies, but these are not modeled here.

where λ is the Lagrange multiplier, which leads to the following first-order conditions:

$$\frac{\partial \mathcal{L}(q^*_{TPR}, \lambda^*)}{\partial q} = p - \frac{\partial C(q)}{\partial q} + \alpha \frac{\partial U}{\partial q} - \lambda p = 0 \tag{4.6a}$$

$$\frac{\partial \mathcal{L}(q^*_{TPR}, \lambda^*)}{\partial \lambda} = B - q_{TPR} \cdot p = 0 \tag{4.6b}$$

To see how the quantity of services supplied in the case-based payment system, q^*_{DRG}, compares to the quantity supplied in the global budget system, q^*_{TPR}, we simplify the analysis by assuming specific functional forms for the hospital cost function and patient utility presented above above. Specifically, we assume that $C = cq^2$ with cost parameter $c > 0$, and that $U(q) = q - bq^2$ with an overuse disutility parameter $b > 0$.

With these assumptions, the first-order conditions for hospital optimization under case-based DRG payment yield:

$$\frac{\partial \Pi(q^*_{DRG})}{\partial q} = p - 2cq + \alpha - 2\alpha bq = 0 \Rightarrow 2cq + 2\alpha bq = p + \alpha \tag{4.7}$$

so the hospital's choice for the quantity of services under DRG payments is:

$$q^*_{DRG} = \frac{1}{2} \frac{p + \alpha}{c + \alpha b} \tag{4.8}$$

The interpretation of this result is relatively straightforward. An increase in hospital visits under DRG payment results from increases in the price, increases in the first-order effect of altruism on patient utility, decreases in the costs, and decreases in the second-order effect of altruism on patient disutility from overuse.

Alternatively, the first-order conditions for hospital optimization under the TPR global budget situation yield:

$$\frac{\partial \mathcal{L}(q^*_{TPR}, \lambda^*)}{\partial q} = p(1-\lambda) - 2cq + \alpha - 2\alpha bq = 0 \tag{4.9a}$$

$$\Rightarrow 2cq + 2\alpha bq - p(1-\lambda) = \alpha \tag{4.9b}$$

$$p = \frac{B}{q} \tag{4.9c}$$

so that by substituting the price from condition (4.9c) into Equation (4.9b) the hospital's choice for the quantity of services under the TPR revenue constraint becomes:

$$\frac{B}{q}(1-\lambda) - 2cq + \alpha - 2\alpha bq = 0 \tag{4.10}$$

The hospital revenue constraint is enforced when $\lambda = 1$, so the quantity supplied becomes:

$$q^*_{TPR} = \frac{\alpha}{2(c+\alpha b)} \tag{4.11}$$

Here, too, an increase in hospital visits under global budgets results from increases in the first-order effect of altruism on patient utility, decreases in the costs, and decreases in the second-order effect of altruism on patient disutility from overuse.

The quantity supplied under global budgets is lower than under case-based DRG payments, which can be seen by noting that:

$$q^*_{DRG} - q^*_{TPR} = \frac{p+\alpha}{(c+\alpha b)} - \frac{\alpha}{2(c+\alpha b)} = \frac{p}{2(c+\alpha b)} > 0 \tag{4.12}$$

This reduction in utilization due to the implementation of TPR is our primary overarching hypothesis. The interpretation of this expression for the magnitude of the reform's effect on reduced utilization is also relatively straightforward. First, the expected reduction in quantity caused by the TPR reform increases with the initial rate p paid per DRG, as higher payment rates imply that there was more supplier-induced demand before the reform. In contrast, the reduction in services under TPR decreases with the cost per case. Finally, the two quantities are closer (i.e., the difference is smaller) as the hospital is more altruistic ($\alpha \gg 0$). One reason is that it seeks to provide more services for patients even under a fixed revenue since its objective function includes a share of patient utility. The other reason is that as higher altruism implies that there was less supplier-induced demand before the reform because of a relatively higher valuation of patient disutility from overuse.

One limitation of our model's framework is that we do not incorporate the effect of quality on patient demand for hospital services, in the sense that better quality should attract more patients. Our model assumes that patient demand is unresponsive to quality levels, as as often patients have insufficient information about, or can judge, hospital performance on clinical outcomes. Instead, the most important determinant of whether a patient demands care from the hospital is likely to be the distance that she has to travel to that hospital. Demand for hospital treatments is also affected by other exogenous factors outside the hospital's control, such as the population and epidemiological profile in the hospital's service area. While the model ignores quality in relation to patient demand, it is still consistent with a setting in which minimal levels of quality are set by hospital accreditation standards and other regulations enforced by the HSCRC and Federal Government agencies.

Another limitation or our model's framework is that it is conceivable that the introduction of the TPR system increased the fixed costs of the hospital, as there may be a need to manage the population differently and to ensure that the budget constraint is not overrun. Meanwhile, the framework above assumes that the underlying cost structure was unchanged. However, the HSCRC did provide hospitals with lump sums to cover these operational costs in the first contract cycle, so this issue is less of a concern.

4.2 Specific study hypotheses

In line with the theoretical predictions outlined above, the overarching objective of our study is to determine whether the implementation of the TPR global budget reform decreased inpatient and outpatient hospital utilization among the population living in the areas served by the participating hospitals in Maryland. Although the hypothesis of a decrease in utilization is relatively straightforward, several factors complicate the implementation of global budgets in Maryland.

First, as discussed in Section 3.1, Maryland's TPR system was not a traditional global budget as implemented in other settings, whereby hospitals would truly receive a fixed payment to treat the population in their service area for the whole fiscal year. Instead, the HSCRC allowed hospitals to continue charging for each service in order to drive cash flow and enforced the budgets using continuous monitoring and adjustment of rates, in addition to year-end adjustments. The structure of the program potentially might not incentivize large decreases in utilization, but rather small reductions that would still allow a hospital's total revenue to fall within close vicinity of its global budget.

Second, as described in Chapter 2, there were volume constraints already in place under Maryland's rate-setting system. Particularly, the VCF policy, under which hospitals were reimbursed partially per DRG above a certain level of utilization, already had a strong embedded incentive to control utilization. Its reintroduction in 2008, as mentioned above, had already led to a reversal in utilization rates in Maryland.

Third, the payment system for physicians was largely unaffected by the TPR reform. In Maryland hospitals, independent physicians with admitting privileges to hospitals are still largely paid fee-for-service.[2] A conflict therefore arises between the inflationary physician incentives and the new constraints for hospital revenues which incentivize economizing on resources. How this conflict was resolved during the first three years of TPR depends on the interactions between hospital management, hospital physician and nursing staff, and independent, FFS physicians (which are beyond the scope of this disserta-

[2]While there is evidence that the number of physicians directly hired by hospitals has been steadily increasing in the US between 2000 and 2010, the exact prevalence of employment agreements in Maryland hospitals is largely unknown and even the national statistics vary widely. Even when the physicians are salaried, they may work for physician outsourcing companies (Keckley 2015).

tion).

Considering these three mitigating factors together, we expect the magnitude of the effect of TPR on inpatient and outpatient services to be relatively small.

The second main hypothesis of this study is that the TPR reform had a higher impact on discretionary services. In particular, discretionary services make a higher proportion of outpatient visits (e.g., ambulatory surgeries), so we expect a higher decrease in outpatient services relative to inpatient services. Moreover, we expect larger reductions in ”potentially deferrable” care relative to ”non-deferrable” care. In particular, we expect a null effect for more essential services such as admissions from the ED or treatments for severe, acute conditions such as hip fractures or Acute Myocardial Infarction (AMI), controlling for temporal changes in underlying population risk factors.

The third main hypothesis of the study is that the TPR program decreased preventable care more than ”non-preventable” care. Specifically, we examine changes in a comprehensive set of inpatient and outpatient categories of services considered preventable or ”low-value” and identifiable using routinely collected administrative data, including preventable admissions as specified by the PQIs. An important question from a policy perspective is whether the program had a discernible effect on health care efficiency and population health. As described in Chapter 2, HSCRC regulators hoped that the payment reform would incentivize hospitals to keep patients healthy and out of the hospital. For instance, perhaps hospital managers could manage patients better in outpatient settings, begin investing in prevention, and establish partnerships with community-based providers and public health agencies, using the initial block grants as a subsidy. In addition, the HSCRC stipulated in the TPR contracts that mortality rates, rates of hospital acquired conditions and preventable readmissions, as well as AHRQ's Prevention Quality Indicators (PQIs), would be *monitored* closely.

Although rates of preventable ED visits are not monitored by HSCRC, we also hypothesize the TPR program to affect ED visits differentially depending on the category of visit. ED visits serve as an indicator of whether there have been changes in access to care or whether the global budget payment system spurred the kind of hospital-physician partnerships that would increase disease prevention (Billings et al. 2000). Often, patients present to the ED since they cannot be turned down. The federal Emergency Medical Treatment and Active Labor Act of 1986 mandates hospitals to treat all patients with medical emergencies, regardless of their ability to pay. Since it does not apply to physician offices, it has historically (prior to global budgets) created an incentive to use the ED for care that could be provided in other settings. Moreover, many medical services are more expensive to provide in an ED compared to a physician's office and overuse of ED care has put an unnecessary strain on the resources in the health care system overall. If being paid a global budget leads hospitals to substitute office-based care for the ED, then the most affected conditions should be those that are not urgent and can most easily be treated in an alternative setting.

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Chapter 5

Methods and Data

In this chapter we first outline the overarching study design strategy and then we describe in detail the data sources, the construction of the analytical sample, the main variables, and the empirical estimation specifications.

5.1 Study design

The main difficulty in empirically estimating the causal effect of the TPR policy change is that estimates may be confounded by concurrent changes in utilization over time due to other factors. For instance, there were downward trends in utilization rates in the state beginning in 2008 and continuing after the implementation of the TPR reform. As discussed in Chapter 2, the reintroduction of the Variable Cost Factor as a method of tapering payments had led to a reversal of the upward trend seen between 2000 and 2008. This study therefore relies on a pre-post difference-in-differences design with several separate models using various control groups. Specifically, we compare changes in utilization per capita after reform implementation in geographic areas served by hospitals that implemented the TPR reform to changes in utilization after reform implementation in the areas served by non-participating hospitals. Our first set of analyses focus on various inpatient utilization measures and our second set of analyses focus on various outpatient utilization measures. For each set of analyses, we first consider simpler models with an indicator for whether the TPR reform is in effect and then consider models with a measure of the number of years that the TPR reform is in effect.

Although we have access to patient-level data for inpatient and outpatient utilization, we aggregate the data up to population-level estimates of utilization for our analyses because people with no hospital utilization do not appear in the HSCRC data we use (described in the next section). The population-level unit of observation for our analyses is the ZIP Code Tabulation Area (ZCTA), as it represents the most granular geographic level present in the Maryland discharge dataset for which population estimates are also available. A reliable estimate of the population size for a given geographic area is critical for creating per-capita measures of utilization. Moreover, the HSCRC uses ZIP codes when delineating hospital service areas in Maryland. In addition to the main analyses, we also conducted multiple sensitivity analyses in which the assignment of ZCTAs to study groups follow different methodologies, as described below.

5.2 Study samples

The main sample in this study consists of the population of Maryland residents living in the rural ZCTAs located in the service areas of the exposed and control hospitals between 2008 and 2013. This time frame uses two years of pre-reform data and four years of post-implementation data.

In the main analysis, ZCTAs are assigned to hospital service areas based on HSCRC methodology. The HSCRC assigned to each hospital's primary service area (PSA) the first ZCTAs that make up a cumulative proportion of at least 65 percent of all admissions to that hospital. The hospital Secondary Service Area (SSA) is assigned to ZCTAs which cumulatively make up for the next 20 percent of admissions. ZCTAs assigned to the PSAs and SSAs of the TPR hospitals were also specified in the contracts that each hospital signed with the HSCRC. We replicate the HSCRC methodology to identify the ZCTAs comprising the service areas of the control hospitals in 2010. We also compare these ZCTAs to those identified in the TPR contracts which these hospitals signed later on in 2014.

As noted above, our main analysis uses only rural areas in the state for the set of control ZCTAs. In order to compare trends in the exposed areas to trends in other Maryland areas and in the state as a whole, we also examine three other samples, increasing progressively in size. First, we include all ZCTAs, except those which are part of the large urban and suburban areas surrounding Baltimore and Washington, DC. Specifically, we exclude ZCTAs located in Core-

Based Statistical Areas (CBSAs) 12580 (Baltimore-Columbia-Towson, MD) and 47900 (Washington-Arlington-Alexandria, DC-VA-WV). A CBSA is defined by the US Office of Management and Budget (OMB) as one or more counties anchored in an urban center that are socioeconomically tied to that center by commuting. This approach essentially compares TPR areas to all non-urban and non-suburban Maryland ZCTAs. Second, we examine a sample which only excludes Baltimore City (county FIPS code 24510), as this urban area differs significantly in terms of demographic characteristics from the rural TPR ZCTAs and is served by the two large academic medical centers in Maryland, Johns Hopkins and the University of Maryland Medical Center. Finally, the third sample consists of all ZCTAs in Maryland, including the urban center of Baltimore.

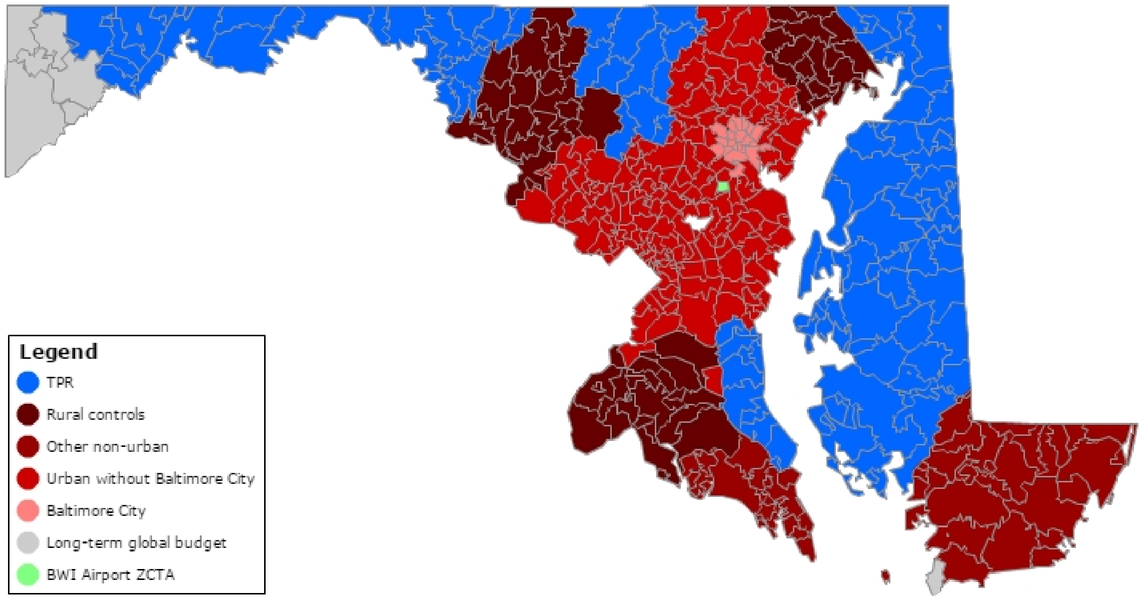
One hospital in the intervention group, Western Maryland Regional Medical Center (WMRMC), was formed in 2009 by the merger of Memorial Hospital and Sacred Heart Hospital, both located in Cumberland. This merger has the potential to confound the analysis, as the merger partially coincides temporally with the introduction of the TPR reform. Therefore, in separate analyses we exclude the ZCTAs served by this hospital from the analytical sample.

The HSCRC also assigns to the service areas of participating hospitals several ZCTAs that are part of the neighboring states Pennsylvania and West Virginia. To ensure that the results are not confounded by other demographic, regulatory, and economic differences in these states, our main analysis excludes these out-of-state ZCTAs. However, secondary analyses which also include these ZCTAs in the analytic sample (not shown) do not qualitatively change the conclusions of the study.

Figure 5.1 illustrates how the Maryland ZCTAs are distributed across these different analytical groups. The treatment TPR ZCTAs are shown in blue. The main set of control ZCTAs comprising of the “Rural Controls Only” are shown in dark red. Moreover, the smaller suburban ZCTAs added to the first alternative “No Large Urban Areas” control group are shown in medium red, the larger suburban ZCTAs added to the second alternative “No Inner City Baltimore” control group are shown in medium-to-light red, and the Baltimore City ZCTAs added to the third “All of Maryland” control group is shown in light red. As a result, the control ZCTAs comprising the first alternative “No Large Urban Areas” control group include both the dark red and medium red ZCTAs on the map. As discussed in Chapter 2, two small hospitals in Maryland have also utilized a payment system similar to TPR for a long time. The ZCTAs assigned to these hospitals’ service areas are shown on the map in gray and are excluded from all the control groups.

While our main analyses use HSCRC’s allocation of ZCTAs to hospitals (actually tied with the change in TPR reimbursement), we conduct additional analyses to determine if alternative allocations of ZCTAs to hospitals generate different results. Specifically, in a set of separate analyses, we use crosslink files from the Dartmouth Health Atlas research group at the Dartmouth Institute for Health Policy and Clinical Practice to assign ZIP codes to Hospital Service Area (HSA)s and link these with their respective hospitals (Wennberg

Figure 5.1: Maryland Zip Code Tabulation Areas by Assignment to Treatment and Control Groups in the main analysis



Notes: Rural controls include ZCTAs assigned by the HSCRC to the service areas of hospitals that were eligible to participate in TPR but declined. Other non-urban include ZCTAs assigned to non-participating hospitals outside of the Core-Based Statistical Areas (CBSAs) 12580 (Baltimore-Columbia-Towson, MD) and 47900 (Washington-Arlington-Alexandria, DC-VA-WV). Urban without Baltimore City include the CBSAs 12580 and 47900 but exclude Baltimore City County. Baltimore City refers to the ZCTAs contained in Baltimore City County (FIPS code 24510).

and Cooper 1998). Even though there is significant overlap between the Dartmouth Atlas HSAs and the PSAs/SSAs assigned using HSCRC's methodology, there are also some notable differences. These differences stem from the fact that the Dartmouth methodology relies on patterns of hospital care seeking behavior for Medicare beneficiary claims and may not be applicable to the entire population. The Dartmouth Atlas method therefore assigns a small number of ZIP codes to different hospital areas compared to the HSCRC method.

In a third set of separate analyses, we assign ZCTAs to treatment and control groups simply based on county location. Under this method, each county is classified as TPR or control based on the status of the hospitals located in it, and each ZCTA located in that county receives the same designation. This method may provide more stability if care-seeking patterns change idiosyncratically over time for some ZCTAs or if ZCTAs are misclassified based on the relatively arbitrary cut-offs used by the HSCRC and Dartmouth Atlas classifications. However, this assignment method may have its own limitations if the residents of certain ZCTAs (particularly those on a county border) seek hospital care in hospitals outside the county.

5.3 Data

We assemble data from multiple sources to construct a panel of ZCTAs followed for two years in the pre-intervention period and four years in the post-intervention periods. The year of the intervention, 2010, is categorized as post-intervention even though the TPR program was in effect starting in July that year, because the contracts were finalized in December 2009. Therefore, the hospitals knew they would face total revenue constraints in 2010. Separate models in which data for 2010 is excluded as an implementation year do not meaningfully change the results, so this year was kept to improve precision by increasing the analytical sample size.

5.3.1 Discharge abstracts

We use data on both all inpatient hospitalizations and all visits to outpatient departments reported by Maryland hospitals between 2008 and 2013 from the discharge abstract database maintained by the HSCRC. This database contains patient-level information including demographic characteristics (i.e., age, sex, race and ethnicity, etc.), expected payment sources, ZIP code of residence, as well as encounter attributes such as source of admission, clinical diagnoses recorded using International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM) codes[1], procedures performed recorded using Current Procedural Terminology (CPT) codes, and charges by revenue center. The HSCRC data contains complete records on patients covered by all payers (private and public), thus representing a comprehensive source of clinical information for Maryland patients.

5.3.2 ZCTA and county characteristics

We link the discharge abstract data for inpatient and outpatient utilization with ZCTA-level information from the Claritas Demographic Reports, a private vendor of geographic data products (Claritas, Inc. 2006). This vendor was the same source of ZCTA-level demographic information that the HSCRC used in the process of projecting the demand for hospital care while drafting the TPR contracts with the participating hospitals. The data include ZCTA population estimates and composition by age, sex, race, and ethnicity, as well as household income, educational attainment, and rate of unemployment.

[1] ICD-9-CM was the official system of assigning codes to diagnoses and procedures associated with hospital utilization in the United States during the period of the study, and it was replaced by the Tenth Revision, ICD-10-CM, in October 2015. It is based on the World Health Organization's Ninth Revision, International Statistical Classification of Diseases and Related Health Problems (ICD-9)

We also link discharge abstract data for inpatient and outpatient utilization with county-level information from multiple sources. These characteristics include rates of uninsurance from the US Census Bureau's Small Area Health Insurance Estimates (SAHIE), which are based on ACS data; Medicare Advantage penetration rates extracted from HRSA's Area Health Resource File (AHRF), as provided by CMS; rates of primary care physicians per capita, specialists per capita, and the number of Federally Qualified Health Centers (FQHCs) from the AHRF. We use these measures to control for the supply of non-hospital providers operating in the study areas, which have been shown to be a key driver for the provision of hospital care (Fisher and Wennberg 2003; Wennberg, Fisher, et al. 2007).

Table 5.1 presents the distribution of the ZCTA- and county-level indicators in the main treatment and control areas both before and after the implementation of the TPR reform. On average, ZCTAs in the TPR areas are less populated (5,771 vs. 9,088 average population) and also display less population growth over the course of the study. The average median household income is significantly lower in the TPR areas compared to the rural controls, and the TPR population is also older, less likely to be employed, and less educated on average compared to the population in the rural control ZCTAs. But although the TPR counties have more physicians per capita and more FQHCs compared to rural control counties, the average number of primary care physicians is similar.

Table 5.1: Summary Statistics of ZCTAs in the Intervention and Rural Control Areas, before and after TPR Implementation

	TPR		Controls		All
	Before	After	Before	After	Total
Average population	5,771	5,779	9,088	9,453	7,029
	(9,746)	(9,856)	(10,965)	(10,923)	(10,353)
Percent adult	74.8	77.4	71.5	74.7	75.2
	(3.8)	(3.2)	(2.5)	(2.7)	(3.6)
Percent female	50.2	50.7	50.6	51.2	50.7
	(2.8)	(2.1)	(1.1)	(1.5)	(2.0)
Median age	38.2	40.8	35.5	38.4	38.8
	(3.9)	(3.8)	(3.0)	(3.8)	(4.1)
Percent non-white	13.0	15.0	18.5	27.3	19.1
	(9.1)	(8.4)	(13.8)	(21.2)	(15.6)
Median household income (10K)	6.0	7.1	7.9	9.4	7.8
	(1.6)	(2.1)	(1.2)	(1.6)	(2.1)
Percent unemployed	4.2	6.6	3.2	5.5	5.3
	(2.0)	(2.6)	(1.4)	(2.0)	(2.5)
Percent at least college	20.5	22.6	29.3	32.0	26.2
	(6.9)	(7.5)	(8.4)	(8.3)	(9.1)
Percent uninsured	12.5	10.9	10.3	9.3	10.6
	(2.1)	(2.1)	(0.9)	(1.2)	(2.1)
Physicians per 1,000 pop.	1.6	1.6	1.4	1.4	1.5
	(0.9)	(0.8)	(0.4)	(0.3)	(0.7)
PCPs per 1,000 pop.	0.2	0.2	0.2	0.2	0.2
	(0.08)	(0.06)	(0.08)	(0.07)	(0.07)
Number of FQHCs	1.2	1.3	0.5	0.6	0.9
	(1.1)	(1.1)	(0.7)	(0.8)	(1.0)
Observations	228	456	124	248	1,056

Notes: All characteristics are weighted by ZCTA population. Before period consists of years 2008 and 2009, while after period refers to 2010-2013. ZCTAs assigned to intervention and control groups based on HSCRC methodology.
Sources: The Claritas Demographic Reports, the US Census Bureau, and the Area Health Resources File (AHRF).

5.4 Dependent Variables

The main study outcomes are population-based measures of total and preventable hospital utilization, in both the inpatient and outpatient settings, as reported by Maryland hospitals. Table 5.2 lists the various outcomes analyzed, with those for inpatient utilization shown in the top panel and those for outpatient utilization shown in the bottom panel.

For inpatient utilization, we first examine ZCTA-level models for total inpatient admissions per 1,000 residents and total inpatient days per capita. We then take several approaches to distinguish between preventable and non-preventable admissions.

Potentially preventable inpatient utilization measures include intra-hospital, all-cause 30-day readmissions, and admissions due to Ambulatory Care Sensitive Conditions (ACSCs) as defined by AHRQ's Prevention Quality Indicators (PQIs), which are a validated and widely used indicator for indirectly assessing access to and quality of outpatient care (Ansari et al. 2006; Bindman, Grumbach, et al. 1995). The ACSCs are categorized as acute and chronic. Acute conditions include dehydration, bacterial pneumonia, and urinary tract infection. Chronic conditions include diabetes short-term and long-term complications, Chronic Obstructive Pulmonary Disease (COPD), asthma, hypertension, heart failure, angina without procedure, uncontrolled diabetes, and lower-extremity amputation among patients with diabetes. Appendix A shows the specific ICD-9-CM codes included in the definition of each ACSC. The National Quality Fo-

Table 5.2: Main Inpatient and Outpatient Outcome Variables Used in the Study

Variable	**Description**
Inpatient admissions	Total admissions to Maryland hospitals by residents of a ZCTA in a given year
Inpatient days	The total length of stay of all admissions by residents of a ZCTA in a given year
Readmissions	Intra-hospital, all-cause 30-day readmissions by residents of a ZCTA in a given year
Preventable admissions	Admissions which satisfy the inclusion and exclusion criteria for the numerator of PQI #90 as specified by AHRQ Prevention Quality Indicators version 5.0
Chronic	Admissions which satisfy the inclusion and exclusion criteria for the numerator of PQI #92, version 5.0
Acute	Admissions which satisfy the inclusion and exclusion criteria for the numerator of PQI #91, version 5.0
Non-preventable admissions	Admissions which cannot be characterized as preventable according to the AHRQ PQI algorithms
Non-deferrable admissions	Admissions with a principal diagnosis of one of the 10 identified by Card et al. (2009) as having the same rate in the weekdays as during the weekend
Potentially deferrable admissions	Admissions not classified as non-deferrable
Admissions from the ED	Hospitalizations where the patient was admitted from the Emergency Department
Outpatient encounters	Total outpatient day visits by residents of a ZCTA in a given year
ED visits	Visits to an outpatient department with a CPT Management and Evaluation code of 99281-99285
Non-emergent	Medical care not needed within 12 hours (e.g., sore throats)
Primary care treatable	Medical care needed within 12 hours but safely treatable in a primary care setting (e.g., an ear infection)
Avoidable	Urgent care needed but the patient could have avoided the medical issue if they had received timely and effective outpatient care (e.g., an asthma attack)
Non-preventable	Urgent care needed, not preventable (e.g., a cardiac disrhythmia)
Behavioral	ED visits related to alcohol, drugs, and psychiatric conditions
Injury	Injury-related diagnoses (e.g., a broken leg)
Unclassified	No category assigned

Note: All outcomes are aggregated at the ZCTA-year level.

rum (NQF) endorsed eleven of these conditions (AHRQ 2016).

We also examine the proportion of deliveries via Cesarean section (C-section). In 2008, the most common reason for inpatient hospital stays in the US was childbirth (Podulka et al. 2011). C-section deliveries are associated with worse outcomes compared to vaginal deliveries, including neonatal mortality and complications in subsequent deliveries (National Institutes of Health 2006). Elective C-sections are also associated with longer maternal hospital stays and a higher likelihood of readmission, and are more costly than vaginal deliveries (Declercq et al. 2007). Analyzing the proportion of C-section deliveries thus allows us to examine whether hospitals were more likely to use less intensive care during deliveries post-implementation of TPR. We identify hospital delivery discharges using DRG codes of 767–768 and 774–775 (vaginal delivery) or 765–766 (C-section) (Correa et al. 2015).

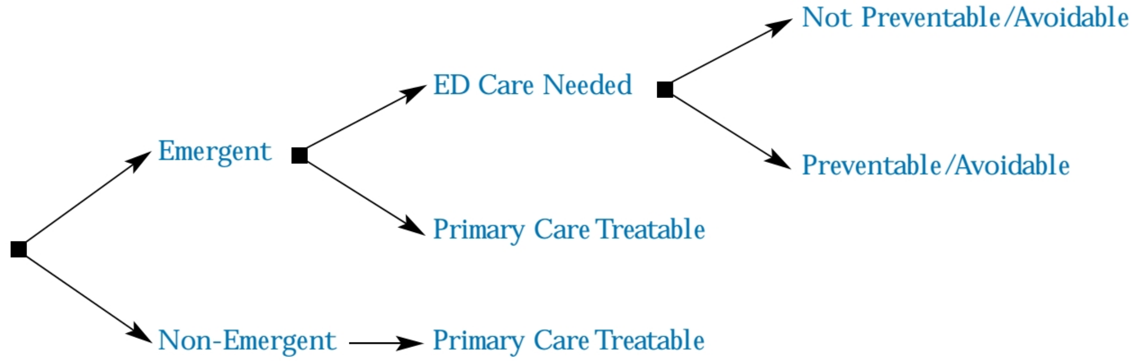
For outpatient utilization, we first examine ZCTA-level models for total outpatient encounters per 1,000 residents and total ED visits per 1,000 residents. We identify ED visits as outpatient encounters with a Current Procedural Terminology (CPT) Management and Evaluation code of 99281-99285, indicating Emergency Department visit for the evaluation and management of a patient. As with inpatient utilization, we then take several approaches to distinguish between preventable and non-preventable ED utilization. Measures of potentially preventable utilization included rates of ED visits categorized as avoidable/preventable or primary-care treatable based on the ICD-9-CM codes as described by Billings et al. (2000). The Billings algorithm[2] was developed using health care claims in the State of New York. It assigns to each ED visit a probability of falling into one of a mutually exclusive set of categories, based on ICD-9-CM codes, according to the process shown in Figure 5.2. Besides the potentially preventable and primary-care treatable categories, we also analyze other categories considered non-preventable as a sensitivity check to the main analyses (Table 5.2).

The second category of visits which are not amenable to non-hospital care are those related to injuries. In the absence of any differential changes in technology or local interventions to reduce injuries, the underlying trends in the population rates of injuries from different sources (e.g., household, workplace, or traffic injuries) should be similar across different Maryland areas. We therefore expect minimal effects of the TPR global budget system on these types of ED visits.

Finally, we present the results from analyses of a category of ED visits which we term ”behavioral” and which includes visits related to alcohol, drugs, and psychiatric conditions. *Ex ante* it is more difficult to draw a clear expectation for this category, but overall we have little reason to expect that the global budget payments induced any incentive to decrease these types of visits.

[2]The algorithm used to assign ED visits to specific categories is available at `http://wagner.nyu.edu/faculty/billings/nyued-background`

Figure 5.2: Process of Classifying Emergency Department Visits



Source: Adapted from Billings et al. (2000).

5.5 Patient samples

Table 5.3 presents the characteristics of the patients with an admission to Maryland hospitals for the pooled 2008-2013 sample. Maryland patients had a total of 3.99 million admissions to Maryland hospitals over the study period, with 843,041 of these by residents in the ZCTAs serviced by the TPR and rural control hospitals. Patients in the rural sample had more comorbidities than the sample as a whole, with 11.8 diagnoses coded on average compared to 11.1 in the full sample. Reflecting the population residing in these areas, patients admitted from rural ZCTAs were more likely to be white (81.2 percent vs. 55.9 percent), older (36.5 percent vs. 33.0 percent aged 65 and older), and more likely to have a readmission to the same hospital within 30 days. They were also more likely to have Medicare or commercial insurance coverage, but less likely to be Medicaid beneficiaries.

Table 5.4 presents the characteristics of the patients visiting the outpatient departments of Maryland hospitals during 2008-2013, for the rural and full

Table 5.3: Characteristics of Patients Residing in Maryland and Admitted to Maryland Hospitals, 2008-2013

	Rural Sample	Full Sample
Number of diagnoses	11.8	11.1
Female	57.8	58.3
Age		
0-17	13.3	13.9
18-39	19.7	21.2
40-64	30.6	31.9
65+	36.5	33.0
Race/ethnicity		
White	81.2	55.9
Black	13.4	33.5
Hispanic	2.1	4.2
Other race	3.2	6.4
Primary payer		
Medicare	40.4	37.3
Medicaid	16.3	21.3
Commercial payer	36.7	34.0
Self-pay	3.6	4.8
No charge	0.4	0.6
Other payer	2.5	2.0
Type of admission		
Preventable (PQI90)	11.4	11.1
Acute preventable (PQI91)	4.3	3.9
Chronic preventable (PQI92)	7.1	7.2
Admitted from ER	57.9	58.2
Readmission	16.0	12.1
Non-deferrable	3.7	3.5
Vaginal birth	6.0	6.3
Cesarean section	3.0	3.3
Intensity of care		
Number of procedures	1.6	1.6
Average length of stay	4.0	4.2
Observations	843,041	3,990,153

Notes: Categorical values present percentages of all admissions.
Source: Authors' calculations based on discharge data from the HSCRC.

sample. There were about 30 million total outpatient encounters for Maryland residents during the study period, with over 7 million encounters from the ZCTAs in the rural sample. The same general patterns hold as for the inpatient sample, with rural patients having on average more comorbidities and procedures performed than the sample as a whole, as well as a higher likelihood of being white (83.3 percent vs. 54.6 percent), older (24.7 percent vs. 21.7 percent aged 65 and older), and of having an ED visit.

5.6 Regression Analyses

We conduct all analyses at the ZCTA-year level. Because the data on population rates can be skewed for most utilization measures (and thus inappropriate for OLS), our preferred specification is a Poisson model. Specifically, we estimate quasi difference-in-differences Poisson regression models with the utilization count in the ZCTA-year N_{it} as the outcome measure and the population estimate n_{it} as the population at risk[3]:

$$\begin{aligned} Y_{it} &\sim Poisson(\lambda_{it}, \omega) \\ \lambda_{it} &= n_{it} \times exp\{\gamma T_{it} + \beta X_{it} + \delta_i + \theta_t\} \end{aligned} \tag{5.1}$$

The main identifying assumption of this model is the conditional exogeneity of the program implementation. Since the program was voluntary, this assumption seems too strong. To make conditional exogeneity more convincing, we account for time-invariant unobserved heterogeneity by including ZCTA-

[3]This is equivalent to controlling for $\log n_{it}$ as a covariate and setting its coefficient to 1.

Table 5.4: Characteristics of Patients Residing in Maryland an Outpatient Visit to Maryland Hospitals, 2008-2013

	Rural Sample	Full Sample
Number of diagnoses	2.8	2.5
Female	58.0	59.3
Age		
0-17	12.8	13.6
18-39	25.3	27.1
40-64	37.1	37.6
65+	24.7	21.7
Race/ethnicity		
White	83.3	54.6
Black	10.5	33.2
Hispanic	2.6	4.1
Other race	3.6	8.1
Primary payer		
Medicare	27.3	24.8
Medicaid	17.6	22.8
Commercial payer	43.8	39.3
Self-pay	6.2	7.8
No charge	0.6	1.2
Other payer	4.3	3.8
Type of encounter		
ED visit	41.4	39.9
Non-emergent	19.3	21.4
Primary care treatable	20.2	20.8
Preventable	5.4	5.9
Non-preventable	11.9	11.4
Injury-related	26.3	24.0
Behavioral	3.7	3.9
Other/unclassified	13.4	12.8
Intensity of care		
Number of procedures	5.1	4.8
Observations	7,185,415	30,012,114

Notes: Categorical values present percentages of all visits.
Source: Authors' calculations based on discharge data from the HSCRC.

level fixed effects, δ_i. We also control for sample-wide secular temporal shocks using year fixed effects θ_t. Finally, we control for the time-varying potential confounders at the ZCTA and county levels X_{it}. Clearly, one immediate concern is whether these variables are proper covariates which comprehensively account for differential outcome trends in the treatment and control groups. While we cannot possibly capture all the unobserved time-varying covariates that may account for bias in our model, we account for several types of variables which may influence hospital utilization while keeping our models parsimonious, as described above. Still, another key distributional assumption is that the covariates enter linearly into Equation 5.1. However, sample imbalance means that the estimates may be sensitive to the specification of X_{it}, which is a potential limitation of our study.

Our choice of the Poisson model in our preferred specification also relies on its lower sensitivity to measurement error (for example, in the ZCTA yearly population estimates) and accounts for the fact that utilization rates are never negative. The parameter ω accounts for the fact that there is overdispersion in the data, i.e. the variance is higher than the mean (see, for example, Zheng et al. 2006). To model the overdispersion explicitly, in additional analyses we estimate negative binomial models. The results of these analyses, not shown here, are not qualitatively different from the Poisson regression results.

In additional analyses we estimate a set of Ordinary Least Squares (OLS) models for the utilization rates per 1,000 residents in the ZCTA-year. Specifically, in these analyses, we estimate linear difference-in-differences (DD) regression models, weighted by average ZCTA population estimates (using `Stata`'s *analytic weights* option) and with population utilization rates Y_{it} as dependent variables:

$$Y_{it} = \gamma T_{it} + \beta X_{it} + \delta_i + \theta_t + \epsilon_{it} \tag{5.2}$$

where, consistent with a difference-in-differences analysis, T_{it} is an indicator for the TPR treatment being in effect in the ZCTA i during time period t and γ is the treatment coefficient of interest.

For PQI models, we use the adult population in each ZCTA as weight for the linear models and as exposure for the Poisson models, since this is the denominator specified by AHRQ for the indicators. Similarly, we use the female adult population in each ZCTA as weight (and exposure, respectively) for the C-section rate, as births are only defined for females in the sample.

In separate models, we instead use a main explanatory variable calculated as the interaction between the treatment indicator and a variable representing the number of years post TPR implementation (set to zero for all pre-TPR periods). The regression coefficient on this variable can be interpreted as the additive effect of an additional year of TPR implementation, thus indicating whether the effects ”accelerate” over time. In all our models, we obtain robust standard error estimates which account for clustering at the ZCTA level.

5.7 Quantile treatment effects

While mean regression techniques are useful in providing point estimates of the impact of reform, there may be extensive heterogeneity in treatment effects across the conditional distribution of the outcome. *A priori* the form of this heterogeneity is ambiguous. For example, it is possible to see larger reductions in utilization among areas with higher utilization rates, since there is more to ”cut”. At the same time, if areas with larger populations tend to have less fluctuating rates (simply because of a higher denominator), much of the impact could be realized in the middle of the distribution as opposed to the tails.

We therefore estimate quantile regression models with fixed effects using an estimator developed by Powell (2014), which is well-suited for panel data. This estimator relies strictly on within-group variation for identification while maintaining the nonseparable error property of cross-sectional quantile regression. This allows the resulting estimates to be interpreted in the same way as the cross-sectional estimates. We estimate the quantile treatment effects using the `Stata` module `qregpd`, which uses an adaptive Markov Chain Monte Carlo (MCMC) optimization procedure. We perform 2,000 draws for each estimation and drop 200 draws as a burn-in period, thus allowing the procedure to converge to the desired distribution.

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Chapter 6

Impact on Inpatient Utilization

This chapter presents the estimated effects of the TPR reform on inpatient utilization. We begin with the results for two overall utilization measures. We then distinguish between services which are considered preventable versus non-preventable in the next two sections, with an expectation that there will be stronger effects for the former. We then distinguish between services which are considered non-deferrable versus deferrable, with an expectation that there will be stronger effects for the latter.

