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ESSAYS ON THE ROLE OF GOVERNMENT REGULATION AND POLICY IN HEALTH CARE MARKETS

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ESSAYS ON THE ROLE OF GOVERNMENT REGULATION AND POLICY IN HEALTH CARE MARKETS

DISSERTATION

A dissertation submitted in partial
fulfillment of the requirements for the
degree of Doctor of Philosophy in the
College of Business and Economics at
the University of Kentucky

By
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ABSTRACT OF DISSERTATION

ESSAYS ON THE ROLE OF GOVERNMENT REGULATION AND POLICY IN HEALTH CARE MARKETS

Understanding how health care markets function is important not only because competition has a direct influence on the price and utilization of health care services, but also because the proper functioning, or lack thereof, of health care markets has a very real impact on patients who depend on health care markets and providers for their personal well-being. In this dissertation, I examine the role of government policies and regulation in health care markets, with a focus on the response of health care providers. In Chapter 1, I analyze the impact of Medicare payment rules on hospital ownership of physician practices. Since the mid-2000's, there has been a rapid increase in hospital ownership of physician practices, however, there is little empirical research which addresses the causes of this recent wave of integration. Medicare's "provider-based" billing policy allows hospital-owned physician practices to charge higher reimbursement rates for services provided compared to a freestanding, independent physician practice, without altering how or where services are provided. This "site-based" differential creates a premium for physicians to integrate with hospitals, and the size of this differential varies with the types of health care services provided. I find that Medicare payment rules have contributed to hospital ownership of physician practices and that the response varies across physician specialties. A 10 percent increase in the relative reimbursement rate paid to integrated physicians leads to a 1.9 percentage point increase in the probability of hospital ownership for Medical Care specialties, including cardiology, neurology, and dermatology, which explains about one-third of observed integration of these specialties from 2005 through 2015. Magnitudes for Surgical Care specialties are similar, but more sensitive across specifications. There is no significant response for Primary Care physicians. In combination with other empirical literature which finds that integration between physicians and hospitals typically results in higher prices with no impact on costs or quality of care, I cautiously interpret this responsiveness as evidence that Medicare's provider-based billing policy overcompensates integrated physician practices and leads to an inefficiently high level of vertical integration between physician and hospitals.

In Chapter 2, I analyze the effect of anti-fraud enforcement activity on Medicaid spending, with a particular focus on the False Claims Act. The False Claims Act (FCA) is a federal statute which protects the government from making undeserved payments to contractors and suppliers. Individual states have chosen to enact their own versions of the federal FCA, and these statutes have increasingly been used to target health care fraud. FCA statutes commonly include substantial monetary penalties such as "per-violation" monetary fines and tripled damages, as well as a "whistleblower" provision which allows private plaintiffs to initiate a lawsuit and collect a portion of recoveries as a reward. Using variation in state-level FCA legislation, I find state FCAs reduce Medicaid prescription drug spending by 21 percent, while other spending categories - which are less lucrative for FCA lawsuits - are unresponsive. Within the prescription drug category, drugs prone to off-label use show larger

declines in response to the whistleblower laws, consistent with FCA lawsuits being used to prosecute pharmaceutical manufacturers for off-label marketing and promotion. Spending and prescription volume for drugs prone to off-label use fall by up to 14 percent. This effect could be driven by pharmaceutical manufacturers' changes in physician detailing for drugs prone to off-label use and/or physicians' changes in prescribing behavior.

KEYWORDS: Medicare; Vertical Integration; Hospital ownership of physician practices; Medicaid; False Claims Act; Anti-fraud enforcement

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For Ashley and Maxwell

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1.1 Introduction

Physicians are rapidly integrating with hospitals through practice acquisitions and direct employment. This type of vertical integration may lower health care costs by coordinating care between providers or potentially increase prices by limiting competition between physicians and conferring market power to integrated providers. Despite the explosive rate at which physicians are seeking hospital employment and the significant portion of health expenditures devoted to hospital and physician services, there has been little recent work which identifies the factors which are driving physician-hospital integration.[1]

This paper analyzes the relative importance of factors which drive the integration decisions of physicians and hospitals. There is a growing literature which examines the consequences of physician-hospital integration on prices and service utilization. While there is no general consensus on the effects of physician-hospital integration, there is increasing evidence that integration decreases competition, increases prices and utilization, and does not improve quality of care.[2] Few studies focus specifically on consequences in physician markets or analyze which factors drive the integration decision on the extensive margin. Understanding why physicians are seeking hospital employment through acquisition of physician practices may inform the debate as to how integration may lead to cost and utilization reductions or increases.

I empirically estimate the responsiveness of physicians to Medicare "provider-based" billing policies, which compensate integrated hospital-owned and independent free-standing physician practices differentially. Provider-based billing has long been criticized by gov-

[1] Spending on physician and hospital services alone accounts for over half of national health expenditures or a combined 9.3% of GDP in 2015 (see National Health Expenditure data for 2015 "Hospital" and "Physician and Clinical Services" expenditure categories (CMS, 2016)).

[2] Gaynor, Mostashari, and Ginsburg (2017) provide a brief discussion of recent consolidation in health care markets, including vertical integration between hospitals and physicians. See Madison (2004), Ciliberto and Dranove (2006), Cuellar and Gertler (2006), Baker, Bundorf, and Kessler (2014), Robinson and Miller (2014), Neprash, Chernew, Hicks, et al. (2015), Capps, Dranove, and Ody (2017), and Koch, Wendling, and Wilson (2017a) which study the effects of physician-hospital integration.

ernment agencies and economists as inadvertently encouraging consolidation of physician practices and hospitals, but until recently no study has quantified its effect on organizational structure or examined the impact across multiple physician specialties.[3] Recent studies indicate that Medicare's role in driving integration may be heterogeneous across specialties. Ody and Dranove (2016) find that changes in the relative prices paid for Medicare services provided in integrated versus independent practices account for roughly one-third of the observed integration between physicians and hospitals since 2007. On the other hand, Alpert, Hsi, and Jacobson (2017) find that neither a 2005 payment cut in chemotherapy drugs, nor increased eligibility for the 340B drug program under the Affordable Care Act explained the observed increase in vertical integration of oncology practices from 2003 through 2015. This paper complements these studies by examining the effect of Medicare reimbursement changes across multiple specialties and allowing responses to differ across physician type. This paper also documents differential changes in hospital ownership of physician practices across specialties, which has received little attention in previous work.

I link Medicare administrative prices and service utilization and payment data from the Centers for Medicare and Medicaid (CMS) with physician practice characteristics and ownership status from the National Ambulatory Medical Care Survey (NAMCS) for years 2005 through 2015 to empirically estimate the effect of changes in relative reimbursement rates for hospital and physician-owned practices on vertical integration between hospitals and physicians. I utilize a difference-in-differences methodology where annual updates to Medicare reimbursement rates and differential service utilization across physician specialties result in varying intensity of exposure of each specialty to Medicare's provider-based billing policy. Identification relies on variation in relative reimbursement rates over time, within a physician specialty, and across specialties since providers in each specialty typically bill for different types of services.

Results indicate that some physician specialties are responsive to increases in relative Medicare reimbursement rates paid to integrated providers. A 10 percent increase in the relative price paid to integrated providers results in a 1.9 percentage point increase in hos-

[3]See OIG (1999), OIG (2016), GAO (2015), and Gaynor, Mostashari, and Ginsburg (2017).

pital ownership of physician practices in Medical Care specialties (cardiology, dermatology, and neurology). This accounts for about one-third of the observed increase in hospital ownership in these specialties over 2005 through 2015. Allowing for a lag in the response in hospital ownership to changes in relative prices, Medical Care and Surgical Care specialties (general surgery, orthopedic surgery, ophthalmology, and urology) exhibit an increase in hospital ownership of 1.4 and 2.1 percent in response a 10 percent increase in relative prices. Primary care specialties do not seem responsive to changes in Medicare reimbursement. Across all specialties, there is some evidence that physicians who see relatively more Medicare patients are more responsive to increases in the gap in Medicare reimbursement rates between hospitals and physician offices. Since acquired practices may charge higher rates to Medicare and private insurers without any subsequent changes in where or how health care services are delivered as well as refer patients to the acquiring hospital, there exists little incentive for providers who integrate in response to Medicare's provider-based billing policy to reduce costs or improve the quality of care. If integration is only a response to a growing premium in Medicare reimbursement rates for integrated providers, then this may result in an inefficiently high level of vertical integration between physicians and hospitals.

This paper adds to the growing literature addressing vertical integration between hospitals and physicians. It is one of only a few recent studies which address the motivation for vertical integration, as opposed to consequences, and shows that, while Medicare payment rules may be an important contributing factor to the recent, rapid growth in the number of hospital-owned practices, it does not seem to explain increased integration for all physician specialties. Specifically, the increase in hospital ownership of Primary Care specialties, including general and family practice, obstetrics and gynecologists, and pediatricians, does not appear to be explained by changes in Medicare provider-based billing payment rates. CMS' recent implementation of "site-neutral" payments which eliminate the provider-based payment differential for some newly acquired physician practices may slow the pace of integration, but we should not expect this to affect all specialties equally.

1.2 Background and Literature

1.2.1 Integration in the 1990s

Physician-hospital integration is not a new phenomenon. Growth in the use of managed care organizations (MCOs) and health maintenance organizations (HMOs), which attempt to steer insured patients to preferred lower-cost providers, led to hospital and physician alignment to maintain bargaining leverage in negotiating reimbursement rates with insurers and securing managed care contracts (Burns, Bazzoli, et al., 2000; Cuellar and Gertler, 2006). Partnerships between physicians and hospitals in the 1990s are generally regarded as a failure and most partnerships subsequently dissolved (Burns and Pauly, 2002). Figure 1.1 presents data from the American Hospital Association (AHA) detailing the percent of hospitals engaged in various affiliations with physicians. Each organizational structure represents some level of vertical integration between physicians and hospitals; models such as integrated salary models (ISM) (not shown in the chart) represent the tightest form of vertical integration and include direct hospital employment or ownership of a physician practice. In a physician hospital organization (PHO), the joint entity negotiates payment and contracts, but physicians retain ownership of the group or practice. Management service organizations (MSO) simply provide administrative support to physician practices and may purchase services such as outsourced billing, malpractice insurance, or lease equipment on behalf of the practice. Independent practice associations (IPA) are the weakest form of vertical integration where the organization acts as an intermediary between managed care plans and independent physicians. Physician-hospital affiliations peaked around 1995 and have since declined. Not shown in this chart are integrated salary models or direct employment, which has consistently increased since 1993 and has become the dominant form of physician-hospital vertical integration (Burns, Goldsmith, and Sen, 2013).

1.2.2 Integration Today

There has been a renewed interest in vertical integration between physicians and hospitals since the early 2000's. More recently, the Affordable Care Act established incentives for providers to form Accountable Care Organizations, which bring together providers both

horizontally and vertically to coordinate care for chronically ill patients (Burns and Pauly, 2012; Frech et al., 2015). Although many physician-hospital partnerships of the 1990's dissolved, direct employment and hospital acquisition of physician practices has increased rapidly.[4]

Figure 1.2 shows the place of employment for physicians and surgeons (henceforth referred to as "physicians") from 2005 through 2015, as defined by industry and occupation codes in the American Community Survey (ACS).[5] Trends in Figure 1.2 are consistent with other reported estimates and show a consistent decrease in physician office employment and simultaneous increase in hospital employment of physicians. From 2005 to 2015, the percent of physicians working in a physician office declined from just under 50 percent to about 40 percent (a relative decrease of 19.4 percent). Hospital employment increased by a relative 20.8 percent, surpassing physician office employment in 2009.

Figure 1.3 further breaks down physician employment by age group. If recent medical school graduates today value a better balance of work and leisure and choose to forgo higher incomes for less administrative responsibility by seeking hospital employment, then the trend of increasing hospital employment may be driven by the changing preferences of younger physicians relative to older physicians (Kocher and Sahni, 2011). Figure 1.3 shows that younger physicians, age 25 to 44, are much more likely to work in a hospital setting across all years, but the trend of increasing hospital employment does not seem to have differentially affected this group, relative to older physicians. There is also no evidence that older physicians, over 65, are increasingly looking to sell their practice

[4]Kocher and Sahni (2011) present data from the Medical Group Management Association showing physician ownership of practices decreasing from about 70% of practices in 2002 to less than 50% in 2008. Hospital ownership increased from just over 20% to over 50% over the same time period. Kane and Emmons (2013) find that, according to the American Medical Association's 2012 Physician Practice Benchmark Survey, 60% of physicians work in practices wholly owned by physicians, compared to 23% in practices at least partly owned by a hospital, and an 5.6% that are directly employed by hospitals. Subsequent AMA surveys show hospital ownership increasing to 25.6 and 25.4 percent and direct hospital employment to 7.2 and 7.4 percent in 2014 and 2016 respectively (Kane, 2015; Kane, 2017). Using SK&A data Richards, Nikpay, and Graves, 2016 find that the independent physician practice share declined from 73 to 60 percent from 2009 to 2015, and the share of practices integrated with a health system increased from 7 to 25 percent over the same period.

[5]The shift from physician office to hospital place-of-employment also represents a shift from ownership to employee status. Physicians who report working in physician offices are predominantly self-employed, with about 54 percent reporting self employment versus 5 percent of those working in a hospital.

or seek hospital employment. Across all age groups, physicians are increasingly likely to seek hospital employment.[6] Although this is only suggestive evidence, it does not appear that changing physician preferences or demographics are driving the overall trend towards physician-hospital integration.

If the trend of increasing hospital employment is present in other medical occupations besides physicians and surgeons, then we may suspect that more general industry trends are pushing all medical professionals into hospitals. Hospital market concentration has increased gradually over the last decade, and hospitals may seek more employees to differentiate themselves from competitors, gain market power, or take advantage of economies of scale and coordinate care from numerous providers and settings (Gaynor and Town, 2011; Cutler and Scott Morton, 2013). As a comparison of physician employment to other medical occupations, Figure 1.4 shows the proportion of nurses (RN's and LPN's) and physician assistants employed by hospitals and physician offices from 2005 to 2015. Overall, place-of-employment trends for other medical occupations show little change over this time period. Therefore the trend of increasing hospital employment and decreasing physician office employment appears unique to physicians and provides evidence that there is some fundamental difference in physician markets versus other health care providers. It is important to understand what factors are rapidly pushing physicians from self-employment in physician practices to employment in hospital settings.

1.2.3 Consequences and Causes of Physician-Hospital Integration

Consequences of Vertical Integration

Empirical literature on the consequences of vertical integration between physicians and hospitals has grown tremendously since 2006. Studies typically examine the impact of integration on prices and utilization, with less attention given to heath care quality. Until recently, most studies focused on hospital, rather than physician markets. Earlier studies were inconclusive on the net effects of integration. Using similar categorizations of

[6] Grouping physicians into five 10-year age groups yields similar trends as presented in Figure 1.3.

physician-hospital integration, Cuellar and Gertler (2006) found that integration led to higher hospital prices with no reduction in cost or quality improvements, but Ciliberto and Dranove (2006) found no evidence of hospital price increases over a similar time period.[7] More recently, Baker, Bundorf, and Kessler (2014) associate "tight" vertical integration of physicians and hospitals with higher prices and total spending for Medicare beneficiaries at the county level.[8] Robinson and Miller (2014) find that local and multi-hospital-owned physician organizations in California incur 10 to 20 percent higher expenditures per patient, respectively, compared to physician-owned organizations.

There has been almost no discussion of whether not-for-profit and for-profit hospitals differ in either the incidence or outcomes of vertical integration with physicians. As Duggan (2000) points out, for-profit and not-for-profit hospitals do not necessarily differ in their response to financial incentives. Cuellar and Gertler (2006) briefly discuss for versus not-for-profit status and integration with physicians and find that integration for both types results in higher prices for managed care patients, yet for-profit hospitals have slightly higher prices for indemnity patients. Integration is common for large, not-for-profit teaching hospitals, and integration for these hospitals does not seem to result in higher prices or lower costs, but does improve quality outcomes for patients.[9]

To date, studies examining potential quality improvements in health care services due to integration between hospitals and physicians have not found strong evidence of gains in quality. Madison, 2004 examines the effect of physician-hospital integration on Medicare beneficiaries admitted to a hospital with acute myocardial infarction (AMI). Although integrated organizations do result in a higher intensity of treatment, there is no measurable reduction in mortality or readmissions. Cuellar and Gertler (2006) examine inpatient mortality and measures of overuse and patient safety and find that only some forms of integration lead to quality improvements. Tightly integrated, "Fully Integrated Organiza-

[7] Cuellar and Gertler (2006) analyze hospital data from Arizona, Florida, and Wisconsin whereas Ciliberto and Dranove (2006) analyze California data.

[8] Baker, Bundorf, and Kessler (2014) use categorizations of physician-hospital integration similar to AHA categories. Ciliberto and Dranove (2006) and Cuellar and Gertler (2006) use these measures as well.

[9] There are no for-profit "Fully Integrated Organizations" in the data; it is difficult to make any distinction between this type of integration and for versus not-for-profit status.

tions" are the only organizational form associated with mortality reductions, however, this form of organization is also comprised mostly of large, nonprofit academic and teaching hospitals. Most integrated organizational forms had no statistically significant relationship with any of the quality measures examined. More recently, Bishop et al. (2016) find that physician practices that were acquired by a hospital increased their use of "care management processes," including disease registries, nurse care managers, reporting quality data to physicians, patient reminders, and patient education. Although care processes may be changed as a result of integration, there has been little evidence showing that any effect carries through to patient outcomes. Scott et al. (2017) examine hospitals who switch from physicians with privileges to direct employment and find no effects on quality as measured by hospital mortality rates, 30-day readmission, length of stay, and patient satisfaction scores. In a working paper, Koch, Wendling, and Wilson (2017b) find no consistent or sizable quality improvements subsequent to hospital acquisition across a range of diabetes and hypertension health outcomes and indicators. Combined, the few studies which examine quality and outcomes indicate that any observed increase in price is likely not caused by changes in the underlying quality of care. As a side note, however, all studies which have examined quality outcomes of physician-hospital integration have measured integration as reported at the hospital level with AHA data. It could be that changes in integration status of the hospital only affect a small proportion of total physician employees and that the organizational change is not large enough to affect quality outcomes measured at the hospital level. No study has quantified the effect of hospital ownership or employment on quality outcomes using data on individual physician-level ownership status.[10]

More closely related to this paper are empirical studies which have examined the consequences of physician-hospital integration in physician markets. Neprash, Chernew, Hicks, et al. (2015) find that prices paid by commercially insured patients for outpatient services increased by 3.1 percent as vertical integration between hospitals and physicians increased,

[10]Baker, Bundorf, Devlin, et al. (2016) compare American Hospital Association data and SK&A marketing data, both of which measure hospital ownership and employment of physicians, but each using different methods. AHA data measures ownership from the hospital's perspective, and cannot be used to identify individual, hospital-owned physicians. SK&A data is based on a sample of office-based physicians and measures hospital-ownership from the physician's perspective.

with no significant effect on service utilization. Capps, Dranove, and Ody (2017) find that vertical integration of physicians leads to about a 14 percent increase in prices, and almost half of the estimated price increase is attributable to Medicare's provider-based billing policy which allows integrated physician offices to bill Medicare at higher rates and charge additional "facility fees." Estimated price increases vary across specialties, with prices for services provided by primary care physicians increasing by 12 percent and cardiologist services increasing by over 34 percent post integration. Anesthesia and diagnostic radiology specialties exhibit only a small and insignificant increase in prices after vertical integration with a hospital. This paper is the only study which highlights the heterogeneous effects of vertical integration across physician specialties. If price increases due to vertical integration vary by physician specialty, then perhaps the motivation for integrating also varies by specialty. The authors do point out that they see no obvious link between specialties with higher expected price increases due to vertical integration and the share of spending by vertically integrated physicians, except for cardiology.[11]

Koch, Wendling, and Wilson (2017a) perform a post-merger analysis of acquired physician practices using Medicare claims data and industry reports on acquisitions. Three facets of physician behavior are measured: physician billing in the acquired office, physician billing in the acquiring hospital, and aggregate acquiring hospital system billing. They find that acquired physicians bill roughly 70 percent less in terms of claims and total spending in an office setting. Those same physicians bill for relatively more work in the acquiring hospital, with total claims increasing over 50 percent on average with a similar magnitude effect on spending. This could represent a true change in the location where the services are performed, pre- versus post-merger, or this could represent a change in how the services are billed, with acquired practices billing as provider-based departments. There is some evidence that acquired physicians bill less at rival, non-acquiring hospitals after a merger. Overall, acquiring hospitals see a relatively smaller change post-merger, with total claims increasing by less than 10 percent and an insignificant 2 to 3 percent increase in total spending. This could be because of the small fraction of total doctors at the acquiring hospital

[11] See Capps, Dranove, and Ody (2017) Figure 3, pg. 35.

made up by acquired doctors, variation in the number of affected doctors across mergers, and variation in individual hospital use among acquired physicians in multi-hospital systems. It is estimated that total spending increases by 18 percent on net. These results are consistent with acquiring physicians and hospitals responding to Medicare's provider-based billing policies. Acquired physicians shift billing to hospital outpatient departments, especially for evaluation and management "clinical" services where Medicare payment policy most likely overcompensates hospitals relative to independent physician offices.

Causes of Vertical Integration

Less attention has been devoted to identifying the motivating factors which have contributed to the recent increase in integration between physicians and hospitals. Brunt and Bowblis (2014) find that increases in insurance market concentration result in increased hospital ownership of primary care practices. McCarthy and Huang (2016) also find that physicians align with hospitals in response to increased insurance market concentration and that hospitals seek vertical integration with physicians in more competitive hospital markets. Although there is potential for hospitals and physicians to integrate in response to ACO's formed by the Accountable Care Act, Neprash, Chernew, and McWilliams (2017) find no evidence that physician-hospital integration increased in markets with higher ACO penetration. Instead, consolidation was already increasing prior to the passage of the ACA and establishment of the ACO program.

Only recently has any study examined Medicare provider-based reimbursement as a potential factor driving integration on the extensive margin. Song et al. (2015) analyze Medicare and private insurance claims data and focus on a select group of cardiology services where Medicare reimbursement rates were cut for independent physician offices relative to hospital outpatient rates.[12] They find that after the reimbursement cuts, billing volume shifts to hospital outpatient settings at an increasing rate for both Medicare and privately insured patients. They interpret this shift in volume as evidence of both increasing vertical

[12]Song et al. (2015) analyze the share of HOPD billing volume of myocardial perfusion imaging (MPI), echocardiograms, and electrocardiograms.

integration of cardiologists and a change in the setting where services are provided. This study cannot rule out other factors that may be shifting health care services to outpatient settings, such as the general decline in demand for inpatient services, and results may not be causal or generalizable to other specialties. Alpert, Hsi, and Jacobson (2017) examine the impact of both a 2005 Medicare payment reform, which reduced reimbursement for chemotherapy drugs, and the 2010 ACA eligibility rule changes for the 340B Drug Discount Program on vertical integration of oncologists.[13] The authors find that neither of these policy changes explain the rapid increase in physician-hospital integration in oncology, which doubled from 30 to 60 percent over the 2003 through 2015 period. The authors conclude that the rapid growth in vertical integration in oncology markets, largely accelerating since 2010, may be due to other post-ACA factors such as bundled payments, incentive to form ACOs, increasingly complex payment design, and/or increased administrative burden such as electronic health record requirements.

The only study to examine the effect of Medicare payment policy on vertical integration across multiple physician specialties is Ody and Dranove (2016). The authors use a 2010 change in how Medicare reimbursement rates are calculated to identify a causal relationship between a measure of the relative price of site-specific reimbursement, physician employment, and increasing utilization of hospital outpatient departments for services that could be delivered in a physician office setting. Overall, Ody and Dranove (2016) find that the 2010 update to Medicare payment rules explains 20 percent of the observed increase in physician hospital integration from 2010 to 2013. Although, in their companion paper, Capps, Dranove, and Ody (2017) show that changes in price due to vertical integration and the ability to charge additional "facility fees" varies substantially by physician specialty, Ody and Dranove (2016) do not explore variation in response to Medicare payment rates across specialties.

[13] As Alpert, Hsi, and Jacobson (2017) explain, both of these policies should potentially result in increased vertical integration between oncologists and hospitals. Payment cuts affecting physician practices could be mitigated by integrating with a hospital and leveraging a subsequent increase in market power to negotiate higher discounts from pharmaceutical companies. The 340B Drug Discount program provides discounts to certain hospitals when purchasing drugs. Newly eligible hospitals may wish take advantage of lower drug costs (and increased profit margins) by expanding their patient base through integration with oncology practices.

1.3 Medicare Reimbursement

Medicare reimbursement policies have been criticized for inadvertently encouraging hospital acquisition of physician practices and physician employment by paying higher "facility fees" to hospital outpatient departments who provide identical services as free-standing physician offices (Gaynor, Mostashari, and Ginsburg, 2017).[14] Government advisory agencies have also expressed concern over Medicare payment policies' adverse effects including health care provider consolidation, increased service utilization, and increased total spending (MedPAC, 2012; MedPAC, 2013; GAO, 2015). A 2012 Medicare Payment Advisory Commission (MedPAC) report estimates that 20 percent of the growth in outpatient service volume, which increased by 28 percent from 2004 through 2010, is due to an increase in outpatient department evaluation and management "office" visits. The report notes that this increase could be driven by hospital acquisition of physician practices. The commission recommended that payment rates for evaluation and management visits be equalized across payment settings to remove the financial incentive for hospitals to purchase physician practices and shift service billing to the more costly outpatient setting. As an example, the report shows that in 2011 a midlevel office visit was over 80 percent more expensive in an outpatient facility versus a free-standing physician practice. (MedPAC, 2012).

Medicare rates are relevant not only to providers who see Medicare patients, but the privately insured as well. Clemens and Gottlieb (2017) show that private insurance reimbursement rates follow Medicare prices, on average about 16 percent higher, and that the extent of price following is related to physician market competition relative to insurers. Price following behavior may be due to mechanical benchmarking of private insurance rates

[14] Facilities that are determined to have "provider-based" status, as defined by 42 CFR §413.65, are reimbursed under the hospital Outpatient Prospective Payment System. Requirements for provider-based status include the facility operating under the same license as the main provider, professional staff of the facility have clinical privileges at the main provider facility, medical records for patients treated at the facility are integrated in a unified system of the main provider, patients who require further care have full access to all services of the main provider and are referred when appropriate. "Off-campus" facilities are additionally required to be 100 percent owned by the main provider, share a governing body, and be within a 35-mile radius of the main provider's facility. See https://www.law.cornell.edu/cfr/text/42/413.65. Beginning January 1, 2017, off-campus provider-based departments which provide outpatient services are no longer reimbursed under the OPPS, unless they were established prior to November 2, 2015 and have continuously billed for covered outpatient services from the same location. See https://www.cms.gov/Newsroom/MediaReleaseDatabase/Fact-sheets/2016-Fact-sheets-items/2016-11-01-3.html.

to Medicare rates (i.e. a rate of 120% of Medicare) to reduce negotiation costs, or it may reflect providers' outside option of serving Medicare patients. Consistent with a bargaining power framework, price following is less intense in markets where provider concentration is high relative to insurance market concentration. If vertical integration increases provider bargaining power, then payment differentials that overcompensate integrated practices could be exacerbated as providers demand higher reimbursement rates.

Empirical work analyzing the consequences of hospital acquisition of physician practices supports the relationship between Medicare's administrative prices and private insurance reimbursement rates. Ody and Dranove (2016) find evidence that a 2010 update to prices in Medicare's physician fee schedule impacts private insurance rates for non-facility services (with a coefficient of about .5, indicating that private rates are roughly twice as high as Medicare rates). Private insurers, therefore, do set prices that reflect Medicare's provider-based billing policy.[15]

Medicare's provider-based billing policies combined with differences in how reimbursement is determined across payment systems and federal regulation including the anti-kickback statute and the Stark Act's anti-self-referral laws work together to create a wedge in the prices paid for services furnished in freestanding independent physician offices versus hospital-owned offices, which may bill as a hospital outpatient care setting. Higher Medicare reimbursement paid for outpatient services is meant to compensate a hospital for the additional overhead costs associated with providing care, but these payment policies could overcompensate hospital-acquired physician practices, which may treat the same patients, provide the same services, and remain in the same location as they did as an independent practice, yet which may bill higher rates as an outpatient clinic. Integration between hospitals and physicians in response to payment rate distortions seems contrary to efficiency-improving motivations for integration. To the extent that the differential in

[15]Ody and Dranove (2016) also find that utilization of services in a facility setting for Medicare and privately insured patients are extremely similar, with the exception of evaluation and management visits. They verify with their claims data provider that E&M visits are not reimbursed in a facility setting, reflecting a rejection of Medicare's provider-based billing policy for this specific set of services. It is unclear whether this is unique to this data provider, or if private insurers are generally able to choose which services are reimbursed at higher facility-setting rates and which they are unwilling to do so.

Medicare reimbursement drives physician-hospital integration, we should not be optimistic that integration will lead to cost reductions, decreases in utilization, or any improvements in quality of care.

1.3.1 Medicare Payment Systems

The two relevant Medicare payment systems for Medicare Part B services are the Medicare Physician Fee Schedule (MPFS) and the Hospital Outpatient Prospective Payment System (HOPPS). The MPFS is used to compensate physicians, and other Part B providers, who provide a service for a Medicare patient in any care setting.[16] In 2014, payments under the MPFS made up 16% ($69 billion) of all Medicare fee-for-service expenditure (MedPAC, 2016). The MPFS lists payment rates for each unique service for which a provider may bill Medicare, with approximately 7,400 distinct services.[17] Payment rules are updated quarterly by CMS with the most significant changes occurring in the beginning of the year.[18]

Further, The MPFS compensates "facility" and "non-facility" providers differently. Non-facility rates apply to providers in free-standing physician office settings and are typically higher than facility rates, which apply to services furnished within a hospital. Non-facility rates are higher than facility rates since they are meant to cover overhead costs of maintaining an office. Differences in these rates, however, are typically small, and in many cases the facility and non-facility rates are equal.

The HOPPS payment system compensates hospital outpatient departments for each service provided, defined by a HCPCS code, with services grouped into Ambulatory Payment Classifications (APC's) where reimbursement for each service within an APC is the

[16] Settings include a physician office, hospital, ambulatory surgical center, skilled nursing facility, other post-acute care facilities, hospices, outpatient dialysis facilities, clinical laboratories, and in-home care.

[17] Unique services are defined as 5-digit Healthcare Common Procedure Coding System (HCPCS) codes, which are comparable to the American Medical Association's Current Procedural Terminology (CPT) codes.

[18] MPFS payments are based upon "relative value units" (RVUs) and include three categories of physician practice costs, (1) work RVUs, (2) practice expense RVUs, and (3) malpractice RVUs. Work RVUs measure the time and intensity required of a physician to provide a service, practice RVUs cover the cost of maintaining an office such as office rent, supplies, staff, and other overhead costs. Malpractice RVUs measure the cost of malpractice insurance. Each RVU category is further adjusted with a geographic practice cost index (GPCI) adjustment factor (CMS, 2016 "Medicare Physician Fee Schedule - Payment System Fact Sheet Series").

same flat rate.[19] This payment, sometimes referred to as a "facility-fee," is separate from reimbursement paid to a physician if he or she provides services in an outpatient setting.[20] The HOPPS payment is usually much larger than the difference in facility and non-facility rates paid to physicians and results in total payments to hospital outpatient departments that are much higher than payments made to free-standing physicians offices for the same service (MedPAC, 2011).

1.3.2 Federal Anti-fraud and Abuse Regulations

Federal anti-kickback laws and the Stark anti-self-referral law prevent hospitals and physicians from engaging in financial relationships based on referrals or service utilization. Without anti-kickback laws in place, an independent physician could refer patients to a hospital outpatient department and receive a cut of the higher payment rate as a bonus for his or her referrals. Stark and anti-kickback laws prevent independent physician practices from sharing in higher payment rates to hospitals generated by provider-based billing. Notably, however, both Stark laws and the anti-kickback statute provide an exception for hospitals which directly employ physicians.[21] While it is illegal for a hospital employer to pay outright for referrals from an acquired physician, it may be able to offer a higher salary since many services are valued more highly by Medicare when billed in a hospital outpatient department. A 2010 Medical Group Management Association survey shows that although physicians in non-hospital-owned practices have a higher median income, the median income per work relative value unit (RVU) is about 7 percent higher for specialists, indicating that hospital owned physicians are paid more conditional on their productivity.[22] Physician practices that are hospital owned may be pushed to self-refer to the owning hospital and

[19] HOPPS payment rates are adjusted by a geographic cost index, similar to MPFS adjustments. The adjustment factor is based upon the CMS's hospital wage index and applies to 60% of the payment rate. Hospitals may also receive additional payments for new technologies, costly outlier services, and specific payments to cancer centers and children's hospitals.

[20] I refrain from using the term "facility-fee," although this is the terminology used by Capps, Dranove, and Ody (2017) and Ody and Dranove (2016), to avoid confusion between the HOPPS payment and facility versus non-facility rates in the MPFS.

[21] See *Code of Federal Regulations* Title 42 Ch. 4 §411.357. Employers must pay physicians for identifiable services at a fair market rate and may not take into account volume or value of any referrals.

[22] see https://www.mgma.com/blog/highlights-of-mgma-s-2010-physician-compensation-survey

increase the volume of services for which higher reimbursement applies. Vertical integration between physicians and hospitals is one way which providers can take advantage of differential Medicare payments.

1.4 Data

I combine data on Medicare administrative prices from annual updates of the MPFS relative value files and HOPPS payment rates, utilization volume and payment data from CMS Medicare Utilization Data used in updating the Medicare Physician Fee Schedule, and physician practice characteristics from the National Ambulatory Medical Care Survey (NAMCS) for years 2005 through 2015 to measure the impact of Medicare payment rate changes on physician-hospital integration.

1.4.1 Medicare Physician Fee Schedule and Hospital Outpatient Prospective Payment System

I use MPFS relative value files from 2005 through 2015 to construct procedure-level administrative payment rates for services provided by physicians in offices and outpatient hospital-based departments.[23] Physician office rates are constructed using the non-facility payment rate, and hospital outpatient-department rates are constructed using the facility rate. Services in the MPFS are linked to the Hospital Outpatient Prospective Payment System by HCPCS code in each year.

Equations 1.1 and 1.2 below summarize how the reimbursement rate for service j in year t is calculated for both an independent, physician-office-based provider ("PO") and an integrated physician office billing as a hospital outpatient department ("HOPD"):

$$\text{Pay}_{jt}^{PO} = \text{MPFS}_{jt}^{N} \tag{1.1}$$

[23] See https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/PhysicianFeeSched/PFS-Relative-Value-Files.html. I use annual January updates of the MPFS RVU files and HOPPS payment rates to construct the relative reimbursement rates. If rates for January are revised, I use the latest revision.

$$\text{Pay}_{jt}^{HOPD} = \text{MPFS}_{jt}^{F} + \text{OPPS}_{jt} \tag{1.2}$$

N represents the non-facility MPFS rate and F represents the facility rate. The OPPS payment rate is determined at the service-level and is paid only to providers billing in a hospital outpatient setting.[24,25] Since payment rates are defined at the HCPCS code level, and codes are sometimes added, modified, or deleted with each annual update, CMS HCPCS code crosswalks are used to ensure that comparisons of services across years are valid.

1.4.2 Medicare Utilization and Payment Data

Medicare payment rates are calculated for each service in the MPFS. Physicians are differentially exposed to disparities in HOPD and physician office payment rates depending upon the types of services for which that physician bills. Since I do not have claims-level data and the NAMCS data does not contain information on HCPCS/CPT codes billed for each physician-patient encounter, I construct an aggregate measure of service utilization and spending which reflects the various types of services most commonly billed by each physician specialty in the NAMCS data. CMS provides utilization "crosswalk" data for select years included with quarterly updates to the Medicare Physician Fee Schedule. Aggregate service volume and charges are reported by specialty, year, and HCPCS code.[26]

I aggregate payment and utilization by service and specialty to construct an average "basket" of services that each specialty typically bills Medicare. Since each specialty varies in the types of services provided and provider-based billing differences in HOPD and physician office payment rates vary at the service level, I am able to calculate a weighted average HOPD-to-PO ratio of reimbursement rates for each specialty. The weighted average HOPD-to-PO ratio, which I will refer to as a "relative price" reflects the gap in Medicare payment

[24] National-level payment rates which do not include geographic adjustments are used in calculations.

[25] The MPFS includes separate professional and technical components for many services, denoted with indicators "26" and "TC". These two components sum to equal the total reimbursement amount for a given service. For reimbursement paid for services provided in a facility setting, the physician only receives the professional fee component. For services with separate professional and technical components, I include only the professional component for calculated HOPD reimbursement rates.

[26] I use CMS "crosswalk" utilization data for years 2003, and 2007 through 2015. 2003 data are used to estimate weights for year 2005, and 2007 utilization data are used in 2006.

rates for hospital-owned physician practices billing as outpatient departments versus independent physician-owned practices for a group of services commonly billed by physicians in a particular specialty. The relative price measures the multiple of revenue on Medicare services that would be generated if an independent physician practicing in an office were to shift all of his or her billing to a hospital outpatient department setting, but maintain an identical service mix.

Service utilization weights, which are used to calculate the weighted-average relative price, are calculated separately for each HCPCS code, specialty, and year. Specialties include cardiology, dermatology, family practice, general practice, general surgery, internal medicine, neurology, obstetrics/gynecology, opthalmology, orthopedic surgery, otolaryngology, pediatrics, psychiatry, and urology. Each weight is calculated as proportion of allowed charges for each service provided in an office setting.[27] I attempt and limit the sample of services to those that may be performed both in a physician office and hospital setting. To do this, I calculate a facility-share for each service which represents the amount of revenue generated for that service in a hospital (facility) setting. I exclude the top and bottom 1 percent (services performed in a facility or hospital setting 99 percent of the time or greater or less than 1 percent of the time). Figure 1.5 shows the distribution of service-level facility-shares. There are two clear bunching points at zero and one where some services are almost never performed across facility and non-facility settings. Limiting the sample to HCPCS codes with a facility share between 1 and 99 percent leaves about 54 percent of services in the sample, and 71 percent of charges (see Figure 1.6). Limiting the sample to services with a facility-share between 5 and 95 percent leaves 33 percent of services which comprise 29 percent of total charges. In calculating the relative prices and utilization of Medicare services, I limit the sample to services with a facility-share between 1 and 99 percent. Omitting these services does not greatly affect the final weighted-average relative price.

The CMS utilization data have a couple of limitations: First, utilization and payments

[27]The average of the Medicare allowed amount for any given service is the sum of the amount Medicare pays, the deductible and coinsurance amounts that the beneficiary is responsible for paying, and any amount that a third party is responsible for paying.

are reported only for Medicare beneficiaries and may not be generalizable to all patients served by a particular practice or specialty. If physicians bill for a substantially different mix of services for non-Medicare patients and these patients make up proportionally more of the physician's practice, then the calculated weights for each service may not represent the true mix of services performed by the physician. This would induce measurement error in the weighted average relative price. In their analysis of a 2010 cost survey update and MPFS pricing, Ody and Dranove (2016) compare Medicare services performed in both facility and office settings to services performed for privately insured and find that the setting of care for all major procedures is highly correlated across both patient types.

Second, CMS utilization data are not available for all years in the NAMCS sample window, and in years where the data are available the HCPCS codes must be crosswalked "backwards" so that they are consistent with code values listed in the corresponding year of the MPFS and HOPPS. CMS provides HCPCS crosswalks which link codes through updates over time, however, these files are only available from the 2009-2010 HCPCS code update and forward, and they are sometimes incomplete or contain errors. Due to these limitations, it is not always possible to match a HCPCS code and its estimated utilization weight to a corresponding service in the MPFS and HOPPS. In the case where HCPCS codes are not matched, estimated utilization weights are constrained to sum to one within each specialty and year. This implicitly assumes that the weighted-average relative price for unmatched services is similar to that of matched services.

Table 1.1 summarizes changes in weighted-average reimbursement rates for a freestanding physician office (PO), an integrated hospital-owned physician practice (HOPD), and relative price between 2005 and 2015.[28] Cardiology, urology, and orthopedic surgeons witness the largest increase in the gap between HOPD and PO reimbursement, with the relative price increasing by 47 percent, 34 percent, and 30 percent respectively. The gap between HOPD and PO reimbursement increases only slightly for dermatology, general and family practice, and internal medicine, and decreases by 11 percent for psychiatry. Figure 1.7

[28]The basket of procedures included are based upon 2003 and 2007 through 2015 utilization aggregates from CMS. Prices reflect annual updates to these procedures in the MPFS and HOPPS payment systems.

shows graphically for each specialty how the relative price paid to integrated providers changes over time. The light-gray lines track changes in the relative price for all specialties in the NAMCS data, and the specialty of interest is bold and in blue. Figure 1.7 makes it clear that some specialties have been more greatly exposed to price differentials resulting from Medicare's provider-based billing rules. I utilize variation in this "treatment" within specialty and across time to identify the impact of Medicare payment rules on integration.

Increases in the weighted-average relative price could be caused by changes either in reimbursement rates as CMS updates payments in the MPFS and HOPPS systems, or it could be due to a shift in utilization (in the office setting) towards services where the relative reimbursement rate is higher for providers in the HOPD setting. To see which factor is driving changes in the aggregate HOPD-to-PO measure, Figure 1.8 shows the distribution of relative reimbursement rates by service for 2005, 2008, 2011, and 2014. This figure shows that the gap in reimbursement between HOPD and PO settings is increasing over time. There is a bunching of services where the relative reimbursement is between one and two, but over time the distribution shifts left, indicating an increase in HOPD reimbursement relative to PO reimbursement.[29]

1.4.3 National Ambulatory Medical Care Survey

NAMCS data from 2005 through 2015 provides information on physician practice characteristics including ownership status, physician specialty, solo versus group ownership, and patient visit characteristics such as patient age, sex, and race, diagnoses, and some types of services provided. Physicians included in the survey are limited to non-federally employed office-based physicians primarily engaged in patient care in freestanding outpatient clinics and physician offices. Excluded from the survey are physicians in the specialties of anesthesiology, pathology, or radiology, and physicians directly employed in hospital outpatient

[29] This could reflect true reimbursement differentials or changes in how services are bundled in the HOPPS system. For some services that are frequently performed together, payment for both will be bundled into the HOPPS payment rate for only one of the services. Bundling is less common in the MPFS, and so if a service is bundled in the HOPPS the ratio of HOPD-to-PO reimbursement will overstate the payment difference for that service, but understate it for the other bundled services where there is no separate HOPPS payment rate.

departments, emergency departments, and ambulatory surgery centers (which are included in the NHAMCS survey). Therefore, the NAMCS data may not capture the entire shift of physicians from independent practice to hospital employment and will likely underestimate hospital ownership rates. The NAMCS also does not track individual physicians over time, making it impossible to follow a particular physician before and after acquisition; I am only able to calculate the average probability of hospital ownership for an annual sample of physicians and compare changes in the probability of ownership over time and specialties.

Analysis of ACS data (Figures 1.2 through 1.4) reveals a striking trend of increasing hospital employment and decreasing physician-office employment among physicians. The shift away from independent practice surely varies across physician specialties who face different input costs, differentially rely on hospital resources and affiliations, and who provide different medical services and treat potentially very different patient populations. Data from the NAMCS allows us to analyze trends in the integration status of physician practices by physician specialty.

Figure 1.9 presents the composition of physician practice ownership by specialty.[30] The majority of practices across all specialties are owned by a physician or physician group, yet ownership composition varies across specialties. Figure 1.9 ranks specialties by share of non-physician ownership. General/family practices, psychiatry, and pediatrics have the highest rates of hospital/other ownership with 25.0 percent, 24.1, and 20.7 percent of practices owned by a non-physician entity, respectively. Ophthalmologists, urologists, and dermatologists have the lowest shares of non-physician ownership (7.5 percent, 8.7 percent, and 9.6 percent respectively).

Differences in the overall organizational ownership structure across specialties may reflect differences in costs of practice ownership incurred by administrative or non-physician labor costs; medical malpractice liability; costs of technology such as imaging devices or

[30] Statistics calculated with NAMCS data measure the proportion of physician practices organized under each respective ownership type, as opposed to physician employment statistics in the ACS. The percentage of physicians employed by hospitals is not directly comparable to the percentage of physician practices owned by hospitals. Employment statistics may show a larger proportion of hospital ownership/employment since hospitals tend to acquire larger physician practices (Burns, Goldsmith, and Sen, 2013) and physicians such as hospitalists and laborists are included in the measure.

adopting electronic health record-keeping; economies of scale that may potentially be realized by large physician owned group practices; differences in types of services provided; and hospital incentives which encourage the acquisition of certain specialties over others. Primary care specialties, such as general practice, family practice, internal medicine, and pediatrics, offer office-based "cognitive" evaluation and management services which are not capital-intensive, and typically do not offer diagnostic and treatment services within their own facility. Medical specialties and surgical specialties offer more intensive procedures which utilize practice-owned diagnostic equipment, and facilities (Hough, Liu, and Gans, 2010).