For each outcome, we first show a figure for the unadjusted utilization rates in the intervention group and the four progressively larger control groups, and we then show a table of TPR's coefficient estimates from the different model specifications. For the first outcome presented, total admission rates, we show the model's full set of estimates to illustrate the exact empirical specifications. For all of the subsequent outcomes, we omit the full set of estimates and present instead just the coefficients of interest for the effects of TPR.

In the summary table for each specific outcome, the different control groups are shown in four different panels from top to bottom. The Poisson models for utilization counts are shown as the left-side columns (1) through (4), while the linear models for utilization rates per 1,000 residents are shown as the right-side columns (5) through (8). Within both of those groups, the results from the TPR indicator are shown first (e.g., columns (1) and (2)), and the results from the number of years TPR has been in effect are shown second (e.g., columns (3) and (4)). Finally, we first show the TPR coefficients from the models which exclude time-varying controls (in the odd-numbered columns), and we then show the TPR coefficients from the models which include the time-varying controls (in the even-numbered columns), in order to examine the potential confounding which stems from compositional differences in the ZCTA populations over time.

6.1 Effects on total inpatient utilization

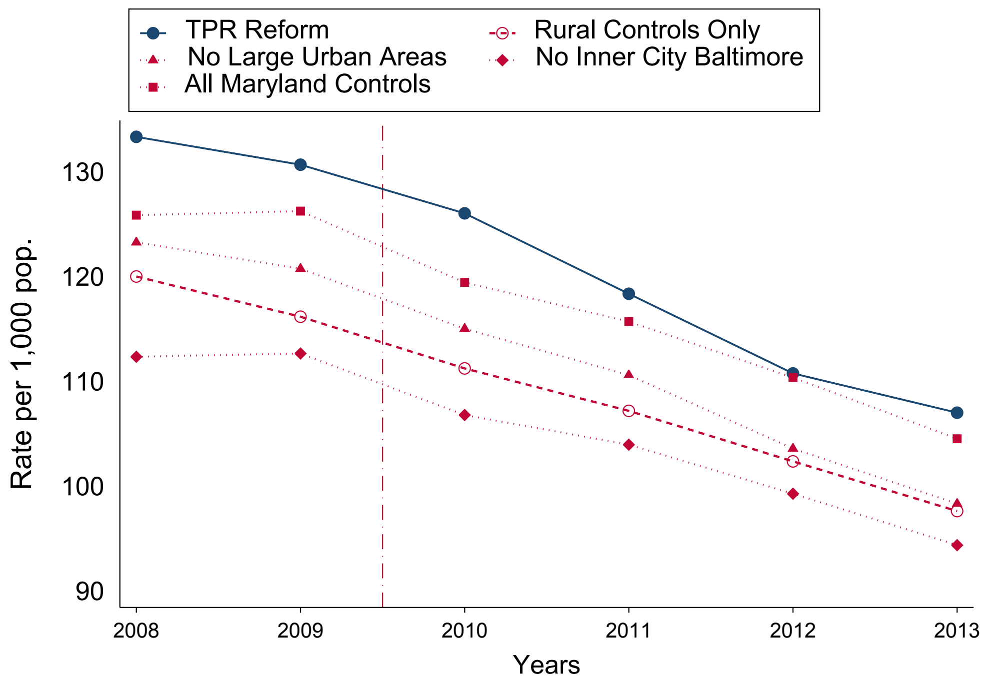
Figure 6.1 shows the unadjusted rates of inpatient admissions per 1,000 residents in the areas assigned to the intervention group (i.e., TPR reform) and to the four control groups (i.e., rural areas only, no large urban areas, no inner city Baltimore, and all of Maryland). These trends suggest that the baseline rates in the TPR hospital service areas are higher those than the control areas and, prior to the intervention, are generally following a descending trend that is approximately parallel to the trends in the control areas. Beginning in 2010, admission rates in areas exposed to TPR visibly decrease more quickly than those in rural control areas, partially closing the pre-intervention gap.

Table 6.1 shows the full set of regression coefficients for the eight different model specifications with just the rural counties only as the control group. The first panel of Table 6.2 then repeats the TPR regression coefficients in the top line of Table 6.1, while the next three panels of Table 6.2 present the TPR regression coefficients for the three other control groups.

Before moving on to the main effects of TPR on hospital inpatient utilization, we note that most of the time-varying ZCTA-level characteristics serving as controls have effects in the expected direction, which suggests that our model is generally well-specified to examine hospital utilization. Notably, changes in inpatient admissions over time are positively associated with changes in average age, negatively associated with changes in Medicare Advantage penetration, negatively associated with changes in primary care physicians per capita, and positively associated with changes in specialists per capita.

Confirming the visual trends presented in Figure 6.1, the effects of TPR reform on total admission rates from virtually all model specifications in Table 6.2 point to a small decrease, though statistically significant in just 12 of the 32 models presented. Two of the 32 models have an insignificant positive coefficient. For the preferred Poisson models using the only rural ZCTAs as a control group, for instance, model (2) indicates that the TPR program led to a statistically insignificant decrease of 1.77 percent compared to rural controls after accounting for ZCTA and county characteristics. Model (4) indicates that

Figure 6.1: Trends in Inpatient Admission Rates for the Treatment and Control Groups, 2008-2013



each additional year of the TPR program led to a marginally statistically significant decrease of 0.80 percent. These effects are consistent with the estimates from models (6) and (8) using linear regressions controlling for ZCTA characteristics, which find a statistically insignificant decrease of 3.57 admissions per 1,000 residents from TPR or a decrease of 1.79 admissions per 1,000 residents with each year of TPR implementation.

The results are generally consistent across the four different groups of control ZCTAs in indicating a small and imprecisely estimated reduction. When suburban areas other than the ZCTAs outside urban CBSAs are included in the comparison group (i.e., the second panel downward), the effects of the TPR reform are smaller in magnitude—specifically a statistically insignificant de-

Table 6.1: Full Estimates of the Effect of TPR on the Rates of Total Inpatient Admissions per 1,000 Residents

	Poisson (offset = log(population))				Weighted OLS (admissions per 1,000 capita)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TPR Reform in Effect	−1.26	−1.77			−3.78	−3.57		
	(2.88)	(2.81)			(4.09)	(3.87)		
Years TPR Reform in Effect			−0.60	−0.80			−1.61	−1.79*
			(0.75)	(0.73)			(1.09)	(1.06)
Percent female		0.69		0.62		1.03**		0.89**
		(0.44)		(0.45)		(0.43)		(0.44)
Median age		1.52**		1.48**		2.60***		2.51***
		(0.67)		(0.66)		(0.96)		(0.93)
Percent non-white		0.15		0.12		0.16		0.084
		(0.23)		(0.23)		(0.33)		(0.34)
Median household income (10K)		−2.70*		−2.89*		−2.54		−3.00
		(1.50)		(1.48)		(2.45)		(2.41)
Percent unemployed		0.55		0.56		0.22		0.25
		(0.50)		(0.51)		(0.88)		(0.89)
Percent at least college		−0.56		−0.56		−1.14		−1.14
		(0.43)		(0.42)		(0.70)		(0.70)
Percent uninsured		−1.14		−1.16		−0.16		−0.31
		(0.84)		(0.87)		(1.65)		(1.62)
Medicare Advantage penetration		−2.26***		−2.27***		−2.77***		−2.76***
		(0.64)		(0.63)		(0.94)		(0.90)
PCPs per 1,000 pop.		−25.7		−21.4		−102.3***		−89.8**
		(16.4)		(18.0)		(38.5)		(36.5)
Specialists per 1,000 pop.		16.1**		17.7**		32.2***		36.4***
		(8.55)		(8.42)		(9.87)		(9.64)
Number of FQHCs		−2.61		−2.74		−2.94		−3.18
		(2.03)		(2.10)		(3.14)		(3.22)
Constant					129.1***	17.4	128.2***	25.2
					(1.41)	(42.2)	(1.67)	(40.4)
Observations	1206	1206	1206	1206	1206	1206	1206	1206

Notes: Standard errors in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. All models control for ZCTA and year fixed effects. OLS models are weighted by average ZCTA population. Poisson models report percent incidence rate differences.

crease of only 0.87 admissions per 1,000 residents in model (6) or a statistically insignificant decrease of 0.77 admissions per 1,000 per residents for each additional year in model (8). Models (2) and (4) for the Poisson regression have the two (out of 32) positive signs noted above, although their magnitudes are very close to zero.

When urban areas except Baltimore are included in the comparison group (i.e., the third panel downward), the effects of the TPR reform are similar in magnitude to those using the rural controls—-specifically, Poisson models (2) and (4) suggest that TPR led to an insignificant decrease of 2.03 percent in the admission rate overall, or a 1.18 percent decrease ($p < 0.05$) for each additional year of the TRP program. The linear models indicate a statistically insignificant decrease of 2.90 admissions per 1,000 residents in model (6) or a marginally significant decrease of 1.73 admissions per 1,000 residents for each additional year of TPR in model (8).

When the entire state is used as the comparison group (i.e., the fourth panel downward), the effects of the TPR reform range are also similar in magnitude to those using the rural controls. Poisson models (2) and (4) suggest that TPR led to a decrease of 3.17 percent ($p < 0.1$) in the admission rate compared to the state-wide trend, or a 1.41 percent decrease ($p < 0.05$) for each additional year of the TPR program. In the linear models we estimate a statistically insignificant reduction to 2.44 admissions per 1,000 residents in model (2) or, similarly, an insignificant reduction of 1.56 admission per 1,000 residents for each additional year of TPR in model (4).

Our assessment is that there is a low degree of potential confounding stemming from compositional differences in the ZCTA populations (both here for this outcome and for the various subsequent outcomes). More explicitly, the results for TPR's effects in the odd-numbered columns where these time-varying ZCTA characteristics are excluded are generally relatively similar to the results for TPR's effects in the even-numbered columns where these time-varying ZCTA characteristics are included. In the tables that follow, we continue to show results both excluding and including these time-varying ZCTA-level controls; but in the text that follows, we continue to focus only on the results including these time-varying controls.

The quantile regression results in Appendix Figure C.1 indicate that while there is notable heterogeneity in the treatment effects across the distribution of the ZCTA admission rate, the impact is negative for most values of the outcome. According to these estimates, TPR has led to a decrease in the median admission rate by almost 12 admissions per 1,000 residents. In contrast, at quantile 40, the effect of the TPR reform on the admission rate is close to zero. Overall however, the effect of the TPR reform on the distribution of the ZCTA admission rate is negative, which gives us further confidence that the reduction in rates does not occur mainly in areas with high or low utilization levels.

Figure 6.2 shows the unadjusted rates of inpatient days per 1,000 residents in the TPR ZCTAs versus the four control group. The impact of the TPR program is apparent graphically, as TPR's inpatient days appear to have decreased more quickly than those in the control areas after the TPR program implemen-

Table 6.2: Estimates of the Effects of TPR on the Rates of Total Admissions, with Various Sample Restrictions

	Poisson (offset = log(population))				Weighted OLS (rate per 1,000 capita)			
	(1) TPR	(2) TPR	(3) TPR Years	(4) TPR Years	(5) TPR	(6) TPR	(7) TPR Years	(8) TPR Years
RURAL AREAS ONLY	-1.26	-1.77	-0.60	-0.80	-3.78	-3.57	-1.61	-1.79^{*}
(N=1206)	(2.88)	(2.81)	(0.75)	(0.73)	(4.09)	(3.87)	(1.09)	(1.06)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO LARGE URBAN AREAS	-0.15	0.50	-0.10	0.076	-2.38	-0.87	-1.02	-0.77
(N=1566)	(2.34)	(2.34)	(0.63)	(0.63)	(3.40)	(3.13)	(0.95)	(0.89)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO INNER CITY	-2.82^{*}	-2.03	-1.14^{**}	-1.18^{**}	-5.47^{**}	-2.90	-2.03^{***}	-1.73^{*}
BALTIMORE (N=2634)	(1.54)	(1.78)	(0.47)	(0.56)	(2.54)	(3.30)	(0.77)	(1.01)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
ALL OF MARYLAND	-2.69^{*}	-3.17^{*}	-1.05^{**}	-1.41^{**}	-4.03	-2.44	-1.50^{*}	-1.56
(N=2760)	(1.52)	(1.70)	(0.47)	(0.55)	(2.55)	(3.14)	(0.77)	(0.98)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓

Notes: Standard errors in parentheses. $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$. All models control for ZCTA and year fixed effects. OLS models are weighted for average ZCTA population. Poisson models report percent incidence rate differences. Models (1), (2), (5), and (6) report the effect of the TPR reform as the coefficient on the interaction between the reform indicator and the post period indicator (equal to 1 for years 2010-2013, 0 otherwise). Models (3), (4), (7), and (8) report the effect of an additional year of TPR reform implementation as the coefficient on the interaction between the reform indicator and a post linear time trend indicator (equal to 0 in the pre-reform period, 1 in the first reform year, 2 in the second, etc. The first sample includes ZCTAs assigned to the 8 TPR hospitals and 3 rural control hospitals. The second sample contains the ZCTAs in the first sample plus ZCTAs assigned to non-participating hospitals which don't belong to the CBSAs 12580 (Baltimore-Columbia-Towson) and 47900 (Washington-Arlington-Alexandria). The third sample uses as controls all Maryland ZCTAs assigned to non-participating hospitals which are outside the Baltimore City county (FIPS code 24510). The fourth sample includes all Maryland ZCTAs assigned to non-participating hospitals.

tation, although there was an evident slowdown in the reduction between 2012 and 2013.

The DD estimate for the TPR program effect relative to other rural controls is a 5.09 percent decrease ($p<0.1$) estimated via Poisson regression (model (2) in the first panel), corroborated with a decrease of 29.6 inpatient days per 1,000 residents ($p<0.05$) via the linear regression model (6) in the first panel). Similarly, the time-trend estimate for TPR's effect over time (relative to other rural controls) is a 1.90 percent decrease per year ($p<0.01$) via the Poisson model (4) and a decrease of 12.2 inpatient days per 1,000 residents per additional year ($p<0.01$) via the OLS model (8).

The treatment effect estimates from analogous models in the second, third, and fourth panels using the alternative control groups generally display similar patterns, though they are somewhat smaller in magnitude (and sometimes statistically insignificant). For instance, models (2) and (6) have decreases in inpatient day rates in the range of 2.29-4.43 percent or 17.2-18.1 days per 1,000 residents, while models (4) and (8) have decreases in inpatient days per year in the range of 0.65-1.71 percent per year or 7.05-8.14 days per 1,000 residents per year.

The quantile treatment effects shown in Figure C.2 reveal some variation in the program's impact, particularly at the higher end of the distribution. For example, estimated coefficient at the 75^{th} percentile is almost -60 days per 1,000 residents. This suggests that there is a larger decrease in length of stay at the margin from ZCTAs with higher inpatient day rates. Together with the results on total admission rates, this suggests that TPR reform decreases the length of admissions at the higher end of the distribution.

6.2 Effects on preventable utilization

In this section we present the effects of the TPR reform on 30-day readmissions and on preventable admissions as defined by the AHRQ PQIs. As noted above, we expect the effects of TPR to be slightly more pronounced for the preventable utilization measures than for the non-preventable utilization measures (shown in the next section) if the monitoring of PQIs stipulated in the TPR contracts had an impact on hospitals.

Figure 6.3 shows unadjusted rates for 30-day readmissions and indicates that, similar to overall admission rates, the TPR reform areas have higher baseline levels of readmission rates, and the trends in 30-day readmissions in the TPR hospital areas began to decrease significantly in 2011, after a relatively flat trajectory between 2008 and 2010. Readmission rates in the rural control areas also decreased after the reform but this decrease followed a large increase in pre-reform years. Readmission rates in the larger control areas also decreased after the reform but these decreases were smaller in magnitude.

Table 6.4 indicates that the reform had a statistically insignificant effect on readmissions for TPR hospitals compared to the rural controls (models (2), (4), (6), and (8) in the first panel), but led to several statistically significant decreases in readmissions compared to the larger sets of controls. This suggests

Figure 6.2: Trends in Inpatient Day Rates for the Treatment and Control Groups, 2008-2013

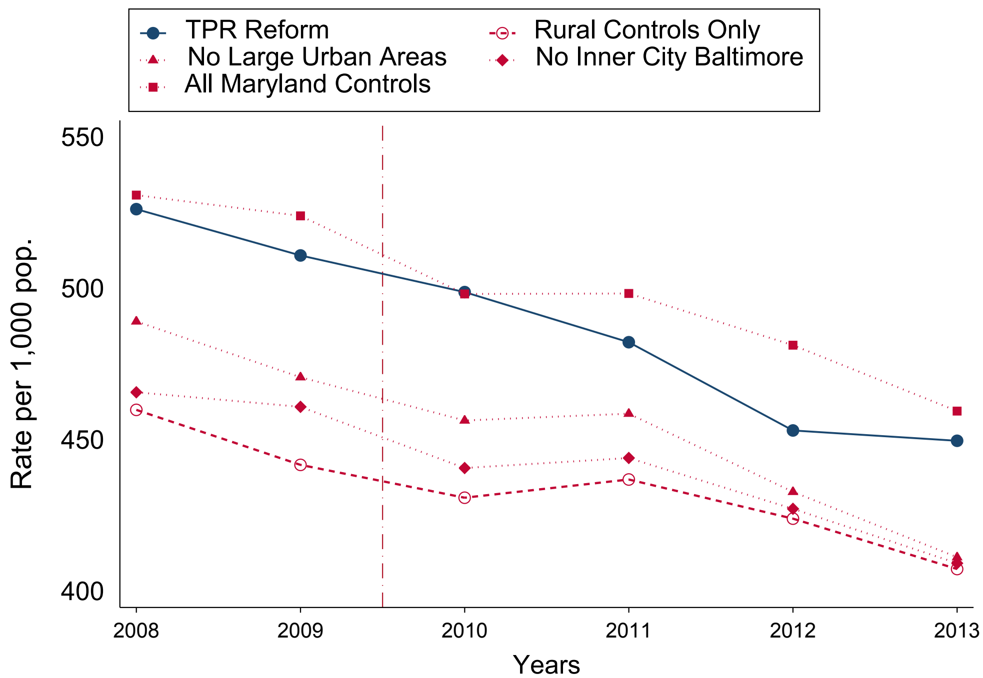


Table 6.3: Estimates of the Effects of TPR on the Rates of Total Inpatient Days, with Various Sample Restrictions

	Poisson (offset = log(population))				Weighted OLS (rate per 1,000 capita)			
	(1) TPR	(2) TPR	(3) TPR Years	(4) TPR Years	(5) TPR	(6) TPR	(7) TPR Years	(8) TPR Years
RURAL AREAS ONLY	-3.93	-5.09^{*}	-1.39^{**}	-1.90^{***}	-24.4^{*}	-29.6^{**}	-8.98^{**}	-12.2^{***}
(N=1206)	(2.64)	(2.72)	(0.65)	(0.65)	(14.7)	(14.6)	(3.76)	(3.69)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO LARGE URBAN AREAS	-1.23	-2.29	-0.29	-0.65	-12.9	-17.5	-4.69	-7.05^{*}
(N=1566)	(2.24)	(2.31)	(0.61)	(0.60)	(13.0)	(12.4)	(3.78)	(3.62)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO INNER CITY	-2.62^{*}	-3.07^{*}	-1.00^{**}	-1.41^{***}	-17.0^{*}	-17.2	-6.38^{**}	-8.08^{**}
BALTIMORE (N=2634)	(1.37)	(1.65)	(0.41)	(0.47)	(9.17)	(12.1)	(2.79)	(3.57)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
ALL OF MARYLAND	-2.12	-4.43^{***}	-0.85^{**}	-1.71^{***}	-10.2	-18.1	-4.26	-8.14^{**}
(N=2760)	(1.35)	(1.48)	(0.40)	(0.44)	(9.30)	(11.3)	(2.82)	(3.42)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓

Notes: Standard errors in parentheses. $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$. All models control for ZCTA and year fixed effects. OLS models are weighted for average ZCTA population. Poisson models report percent incidence rate differences. Models (1), (2), (5), and (6) report the effect of the TPR reform as the coefficient on the interaction between the reform indicator and the post period indicator (equal to 1 for years 2010-2013, 0 otherwise). Models (3), (4), (7), and (8) report the effect of an additional year of TPR reform implementation as the coefficient on the interaction between the reform indicator and a post linear time trend indicator (equal to 0 in the pre-reform period, 1 in the first reform year, 2 in the second, etc. The first sample includes ZCTAs assigned to the 8 TPR hospitals and 3 rural control hospitals. The second sample contains the ZCTAs in the first sample plus ZCTAs assigned to non-participating hospitals which don't belong to the CBSAs 12580 (Baltimore-Columbia-Towson) and 47900 (Washington-Arlington-Alexandria). The third sample uses as controls all Maryland ZCTAs assigned to non-participating hospitals which are outside the Baltimore City county (FIPS code 24510). The fourth sample includes all Maryland ZCTAs assigned to non-participating hospitals.

that other factors may have influenced the trends in readmissions in urban areas during the study period.

For the PQIs, we focus on the effects of three composite indicators (i.e., an overall composite for all ACSCs, a composite for acute ACSCs, and a composite for chronic ACSCs) and show a full set of effects for each individual ambulatory care sensitive condition in Appendix B.

Figure 6.4 presents the trends in the unadjusted PQI #90 overall composite, which includes all ACSCs. The figure shows relatively flat trends in total preventable admissions in the pre-reform period, followed by a decrease between 2010 and 2012 for all control groups and a leveling of the rates in 2013. The unadjusted rates of preventable admissions decreased more abruptly in the treatment areas, from an average of about 22 admissions per 1,000 residents in 2008 to approximately 16 admissions per 1,000 residents in 2013. In contrast, in the rural control areas it decreased from about 18.0 to 14.0 admissions per 1,000 residents during the same period. Despite this decrease, the indicator for TPR hospitals still had the highest level in the state, which is most likely explained by the higher rates of risk factors in the reform areas.

Table 6.5 presents estimates of TPR's effect on total preventable admissions from the difference-in-differences models estimated with the four different control groups. Compared to rural controls shown in the first panel, TPR reduced preventable hospitalization rates by a statistically insignificant 1.16 percent in model (2) or 0.91 percent per year of TPR implementation in model (4). As with the effect on total admissions, these estimates are bounded by the esti-

Figure 6.3: Trends in 30-Day Readmission Rates for the Treatment and Control Groups, 2008-2013

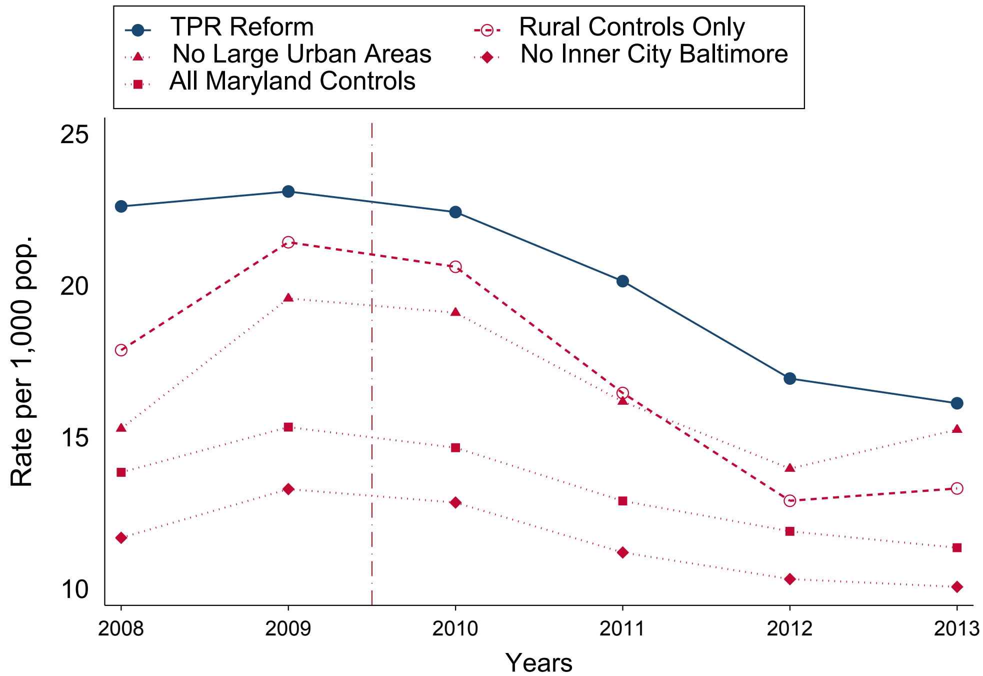


Table 6.4: Estimates of the Effects of TPR on the Rates of 30-day Readmissions, with Various Sample Restrictions

	Poisson (offset = log(population))				Weighted OLS (rate per 1,000 capita)			
	(1) TPR	(2) TPR	(3) TPR Years	(4) TPR Years	(5) TPR	(6) TPR	(7) TPR Years	(8) TPR Years
RURAL AREAS ONLY	2.02	2.34	1.20	0.46	−0.31	0.0027	−0.11	−0.40
(N=1206)	(5.75)	(6.74)	(2.15)	(2.44)	(1.19)	(1.34)	(0.41)	(0.51)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO LARGE URBAN AREAS	−10.8*	−7.95*	−4.18*	−4.64**	−2.90**	−2.47**	−1.07**	−1.30***
(N=1566)	(5.59)	(4.31)	(2.27)	(1.91)	(1.22)	(1.07)	(0.43)	(0.42)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO INNER CITY	−7.44*	−9.82**	−3.10**	−3.31**	−2.79***	−2.10**	−1.05***	−0.84**
BALTIMORE (N=2634)	(3.77)	(4.10)	(1.49)	(1.59)	(0.88)	(0.99)	(0.30)	(0.35)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
ALL OF MARYLAND	−6.10	−5.43	−2.63*	−2.37	−2.39***	−1.12	−0.91***	−0.63*
(N=2760)	(3.64)	(4.59)	(1.43)	(1.72)	(0.87)	(1.00)	(0.30)	(0.36)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓

Notes: Standard errors in parentheses. $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$. All models control for ZCTA and year fixed effects. OLS models are weighted for average ZCTA population. Poisson models report percent incidence rate differences. Models (1), (2), (5), and (6) report the effect of the TPR reform as the coefficient on the interaction between the reform indicator and the post period indicator (equal to 1 for years 2010-2013, 0 otherwise). Models (3), (4), (7), and (8) report the effect of an additional year of TPR reform implementation as the coefficient on the interaction between the reform indicator and a post linear time trend indicator (equal to 0 in the pre-reform period, 1 in the first reform year, 2 in the second, etc. The first sample includes ZCTAs assigned to the 8 TPR hospitals and 3 rural control hospitals. The second sample contains the ZCTAs in the first sample plus ZCTAs assigned to non-participating hospitals which don't belong to the CBSAs 12580 (Baltimore-Columbia-Towson) and 47900 (Washington-Arlington-Alexandria). The third sample uses as controls all Maryland ZCTAs assigned to non-participating hospitals which are outside the Baltimore City county (FIPS code 24510). The fourth sample includes all Maryland ZCTAs assigned to non-participating hospitals.

mates from the expanded control groups.

The linear model estimates are largely consistent with these effects. Model (6) points to an insignificantly small reduction among rural areas of 1.09 admissions per 1,000 residents (first panel), and a slightly larger reduction in preventable admissions compared to the larger Maryland control groups, ranging between 1.33 admissions per 1,000 residents (fourth panel) and 1.60 admissions per 1,000 residents (third panel). Moreover, the effect was sustained across the outcome distribution, as shown in Figure C.4, with an even higher effect for higher quantiles.

As noted above, these AHRQ Prevention Quality Indicators allow us to explore the composition of preventable admissions by the type of ambulatory care sensitive condition present as the main diagnosis. We first present rates of preventable admissions classified as chronic and then present rates classified as acute.

Figure 6.5 shows a sharper decrease in preventable admissions categorized as chronic for the TPR reform group relative to the control groups. Specifically, the reduction is from a higher level of about 14.0 admissions per 1,000 adults in 2008 to about 9.0 in 2013, while the rate in the rural control group decreases from 11.5 to approximately 8.5 over the same period. This leads to a lower rate in the reform areas than the overall Maryland average in 2013, suggesting that the reform was successful in reducing chronic ACSC admissions beyond trends in the control groups.

Figure 6.4: Trends in Overall Preventable Admission Rates for the Treatment and Control Groups, 2008-2013

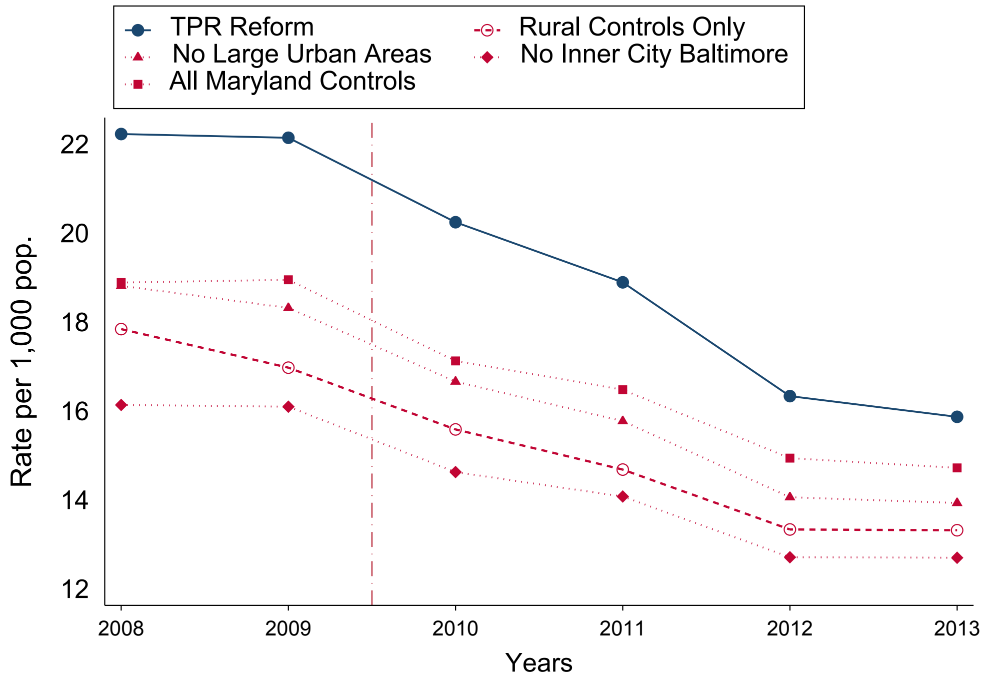


Table 6.5: Estimates of the Effects of TPR on the Rates of Overall Preventable Admissions, with Various Sample Restrictions

	Poisson (offset = log(population))				Weighted OLS (rate per 1,000 capita)			
	(1) TPR	(2) TPR	(3) TPR Years	(4) TPR Years	(5) TPR	(6) TPR	(7) TPR Years	(8) TPR Years
RURAL AREAS ONLY	−1.58	−1.16	−1.06	−0.91	−1.54	−1.09	-0.60^{**}	-0.56^{*}
(N=1206)	(4.00)	(4.49)	(1.28)	(1.39)	(0.96)	(0.90)	(0.30)	(0.30)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO LARGE URBAN AREAS	−1.22	0.55	−0.81	−0.35	−1.26	−0.67	-0.49^{*}	−0.41
(N=1566)	(3.68)	(4.05)	(1.22)	(1.30)	(0.91)	(0.87)	(0.29)	(0.29)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO INNER CITY	−4.38	-6.45^{**}	-2.01^{*}	-2.91^{**}	-1.82^{**}	-1.60^{*}	-0.70^{**}	-0.71^{**}
BALTIMORE (N=2634)	(2.98)	(2.92)	(1.10)	(1.11)	(0.86)	(0.83)	(0.28)	(0.28)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
ALL OF MARYLAND	−4.76	-7.94^{***}	-2.08^{*}	-3.33^{***}	-1.47^{*}	−1.33	-0.58^{**}	-0.66^{**}
(N=2760)	(2.95)	(2.89)	(1.10)	(1.15)	(0.85)	(0.86)	(0.28)	(0.30)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓

Notes: Standard errors in parentheses. $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$. All models control for ZCTA and year fixed effects. OLS models are weighted for average ZCTA population. Poisson models report percent incidence rate differences. Models (1), (2), (5), and (6) report the effect of the TPR reform as the coefficient on the interaction between the reform indicator and the post period indicator (equal to 1 for years 2010-2013, 0 otherwise). Models (3), (4), (7), and (8) report the effect of an additional year of TPR reform implementation as the coefficient on the interaction between the reform indicator and a post linear time trend indicator (equal to 0 in the pre-reform period, 1 in the first reform year, 2 in the second, etc. The first sample includes ZCTAs assigned to the 8 TPR hospitals and 3 rural control hospitals. The second sample contains the ZCTAs in the first sample plus ZCTAs assigned to non-participating hospitals which don't belong to the CBSAs 12580 (Baltimore-Columbia-Towson) and 47900 (Washington-Arlington-Alexandria). The third sample uses as controls all Maryland ZCTAs assigned to non-participating hospitals which are outside the Baltimore City county (FIPS code 24510). The fourth sample includes all Maryland ZCTAs assigned to non-participating hospitals.

Figure 6.5: Trends in Preventable Admission Rates due to Chronic Ambulatory Care Sensitive Conditions for the Treatment and Control Groups, 2008-2013

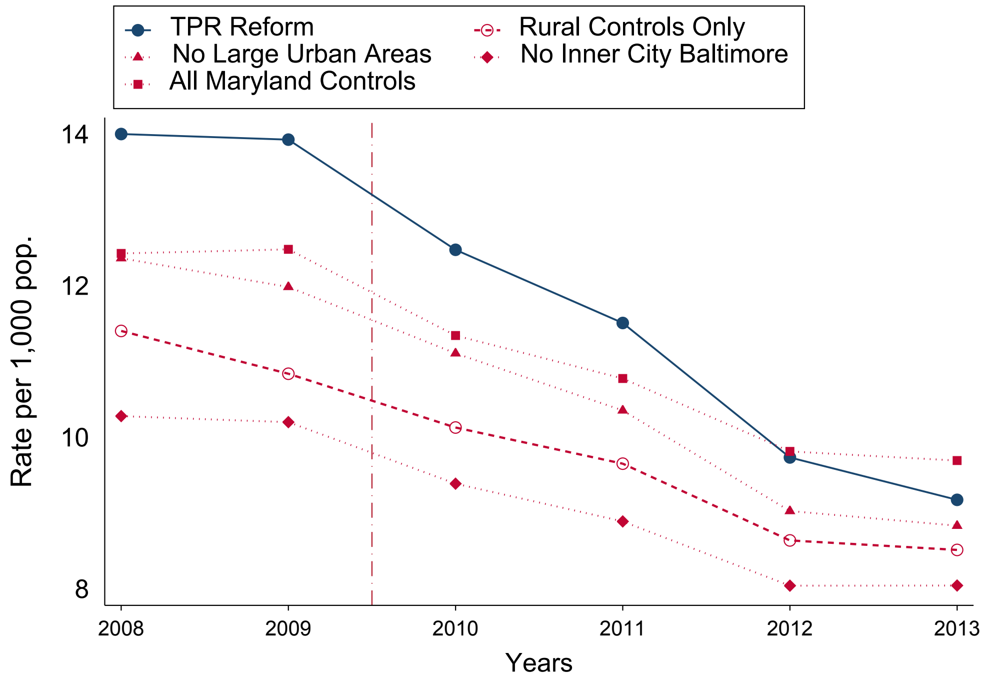


Table 6.6 indeed indicates a small and imprecisely estimated negative effect of the TPR reform on chronic ACSC admissions. The Poisson estimates in model (2) indicate an insignificant decrease of 5.53 percent when compared to rural controls and a highly significant effect of between 8.37 percent and 10.50 percent when compared to the more expansive control groups in the state. The Poisson estimates in model (4) indicate a similar pattern. Model (6) using the rural controls in the first panel implies a reduction of 1.17 ($p < 0.1$) chronic ACSC admissions per 1,000 residents due to TPR, with a range between 0.61 in the second panel to 1.07 in the third panel. Model (8) using the rural controls in the first panel implies a reduction of 0.51 ($p < 0.05$) chronic ACSC admissions per 1,000 residents for each year after the implementation of TPR.

Table 6.6: Estimates of the Effects of TPR on the Rates of Preventable Admissions due to Chronic Ambulatory Care Sensitive Conditions, with Various Sample Restrictions

	Poisson (offset = log(population))				Weighted OLS (rate per 1,000 capita)			
	(1) TPR	(2) TPR	(3) TPR Years	(4) TPR Years	(5) TPR	(6) TPR	(7) TPR Years	(8) TPR Years
RURAL AREAS ONLY	-7.49^{*}	-5.53	-2.90^{**}	-2.34	-1.58^{**}	-1.17^{*}	-0.56^{***}	-0.51^{**}
(N=1206)	(4.13)	(4.50)	(1.46)	(1.52)	(0.65)	(0.62)	(0.21)	(0.21)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO LARGE URBAN AREAS	-4.94	-2.41	-1.80	-1.12	-1.12^{*}	-0.61	-0.39^{*}	-0.31
(N=1566)	(3.82)	(3.78)	(1.35)	(1.30)	(0.62)	(0.54)	(0.20)	(0.19)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO INNER CITY	-8.66^{***}	-8.37^{***}	-3.50^{***}	-3.78^{***}	-1.55^{***}	-1.07^{*}	-0.58^{***}	-0.49^{**}
BALTIMORE (N=2634)	(3.05)	(2.94)	(1.18)	(1.09)	(0.60)	(0.58)	(0.20)	(0.20)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
ALL OF MARYLAND	-9.20^{***}	-10.5^{***}	-3.71^{***}	-4.47^{***}	-1.29^{**}	-0.89	-0.49^{**}	-0.47^{**}
(N=2760)	(3.04)	(2.87)	(1.19)	(1.15)	(0.59)	(0.58)	(0.20)	(0.20)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓

Notes: Standard errors in parentheses. $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$. All models control for ZCTA and year fixed effects. OLS models are weighted for average ZCTA population. Poisson models report percent incidence rate differences. Models (1), (2), (5), and (6) report the effect of the TPR reform as the coefficient on the interaction between the reform indicator and the post period indicator (equal to 1 for years 2010-2013, 0 otherwise). Models (3), (4), (7), and (8) report the effect of an additional year of TPR reform implementation as the coefficient on the interaction between the reform indicator and a post linear time trend indicator (equal to 0 in the pre-reform period, 1 in the first reform year, 2 in the second, etc. The first sample includes ZCTAs assigned to the 8 TPR hospitals and 3 rural control hospitals. The second sample contains the ZCTAs in the first sample plus ZCTAs assigned to non-participating hospitals which don't belong to the CBSAs 12580 (Baltimore-Columbia-Towson) and 47900 (Washington-Arlington-Alexandria). The third sample uses as controls all Maryland ZCTAs assigned to non-participating hospitals which are outside the Baltimore City county (FIPS code 24510). The fourth sample includes all Maryland ZCTAs assigned to non-participating hospitals.

Although the effect on the chronic composite preventable admissions is consistently negative across specifications, it stems mainly from several specific conditions where the impact is particularly pronounced. Appendix B points to a 10.8 percent reduction of in the rate of Chronic Obstructive Pulmonary Disease (COPD) or asthma among older adults (PQI #05) (Table B.4). This represents a decrease of 0.7 admissions per 1,000 residents ($p<0.05$) in the admission rate according to the linear model. Admissions for heart failure (PQI #08) also decreased by about 0.3 admissions per 1,000 residents (Table B.6), although the effect is not statistically significant.

Figure 6.6 shows the trends in the rates of preventable admissions classified as acute (PQI #91). The TPR intervention group has the highest rates throughout the study period at a baseline of just over 8.0 admissions per 1,000 residents. The rates are fairly constant pre-reform and begin to decrease similarly overall in all groups in the post-reform period, with a slight reversal towards an increase from 2012 to 2013.