Fundamental differences in the production of health services by various physician specialties may explain the "baseline" level of physician practice ownership within a specialty, however, they likely do not explain within-specialty changes in ownership structure. Figure 1.10 depicts changes in hospital ownership by physician specialty for years 2005 through 2015, in addition to the relative price measure. Cardiology, general surgery, neurology, and urology exhibit the largest increase in hospital ownership over the sample period. Many of these specialties also have experienced a large increase in the relative price, indicating an increase in the reimbursement premium associated with integrating. Cardiology practices shift away from physician ownership at a striking rate beginning in 2009-2010, increasing from 5.5 percent in 2005-2006 to 37.7 percent in 2012-2014 (an increase of 586%). This shift in ownership coincides with 2010 Medicare fee-cuts for cardiologists practicing in an office setting. Other specialties have not exhibited much change in ownership, and the relative price has remained flat (see dermatology, general and family practice, and pediatrics).

Table 1.2 presents summary statistics by ownership type for physician practices in the NAMCS data. Physician owned practices are more likely to be solo practices, locate in an MSA, and see more privately insured patients than hospital owned practices. Physicians in hospital owned practices refer more patients out to other physicians. Table 1.3 shows summary statistics by physician specialty. General and family practice specialties are less represented in physician owned offices than other ownership types. Most specialties are comprised of about one-third solo practices, except for dermatology and psychiatry which have relatively more solo practices. Cardiologists, urologists, and ophthalmologists are much

more likely to see older and more Medicare patients.

1.5 Model and Methodology

I construct service-level reimbursement rates for a free-standing independent physician office versus an integrated provider billing as an outpatient clinic. These rates vary over time as CMS updates payment rules annually and as relative weights of each service change over time. I estimate the average weight for each service using physician's total Medicare revenue generated in an office setting. Weights vary at the specialty-year level and are estimated using the CMS crosswalk utilization data. The weighted average of the relative differential in reimbursement paid to integrated versus independent providers represents the average potential gain in Medicare reimbursement that would be realized if an independent physician integrated with a hospital and shifted all of her billing to an outpatient department setting. The relative exposure to Medicare reimbursement differentials varies by specialty due to the difference in services typically provided.

The ratio of the two reimbursement rates for each service is constructed as:

$$\frac{\text{HOPD}_{jt}}{\text{PO}_{jt}} = \frac{\text{MPFS}^{F}_{jt} + \text{OPPS}_{jt}}{\text{MPFS}^{N}_{jt}} = \frac{\text{Pay}^{HOPD}_{jt}}{\text{Pay}^{PO}_{jt}} \tag{1.3}$$

and the weighted average relative price is then:

$$\text{R}_{st} = \sum_{j=1}^{J} \omega_{jst} \frac{\text{HOPD}_{jt}}{\text{PO}_{jt}} \tag{1.4}$$

for service j and year t, where ω_{jst} varies by service, year, and physician specialty, and sums to one in each year for each specialty. Some procedures are not associated with a price in the MPFS for various reasons, and so these services do not contribute to the weighted average reimbursement measure.[31] Services where a ratio of HOPD to PO reimbursement can be calculated typically make up 70 to 90 percent of revenue in the CMS Medicare utilization data.

[31] Some prices are not included in the MPFS because they are determined by the carrier, are not reimbursed under the MPFS, or the code is otherwise excluded or deleted.

I estimate the effect of Medicare reimbursement policy on hospital ownership of physician practices using a model of the following form:

$$Y_{ist} = \beta R_{st} + \gamma X_{it} + \alpha_s + \delta_t + \varepsilon_{ist} \tag{1.5}$$

where Y_{ist} is a binary indicator for hospital ownership of physician practice i, of specialty s, in year t, R_{st} is the weighted average relative Medicare reimbursement rate paid to provider-based hospital outpatient departments, X_{it} includes physician practice and patient characteristics such as MSA-status, census region, solo versus group practice, and measures of each provider's average patient age, sex, race, percent of patients referred to another physician, percent of patients where the physician is the primary care provider, and percent Medicare patients. Included in all model specifications are year and specialty fixed effects. This creates a difference-in-difference model over physician specialties and time where specialties are differentially affected by reimbursement rate changes since the exposure to relative Medicare prices varies by specialty and time, due to differences in the types of services that are billed to Medicare by each specialty.

Identification of β requires exogenous changes in Medicare payments that are uncorrelated with other factors which might drive physician-hospital integration. This implies that relatively sharp changes in the reimbursement differential are necessary, otherwise we may be concerned that long-run trends in procedure costs may be correlated with integration of hospitals and physicians. Ody and Dranove (2016) point out that changes in Medicare's administrative prices are usually not exogenous, since they are meant to compensate providers for the costs of services and procedures and as such are influenced by factors which affect the cost of running a physician practice. To overcome this potential endogeneity, Ody and Dranove (2016) use a 2010 change in the method used to calculate Medicare reimbursement rates. This survey change is implicit in my identification strategy, although it is specified differently. CMS also adjusted their methodology for calculating practice expense costs in 2007, with changes phased in from 2007 through 2010.[32]

[32] see https://www.cms.gov/Regulations-and-Guidance/Guidance/Transmittals/downloads/R258OTN.pdf

It is also likely that the observed rapid changes in relative reimbursement rates for integrated versus independent physicians do not reflect changes in actual procedure costs across the two settings. This is especially true for physician practices which integrate with hospitals and bill as a hospital outpatient department, but still serve a similar patient population, in the same location, and perform similar services.

Integrating vertically is only one potential outcome decision that may be made by physicians and hospitals in response to changes in reimbursement. If physicians increase the quantity of services billed (demand inducement), shift billing to other types of services, or move to larger group practices in the face of falling reimbursement rates, then we should not see any effect of relative reimbursement on hospital ownership.

1.6 Empirical Results

Results from estimating equation 1.5 are presented in Table 1.4.[33,34] Column 1 presents a basic model with no additional controls besides specialty and year fixed effects.[35] Column 2 includes controls for physician practice and patient characteristics. Column 3 includes ad-

[33] All regression results are estimated with models which utilize the provided NAMCS physician-level survey weights. This is to maintain consistency with reported statistics which utilize the survey weights. If physician-level survey weights are not utilized, the standard errors increase slightly, but magnitudes and interpretation remain largely unchanged. The sample is limited to one observation per physician when survey weights are not used. See appendix for unweighted results.

[34] I omit psychiatry specialties from all regression models. This is done for two reasons: First, psychiatry services may be reimbursed under the HOPPS in some other care settings including community mental health centers and for certain services such as partial hospitalizations. Psychiatry has the highest average rate of "other" ownership across the sample period. It is not clear that hospital ownership of psychiatry providers will respond in a similar way as other Medical Care specialties. Second, in constructing the relative price measure for psychiatry, there are multiple years for which a sizable amount of services are not matched to Medicare payment rates, possibly resulting in a poor characterization of the exposure of psychiatry to Medicare's provider-based billing policy. Appendix Tables A.1 - A.3 present models with and without psychiatry included.

[35] All standard errors are heteroscedastic robust. Clustering standard errors at the physician specialty level does not greatly affect significance and does not alter the interpretation of results. Clustering in the presence of a small number of groups may result in incorrect standard errors (Cameron and Miller, 2015). This is discussed in greater detail in the appendix, but adjusting standard errors for a small number of clusters does not result in substantively different standard errors or significance.

ditional Primary Care, Surgical Care, and Medical Care specialty fixed effects.[36] Columns 4 and 5 interact the reimbursement ratio measure with aggregate specialty categories.[37] Across all specialties combined, columns 1 through 3 show that there is no consistent statistically significant effect of changes in relative Medicare reimbursement on hospital ownership of physician practices. There is a positive and significant (10 percent level) response in ownership only in column 1, although estimated magnitudes are very similar once other controls are included. Interpreting column 1, a 10 percent increase in the relative price paid to integrated physicians leads to a 0.8 percentage point increase in hospital ownership. Columns 4 and 5 show that when the responsiveness to relative price is allowed to vary by specialty category, there is evidence that physicians respond differently across specialties. Primary care specialties are the least responsive to changes in relative reimbursement rates; estimated coefficients are negative, but insignificant. Estimates for Surgical Care specialties are positive, but insignificant. The largest response in hospital ownership to changes in Medicare reimbursement is for Medical Care specialties. As the relative price increases by 10 percent, hospital ownership increases by 1.7 to 1.9 percentage points.

To put the results into context, Figure 1.13 uses regression models reported in Table 1.4 to construct two alternate predictions.[38] In the first model, hospital ownership is predicted using fitted values from regression models using observed values of covariates. The second prediction constrains Medicare relative prices to remain at their 2005 levels. This is a simple way to compare observed integration versus predicted levels of integration had Medicare relative prices not diverged over time. Results from the model imply that if Medicare rates remained at their 2005 levels, then observed integration for Medical Care specialties would have been about 4 percentage points, or about 32 percent lower in 2015. Surgical care spe-

[36] Models with and without Primary Care, Surgical Care, and Medical Care specialty category fixed effects are presented since the more detailed specialty indicators are somewhat collinear with the aggregate specialty category indicators, with the exception of some overlap of detailed physician specialties. Primary care specialties include general and family practices, internal medicine, pediatrics, and obstetrics/gynecology. Surgical specialties include general surgery, orthopedic surgery, urology, opthalmology, otolaryngology, and a small number of ob/gyn's. Medical specialties include cardiovascular disease, dermatology, psychiatry, and neurology, as well as a some pediatrics and fewer Ob/Gyn and general/family practice physicians.

[37] Instead of omitting one category and interpreting coefficient estimates relative to the omitted category, I include all three categories so that coefficients may be interpreted relative to 0. This makes calculation of the total effect simpler and is equivalent since the interactions include a discrete categorical variable.

[38] Estimated coefficients from Table 1.4, column 5 are used in predictions.

cialties show a smaller gap of about 2 percentage points lower in 2015. Predicted ownership for Primary Care specialties is nearly identical using observed versus 2005 Medicare relative prices.

The negative, although insignificant, estimated coefficient on Medicare reimbursement rates for Primary Care providers (comprised mostly of general and family practice and internal medicine specialties) seems inconsistent with the anticipated effect where it is expected that increases in the relative payment for services furnished in a hospital-owned practice should result in increased hospital ownership. However, even in the raw data, hospital ownership is increasing for Primary Care providers, and the relative price is flat or declining over most of the sample (see Figures 1.7 and 1.10). There are a couple of plausible explanations for this finding: It is possible that hospitals value Primary Care specialties, not for the value of increased reimbursement for a given service, but for the referrals generated by providers in these specialties. The coefficient estimate on relative Medicare prices may also be attenuated if the relative price measure is not accurately capturing the true exposure of a specialty to differential reimbursement rates.

Primary care physicians act as "gatekeepers" who direct patients to other specialists, if necessary. Consistent with this, the percent of patients referred to other physicians is higher for Primary Care specialties, compared to medical and Surgical Care specialties. Physicians who reported hospital ownership also tend to generate more referrals, however, Since the NAMCS data is a repeated cross-section, I am unable to tell whether physicians who generate more referrals are more likely to be acquired, or if physician referrals increase only after a hospital acquires the practice. Baker, Bundorf, and Kessler (2016) find that for Medicare patients hospital ownership of a patient's physician increases the probability that the patient will choose the owning hospital for subsequent inpatient services. Further, hospital ownership results in patients choosing higher cost, lower quality, and hospitals further away from their residence. This behavior suggests that physicians employed by a hospital do tend to send patients to the owning hospital, regardless of how it compares with its competitors.

There may also be measurement error present in the aggregate relative price measure. Capps, Dranove, and Ody (2017) note that for their particular insurance data provider,

the insurance company does not pay a differential for "evaluation and management" visits, which make up a dominant proportion of the services billed for by primary care physicians. If it is common among private insurers to deviate from Medicare provider-based billing rates for evaluation and management services, then the aggregate, specialty-level relative price exposure measure will be a poor characterization of the actual exposure faced by Primary Care providers. Primary Care specialties also include pediatricians and obstetrics and gynecology providers. Services provided to Medicare patients, which include mostly over-65 and a small amount of disabled individuals, by providers in these specialties may be very different than the types of services utilized by privately insured patients. These two factors may result in substantial measurement error in the constructed relative price measure for Primary Care physicians, which would bias the estimated coefficient. I am able to test the sensitivity of results with pediatrics and obstetrics and gynecology omitted from regression models (see Appendix Table A.4). Although the estimated coefficient for relative Medicare price is small and positive for Primary Care physicians, it remains insignificant.

Similarly for Surgical Care specialties, some of the most common procedures are not performed across both settings of care and so the relative price measure may be missing some services which make up a potentially large share of physicians' revenue and will be measured with more error for these specialties.

1.7 Robustness

1.7.1 Parallel Trends

One of the primary identifying assumptions in any difference-in-differences analysis is that "but for" the treatment, the observed outcome for the treated group would have been similar to the control group. The framework presented in this paper employs a continuous treatment measure reflecting exposure of a physician specialty to relative Medicare reimbursement for integrated versus non-integrated providers. As such, there is no clear "treatment" and "control" group distinction. There is also no distinct pre-treatment and post-treatment period, although much of the change in reimbursement rates results from changes in the methodology CMS uses to update reimbursement rates occurring in 2007 and

2010. Examining trends in hospital ownership before these changes occurred for specialties that are eventually exposed to a larger gap in relative prices versus specialties with little change in exposure may still provide some evidence on the reasonableness of the parallel trends assumption.

Figure 1.15 shows trends in hospital ownership for selected physician specialties from 1997 through 2015.[39] Cardiology and urology witness the largest changes in relative reimbursement from 2005 through 2015 (increases of about 47 and 35 percent, respectively), while dermatology and general and family practice witness little change (see Table 1.1). Average hospital ownership rates remain relatively flat across all selected specialties prior to 2007-2008. After 2007-2008, trends in hospital ownership begin to diverge. Ownership for both cardiology and urology begin to increase, while ownership for general and family practice and dermatology remain relatively flat. A lack of diverging trends in ownership across specialties with widely varying eventual treatment exposure provides some evidence in support of the parallel trends assumption in this analysis.

1.7.2 Medicare Patient Share

Alpert, Hsi, and Jacobson (2017) use geographic, county-level variation in the population's share of Medicare-eligible to identify the effect of Medicare Part B payment reforms on vertical integration in oncology. The identifying assumption is that physicians who practice in counties with a higher share of Medicare-eligible individuals (people over age 65) see more Medicare patients as a share of their total patients and have a greater exposure to the Medicare payment reforms. Unfortunately, the public-use NAMCS does not include geographic identifiers, and so I cannot leverage similar geographic variation in patient mix. The NAMCS data, however, does include an indicator for each patient-physician visit identifying Medicare patients; I use this to calculate an average Medicare patient share for each physician. Following the general methodology of Alpert, Hsi, and Jacobson (2017), I interact physicians' shares of Medicare patients with the Medicare relative reimbursement

[39] Years are collapsed into two-year bins for readability. Statistics in Figure 1.15 do not use physician survey weights since these weights are available in the public-use file only after 2004. Weighted and unweighted ownership statistics are generally similar.

measure to see if physicians whose practice depends relatively more on Medicare patients are more responsive to changes in Medicare payment rates. Table 1.5 shows model specifications which include an interaction term for physicians' Medicare patient shares, which is standardized to be mean 0 and have a standard deviation of 1, and Medicare relative reimbursement rates. Results are largely insignificant, although magnitudes are similar to baseline results in Table 1.4. Medical Care specialties still show a significant response to changes in relative Medicare rates, but the only significant Medicare patient-share interaction is negative for Surgical Care specialties. However, the presented coefficients show only an average across the range of values for both the relative Medicare rates and Medicare patient share. Figure 1.11 shows various marginal effects of relative Medicare rates over different values of the (standardized) share of Medicare patients. Estimated results in Figure 1.11 are from Table 1.5 column 3. The average Medicare patient share is about 25 percent with a standard deviation just under 24 percent. Figure 1.11 shows that from a standardized Medicare patient share of about .75 through 2.75 standard deviations, the effect of relative Medicare rates is positive and significant at the 10 percent level. Over this range, the average marginal effect of Medicare relative reimbursement ranges from about 0.85 ppt to 1.12 ppt, and there is a slight upward trajectory indicating that physicians who see more Medicare patients are more responsive to changes in Medicare rates. Note that these results are an average across all specialties, allowing the relative effect of Medicare payment gaps between hospital and office settings to vary only with the share of Medicare patients that a physician sees.

Since the NAMCS is a repeated cross-section, I cannot observe the same physician under different ownership or follow his or her patient mix over time. The above analysis compares physicians who see few versus many Medicare patients and necessarily assumes that patient mix, or at least the share of Medicare patients that a physician sees, is exogenous with ownership status. To relax this assumption, I calculate an average of the provider-level Medicare patient shares for each physician specialty. While there is significant variation in the Medicare patient shares among providers within each specialty, there are also clear

differences across specialties.[40] Perhaps unsurprisingly, pediatrics and Ob/Gyn's treat relatively few Medicare patients, and cardiologists and urologists see relatively more. The specialty-average Medicare patient share should capture the average exposure of providers within a specialty to Medicare payment changes, but should not be influenced by any particular provider or be systematically related to ownership changes. Table 1.6 presents results using the specialty-level average Medicare patient share interactions. Columns 1 through 3 show that the Medicare relative reimbursement measure alone does not seem to matter, but when interacted with the average Medicare patient share, there is a significant and quite large effect on hospital ownership. Figure 1.12 presents the marginal effects of a change in relative Medicare reimbursement across different values of Medicare patient shares. Columns 4 and 5 of table 1.6 show that this interaction effect is driven by Primary Care specialties.

The analysis presented in this section provides some evidence that physicians who see a larger share of Medicare patients are more responsive to Medicare reimbursement rate changes. This is expected if providers are truly responding to Medicare fee schedule changes which alter their potential compensation in hospital and office settings. Although reimbursement for outpatient health care services paid by private insurers do follow Medicare's provider-based differentials (Capps, Dranove, and Ody, 2017; Koch, Wendling, and Wilson, 2017a), these differentials may not be paid for all services, and depending on the negotiation process, may not be as large as those paid by Medicare (Capps, Dranove, and Ody, 2017). If this is true, then providers who see relatively more Medicare patients should be more responsive to changes in provider-based payment differentials.

1.7.3 Dynamic Effects

Tables 1.7 and 1.8 introduce lags and leads of the relative price measure to investigate the dynamic effects of Medicare reimbursement rates. Since the integration decision of a hospital and physician is not easily reversible, there may be a lag between the time CMS updates payment rates and a behavioral response in integration. Physicians and hospitals may also

[40] See appendix Figure A.3.

take time to update their beliefs about future reimbursement updates, given a change in observed reimbursement levels. Therefore, lagged values of reimbursement may be relevant for contemporaneous firm ownership decisions, and leads of the reimbursement rate should arguably not drive the integration decision of hospitals and physicians. According to Table 1.7, there is a larger and significant increase in hospital ownership of physician practices in response to lagged (one year) relative reimbursement (columns 1 through 3). This effect is driven by Medical Care and Surgical Care specialties (see column 5), with Primary Care physicians still exhibiting no statistically significant response.[41] Column 6 shows that lead values of reimbursement do not have a significant effect on hospital ownership, and the magnitudes are typically closer to zero than contemporaneous and lagged values. Table 1.8 presents a regression model with leads and lags of two years. Overall, results are similar to Table 1.7 where estimated magnitudes for contemporaneous and lag values are stronger predictors of hospital ownership, with lead values typically being insignificant and smaller in magnitude. Medical care specialties do show a positive and statistically significant (10 percent level) response to leads of two years, however this may be due to relatively small year-to-year changes in reimbursement and collinearity between leads and contemporaneous reimbursement. Including two-year leads and lagged values of reimbursement also begins to reduce the sample size and range of the sample period considerably.

Overall Tables 1.7 and 1.8 provide some evidence that lagged values of relative reimbursement are driving integration between hospitals and physicians. Lead values of reimbursement have less predictive power for hospital ownership, indicating that the observed response is not due to some spurious correlation driving both reimbursement and ownership. Figure 1.14 performs a similar exercise as 1.13 and predicts hospital ownership under two different relative price assumptions, using regression specifications from Table 1.7 column 5. In Figure 1.14, both Medical care and Surgical care specialties show gaps in predicted hospital ownership when Medicare relative prices are pinned to their 2005-levels versus allowed to change as observed in the data. About one-third of integration for these specialties

[41] Lags and leads of the relative reimbursement rate are entered into regression models separately since year-to-year changes are highly collinear. Results are similar when contemporaneous, lead, and lag values of reimbursement are included within the same model

is due to increases in the relative price paid to providers. Again, there is little difference for Primary care specialties.

1.8 Discussion

1.8.1 Geographic Variation in Hospital Ownership

This paper uses variation in national Medicare fee schedule prices and services provided across specialties to examine the contribution of provider-based billing on hospital ownership of physician practices. This methodology is partly by necessity since the public-use NAMCS data do not have geographic identifiers beyond Census region for most years during the 2005 through 2015 sample period. Therefore, the estimated effect of Medicare's provider-based billing policy on vertical integration between physicians and hospitals represents an average across many different markets with potentially different landscapes of provider competition, insurer bargaining power, patient types, and other factors. As Brunt and Bowblis (2014) and McCarthy and Huang (2016) show, local insurer market competition may be a relevant determining factor in the ownership structure of hospital and physician markets. Examining the effect of vertical integration on prices, Capps, Dranove, and Ody (2017) find that physician offices acquired by hospitals with a larger inpatient market share have subsequently larger price increases than those acquired by a smaller hospital system. It is possible that local provider competition attenuates or exacerbates the response in vertical integration between hospitals and physicians to Medicare price differentials.

Although the (public-use) NAMCS data employed in the main analysis of this paper cannot be used to explore geographic variation in hospital ownership of physician practices, the Provider Utilization and Payment from CMS includes provider-level Medicare utilization data and provides an alternative way to measure integration.[42] I calculate the proportion of services and physician payments made in the facility (hospital) setting and office setting. If a physician practice is owned by a hospital and bills as such, then the Medicare claim should

[42]CMS Provider Utilization and Payment Data is available for Physicians and Other Suppliers for years 2012 through 2015. It includes details on the number of services and dollar amount reimbursed for specific Medicare Part B outpatient services, identified by HCPCS codes, delivered to Medicare patients by a provider by year and setting (office or facility).

indicate that the service took place in a facility setting.[43] Figure 1.16 shows the proportion of services that take place in a facility versus office setting.[44] This measure captures the overall volume of services performed in a hospital versus office for each Hospital Referral Region. Alternatively, Figure 1.17 shows the proportion of providers in each hospital referral region who perform most ($> 95\%$) of their services in a facility setting. This latter measure captures the proportion of providers who provide services almost exclusively in a facility setting and are most likely directly employed by a hospital.

Both measures show that there is a large geographic variation in where services are delivered. The percent of services delivered in a hospital by hospital referral region varies from a low of about 4 percent to a high of almost 76 percent. The proportion of physician providers who perform greater than 95 percent of services in a hospital varies from a low of 6 percent to a high of 60 percent. The upper-Northeast, Northern Midwest, and parts of the Pacific Northwest tend to have a larger proportion of services delivered in a hospital setting.[45] There are numerous potential explanations for this observed variation. According to a GAO report on health insurer concentration, as of 2013 a number of states across the northern U.S., including Idaho, Iowa, Maine, Minnesota, Montana, North Dakota, and South Dakota, had insurance markets (individual, small group, or large group) where the top three insurers represented over 90 percent of enrollment (GAO, 2014). These states also represent many of the Hospital Referral Regions with the highest proportion of integration, as measured by facility share. However, other areas, such as the Southeast, also include a

[43] Neprash, Chernew, Hicks, et al. (2015) use a similar methodology for constructing measures of hospital and physician integration. Henry et al. (2018) use the office and facility indicators in the CMS Provider Utilization and Payment data to determine the proportion of services and billing occurring at hospitals, offices, and ambulatory surgery centers. Although measures of facility-share capture the proportion of services performed in a hospital, they do no inform us on the exact employment arrangement. A service may be performed in a facility if the physician has privileges at a hospital, works directly for the hospital either as a hospitalist or laborist or in an outpatient department, or if he or she works in a practice owned by a hospital and the practice is billing under provider-based billing rules. If a practice is hospital owned, but is not billing Medicare as such, then the service claim should reflect an office setting. However, I still use facility-share as an approximate measure of hospital and physician integration.

[44] I limit the sample of services to those are performed in both facility and office settings at least some of the time; services performed in an office setting either less than 1% of the time or greater than 99% of the time are excluded. I also limit the sample of physician specialties to those included in the NAMCS data.

[45] This geographic relationship also holds for most of the individual physician specialties that are aggregated together in Figures 1.16 and 1.17, indicating that the variation in facility share is not due to different concentrations of specialists across geographies. Figure 1.17 also appears very similar if a 70 or 80 percent facility share cutoff is used instead of 95 percent.

group of states with very concentrated health insurance markets, yet do not exhibit higher levels of integration, as measured in Figures 1.16 and 1.17.

1.9 Conclusion

Integration between physicians and hospitals is becoming increasingly common, yet neither the mechanisms driving the formation of this type of organizational structure nor the consequences in terms of service utilization, prices, or quality are completely understood. This paper finds evidence that Medicare's provider-based payment policies are in part responsible for the rapid increase in physician-hospital integration among certain physician specialties. Medical Care and, to a lesser extent, Surgical Care specialties respond to Medicare payment rules which reimburse hospital-owned physician practices at higher rates than independent physician-owned practices. A 10 percent increase in the relative reimbursement rate increases the probability of hospital ownership of Medical Care specialties by about 1.4 to 1.9 percent. In some model specifications, hospital ownership of surgical specialties increase by about 2.1 percent in response to a 10 percent increase in relative reimbursement. This response explains about one-third of the observed physician-hospital integration from 2005 to 2015. Primary Care physicians do not seem as responsive to changes in the relative Medicare reimbursement rate paid to hospital-owned practices versus physician-owned. There is some evidence that physicians whose practice depends more on Medicare patients are more responsive to changes in Medicare's administrative prices. This helps explain some of the lack of response for Primary Care specialties.

This is an important finding for two reasons. First, finding a positive effect of disparities in Medicare reimbursement rates paid to hospital-owned versus independent physician practices should not be a forgone conclusion where "incentives matter." Physicians who give up owning and operating their own practice as an entrepreneur in favor of hospital ownership or employment are making a potentially career-altering, irreversible decision. Policy-makers should carefully consider what effect payment policies will have on hospital and physician market structures. Second, if hospital acquisitions of physician practices are undertaken only to take advantage of Medicare reimbursement policies and mechanically increase hos-

pitals' profits from providing health care services in these facilities, with no substantial change in how or where services are delivered, then we should be skeptical that integration will lead to lower costs or better quality of care. This paper does not estimate any impact on health care quality or cost, nor does it calculate benefits or costs to patients. However, cost savings from eliminating or narrowing this differential can be substantial. MedPAC reports estimate a cost savings of $900 million per year by reducing fee differentials for only a group of selected services (MedPAC, 2013). A 2014 Office of Inspector General report estimated that CMS could save $15 billion over the 2012 through 2017 period by equalizing hospital outpatient department and (typically lower) ambulatory surgery center rates (OIG, 2014). Payment and utilization data from CMS show that for 2012 to 2015, Part B services provided in a hospital outpatient department setting made up around 17 percent of total utilization but 40 percent of Medicare payments (or almost $66 billion).[46] Further, providers who performed at least 95 percent of procedures in a hospital outpatient setting incurred an additional $7,300 to $11,200 in annual Medicare payments, versus providers who perform relatively more procedure in an office setting.[47] This implies roughly $340 to $520 billion in annual Medicare payments made to physicians who work primarily in a hospital and generate additional Medicare reimbursement through facility fees. Given the quick pace of health care expenditure growth in the United States, the large share of spending that physician and hospital services comprise, and the general trend towards more consolidated health care markets with less competition, this is an area that should continue to be examined closely in the future.

This paper adds to the growing literature addressing vertical integration between hospitals and physicians. There has been little recent work examining the motivation for

[46] Source: CMS Provider Payment and Utilization public-use files from 2012 through 2015. Specialties were limited to those included in the NAMCS data, services were excluded if they were either always or never performed in both office and hospital settings. Hospital outpatient department setting is inferred from the "facility" place code and hospital payments are estimated by adding in the OPPS payment rate, similar to Henry et al. (2018).

[47] A simple regression analysis using the CMS Provider Payment and Utilization data from 2012 to 2015 shows that Medicare reimbursements, including OPPS payments, are roughly $7,300 to $11,200 higher if the physician performs at least 95 percent of his or her services in a "facility" setting. Regression controls include service volume, specialty and year indicators, and alternatively physician fixed-effects. Similar results are obtained using 80, 85, and 90 percent facility-share cutoffs.

physician-hospital integration. The only studies which measure the impact of Medicare payment rates on vertical integration find somewhat conflicting evidence (Alpert, Hsi, and Jacobson, 2017; Ody and Dranove, 2016). Given the heterogeneous effects of integration on prices, we may not expect that all physician specialties should respond in the same way to changes in Medicare payment rates (Capps, Dranove, and Ody, 2017). This paper is the first to show that integration between physicians and hospitals in response to Medicare payment rules may vary across physician specialties.

CMS has recently addressed the disparities in provider-based payments and effective January 2017, a hospital acquired (or built) practice that is located "off-campus" may bill services under the HOPPS, thus eliminating the site-based payment methodology. However, most hospital-owned practices are grandfathered in and may continue to bill services at a higher rate.[48] Future research may examine whether site-neutral payments slow the growth of hospital-owned practices. The findings in this paper suggest that for some specialties, such as Primary Care physicians, differential Medicare rates may be less relevant for the integration decision, and that other factors will potentially continue to drive physicians to hospital employment. These include risk-based capitated payments, required investment in electronic health records systems, pushes for more coordinated care and less fragmentation among health care providers, and increasingly complex regulations.

[48]Section 603 of the Bipartisan Budget Act of 2015 requires "site-neutral" payments for off-campus provider-based departments. Any provider-based department operating, or under certain circumstances planned, before November 2, 2015 may continue billing under the HOPPS. This policy went into effect January 1, 2017. https://www.cms.gov/Newsroom/MediaReleaseDatabase/Fact-sheets/2016-Fact-sheets-items/2016-11-01-3.html

Table 1.1: Medicare Reimbursement by Specialty

	2005			2015			
	PO	HOPD	Ratio	PO	HOPD	Ratio	% Change
Cardiology	240.12	252.88	1.25	665.43	938.89	1.84	47.34
Dermatology	195.04	302.69	1.73	248.73	430.67	1.85	6.93
General/family practice	79.89	122.56	1.65	111.48	184.46	1.76	6.97
General surgery	137.96	208.86	1.58	719.38	1050.83	1.87	18.30
Internal medicine	94.39	133.91	1.59	127.98	212.59	1.72	8.22
Neurology	160.90	182.93	1.33	192.76	266.68	1.52	13.83
Ob/Gyn	102.11	145.35	1.51	119.29	230.45	1.83	20.67
Ophthalmology	167.92	249.45	1.54	146.83	280.42	1.93	24.86
Orthopedic surgery	111.52	165.61	1.72	162.82	264.29	2.24	29.99
Otolaryngology	121.08	210.97	1.62	246.79	449.68	1.92	18.20
Pediatrics	93.55	130.95	1.56	126.68	207.38	1.77	13.67
Psychiatry	89.15	163.76	1.94	95.14	158.52	1.72	-11.18
Urology	240.55	338.25	1.73	158.70	408.69	2.33	34.88

Source: Medicare Physician Fee Schedule, Hospital Outpatient Prospective Payment System. Service revenue is derived from CMS Utilization Data for 2003 and 2007 through 2015. Physician office (PO) and hospital outpatient department (HOPD) rates are expressed in dollars. PO, HOPD, and the ratio of HOPD to PO rates are indexed values constructed by weighting the reimbursement rate for a service (defined by a HCPCS code) by the total physician office revenue share of that service for providers in that specialty. The sample of services is limited to those with between 1% and 99% of revenue geneerated in a facility setting.

Table 1.2: 2005 - 2015 NAMCS: Mean Statistics by Practice Ownership

	Physician Owned	Hospital Owned	Other Owned
Medicare HOPD/PO	1.70	1.70	1.70
	(0.00)	(0.01)	(0.00)
Located in MSA	90.13	82.44	88.71
	(0.36)	(1.44)	(1.03)
Solo practice	41.37	12.71	9.48
	(0.62)	(1.45)	(0.90)
% Medicare visits	24.09	23.00	20.29
	(0.29)	(0.86)	(0.72)
% Private insured visits	52.94	48.74	49.35
	(0.36)	(1.14)	(1.08)
Avg. patient age	46.33	43.04	43.24
	(0.23)	(0.82)	(0.63)
% patients female	58.57	59.43	59.00
	(0.27)	(0.84)	(0.74)
% patients black	10.23	11.19	10.53
	(0.23)	(0.78)	(0.61)
% patients primary care	46.71	52.45	53.15
	(0.59)	(1.84)	(1.46)
% patients referred to other phys.	7.47	9.97	11.12
	(0.16)	(0.58)	(0.48)
N	11,319	1,120	1,624

Source: NAMCS Public-Use file 2005 - 2015. Standard errors are in parenthesis. Statistics are weighted using physician-level weights. Physician owned indicates physician or physician group ownership, hospital owned indicates medical or academic health center ownership or other hospital ownership. Other ownership includes insurance company, health plan, HMO, or other health care corporation ownership.

Table 1.3: 2005 - 2015: Summary Statistics by Specialty

	General family practice	Internal medicine	Ob/Gyn	Pediatrics	General surgery	Ophthalmology	Orthopedic surgery
% Physician owned	73.1	80.8	82.3	79.2	81.2	92.8	88.6
% Hospital owned	10.1	6.2	7.1	8.8	8.9	2.5	4.8
% Other owned	16.7	13.0	10.6	12.1	9.8	4.7	6.6
Medicare HOPD/PO	1.7	1.6	1.7	1.6	1.8	1.6	2.0
Located in MSA	81.5	90.9	92.5	91.6	82.9	91.9	88.5
Solo practice	35.1	40.0	32.0	24.1	36.0	36.9	26.3
% Medicare visits	22.3	34.5	6.2	1.4	26.8	46.4	25.5
% Private insured visits	52.7	47.3	68.8	62.2	53.4	38.7	52.1
Avg. patient age	48.0	57.8	37.8	7.6	53.6	61.4	51.9
% patients female	57.7	56.7	99.6	48.2	59.8	58.7	53.5
% patients black	9.5	12.6	14.0	11.5	9.9	10.7	8.7
% patients p.c.p.	86.2	86.1	15.8	86.6	3.6	2.0	2.2
% patients referred to other phys.	11.1	13.7	4.5	6.0	8.1	4.1	5.7
N	2,572	1,318	1,082	1,567	854	905	980

	Otolaryngology	Urology	Cardiology	Dermatology	Neurology	Psychiatry
% Physician owned	88.2	88.6	82.0	90.0	84.0	77.2
% Hospital owned	5.5	5.9	9.1	2.9	7.7	5.3
% Other owned	6.2	5.4	8.9	7.2	8.4	17.6
Medicare HOPD/PO	1.8	2.0	1.6	1.7	1.5	1.9
Located in MSA	91.8	92.0	94.8	95.7	94.8	95.2
Solo practice	33.5	27.0	24.3	44.6	36.8	66.1
% Medicare visits	22.0	41.5	51.4	28.7	30.6	12.6
% Private insured visits	60.5	44.7	36.4	59.5	46.9	41.0
Avg. patient age	43.9	60.5	66.4	52.9	51.4	41.6
% patients female	53.2	26.2	48.1	55.1	57.5	56.3
% patients black	7.1	8.0	9.9	4.1	8.7	7.3
% patients p.c.p.	2.0	2.7	11.9	2.1	2.7	4.8
% patients referred to other phys.	6.6	4.2	7.3	1.9	10.6	2.9
N	677	746	906	665	798	993

Source: NAMCS Public-Use file 2005 - 2015. Statistics are weighted using physician-level weights. Physician owned indicates physician or physician group ownership, hospital owned indicates medical or academic health center ownership or other hospital ownership. Other ownership includes insurance company, health plan, HMO, or other health care corporation ownership.

Table 1.4: Hospital Ownership of Physician Practices

	(1)	(2)	(3)	(4)	(5)
ln(HOPD/PO)	0.88*	0.84	0.85		
	(0.54)	(0.52)	(0.52)		
Primary care × ln(HOPD/PO)				-0.93	-1.00
				(0.75)	(1.01)
Surgical care × ln(HOPD/PO)				0.86	0.64
				(0.73)	(0.76)
Medical care × ln(HOPD/PO)				1.74***	1.94***
				(0.64)	(0.64)
Region effects	No	Yes	Yes	Yes	Yes
Other controls	No	Yes	Yes	Yes	Yes
Specialty category	No	No	Yes	No	Yes
N	13,070	13,070	13,070	13,070	13,070

Source: NAMCS Public-Use file 2005 - 2015. * P<0.1, ** P<0.5, *** P<0.01. Robust standard errors are presented in parenthesis. Dependent variable is a binary indicator for hospital ownership. Coefficients have been multiplied by 100 and are interpreted as a percentage point in hospital ownership given a 10 percent increase in HOPD/PO. Year and specialty fixed effects are included in all specifications. Controls include an MSA/Non-MSA indicator, census region, solo versus group practice, percent of visits where the physician is the primary care provider, percent visits where the patient is referred to another physicians, percent Medicare and privately insured patient visits, and and average patient age, sex, and race. Models are weighted using physician-level survey weights. Psychiatry is excluded.

Table 1.5: Hospital Ownership of Physician Practices - Medicare Patient Share Interactions

	(1)	(2)	(3)	(4)	(5)
ln(HOPD/PO)	0.78	0.75	0.75		
	(0.58)	(0.57)	(0.57)		
ln(HOPD/PO)×Std. % Medicare patients	0.21	0.12	0.14		
	(0.27)	(0.27)	(0.27)		
Primary care × ln(HOPD/PO)				-0.43	-0.67
				(1.12)	(1.09)
Surgical care × ln(HOPD/PO)				0.79	0.94
				(0.83)	(0.81)
Medical care × ln(HOPD/PO)				1.82*	1.66*
				(1.01)	(0.97)
Primary care×ln(HOPD/PO)×Std. % Medicare patients				1.01	1.03
				(0.92)	(0.92)
Surgical care×ln(HOPD/PO)×Std. % Medicare patients				-0.58	-0.73*
				(0.39)	(0.39)
Medical care×ln(HOPD/PO)×Std. % Medicare patients				0.39	0.43
				(0.61)	(0.59)
Region effects	No	Yes	Yes	No	Yes
Other controls	No	Yes	Yes	No	Yes
Specialty category	No	No	Yes	Yes	Yes
N	13,070	13,070	13,070	13,070	13,070

Source: NAMCS Public-Use file 2005 - 2015. * P<0.1, ** P<0.5, *** P<0.01. Robust standard errors are presented in parenthesis. Dependent variable is a binary indicator for hospital ownership. Coefficients have been multiplied by 100 and are interpreted as a percentage point in hospital ownership given a 10 percent increase in HOPD/PO. Year and specialty fixed effects are included in all specifications. Controls include an MSA/Non-MSA indicator, census region, solo versus group practice, percent of visits where the physician is the primary care provider, percent visits where the patient is referred to another physicians, percent Medicare and privately insured patient visits, and and average patient age, sex, and race. Models are weighted using physician-level survey weights. Psychiatry is excluded.

Table 1.6: Hospital Ownership of Physician Practices - Medicare Patient Share Interactions

	(1)	(2)	(3)	(4)	(5)
ln(HOPD/PO)	-0.07	-0.17	-0.18		
	(0.66)	(0.64)	(0.64)		
ln(HOPD/PO)×Avg. % Medicare patients	1.08***	1.10***	1.13***		
	(0.38)	(0.37)	(0.37)		
Primary care × ln(HOPD/PO)				0.19	-0.03
				(1.18)	(1.15)
Surgical care × ln(HOPD/PO)				0.82	1.10
				(0.91)	(0.91)
Medical care × ln(HOPD/PO)				1.04	0.75
				(2.49)	(2.41)
Primary care×ln(HOPD/PO)×Avg. % Medicare patients				1.77**	1.84**
				(0.85)	(0.83)
Surgical care×ln(HOPD/PO)×Avg. % Medicare patients				-0.66	-0.99
				(0.77)	(0.76)
Medical care×ln(HOPD/PO)×Avg. % Medicare patients				0.58	0.69
				(1.42)	(1.37)
Region effects	No	Yes	Yes	No	Yes
Other controls	No	Yes	Yes	No	Yes
Specialty category	No	No	Yes	Yes	Yes
N	13,070	13,070	13,070	13,070	13,070

Source: NAMCS Public-Use file 2005 - 2015. * P<0.1, ** P<0.5, *** P<0.01. Robust standard errors are presented in parenthesis. Dependent variable is a binary indicator for hospital ownership. Coefficients have been multiplied by 100 and are interpreted as a percentage point in hospital ownership given a 10 percent increase in HOPD/PO. Year and specialty fixed effects are included in all specifications. Controls include an MSA/Non-MSA indicator, census region, solo versus group practice, percent of visits where the physician is the primary care provider, percent visits where the patient is referred to another physicians, percent Medicare and privately insured patient visits, and and average patient age, sex, and race. Models are weighted using physician-level survey weights. Psychiatry is excluded.

Table 1.7: Hospital Ownership of Physician Practices - Lags and Leads of Relative Price

	(1)	(2)	(3)	(4)	(5)	(6)
ln(HOPD/PO)	0.80					
	(0.56)					
ln(HOPD/PO $_{t-1}$)		1.59**				
		(0.65)				
ln(HOPD/PO $_{t+1}$)			0.73			
			(0.64)			
Primary care × ln(HOPD/PO)				-0.35		
				(1.11)		
Surgical care × ln(HOPD/PO)				1.14		
				(0.80)		
Medical care × ln(HOPD/PO)				1.38*		
				(0.73)		
Primary care × ln(HOPD/PO $_{t-1}$)					-2.47	
					(1.61)	
Surgical care × ln(HOPD/PO $_{t-1}$)					2.17**	
					(1.01)	
Medical care × ln(HOPD/PO $_{t-1}$)					1.44**	
					(0.68)	
Primary care × ln(HOPD/PO $_{t+1}$)						0.77
						(1.05)
Surgical care × ln(HOPD/PO $_{t+1}$)						0.43
						(0.80)
Medical care × ln(HOPD/PO $_{t+1}$)						1.01
						(0.91)
Region effects	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Specialty category	Yes	Yes	Yes	Yes	Yes	Yes
N	11,011	11,011	11,011	11,011	11,011	11,011

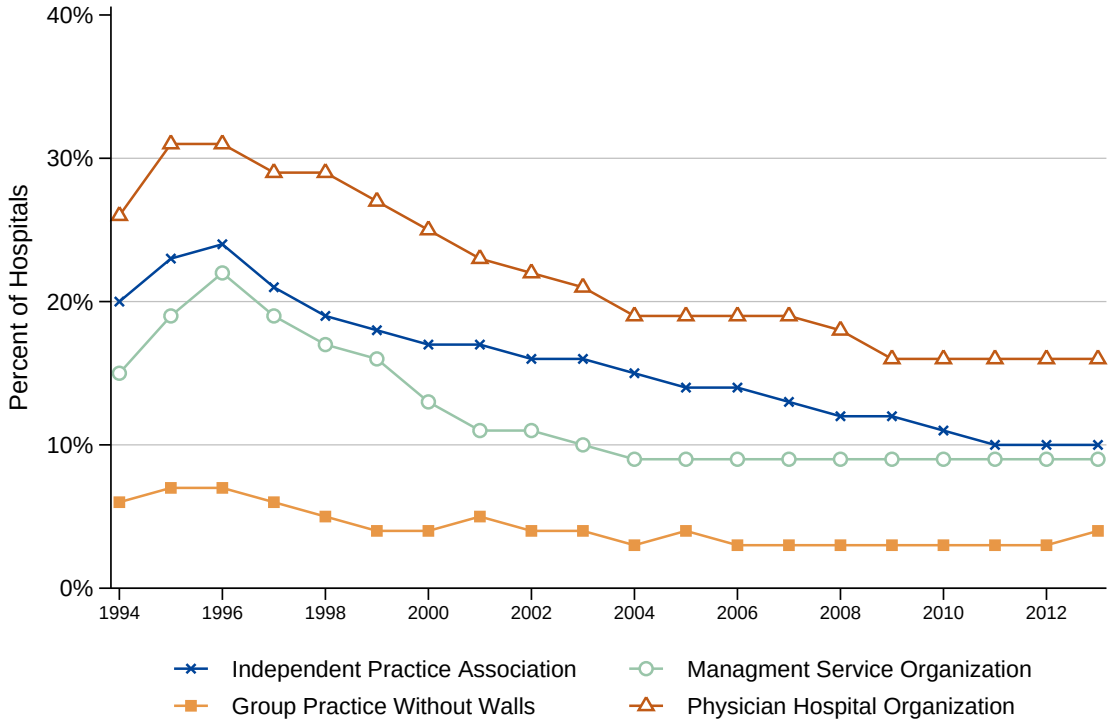
Source: NAMCS Public-Use file 2005 - 2015. * P<0.1, ** P<0.5, *** P<0.01. Robust standard errors are presented in parenthesis. Dependent variable is a binary indicator for hospital ownership. Coefficients are interpreted as a percentage point in hospital ownership given a 10 percent increase in HOPD/PO. Year and specialty fixed effects are included in all specifications. Controls include an MSA/Non-MSA indicator, census region, solo versus group practice, percent of visits where the physician is the primary care provider, percent visits where the patient is referred to another physicians, percent Medicare and privately insured patient visits, and and average patient age, sex, and race.