Table 6.7 suggests that overall, the TPR reform did not affect the rates of acute ACSCs beyond the trends already existing in the other control groups in the state. The Poisson models (2) and (4) provide estimates that are all insignificant and switch signs from positive to negative across the different samples. A similar pattern emerges from the the first through fourth panels for linear models (6) and (8), the estimated effect of the TPR intervention is mostly statistically insignificant and small.

Figure C.6 presents the quantile treatment effects, which are small but positive in the middle of the outcome distribution but hover around zero at the tails.

6.3 Effects on non-preventable utilization

The rates of admissions which are not categorized as preventable by the AHRQ methodology are shown in Figure 6.7. These admissions represent a much higher share of total admissions than those included in the PQIs and thus are important to examine on their own. Overall the trends in this category are decreasing throughout the study period. There is a slightly steeper decrease in the TPR group, which starts from a higher level pre-reform level and converges to levels similar to state-wide rates.

Table 6.8 indicates that while there is also a reduction in non-preventable admissions, these effects are not consistently statistically significant. However, because these admissions represent a higher proportion of the total admissions compared to preventable admissions, the reduction of 2.63 admissions per residents (1.66 percent reduction from the Poisson model) is larger in absolute terms than the effect on PQI #92 shown in Table 6.6 and may be significant at the population level despite being imprecisely estimated.

Figure 6.6: Trends in Acute Preventable Admission Rates for the Treatment and Control Groups, 2008-2013

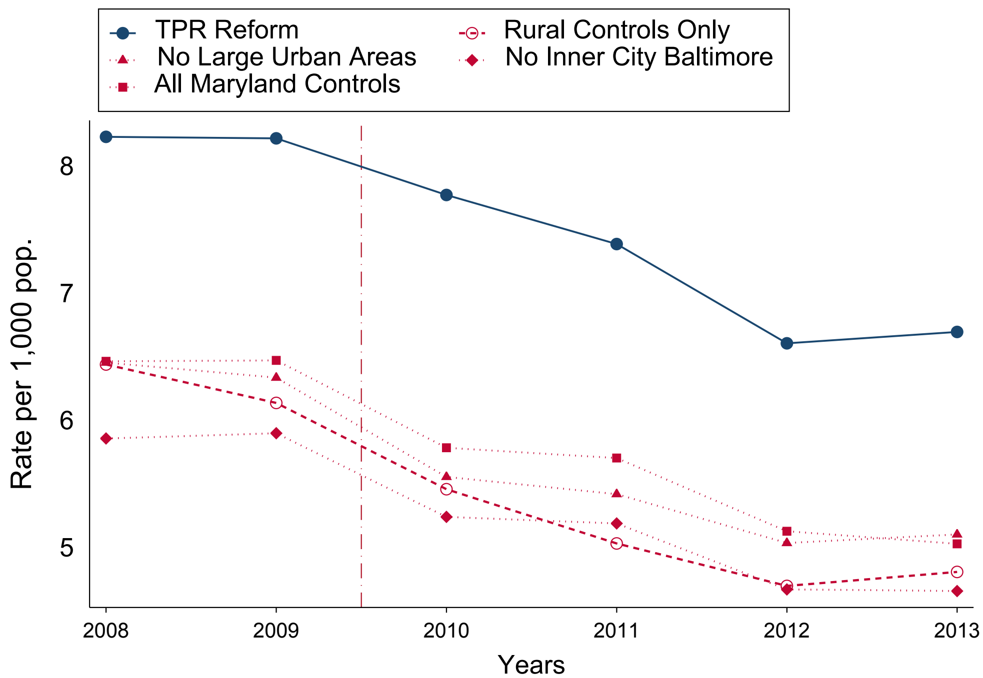


Table 6.7: Estimates of the Effects of TPR on the Rates of Preventable Admissions due to Acute Ambulatory Care Sensitive Conditions, with Various Sample Restrictions

	Poisson (offset = log(population))				Weighted OLS (rate per 1,000 capita)			
	(1) TPR	(2) TPR	(3) TPR Years	(4) TPR Years	(5) TPR	(6) TPR	(7) TPR Years	(8) TPR Years
RURAL AREAS ONLY	9.00^{*}	6.17	1.90	1.22	0.038	0.074	−0.044	−0.044
(N=1206)	(4.94)	(5.60)	(1.38)	(1.49)	(0.37)	(0.37)	(0.11)	(0.11)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO LARGE URBAN AREAS	4.81	4.59	0.52	0.40	−0.14	−0.059	−0.11	−0.099
(N=1566)	(4.65)	(5.52)	(1.41)	(1.57)	(0.36)	(0.40)	(0.11)	(0.12)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO INNER CITY	2.88	−3.57	0.35	−1.69	−0.27	−0.53	−0.12	-0.22^{**}
BALTIMORE (N=2634)	(3.76)	(4.03)	(1.25)	(1.41)	(0.32)	(0.34)	(0.10)	(0.11)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
ALL OF MARYLAND	2.84	−3.93	0.53	−1.59	−0.18	−0.44	−0.086	−0.19
(N=2760)	(3.67)	(3.91)	(1.23)	(1.43)	(0.32)	(0.35)	(0.10)	(0.11)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓

Notes: Standard errors in parentheses. $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$. All models control for ZCTA and year fixed effects. OLS models are weighted for average ZCTA population. Poisson models report percent incidence rate differences. Models (1), (2), (5), and (6) report the effect of the TPR reform as the coefficient on the interaction between the reform indicator and the post period indicator (equal to 1 for years 2010-2013, 0 otherwise). Models (3), (4), (7), and (8) report the effect of an additional year of TPR reform implementation as the coefficient on the interaction between the reform indicator and a post linear time trend indicator (equal to 0 in the pre-reform period, 1 in the first reform year, 2 in the second, etc. The first sample includes ZCTAs assigned to the 8 TPR hospitals and 3 rural control hospitals. The second sample contains the ZCTAs in the first sample plus ZCTAs assigned to non-participating hospitals which don't belong to the CBSAs 12580 (Baltimore-Columbia-Towson) and 47900 (Washington-Arlington-Alexandria). The third sample uses as controls all Maryland ZCTAs assigned to non-participating hospitals which are outside the Baltimore City county (FIPS code 24510). The fourth sample includes all Maryland ZCTAs assigned to non-participating hospitals.

Figure 6.7: Trends in Non-Preventable Admission Rates for the Treatment and Control Groups, 2008-2013

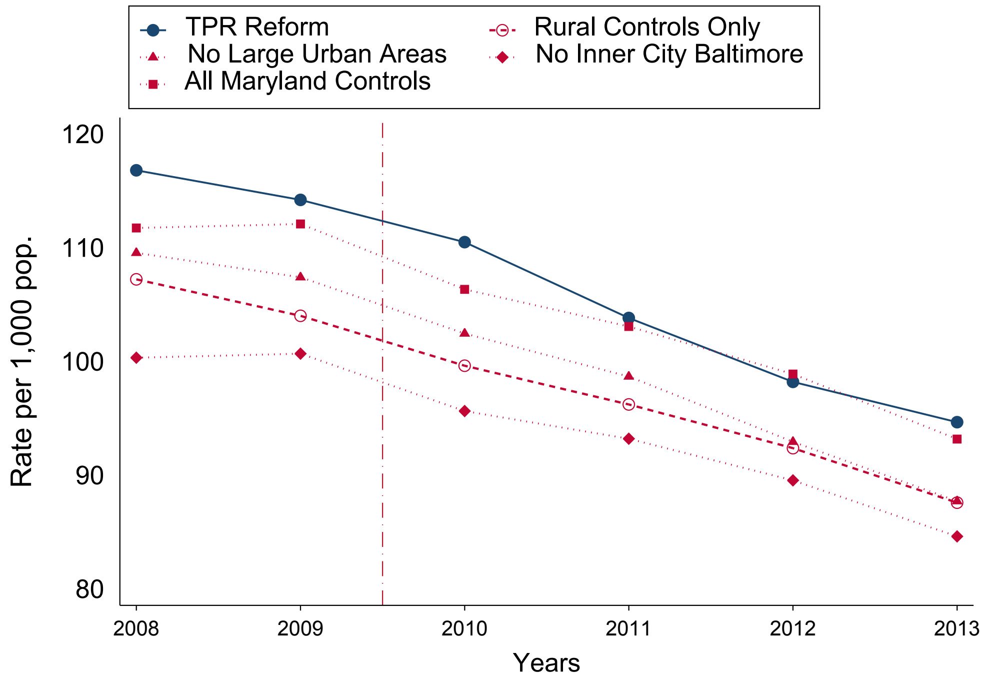


Table 6.8: Estimates of the Effects of TPR on the Rates of Non-Preventable Admissions, with Various Sample Restrictions

	Poisson (offset = log(population))				Weighted OLS (rate per 1,000 capita)			
	(1) TPR	(2) TPR	(3) TPR Years	(4) TPR Years	(5) TPR	(6) TPR	(7) TPR Years	(8) TPR Years
RURAL AREAS ONLY (N=1206)	−1.00	−1.66	−0.48	−0.73	−2.62	−2.63	−1.16	−1.34
	(2.85)	(2.71)	(0.72)	(0.68)	(3.56)	(3.32)	(0.93)	(0.89)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO LARGE URBAN AREAS (N=1566)	0.11	0.60	0.021	0.17	−1.50	−0.40	−0.67	−0.47
	(2.29)	(2.24)	(0.60)	(0.58)	(2.91)	(2.65)	(0.79)	(0.73)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO INNER CITY BALTIMORE (N=2634)	−2.61*	−1.44	−1.02**	−0.94*	−4.29**	−1.74	−1.57**	−1.21
	(1.48)	(1.74)	(0.43)	(0.51)	(2.09)	(2.84)	(0.61)	(0.86)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
ALL OF MARYLAND (N=2760)	−2.45*	−2.54	−0.92**	−1.15**	−3.09	−1.48	−1.11*	−1.08
	(1.45)	(1.66)	(0.42)	(0.50)	(2.09)	(2.66)	(0.61)	(0.82)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓

Notes: Standard errors in parentheses. $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$. All models control for ZCTA and year fixed effects. OLS models are weighted for average ZCTA population. Poisson models report percent incidence rate differences. Models (1), (2), (5), and (6) report the effect of the TPR reform as the coefficient on the interaction between the reform indicator and the post period indicator (equal to 1 for years 2010-2013, 0 otherwise). Models (3), (4), (7), and (8) report the effect of an additional year of TPR reform implementation as the coefficient on the interaction between the reform indicator and a post linear time trend indicator (equal to 0 in the pre-reform period, 1 in the first reform year, 2 in the second, etc. The first sample includes ZCTAs assigned to the 8 TPR hospitals and 3 rural control hospitals. The second sample contains the ZCTAs in the first sample plus ZCTAs assigned to non-participating hospitals which don't belong to the CBSAs 12580 (Baltimore-Columbia-Towson) and 47900 (Washington-Arlington-Alexandria). The third sample uses as controls all Maryland ZCTAs assigned to non-participating hospitals which are outside the Baltimore City county (FIPS code 24510). The fourth sample includes all Maryland ZCTAs assigned to non-participating hospitals.

6.4 Effects on non-deferrable admissions

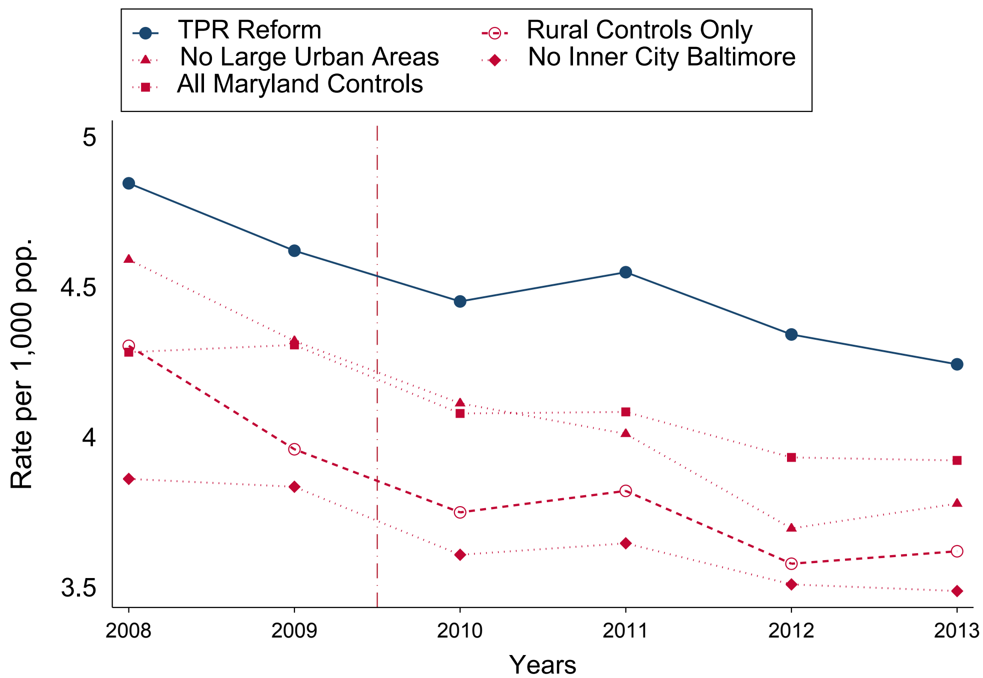
In this section we present the effects on two categories of admissions for which we expect little change as a response to financial incentives, given current clinical guidelines and regulations. Insignificant effects would increase our confidence that the effects we do observe for hospital utilization are not an artifact of confounders such as transient shocks in utilization, unobservable migration patterns, or errors in population estimates and projections.

First we examine the category of admissions considered *non-deferrable*, which includes admissions with one of the top ten diagnoses identified by Card et al. (2009). Figure 6.8 shows that the rates of non-deferrable admissions in the TPR intervention and various control groups remain relatively parallel throughout the study, with the TPR-exposed group having again the highest rates in the state.

The regression results in Table 6.9's models (2) and (4) confirm that there has been virtually no change in the rates of non-deferrable admissions in the TPR regions compared to controls. If anything, the DD estimates of the TPR reform effects are slightly positive, which is not what we would expect if TPR had led to reductions in inpatient utilization across the board. The corresponding Poisson regression results in models (6) and (8) also indicate a small increase, but statistically insignificant in the rural sample and compared to overall Maryland trends.

This finding suggests that TPR hospitals are not skimping on care for pa-

Figure 6.8: Trends in Non-Deferrable Admission Rates for the Treatment and Control Groups, 2008-2013



tients who are unequivocally in need of acute treatment. Overall, we do see a slight decrease in the rates of these types of admissions in both treatment and control areas over time. This merits some explanation. While patients presenting with these diagnoses may not be turned away by hospitals, their rates may decrease in the population over a long period of time. Thus, some of these conditions may still be preventable in the long run, but their rates are not considered easily manipulable by hospitals in the short term. However, to be more confident that this was not the target of hospitals, we also look at what we term *potentially deferrable* admissions, which are simply those admissions which have not already been categorized as non-deferrable. As noted above, we expect that TPR will have a negative effect on these deferrable admissions which will be larger in magnitude than those seen for the non-deferrable admissions.

Figure 6.9 shows the trends in the rates of potentially deferrable admissions in the treatment and the four different control groups. The figure indicates that the rates in this category of admissions decreased more in the TPR group compared to the control groups, particularly in 2011 and 2013. The regression effects presented in Table 6.10 for admissions in this category confirms that the TPR reform led to a reduction in potentially deferrable rates of 2.10 percent compared to the rural control group. This effect is larger than the effect on non-deferrable admissions, and relatively sizable, although not statistically significant. Similarly, the linear effect estimate reflects a decrease of 3.82 admissions per 1,000 residents in this category.

The second category of acute admissions we examine is less specific and includes all admissions from the ED. These patients usually have higher severity and thus require immediate admission, decreasing the likelihood that hospitals would deny them care due to financial incentives. This category also has a high overlap with the non-deferrable category but is more expansive. The rates presented in Figure 6.10 show similar trends to those in non-deferrable admissions, with a slow decrease over time in all areas. ZCTAs exposed to the TPR reform have the highest rates in Maryland both before and after the intervention.

Table 6.11 shows the regression estimates for the models with admissions from the ED as the dependent variable. The results are generally insignificant

Table 6.9: Estimates of the Effects of TPR on the Rates of Non-Deferrable Admissions, with Various Sample Restrictions

	Poisson (offset = log(population))				Weighted OLS (rate per 1,000 capita)			
	(1) TPR	(2) TPR	(3) TPR Years	(4) TPR Years	(5) TPR	(6) TPR	(7) TPR Years	(8) TPR Years
RURAL AREAS ONLY	4.12	6.46	1.00	1.73	0.12	0.25	0.015	0.041
(N=1206)	(3.64)	(4.09)	(1.11)	(1.07)	(0.17)	(0.17)	(0.052)	(0.052)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO LARGE URBAN AREAS	6.04*	9.75***	1.83*	2.82***	0.22	0.41***	0.056	0.099**
(N=1566)	(3.22)	(3.53)	(0.99)	(0.95)	(0.15)	(0.16)	(0.048)	(0.047)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO INNER CITY	0.30	5.74**	−0.18	0.99	−0.030	0.31	−0.023	0.049
BALTIMORE (N=2634)	(2.48)	(2.98)	(0.78)	(0.80)	(0.13)	(0.19)	(0.041)	(0.058)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
ALL OF MARYLAND	−0.94	2.17	−0.49	0.097	−0.050	0.18	−0.028	0.017
(N=2760)	(2.42)	(2.65)	(0.77)	(0.77)	(0.13)	(0.17)	(0.041)	(0.053)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓

Notes: Standard errors in parentheses. $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$. All models control for ZCTA and year fixed effects. OLS models are weighted for average ZCTA population. Poisson models report percent incidence rate differences. Models (1), (2), (5), and (6) report the effect of the TPR reform as the coefficient on the interaction between the reform indicator and the post period indicator (equal to 1 for years 2010-2013, 0 otherwise). Models (3), (4), (7), and (8) report the effect of an additional year of TPR reform implementation as the coefficient on the interaction between the reform indicator and a post linear time trend indicator (equal to 0 in the pre-reform period, 1 in the first reform year, 2 in the second, etc. The first sample includes ZCTAs assigned to the 8 TPR hospitals and 3 rural control hospitals. The second sample contains the ZCTAs in the first sample plus ZCTAs assigned to non-participating hospitals which don't belong to the CBSAs 12580 (Baltimore-Columbia-Towson) and 47900 (Washington-Arlington-Alexandria). The third sample uses as controls all Maryland ZCTAs assigned to non-participating hospitals which are outside the Baltimore City county (FIPS code 24510). The fourth sample includes all Maryland ZCTAs assigned to non-participating hospitals.

Figure 6.9: Trends in Potentially Deferrable Admission Rates for the Treatment and Control Groups, 2008-2013

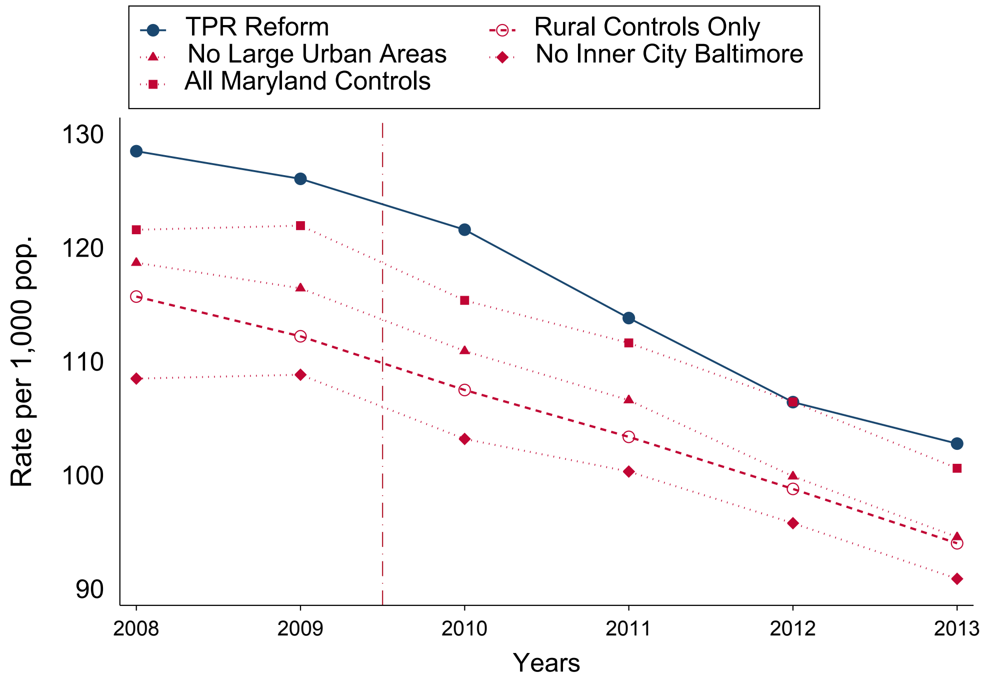
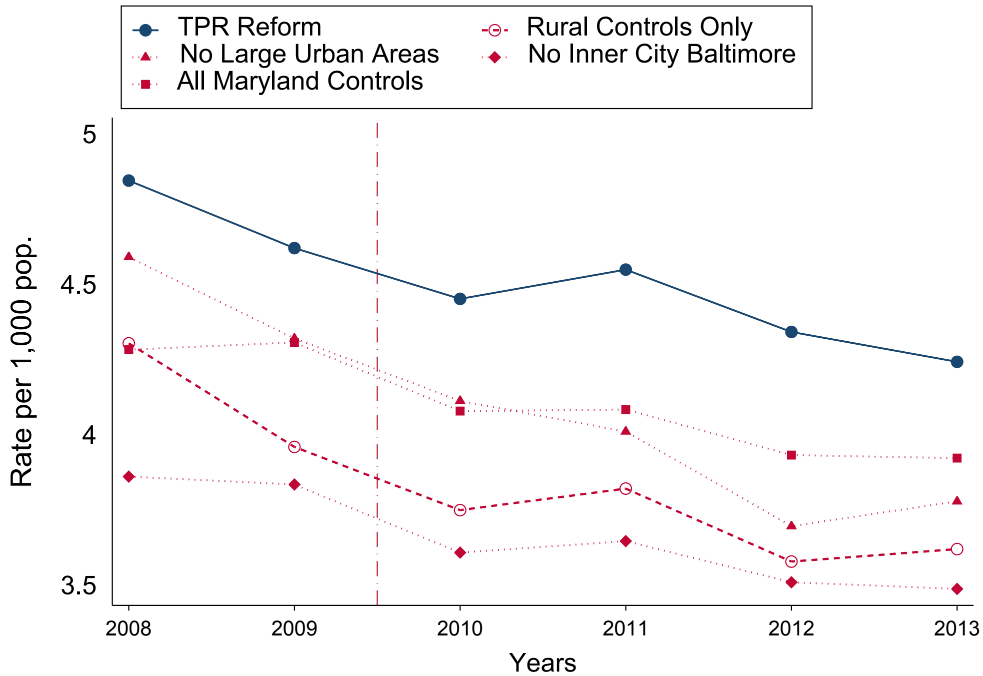


Table 6.10: Estimates of the Effects of TPR on the Rates of Potentially Deferrable Admissions, with Various Sample Restrictions

	Poisson (offset = log(population))				Weighted OLS (rate per 1,000 capita)			
	(1) TPR	(2) TPR	(3) TPR Years	(4) TPR Years	(5) TPR	(6) TPR	(7) TPR Years	(8) TPR Years
RURAL AREAS ONLY	−1.46	−2.10	−0.67	−0.91	−3.89	−3.82	−1.62	-1.83^{*}
(N=1206)	(2.91)	(2.84)	(0.76)	(0.74)	(3.98)	(3.80)	(1.06)	(1.04)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO LARGE URBAN AREAS	−0.38	0.14	−0.18	−0.035	−2.59	−1.28	−1.08	−0.87
(N=1566)	(2.36)	(2.37)	(0.64)	(0.64)	(3.31)	(3.07)	(0.92)	(0.87)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO INNER CITY	-2.95^{*}	−2.32	-1.18^{**}	-1.26^{**}	-5.44^{**}	−3.21	-2.01^{***}	-1.78^{*}
BALTIMORE (N=2634)	(1.56)	(1.79)	(0.48)	(0.56)	(2.47)	(3.16)	(0.74)	(0.97)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
ALL OF MARYLAND	-2.76^{*}	-3.36^{*}	-1.07^{**}	-1.47^{***}	−3.98	−2.62	-1.47^{**}	-1.58^{*}
(N=2760)	(1.54)	(1.73)	(0.48)	(0.56)	(2.48)	(3.03)	(0.74)	(0.95)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓

Notes: Standard errors in parentheses. $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$. All models control for ZCTA and year fixed effects. OLS models are weighted for average ZCTA population. Poisson models report percent incidence rate differences. Models (1), (2), (5), and (6) report the effect of the TPR reform as the coefficient on the interaction between the reform indicator and the post period indicator (equal to 1 for years 2010-2013, 0 otherwise). Models (3), (4), (7), and (8) report the effect of an additional year of TPR reform implementation as the coefficient on the interaction between the reform indicator and a post linear time trend indicator (equal to 0 in the pre-reform period, 1 in the first reform year, 2 in the second, etc. The first sample includes ZCTAs assigned to the 8 TPR hospitals and 3 rural control hospitals. The second sample contains the ZCTAs in the first sample plus ZCTAs assigned to non-participating hospitals which don't belong to the CBSAs 12580 (Baltimore-Columbia-Towson) and 47900 (Washington-Arlington-Alexandria). The third sample uses as controls all Maryland ZCTAs assigned to non-participating hospitals which are outside the Baltimore City county (FIPS code 24510). The fourth sample includes all Maryland ZCTAs assigned to non-participating hospitals.

Figure 6.10: Trends in Rates of Admission from the ED for the Treatment and Control Groups, 2008-2013



with the signs alternating between positive and negative effects. For instance, the linear DD estimate is -0.19 and the time-trend estimate is 0.94 for the rural sample, showing virtually no treatment effect of the TPR reform on admissions from the ED.

6.5 Effects on C-section births

The trends in the percentage of total births by C-section is shown in 6.11. Overall the rates are increasing in all study groups, although there is more noise in the data the smaller the group. The TPR reform group generally has the smallest rate of C-sections, and although this percentage increases between

Table 6.11: Estimates of the Effects of TPR on the Rates of Admissions from the ED, with Various Sample Restrictions

	Poisson (offset = log(population))				Weighted OLS (rate per 1,000 capita)			
	(1) TPR	(2) TPR	(3) TPR Years	(4) TPR Years	(5) TPR	(6) TPR	(7) TPR Years	(8) TPR Years
RURAL AREAS ONLY	0.27	0.94	−0.12	0.17	−1.28	−0.19	−0.70	−0.44
(N=1206)	(3.59)	(3.98)	(0.94)	(0.99)	(2.64)	(2.88)	(0.74)	(0.77)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO LARGE URBAN AREAS	3.39	7.00*	0.46	1.39	0.74	3.75	−0.34	0.36
(N=1566)	(3.30)	(3.77)	(0.82)	(0.86)	(2.37)	(2.47)	(0.65)	(0.65)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO INNER CITY	−0.80	1.30	−0.67	−0.49	−1.79	0.60	−0.92*	−0.58
BALTIMORE (N=2634)	(1.86)	(2.29)	(0.61)	(0.71)	(1.65)	(2.19)	(0.54)	(0.69)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
ALL OF MARYLAND	−0.26	−0.90	−0.51	−0.96	−0.49	1.00	−0.51	−0.46
(N=2760)	(1.83)	(2.11)	(0.61)	(0.69)	(1.67)	(2.08)	(0.55)	(0.68)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓

Notes: Standard errors in parentheses. $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$. All models control for ZCTA and year fixed effects. OLS models are weighted for average ZCTA population. Poisson models report percent incidence rate differences. Models (1), (2), (5), and (6) report the effect of the TPR reform as the coefficient on the interaction between the reform indicator and the post period indicator (equal to 1 for years 2010-2013, 0 otherwise). Models (3), (4), (7), and (8) report the effect of an additional year of TPR reform implementation as the coefficient on the interaction between the reform indicator and a post linear time trend indicator (equal to 0 in the pre-reform period, 1 in the first reform year, 2 in the second, etc. The first sample includes ZCTAs assigned to the 8 TPR hospitals and 3 rural control hospitals. The second sample contains the ZCTAs in the first sample plus ZCTAs assigned to non-participating hospitals which don't belong to the CBSAs 12580 (Baltimore-Columbia-Towson) and 47900 (Washington-Arlington-Alexandria). The third sample uses as controls all Maryland ZCTAs assigned to non-participating hospitals which are outside the Baltimore City county (FIPS code 24510). The fourth sample includes all Maryland ZCTAs assigned to non-participating hospitals.

2008 and 2012, it decreases sharply in 2013 back to its 2008 level. Overall, there is little discernible difference in the unadjusted trends when comparing the reform group with the control groups.

Table 6.12 presents the effects of TPR reform on the proportion of C-sections. Overall, the effects of the TPR reform are small and statistically insignificant. The Poisson estimate in model (2) in the first panel indicates an increase of 6.43 percent in the TPR group compared to the rural controls. The second panel suggests a similar increase of 7.00 percent compared to the larger control areas that exclude urban CBSAs. The effect decreases even more compared to the larger Maryland control groups (3.18 and 2.48 percentage points in the third and fourth panels, respectively), suggesting a no impact overall. The time-trend TPR effects in model (4) are also small but inconsistent in sign across the different panels. These results are supported by the linear estimates in models (6) and (8).

6.6 Summary and sensitivity analyses

Table 6.13 presents a summary of the coefficients and standard errors from the analyses using models with time-varying ZCTA controls and the sample with only rural ZCTAs for the comparison. For overall hospitalizations, we find a small and statistically insignificant reduction of TPR of 1.77 percent in the admission rate and a similarly insignificant effect of TPR of 0.80 percent reduction in the rate for each year that TPR was in effect. However, the effects

Figure 6.11: Trends in C-Section Rates for the Treatment and Control Groups, 2008-2013

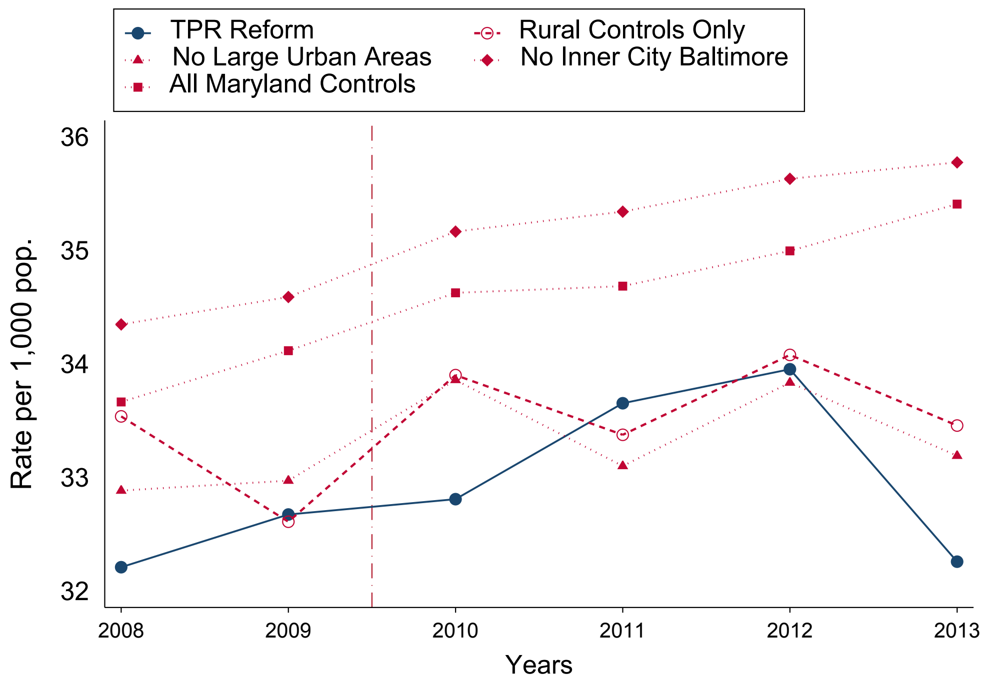


Table 6.12: Estimates of the Effects of TPR on C-section Rates, with Various Sample Restrictions

	Poisson (offset = log(population))				Weighted OLS (rate per 1,000 capita)			
	(1) TPR	(2) TPR	(3) TPR Years	(4) TPR Years	(5) TPR	(6) TPR	(7) TPR Years	(8) TPR Years
RURAL AREAS ONLY	14.4*	6.43	3.56*	1.97	0.058	0.84	0.0087	0.44*
(N=1138)	(8.86)	(9.37)	(1.97)	(2.36)	(0.75)	(0.99)	(0.20)	(0.25)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO LARGE URBAN AREAS	6.06	7.00	1.21	1.63	0.042	0.89	−0.0014	0.36*
(N=1477)	(6.72)	(6.76)	(1.76)	(1.84)	(0.68)	(0.78)	(0.18)	(0.21)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO INNER CITY	4.26	3.18	1.49	1.14	−0.38	0.21	−0.20	−0.048
BALTIMORE (N=2507)	(5.13)	(6.05)	(1.50)	(1.75)	(0.55)	(0.66)	(0.15)	(0.17)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
ALL OF MARYLAND	3.89	2.48	1.35	1.08	−0.37	0.15	−0.21	−0.062
(N=2629)	(5.05)	(5.77)	(1.48)	(1.70)	(0.54)	(0.60)	(0.15)	(0.16)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓

Notes: Standard errors in parentheses. $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$. All models control for ZCTA and year fixed effects. OLS models are weighted for average ZCTA population. Poisson models report percent incidence rate differences. Models (1), (2), (5), and (6) report the effect of the TPR reform as the coefficient on the interaction between the reform indicator and the post period indicator (equal to 1 for years 2010-2013, 0 otherwise). Models (3), (4), (7), and (8) report the effect of an additional year of TPR reform implementation as the coefficient on the interaction between the reform indicator and a post linear time trend indicator (equal to 0 in the pre-reform period, 1 in the first reform year, 2 in the second, etc. The first sample includes ZCTAs assigned to the 8 TPR hospitals and 3 rural control hospitals. The second sample contains the ZCTAs in the first sample plus ZCTAs assigned to non-participating hospitals which don't belong to the CBSAs 12580 (Baltimore-Columbia-Towson) and 47900 (Washington-Arlington-Alexandria). The third sample uses as controls all Maryland ZCTAs assigned to non-participating hospitals which are outside the Baltimore City county (FIPS code 24510). The fourth sample includes all Maryland ZCTAs assigned to non-participating hospitals.

on inpatient days are highly statistically significant, and point to a 5.09 percent reduction compared to the rural controls.

Contrary to our expectations, we do not observe larger relative reductions in preventable hospitalizations (relative to non-preventable hospitalizations). However, there are small reductions in deferrable hospitalizations, while the rates of non-deferrable hospitalizations increased slightly more in the TPR areas, although the effects are imprecisely estimated. Most of the small reduction in preventable hospitalizations stems from a decrease in chronic conditions, of 5.53 percent or a marginally statistically significant 1.14 admissions per 1,000 residents. These estimates are statistically significant in the linear model but lose significance in the Poisson model. This model dependence suggests that the linear model results might be influenced by the skewed distribution of the data. An alternative explanation is that the data is measured with error, which has worse effects on the Poisson model compared to the linear model. Overall, the effect is also imprecisely estimated but does point towards a modest effect of the TPR reform on chronic preventable admissions. We observe a smaller relative decrease in non-preventable admission rates. However, these admissions form a larger proportion of total admissions and therefore lead to a larger (though statistically insignificant) absolute effect overall.

We also find no reductions in the rates of non-deferrable admissions. In fact, this type of admissions shows a small increase compared to the control groups, although the effects are not statistically significant. In contrast, potentially deferrable admissions show a small reduction, though again not statistically significant. Overall these results are in line with our expectations and suggest that hospitals decreased admissions that are not as acute while not reducing inpatient access to high-acuity cases. This is corroborated with the fact that we also find no effects of TPR on admissions from the ED.

Finally, we find no effect of the TPR reform on C-section rates as a measure of discretionary and overutilized services. Although the linear and Poisson models using rural areas as controls show an increase, it is likely that these effects are imprecisely estimated due to the small sample size.

As described in the Methods chapter, we conduct several sets of additional sensitivity analyses. Specifically, we first test whether our results are robust to excluding Western Maryland Regional Medical Center's merger. We then test whether our results are robust to using the Dartmouth Atlas data to assign hospitals to ZCTAs rather than what HSCRC actually did.

Table 6.14 presents the coefficients from regression models which exclude the ZCTAs assigned to the hospital service area of Western Maryland Regional Medical Center (WMRMC) in Cumberland, which opened in 2009 as a merger of Memorial Hospital (Cumberland) and Sacred Heart Hospital (Cumberland), both of which subsequently closed. The qualitative results do not change dramatically by excluding these ZCTAs, although the effects on total and preventable utilization are smaller. The effect on inpatient days remains statistically significant, whereas the effect on chronic preventable admissions, while still negative, loses statistical significance.

We also present summaries of the estimated effects from analyses which

Table 6.13: Summary of Estimated TPR Effects on Inpatient Outcomes—ZCTA Assignment Based on HSCRC Hospital Service Areas

		Poisson		Weighted OLS	
		(1) TPR	(2) TPR Years	(3) TPR	(4) TPR Years
Hospitalizations	Rural controls	-1.77	-0.80	-3.57	-1.79*
		(2.81)	(0.73)	(3.87)	(1.06)
	All Maryland	-3.17*	-1.41**	-2.44	-1.56
		(1.70)	(0.55)	(3.14)	(0.98)
Inpatient days	Rural controls	-5.09*	-1.90***	-29.6**	-12.2***
		(2.72)	(0.65)	(14.6)	(3.69)
	All Maryland	-4.43***	-1.71***	-18.1	-8.14**
		(1.48)	(0.44)	(11.3)	(3.42)
30-day readmissions	Rural controls	2.34	0.46	0.0027	-0.40
		(6.74)	(2.44)	(1.34)	(0.51)
	All Maryland	-5.43	-2.37	-1.12	-0.63*
		(4.59)	(1.72)	(1.00)	(0.36)
Preventable admissions	Rural controls	-1.16	-0.91	-1.05	-0.56*
		(4.49)	(1.39)	(0.89)	(0.30)
	All Maryland	-7.94***	-3.33***	-1.30	-0.66**
		(2.89)	(1.15)	(0.85)	(0.29)
Chronic preventable	Rural controls	-5.53	-2.34	-1.14*	-0.51**
		(4.50)	(1.52)	(0.61)	(0.21)
	All Maryland	-10.5***	-4.47***	-0.86	-0.46**
		(2.87)	(1.15)	(0.57)	(0.20)
Acute preventable	Rural controls	6.17	1.22	0.091	-0.045
		(5.60)	(1.49)	(0.37)	(0.11)
	All Maryland	-3.93	-1.59	-0.44	-0.19*
		(3.91)	(1.43)	(0.35)	(0.11)
Non-preventable admissions	Rural controls	-1.66	-0.73	-2.63	-1.34
		(2.71)	(0.68)	(3.32)	(0.89)
	All Maryland	-2.54	-1.15**	-1.48	-1.08
		(1.66)	(0.50)	(2.66)	(0.82)
Non-deferrable admissions	Rural controls	6.46	1.73	0.25	0.041
		(4.09)	(1.07)	(0.17)	(0.052)
	All Maryland	2.17	0.097	0.18	0.017
		(2.65)	(0.77)	(0.17)	(0.053)
Deferrable admissions	Rural controls	-2.10	-0.91	-3.82	-1.83*
		(2.84)	(0.74)	(3.80)	(1.04)
	All Maryland	-3.36*	-1.47***	-2.62	-1.58*
		(1.73)	(0.56)	(3.03)	(0.95)
Admissions via ED	Rural controls	0.94	0.17	-0.19	-0.44
		(3.98)	(0.99)	(2.88)	(0.77)
	All Maryland	-0.90	-0.96	1.00	-0.46
		(2.11)	(0.69)	(2.08)	(0.68)
Percent of births by C-section	Rural controls	6.43	1.97	0.84	0.44*
		(9.37)	(2.36)	(0.99)	(0.25)
	All Maryland	2.48	1.08	0.15	-0.062
		(5.77)	(1.70)	(0.60)	(0.16)

Notes: Standard errors in parentheses. $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$. Models control for ZCTA and year fixed effects, and time-varying controls at the ZCTA and county level. OLS models are weighted by average ZCTA population. Poisson models report percent incidence rate differences. Models (1) and (3) report the effect of TPR as the coefficient on the interaction between the reform indicator and the post period indicator (equal to 1 for years 2010-2013, 0 otherwise). Models (2) and (4) report the effect of an additional year of TPR implementation.

rely on different sample assignments for the treatment vs. control ZCTAs. Table 6.15 shows results from analyses with ZCTAs assigned to Hospital Service Areas using Dartmouth Atlas crosslink files and Table 6.16 shows results of analyses with ZCTAs assigned to Hospital Service Areas using the county where they are located. Again, the conclusions of our analysis do not change qualitatively.