Table 1.8: Hospital Ownership of Physician Practices - Two-Year Lags and Leads of Relative Price

	(1)	(2)	(3)	(4)	(5)	(6)
ln(HOPD/PO)	1.43					
	(0.94)					
ln(HOPD/PO $_{t-2}$)		2.17***				
		(0.75)				
ln(HOPD/PO $_{t+2}$)			0.97			
			(0.76)			
Primary care × ln(HOPD/PO)				-0.19		
				(2.17)		
Surgical care × ln(HOPD/PO)				1.91		
				(1.44)		
Medical care × ln(HOPD/PO)				1.26		
				(0.88)		
Primary care × ln(HOPD/PO $_{t-2}$)					0.21	
					(1.93)	
Surgical care × ln(HOPD/PO $_{t-2}$)					2.39**	
					(1.14)	
Medical care × ln(HOPD/PO $_{t-2}$)					2.02**	
					(0.79)	
Primary care × ln(HOPD/PO $_{t+2}$)						1.47
						(0.95)
Surgical care × ln(HOPD/PO $_{t+2}$)						-0.96
						(1.52)
Medical care × ln(HOPD/PO $_{t+2}$)						3.45*
						(2.00)
Region effects	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Specialty category	Yes	Yes	Yes	Yes	Yes	Yes
N	8,603	8,603	8,603	8,603	8,603	8,603

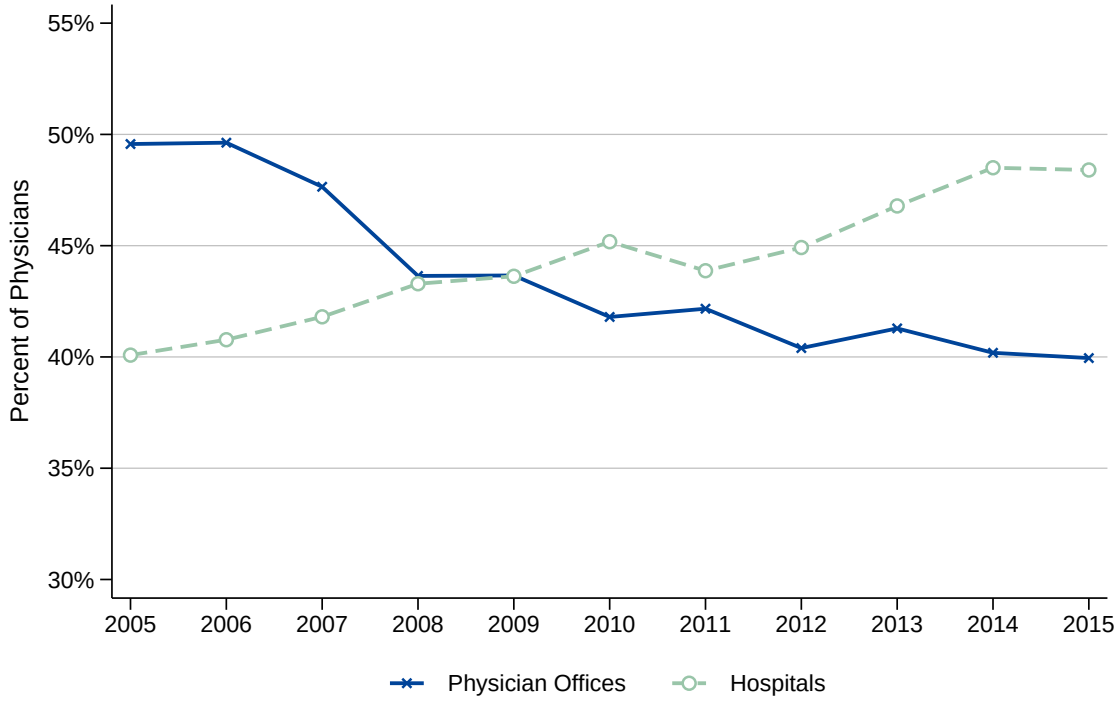
Source: NAMCS Public-Use file 2005 - 2015. * P<0.1, ** P<0.5, *** P<0.01. Robust standard errors are presented in parenthesis. Dependent variable is a binary indicator for hospital ownership. Coefficients are interpreted as a percentage point in hospital ownership given a 10 percent increase in HOPD/PO. Year and specialty fixed effects are included in all specifications. Controls include an MSA/Non-MSA indicator, census region, solo versus group practice, percent of visits where the physician is the primary care provider, percent visits where the patient is referred to another physicians, percent Medicare and privately insured patient visits, and and average patient age, sex, and race.

Figure 1.1: Percent of Hospitals Engaged in Affiliations With Physicians



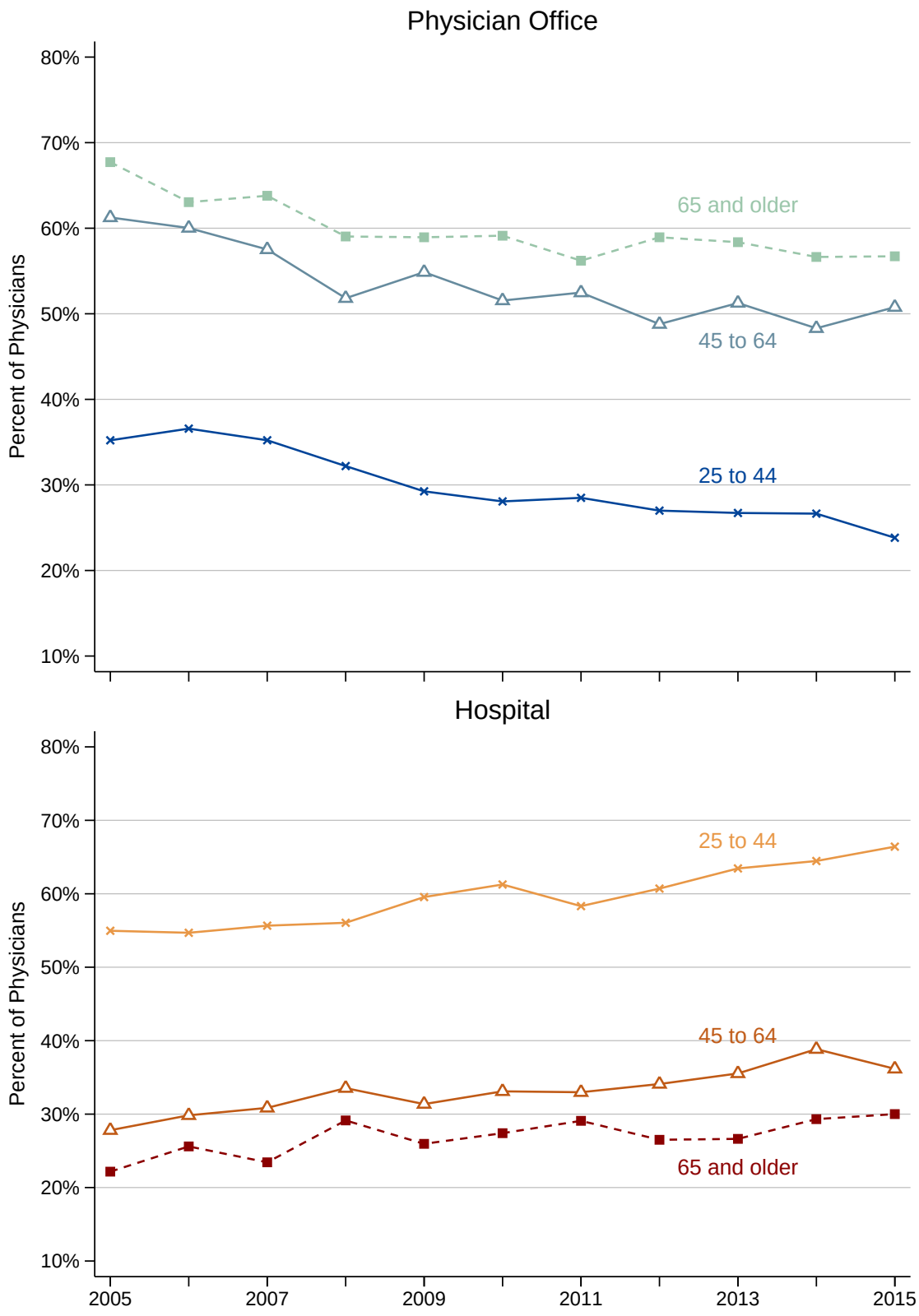
Source: American Hospital Association 2004 Trendwatch Chartbook Appendix 2, Table 2.5 and 2015 Trendwatch Chartbook Appendix, Table 2.4

Figure 1.2: Physicians' Place of Employment



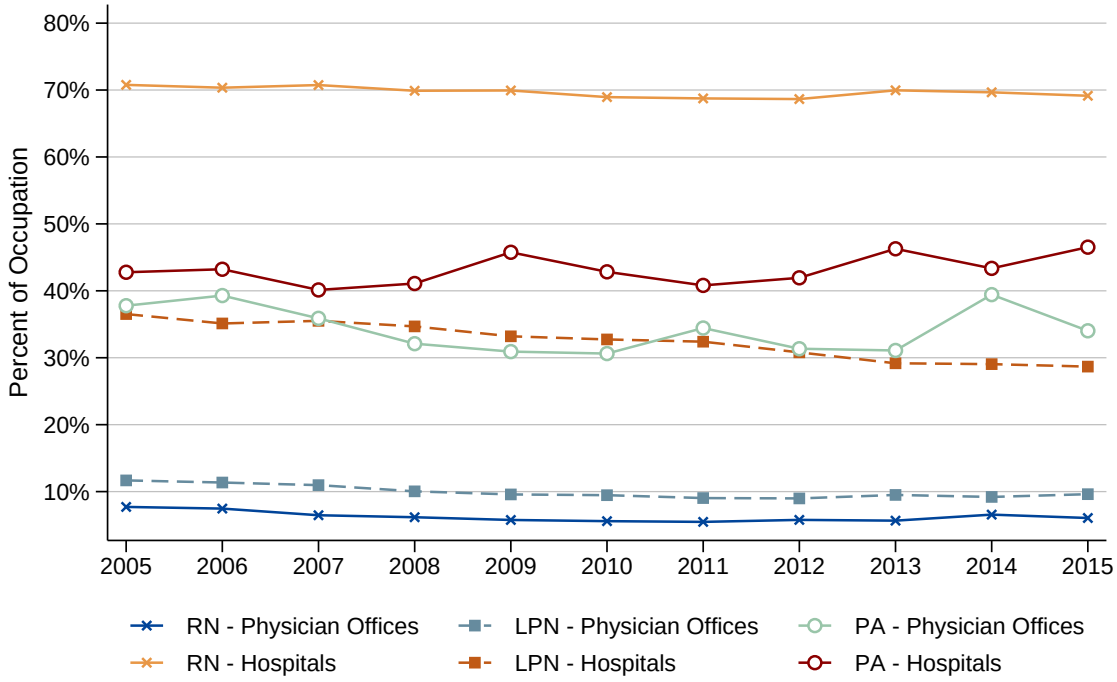
Source: American Community Survey PUMS 1-year estimates. Estimates calculated using person-level weights. Industry codes 7970 (Offices of Physicians), 8080 (Offices of other Medical Professionals), and 8190 (Hospitals). Occupation codes 3060 (Physicians/Surgeons).

Figure 1.3: Physicians' Place of Employment by Physician Age Group



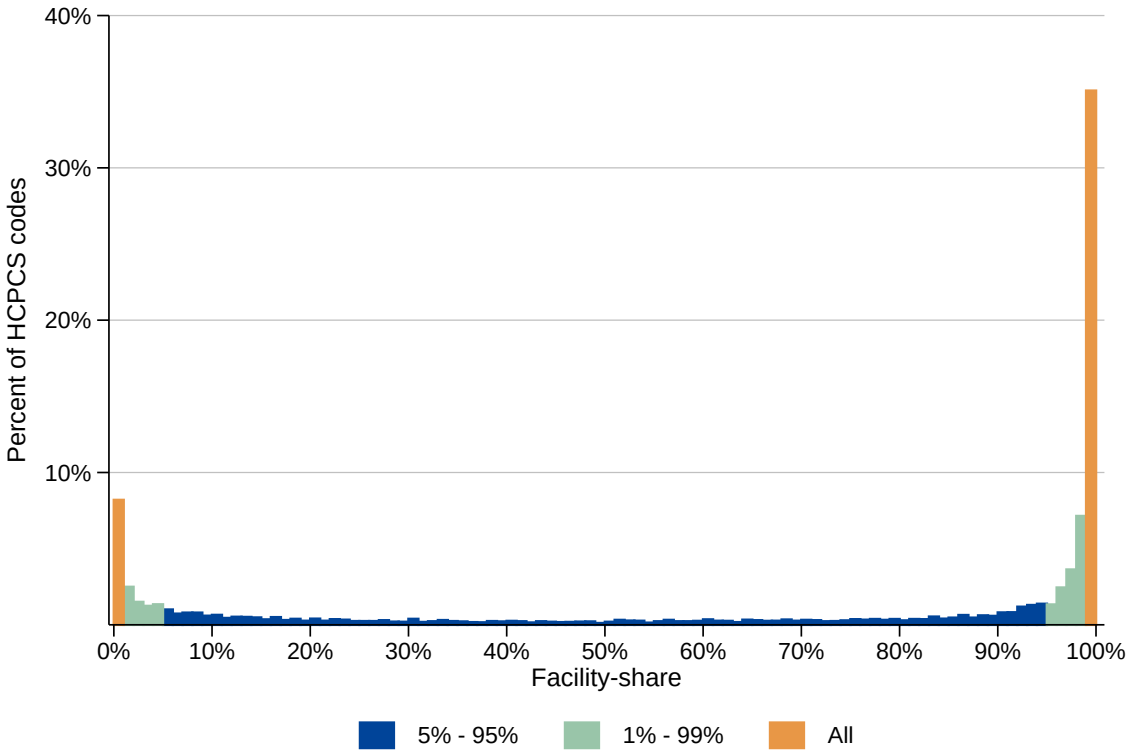
Source: American Community Survey PUMS 1-year estimates. Estimates weighted using person-level weights. Industry codes 7970 (Offices of Physicians), 8080 (Offices of other Medical Professionals), and 8190 (Hospitals). Occupation codes 3060 (Physicians/Surgeons).

Figure 1.4: Other Medical Occupations' Place of Employment



Source: American Community Survey PUMS 1-year estimates. Estimates calculated using person-level weights. Industry codes 7970 (Offices of Physicians), 8080 (Offices of other Medical Professionals), and 8190 (Hospitals). Occupation codes 3130 (pre-2010 RN's), 3255 (post-2010 RN's), 3256 (Nurse Anesthetists), 3257 (Nurse Midwives), 3258 (Nurse Practitioners), 3500 (LPN's), and 3110 (Physician Assistants).

Figure 1.5: Distribution of Facility-Shares for Medicare Services



Source: CMS Medicare utilization 2003, 2007-2015.

Figure 1.6: Percent of Total Services and Revenue by Facility-Share

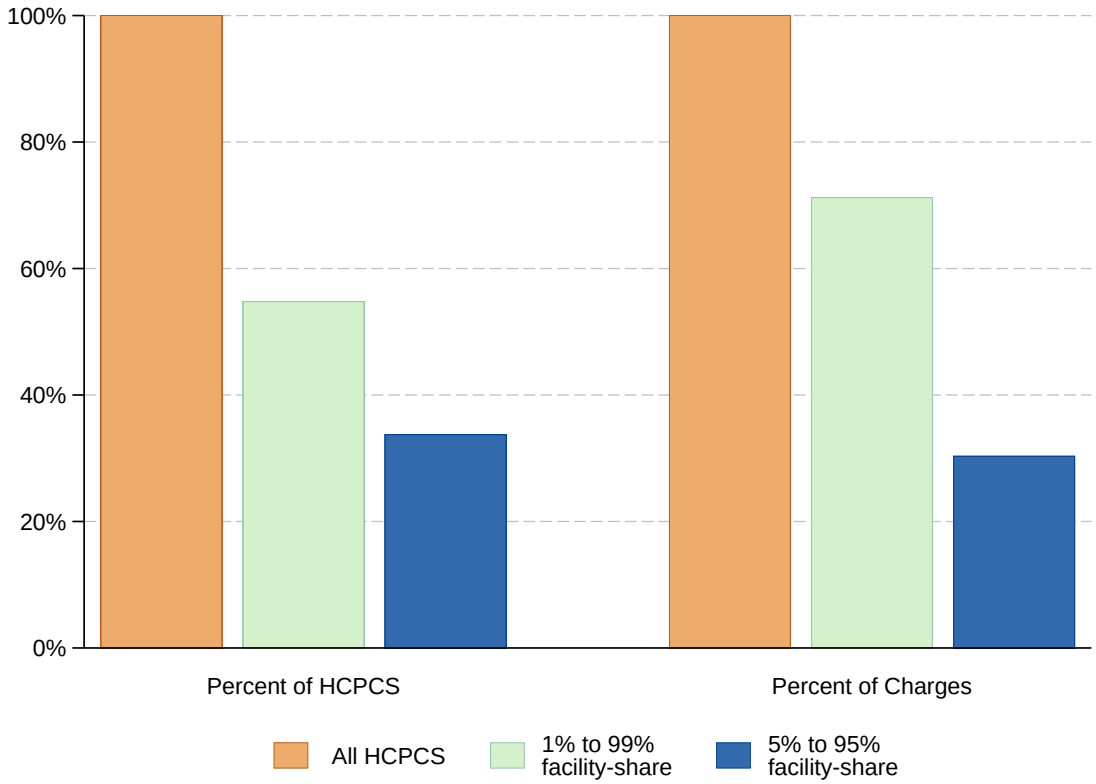
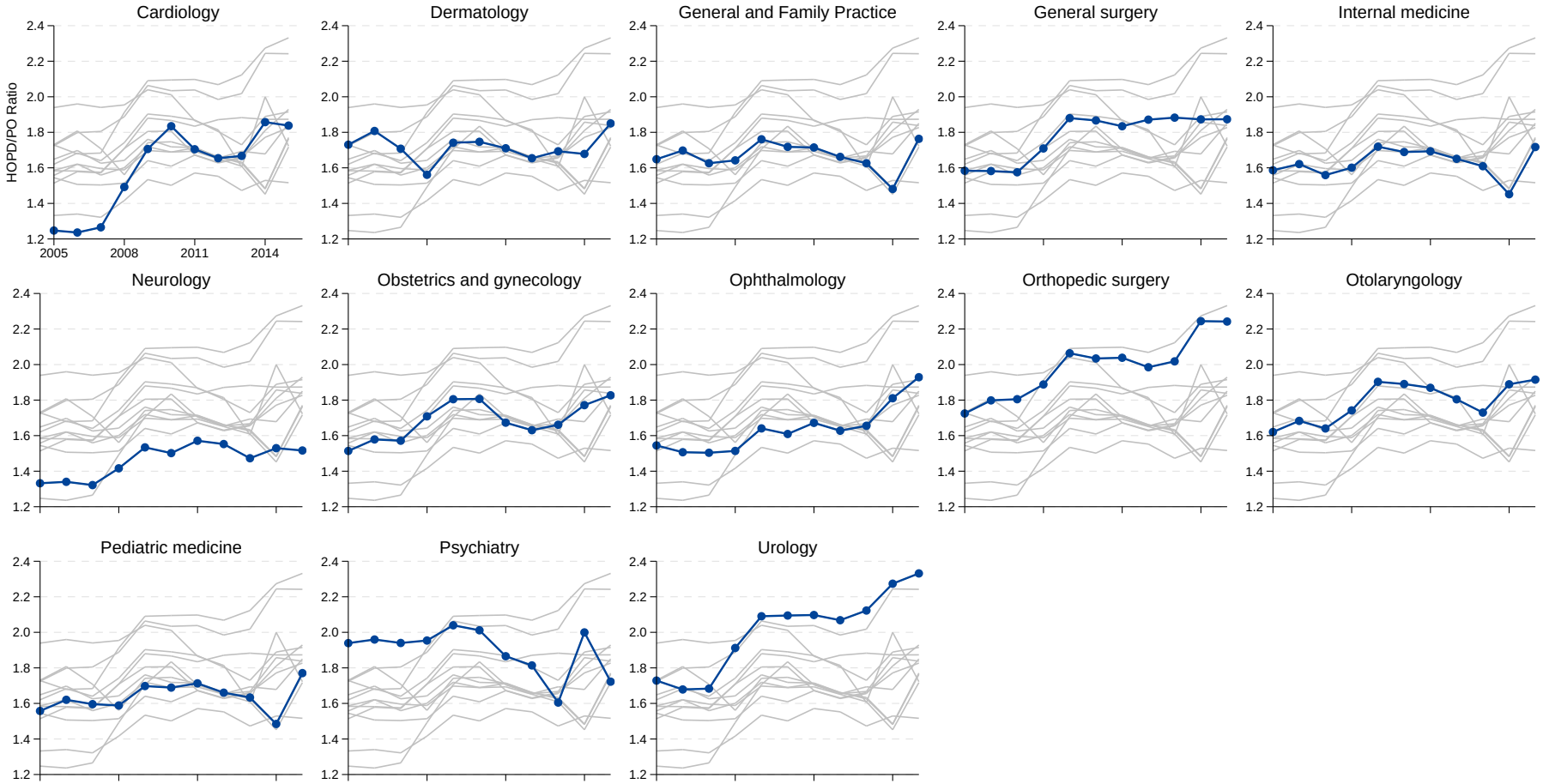
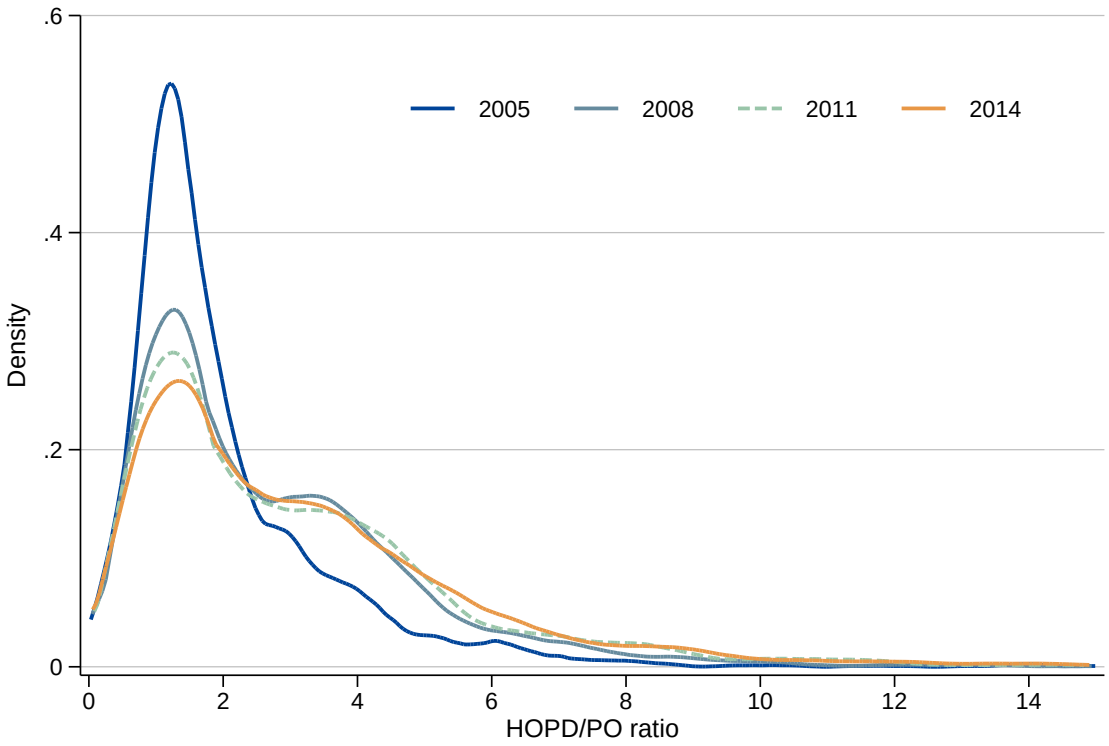