Table 6.14: Summary of Estimated TPR Effects on Inpatient Outcomes Compared to Rural Controls and All of Maryland, Excluding ZCTAs Served by Western Maryland Regional Medical Center

		Poisson		Weighted OLS	
		(1) TPR	(2) TPR Years	(3) TPR	(4) TPR Years
Hospitalizations	Rural controls	-0.62	-0.34	-2.03	-1.18
		(2.73)	(0.69)	(3.81)	(1.06)
	All Maryland	-2.43	-1.19**	-1.25	-1.18
		(1.77)	(0.58)	(3.23)	(1.02)
Inpatient days	Rural controls	-4.37	-1.52**	-25.3*	-9.97***
		(2.73)	(0.64)	(14.8)	(3.74)
	All Maryland	-3.86**	-1.46***	-13.3	-6.18*
		(1.57)	(0.46)	(11.6)	(3.47)
30-day readmissions	Rural controls	3.59	0.39	0.23	-0.37
		(6.98)	(2.53)	(1.39)	(0.56)
	All Maryland	-3.83	-1.93	-0.65	-0.49
		(5.04)	(1.90)	(1.05)	(0.38)
Preventable admissions	Rural controls	1.90	0.54	-0.28	-0.20
		(4.15)	(1.17)	(0.78)	(0.25)
	All Maryland	-4.77*	-2.19**	-0.58	-0.41
		(2.80)	(1.08)	(0.77)	(0.27)
Chronic preventable	Rural controls	-2.57	-0.64	-0.62	-0.24
		(4.11)	(1.26)	(0.52)	(0.17)
	All Maryland	-6.85**	-2.94***	-0.31	-0.26
		(2.79)	(1.00)	(0.50)	(0.17)
Acute preventable	Rural controls	9.24*	2.22	0.33	0.042
		(5.51)	(1.41)	(0.36)	(0.10)
	All Maryland	-1.54	-1.08	-0.27	-0.15
		(4.08)	(1.50)	(0.35)	(0.12)
Non-preventable admissions	Rural controls	-0.78	-0.42	-1.68	-1.01
		(2.69)	(0.66)	(3.33)	(0.90)
	All Maryland	-2.16	-1.07**	-0.88	-0.90
		(1.75)	(0.54)	(2.81)	(0.87)
Non-deferrable admissions	Rural controls	7.77*	2.53**	0.31*	0.086
		(4.34)	(1.09)	(0.18)	(0.052)
	All Maryland	3.17	0.62	0.25	0.049
		(2.87)	(0.81)	(0.18)	(0.055)
Deferrable admissions	Rural controls	-0.94	-0.46	-2.34	-1.27
		(2.77)	(0.70)	(3.74)	(1.04)
	All Maryland	-2.63	-1.26**	-1.50	-1.23
		(1.80)	(0.59)	(3.12)	(0.98)
Admissions via ED	Rural controls	2.36	0.73	0.84	-0.0016
		(3.89)	(0.95)	(2.81)	(0.77)
	All Maryland	0.24	-0.62	2.00	-0.13
		(2.17)	(0.72)	(2.12)	(0.70)
Percent of births by C-section	Rural controls	7.29	1.75	0.90	0.51*
		(9.79)	(2.54)	(1.02)	(0.26)
	All Maryland	0.88	0.37	-0.090	-0.12
		(5.83)	(1.75)	(0.62)	(0.17)

Notes: Standard errors in parentheses. $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$. Models control for ZCTA and year fixed effects, and time-varying controls at the ZCTA and county level. OLS models are weighted by average ZCTA population. Poisson models report percent incidence rate differences. Models (1) and (3) report the effect of TPR as the coefficient on the interaction between the reform indicator and the post period indicator (equal to 1 for years 2010-2013, 0 otherwise). Models (2) and (4) report the effect of an additional year of TPR implementation.

Table 6.15: Summary of Estimated TPR effects on Inpatient Outcomes Compared to Rural Controls and All of Maryland—Dartmouth Atlas Assignment

		Poisson		Weighted OLS	
		(1) TPR	(2) TPR Years	(3) TPR	(4) TPR Years
Hospitalizations	Rural controls	-4.78*	-1.50**	-8.22**	-3.00***
		(2.71)	(0.71)	(3.83)	(1.09)
	All Maryland	-2.01	-0.95	-1.15	-1.03
		(1.77)	(0.58)	(3.21)	(1.02)
Inpatient days	Rural controls	-7.78***	-2.47***	-44.9***	-15.7***
		(2.71)	(0.68)	(15.3)	(4.10)
	All Maryland	-3.60**	-1.32***	-14.3	-6.33*
		(1.54)	(0.46)	(11.6)	(3.52)
30-day readmissions	Rural controls	7.86*	1.25	0.39	-0.49
		(4.19)	(1.58)	(0.76)	(0.38)
	All Maryland	-3.40	-1.50	-0.89	-0.52
		(4.83)	(1.80)	(1.05)	(0.38)
Preventable admissions	Rural controls	-3.92	-1.83	-1.77*	-0.79***
		(4.49)	(1.34)	(0.90)	(0.30)
	All Maryland	-6.02*	-2.69**	-0.96	-0.55*
		(3.10)	(1.23)	(0.93)	(0.32)
Chronic preventable	Rural controls	-8.36*	-3.45**	-1.67***	-0.70***
		(4.53)	(1.51)	(0.60)	(0.21)
	All Maryland	-8.60***	-3.94***	-0.67	-0.41*
		(3.05)	(1.23)	(0.62)	(0.22)
Acute preventable	Rural controls	3.64	0.66	-0.10	-0.091
		(5.73)	(1.49)	(0.40)	(0.12)
	All Maryland	-1.86	-0.76	-0.30	-0.14
		(4.14)	(1.50)	(0.38)	(0.12)
Non-preventable admissions	Rural controls	-4.68*	-1.40**	-6.73**	-2.37**
		(2.63)	(0.66)	(3.28)	(0.92)
	All Maryland	-1.45	-0.72	-0.39	-0.62
		(1.72)	(0.52)	(2.69)	(0.83)
Non-deferrable admissions	Rural controls	2.95	0.70	0.069	-0.014
		(4.48)	(1.19)	(0.19)	(0.056)
	All Maryland	2.70	0.37	0.18	0.023
		(2.76)	(0.80)	(0.17)	(0.054)
Deferrable admissions	Rural controls	-5.08*	-1.60**	-8.29**	-2.99***
		(2.74)	(0.72)	(3.75)	(1.07)
	All Maryland	-2.19	-1.01*	-1.32	-1.05
		(1.80)	(0.58)	(3.10)	(0.98)
Admissions via ED	Rural controls	-4.28	-0.98	-4.22	-1.41*
		(3.48)	(0.91)	(2.64)	(0.74)
	All Maryland	0.021	-0.54	1.61	-0.17
		(2.17)	(0.72)	(2.13)	(0.71)
Percent of births by C-section	Rural controls	10.5	3.01	1.00	0.44
		(10.3)	(2.62)	(1.13)	(0.29)
	All Maryland	5.42	1.95	0.48	0.049
		(6.15)	(1.77)	(0.63)	(0.17)

Notes: Standard errors in parentheses. $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$. Models control for ZCTA and year fixed effects, and time-varying controls at the ZCTA and county level. OLS models are weighted by average ZCTA population. Poisson models report percent incidence rate differences. Models (1) and (3) report the effect of TPR as the coefficient on the interaction between the reform indicator and the post period indicator (equal to 1 for years 2010-2013, 0 otherwise). Models (2) and (4) report the effect of an additional year of TPR implementation.

Table 6.16: Summary of Estimated TPR Effects on Inpatient Outcomes Compared to Rural Controls and to All of Maryland—County-BasedAssignment

		Poisson		Weighted OLS	
		(1) TPR	(2) TPR Years	(3) TPR	(4) TPR Years
Hospitalizations	Rural controls	-3.26	-0.95	-0.47	0.084
		(2.85)	(0.76)	(7.93)	(2.68)
	All Maryland	-3.55**	-1.46**	-1.51	-1.19
		(1.74)	(0.57)	(3.11)	(0.97)
Inpatient days	Rural controls	-6.34**	-1.96***	-15.9	-4.58
		(2.73)	(0.69)	(30.4)	(9.88)
	All Maryland	-5.21***	-1.89***	-17.5	-7.45**
		(1.47)	(0.45)	(11.2)	(3.33)
30-day readmissions	Rural controls	9.58**	2.86	3.46	0.69
		(4.44)	(1.77)	(2.68)	(0.94)
	All Maryland	-3.18	-1.44	-0.50	-0.40
		(4.69)	(1.73)	(0.99)	(0.36)
Preventable admissions	Rural controls	-1.20	-0.68	-0.41	-0.31
		(4.79)	(1.46)	(1.58)	(0.43)
	All Maryland	-8.95***	-3.58***	-1.00	-0.55*
		(2.98)	(1.21)	(0.89)	(0.30)
Chronic preventable	Rural controls	-5.42	-2.04	-0.56	-0.27
		(4.88)	(1.60)	(1.22)	(0.35)
	All Maryland	-11.7***	-4.86***	-0.73	-0.41**
		(2.96)	(1.21)	(0.62)	(0.20)
Acute preventable	Rural controls	5.57	1.25	0.15	-0.039
		(5.86)	(1.50)	(0.47)	(0.12)
	All Maryland	-4.61	-1.64	-0.27	-0.14
		(4.03)	(1.49)	(0.35)	(0.12)
Non-preventable admissions	Rural controls	-3.32	-0.92	-0.097	0.31
		(2.72)	(0.71)	(6.92)	(2.38)
	All Maryland	-2.84*	-1.18**	-0.63	-0.75
		(1.69)	(0.52)	(2.62)	(0.80)
Non-deferrable admissions	Rural controls	6.09	2.02*	0.65	0.21
		(4.41)	(1.13)	(0.52)	(0.18)
	All Maryland	2.84	0.36	0.25	0.047
		(2.75)	(0.79)	(0.17)	(0.052)
Deferrable admissions	Rural controls	-3.62	-1.07	-1.12	-0.13
		(2.88)	(0.78)	(7.48)	(2.51)
	All Maryland	-3.78**	-1.53***	-1.76	-1.23
		(1.76)	(0.58)	(3.01)	(0.93)
Admissions via ED	Rural controls	-1.06	0.10	1.92	0.87
		(3.77)	(1.01)	(5.41)	(1.79)
	All Maryland	-1.76	-1.12	0.91	-0.38
		(2.13)	(0.72)	(2.12)	(0.69)
Percent of births by C-section	Rural controls	15.3	4.83	0.86	0.39
		(13.3)	(3.54)	(1.07)	(0.26)
	All Maryland	5.19	2.65	0.13	-0.015
		(6.56)	(1.94)	(0.62)	(0.17)

Notes: Standard errors in parentheses. $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$. Models control for ZCTA and year fixed effects, and time-varying controls at the ZCTA and county level. OLS models are weighted by average ZCTA population. Poisson models report percent incidence rate differences. Models (1) and (3) report the effect of TPR as the coefficient on the interaction between the reform indicator and the post period indicator (equal to 1 for years 2010-2013, 0 otherwise). Models (2) and (4) report the effect of an additional year of TPR implementation.

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Chapter 7

Impact on Outpatient Utilization

This chapter presents the estimated effects of the TPR reform on outpatient utilization. As in the previous chapter with our results for inpatient utilization, we begin with the results for two overall outpatient utilization measures. We then distinguish between outpatient services which are considered preventable versus non-preventable in the next two sections, with an expectation that there will be more pronounced effects for the former category.

As before, we first show for each outcome a figure for the unadjusted utilization rates in the intervention group and the four progressively larger control groups, as graphical evidence of the potential different trends in the outcome measures across study groups. We then show a table of TPR effect estimates from the different model specifications. For all outpatient outcomes we omit the full set of estimates and present instead just the coefficients of interest for the effects of TPR.

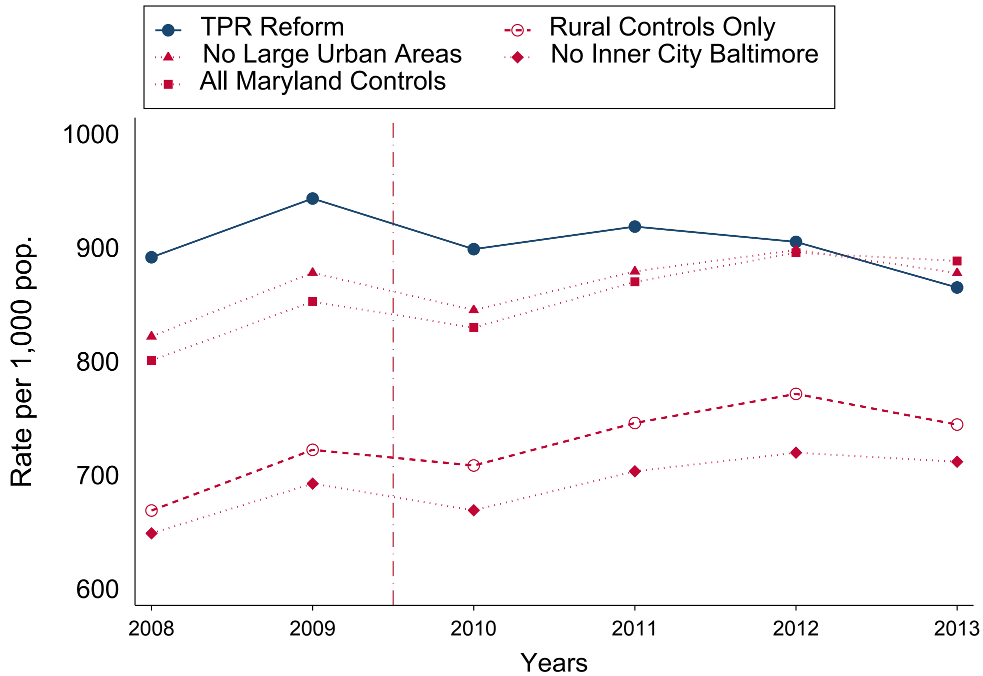
Also as before, the different control groups are shown in four different panels in the summary table for each specific outcome. The Poisson models for utilization counts are shown as the left-side columns, while the linear models for utilization rates are shown as the right-side columns. Within both of those groups, the results from the TPR reform indicator are shown first, and the results from the number of years TPR has been in effect are shown second. Finally, we first show the TPR coefficients from the models which exclude time-varying controls, and we then show the TPR coefficients from the models which include the time-varying controls. However, in the text we focus on summarizing only the results from the fully controlled models.

7.1 Effects on total outpatient utilization

First, we analyze the effect of TPR on total outpatient encounters. This measure includes outpatient clinic visits, emergency department visits, as well as day visits for ambulatory surgeries and other services provided in outpatient facilities. Figure 7.1 shows the population rates of outpatient encounters in the treatment and control groups over the 2008-2013 period. Outpatient utilization rates in the treatment group are the highest in the state in the pre-intervention period, but begin to decrease slightly post-intervention. In contrast, outpatient encounter rates in the control groups increase slowly throughout the entire period, and by 2013 the rates in the TPR group end up at a slightly lower level than the state-wide rates.

Table 7.1 presents regression results confirming that the TPR reform led to

Figure 7.1: Trends in Rates of Outpatient Encounters for the Treatment and Control Groups, 2008-2013



a reduction in outpatient visits after adjusting for potential confounders. The average treatment effect estimates from the Poisson model range between a statistically insignificant 3.58 percent reduction in the second panel and a 9.05 percent reduction in the fourth panel (significant at the 0.01 level). The estimate of the program's effect compared to rural controls is bounded by these values, indicating a highly statistically significant 8.19 percent reduction. Similarly, the effect of each additional TPR year is statistically significant at the 0.01 level using each of the four different control groups and suggests a decrease of between 2.01 percent and 3.63 percent per year.

The linear model estimates in the right side of the table are largely consistent with the linear model estimates. In model (6), the estimate of the TPR effect ranges between -54.6 visits per 1,000 residents (compared to the control areas excluding urban CBSAs) and -103.8 (compared to all of Maryland). The effect of TPR estimated using the rural areas only is a mid-point in this range, at -86.9 visits per 1,000 residents ($p<0.01$). Each additional year post-intervention led to a reduction of between 24.3 and 39.7 admissions per 1,000 residents (model (4), fourth and first panels, respectively), suggesting that the reform effects accumulate over time.

The quantile treatment effects shown in figure C.11 indicate that most of the impact has taken place in the upper end of the distribution, suggesting that the areas with the highest rates of outpatient encounter are responsible for the highest decreases.

Figure 7.2 shows the unadjusted population rates of ED visits in the treatment and control groups. The figure indicates that the TPR group has the highest rates of ED visits, similarly to other utilization rates presented thus far. Moreover, ED visit rates increase in the TPR areas from about 340 to about 375 visits per 1,000 residents. In contrast, the rates of ED visits have increased just slightly in all other control groups, although there is a decrease in 2013 after a peak in 2012 across all groups.

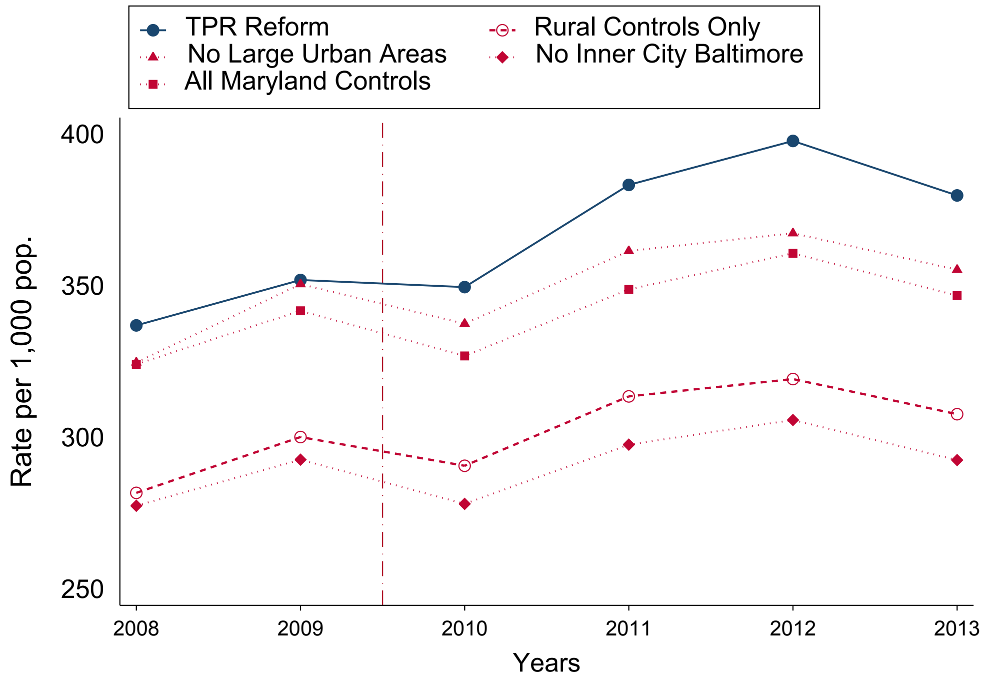
The regression results in Table 7.2 suggest that the TPR areas experienced a slight increase in ED visits compared to the control groups, but this effect is not consistent across the the different study samples. Compared to the rural controls only, we observe statistically insignificant reductions of 0.017 percent in Poisson model (2) and of 3.70 ED visits per 1,000 residents in OLS model

Table 7.1: Estimates of the Effects of TPR on the Rates of Outpatient Encounters, with Various Sample Restrictions

	Poisson (offset = log(population))				Weighted OLS (rate per 1,000 capita)			
	(1) TPR	(2) TPR	(3) TPR Years	(4) TPR Years	(5) TPR	(6) TPR	(7) TPR Years	(8) TPR Years
RURAL AREAS ONLY	-8.75^{**}	-8.19^{***}	-3.02^{***}	-3.63^{***}	-76.3^{**}	-86.9^{***}	-26.5^{***}	-39.7^{***}
(N=1206)	(3.72)	(2.88)	(0.99)	(0.70)	(37.1)	(30.7)	(9.57)	(8.00)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO LARGE URBAN AREAS	-5.50	-3.58	-2.07^{**}	-2.01^{***}	-58.4	-54.6^{*}	-22.9^{**}	-30.3^{***}
(N=1566)	(3.71)	(2.77)	(0.97)	(0.69)	(36.9)	(29.7)	(9.56)	(7.88)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO INNER CITY	-6.88^{*}	-6.25^{**}	-2.60^{***}	-2.62^{***}	-55.3	-57.8^{*}	-20.5^{**}	-24.3^{***}
BALTIMORE (N=2634)	(3.42)	(2.95)	(0.91)	(0.70)	(34.5)	(33.5)	(8.87)	(8.05)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
ALL OF MARYLAND	-8.35^{**}	-9.05^{***}	-3.05^{***}	-3.33^{***}	-76.0^{**}	-103.8^{***}	-27.5^{***}	-34.9^{***}
(N=2760)	(3.36)	(2.95)	(0.90)	(0.76)	(34.9)	(33.7)	(9.00)	(8.44)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓

Notes: Standard errors in parentheses. $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$. All models control for ZCTA and year fixed effects. OLS models are weighted for average ZCTA population. Poisson models report percent incidence rate differences. Models (1), (2), (5), and (6) report the effect of the TPR reform as the coefficient on the interaction between the reform indicator and the post period indicator (equal to 1 for years 2010-2013, 0 otherwise). Models (3), (4), (7), and (8) report the effect of an additional year of TPR reform implementation as the coefficient on the interaction between the reform indicator and a post linear time trend indicator (equal to 0 in the pre-reform period, 1 in the first reform year, 2 in the second, etc. The first sample includes ZCTAs assigned to the 8 TPR hospitals and 3 rural control hospitals. The second sample contains the ZCTAs in the first sample plus ZCTAs assigned to non-participating hospitals which don't belong to the CBSAs 12580 (Baltimore-Columbia-Towson) and 47900 (Washington-Arlington-Alexandria). The third sample uses as controls all Maryland ZCTAs assigned to non-participating hospitals which are outside the Baltimore City county (FIPS code 24510). The fourth sample includes all Maryland ZCTAs assigned to non-participating hospitals.

Figure 7.2: Trends in Rates of ED Visits for the Treatment and Control Groups, 2008-2013



(6). However, using the more expansive control groups, as shown in the lower three panels, we observe increases in ED visits from the Poisson model ranging between an insignificant 2.54 percent and statistically significant 4.81 percent, corresponding to increases in ED visits from the OLS model ranging between an insignificant 2.74 and a significant 17.70 visits per 1,000 residents.

7.2 Effects on preventable ED utilization

The results in the previous section for the effect of TPR on overall ED usage in Maryland are inconclusive. In this section we present analyses for the subset of preventable ED visits which are expected to decrease if the TPR reform in-

Table 7.2: Estimates of the Effects of TPR on the Rates of ED Visits, with Various Sample Restrictions

	Poisson (offset = log(population))				Weighted OLS (rate per 1,000 capita)			
	(1) TPR	(2) TPR	(3) TPR Years	(4) TPR Years	(5) TPR	(6) TPR	(7) TPR Years	(8) TPR Years
RURAL AREAS ONLY	3.68*	−0.017	1.03*	0.011	13.3*	−3.70	3.36	−1.62
(N=1206)	(2.18)	(2.01)	(0.57)	(0.54)	(7.35)	(9.41)	(2.31)	(3.04)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO LARGE URBAN AREAS	4.17**	2.54	1.17**	0.68	11.5*	2.74	2.36	−0.43
(N=1566)	(1.88)	(1.83)	(0.50)	(0.50)	(6.79)	(7.39)	(2.20)	(2.50)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO INNER CITY	6.13***	4.81**	1.62***	1.28***	23.1***	17.7**	6.46***	4.78**
BALTIMORE (N=2634)	(1.70)	(1.92)	(0.50)	(0.47)	(5.42)	(7.88)	(1.77)	(2.33)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
ALL OF MARYLAND	4.47***	3.17*	1.14**	1.03**	16.4***	6.60	4.15**	2.41
(N=2760)	(1.68)	(1.74)	(0.49)	(0.45)	(5.76)	(7.24)	(1.85)	(2.16)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓

Notes: Standard errors in parentheses. $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$. All models control for ZCTA and year fixed effects. OLS models are weighted for average ZCTA population. Poisson models report percent incidence rate differences. Models (1), (2), (5), and (6) report the effect of the TPR reform as the coefficient on the interaction between the reform indicator and the post period indicator (equal to 1 for years 2010-2013, 0 otherwise). Models (3), (4), (7), and (8) report the effect of an additional year of TPR reform implementation as the coefficient on the interaction between the reform indicator and a post linear time trend indicator (equal to 0 in the pre-reform period, 1 in the first reform year, 2 in the second, etc. The first sample includes ZCTAs assigned to the 8 TPR hospitals and 3 rural control hospitals. The second sample contains the ZCTAs in the first sample plus ZCTAs assigned to non-participating hospitals which don't belong to the CBSAs 12580 (Baltimore-Columbia-Towson) and 47900 (Washington-Arlington-Alexandria). The third sample uses as controls all Maryland ZCTAs assigned to non-participating hospitals which are outside the Baltimore City county (FIPS code 24510). The fourth sample includes all Maryland ZCTAs assigned to non-participating hospitals.

duces hospitals to curb expensive services as desired by Maryland policy makers. As described earlier in Chapter 5, these preventable ED visits include non-emergent ED visits, emergent but primary care treatable ED visits, and emergent but avoidable ED visits.

We first focus on conditions classified as non-emergent; i.e. those for which medical care is not needed within 12 hours. Examples in this category include conditions such as sore throat and sunburn. Figure 7.3 shows the unadjusted trends in non-emergent ED visits in the treatment and control groups during 2008-2013 and indicates growth in the rates across all groups, but a slight relative increase in the TPR group compared to control groups. The rate in the TPR group is about 63 visits per 1,000 residents at baseline, but increases to 72 visits per 1,000 residents.

Table 7.3 shows the regression coefficients for non-emergent ED visits. Overall, the results generally indicate a small increase resulting from the TPR reform, but relatively few of the results controlling for time-varying measures are statistically significant.

The second category of preventable utilization consists of ED visits which are considered emergent but primary care treatable; that is, conditions that require medical care within twelve hours but are safely treatable in a primary care setting. Examples in this category include ear infections or asymptomatic varicose veins. Figure 7.4 shows the unadjusted rates in this primary care treatable category of ED visits between 2008 and 2013. These rates have increased for all groups, but the increase appears higher in the TPR reform group

Figure 7.3: Trends in Rates of Non-Emergent ED Visits for the Treatment and Control Groups, 2008-2013

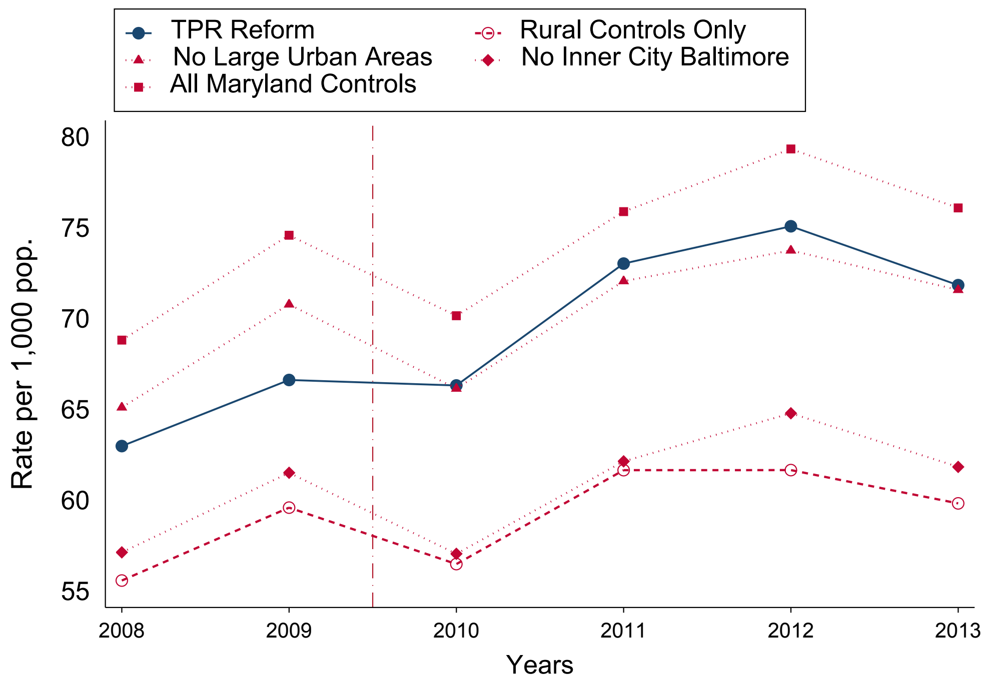
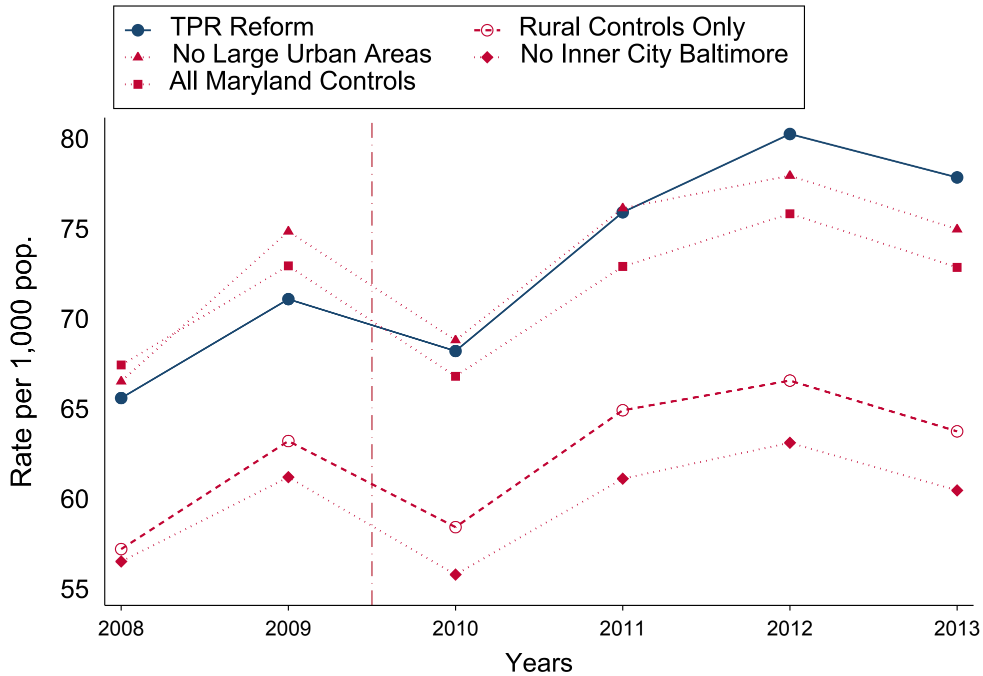


Table 7.3: Estimates of the Effects of TPR on the Rates of Non-Emergent ED visits, with Various Sample Restrictions

	Poisson (offset = log(population))				Weighted OLS (rate per 1,000 capita)			
	(1) TPR	(2) TPR	(3) TPR Years	(4) TPR Years	(5) TPR	(6) TPR	(7) TPR Years	(8) TPR Years
RURAL AREAS ONLY	6.30**	1.72	1.62**	0.14	3.86**	−0.23	0.93*	−0.40
(N=1206)	(2.88)	(2.78)	(0.80)	(0.79)	(1.71)	(2.21)	(0.55)	(0.73)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO LARGE URBAN AREAS	5.93**	4.33*	1.24*	0.55	3.03*	1.09	0.39	−0.38
(N=1566)	(2.58)	(2.52)	(0.75)	(0.76)	(1.65)	(1.75)	(0.56)	(0.63)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO INNER CITY	6.14***	5.35**	1.24*	0.92	4.16***	3.58*	0.92*	0.62
BALTIMORE (N=2634)	(2.39)	(2.67)	(0.74)	(0.75)	(1.40)	(2.00)	(0.48)	(0.63)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
ALL OF MARYLAND	3.79*	3.81	0.66	0.75	2.07	1.06	0.24	0.095
(N=2760)	(2.34)	(2.50)	(0.72)	(0.71)	(1.50)	(1.90)	(0.50)	(0.61)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓

Notes: Standard errors in parentheses. $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$. All models control for ZCTA and year fixed effects. OLS models are weighted for average ZCTA population. Poisson models report percent incidence rate differences. Models (1), (2), (5), and (6) report the effect of the TPR reform as the coefficient on the interaction between the reform indicator and the post period indicator (equal to 1 for years 2010-2013, 0 otherwise). Models (3), (4), (7), and (8) report the effect of an additional year of TPR reform implementation as the coefficient on the interaction between the reform indicator and a post linear time trend indicator (equal to 0 in the pre-reform period, 1 in the first reform year, 2 in the second, etc. The first sample includes ZCTAs assigned to the 8 TPR hospitals and 3 rural control hospitals. The second sample contains the ZCTAs in the first sample plus ZCTAs assigned to non-participating hospitals which don't belong to the CBSAs 12580 (Baltimore-Columbia-Towson) and 47900 (Washington-Arlington-Alexandria). The third sample uses as controls all Maryland ZCTAs assigned to non-participating hospitals which are outside the Baltimore City county (FIPS code 24510). The fourth sample includes all Maryland ZCTAs assigned to non-participating hospitals.

Figure 7.4: Trends in Rates of Primary Care Treatable ED Visits for the Treatment and Control Groups, 2008-2013



relative to all other control groups.

Table 7.4 shows the DD effect estimates for primary care treatable ED visits. The results indicate an increase due to the TPR program relative to the more expansive control groups (third and fourth panels from top to bottom), but a modest effect (and even a potential decrease) compared to the rural control areas (first and second panels). The effect estimates range between an increase of between 1.26 (first panel) and 5.61 percent (third panel) in Poisson model (6) and between -0.71 and 3.78 visits per 1,000 residents in model (2) for the TPR group relative to the control groups. The effects estimated from models (4) and (8) with a yearly reform variable generally follow the same patterns, with a smaller and statistically insignificant effect when compared to a smaller rural control and a larger, significant effect when compared to the more expansive control groups.

The third category of preventable ED visits are those that are considered emergent and require ED care (as opposed to immediate care in a primary care setting), but these patients could have avoided the medical issue if they had received timely and effective outpatient care (e.g., an asthma attack or diabetes with ketoacidosis). Figure 7.5 shows the trends in this category of avoidable ED visits among the intervention and control groups during the study period. Similar to the non-emergent ED visits, the rates in this category increase in the TPR ZCTAs compared to a relatively flat trend in the four control groups. After starting in the middle at about 18.3 avoidable ED visits per 1,000 residents in 2008, the rate increases to 20.5 visits per 1,000 residents in 2013.

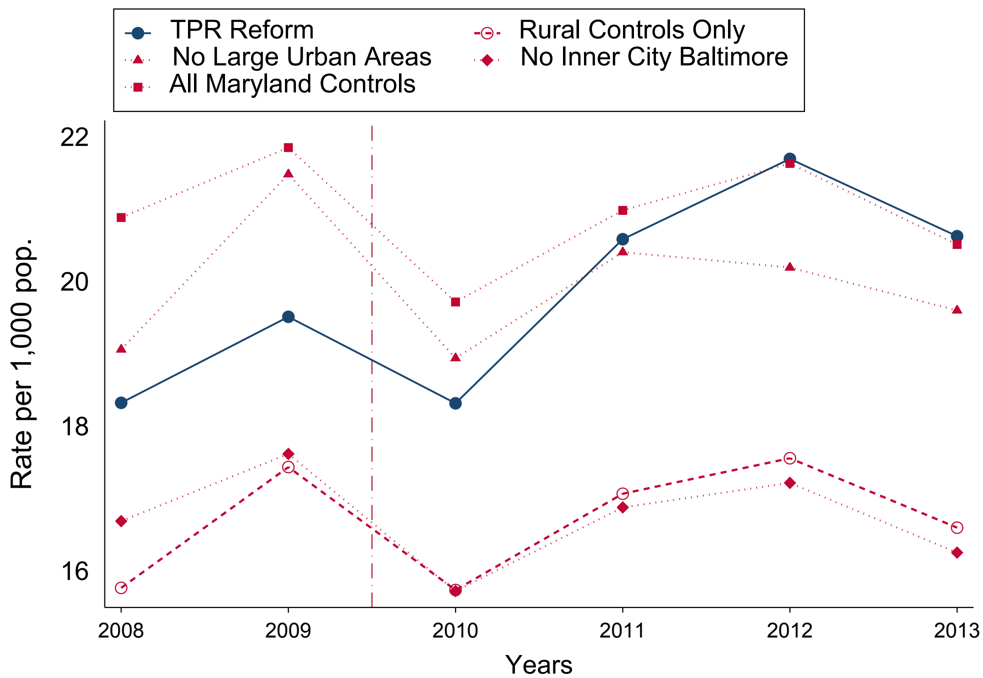
Table 7.5 shows the DD effect estimates for avoidable ED visits. All the coefficients are positive, and statistically significant for all samples except the top panel restricted to the rural-only control group. The Poisson model estimates show an insignificant increase of 3.25 percent using the rural control group (model (2)), but significantly positive estimates in the second through fourth panels using more expansive control areas in the state, ranging between 7.33 and 9.71 percent. Model (4) reinforces the finding that TPR led to an increase in avoidable ED visits, with estimates ranging from 1.31 to 2.93 percent for each year the TPR reform was in effect. The linear models show similar patterns. Compared to the larger control groups, TPR reform reduced avoidable

Table 7.4: Estimates of the Effects of TPR on the Rates of Primary Care Treatable ED Visits, with Various Sample Restrictions

	Poisson (offset = log(population))				Weighted OLS (rate per 1,000 capita)			
	(1) TPR	(2) TPR	(3) TPR Years	(4) TPR Years	(5) TPR	(6) TPR	(7) TPR Years	(8) TPR Years
RURAL AREAS ONLY	5.05*	1.26	1.53*	0.50	3.42*	−0.71	1.01*	−0.19
(N=1206)	(2.93)	(2.65)	(0.81)	(0.73)	(1.78)	(2.15)	(0.55)	(0.70)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO LARGE URBAN AREAS	5.00**	3.21	1.51**	1.03	2.58	−0.0034	0.60	−0.19
(N=1566)	(2.53)	(2.22)	(0.70)	(0.63)	(1.67)	(1.74)	(0.53)	(0.59)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO INNER CITY	7.78***	5.61**	2.22***	1.81***	5.64***	3.78**	1.72***	1.26**
BALTIMORE (N=2634)	(2.23)	(2.37)	(0.65)	(0.60)	(1.28)	(1.75)	(0.40)	(0.51)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
ALL OF MARYLAND	6.35***	4.43**	1.80***	1.60***	4.44***	1.85	1.25***	0.79
(N=2760)	(2.15)	(2.17)	(0.63)	(0.57)	(1.32)	(1.63)	(0.41)	(0.48)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓

Notes: Standard errors in parentheses. $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$. All models control for ZCTA and year fixed effects. OLS models are weighted for average ZCTA population. Poisson models report percent incidence rate differences. Models (1), (2), (5), and (6) report the effect of the TPR reform as the coefficient on the interaction between the reform indicator and the post period indicator (equal to 1 for years 2010-2013, 0 otherwise). Models (3), (4), (7), and (8) report the effect of an additional year of TPR reform implementation as the coefficient on the interaction between the reform indicator and a post linear time trend indicator (equal to 0 in the pre-reform period, 1 in the first reform year, 2 in the second, etc. The first sample includes ZCTAs assigned to the 8 TPR hospitals and 3 rural control hospitals. The second sample contains the ZCTAs in the first sample plus ZCTAs assigned to non-participating hospitals which don't belong to the CBSAs 12580 (Baltimore-Columbia-Towson) and 47900 (Washington-Arlington-Alexandria). The third sample uses as controls all Maryland ZCTAs assigned to non-participating hospitals which are outside the Baltimore City county (FIPS code 24510). The fourth sample includes all Maryland ZCTAs assigned to non-participating hospitals.

Figure 7.5: Trends in Rates of Avoidable ED Visits for the Treatment and Control Groups, 2008-2013



ED visits by between 1.11 and 1.81 ED visits per 1,000 residents (model (6), second and third panels respectively, p<0.01). Similarly, the effect of an additional year of the program is between 0.29 and 0.54 avoidable ED visits per 1,000 residents (model (8), p<0.10 and p<0.01, respectively), while compared to the rural controls this effect is a statistically insignificant increase of 0.10 avoidable ED visits per 1,000 residents.

7.3 Effects on non-preventable ED utilization

In this section we focus on the category of ED visits which are not amenable to improved or more accessible care in physician offices and outpatient set-

Table 7.5: Estimates of the Effects of TPR on the Rates of Avoidable ED Visits, with Various Sample Restrictions

	Poisson (offset = log(population))				Weighted OLS (rate per 1,000 capita)			
	(1) TPR	(2) TPR	(3) TPR Years	(4) TPR Years	(5) TPR	(6) TPR	(7) TPR Years	(8) TPR Years
RURAL AREAS ONLY	6.48^{***}	3.25	1.95^{***}	1.31^{**}	1.15^{**}	0.26	0.33^{**}	0.10
(N=1206)	(2.50)	(2.28)	(0.71)	(0.64)	(0.44)	(0.56)	(0.14)	(0.18)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO LARGE URBAN AREAS	9.88^{***}	7.33^{***}	2.91^{***}	2.31^{***}	1.73^{***}	1.11^{**}	0.47^{***}	0.29^{*}
(N=1566)	(2.30)	(2.28)	(0.63)	(0.62)	(0.45)	(0.50)	(0.14)	(0.15)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO INNER CITY	10.7^{***}	9.71^{***}	3.19^{***}	2.93^{***}	1.94^{***}	1.81^{***}	0.60^{***}	0.54^{***}
BALTIMORE (N=2634)	(1.78)	(2.13)	(0.53)	(0.55)	(0.32)	(0.46)	(0.10)	(0.13)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
ALL OF MARYLAND	8.92^{***}	7.40^{***}	2.69^{***}	2.55^{***}	1.75^{***}	1.20^{***}	0.51^{***}	0.40^{***}
(N=2760)	(1.69)	(1.96)	(0.50)	(0.54)	(0.33)	(0.43)	(0.10)	(0.13)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓

Notes: Standard errors in parentheses. $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$. All models control for ZCTA and year fixed effects. OLS models are weighted for average ZCTA population. Poisson models report percent incidence rate differences. Models (1), (2), (5), and (6) report the effect of the TPR reform as the coefficient on the interaction between the reform indicator and the post period indicator (equal to 1 for years 2010-2013, 0 otherwise). Models (3), (4), (7), and (8) report the effect of an additional year of TPR reform implementation as the coefficient on the interaction between the reform indicator and a post linear time trend indicator (equal to 0 in the pre-reform period, 1 in the first reform year, 2 in the second, etc. The first sample includes ZCTAs assigned to the 8 TPR hospitals and 3 rural control hospitals. The second sample contains the ZCTAs in the first sample plus ZCTAs assigned to non-participating hospitals which don't belong to the CBSAs 12580 (Baltimore-Columbia-Towson) and 47900 (Washington-Arlington-Alexandria). The third sample uses as controls all Maryland ZCTAs assigned to non-participating hospitals which are outside the Baltimore City county (FIPS code 24510). The fourth sample includes all Maryland ZCTAs assigned to non-participating hospitals.

tings. As described earlier in Chapter 5, these non-preventable ED visits include emergent non-preventable ED visits, injury-related ED visits, and behavioral ED visits. As noted earlier, if the TPR program impacted care through the mechanisms envisioned by Maryland policy makers, then we expect a smaller effect in these categories compared to the preventable types of ED visits examined in the prior section.

Unadjusted rates of emergent non-preventable ED visits, which include conditions such as cardiac disrhythmias or meningitis, are shown in Figure 7.6. These non-preventable ED rates increase in all the treatment and control groups between 2008 and 2013, but a slightly larger increase occurs in the TPR treatment group from about 35 to more than 45 non-preventable ED visits per 1,000 residents. For the control group excluding large urban areas, in contrast, the non-preventable ED rate starts out equal to that in the treatment group in 2008 but increases to 43 ED visits per 1,000 residents in 2013.

The regression results shown in Table 7.6 indicate that relative to the Maryland control groups, the TPR reform leads to an increase in non-preventable ED visits, but the magnitude of this effect is small and not consistently significant statistically. The strongest effects are evident relative to the areas that exclude Baltimore City County (third panel), which indicate a 6.19 percent increase in Poisson model (2) and an increase of 2.66 non-preventable ED visits per 1,000 residents ($p<0.01$) in OLS model (6). Overall, we find that the TPR program is associated with a modest uptick in non-preventable ED visits.

Figure 7.7 shows the unadjusted rates of injury-related ED visits during

Figure 7.6: Trends in Rates of Non-Preventable ED Visits for the Treatment and Control Groups, 2008-2013

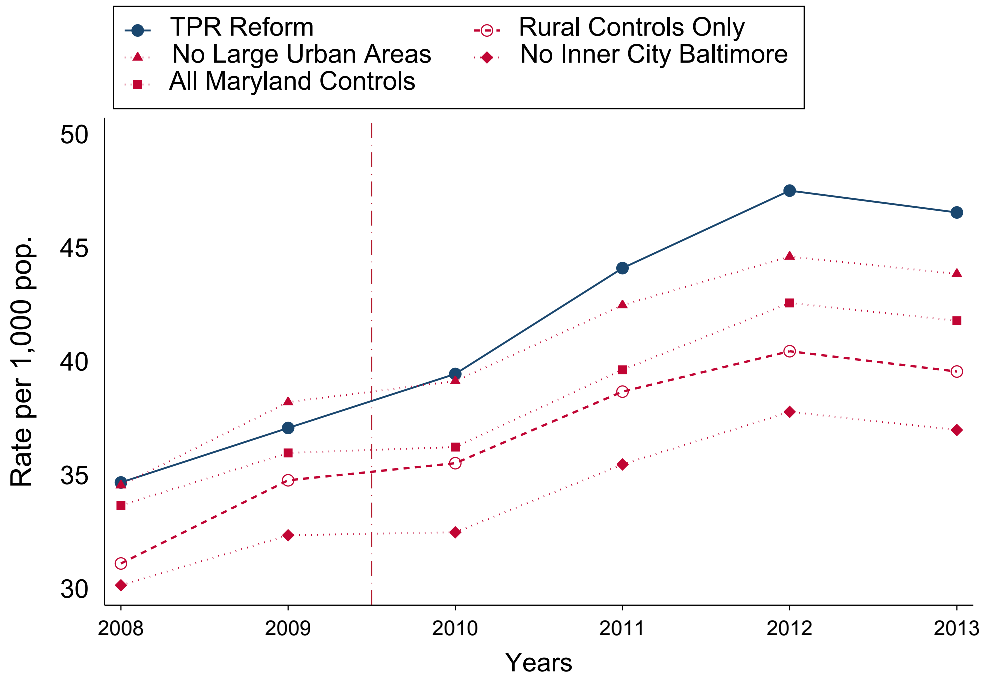


Table 7.6: Estimates of the Effects of TPR on the Rates of Non-Preventable ED Visits, with Various Sample Restrictions

	Poisson (offset = log(population))				Weighted OLS (rate per 1,000 capita)			
	(1) TPR	(2) TPR	(3) TPR Years	(4) TPR Years	(5) TPR	(6) TPR	(7) TPR Years	(8) TPR Years
RURAL AREAS ONLY	5.89**	3.03	1.76**	0.92	2.82***	1.18	0.85***	0.38
(N=1206)	(2.66)	(2.82)	(0.73)	(0.66)	(0.96)	(1.08)	(0.29)	(0.30)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO LARGE URBAN AREAS	6.05***	4.54**	1.76***	1.23**	2.11**	1.15	0.57**	0.26
(N=1566)	(2.20)	(2.13)	(0.61)	(0.54)	(0.85)	(0.80)	(0.28)	(0.26)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO INNER CITY	8.32***	6.19***	2.12***	1.45***	4.12***	2.66***	1.17***	0.72***
BALTIMORE (N=2634)	(1.89)	(2.03)	(0.55)	(0.49)	(0.66)	(0.90)	(0.22)	(0.27)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
ALL OF MARYLAND	6.92***	3.98**	1.66***	1.07**	3.10***	0.92	0.81***	0.35
(N=2760)	(1.84)	(1.83)	(0.54)	(0.48)	(0.70)	(0.82)	(0.23)	(0.25)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓

Notes: Standard errors in parentheses. $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$. All models control for ZIP code and year fixed effects. OLS models are weighted for average ZIP code population. Poisson models report percent incidence rate differences. Models (1), (2), (5), and (6) report the effect of the TPR reform as the coefficient on the interaction between the reform indicator and the post period indicator (equal to 1 for years 2010-2013, 0 otherwise). Models (3), (4), (7), and (8) report the effect of an additional year of TPR reform implementation as the coefficient on the interaction between the reform indicator and a post linear time trend indicator (equal to 0 in the pre-reform period, 1 in the first reform year, 2 in the second, etc. The first sample includes ZCTAs assigned to the 8 TPR hospitals and 3 rural control hospitals. The second sample contains the ZCTAs in the first sample plus ZCTAs assigned to non-participating hospitals which don't belong to the CBSAs 12580 (Baltimore-Columbia-Towson) and 47900 (Washington-Arlington-Alexandria). The third sample uses as controls all Maryland ZCTAs assigned to non-participating hospitals which are outside the Baltimore City county (FIPS code 24510). The fourth sample includes all Maryland ZCTAs assigned to non-participating hospitals.

the study period for the treatment and control groups. These rates mostly experienced modest decreases over the study period, which are similar for the treatment and control groups, supporting the *ex ante* expectation that the TPR reform should have no effect on injury-related ED visits.

Table 7.7 shows the regression results for injury-related ED visits. As expected, the estimates are small and mostly statistically insignificant, and do not point consistently towards either an increase or a decrease. For example, four of the eight estimates in models (2) and (6) are negative (first and second panel) and the other four are positive (third and fourth panel), and only one estimate is marginally significant. The estimated effect of the TPR reform is between -1.01 and 3.73 percent from the Poisson model and between -2.49 and 3.10 injury-related visits per 1,000 residents from the OLS model. A similar pattern of mostly insignificant positive and negative estimates essentially centered on zero is also evident in models (4) and (8).

Unadjusted rates of behavioral ED visits, which include visits related to alcohol, drugs, and psychiatric conditions, are shown in Figure 7.8 for the treatment and control groups during 2008-2013. The trends look remarkably parallel with a steady increase from 2008 to 2012 and a leveling off in 2013, suggesting little effect caused by the TPR program.

Regression results for behavioral ED visits are shown in Table 7.8 and support the patterns observed in Figure 7.8, as all of the effect estimates are statistically insignificant, most are small in magnitude, and alternate in sign. This indicates that the TPR reform had no effect on behavioral ED visits.

Figure 7.7: Trends in Rates of Injury-Related ED Visits for the Treatment and Control Groups, 2008-2013

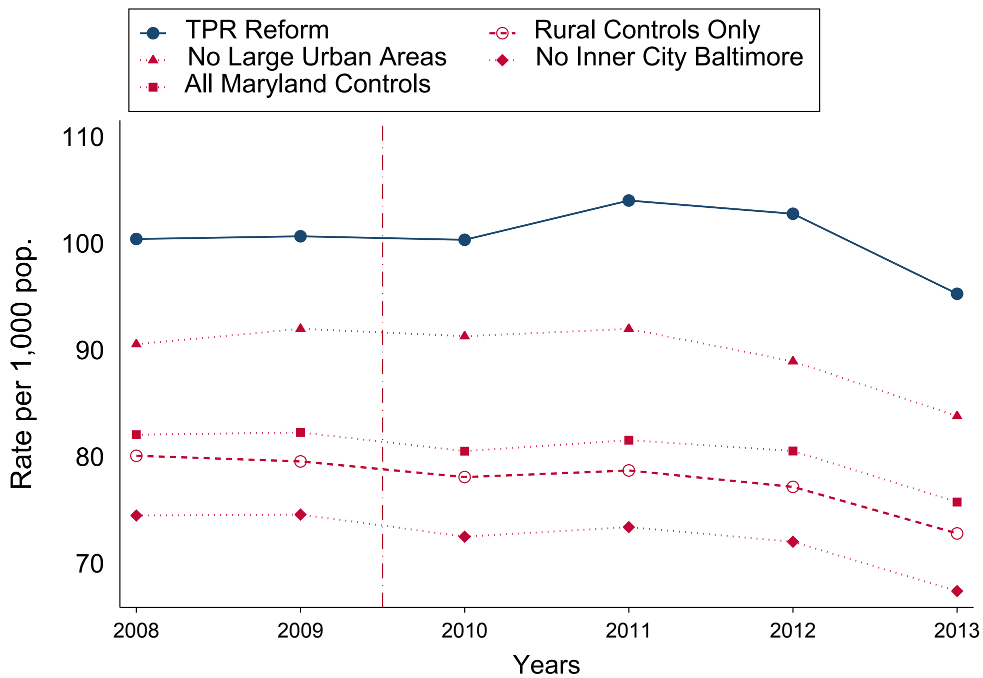


Table 7.7: Estimates of the Effects of TPR on the Rates of Injury-Related ED Visits, with Various Sample Restrictions

	Poisson (offset = log(population))				Weighted OLS (rate per 1,000 capita)			
	(1) TPR	(2) TPR	(3) TPR Years	(4) TPR Years	(5) TPR	(6) TPR	(7) TPR Years	(8) TPR Years
RURAL AREAS ONLY	4.30*	−1.01	1.17*	−0.079	2.46	−2.49	0.34	−1.00
(N=1206)	(2.47)	(2.32)	(0.68)	(0.67)	(2.38)	(2.80)	(0.75)	(0.88)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO LARGE URBAN AREAS	2.69	−0.087	0.93	0.38	1.37	−1.77	0.21	−0.55
(N=1566)	(2.15)	(2.10)	(0.61)	(0.61)	(2.23)	(2.38)	(0.70)	(0.75)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO INNER CITY	4.37**	3.73*	1.20**	1.16**	2.94	3.10	0.59	0.59
BALTIMORE (N=2634)	(1.95)	(2.03)	(0.60)	(0.54)	(1.83)	(2.29)	(0.60)	(0.68)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
ALL OF MARYLAND	2.63	2.47	0.66	0.97*	1.95	1.48	0.30	0.32
(N=2760)	(1.90)	(1.92)	(0.58)	(0.52)	(1.84)	(2.11)	(0.59)	(0.63)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓

Notes: Standard errors in parentheses. $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$. All models control for ZCTA and year fixed effects. OLS models are weighted for average ZCTA population. Poisson models report percent incidence rate differences. Models (1), (2), (5), and (6) report the effect of the TPR reform as the coefficient on the interaction between the reform indicator and the post period indicator (equal to 1 for years 2010-2013, 0 otherwise). Models (3), (4), (7), and (8) report the effect of an additional year of TPR reform implementation as the coefficient on the interaction between the reform indicator and a post linear time trend indicator (equal to 0 in the pre-reform period, 1 in the first reform year, 2 in the second, etc. The first sample includes ZCTAs assigned to the 8 TPR hospitals and 3 rural control hospitals. The second sample contains the ZCTAs in the first sample plus ZCTAs assigned to non-participating hospitals which don't belong to the CBSAs 12580 (Baltimore-Columbia-Towson) and 47900 (Washington-Arlington-Alexandria). The third sample uses as controls all Maryland ZCTAs assigned to non-participating hospitals which are outside the Baltimore City county (FIPS code 24510). The fourth sample includes all Maryland ZCTAs assigned to non-participating hospitals.

Figure 7.8: Trends in Rates of Behavioral ED Visits for the Treatment and Control Groups, 2008-2013

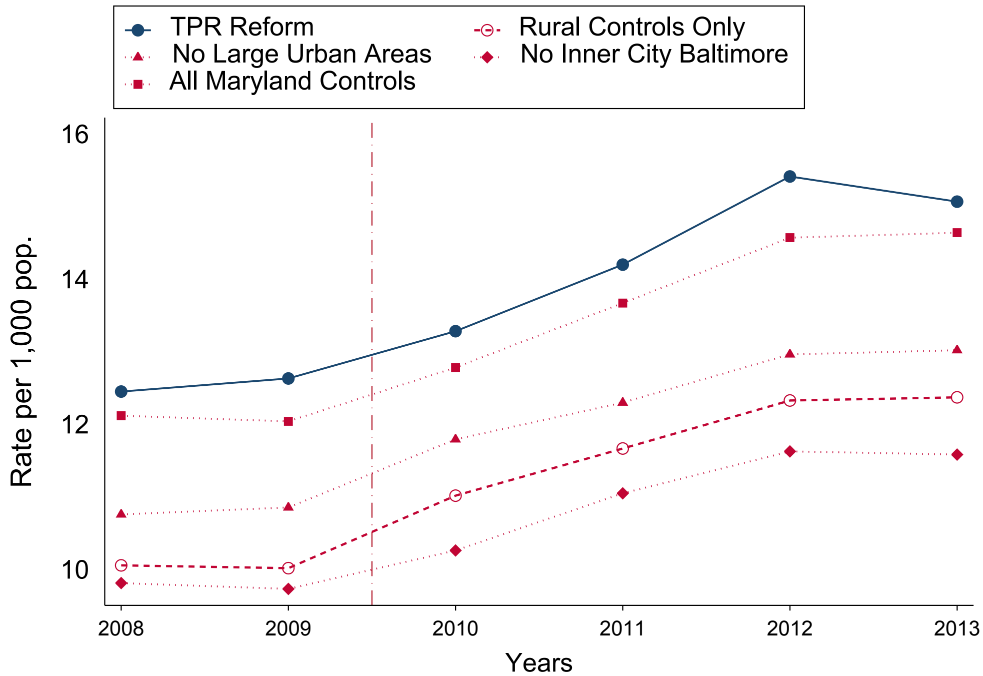


Table 7.8: Estimates of the Effects of TPR on the Rates of Behavioral ED Visits, with Various Sample Restrictions

	Poisson (offset = log(population))				Weighted OLS (rate per 1,000 capita)			
	(1) TPR	(2) TPR	(3) TPR Years	(4) TPR Years	(5) TPR	(6) TPR	(7) TPR Years	(8) TPR Years
RURAL AREAS ONLY	−2.90	0.14	−0.47	0.0081	−0.13	−0.10	−0.025	−0.065
(N=1206)	(3.69)	(3.63)	(1.06)	(1.00)	(0.56)	(0.75)	(0.19)	(0.24)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO LARGE URBAN AREAS	−0.95	3.08	0.11	0.95	−0.00071	0.41	0.013	0.093
(N=1566)	(3.31)	(3.32)	(0.96)	(0.94)	(0.52)	(0.60)	(0.17)	(0.19)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO INNER CITY	1.05	1.07	0.42	0.32	0.54	0.29	0.18	0.100
BALTIMORE (N=2634)	(2.70)	(2.85)	(0.83)	(0.88)	(0.42)	(0.50)	(0.14)	(0.16)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
ALL OF MARYLAND	−1.06	−2.69	−0.26	−0.45	−0.044	−0.89	−0.012	−0.15
(N=2760)	(2.79)	(2.76)	(0.86)	(0.92)	(0.46)	(0.55)	(0.15)	(0.17)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓

Notes: Standard errors in parentheses. $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$. All models control for ZCTA and year fixed effects. OLS models are weighted for average ZCTA population. Poisson models report percent incidence rate differences. Models (1), (2), (5), and (6) report the effect of the TPR reform as the coefficient on the interaction between the reform indicator and the post period indicator (equal to 1 for years 2010-2013, 0 otherwise). Models (3), (4), (7), and (8) report the effect of an additional year of TPR reform implementation as the coefficient on the interaction between the reform indicator and a post linear time trend indicator (equal to 0 in the pre-reform period, 1 in the first reform year, 2 in the second, etc. The first sample includes ZCTAs assigned to the 8 TPR hospitals and 3 rural control hospitals. The second sample contains the ZCTAs in the first sample plus ZCTAs assigned to non-participating hospitals which don't belong to the CBSAs 12580 (Baltimore-Columbia-Towson) and 47900 (Washington-Arlington-Alexandria). The third sample uses as controls all Maryland ZCTAs assigned to non-participating hospitals which are outside the Baltimore City county (FIPS code 24510). The fourth sample includes all Maryland ZCTAs assigned to non-participating hospitals.

7.4 Summary and sensitivity analyses

Table 7.9 presents a summary of the estimated effects and standard errors from analyses of outpatient utilization comparing the TPR group to the group of rural control ZCTAs and to the full Maryland controls. As with our summary of results for inpatient utilization, we show these results for the former group as these rural areas are most similar to the TPR hospital service areas. We show results for the latter group as a comparison to the overall utilization trends in Maryland.

As shown above, we find a statistically significant reduction of 8.19 percent in outpatient encounters due to the TPR reform, while the linear model indicates a reduction of 86.9 outpatient encounters per 1,000 residents ($p<0.01$). These effects are similar to those estimated from comparisons with the expanded control groups.

For ED visits, the results are less conclusive. While the effects in the restricted rural sample are indicative of a slight and statistically insignificant reduction, the coefficients change signs and increase in magnitude when the TPR groups is compared to the more expansive controls in Maryland, indicating an increase. For preventable ED visits, including non-emergent, primary care treatable, and avoidable ED visits, the estimated effects are small in magnitude and statistically insignificant in the rural-only sample. However, as with total ED visits, they indicate a significant increase in the TPR group compared to the larger Maryland controls. This sample dependence suggests that other unmeasured factors may be affecting these indicators in other areas of Maryland or that the results are vulnerable to limitations in the Billings algorithm. Nevertheless, for non-preventable, injury-related, and behavioral ED visits, we find the expected results of no effect of the TPR reform.

As in the previous chapter, we also show the results of several analyses which rely on different sample assignment methodologies for the treatment and control ZCTAs. Table 7.11 shows results from the analyses for outpatient utilization with ZCTAs instead assigned to Hospital Service Areas using Dartmouth Atlas crosslink files and Table 7.12 shows analogous results of analyses with ZCTAs assigned to Hospital Service Areas using the county where they are located. Again, the conclusions of our analysis do not change qualitatively.

Table 7.9: Summary of Estimated TPR Effects on Outpatient Outcomes—ZCTA Assignment Based on HSCRC Hospital Service Areas

		Poisson		Weighted OLS	
		(1) TPR	(2) TPR Years	(3) TPR	(4) TPR Years
Outpatient visits	Rural controls	-8.19***	-3.63***	-86.9***	-39.7***
		(2.88)	(0.70)	(30.7)	(8.00)
	All Maryland	-9.05***	-3.33***	-103.8***	-34.9***
		(2.95)	(0.76)	(33.7)	(8.44)
ED visits	Rural controls	-0.017	0.011	-3.70	-1.62
		(2.01)	(0.54)	(9.41)	(3.04)
	All Maryland	3.17*	1.03**	6.60	2.41
		(1.74)	(0.45)	(7.24)	(2.16)
Non-emergent ED visits	Rural controls	1.72	0.14	-0.23	-0.40
		(2.78)	(0.79)	(2.21)	(0.73)
	All Maryland	3.81	0.75	1.06	0.095
		(2.50)	(0.71)	(1.90)	(0.61)
PC treatable ED visits	Rural controls	1.26	0.50	-0.71	-0.19
		(2.65)	(0.73)	(2.15)	(0.70)
	All Maryland	4.43**	1.60***	1.85	0.79
		(2.17)	(0.57)	(1.63)	(0.48)
Avoidable ED visits	Rural controls	3.25	1.31**	0.26	0.10
		(2.28)	(0.64)	(0.56)	(0.18)
	All Maryland	7.40***	2.55***	1.20***	0.40***
		(1.96)	(0.54)	(0.43)	(0.13)
Non-preventable ED visits	Rural controls	3.03	0.92	1.18	0.38
		(2.82)	(0.66)	(1.08)	(0.30)
	All Maryland	3.98**	1.07**	0.92	0.35
		(1.83)	(0.48)	(0.82)	(0.25)
Injury-related ED visits	Rural controls	-1.01	-0.079	-2.49	-1.00
		(2.32)	(0.67)	(2.80)	(0.88)
	All Maryland	2.47	0.97*	1.48	0.32
		(1.92)	(0.52)	(2.11)	(0.63)
Behavioral ED visits	Rural controls	0.14	0.0081	-0.10	-0.065
		(3.63)	(1.00)	(0.75)	(0.24)
	All Maryland	-2.69	-0.45	-0.89	-0.15
		(2.76)	(0.92)	(0.55)	(0.17)

Notes: Standard errors in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. All models control for ZCTA and year fixed effects, as well as time-varying controls at the ZCTA and county level. OLS models are weighted for average ZCTA population. Poisson models report percent incidence rate differences. Models (1) and (3) report the effect of the TPR reform as the coefficient on the interaction between the reform indicator and the post period indicator (equal to 1 for years 2010-2013, 0 otherwise). Models (2) and (4) report the effect of an additional year of TPR reform implementation.

Table 7.10: Summary of Estimated TPR Effects on Outpatient Outcomes Compared to Rural Controls and All of Maryland, Excluding ZCTAs Served by Western Maryland Regional Medical Center

		Poisson		Weighted OLS	
		(1) TPR	(2) TPR Years	(3) TPR	(4) TPR Years
Outpatient visits	Rural controls	-4.56*	-2.53***	-47.0*	-27.7***
		(2.63)	(0.64)	(24.4)	(7.34)
	All Maryland	-4.19*	-2.07***	-57.6**	-23.8***
		(2.15)	(0.59)	(23.0)	(6.67)
ED visits	Rural controls	0.83	0.42	-0.81	-0.36
		(2.12)	(0.58)	(9.74)	(3.26)
	All Maryland	4.22**	1.31***	9.76	3.29
		(1.79)	(0.47)	(7.40)	(2.29)
Non-emergent ED visits	Rural controls	3.33	0.85	0.92	0.091
		(2.92)	(0.84)	(2.27)	(0.78)
	All Maryland	6.07**	1.34*	2.44	0.46
		(2.51)	(0.77)	(1.89)	(0.65)
PC treatable ED visits	Rural controls	1.63	0.93	-0.50	0.078
		(2.72)	(0.79)	(2.22)	(0.76)
	All Maryland	5.61**	2.09***	2.52	1.09**
		(2.32)	(0.62)	(1.65)	(0.50)
Avoidable ED visits	Rural controls	4.15*	1.81***	0.41	0.18
		(2.37)	(0.70)	(0.58)	(0.20)
	All Maryland	8.38***	2.88***	1.35***	0.45***
		(2.04)	(0.60)	(0.44)	(0.13)
Non-preventable ED visits	Rural controls	3.38	0.89	1.29	0.33
		(2.93)	(0.69)	(1.09)	(0.31)
	All Maryland	4.03**	0.93*	0.93	0.28
		(1.97)	(0.48)	(0.86)	(0.26)
Injury-related ED visits	Rural controls	-0.34	0.34	-1.78	-0.58
		(2.39)	(0.69)	(2.89)	(0.93)
	All Maryland	3.33*	1.22**	2.20	0.57
		(2.00)	(0.54)	(2.19)	(0.66)
Behavioral ED visits	Rural controls	1.56	0.44	0.092	-0.010
		(3.67)	(1.03)	(0.76)	(0.25)
	All Maryland	-1.81	-0.30	-0.74	-0.13
		(2.91)	(0.99)	(0.59)	(0.18)

Notes: Standard errors in parentheses. $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$. All models control for ZCTA and year fixed effects, as well as time-varying controls at the ZCTA and county level. OLS models are weighted for average ZCTA population. Poisson models report percent incidence rate differences. Models (1) and (3) report the effect of the TPR reform as the coefficient on the interaction between the reform indicator and the post period indicator (equal to 1 for years 2010-2013, 0 otherwise). Models (2) and (4) report the effect of an additional year of TPR reform implementation.

Table 7.11: Summary of Estimated TPR Effects on Outpatient Outcomes Compared to Rural Controls and All of Maryland—Dartmouth Atlas Assignment

		Poisson		Weighted OLS	
		(1) TPR	(2) TPR Years	(3) TPR	(4) TPR Years
Outpatient visits	Rural controls	-10.5***	-4.31***	-103.0***	-44.0***
		(3.10)	(0.72)	(35.2)	(9.17)
	All Maryland	-9.48***	-3.39***	-109.4***	-36.1***
		(3.12)	(0.81)	(36.2)	(8.98)
ED visits	Rural controls	-0.54	-0.20	-3.50	-1.96
		(2.17)	(0.59)	(11.6)	(3.88)
	All Maryland	3.70**	1.19**	9.21	3.11
		(1.83)	(0.47)	(7.26)	(2.20)
Non-emergent ED visits	Rural controls	0.066	-0.24	-0.74	-0.54
		(2.86)	(0.85)	(2.65)	(0.90)
	All Maryland	4.24*	0.88	1.45	0.22
		(2.63)	(0.75)	(1.93)	(0.62)
PC treatable ED visits	Rural controls	0.35	0.16	-0.71	-0.27
		(2.58)	(0.72)	(2.47)	(0.85)
	All Maryland	4.87**	1.70***	2.41	0.92*
		(2.30)	(0.60)	(1.67)	(0.50)
Avoidable ED visits	Rural controls	2.65	1.08	0.17	0.056
		(2.38)	(0.70)	(0.66)	(0.23)
	All Maryland	8.19***	2.73***	1.41***	0.45***
		(2.04)	(0.57)	(0.43)	(0.13)
Non-preventable ED visits	Rural controls	3.86	1.08	2.05*	0.59*
		(3.34)	(0.76)	(1.20)	(0.34)
	All Maryland	4.42**	1.21**	1.23	0.43
		(1.96)	(0.50)	(0.83)	(0.26)
Injury-related ED visits	Rural controls	-1.00	-0.32	-2.74	-1.36
		(2.19)	(0.64)	(3.23)	(1.06)
	All Maryland	3.74*	1.37**	2.69	0.69
		(2.03)	(0.54)	(2.17)	(0.65)
Behavioral ED visits	Rural controls	-0.97	-0.17	-0.25	-0.10
		(4.26)	(1.19)	(0.93)	(0.30)
	All Maryland	-3.05	-0.52	-0.89	-0.16
		(2.85)	(0.96)	(0.58)	(0.18)

Notes: Standard errors in parentheses. $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$. All models control for ZCTA and year fixed effects, as well as time-varying controls at the ZCTA and county level. OLS models are weighted for average ZCTA population. Poisson models report percent incidence rate differences. Models (1) and (3) report the effect of the TPR reform as the coefficient on the interaction between the reform indicator and the post period indicator (equal to 1 for years 2010-2013, 0 otherwise). Models (2) and (4) report the effect of an additional year of TPR reform implementation.

Table 7.12: Summary of Estimated TPR Effects on Outpatient Outcomes Compared to Rural Controls and All of Maryland—County-Based Assignment

		Poisson		Weighted OLS	
		(1) TPR	(2) TPR Years	(3) TPR	(4) TPR Years
Outpatient visits	Rural controls	-7.95***	-3.48***	-49.5	-25.4
		(2.85)	(0.69)	(52.1)	(17.1)
	All Maryland	-9.58***	-3.46***	-101.3***	-33.2***
		(3.17)	(0.82)	(36.5)	(9.01)
ED visits	Rural controls	1.26	0.48	10.4	4.55
		(2.26)	(0.62)	(19.2)	(6.76)
	All Maryland	0.98	0.42	2.22	1.51
		(1.62)	(0.43)	(7.02)	(2.05)
Non-emergent ED visits	Rural controls	2.44	0.49	3.38	1.22
		(2.95)	(0.84)	(5.21)	(1.87)
	All Maryland	1.45	0.10	0.093	-0.084
		(2.41)	(0.71)	(1.87)	(0.60)
PC treatable ED visits	Rural controls	3.56	1.23	2.77	1.17
		(2.83)	(0.76)	(3.87)	(1.32)
	All Maryland	1.95	0.93*	0.83	0.57
		(2.02)	(0.56)	(1.61)	(0.47)
Avoidable ED visits	Rural controls	4.31*	1.54**	0.81	0.35
		(2.49)	(0.66)	(0.98)	(0.34)
	All Maryland	4.00**	1.55***	0.65	0.26**
		(1.81)	(0.49)	(0.43)	(0.12)
Non-preventable ED visits	Rural controls	3.59	1.33*	2.59	1.04
		(3.10)	(0.72)	(2.01)	(0.66)
	All Maryland	3.08*	0.92*	1.03	0.45*
		(1.84)	(0.49)	(0.82)	(0.25)
Injury-related ED visits	Rural controls	1.00	0.49	1.16	0.53
		(2.41)	(0.72)	(4.77)	(1.71)
	All Maryland	-0.84	-0.047	-0.97	-0.35
		(1.78)	(0.51)	(2.06)	(0.60)
Behavioral ED visits	Rural controls	2.98	1.00	0.82	0.23
		(4.02)	(1.13)	(1.12)	(0.35)
	All Maryland	-1.47	-0.0074	-0.67	-0.064
		(2.84)	(0.93)	(0.55)	(0.17)

Notes: Standard errors in parentheses. $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$. All models control for ZCTA and year fixed effects, as well as time-varying controls at the ZCTA and county level. OLS models are weighted for average ZCTA population. Poisson models report percent incidence rate differences. Models (1) and (3) report the effect of the TPR reform as the coefficient on the interaction between the reform indicator and the post period indicator (equal to 1 for years 2010-2013, 0 otherwise). Models (2) and (4) report the effect of an additional year of TPR reform implementation.

Chapter 8

Conclusions and Policy Implications

This dissertation examines the impact of global budgets on hospital utilization in rural areas in Maryland. A better understanding of the effects of this reform on different types of inpatient and outpatient utilization sheds light on the benefits and limitations of this payment system for promoting efficiency and quality in the US and internationally. In particular, we are able to estimate the effects of Maryland's global budget program over a longer period of four years after its inception, bringing evidence for the newer statewide expansion.

The potential effectiveness of using global budgets to realign incentives for hospitals is drawing the attention of both policymakers and researchers. For the first time in several decades, the concept is again getting traction more broadly in the United States. The waiver received by the State of Maryland from CMS has global budget payments as its central tool for containing per-capita health care spending. Moreover, Pennsylvania has recently signed an agreement with CMS laying the foundation for similar systems, at least for rural hospitals. This signals that policymakers may believe that, given the fragmented nature of health care in the US, fully integrated delivery systems like ACOs may not always be feasible, at least in the short term. In contrast, hospital global budgets may be a more gradual first step in moving from FFS payment to population-based reimbursement.

However, several unanswered questions have likely made decision-makers reluctant to embrace global budgets more widely: Can global budgets actually reduce total inpatient and outpatient utilization? What are the effects of global budgets on preventable versus non-preventable services? What are the effects of global budgets on more discretionary, deferrable services versus more essential, non-deferrable services?

This dissertation provides empirical evidence from Maryland's 2010 TPR reform for rural hospitals in an attempt to address these three questions. This concluding chapter first summarizes these empirical findings and discusses the limitations of our analyses. It then discusses the research and policy implications of this study and suggests future directions for research.

8.1 Discussion of the empirical findings

Our empirical findings are that global budgets lead to a small decrease in total outpatient use. For inpatient care, the reduction in overall admissions is small, about 3 admissions per 1,000 residents, and generally statistically insignificant across our different specifications. The magnitude of this effect is smaller than that of other studies. For example, the evaluation of the Rochester experiment in the 1980s found a decrease of about 4 admissions per 1,000 residents, from a similar baseline as in our case (Block et al. 1987).

We find similarly small and imprecisely estimated reductions in chronic preventable admissions and deferrable admissions. Specifically, we find that TPR led to a small but significant reduction in chronic preventable hospitalizations of about 1 admission per 1,000 residents, or about 5 percent on average over the course of the intervention. The magnitude of this effect seems sensible. One study examining the effect of Medicaid managed care on rates in ACSCs estimated a reduction of about 3 preventable admissions per 1,000 residents (Bindman, Chattopadhyay, et al. 2005). Given that managed care relies on capitation and more aggressive care management techniques across the care continuum, a relatively smaller effect is expected for a more limited intervention like TPR. Moreover, while it is encouraging to see that there was a decrease driven by conditions with a high morbidity and cost burden on the health system (i.e., asthma, diabetes, and heart failure), it is possible that these effects were driven by changes in medical coding or regression to the mean, as improving quality to curb acute episodes of chronic conditions is a lengthy process.

We find no effect of TPR on 30-day readmissions, although all-cause readmissions have been shown to have considerable limitations as quality metrics, including a strong pattern of regression to the mean (Press et al. 2013). That said, we discuss some potential methodological limitations with our analyses of Maryland data for readmissions in the section below.

For outpatient hospital care, the reduction in total encounters is significant and robust to different model specifications. Overall, we find a decrease of about 87 encounters per 1,000 residents, but more conservative estimates in alternatively specified models are closer to 50 encounters per 1,000 residents. Given the high baseline rate in the TPR hospital service areas of over 900 encounters per 1,000 residents, and the highly discretionary nature of a large portion of outpatient visits, the magnitude of this effect seems quite reasonable. This finding suggests that even if there had been some substitution of outpatient visits for inpatient admissions, this effect was dominated by the overall reduction in outpatient use.

Our results with respect to ED visits tend to show more dependency on model specifications and sample restrictions. Overall, the estimates indicate little to no effect on ED use. Although some of our models indicate a slight increase in total ED visit rates, the results are generally not statistically significant. That said, there is a pattern of results consistent with increased utilization for non-emergent, preventable, and non-preventable ED visits. In contrast, injury-related and behavioral ED visits show no effect, increasing our confidence in the validity of our results and suggesting that global budgets did not induce hospitals to shirk on appropriate emergency care.

8.2 Research limitations

Our study is not without notable limitations. The most important limitations relate to the following five issues: data availability, measure validity, control group selection, unobserved hospital behavior, and confounding by other concurrent policy changes. We discuss these five in turn below.

First, with respect to data availability, we only use data on Maryland residents admitted to Maryland hospitals. One implicit assumption is that the patterns of seeking hospital care at out-of-state hospitals have remained constant or at least evolved similarly over the course of the study for the individuals living in the treatment and control areas. This assumption is not testable in the absence of discharge data from neighboring hospitals. This could be a relatively significant limitation considering that many of the hospitals in the study are close to the state's borders.