Figure 1.7: Relative Medicare Reimbursement by Specialty



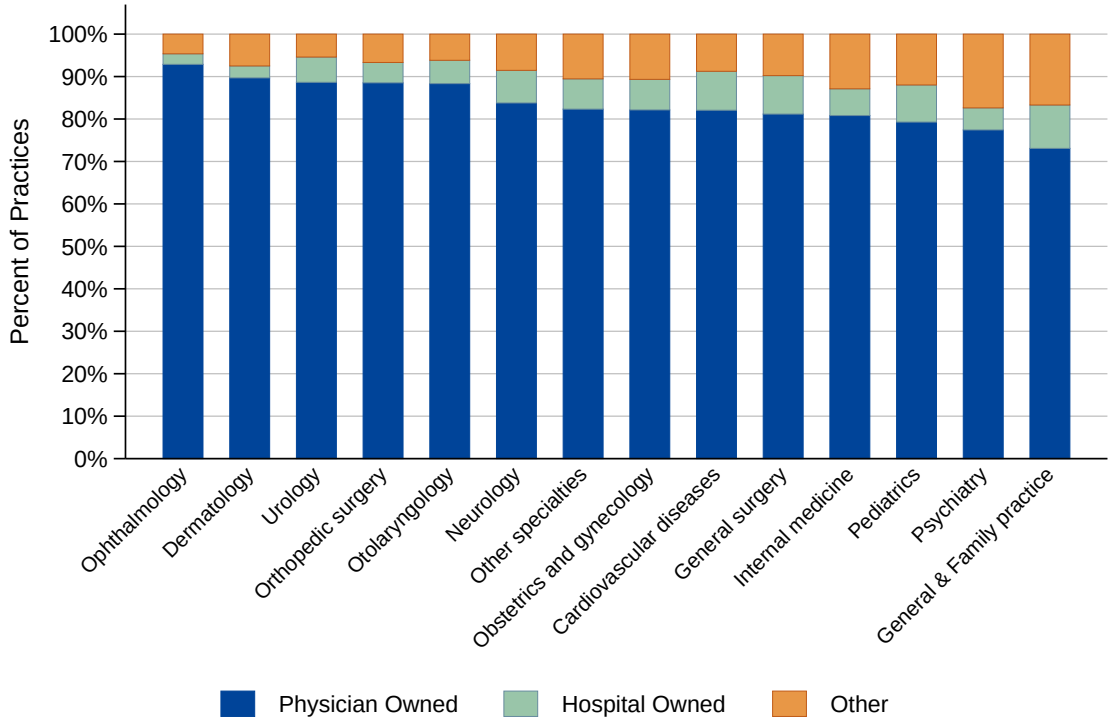
Weighted average reimbursement rate measures are constructed using 2003 and 2007 through 2015 Utilization Crosswalk Data from CMS. 2003 utilization data is used for year 2005 and 2007 utilization data is used for year 2006. Utilization weights are estimated for each specialty and year and sum to one. The sample is limited to HCPCS service codes with an average of between 1% and 99% of revenue generated in a facility setting.

Figure 1.8: Distribution of Relative Medicare Reimbursement by Service and Year



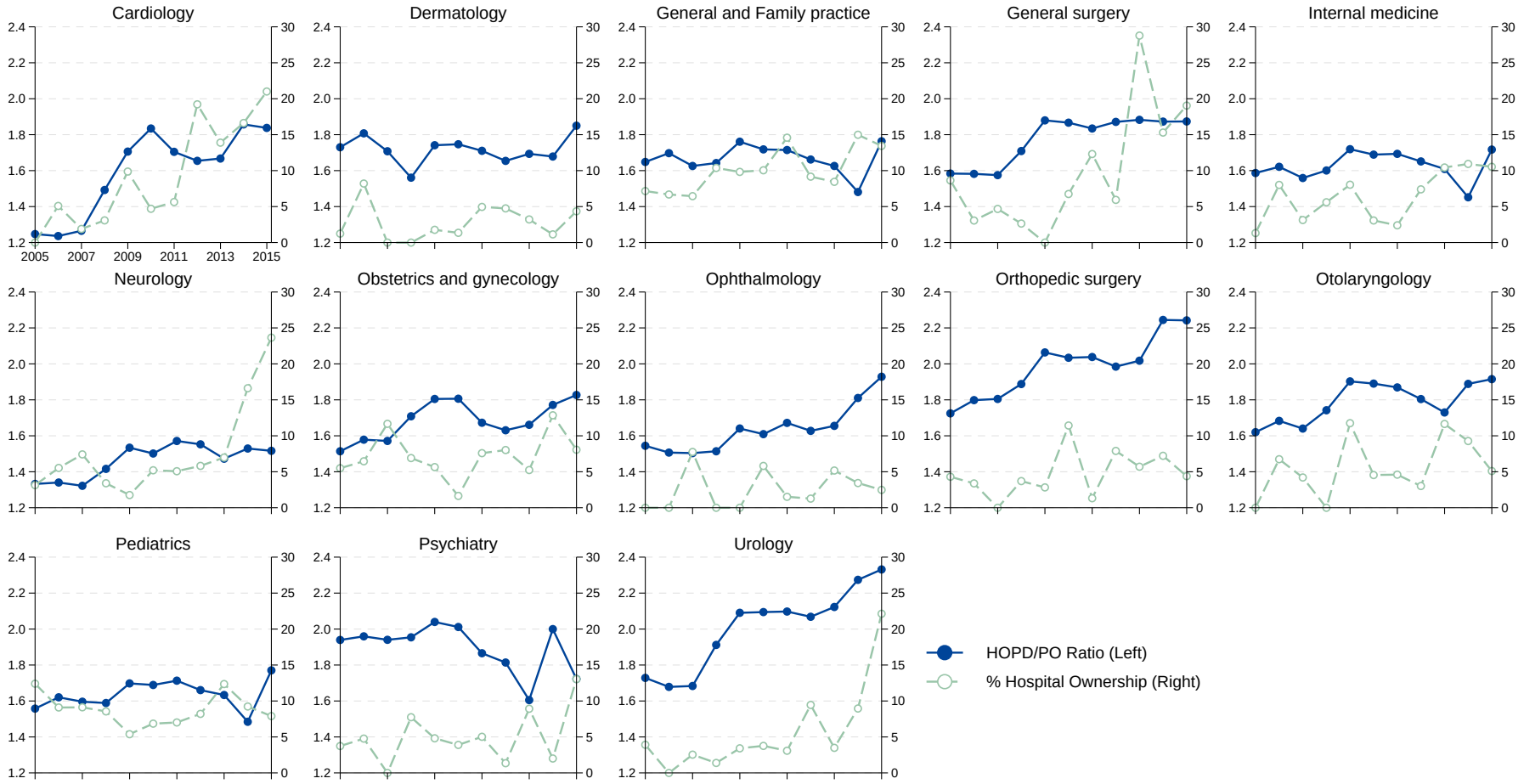
Source: 2005-2015 CMS Medicare Physician Fee Schedule RVU files and Hospital Outpatient Prospective Payment System Addendum B.

Figure 1.9: Physician, Hospital, and Other Ownership of Physician Practices by Specialty



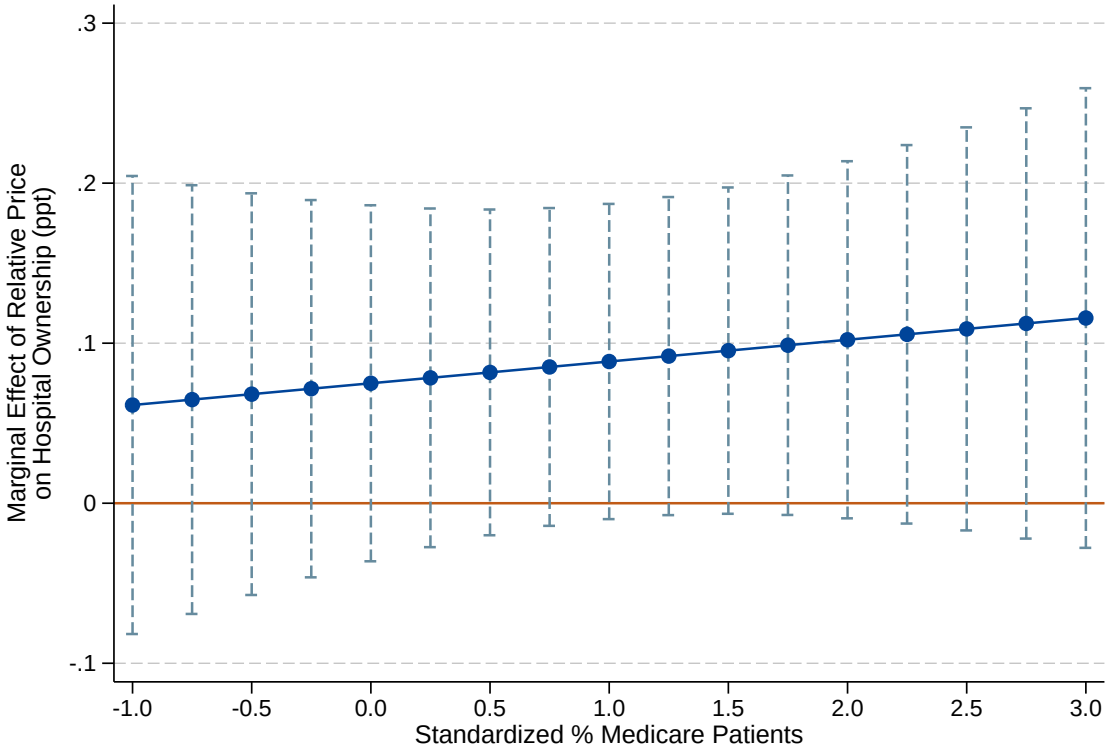
Source: NAMCS Public-Use file 2005-2015. Statistics are calculated using physician-level survey weights.
Other ownership includes insurance company, health plan, HMO, or other health care corporation ownership.

Figure 1.10: Relative Medicare Reimbursement and Hospital Ownership by Specialty



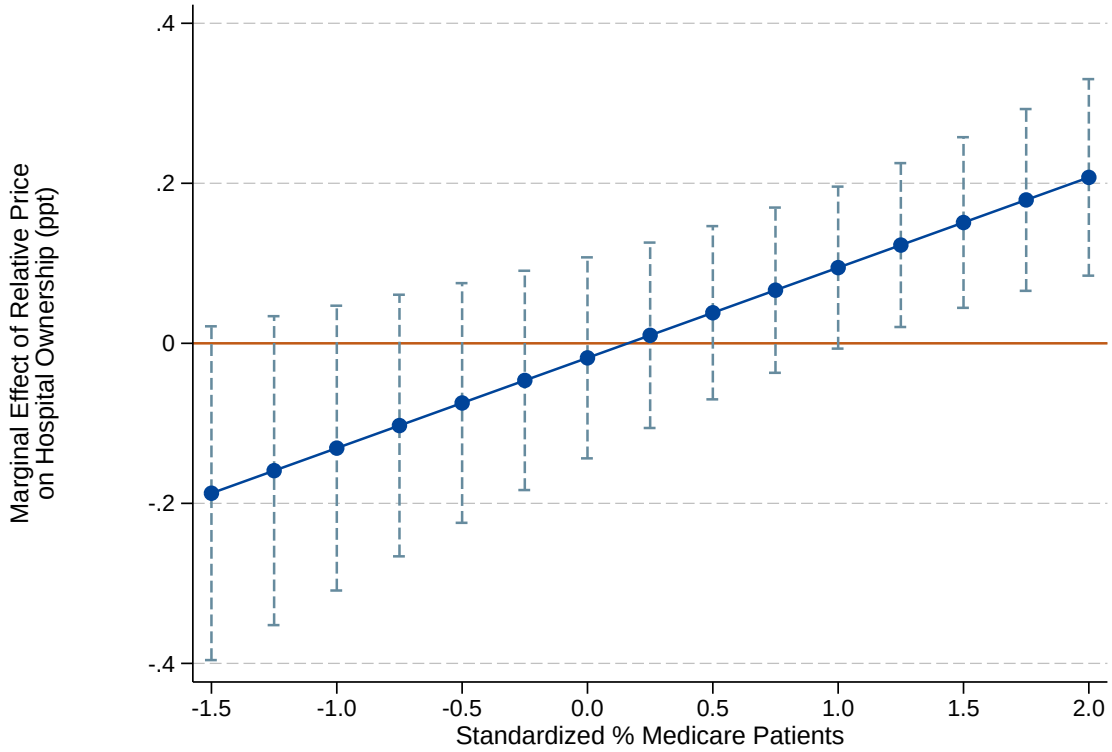
Weighted average reimbursement rate measures are constructed using 2003 and 2007 through 2015 Utilization Crosswalk Data from CMS. 2003 utilization data is used for year 2005 and 2007 utilization data is used for year 2006. Utilization weights are estimated for each specialty and year and sum to one. The sample is limited to HCPCS service codes with an average of between 1% and 99% of revenue generated in a facility setting.

Figure 1.11: Medicare Patient Share Interactions with Relative Medicare Rates



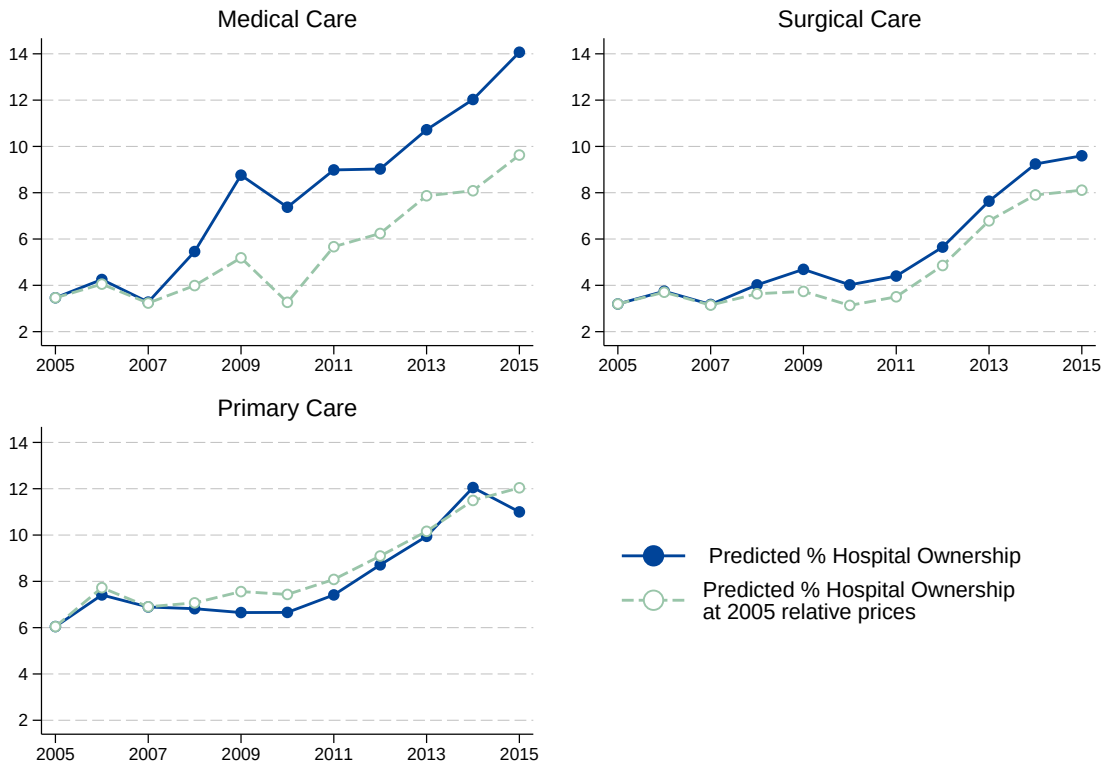
Source: NAMCS Public-Use file 2005-2015. Dotted lines represent 95% confidence intervals.

Figure 1.12: Specialty-Level Medicare Patient Share Interactions with Relative Medicare Rates



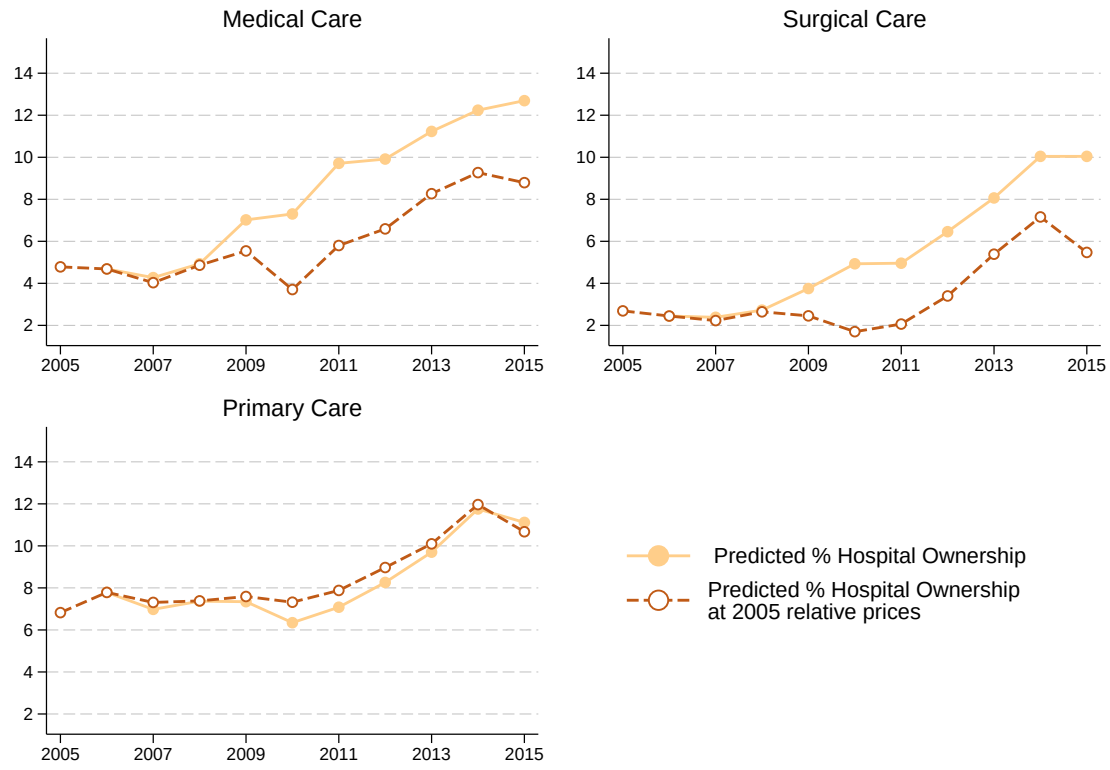
Source: NAMCS Public-Use file 2005-2015. Dotted lines represent 95% confidence intervals.