Additionally, we were also not able to perform individual level analyses due to the fact that data is only available at the discharge level. Instead, we aggregated our data to the most granular level possible, namely the ZCTA. But despite being a natural geographic unit of analysis, ZCTAs present potential pitfalls for researchers. The most common one stems from the fact that ZIP codes do not represent discretely bounded geographic areas (i.e., polygons), but are instead linear features associated with specific roads and addresses (Grubesic 2008), first implemented in 1963 as a way to codify US Postal Service delivery routes. ZCTAs, in contrast, are geographic areas created by the

US Census Bureau in 2000 based on allocation of entire census blocks to aid research activities using administrative data which contain patient addresses (Grubesic and Matisziw 2006). Although ZCTAs represent a five-digit ZIP code where possible, there are a number of ”point” ZIP codes which tend to correspond to large businesses or other non-residential settings.

Another feature of ZIP codes that may introduce the potential for geographic mismatch is the fact that some residents (particularly in rural areas) use Postal Office (PO) boxes to receive their mail. These PO boxes may be near work, in commercial zones, or other locations, making the ZIP code reported by patients an improper indicator of residence location. To mitigate the impact of this, we conducted additional analyses in which we exclude ZIP codes labeled as PO boxes and aggregated at the ZCTA level, including the utilization of point ZIP codes in their containing ZCTAs.

The issue of data availability for the ZCTA population counts which serve as the denominator for our outcome measures may also introduce bias in our analyses. Our data are based on the best available estimates from the same vendor used by HSCRC. They are constructed by allocating Census tracts to ZCTAs and aggregating population projections from the decennial Census and estimates from the American Community Survey, but are still measured with error. Moreover, because the ZCTA is not a standard place in the methodology of the US Census Bureau, these estimates may not be fully reliable. To mitigate these concerns at least partially, we repeated our analyses with official estimates from the Census Bureau for 2010-2013 and extrapolated for 2008-

2009. Our results (not shown here) do not change appreciably when we use this alternative source of data. In principle, this limitation could be overcome with the use of health insurance claims data, which would allow an individual level analysis including people with no hospital utilization, but Maryland's Department of Mental Health and Hygiene (DHMH) only recently began making the subset of private insurance claims data available to researchers. Finally, a related limitation here is that we may be underpowered to detect policy-relevant effects as we aggregate the data to the ZCTA level.

The second main set of limitations relates to measure validity—particularly those for the measures of preventable utilization. For inpatient care, although AHRQ's Preventable Quality Indicators have been validated rigorously and have a strong track record of being used by researchers, they reflect the product of expert consensus based on available evidence and may exclude many other types of conditions for which the evidence is lacking. Moreover, our analyses of readmissions only capture intra-hospital readmissions due to the absence of unique patient identifiers. If inter-hospital readmissions increased in either the treatment or the control group at different rates, our analysis would not capture this trend. A mitigating factor here, however, is the fact that intra-hospital readmissions make up approximately 70 percent of total readmissions, and this figure is likely much higher for rural hospitals like those in our study.

Regarding the validity of our outpatient care measures, it is generally not possible to assess with certainty using administrative data whether a specific ED visit was preventable without detailed chart review. Therefore, the Billings algorithm assigns each visit a probability of being in one of the categories of interest. Despite evidence suggesting that the Billings categories differentiate ED visits based on the need for hospitalization and mortality risk in commercially insured patients (Ballard et al. 2010), the algorithm was formulated using claims data from New York City in 1994 and 1998 (Billings et al. 2000). It is possible that patterns of emergency care are different in Maryland hospitals or that they have evolved considerably over the past two decades.

The third limitation relates to the choice of control groups to identify the appropriate counterfactual for the treated units. In our particular case, the main challenge is the non-random assignment of hospitals to the treatment group. As evident from the summary tables in Chapter 5, TPR hospitals serve rural populations with a higher level of morbidity and lower socioeconomic status than those served by rural control hospitals. This translates into consistently higher levels of hospital care utilization in treatment areas. On a more fundamental level, the fact that enrollment in the TPR program was voluntary raises the question of whether the managers of the three rural hospitals that declined participation had a reason to expect that their hospitals would not perform well under global budgets due to factors that are unobservable to researchers. Although informal conversations with HSCRC staff suggest that this was not the case, the voluntary enrollment without randomization still raises the possibility of confounding due to characteristics which affect hospital behavior over time in unobserved ways. Our analyses which include the suburban and urban areas in Maryland into our control group partially mitigate this self-selection concern. Even without obvious self-selection, the assumption of conditional exogeneity upon which the difference-in-differences technique relies may be violated. The conventional DD estimator assumes independent state-year assignment, but in our sample hospitals adopt the global budget system only once, leading to inadequately short confidence intervals and therefore a large Type I error (Bertrand et al. 2004).

The fourth limitation relates to unobserved hospital behavior after the global budget program was introduced. One powerful tool that hospitals have to game the regulatory system is the ability to change their coding practices. The reporting system in Maryland, like in other countries, relies on voluntary data submissions by hospitals to the HSCRC. This system is susceptible to gaming by hospitals. Previous studies have shown that "upcoding" is relatively prevalent when reporting DRGs (Busse et al. 2013). One other potential avenue for hospitals to game the payment system would be to more carefully code Present-on-Admission (POA) indicators.

The fifth limitation relates to potential confounding by other concurrent policy changes. That is, other changes in the demand for hospital care or programs affecting either health status or utilization may have differentially affected the treatment and control groups. One possibility is that geographic patterns of travel for care change over time in a way that is not captured in our assignment of ZCTAs to hospital service areas. Another possibility relates to changes induced by Accountable Care Organizations and other initiatives which were started during the study period. A third possibility relates to our analyses of readmission rates. As described in Chapter 2, in 2011 a group of 27 hospitals implemented the Admission-Readmission Revenue (ARR) program, a bundled payment initiative grouping each admission with the readmissions following it within a 30-day period. All three rural control hospitals (and many other urban hospitals in the state) were part of this group of hospitals, but none of the TPR hospitals implemented the program. Thus, we expect the control hospitals to pay particular attention to this measure. Because we observe readmission rates decreasing at similar rates in both groups, one possibility is that the TPR program is at least as effective as another intervention more specifically targeted at reducing readmissions.

8.3 Policy implications and recommendations

Even in the absence of complete evidence on the impact of global budgets, these findings suggest several potential avenues for health policy in Maryland and in other states.

In Maryland, one important such direction is to foster hospital collaboration as a way to strengthen care coordination and achieve population health. Maryland policymakers could accelerate the formation of hospital collaborations springing up across the state by rewarding coordination and shared learning. One example in which the HSCRC is already doing this is the eight recently awarded Regional Partnerships for Health System Transformation grants totaling $2.5 million (Department of Health and Mental Hygiene 2015). One such partnership is the Southern Maryland Regional Coalition for Health System Transformation which focuses on the care coordination of high-risk Medicare beneficiaries in Calvert and Prince George's County (Doctors Community Hospital 2015). Another partnership is the Advanced Health Collaborative, comprised of nine hospitals from five different hospital systems (which do not compete with each other in any of their markets) which focuses on sharing best practices for integration of primary care and behavioral health services (Adventist Healthcare 2015).

Global budgets can play an important role in this transformation, as the incentives to keep patients in the hospital and to compete for as many patients as possible are loosened. Of course, this approach still requires a delicate balance between improving care coordination and collaboration while preventing hospital collusion, although concerns surrounding market consolidation are less of an issue in Maryland's system of rate setting.

Second, Maryland policymakers should address hospital fears that their revenues will be reduced drastically over time through shrinking the global budgets. Part of the long-term transformation of care may require downsizing and repurposing some hospital facilities towards other types of care, but it is reasonable that some hospitals managers would find this transformation difficult and would be skeptical of its outcomes. State leaders could facilitate the expansion of the scope of hospitals to support other aspects of population health.

Third, the realignment of incentives should not be limited to hospitals. One potential reason why our analysis shows relatively small effects is the fact that most physicians were still paid FFS. Maryland could use hospital global budgets as a lever to drive care coordination further through the health care system, towards truly integrated services that achieve population health. Partnerships could be promoted between hospitals, physicians, and other non-acute care providers, including local health departments, community groups, and social service providers. This would allow Maryland to address health not just medically but with a focus on public health and socioeconomic determinants. An example of such a partnership already developing is the collaboration between Baltimore hospitals and the Baltimore City Health Department on a project that identifies high users of ED visits (Cornish et al. 2015).

There are policy implications for stakeholders in other states as well, taken with the caveat that global budgets will surely be more difficult to implement in the absence of all-payer rate regulation. Nevertheless, the experience in Maryland suggests that hospitals can accept limits on their revenues in exchange for financial stability and predictability. This stability frees up staff to focus on keeping patients healthy instead of worrying about driving up admissions for increased revenue. Rural hospitals in other states are a particularly good candidate for programs resembling TPR, because of their non-overlapping markets and relatively higher share of Medicare beneficiaries. The Centers for Medicare and Medicaid Services can thus play a crucial role in facilitating the implementation of global budgets, by supporting states through state-specific waivers, federal regulations, and facilitation of learning communities across states and health system stakeholders.

Other agencies and state-based partners can play an important role as well, first by recognizing that health care spending competes with other priorities for limited state resources. The growth in health care expenditures can be changed by incentivizing population health, and the evidence so far suggests that global budgets have the potential to decrease low-value care while protecting access to acute and emergent conditions in rural areas. Nevertheless, we would encourage policymakers to implement global budgets with an eye for continuous evaluation so that policies may be adapted as new evidence emerges.

8.4 Future research directions

First, it will be important to examine the continued effects of Maryland's TPR reform past 2013, as our study may not capture the full long-term effects of global budgets. Chronic disease management and prevention are difficult in a system built under FFS payment, and transforming care processes to promote coordination of services takes considerable leadership, effort, and time. Future research should also study the impact of the GBR program introduced in 2014. However, this research is likely to face limitations as well, because ideal control groups would have to be out-of-state areas, introducing further bias given Maryland's unique rate-setting system, and because the program implementation coincides with the health insurance coverage expansion of the Affordable Care Act.

Second, more in-depth research is needed on whether hospitals changed their clinical processes to improve quality of care or if they improved coordination of services. Other outcomes like the rates of discretionary and non-discretionary services should also be examined. Indicators of mortality or relevant outcomes for important conditions should reveal whether hospitals restructured care in meaningful ways. Moreover, examining the data from the Consumer Assessment of Health Plans and Systems (CAHPS) surveys would shed light on any changes in patient satisfaction with care communication, timeliness, and coordination. Semi-structured interviews with clinical staff and hospital managers would also help elucidate the impact of global budgets on clinical care processes and staff incentives on the front lines of care.

Third, individual-level claims data would allow an in-depth analysis of specific subgroups of patients, particularly vulnerable populations such as Medicare and Medicaid beneficiaries and patients with multiple chronic conditions. Moreover, it would be important to determine whether global budgets have any impact on racial and ethnic disparities in care, particularly in a racially diverse population like Maryland's.

Fourth, it is essential to examine the impact of global budgets on the total cost of care per capita and on non-hospital service utilization, given the payment system's central role in accomplishing Maryland's goal of limiting health care spending growth to within the growth of the gross state product. While hospital services are a large portion of total expenditures, physician services and prescription drugs are often substitutes to inpatient care. Any changes in these categories of services may affect total spending and therefore contribute to achieving Maryland's waiver target.

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Appendix A

Definitions of the Prevention Quality Indicator Conditions

Table A.1: ICD-9-CM Diagnosis Codes for PQI Ambulatory Care Sensitive Conditions

Indicator	**ICD-9-CM Codes**
PQI 01 - Diabetes Short-Term Complications	250.10-250.13, 250.20-250.23, 250.30-250.33
PQI 02 - Perforated Appendix	540.0, 540.1, 540.9, 541
PQI 03 - Diabetes Long-Term Complications	250.40-250.43, 250.50-250.53, 250.60-250.63, 250.70-250.73, 250.80-250.83, 250.90-250.93
PQI 05 - COPD or Asthma in Older Adults	COPD: 491.0, 491.1, 491.20-491.22, 491.8, 491.9, 492.0, 492.8, 494, 494.0, 494.1, 496; Asthma: 493.00-493.02, 493.10-493.12, 493.20-493.22, 493.81, 493.82, 483.90-493.92 Acute bronchitis: 466.0, 490
PQI 07 - Hypertension	401.0, 401.9, 402.00, 402.10, 402.90, 403.00, 403.10, 403.90, 404.00, 404.10, 404.90
PQI 08 - Heart Failure	398.91, 402.01, 402.11, 402.91, 404.01, 404.03, 404.11, 404.13, 404.91, 404.93, 428.0, 428.1, 428.20-428.23, 428.30-428.33, 428.40-428.43, 428.9
PQI 09 - Low Birth Weight	764.01-764.28, 764.90-764.98, 765.01-765.18
PQI 10 - Dehydration	276.5, 276.50-276.52, 276.0, 008.61-008.67, 008.69, 008.8, 009.0-009.3, 558.9, 584.5-584.9, 586, 997.5
PQI 11 - Bacterial Pneumonia	481, 482.2, 482.30-482.32, 482.39, 482.41, 482.42, 482.9, 483.0, 483.1, 483.8, 485, 486
PQI 12 - Urinary Tract Infection	590.10, 590.11, 590.2, 590.3, 590.80, 590.81, 590.9, 595.0, 595.9, 599.0
PQI 13 - Angina without Procedure	411.1, 411.81, 411.89, 413.0, 413.1, 413.9
PQI 14 - Uncontrolled Diabetes	250.02, 250.03
PQI 15 - Asthma in Younger Adults	493.00-493.02, 493.10-493.12, 493.20-493.22, 493.81, 493.82, 493.90-493.92
PQI 16 - Lower-Extremity Amputation in Diabetics	841.0-841.9

Source: Version 5.0 (March 2015) of the Prevention Quality Indicators Technical Specifications `http://www.qualityindicators.ahrq.gov/Modules/PQI_TechSpec.aspx`.

Appendix B

Effects on Ambulatory Care Sensitive Admission Rates

Figure B.1: Trends in Diabetes Short-Term Complications Admissions Rate for the Treatment and Control Groups, 2008-2013

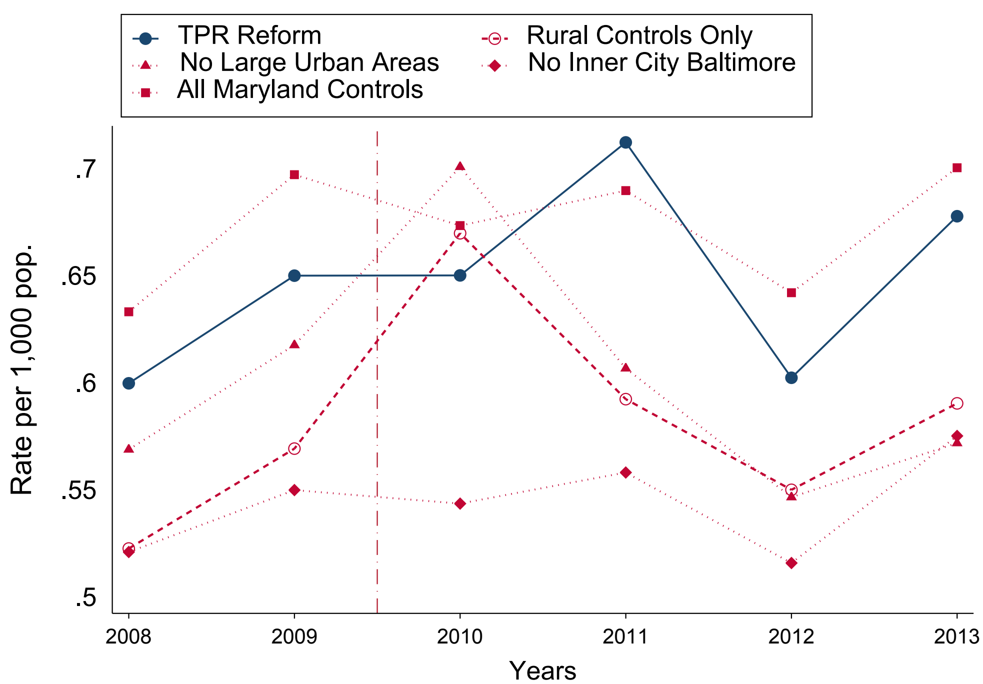


Table B.1: Estimates of the effects of TPR on diabetes short-term complications admissions rate, with various sample restrictions

	Poisson (offset = log(population))				Weighted OLS (rate per 1,000 capita)			
	(1) TPR	(2) TPR	(3) TPR Years	(4) TPR Years	(5) TPR	(6) TPR	(7) TPR Years	(8) TPR Years
RURAL AREAS ONLY	−5.42	−9.01	0.075	0.042	−0.014	0.011	−0.0067	0.0043
(N=1206)	(8.87)	(11.7)	(3.11)	(3.97)	(0.063)	(0.11)	(0.020)	(0.030)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO LARGE URBAN AREAS	2.23	−1.56	2.65	2.68	0.031	0.044	0.0094	0.020
(N=1566)	(8.70)	(10.3)	(2.89)	(3.70)	(0.059)	(0.091)	(0.018)	(0.025)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO INNER CITY	2.21	−2.99	0.11	−1.70	0.040	0.025	−0.00067	−0.0098
BALTIMORE (N=2634)	(7.60)	(8.67)	(2.39)	(2.87)	(0.053)	(0.069)	(0.016)	(0.019)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
ALL OF MARYLAND	1.74	−5.24	−0.00035	−2.60	0.035	0.016	−0.0025	−0.013
(N=2760)	(7.50)	(7.99)	(2.39)	(2.75)	(0.054)	(0.066)	(0.016)	(0.019)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓

Notes: Standard errors in parentheses. $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$. All models control for ZIP code and year fixed effects. OLS models are weighted for average ZIP code population. Poisson models report percent incidence rate differences. Models (1), (2), (5), and (6) report the effect of the TPR reform as the coefficient on the interaction between the reform indicator and the post period indicator (equal to 1 for years 2010-2013, 0 otherwise). Models (3), (4), (7), and (8) report the effect of an additional year of TPR reform implementation as the coefficient on the interaction between the reform indicator and a post linear time trend indicator (equal to 0 in the pre-reform period, 1 in the first reform year, 2 in the second, etc. The first sample includes ZCTAs assigned to the 8 TPR hospitals and 3 rural control hospitals. The second sample contains the ZCTAs in the first sample plus ZCTAs assigned to non-participating hospitals which don't belong to the CBSAs 12580 (Baltimore-Columbia-Towson) and 47900 (Washington-Arlington-Alexandria). The third sample uses as controls all Maryland ZCTAs assigned to non-participating hospitals which are outside the Baltimore City county (FIPS code 24510). The fourth sample includes all Maryland ZCTAs assigned to non-participating hospitals.

Figure B.2: Trends in Perforated Appendix Admission Rate for the Treatment and Control Groups, 2008-2013

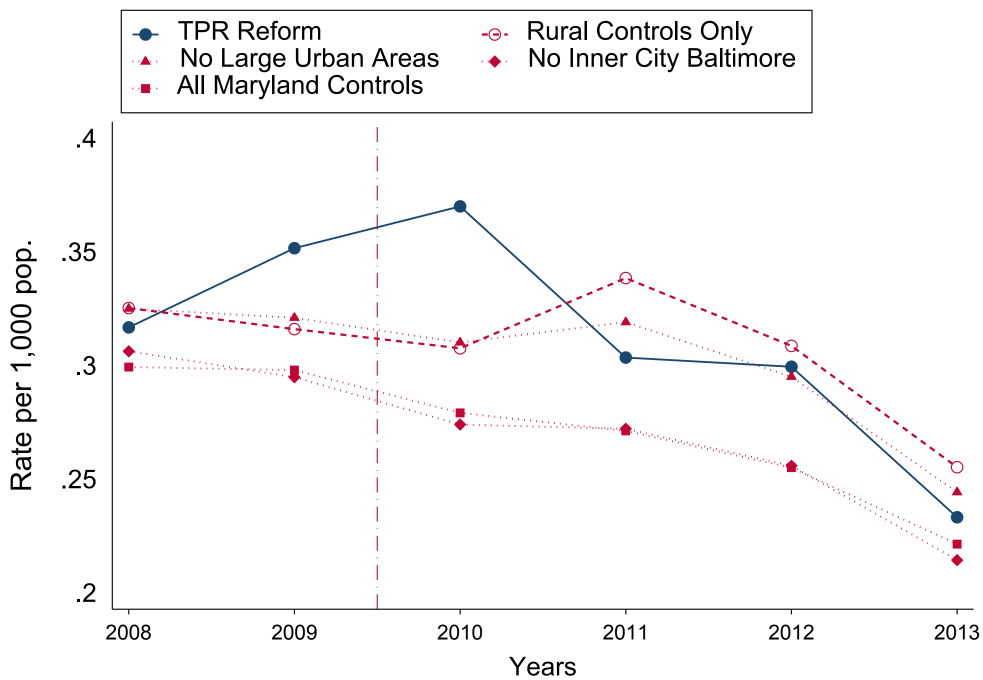


Table B.2: Estimates of the effects of TPR on the perforated appendix admission rate, with various sample restrictions

	Poisson (offset = log(population))				Weighted OLS (rate per 1,000 capita)			
	(1) TPR	(2) TPR	(3) TPR Years	(4) TPR Years	(5) TPR	(6) TPR	(7) TPR Years	(8) TPR Years
RURAL AREAS ONLY	−4.79	0.48	−3.03	−3.17	−0.026	−0.014	−0.013	−0.013
(N=1206)	(10.2)	(12.9)	(3.00)	(3.46)	(0.036)	(0.045)	(0.0100)	(0.012)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO LARGE URBAN AREAS	−0.54	0.65	−1.63	−1.87	−0.010	−0.0035	−0.0080	−0.0074
(N=1566)	(10.1)	(11.2)	(2.90)	(3.14)	(0.034)	(0.038)	(0.0092)	(0.010)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO INNER CITY	6.52	3.13	0.15	−0.79	0.013	0.0083	−0.0023	−0.0046
BALTIMORE (N=2634)	(8.50)	(9.26)	(2.24)	(2.26)	(0.026)	(0.030)	(0.0069)	(0.0074)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
ALL OF MARYLAND	4.79	3.16	−0.43	−0.70	0.0089	0.0089	−0.0037	−0.0039
(N=2760)	(8.27)	(8.59)	(2.20)	(2.17)	(0.025)	(0.028)	(0.0068)	(0.0070)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓

Notes: Standard errors in parentheses. $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$. All models control for ZIP code and year fixed effects. OLS models are weighted for average ZIP code population. Poisson models report percent incidence rate differences. Models (1), (2), (5), and (6) report the effect of the TPR reform as the coefficient on the interaction between the reform indicator and the post period indicator (equal to 1 for years 2010-2013, 0 otherwise). Models (3), (4), (7), and (8) report the effect of an additional year of TPR reform implementation as the coefficient on the interaction between the reform indicator and a post linear time trend indicator (equal to 0 in the pre-reform period, 1 in the first reform year, 2 in the second, etc. The first sample includes ZCTAs assigned to the 8 TPR hospitals and 3 rural control hospitals. The second sample contains the ZCTAs in the first sample plus ZCTAs assigned to non-participating hospitals which don't belong to the CBSAs 12580 (Baltimore-Columbia-Towson) and 47900 (Washington-Arlington-Alexandria). The third sample uses as controls all Maryland ZCTAs assigned to non-participating hospitals which are outside the Baltimore City county (FIPS code 24510). The fourth sample includes all Maryland ZCTAs assigned to non-participating hospitals.

Figure B.3: Trends in Diabetes Long-Term Complications Admission Rates for the Treatment and Control Groups, 2008-2013

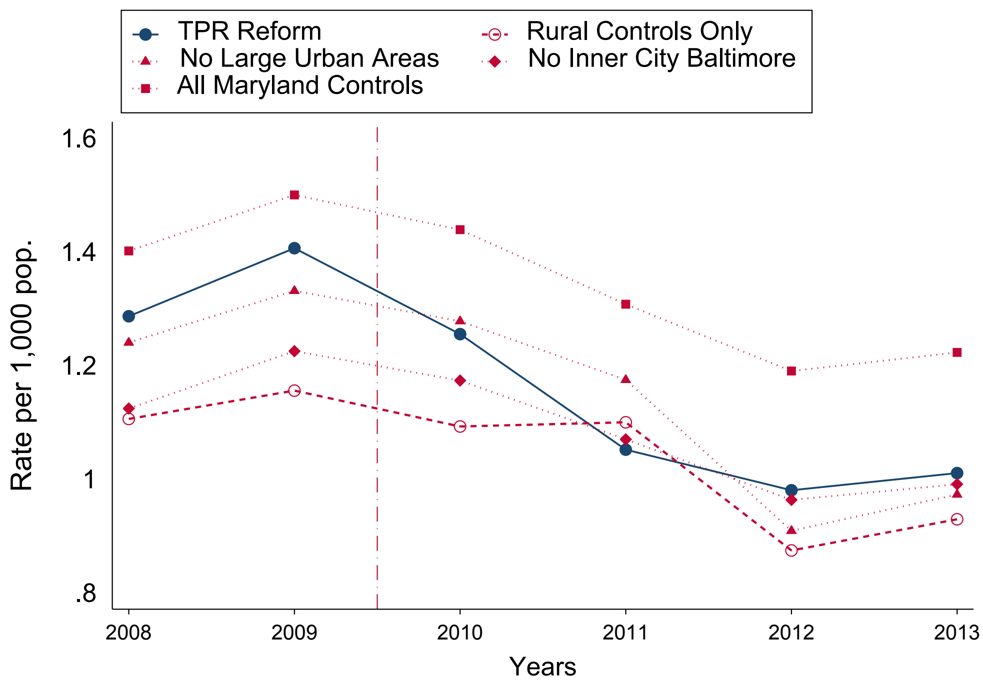


Table B.3: Estimates of the effects of TPR on diabetes long-term complications, with various sample restrictions

	Poisson (offset = log(population))				Weighted OLS (rate per 1,000 capita)			
	(1) TPR	(2) TPR	(3) TPR Years	(4) TPR Years	(5) TPR	(6) TPR	(7) TPR Years	(8) TPR Years
RURAL AREAS ONLY	−10.1	−9.62	−2.38	−2.19	−0.14	−0.11	−0.041	−0.033
(N=1206)	(7.14)	(8.22)	(2.29)	(2.82)	(0.11)	(0.14)	(0.030)	(0.037)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO LARGE URBAN AREAS	−5.53	−5.05	−0.30	−0.22	−0.062	−0.019	−0.010	0.0014
(N=1566)	(6.93)	(6.67)	(2.24)	(2.31)	(0.10)	(0.12)	(0.030)	(0.032)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO INNER CITY	-11.3^{**}	-11.3^{*}	−3.14	-3.61^{*}	−0.12	−0.10	−0.040	-0.041^{*}
BALTIMORE (N=2634)	(5.32)	(5.42)	(1.95)	(1.96)	(0.087)	(0.089)	(0.026)	(0.025)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
ALL OF MARYLAND	-11.9^{**}	-15.7^{***}	-3.34^{*}	-4.98^{**}	−0.10	−0.099	−0.033	−0.041
(N=2760)	(5.19)	(5.12)	(1.92)	(1.98)	(0.088)	(0.092)	(0.026)	(0.027)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓

Notes: Standard errors in parentheses. $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$. All models control for ZIP code and year fixed effects. OLS models are weighted for average ZIP code population. Poisson models report percent incidence rate differences. Models (1), (2), (5), and (6) report the effect of the TPR reform as the coefficient on the interaction between the reform indicator and the post period indicator (equal to 1 for years 2010-2013, 0 otherwise). Models (3), (4), (7), and (8) report the effect of an additional year of TPR reform implementation as the coefficient on the interaction between the reform indicator and a post linear time trend indicator (equal to 0 in the pre-reform period, 1 in the first reform year, 2 in the second, etc. The first sample includes ZCTAs assigned to the 8 TPR hospitals and 3 rural control hospitals. The second sample contains the ZCTAs in the first sample plus ZCTAs assigned to non-participating hospitals which don't belong to the CBSAs 12580 (Baltimore-Columbia-Towson) and 47900 (Washington-Arlington-Alexandria). The third sample uses as controls all Maryland ZCTAs assigned to non-participating hospitals which are outside the Baltimore City county (FIPS code 24510). The fourth sample includes all Maryland ZCTAs assigned to non-participating hospitals.

Figure B.4: Trends in the Rates of COPD or Asthma Admissions for the Treatment and Control Groups, 2008-2013

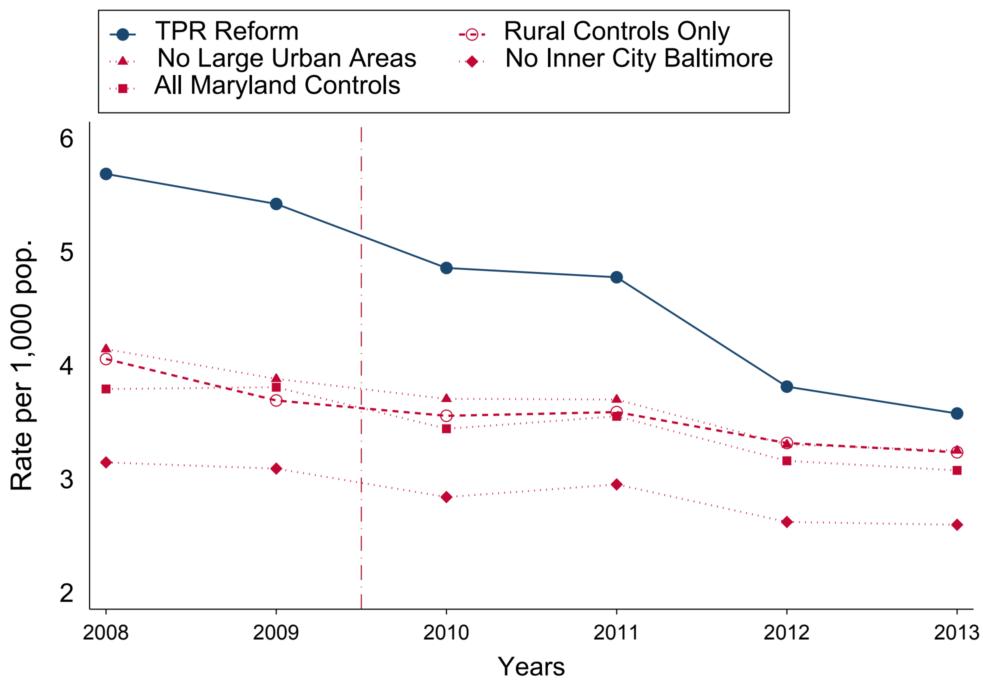


Table B.4: Estimates of the effects of TPR on the rates of COPD or asthma admissions in older adults, with various sample restrictions

	Poisson (offset = log(population))				Weighted OLS (rate per 1,000 capita)			
	(1) TPR	(2) TPR	(3) TPR Years	(4) TPR Years	(5) TPR	(6) TPR	(7) TPR Years	(8) TPR Years
RURAL AREAS ONLY	-13.0^{**}	-10.8^{*}	-5.14^{***}	-4.42^{**}	-0.88^{***}	-0.72^{**}	-0.32^{***}	-0.31^{***}
(N=1206)	(5.05)	(5.32)	(1.80)	(1.76)	(0.29)	(0.30)	(0.096)	(0.10)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO LARGE URBAN AREAS	-11.7^{**}	-7.10	-4.50^{***}	-3.26^{**}	-0.80^{***}	-0.53^{**}	-0.29^{***}	-0.25^{***}
(N=1566)	(4.71)	(4.58)	(1.63)	(1.51)	(0.28)	(0.24)	(0.089)	(0.082)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO INNER CITY	-12.8^{***}	-13.4^{***}	-5.25^{***}	-5.68^{***}	-0.80^{***}	-0.70^{***}	-0.31^{***}	-0.29^{***}
BALTIMORE (N=2634)	(3.87)	(3.65)	(1.41)	(1.26)	(0.29)	(0.26)	(0.087)	(0.083)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
ALL OF MARYLAND	-12.4^{***}	-13.3^{***}	-5.07^{***}	-5.76^{***}	-0.71^{**}	-0.57^{**}	-0.28^{***}	-0.27^{***}
(N=2760)	(3.87)	(3.55)	(1.41)	(1.32)	(0.28)	(0.26)	(0.087)	(0.085)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓

Notes: Standard errors in parentheses. $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$. All models control for ZIP code and year fixed effects. OLS models are weighted for average ZIP code population. Poisson models report percent incidence rate differences. Models (1), (2), (5), and (6) report the effect of the TPR reform as the coefficient on the interaction between the reform indicator and the post period indicator (equal to 1 for years 2010-2013, 0 otherwise). Models (3), (4), (7), and (8) report the effect of an additional year of TPR reform implementation as the coefficient on the interaction between the reform indicator and a post linear time trend indicator (equal to 0 in the pre-reform period, 1 in the first reform year, 2 in the second, etc. The first sample includes ZCTAs assigned to the 8 TPR hospitals and 3 rural control hospitals. The second sample contains the ZCTAs in the first sample plus ZCTAs assigned to non-participating hospitals which don't belong to the CBSAs 12580 (Baltimore-Columbia-Towson) and 47900 (Washington-Arlington-Alexandria). The third sample uses as controls all Maryland ZCTAs assigned to non-participating hospitals which are outside the Baltimore City county (FIPS code 24510). The fourth sample includes all Maryland ZCTAs assigned to non-participating hospitals.

Figure B.5: Trends in Preventable Admission Rates due to Chronic Ambulatory Care Sensitive Conditions for the Treatment and Control Groups, 2008-2013

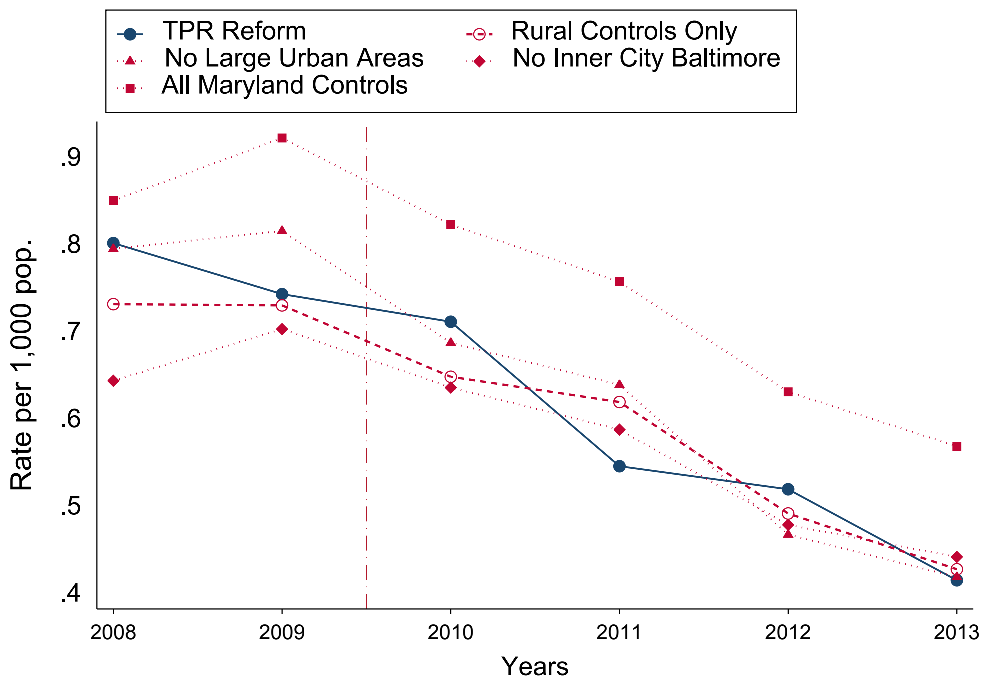


Table B.5: Estimates of the effects of TPR on the rates of preventable admissions due to chronic ambulatory care sensitive conditions, with various sample restrictions

	Poisson (offset = log(population))				Weighted OLS (rate per 1,000 capita)			
	(1) TPR	(2) TPR	(3) TPR Years	(4) TPR Years	(5) TPR	(6) TPR	(7) TPR Years	(8) TPR Years
RURAL AREAS ONLY	-5.01	-9.60	-2.12	-4.39	-0.043	-0.12	-0.019	-0.049^{*}
(N=1206)	(10.6)	(12.4)	(3.17)	(4.07)	(0.077)	(0.099)	(0.021)	(0.029)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO LARGE URBAN AREAS	3.80	8.72	0.84	1.44	0.030	0.051	0.0037	0.00060
(N=1566)	(9.86)	(12.1)	(2.87)	(3.65)	(0.072)	(0.090)	(0.020)	(0.025)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO INNER CITY	-11.5^{**}	0.81	-4.58^{***}	-2.24	-0.093^{**}	-0.012	-0.031^{***}	-0.017
BALTIMORE (N=2634)	(4.81)	(7.94)	(1.62)	(2.45)	(0.041)	(0.058)	(0.012)	(0.016)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
ALL OF MARYLAND	-11.3^{**}	-7.95	-4.58^{***}	-4.78^{**}	-0.049	0.032	-0.016	-0.0077
(N=2760)	(4.86)	(6.12)	(1.62)	(2.01)	(0.045)	(0.055)	(0.013)	(0.016)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓

Notes: Standard errors in parentheses. $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$. All models control for ZIP code and year fixed effects. OLS models are weighted for average ZIP code population. Poisson models report percent incidence rate differences. Models (1), (2), (5), and (6) report the effect of the TPR reform as the coefficient on the interaction between the reform indicator and the post period indicator (equal to 1 for years 2010-2013, 0 otherwise). Models (3), (4), (7), and (8) report the effect of an additional year of TPR reform implementation as the coefficient on the interaction between the reform indicator and a post linear time trend indicator (equal to 0 in the pre-reform period, 1 in the first reform year, 2 in the second, etc. The first sample includes ZCTAs assigned to the 8 TPR hospitals and 3 rural control hospitals. The second sample contains the ZCTAs in the first sample plus ZCTAs assigned to non-participating hospitals which don't belong to the CBSAs 12580 (Baltimore-Columbia-Towson) and 47900 (Washington-Arlington-Alexandria). The third sample uses as controls all Maryland ZCTAs assigned to non-participating hospitals which are outside the Baltimore City county (FIPS code 24510). The fourth sample includes all Maryland ZCTAs assigned to non-participating hospitals.

Figure B.6: Trends in Heart Failure Admission Rates for the Treatment and Control Groups, 2008-2013

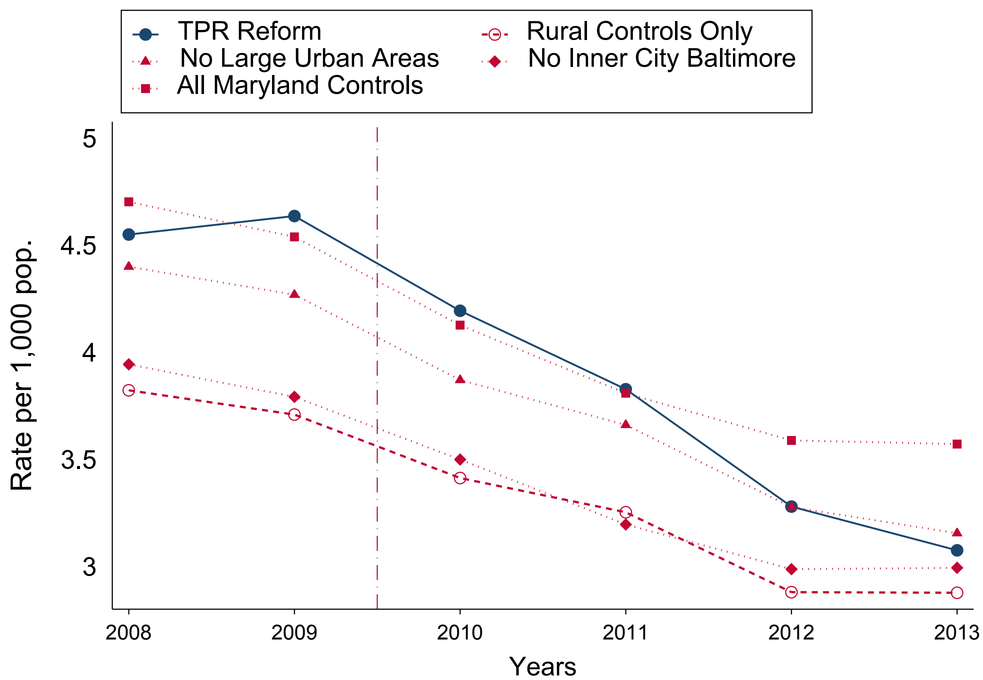


Table B.6: Estimates of the effects of TPR on the rates of heart failure admissions, with various sample restrictions

	Poisson (offset = log(population))				Weighted OLS (rate per 1,000 capita)			
	(1) TPR	(2) TPR	(3) TPR Years	(4) TPR Years	(5) TPR	(6) TPR	(7) TPR Years	(8) TPR Years
RURAL AREAS ONLY	-5.07	-0.86	-2.28	-1.26	-0.55^{*}	-0.30	-0.17^{**}	-0.14^{*}
(N=1206)	(3.98)	(4.04)	(1.42)	(1.37)	(0.29)	(0.24)	(0.082)	(0.076)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO LARGE URBAN AREAS	-3.04	-1.87	-1.54	-1.36	-0.38	-0.29	-0.12	-0.12
(N=1566)	(3.91)	(3.96)	(1.42)	(1.29)	(0.30)	(0.29)	(0.084)	(0.085)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO INNER CITY	-4.89	-6.68^{**}	-2.44^{*}	-3.24^{***}	-0.49^{*}	-0.39	-0.16^{**}	-0.15^{*}
BALTIMORE (N=2634)	(3.36)	(3.24)	(1.29)	(1.14)	(0.28)	(0.28)	(0.080)	(0.079)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
ALL OF MARYLAND	-5.50	-8.49^{**}	-2.73^{**}	-3.79^{***}	-0.38	-0.37	-0.14^{*}	-0.15^{*}
(N=2760)	(3.27)	(3.22)	(1.27)	(1.23)	(0.28)	(0.29)	(0.080)	(0.082)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓

Notes: Standard errors in parentheses. $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$. All models control for ZIP code and year fixed effects. OLS models are weighted for average ZIP code population. Poisson models report percent incidence rate differences. Models (1), (2), (5), and (6) report the effect of the TPR reform as the coefficient on the interaction between the reform indicator and the post period indicator (equal to 1 for years 2010-2013, 0 otherwise). Models (3), (4), (7), and (8) report the effect of an additional year of TPR reform implementation as the coefficient on the interaction between the reform indicator and a post linear time trend indicator (equal to 0 in the pre-reform period, 1 in the first reform year, 2 in the second, etc. The first sample includes ZCTAs assigned to the 8 TPR hospitals and 3 rural control hospitals. The second sample contains the ZCTAs in the first sample plus ZCTAs assigned to non-participating hospitals which don't belong to the CBSAs 12580 (Baltimore-Columbia-Towson) and 47900 (Washington-Arlington-Alexandria). The third sample uses as controls all Maryland ZCTAs assigned to non-participating hospitals which are outside the Baltimore City county (FIPS code 24510). The fourth sample includes all Maryland ZCTAs assigned to non-participating hospitals.

Figure B.7: Trends in the Rates of Dehydration Admission for the Treatment and Control Groups, 2008-2013

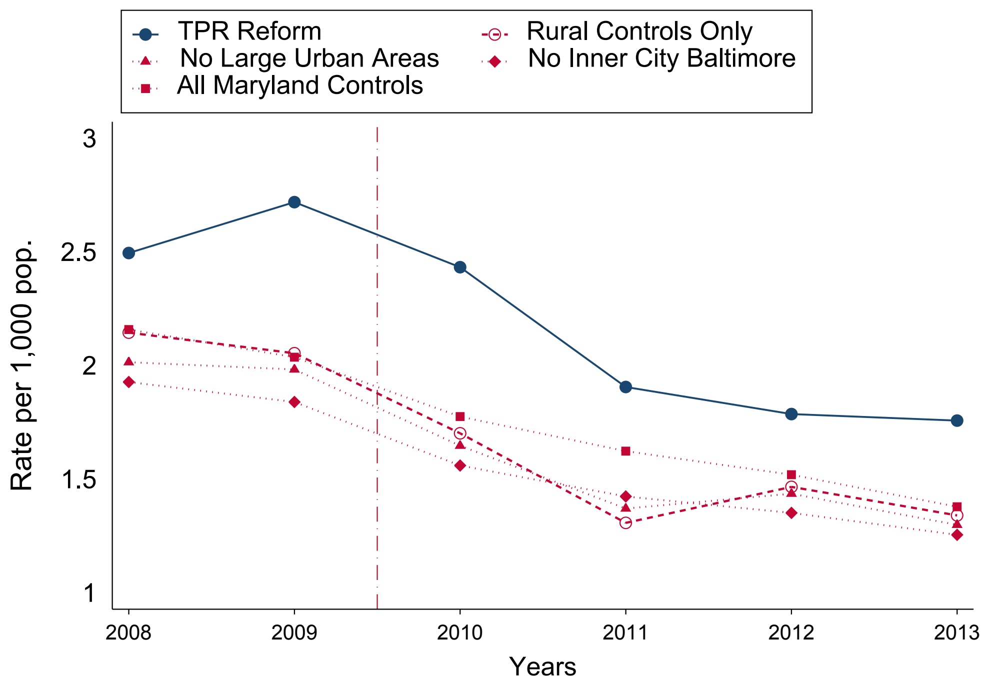


Table B.7: Estimates of the effects of TPR on the rates of dehydration admissions, with various sample restrictions

	Poisson (offset = log(population))				Weighted OLS (rate per 1,000 capita)			
	(1) TPR	(2) TPR	(3) TPR Years	(4) TPR Years	(5) TPR	(6) TPR	(7) TPR Years	(8) TPR Years
RURAL AREAS ONLY	8.95*	8.12	1.33	0.99	−0.046	0.060	−0.044	−0.027
(N=1206)	(5.27)	(6.19)	(1.46)	(1.78)	(0.14)	(0.14)	(0.041)	(0.042)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO LARGE URBAN AREAS	4.85	7.43	0.42	1.16	−0.14	−0.0056	−0.070*	−0.038
(N=1566)	(4.87)	(5.62)	(1.33)	(1.50)	(0.13)	(0.12)	(0.039)	(0.038)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO INNER CITY	1.47	−2.69	−0.22	−1.90	−0.19	−0.23**	−0.077**	−0.096***
BALTIMORE (N=2634)	(3.85)	(4.30)	(1.09)	(1.19)	(0.12)	(0.10)	(0.035)	(0.033)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
ALL OF MARYLAND	−0.28	−4.19	−0.31	−1.83	−0.16	−0.18*	−0.062*	−0.078**
(N=2760)	(3.75)	(3.87)	(1.07)	(1.17)	(0.12)	(0.11)	(0.035)	(0.035)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓

Notes: Standard errors in parentheses. $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$. All models control for ZIP code and year fixed effects. OLS models are weighted for average ZIP code population. Poisson models report percent incidence rate differences. Models (1), (2), (5), and (6) report the effect of the TPR reform as the coefficient on the interaction between the reform indicator and the post period indicator (equal to 1 for years 2010-2013, 0 otherwise). Models (3), (4), (7), and (8) report the effect of an additional year of TPR reform implementation as the coefficient on the interaction between the reform indicator and a post linear time trend indicator (equal to 0 in the pre-reform period, 1 in the first reform year, 2 in the second, etc. The first sample includes ZCTAs assigned to the 8 TPR hospitals and 3 rural control hospitals. The second sample contains the ZCTAs in the first sample plus ZCTAs assigned to non-participating hospitals which don't belong to the CBSAs 12580 (Baltimore-Columbia-Towson) and 47900 (Washington-Arlington-Alexandria). The third sample uses as controls all Maryland ZCTAs assigned to non-participating hospitals which are outside the Baltimore City county (FIPS code 24510). The fourth sample includes all Maryland ZCTAs assigned to non-participating hospitals.

Figure B.8: Trends in Bacterial Pneumonia Admission Rates for the Treatment and Control Groups, 2008-2013

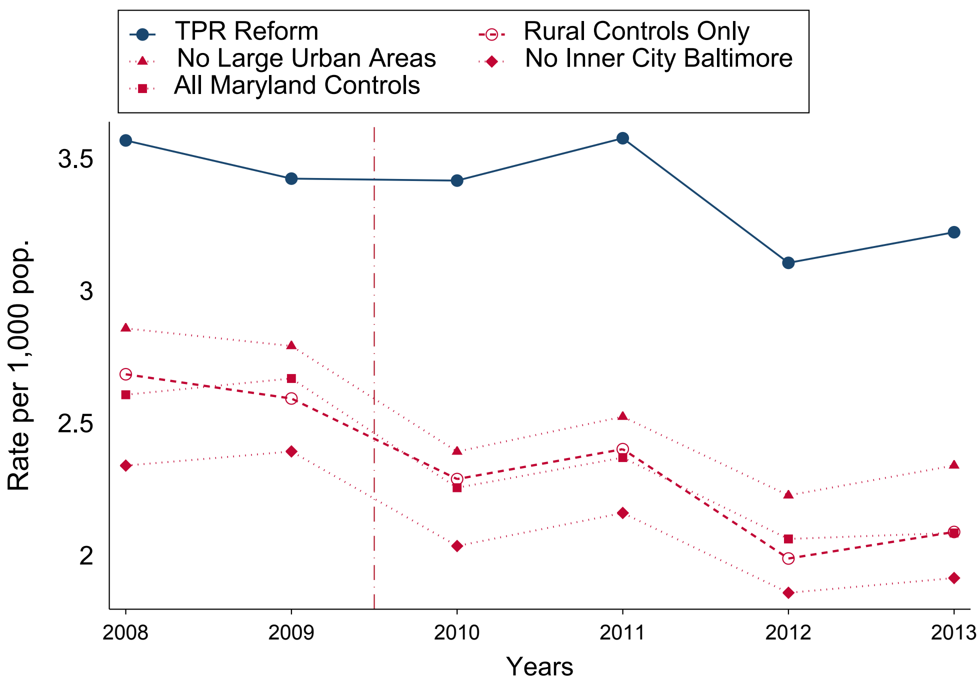


Table B.8: Estimates of the effects of TPR on the rates of bacterial pneumonia admissions, with various sample restrictions

	Poisson (offset = log(population))				Weighted OLS (rate per 1,000 capita)			
	(1) TPR	(2) TPR	(3) TPR Years	(4) TPR Years	(5) TPR	(6) TPR	(7) TPR Years	(8) TPR Years
RURAL AREAS ONLY	15.2^{***}	13.3^{*}	3.74^{**}	3.21^{*}	0.19	0.23	0.040	0.046
(N=1206)	(6.32)	(7.34)	(1.61)	(1.70)	(0.19)	(0.21)	(0.052)	(0.054)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO LARGE URBAN AREAS	13.7^{**}	11.2^{*}	2.59	1.76	0.20	0.16	0.026	0.0050
(N=1566)	(5.82)	(6.74)	(1.63)	(1.91)	(0.18)	(0.21)	(0.052)	(0.062)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO INNER CITY	13.5^{***}	6.54	2.83^{**}	0.61	0.15	0.064	0.017	−0.025
BALTIMORE (N=2634)	(4.89)	(5.61)	(1.44)	(1.76)	(0.16)	(0.19)	(0.048)	(0.055)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
ALL OF MARYLAND	14.3^{***}	6.02	3.11^{**}	0.68	0.20	0.089	0.034	−0.016
(N=2760)	(4.80)	(5.37)	(1.41)	(1.73)	(0.16)	(0.19)	(0.048)	(0.057)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓

Notes: Standard errors in parentheses. $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$. All models control for ZIP code and year fixed effects. OLS models are weighted for average ZIP code population. Poisson models report percent incidence rate differences. Models (1), (2), (5), and (6) report the effect of the TPR reform as the coefficient on the interaction between the reform indicator and the post period indicator (equal to 1 for years 2010-2013, 0 otherwise). Models (3), (4), (7), and (8) report the effect of an additional year of TPR reform implementation as the coefficient on the interaction between the reform indicator and a post linear time trend indicator (equal to 0 in the pre-reform period, 1 in the first reform year, 2 in the second, etc. The first sample includes ZCTAs assigned to the 8 TPR hospitals and 3 rural control hospitals. The second sample contains the ZCTAs in the first sample plus ZCTAs assigned to non-participating hospitals which don't belong to the CBSAs 12580 (Baltimore-Columbia-Towson) and 47900 (Washington-Arlington-Alexandria). The third sample uses as controls all Maryland ZCTAs assigned to non-participating hospitals which are outside the Baltimore City county (FIPS code 24510). The fourth sample includes all Maryland ZCTAs assigned to non-participating hospitals.

Figure B.9: Trends in UTI Admission Rates for the Treatment and Control Groups, 2008-2013

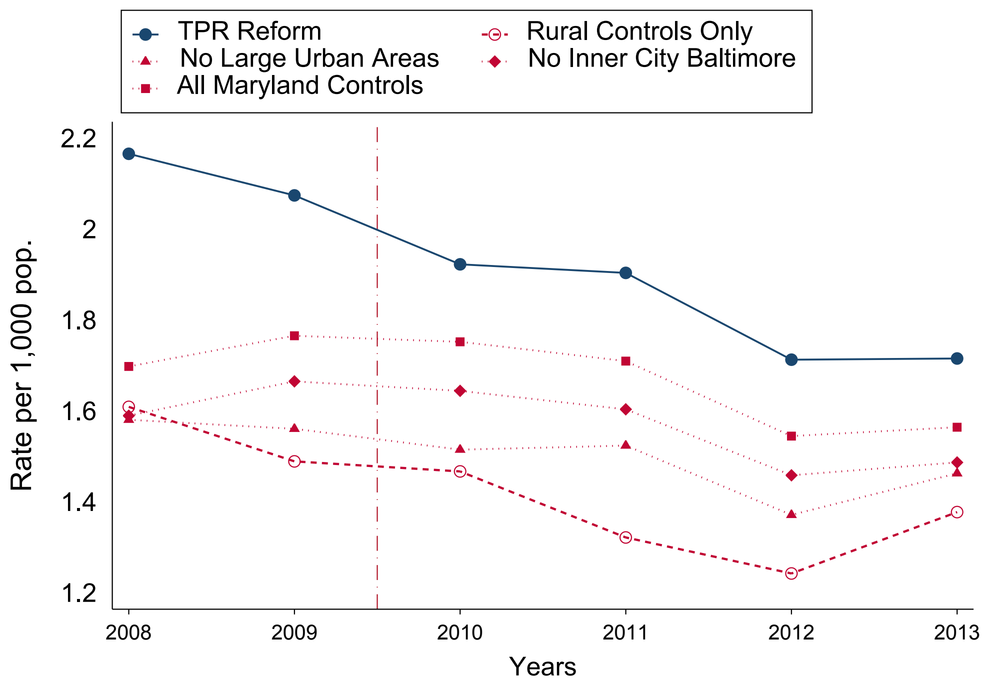


Table B.9: Estimates of the effects of TPR on the rates of UTI admissions, with various sample restrictions

	Poisson (offset = log(population))				Weighted OLS (rate per 1,000 capita)			
	(1) TPR	(2) TPR	(3) TPR Years	(4) TPR Years	(5) TPR	(6) TPR	(7) TPR Years	(8) TPR Years
RURAL AREAS ONLY	−2.04	−9.11	−0.87	−2.31	−0.11	−0.22	−0.040	−0.064
(N=1206)	(6.76)	(7.58)	(2.02)	(2.34)	(0.14)	(0.16)	(0.040)	(0.045)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO LARGE URBAN AREAS	−8.62	−9.20	−2.76	−2.74	−0.20	−0.21	−0.064	−0.066
(N=1566)	(6.18)	(7.16)	(1.96)	(2.21)	(0.13)	(0.15)	(0.039)	(0.043)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO INNER CITY	-10.4^{**}	-18.5^{***}	-2.92^{*}	-5.11^{***}	-0.23^{**}	-0.37^{***}	-0.062^{*}	-0.097^{**}
BALTIMORE (N=2634)	(4.77)	(4.95)	(1.67)	(1.90)	(0.12)	(0.13)	(0.035)	(0.038)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
ALL OF MARYLAND	-10.4^{**}	-18.4^{***}	-2.79^{*}	-5.15^{***}	-0.22^{*}	-0.35^{***}	-0.058^{*}	-0.095^{**}
(N=2760)	(4.67)	(4.81)	(1.64)	(1.89)	(0.11)	(0.13)	(0.035)	(0.039)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓

Notes: Standard errors in parentheses. ${}^{*}p < 0.1, {}^{**}p < 0.05, {}^{***}p < 0.01$. All models control for ZIP code and year fixed effects. OLS models are weighted for average ZIP code population. Poisson models report percent incidence rate differences. Models (1), (2), (5), and (6) report the effect of the TPR reform as the coefficient on the interaction between the reform indicator and the post period indicator (equal to 1 for years 2010-2013, 0 otherwise). Models (3), (4), (7), and (8) report the effect of an additional year of TPR reform implementation as the coefficient on the interaction between the reform indicator and a post linear time trend indicator (equal to 0 in the pre-reform period, 1 in the first reform year, 2 in the second, etc. The first sample includes ZCTAs assigned to the 8 TPR hospitals and 3 rural control hospitals. The second sample contains the ZCTAs in the first sample plus ZCTAs assigned to non-participating hospitals which don't belong to the CBSAs 12580 (Baltimore-Columbia-Towson) and 47900 (Washington-Arlington-Alexandria). The third sample uses as controls all Maryland ZCTAs assigned to non-participating hospitals which are outside the Baltimore City county (FIPS code 24510). The fourth sample includes all Maryland ZCTAs assigned to non-participating hospitals.

Figure B.10: Trends in the Rates of Angina without Procedure Admissions for the Treatment and Control Groups, 2008-2013

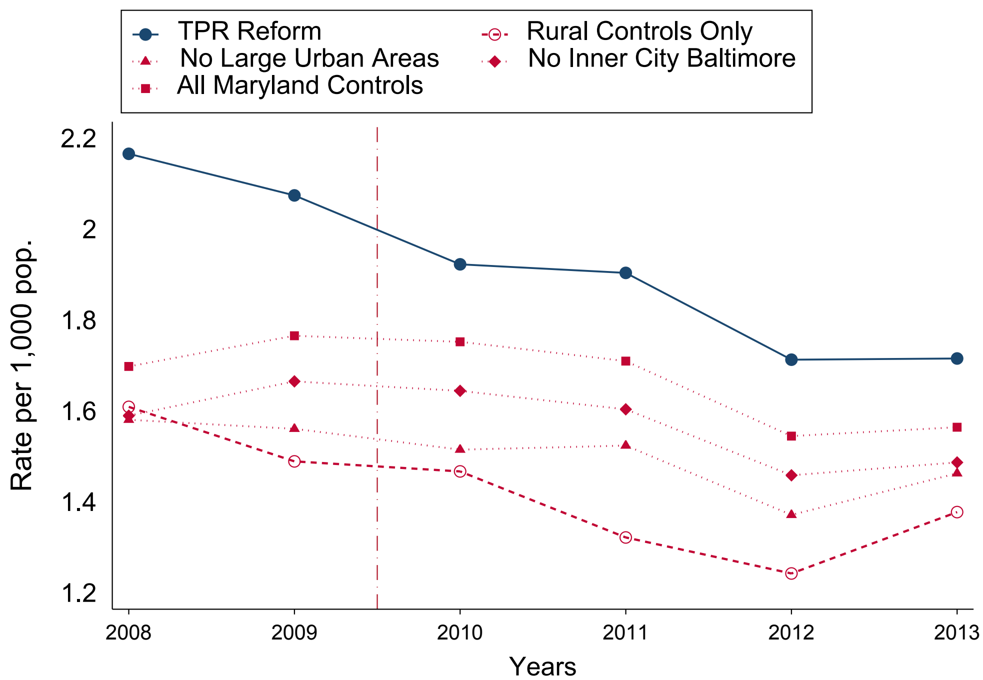


Table B.10: Estimates of the effects of TPR on the rates of angina without procedure admissions, with various sample restrictions

	Poisson (offset = log(population))				Weighted OLS (rate per 1,000 capita)			
	(1) TPR	(2) TPR	(3) TPR Years	(4) TPR Years	(5) TPR	(6) TPR	(7) TPR Years	(8) TPR Years
RURAL AREAS ONLY	44.4^{**}	32.6	7.85	1.28	0.10	0.15^{*}	0.012	0.019
(N=1206)	(21.4)	(22.8)	(5.26)	(5.67)	(0.077)	(0.087)	(0.020)	(0.024)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO LARGE URBAN AREAS	31.2^{**}	29.2^{*}	6.59	6.40	0.10	0.19^{**}	0.018	0.040^{**}
(N=1566)	(17.0)	(17.1)	(4.50)	(4.65)	(0.065)	(0.073)	(0.017)	(0.020)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO INNER CITY	3.76	23.1^{*}	-0.87	3.53	-0.065	0.11	-0.027^{*}	0.016
BALTIMORE (N=2634)	(11.2)	(14.7)	(3.35)	(3.70)	(0.059)	(0.088)	(0.015)	(0.023)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
ALL OF MARYLAND	-3.56	18.5	-3.48	2.43	-0.069	0.073	-0.027^{*}	0.0058
(N=2760)	(10.2)	(13.6)	(3.22)	(3.57)	(0.055)	(0.074)	(0.014)	(0.019)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓

Notes: Standard errors in parentheses. $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$. All models control for ZIP code and year fixed effects. OLS models are weighted for average ZIP code population. Poisson models report percent incidence rate differences. Models (1), (2), (5), and (6) report the effect of the TPR reform as the coefficient on the interaction between the reform indicator and the post period indicator (equal to 1 for years 2010-2013, 0 otherwise). Models (3), (4), (7), and (8) report the effect of an additional year of TPR reform implementation as the coefficient on the interaction between the reform indicator and a post linear time trend indicator (equal to 0 in the pre-reform period, 1 in the first reform year, 2 in the second, etc. The first sample includes ZCTAs assigned to the 8 TPR hospitals and 3 rural control hospitals. The second sample contains the ZCTAs in the first sample plus ZCTAs assigned to non-participating hospitals which don't belong to the CBSAs 12580 (Baltimore-Columbia-Towson) and 47900 (Washington-Arlington-Alexandria). The third sample uses as controls all Maryland ZCTAs assigned to non-participating hospitals which are outside the Baltimore City county (FIPS code 24510). The fourth sample includes all Maryland ZCTAs assigned to non-participating hospitals.

Figure B.11: Trends in the Rates of Uncontrolled Diabetes for the Treatment and Control Groups, 2008-2013

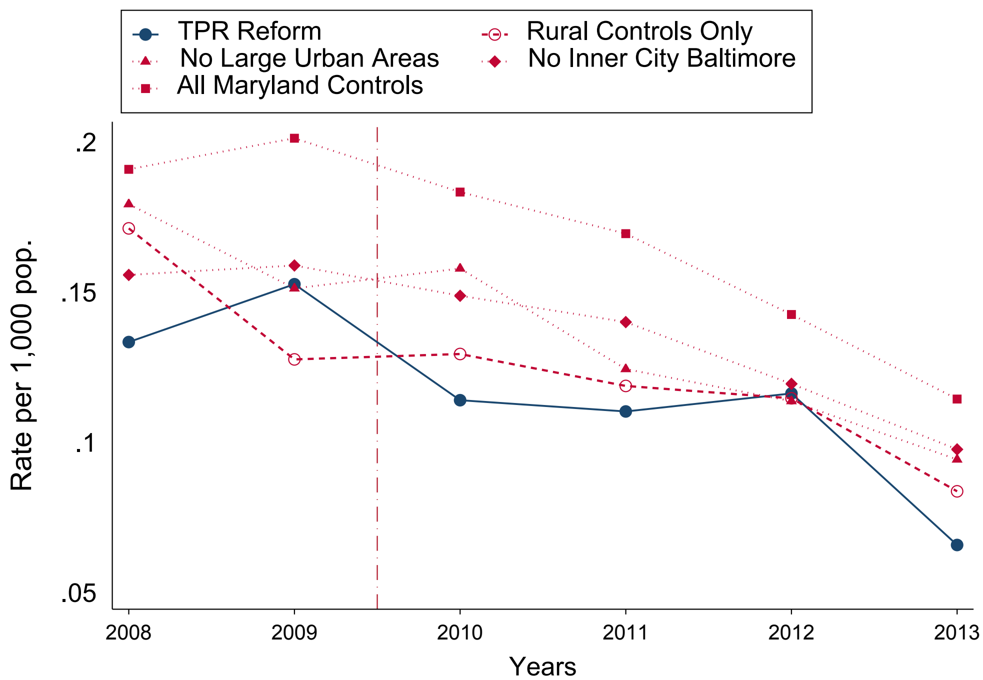


Table B.11: Estimates of the effects of TPR on the rates of uncontrolled diabetes admissions, with various sample restrictions

	Poisson (offset = log(population))				Weighted OLS (rate per 1,000 capita)			
	(1) TPR	(2) TPR	(3) TPR Years	(4) TPR Years	(5) TPR	(6) TPR	(7) TPR Years	(8) TPR Years
RURAL AREAS ONLY	−4.10	−10.9	0.20	−1.33	0.0028	−0.00043	0.0029	0.0027
(N=1206)	(16.3)	(19.0)	(4.65)	(5.67)	(0.025)	(0.032)	(0.0063)	(0.0083)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO LARGE URBAN AREAS	−2.94	−10.5	1.14	−1.11	0.0078	0.0028	0.0052	0.0035
(N=1566)	(13.9)	(14.7)	(3.84)	(4.53)	(0.021)	(0.024)	(0.0052)	(0.0063)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO INNER CITY	−12.1	−5.38	−2.71	−1.15	0.0026	0.029	0.0028	0.0087
BALTIMORE (N=2634)	(10.2)	(12.8)	(2.94)	(3.42)	(0.020)	(0.038)	(0.0050)	(0.0097)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
ALL OF MARYLAND	−10.1	−6.11	−1.88	−1.68	0.011	0.040	0.0062	0.011
(N=2760)	(10.3)	(11.6)	(2.96)	(3.05)	(0.019)	(0.031)	(0.0049)	(0.0076)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓

Notes: Standard errors in parentheses. $^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$. All models control for ZIP code and year fixed effects. OLS models are weighted for average ZIP code population. Poisson models report percent incidence rate differences. Models (1), (2), (5), and (6) report the effect of the TPR reform as the coefficient on the interaction between the reform indicator and the post period indicator (equal to 1 for years 2010-2013, 0 otherwise). Models (3), (4), (7), and (8) report the effect of an additional year of TPR reform implementation as the coefficient on the interaction between the reform indicator and a post linear time trend indicator (equal to 0 in the pre-reform period, 1 in the first reform year, 2 in the second, etc. The first sample includes ZCTAs assigned to the 8 TPR hospitals and 3 rural control hospitals. The second sample contains the ZCTAs in the first sample plus ZCTAs assigned to non-participating hospitals which don't belong to the CBSAs 12580 (Baltimore-Columbia-Towson) and 47900 (Washington-Arlington-Alexandria). The third sample uses as controls all Maryland ZCTAs assigned to non-participating hospitals which are outside the Baltimore City county (FIPS code 24510). The fourth sample includes all Maryland ZCTAs assigned to non-participating hospitals.

Figure B.12: Trends in Admission Rates for Asthma in Younger Adults in the Treatment and Control Groups, 2008-2013

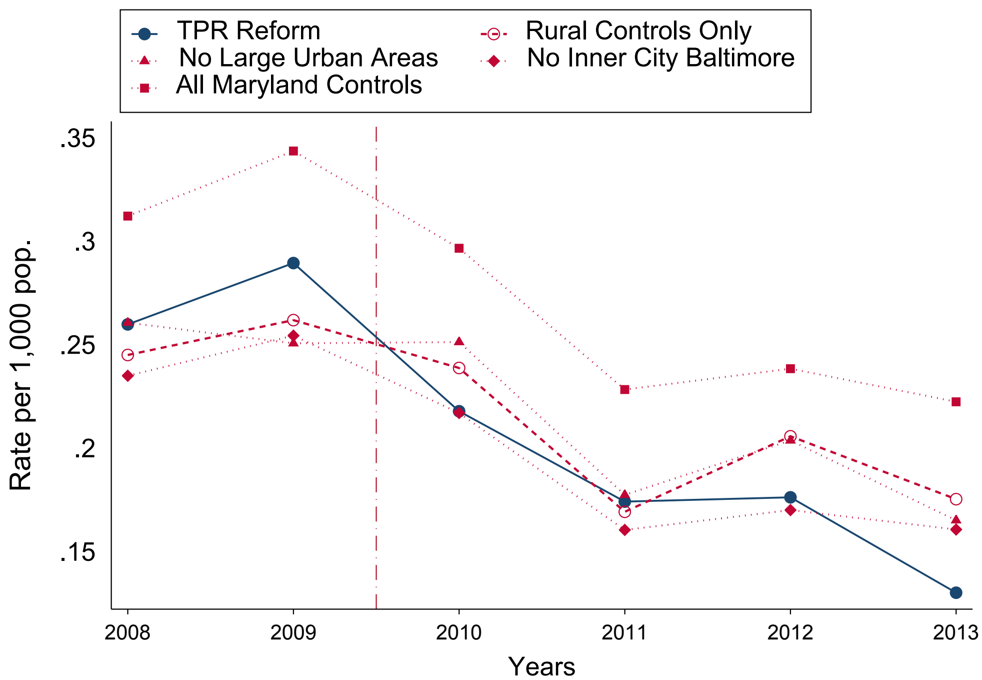


Table B.12: Estimates of the effects of TPR on the rates of admission for asthma in younger adults, with various sample restrictions

	Poisson (offset = log(population))				Weighted OLS (rate per 1,000 capita)			
	(1) TPR	(2) TPR	(3) TPR Years	(4) TPR Years	(5) TPR	(6) TPR	(7) TPR Years	(8) TPR Years
RURAL AREAS ONLY	-19.1^{*}	-17.4	-6.76	-6.31	-0.040	-0.038	-0.012	-0.013
(N=1206)	(10.4)	(15.0)	(4.31)	(5.40)	(0.034)	(0.044)	(0.011)	(0.014)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO LARGE URBAN AREAS	-18.8^{*}	-18.5	-5.36	-4.79	-0.041	-0.046	-0.0096	-0.012
(N=1566)	(9.24)	(11.6)	(3.78)	(4.74)	(0.030)	(0.034)	(0.0094)	(0.011)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO INNER CITY	-12.9	-15.8	-4.77	-5.68	-0.033	-0.036	-0.011	-0.010
BALTIMORE (N=2634)	(7.49)	(8.83)	(3.02)	(3.78)	(0.022)	(0.026)	(0.0074)	(0.0087)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
ALL OF MARYLAND	-17.4^{**}	-19.8^{**}	-6.19^{**}	-6.87^{**}	-0.023	-0.022	-0.0072	-0.0076
(N=2760)	(6.93)	(7.76)	(2.92)	(3.37)	(0.022)	(0.026)	(0.0075)	(0.0086)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓

Notes: Standard errors in parentheses. ${}^{*}p < 0.1, {}^{**}p < 0.05, {}^{***}p < 0.01$. All models control for ZIP code and year fixed effects. OLS models are weighted for average ZIP code population. Poisson models report percent incidence rate differences. Models (1), (2), (5), and (6) report the effect of the TPR reform as the coefficient on the interaction between the reform indicator and the post period indicator (equal to 1 for years 2010-2013, 0 otherwise). Models (3), (4), (7), and (8) report the effect of an additional year of TPR reform implementation as the coefficient on the interaction between the reform indicator and a post linear time trend indicator (equal to 0 in the pre-reform period, 1 in the first reform year, 2 in the second, etc. The first sample includes ZCTAs assigned to the 8 TPR hospitals and 3 rural control hospitals. The second sample contains the ZCTAs in the first sample plus ZCTAs assigned to non-participating hospitals which don't belong to the CBSAs 12580 (Baltimore-Columbia-Towson) and 47900 (Washington-Arlington-Alexandria). The third sample uses as controls all Maryland ZCTAs assigned to non-participating hospitals which are outside the Baltimore City county (FIPS code 24510). The fourth sample includes all Maryland ZCTAs assigned to non-participating hospitals.

Figure B.13: Trends in the Rates of Lower-Extremity Amputation among Patients with Diabetes for the Treatment and Control Groups, 2008-2013

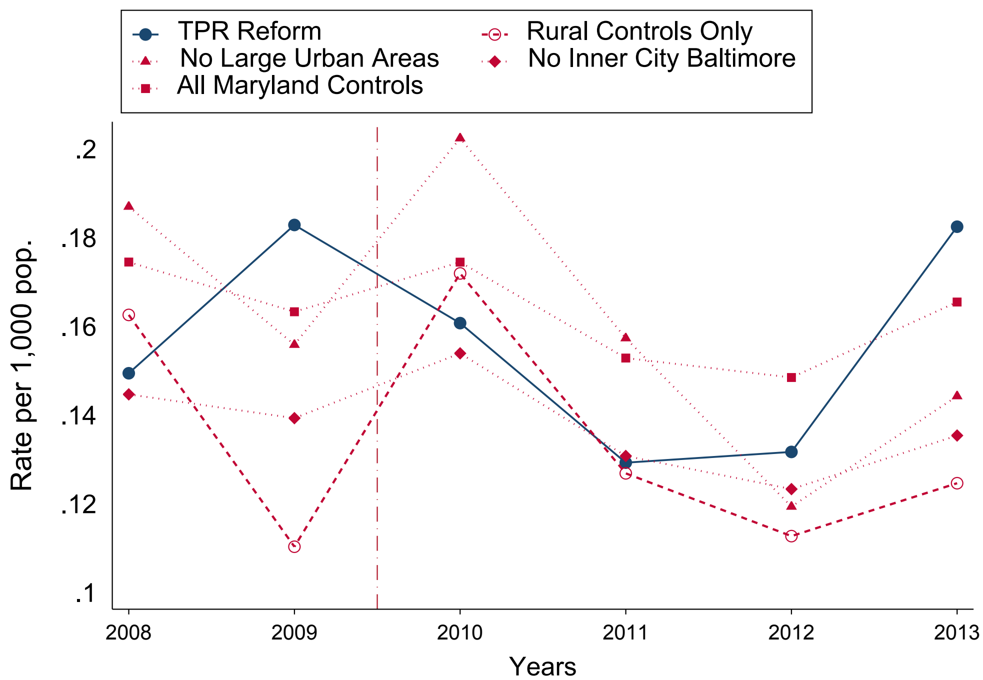


Table B.13: Estimates of the effects of TPR on the rates of lower-extremity amputation among patients with diabetes, with various sample restrictions

	Poisson (offset = log(population))				Weighted OLS (rate per 1,000 capita)			
	(1) TPR	(2) TPR	(3) TPR Years	(4) TPR Years	(5) TPR	(6) TPR	(7) TPR Years	(8) TPR Years
RURAL AREAS ONLY	−7.31	−16.1	4.60	5.40	−0.012	−0.025	0.0060	0.0088
(N=1206)	(16.0)	(17.6)	(4.72)	(5.44)	(0.025)	(0.032)	(0.0067)	(0.0083)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO LARGE URBAN AREAS	−0.47	−1.12	6.31	8.14*	−0.00028	0.0024	0.0098	0.014*
(N=1566)	(14.5)	(16.8)	(4.19)	(4.61)	(0.023)	(0.030)	(0.0064)	(0.0077)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
NO INNER CITY	−5.27	−0.92	2.05	3.99	−0.0096	0.0014	0.0026	0.0066
BALTIMORE (N=2634)	(11.3)	(12.5)	(3.42)	(3.55)	(0.019)	(0.021)	(0.0052)	(0.0055)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓
ALL OF MARYLAND	−5.64	−2.26	1.22	2.68	−0.0092	−0.0039	0.0019	0.0045
(N=2760)	(11.1)	(12.1)	(3.29)	(3.33)	(0.019)	(0.021)	(0.0052)	(0.0054)
Time-varying controls	✗	✓	✗	✓	✗	✓	✗	✓

Notes: Standard errors in parentheses. $^{*}p < 0.1, ^{**}p < 0.05, ^{***}p < 0.01$. All models control for ZIP code and year fixed effects. OLS models are weighted for average ZIP code population. Poisson models report percent incidence rate differences. Models (1), (2), (5), and (6) report the effect of the TPR reform as the coefficient on the interaction between the reform indicator and the post period indicator (equal to 1 for years 2010-2013, 0 otherwise). Models (3), (4), (7), and (8) report the effect of an additional year of TPR reform implementation as the coefficient on the interaction between the reform indicator and a post linear time trend indicator (equal to 0 in the pre-reform period, 1 in the first reform year, 2 in the second, etc. The first sample includes ZCTAs assigned to the 8 TPR hospitals and 3 rural control hospitals. The second sample contains the ZCTAs in the first sample plus ZCTAs assigned to non-participating hospitals which don't belong to the CBSAs 12580 (Baltimore-Columbia-Towson) and 47900 (Washington-Arlington-Alexandria). The third sample uses as controls all Maryland ZCTAs assigned to non-participating hospitals which are outside the Baltimore City county (FIPS code 24510). The fourth sample includes all Maryland ZCTAs assigned to non-participating hospitals.