Figure 1.13: Predicted Hospital Ownership Rates



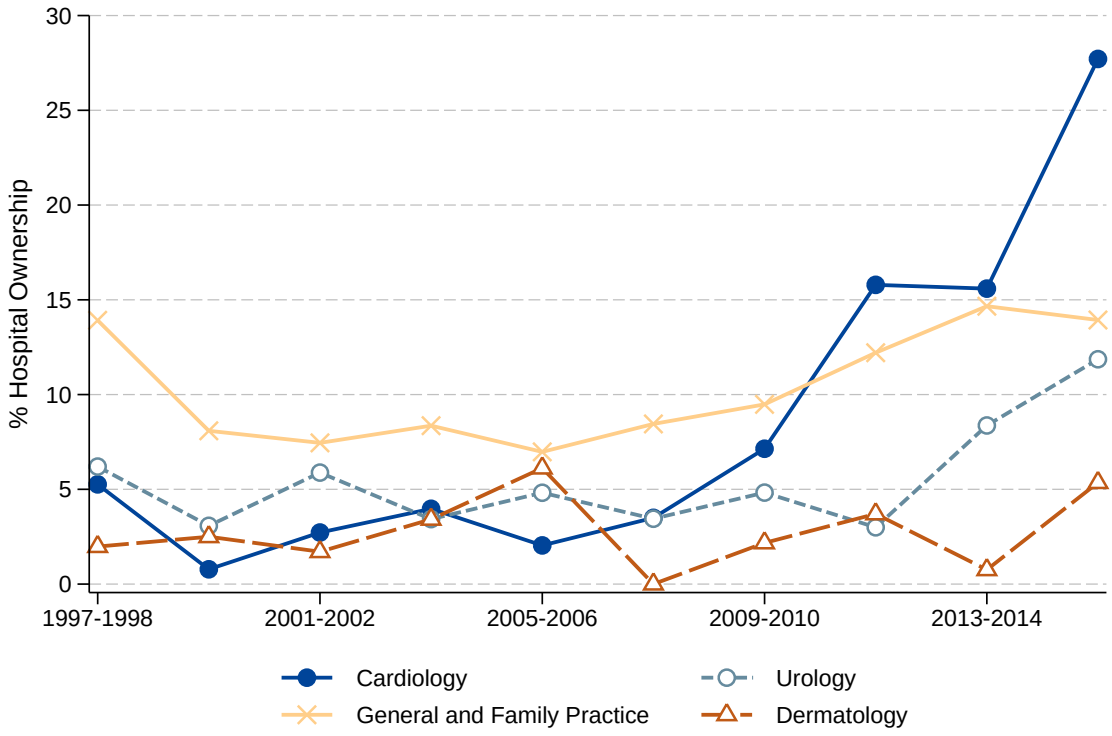
Predicted values are based upon model specifications shown in coulumn 5, of Table 4.

Figure 1.14: Predicted Hospital Ownership Rates - Lagged Models



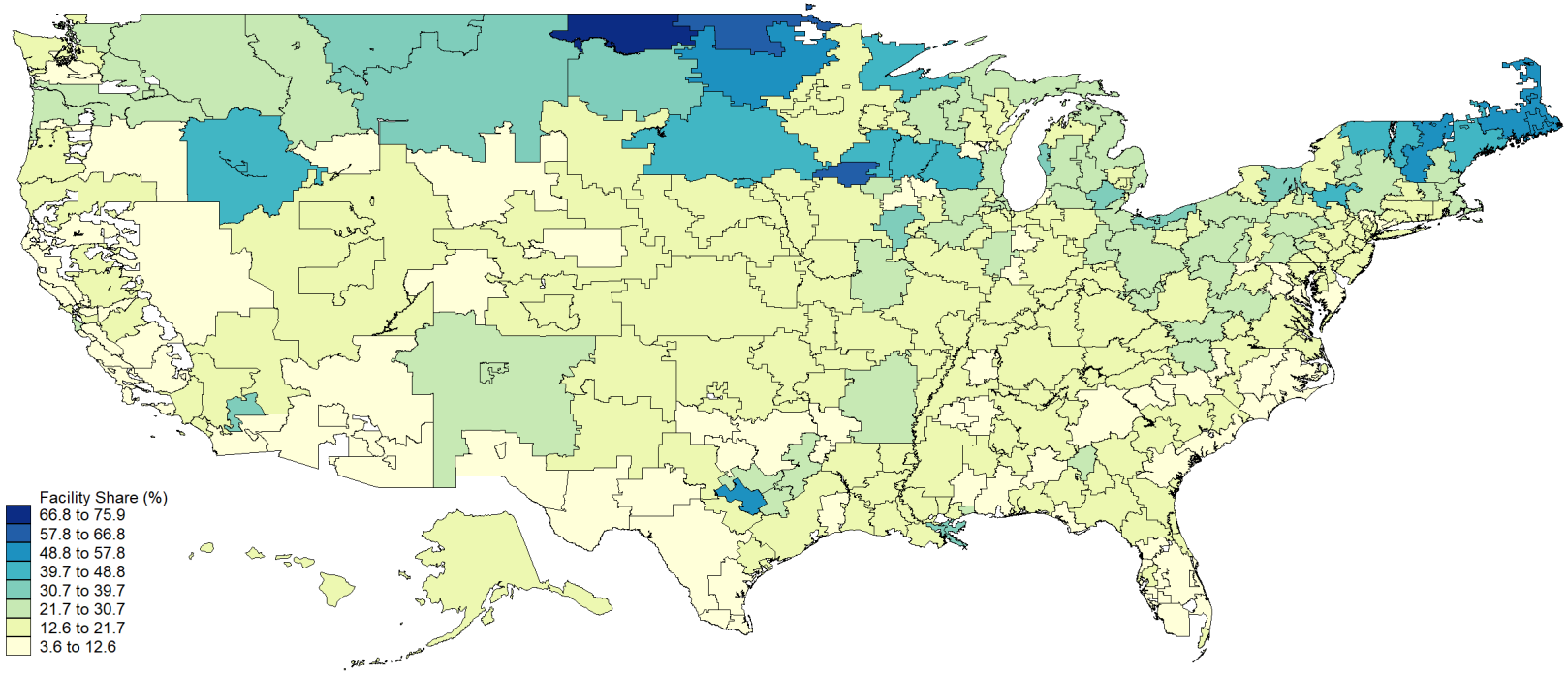
Predicted values are based upon model specifications shown in column 5, of Table 5.

Figure 1.15: "Pretreatment" Trends in Hospital Ownership



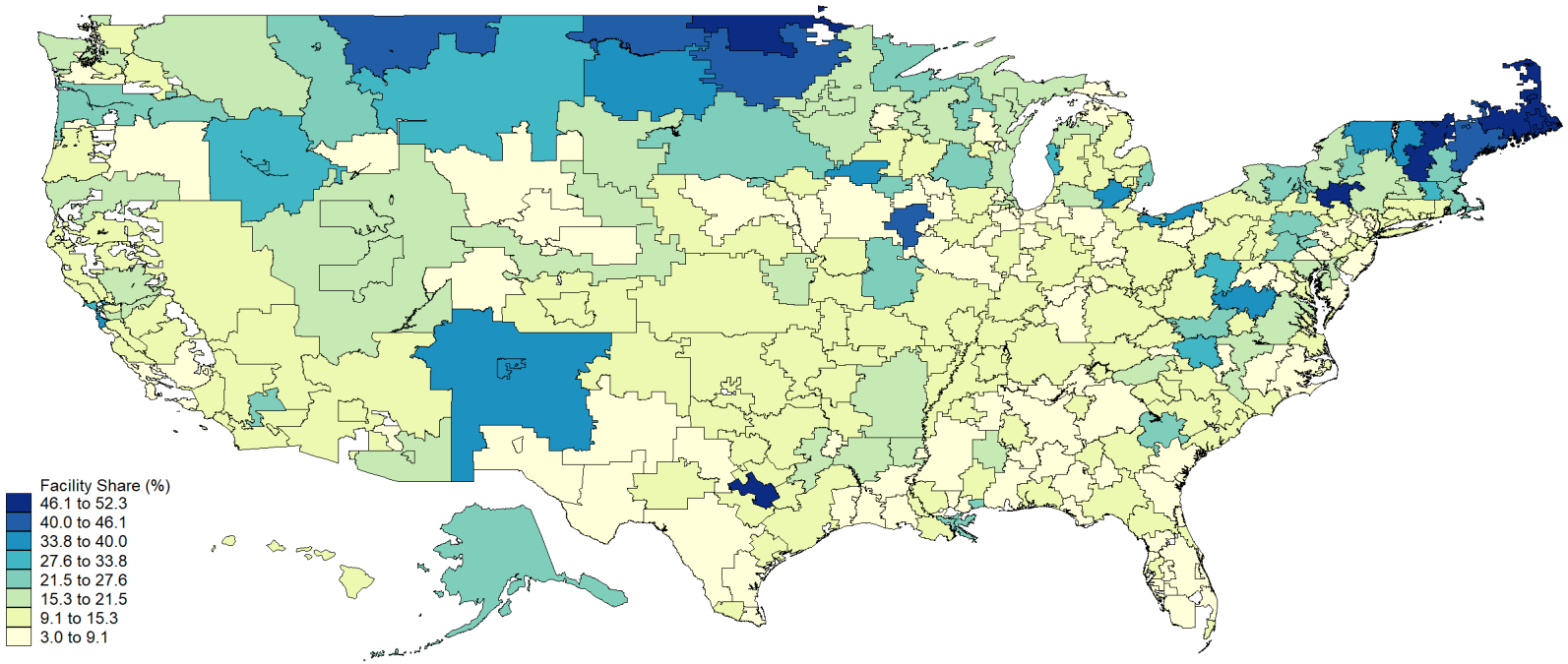
Source: NAMCS Public-Use file 1997-2015. Statistics are unweighted since physician survey weights are only availble in the public-use file beginning in 2005.

Figure 1.16: Facility-Share of Outpatient Physician Services Delivered to Medicare Patients: 2012 - 2015



*Source: CMS Provider Utilization and Payment Data Public Use File - Physicians and Other Suppliers 2012-2015. Specialties limited to Cardiology, Dermatology, Family Practice, General Practice, General Surgery, Internal Medicine, Neurology, Obstetrics/Gynecology, Ophthalmology, Orthopedic Surgery, Otolaryngology, Pediatrics, Psychiatry, and Urology Facility share is calculated as the percent of Medicare services performed in a facility setting. Only servces (HCPCS) performed in an office setting between 1% and 99% of the time are included. The average facility share is calculated for each Hospital Referral Region.

Figure 1.17: Proportion of Medicare Providers Who Perform At Least 95% of Outpatient Services in a Hospital: 2012 - 2015



*Source: CMS Provider Utilization and Payment Data Public Use File - Physicians and Other Suppliers 2012-2015. Specialties limited to Cardiology, Dermatology, Family Practice, General Practice, General Surgery, Internal Medicine, Neurology, Obstetrics/Gynecology, Ophthalmology, Orthopedic Surgery, Otolaryngology, Pediatrics, Psychiatry, and Urology Facility share is calculated as the percent of Medicare services performed in a facility setting. Only servces (HCPCS) performed in an office setting between 1% and 99% of the time are included. The proportion of providers with a facility-share greater than 95% is calculated for each Hospital Referral Region.

Chapter 2: Outsourcing Fraud Enforcement – Whistleblower Laws and Medicaid Expenditure

2.1 Introduction

The United States is a global leader in health care spending, with national health expenditures reaching $3.2 trillion in 2015, while spending on Medicaid was $532 billion (NCHS, 2016; Martin et al., 2016). Complex billing requirements combined with vulnerable patient populations and sheer size of the Medicaid program create opportunities for fraud and abuse. Health care fraud comprises up to 10 percent of total health care expenditures and can manifest itself through kickbacks, unnecessary services, over-billing, or illegal marketing and promotion (FBI, 2012; Morris, 2009). Medicare and Medicaid fraud ranges from $30 billion to $98 billion (Berwick and Hackbarth, 2012).

Underlying the problem of health care fraud in public programs is a principal-agent problem; the principal – the government – intends to pay for appropriate goods and services, but agents have incentives to provide additional services which may go beyond those guidelines, whether for profit motives or disagreements regarding the appropriateness of care. Certain features of the health care system exacerbate the misalignment of incentives: reimbursement is mostly fee-for-service where claims are assumed to be legitimate unless there are indications otherwise, claims-processing tends to be highly automated, and verification is deemphasized making monitoring of inappropriate claims extremely difficult (Sparrow, 2008). Health care providers also bear responsibility for their patients' well-being, and a fee-for-service system with minimal patient cost-sharing incentives results in potential over-utilization of treatments and tests with marginal positive expected medical benefit (Buchanan, 1988).

Allegations of fraud are pervasive within health care. Hospitals engage in "upcoding" of patients into more highly reimbursed diagnoses groups (Silverman and Skinner, 2004; Dafny, 2005). Physicians similarly upcode patients to take advantage of Medicare fee differentials (Brunt, 2011) and overbill for services (Fang and Gong, 2017). Pharmaceutical companies report inflated benchmark prices for Medicaid reimbursement purposes (Alpert, Duggan,

and Hellerstein, 2013), misclassify drugs to avoid required rebate payments[1], deceptively market prescription drugs[2], and use inappropriate "detailing" techniques and financial incentives to promote "off-label" uses to physicians (Stafford, 2008; Kesselheim, Mello, and Studdert, 2011).

The United States government has, in the last decade, more aggressively pursued fraud and deterrence with False Claims Act (FCA) –"whistleblower" statutes.[3] Although litigation for health care fraud under the FCA has increased, little is known about deterring fraudulent behavior, which is a key measure of success.[4] A frequent motivation for additional administrative spending is that the deterrent effect is large (Aaron, 2015). However there is little evidence to support such a claim, with one notable exception, Becker, Kessler, and McClellan (2005).

This paper measures the deterrent effect of state FCA statutes and Medicaid Fraud Control Unit (MFCU) expenditures on Medicaid program spending. The main contribution is quantifying the deterrent effect of whistleblower laws. To do so we extensively document state FCAs and amendments over time. Some surveys have summarized state FCA laws, but none provide sufficient information for quantitative analysis. We focus our attention on Medicaid program spending where state resources on anti-fraud efforts directly impact state budgets. We examine both Medicaid prescription drug expenditures, where penalties and whistleblower provisions provide strong incentives to deter fraud, and also other services where the incentives are weaker.

Using a difference-in-difference analysis, we find that the presence of such laws has a

[1]Mylan paid $465 million to the DOJ to resolve questions regarding its classification of EpiPens as generic, rather than brand name for the Medicaid Drug Rebate Program.

[2]Perdue Pharma and three of its executives plead guilty in 2007 for the misbranding of OxyContin and paid almost $635 million in civil and criminal charges for making claims that the drug was less addictive that its competitors due to its extended release nature. See http://www.nytimes.com/2007/05/10/business/11drug-web.html.

[3]We use the term "fraud" as consistent with the legal definition. This includes "knowingly submitting false statements or making misrepresentations of fact to obtain a federal health care payment for which no entitlement would otherwise exist, knowingly soliciting, paying, and/or accepting remuneration to induce or reward referrals for items or services reimbursed by federal health care programs, or making prohibited referrals for certain designated health services" (HHS, 2016).

[4]CMS reports "Success in combating health care fraud, waste, and abuse is measured not only by convictions, but also by effective deterrent efforts." See https://www.cms.gov/medicare-medicaid-coordination/fraud-prevention/fraudabuseforconsumers/report_fraud_and_suspected_fraud.html

sizable effect on prescription drug expenditures. We estimate that per-eligible prescription drug expenditure falls by 21 percent, a sizable cost-saving from the net $22 billion spent per year on Medicaid prescription drugs (MACPAC, 2016).[5] There are clear reasons to expect the FCA laws to matter for prescription drugs: highly concentrated, deep-pocketed pharmaceutical companies, a large number of transactions, and a somewhat subjective definition of fraud. At the same time, there is no effect on other service groups which is consistent with anecdotal evidence and actual investigations under the FCA. We find no direct effect of MFCU dollars on Medicaid expenditure.

We further test for the deterrent effect of FCAs through analysis of more fine-grained Medicaid prescription drug utilization data. Using a triple-difference model, we find that in states with FCAs, after passage of the law, spending on "off-label" prone categories of drugs is more responsive than non-off-label prone categories relative to states without their own FCA. Medicaid prescription drug spending on off-label prone drugs falls by 11 to 14 percent and prescription volume falls by 10 to 14 percent in states with a FCA enacted. These results are again consistent with FCAs primarily being targeted at pharmaceutical manufacturers for off-label marketing and promotion.

The remainder of this chapter is organized as follows: section 2.2 reviews literature on FCAs, fraud, and deterrence focusing on private whistleblower litigation, health care fraud and Medicare/Medicaid. Section 2.3 provides institutional background on the False Claims Act. Section 2.4 discusses how state FCAs may matter differentially for different types of fraud and lays out the conceptual model for our estimation strategy. Section 2.5 describes our data sources. Section 2.6 lays out our empirical model, potential issues, and presents our results. Section 2.7 extends our analysis to specific therapeutic classes of drugs using Medicaid drug utilization data. Finally, section 2.8 concludes and discusses implications of our findings.

[5] Medicaid spent approximately $42 billion on prescription drugs in 2014 and collected about $20 billion in rebates.

2.2 Literature

2.2.1 Fraud Committed Against the Government

There is a large literature concerning defrauding the government through tax evasion and the role of detection, penalties, and public disclosure which builds upon Allingham and Sandmo (1972). Much like our emphasis on the FCA, some recent work focuses on outsourcing tax enforcement to private parties. For example, Naritomi (2016) examines the deterrence effect of consumer reporting (whistleblowing) of business value-added taxes in Brazil. Kumler, Verhoogen, and Frías (2015) study third-party employer reporting wages in Mexico. Both show that whistleblower provisions are an effective tool for increasing compliance. Other work focuses on the role of supplementary, third-party information. Examples include Klevin et al. (2011) who analyze a randomized income-tax audit experiment in Denmark, Pomeranz (2015) who studies value added tax enforcement among Chilean firms, Casaburi and Troiano (2016) who examine property tax evasion in Italy, Carrillo, Pomeranz, and Singhal (2017) who study corporate income tax reporting in Ecuador, and Slemrod et al. (2017) who study small-business tax compliance. Work on third-party information finds that tax compliance increases with visibility to the public and enforcing agency, perceived risk of detection, and threat of enforcement.

Private enforcement is also an important source of deterrence and remediation in antitrust violations. While the Department of Justice may pursue criminal and civil penalties for firms and their employees for engaging in illegal anti-competitive behavior, secondary civil suits may result in large payouts for victims.[6] Lande and Davis (2011) estimate a value of $6.8 to $7.7 billion for federal antitrust remedies from 1990 through 2007. They compare this to recoveries from 40 of the largest private antitrust cases over the same time period, which total $18.0 to $19.6 billion.[7] They conclude that private enforcement exhibits a stronger deterrent effect on antitrust violations due to the size of recoveries.

[6] Civil anti-trust laws also resemble False Claims Act statutes; both include treble damages and may be brought by private third parties. States also frequently have their own anti-trust statutes, in addition to the federal Sherman and Clayton Acts.

[7] These figures come from an earlier study of private anti-trust actions. See Lande and Davis (2007).

Tax evasion and anti-trust violations differ from health care fraud in that they represent a transfer from the government to the evader or from victims to firms. Health care fraud committed against the government not only acts as a transfer, but also has potential impacts on health through inefficient levels of health care provision to patients.

2.2.2 The Social Optimality of Whistleblower Laws

The social optimality of whistleblower litigation and private "bounties" has been widely discussed.[8] Whistleblower laws incorporate private individuals seeking profit through the judicial system, and while this "outsourcing" of fraud monitoring from government agencies to private individuals can dramatically increase the resources utilized in anti-fraud activities, it also inevitably introduces additional distortions. Whistleblowers may be over-zealous in reporting potential fraud cases, some of which will be dropped and others which may be settled out of court to avoid uncertainy from a jury's verdict. There is mixed evidence that whistleblowers overcrowd the Attorney General with poor cases. Matthew (2007) argues that pharmaceutical manufacturers may be the target of a flood of unmeritorious cases initiated by FCA whistleblowers, and cites the large number of suits against pharmaceutical manufacturers and staggering settlements as evidence. Kwok (2013) analyzes whistleblower-initiated FCA cases in search of evidence of high-volume, low effort "filing mill" strategies pursued by plaintiff attorneys, but finds no indication that this behavior is common.

2.2.3 Empirical Studies on Health Care Fraud in Public Programs

There has been limited work which attempts to empirically analyze the economic effects of anti-fraud enforcement activity in public programs. DOJ officials only provide anecdotal evidence of FCA cases preventing fraud. Total "Health Care Fraud and Abuse Control" program investments resulted in a return-on-investment of $4.90 to $1.00 in fiscal years 2006 to 2008, and $7.90 to $1.00 in fiscal years 2010 and 2012 (United States Government Accountability Office, 2013). These estimates exclude any deterrent effect. Similarly, in a

[8] See Breit and Elzinga (1985) as private enforcement relates to antitrust actions and Depoorter and De Mot (2006), Broderick (2007), Matthew (2007), Heyes and Kapur (2009), Engstrom (2013), and Kwok (2013) related to the False Claims Act.

survey of prosecutors in state Attorney General's offices in states with and without their own FCAs, most respondents did not know if the statute is effective in deterring fraud (Bucy et al., 2010).

One case study, Kesselheim, Darby, et al. (2011), attempts to quantify the deterrent effect of FCA enforcement on prescription rates in a lawsuit against Warner-Lambert, a pharmaceutical manufacturing company and producer of Neurontin. They find that upward trends in the number of new prescriptions and spending for Gabapentin continued during all phases of the DOJ investigation and these trends were greatest for off-label uses. Only after settlement of the case did growth rates become negative, but this occurred for both on and off-label uses.

Becker, Kessler, and McClellan (2005) measure the impact of anti-fraud activity on abusive behavior by examining Medicare patient spending and health outcomes for groups of illnesses identified as being vulnerable to fraud and abuse. State anti-fraud activity is measured as state MFCU expenditures per Medicare beneficiary, and alternatively as MFCU expenditures per hospital. The authors find no overall aggregate effect of state anti-fraud activity, but certain patient groups and providers were found to be more responsive, with a greater response to anti-fraud activity in patient populations for whom additional treatment and expenditures would be of marginal benefit.

The aggregate result of no effect of Medicaid anti-fraud activity on Medicare patients raises a question about overlapping program administration and enforcement. States have little motivation to focus MFCU expenditures on Medicare patients, as Medicare is federally funded, while Medicaid spending is jointly financed by the state and federal government.

2.3 The False Claims Act

Various studies summarize the federal and state FCAs, which we highlight here.[9] State statutes generally mirror the federal FCA with subtle differences. The original 1863 statute contained a "qui tam," or whistleblower, provision which allowed private parties to bring

[9]Barger et al. (2005), Depoorter and De Mot (2006), Broderick (2007), Doyle (2009), Bucy et al. (2010), and Kwok (2013), in addition to others.

a suit, even if they, themselves, were not directly affected by the fraudulent perpetration. The FCA was infrequently used until 1986 when amendments strengthened the qui tam provisions and made it easier to file a suit as well as substantially increased the civil damages for a violation.