Appendix C

Quantile Regression Results

APPENDIX C. QUANTILE REGRESSION RESULTS

Figure C.1: Quantile Treatment Effects for Hospitalization Rates, 2008-2013

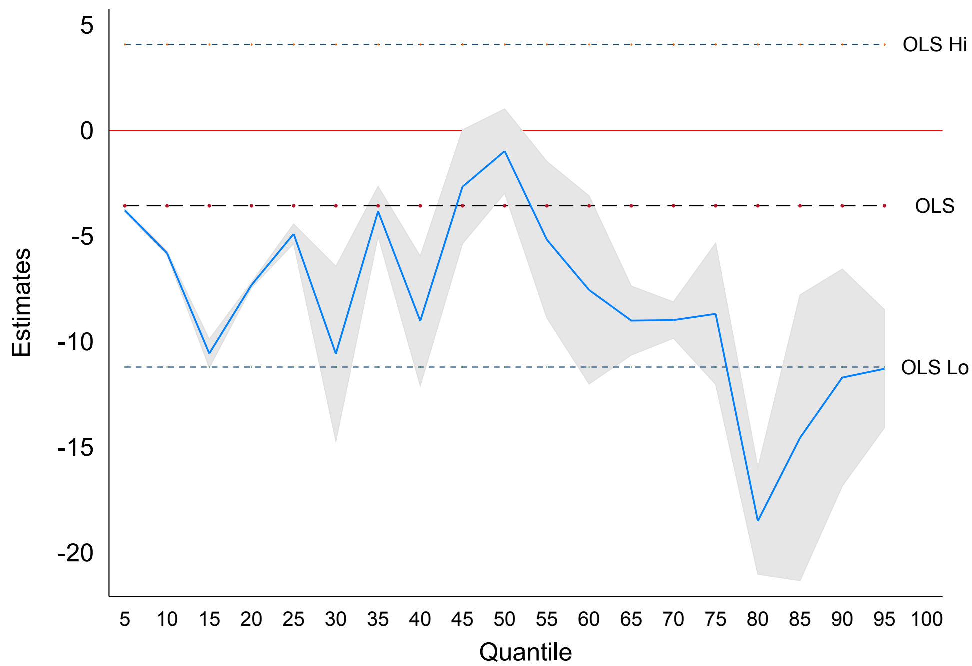


Figure C.2: Quantile Treatment Effects for Inpatient Day Rates, 2008-2013

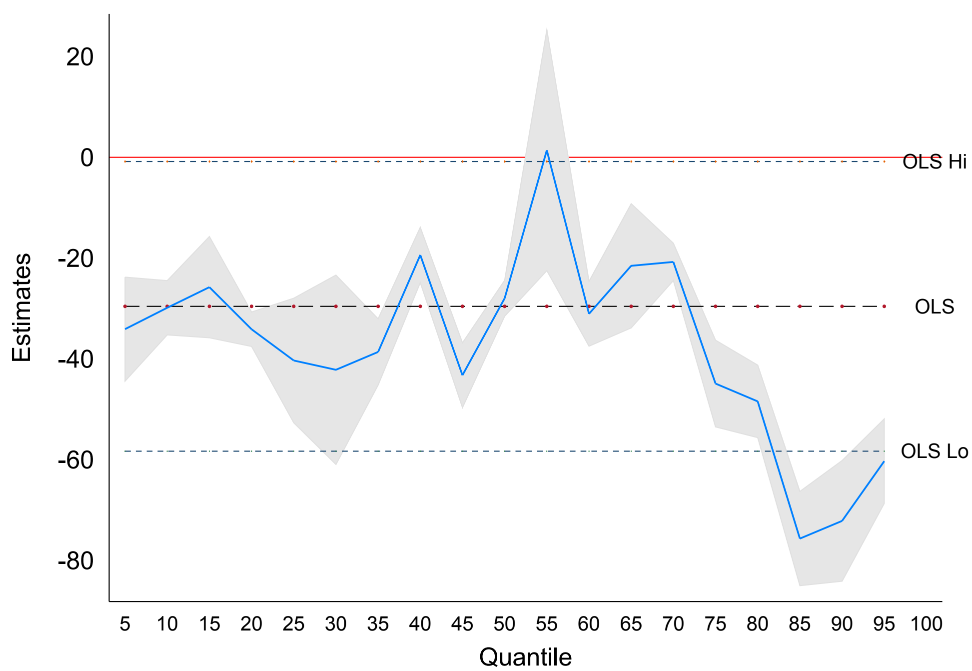


Figure C.3: Quantile Treatment Effects for 30-Day Readmission Rates, 2008-2013

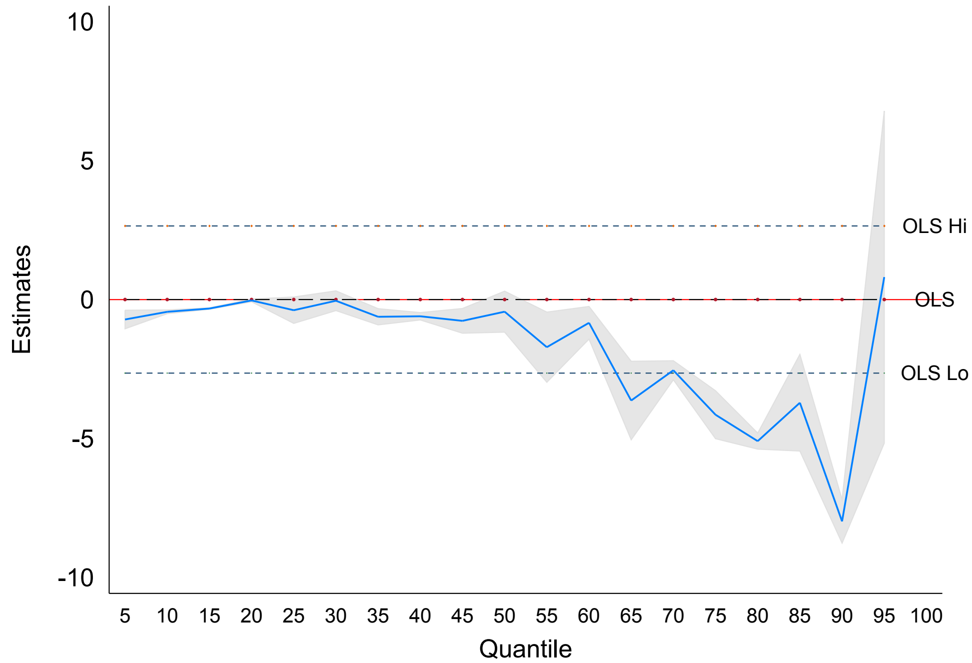


Figure C.4: Quantile Treatment Effects for Preventable Admission Rates, 2008-2013

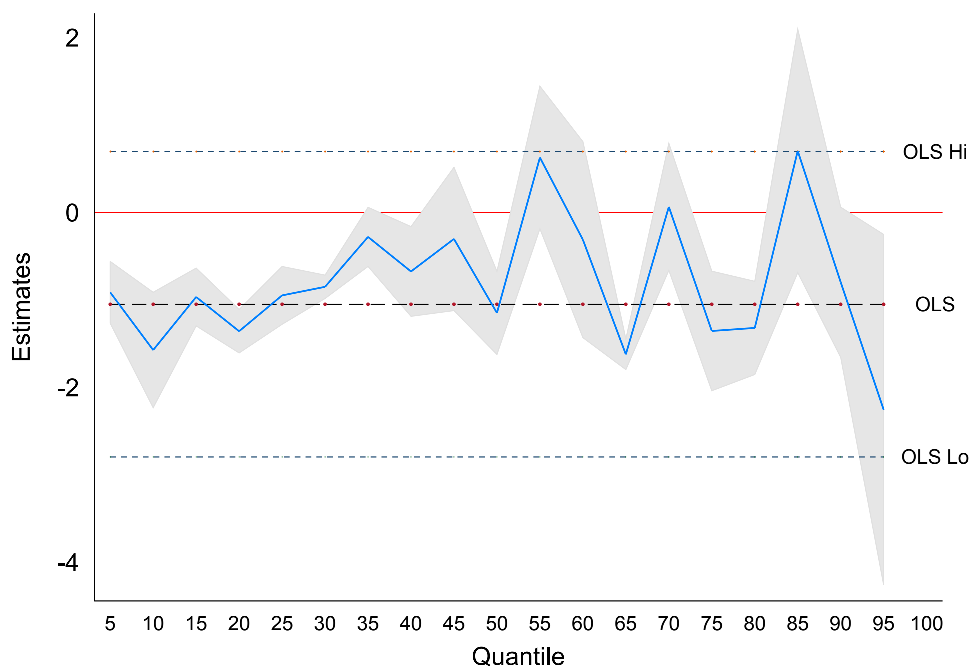


Figure C.5: Quantile Treatment Effects for Chronic Preventable Admission Rates, 2008-2013

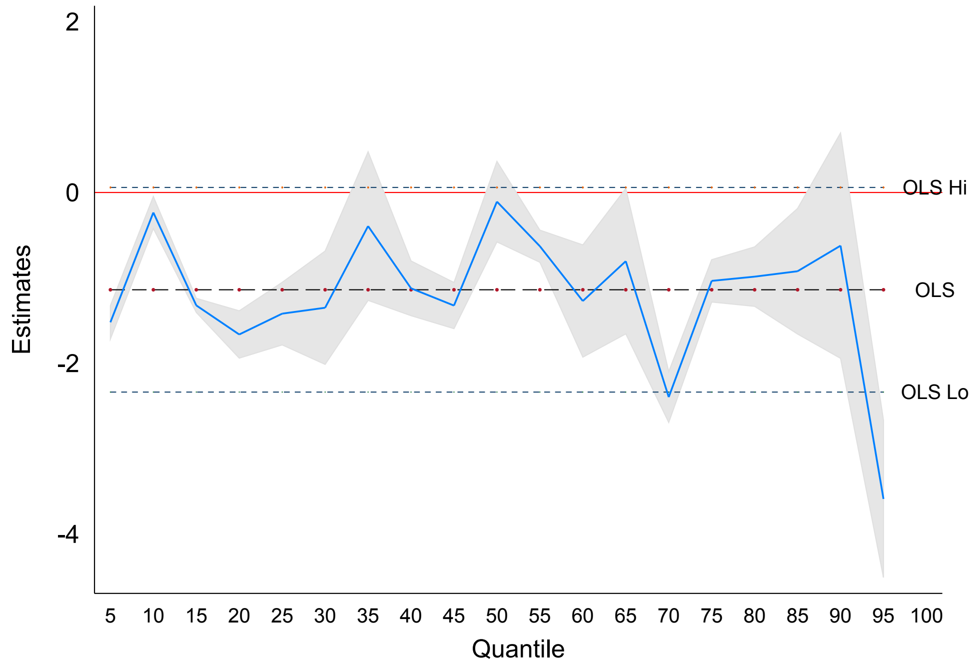


Figure C.6: Quantile Treatment Effects for Acute Preventable Admission Rates, 2008-2013

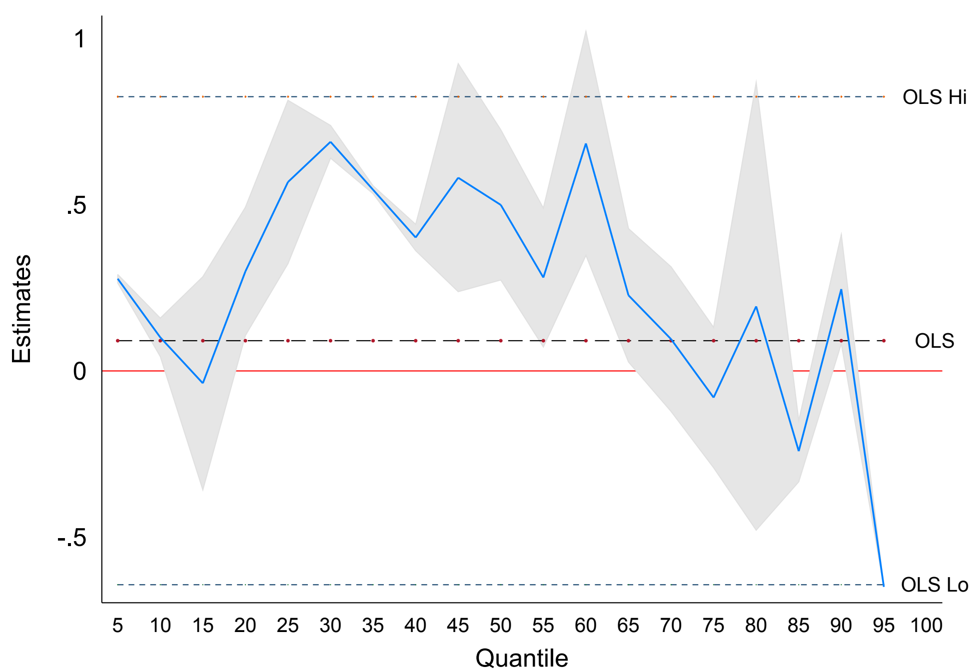


Figure C.7: Quantile Treatment Effects for Non-Preventable Admission Rates, 2008-2013

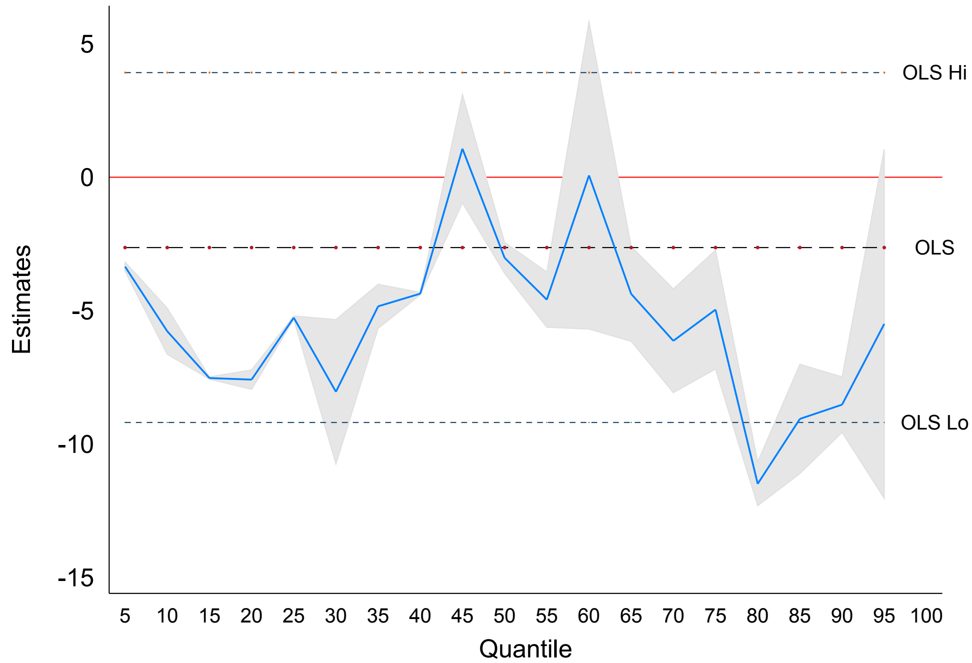


Figure C.8: Quantile Treatment Effects for Non-Deferrable Admission Rates, 2008-2013

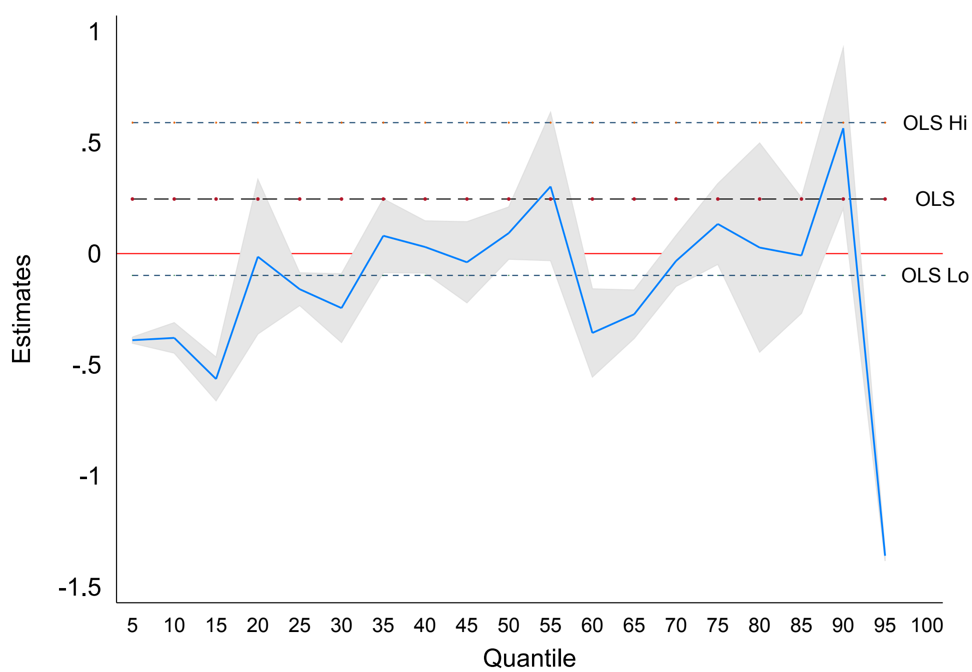


Figure C.9: Quantile Treatment Effects for Potentially Deferrable Admission Rates, 2008-2013

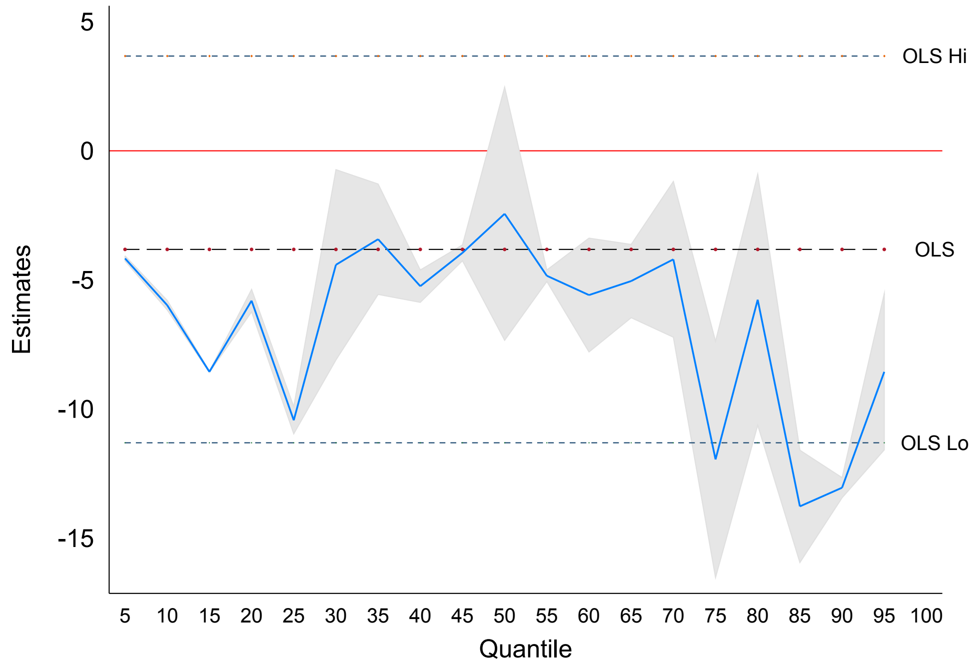


Figure C.10: Quantile Treatment Effects for Rates of Admission from the ED, 2008-2013

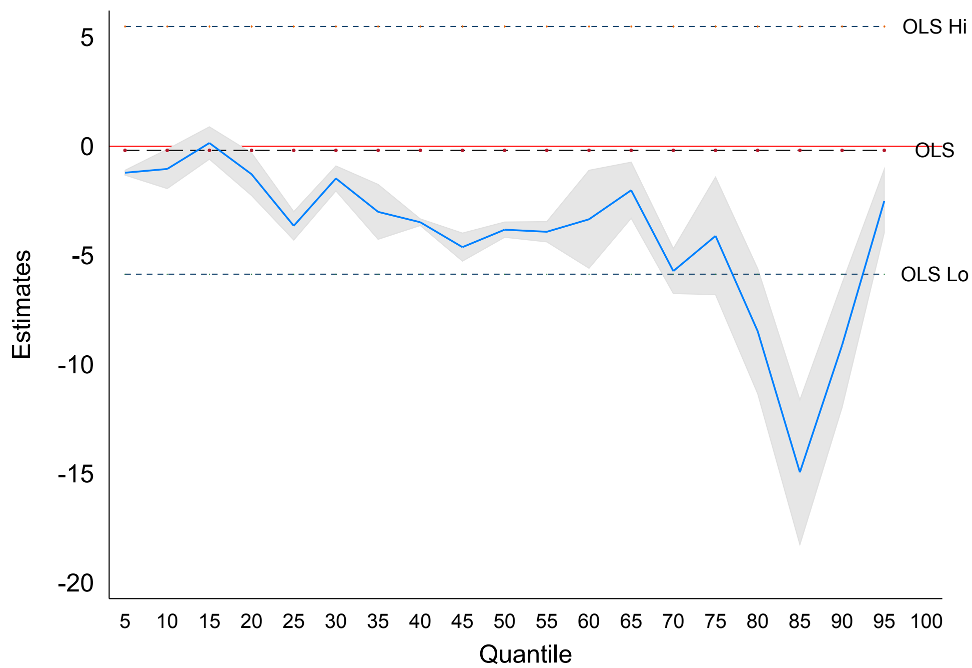


Figure C.11: Quantile Treatment Effects for Outpatient Encounters Rates, 2008-2013

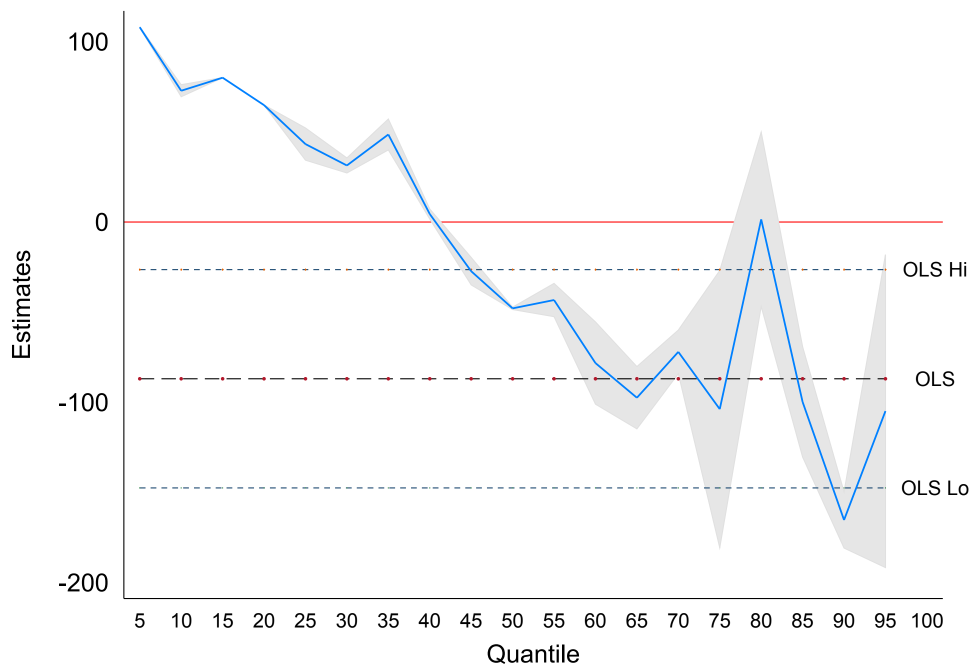


Figure C.12: Quantile Treatment Effects for ED Visit Rates, 2008-2013

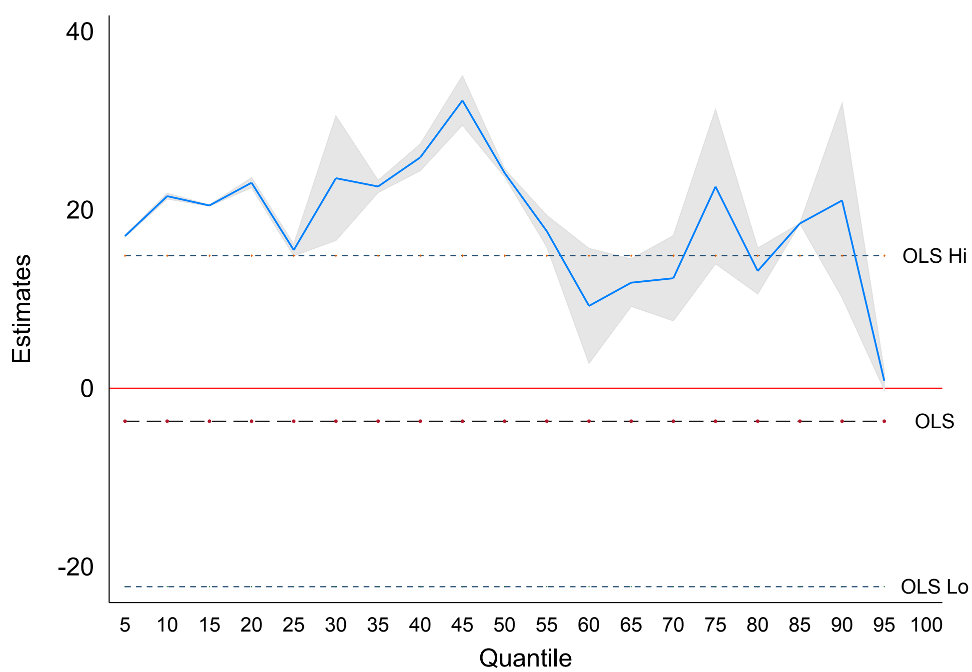


Figure C.13: Quantile Treatment Effects for Non-Emergent ED Visit Rates, 2008-2013

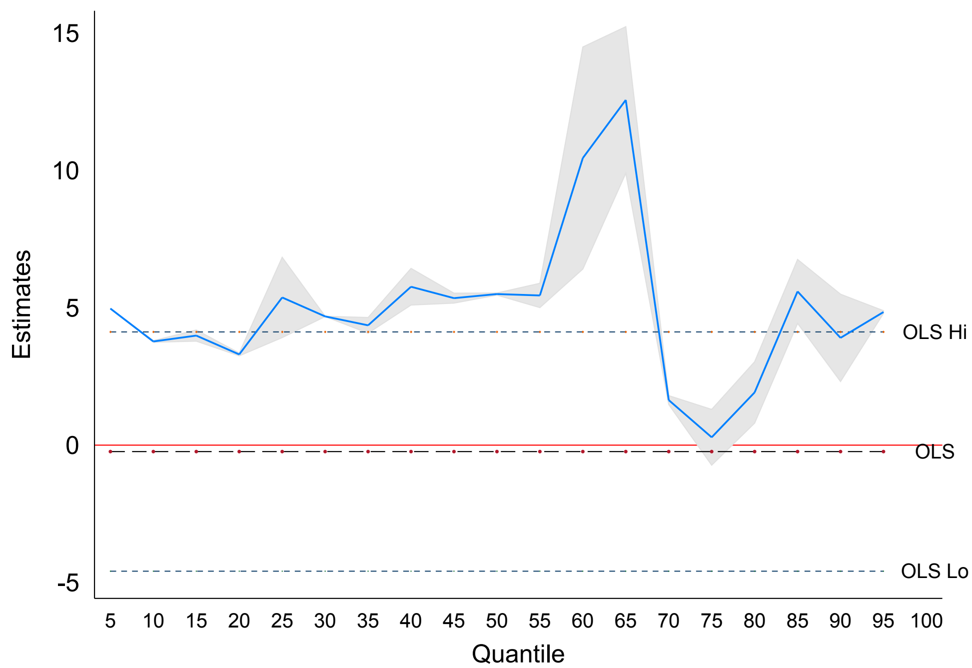


Figure C.14: Quantile Treatment Effects for Primary Care Treatable ED Visit Rates, 2008-2013

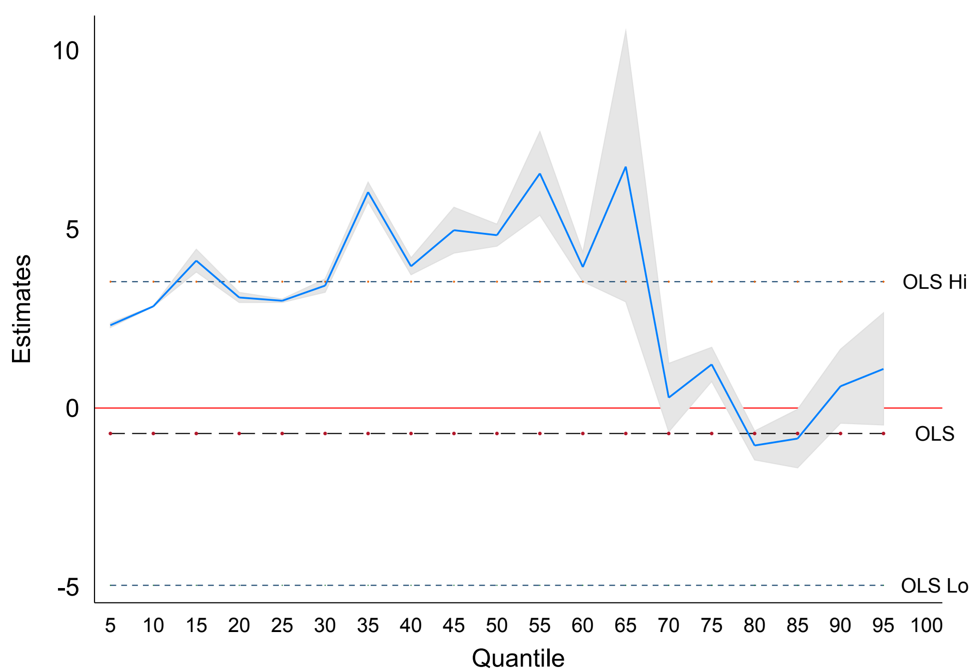


Figure C.15: Quantile Treatment Effects for Avoidable ED Visit Rates, 2008-2013

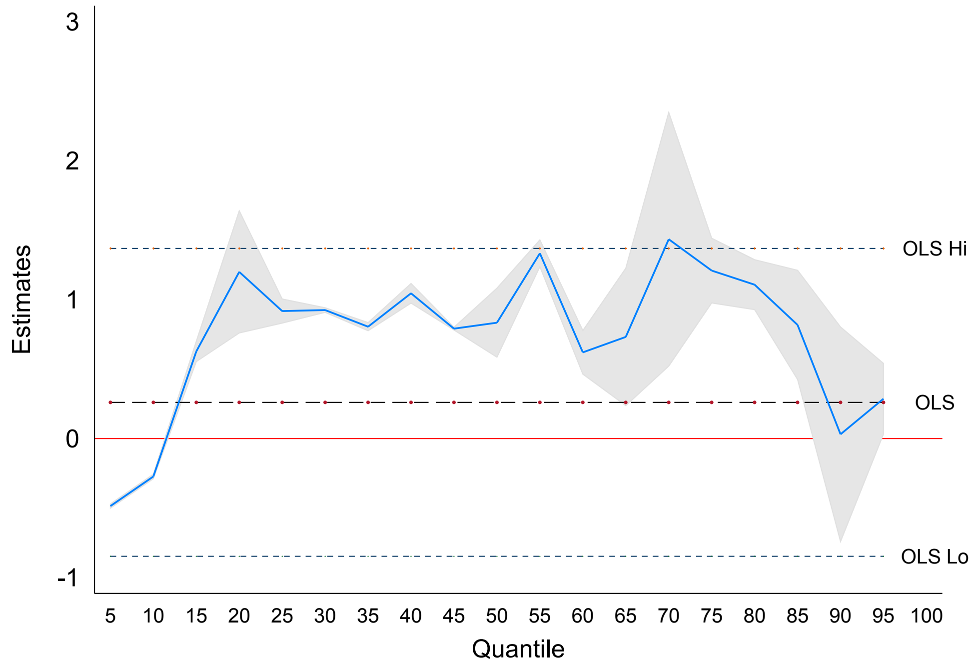


Figure C.16: Quantile Treatment Effects for Non-Preventable ED Visit Rates, 2008-2013

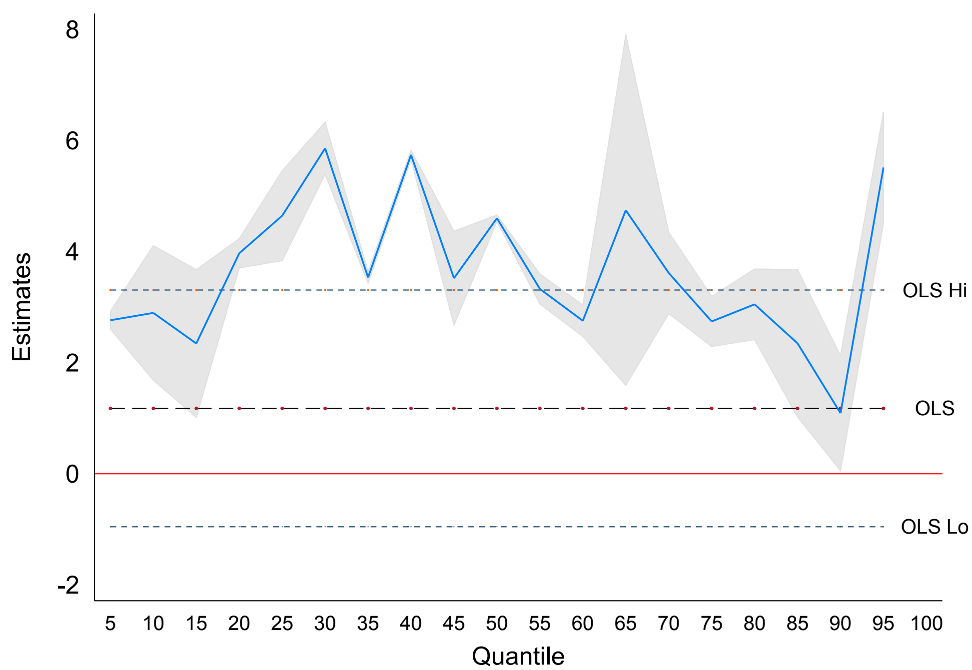


Figure C.17: Quantile Treatment Effects for Injury-Related ED Visit Rates, 2008-2013

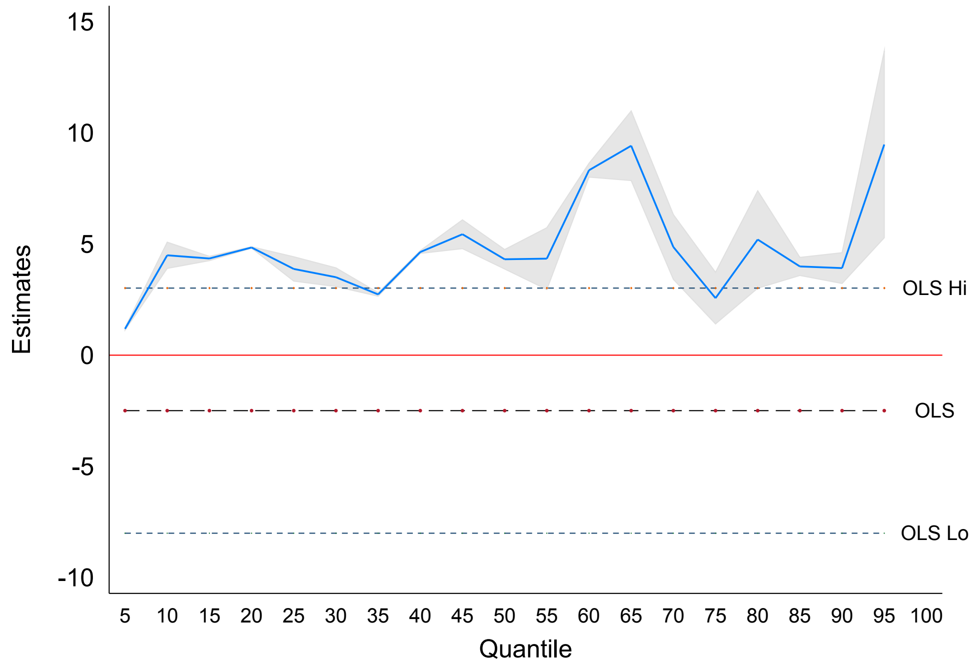
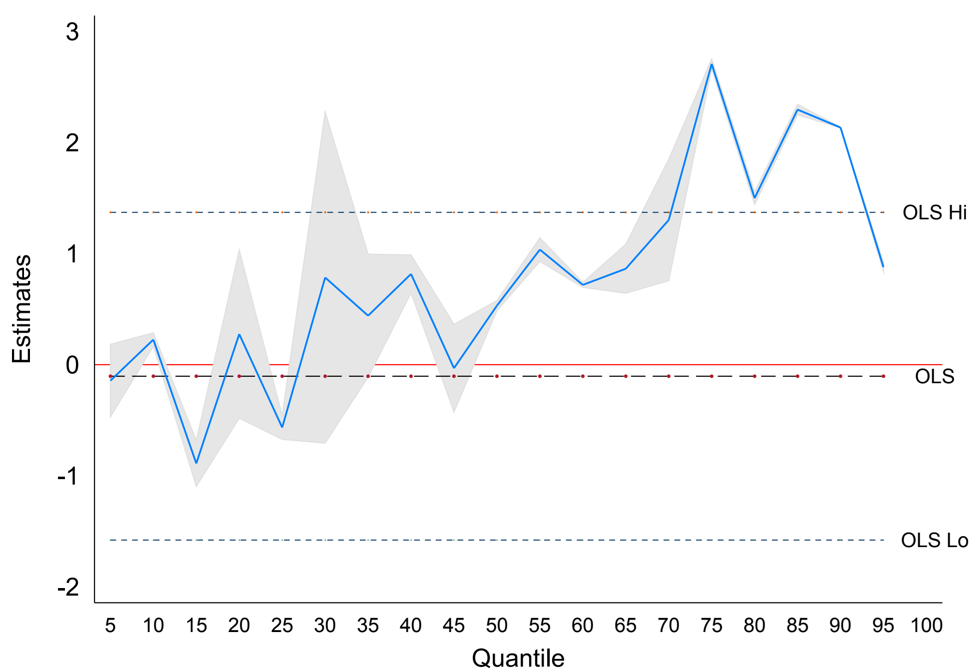


Figure C.18: Quantile Treatment Effects for Behavioral ED Visit Rates, 2008-2013



Acronyms

ABF Activity-Based Funding. 53

ACC Accountable Care Collaborative. 5

ACO Accountable Care Organization. 174

ACOs Accountable Care Organizations. 4

ACS American Community Survey. 84

ACSC Ambulatory Care Sensitive Condition. iii, 114, 117

ACSCs Ambulatory Care Sensitive Conditions. 7, 86, 111, 119, 175

AHA American Hospital Association. 17

AHRF Area Health Resource File. 84

AHRQ Agency for Healthcare Research and Quality. iii, 36, 74, 86, 108, 120, 179

AMI Acute Myocardial Infarction. 73

AQC Alternative Quality Contract. 5

Acronyms

ARR Admission-Readmission Revenue. 31, 182

CAHPS Consumer Assessment of Health Plans and Systems. 30, 36, 186

CBSA Core-Based Statistical Area. 79, 102

CBSAs Core-Based Statistical Areas. 78, 79, 81

CMMI Center for Medicare and Medicaid Innovation. 3

CMS Centers for Medicare and Medicaid Services. 3–6, 8, 9, 19, 24, 29, 30, 37, 38, 84, 173, 174

CON Certificate-of-Need. 17, 51

COPD Chronic Obstructive Pulmonary Disease. 86, 119

CPT Current Procedural Terminology. 83, 87, 88

DD difference-in-differences. iii, 6, 7, 107, 155

DHMH Department of Mental Health and Hygiene. 179

DRG Diagnostic-Related Group. 45, 50, 67

DRGs Diagnostic-Related Groups. 22

EAPG Enhanced Ambulatory Patient Group. 24, 67

ED Emergency Department. ii, iii, 7

FFS fee-for-service. 72, 174, 184

Acronyms

FQHCs Federally Qualified Health Centers. 84

GBR Global Budget Revenue. ii, 37

GSP Gross State Product. 37

HCFA Health Care Financing Administration. 19, 52

HCPCS Healthcare Common Procedure Coding System. 25

HMO Health Maintenance Organization. 2

HRSA Health Resources and Services Administration. 84

HSA Hospital Service Area. 80

HSCRC Health Services Cost Review Commission. ii, 7, 19, 27, 73, 74, 78, 81

ICD-9-CM International Classification of Diseases, Ninth Revision, Clinical Modification. 25, 83

IPPS Inpatient Prospective Payment System. 4, 24, 45

JCAHO Joint Commission on Accreditation of Healthcare Organizations. 30

MCMC Markov Chain Monte Carlo. 96

MHAC Maryland Hospital-Acquired Conditions. 30

MMPP Maryland Multi-Payor Patient Centered Medical Home Program. 31

MS-DRG Medicare Severity DRG. 24

NCQA National Committee for Quality Assurance. 38

NQF National Quality Forum. 38, 86, 88

OLS Ordinary Least Squares. 94

OMB Office of Management and Budget. 79

P4P pay-for-performance. 4

PCMH Patient Centered Medical Homes. 31

PEIA Public Employees Insurance Agency. 16

PO Postal Office. 178

POA Present-on-Admission. 181

PPCs Potentially Preventable Complications. 30, 37

PQIs Prevention Quality Indicators. iii, 74, 86, 108, 111, 120

QBR Quality-Based Reimbursement. 30

RCCOs Regional Care Collaborative Organizations. 5

RVUs Relative Value Units. 23

SAHIE Small Area Health Insurance Estimates. 84

SIM State Innovation Models. 5

SSA Secondary Service Area. 78

TPR Total Patient Revenue. ii, 5, 6, 10, 49, 77

VBP Value-Based Payment. 30

VCF Variable Cost Factor. 26, 67, 72

WMRMC Western Maryland Regional Medical Center. 79, 137

ZCTA ZIP Code Tabulation Area. ii, iii, 7, 77, 178

ZIP Zone Improvement Plan. 177

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Vita

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