2.3.1 FCA Utilization and Recoveries

Statistics from the U.S. Department of Justice show the growing importance of the FCA, especially in health care fraud suits (DOJ, 2016). Figures 2.1 and 2.2 show the number of "new matters" filed since 1986 and associated settlements and judgment amounts. New matters include new referrals, investigations and qui tam actions. In 1987, the number of cases filed in which the Department of Health and Human Services (HHS) was the primary client included only about 4 percent of total cases. In 2015, HHS cases represent roughly 60 percent of total cases and 55 percent of settlements and judgments. Since 2000, HHS cases have made up about 56 percent of all FCA cases and 72 percent of total settlements and judgments.[10] Similarly, the number of qui tam actions has grown from only a few per year to representing the majority of cases filed, growing from 20 percent of HHS cases in 1987 to 94 percent in 2015. Since 2010, total settlements, judgments, and awards averaged over $4 billion annually. Whistleblower-initiated FCA case filings surpass private antitrust filings (Sourcebook of Criminal Justice Statistics, 2012) and settlements and judgment dollar amounts rival that of private securities class action suits (Bulan, Ryan, and Simmons, 2016).[11]

2.3.2 Recent Amendments

Since the 1986 amendments of the FCA, the federal government has heavily relied on the FCA to combat fraud, and this is further evidenced in more recent amendments of the statute. The 2005 Deficit Reduction Act provides states with an incentive to enact their

[10] This is true of FCA suits filed by states as well. In a survey of state FCAs, most states reported that they primarily use their FCA to pursue health care cases (Bucy et al., 2010).

[11] On average, from 2010 through 2012 there were 559 private civil anti-trust cases filed in district courts annually. Settlements from class action securities lawsuits from 2010 - 2015 average $3 billion annually.

own FCAs which follow the federal statute, by receiving an additional 10 percent of any recoveries (HHS,). Between 2005 and 2012, 12 states enacted a FCA and as of 2012, 12 states' FCAs were compliant with the Deficit Reduction Act (NAMFCU, 2006/2015). In 2009, the Fraud Enforcement and Recovery Act further strengthened the 1986 amendments of the FCA, and in 2010 the Patient Protection and Affordable Care Act changed the federal FCA by allowing a violation of the federal anti-kickback statute to automatically trigger a violation of the False Claims Act; until the ACA amendment, it was unclear whether a violation of the anti-kickback statute should result in a per se violation of the FCA (Becker, 2014).

2.3.3 FCA Characteristics, Filing Procedure, and the Role of the Whistleblower

In a typical FCA suit, a sealed complaint submitted by a qui tam plaintiff is reviewed by the DOJ and a United States attorney, who consider the case's merit and evidence. A qui tam plaintiff need not be directly injured by the violation. The DOJ, or state Attorney General, must then decide whether to intervene in the case or not. In the case of government intervention, the qui tam party may remain a plaintiff in the suit, but the government assumes primary responsibility in prosecuting the case. The qui tam plaintiff may still conduct the action even if the DOJ or state Attorney General chooses not to intervene. Generally, a qui tam plaintiff is awarded anywhere from 15 to 25 percent of the total damages if the government intervenes and 25 to 30 percent if the government does not.[12] Although relator awards are slightly smaller in cases where the government intervenes, private plaintiffs gain the significant resources of the state or federal government, and success rates indicate that intervention and resulting settlements and judgments are positively correlated; 95 percent of FCA qui tam cases between 1986 and 2009 where the DOJ intervened resulted in settlements and judgments, compared to only 9 percent of non-intervened cases (Kwok, 2013). Dismissal rates of cases where only a qui tam relator

[12]Only under specific scenarios is a qui tam plaintiff awarded less, for example if the relator provides publicly disclosed information as evidence or if he or she is partially at fault for the violation.

proceeds are much higher, about 80 percent, versus a dismissal rate of 4 percent when the government is also a plaintiff in the suit (Matthew, 2007). Importantly, damages for violations of the FCA include civil monetary penalties of $5,500 to $11,000 per violation plus treble damages. The damage awards may quickly grow to multi-million dollar suits which can potentially attract private plaintiffs who wish to gain up to one-third of the total damage amount.

2.4 Conceptual Issues: Why Prescription Drugs?

2.4.1 FCAs and Different Types of Fraud

It is likely that state FCAs and other anti-fraud activities affect various beneficiary groups and service types differently. We focus on prescription drugs in our analysis.[13] In particular, we focus on off-label pharmaceutical marketing because characteristics of both FCAs and prescription drug markets make pharmaceutical manufacturers a lucrative target for prosecution. Profit motives, whistleblower rewards, and per-violation monetary penalties and treble damages combined with high-volume transactions and deep-pocketed defendants in the pharmaceutical industry all contribute to the FCAs disproportionately large effect on prescription drugs.

Off-label Marketing

Off-label marketing occurs when a pharmaceutical manufacturer engages in marketing efforts towards providers or patients that promote a drug for uses or populations other than what has been approved by the FDA. In a typical off-label marketing case, FCA damages are based upon the inducement of health care providers to prescribe a drug for uses or populations which it was not tested and approved for (Gaier, Scher, and Sharma,

[13] Pharmaceuticals are not the only service that is prone to fraud and abuse. Home health care and durable medical equipment are two other service areas that are highlighted (HHS, 2012). In home health care fraud, providers may falsely verify the necessity of home health services, receive kickbacks for signing beneficiaries, or verify medical necessity for patients not under the physician's care. Other common fraudulent behavior includes overstating the severity of patient's conditions and billing for services that were not provided (HHS and DOJ, 2016). Home health care violations constitute only about 5.5 percent of civil settlements and judgments, and make up only a small percentage of FCA lawsuits (OIG, 2000/2015; Qureshi et al., 2011; Kesselheim and Studdert, 2008).

2013). This type of illegal behavior falls under a FCA violation because the government will only authorize payments for drugs which are safe, effective, and if it will be used for a "medically accepted indication," such as a use approved by the FDA. Otherwise, if a drug is marketed for some other unapproved use, then it arguably does not satisfy this criteria and the government ends up paying for falsely advertised products (Samuelson, 2014). Off-label marketing violations are prosecutable by states under FCAs and/or by using MFCUs (Spacapan and Hutchison, 2013; OIG, 2000/2015).

Consequences of off-label marketing include increasing health care costs, possibly endangering public health, and undermining federal drug regulation. Off-label marketing may provide benefit for some populations. Various anti-depressants, for example, are prescribed for a number of unapproved uses including anxiety, obsessive-compulsive disorders, eating disorders, and PTSD, among other uses (Wittich, Burkle, and Lanier, 2012). Off-label prescribing provides a faster alternative path for effective treatment when medical knowledge outpaces the FDA approval process and gives physicians flexibility when a standard treatment might fail (Klein and Tabarrok, 2004). Note that physicians may prescribe a drug for any reason; FCA prosecution rarely targets physicians for their (off-label) prescribing behavior, but rather is used to limit pharmaceutical manufacturers' influence on physician prescription behavior through promotion of unproven drug benefits or uses (Samuelson, 2014).

High Transaction Volume

One common characteristic of the FCA is that it provides for a civil penalty per violation of the statute, in addition to treble damages. This per-violation penalty would matter more for service categories where the number of transactions is relatively high. One such type of case is off-label marketing cases. In an off-label marketing case, each prescription that is written based upon illegal marketing constitutes a transaction, and consequently civil penalties may quickly add up.[14] Damages resulting from off-label marketing or over-

[14]Under an "implied certification" liability, *all* prescriptions after the submission of a false claim (or incidence of illegal off-label marketing) will be treated as "false claims," not just those prescriptions induced by the off-label marketing.

charging for thousands of prescriptions will result in higher payouts than a typical home health provider, for example, who is double billing for services. Examining MFCU cases in 2014, 48 home health care agency and 413 home health aide criminal convictions resulted in $7.1 million and $12.5 million in recoveries, which is an average of about $150,000 and $30,000 per case. This is paltry compared to the nearly $2.8 million average recovery for a civil case involving a pharmaceutical manufacturer.

Deep-Pocketed Defendants

Cases involving pharmaceutical manufacturers may also entail large settlements or judgments due to the deep pockets of such companies and wide reach of any violations. For example, Johnson & Johnson, in 2013, was ordered to pay over $2.2 billion in civil and criminal penalties for off-label promotion of Risperdal, in addition to other drugs, as well as kickbacks to health care providers (DOJ, 2013). Office of the Inspector General (OIG) reports show that pharmaceutical manufacturers and pharmacies are the most common provider type in civil MFCU cases, representing approximately two-thirds of settlements and judgments and recoveries (OIG, 2000/2015). Kesselheim and Studdert (2008) find that although pharmaceutical manufacturers represent only 4 percent of defendants in whistleblower-initiated FCA cases between 1996 and 2005, this group constitutes almost 40 percent of recoveries. The authors note that the number of cases where hospitals or physician groups are defendants declined over the study period; this may be due to strategic enforcement by the DOJ where prosecuting hospitals, which made up 29 percent of the sample of cases but only 3 percent of recoveries, is forgone in favor of more lucrative cases against pharmaceutical manufacturers.

Insiders and Detection

Off-label promotion by pharmaceutical manufacturers may also engage more potential whistleblowers in the illegal activity and increase the probability of detection. Kesselheim, Mello, and Studdert (2011) find that in 18 federal FCA fraud cases, 71 percent of whistleblowers worked as pharmaceutical sales representatives and another 20 percent worked as sales or accounting managers. Kesselheim and Studdert (2008) find that about 77 percent of

whistleblowers in FCA health care fraud cases are "insiders." If off-label marketing activity involves more individuals, including sales representatives, managers, and executives, than a physician office where only the physician, patient, and possibly a billing specialist could report false billing, then it may be more difficult for the firm to collude with its employees and discourage whistleblowing.

FCAs provide a clear profit motive for whistleblowers to target cases in which expected awards will be the greatest. Evidence from MFCU cases suggests that damages in pharmaceutical cases are far larger, on average, than damages in other cases. Therefore, there is reason to suspect that not all providers and service types should respond similarly to state anti-fraud activity, and further, if civil penalties and enforcement should have a measurable effect on behavior, we should expect to see responses in the prescription drug service area.

2.4.2 Policy Confounders

We hypothesize that state Medicaid prescription drug spending should be more responsive to FCA legislation, relative to other spending categories. Focusing on prescription drug spending, it is necessary to consider other state Medicaid policies which may influence spending. If these state-level policies are correlated with FCA implementation, then omitting them will bias the estimated effect of state FCAs on prescription drug spending and we will attribute reductions in prescription drug spending to FCAs rather than the other state policies.

Prescription drug spending is a common target for state Medicaid cost-containment policies. Although provision of prescription drug benefits is optional, all fifty states and the District of Columbia choose to provide these services. As such, states have greater flexibility in designing their prescription drug benefits, relative to mandatory services (Schneider and Elam, 2002). Periods of rapid prescription drug spending growth have also gained the attention of states looking to control Medicaid program costs. Medicaid drug expenditures grew at 19 percent annually between 1997 and 2000 (Schneider and Elam, 2002). From 1999 to 2009, the average annual number of prescriptions per non-dual beneficiary remained stable, yet the average annual costs per beneficiary nearly doubled (Verdier and Zlatinov, 2013). After a decade of stable growth, and a slight dip in Medicaid prescription drug

expenditures, prescription drug spending growth increased sharply in 2014. This most recent increase in drug expenditures is attributable to high-cost specialty drugs entering the market and ACA Medicaid expansions (MACPAC, 2016; Martin et al., 2016).

States have implemented numerous policies to curb program spending on prescription drugs. Common policies include preferred drug lists (PDLs), prior authorization (PA), cost-sharing with Medicaid enrollees, prescription limits, drug category exclusions, generic substitution laws, and supplemental manufacturer rebates (Sourmerai, 2004; Morden and Sullivan, 2005). Generally, PDLs, PA, cost-sharing, and generic substitution seek to influence the choice of prescription drugs and shift utilization towards more cost effective products. Prescription limits and category exclusions directly limit prescription drug coverage.

PDLs enumerate drugs that state agencies indicate as being the most cost-effective or efficient. Drugs which are not listed on a state's PDL are still available to beneficiaries, but prescribers must go through a prior authorization process and request approval for each prescription. States may also exercise PDLs as a negotiating tool with pharmaceutical manufacturers to demand rebates that exceed the required federal rebates (Mellow, Studdert, and Brennan, 2004). Co-payments represent another policy which a state may use to reduce overall utilization or influence beneficiary choice. Medicaid co-payments are limited to nominal amounts and a beneficiary may not be denied a prescription due to his or her inability to pay. However, states may implement tiered co-payments, where generic drugs typically have a lower co-payment than branded drugs, in order to attempt and shift utilization toward less costly generic drugs (Hoadley, 2005). Generic substitution laws, while not specific to Medicaid programs, also encourage the use of low-cost generics, when available. Laws vary by state, but typically allow a pharmacist to dispense a generic drug, even if a physician has written a prescription for the brand name (Shrank et al., 2010).

Medicaid programs may exclude certain broad categories of drugs including drugs for weight loss, infertility, cosmetic and hair growth, smoking cessation, vitamins, and cold remedies among others (Hoadley, 2005). States may individually choose any or all of these categories for which to exclude Medicaid coverage. Prescription limits are limits on either the quantity of filled prescriptions (i.e. 30 days or 45 days) or on the total amount of

prescriptions per beneficiary per month. Prescription limits more commonly apply to all prescriptions, but as of 2010, 4 states had implemented "brand-only" prescription limits in an attempt to also shift utilization to generic drugs (Lieberman et al., 2016).

States have adopted various forms of policies to control Medicaid prescription drug costs. We account for these common prescription drug policies in our empirical specifications. Specific state program variables and data sources are discussed in sections 5 and 6.

2.4.3 State and Federal FCA Overlap

The presence of a federal FCA, in addition to secondary state-specific FCAs begs the question of the overlap of roles of both statutes in anti-fraud activity and why a state FCA, which is no more punitive than the federal FCA, would additionally deter fraud. We argue that state FCAs represent additional resources devoted by the state to detect and prosecute fraud and provide greater opportunities for whistleblowers to disclose potential fraud. State FCAs (most of which contain whistleblower provisions) provide additional channels through which whistleblowers may come forward and provide information on potential fraudulent behavior. Instead of submitting a case directly to the DOJ, whistleblowers may file complaints to their own state (typically the Attorney General) who then may go forward with the case under the state FCA or submit to the DOJ to involve the federal government in the prosecution. Many states with FCAs also report substantial cooperation with the state MFCU (Bucy et al., 2010). Additional resources and channels for whistleblowers to disclose potential fraud increase the probability of detection and prosecution at the state level.

Our analysis focuses on prescription drugs and we hypothesize that state FCAs should deter illegal off-label marketing and/or prescribing. Why should off-label marketing by pharmaceutical manufacturers respond to state anti-fraud efforts? Although pharmaceutical marketing campaigns (direct-to-consumer advertising) are not tailored for each state, pharmaceutical manufacturers do target advertising by consumer demographics.[15] These types of promotions may potentially exhibit a response to states who target allegedly de-

[15]See Alpert, Lakdawalla, and Sood (2015) who uses variation in direct-to-consumer advertising after Medicare part D implementation and across markets with high versus low elderly population shares to identify the effect of advertising on drug utilization.

ceptive advertising more aggressively. Illegal off-label promotion, however, occurs primarily through physician detailing by pharmaceutical sales representatives and is physician-specific. Detailing practices may respond differentially, depending on the level of anti-fraud activity within a state. Direct-to-physician detailing makes up a significant proportion of pharmaceutical company marketing budgets, and this form of promotion has been found to influence physician prescription behavior (Datta and Dave, 2017). Although we do not focus on lawsuits dealing with pharmaceutical companies' misrepresentations of prescription drug costs to state Medicaid programs to secure higher reimbursements, this type of fraud is also liable under the FCA. The presence of a state FCA places a higher cost on inaccurate reporting of drug prices or generic status to the state Medicaid program.

2.5 Data and Descriptive Statistics

Our analysis combines four data sources containing information on FCA legislation, MFCU expenditures, Medicaid spending and eligible populations, and demographics. State FCAs and MFCU expenditures vary at the state-year level, and we combine these datasets with Medicaid spending measures by group and service category within each state and year. The resulting data set contains state anti-fraud activity and Medicaid spending from 1999 through 2012 for all 50 states and D.C. State Medicaid prescription drug policies are also included in specifications to control for potentially confounding policy effects.

Data on state FCA statutes was collected by analyzing state laws and amendments over time. Information on state statutes was primarily gathered using Lexis Advance legal database. Although there are several documents which catalog various state FCAs, none compiles all of the characteristics of the laws or how the laws have been amended over time.[16] A detailed summary of state FCA statutes is provided in the appendix. The statutes in each state were individually summarized and standardized to facilitate comparisons across states. For each state with a FCA enacted, common characteristics of the law are documented as well as amendments over time. Characteristics of state FCAs include the year that the

[16]See Barger et al. (2005), Rosenbaum, Lopez, and Stifler (2009), Bucy et al. (2010), and NAMFCU (2006/2015).

statute was enacted, whether the statute covers all government programs or just health care (Medicaid), whether the statute has a qui tam, or "whistleblower", provision, the reward for a whistleblower plaintiff, and the monetary penalty for violating the statute. See Table 2.1 for a list of states which have enacted a FCA and the year of enactment; Figures 2.3 and 2.4 summarize FCA implementation over time. States which have enacted FCAs tend to be dispersed geographically, and states have gradually implemented FCAs over time. Between 1991 and 2016, typically one to two FCAs were enacted each year. The years 2006 to 2007 saw the most activity with 5 statutes being passed. Just over half of FCAs passed by 1999 applied to state Medicaid program fraud only, but the majority of FCAs passed since apply to all state government programs. Similarly, most FCAs passed since 1991 contain a whistleblower provision, with more than 80 percent having a whistleblower component in 2016, compared to 60 percent in 1991 (Figure 2.4).

Following Becker, Kessler, and McClellan (2005), we also include a measure of state MFCU expenditures to additionally control for state-level anti-fraud activity. State MFCU expenditures come from "Office of the Inspector General Medicaid Fraud Control Unit Annual Reports" for years 1999 through 2003 and 2009 through 2012. Unfortunately, the OIG MFCU annual reports change format beginning in 2004 and only aggregate program expenditures are included. MFCU expenditures for 2004 and 2005 are based upon reported aggregate program grants for state programs and estimated average state shares of the total program grants. The National Association of Medicaid Fraud Control Units (NAMFCU) began conducting a survey of state MFCU programs in 2006. This survey includes annual budgeted amounts for state MFCU programs for years 2006 through 2015. We use this secondary source to fill in missing years from the OIG reports by adjusting down the budgeted amount to fit trends in the OIG-reported data. Figure 2.6 shows how the two MFCU expenditure data sources compare, along with our imputed measures of MFCU spending. We use OIG spending amounts for every year available, 2004 and 2005 are imputed from state shares of the total program budget, and predicted values are used for years 2006 through 2009. State MFCU expenditures are adjusted using the consumer price index (CPI) and are expressed in 2012 dollars.

Medicaid spending data is from the Medicaid Statistical Information System (MSIS).

MSIS state reporting became compulsory in 1999. States report Medicaid claims to CMS who then produce utilization and program statistics for that state. The MSIS data spans from fiscal year (beginning October 1) 1999 through 2012 and includes total spending by group, or "basis of eligibility," which includes children, adults, disabled/blind, aged, and a total category, and service type which includes 31 categories of services such as inpatient hospital, prescription drugs, and physician services. One category, religious services, which is only present in one year of the data is excluded. All spending figures are adjusted to 2012 dollars using the Medical Care CPI index.

Combining state, year, eligibility group, and service categories, our dataset has 107,100 observations (51 states and D.C. $\times$ 14 years $\times$ 5 groups $\times$ 30 categories). However, we choose to focus on a few select service categories in this paper: "total," "total excluding prescription drugs," and "prescription drugs only." Total and prescription drug categories are included in the MSIS data, and we construct an additional category that excludes prescription drugs by taking the difference of spending in the the total and prescription drug categories. We calculate eligibles at the state-year level as the total number of eligibles for each group, and "all except aged" is calculated as the sum of children, adult, and disabled eligibles.[17]

MSIS data are available for most states in all years.[18] Federal Medical Assistance Percentages (FMAPs) are obtained from the Federal Register, state unemployment data comes from the BLS Local Area Unemployment Statistics, and population estimates are from the U.S. Census Bureau Intercensal Estimates.

State prescription drug policy variables are constructed using the National Pharmaceutical Council's (NPC) "Pharmaceutical Benefits under State Medical Assistance Programs" annual reports from 1999 through 2007. The NPC annual reports are based upon a survey

[17]The sum of eligible counts and spending amounts across individual groups does not equal the eligible count or spending amount "total" category because groups such as "unknown" and eligibles through the Breast and Cervical Cancer Prevention Act are not included in the data. On average, our groups represent 90 percent plus of eligibles and spending. Additionally, eligible counts reflect unique individual counts where an individual is counted separately in each service category if they received that type of service, but only once in the "total" category.

[18]Maine is excluded in 2011, and in 2012 Arizona, Colorado, District of Columbia, Florida, Hawaii, Idaho, Kansas, Louisiana, Massachusetts, Maine, Texas, and Utah are excluded due to data availability. To balance the panel, we assume 2011 values for states missing data in 2012.

of states and include state-by-state tables of current policies.[19] We supplement the NPC data with Medicaid prescription drug benefits data from the Kaiser Family Foundation and Medicaid Analytic Extract statistical compendiums. Kaiser benefits data are available for years 2003, 2004, 2006, 2008, 2010, and 2012, and the Medicaid Analytic Extract compendiums are available from 1999 through 2009.

Table 2.2 summarizes expenditure variables and other model covariates over time. During the sample window, 22 states enacted their own FCAs, increasing the number of states with a FCA statute from 14 in 1999 to 36 states in 2012. As expected, average total state Medicaid expenditures increase over time, yet spending per eligible decreases. MFCU expenditures increase in total, but remain relatively stable on a per Medicaid eligible basis. Table 2.3 summarizes variables in 2012, separately for states which enacted their own FCA, both ever and limiting to enactment only during the sample period 1999 through 2012, and for states which have never enacted their own FCA.

States which have enacted a FCA have, on average, larger Medicaid programs ($8.3 billion versus $4.8 billion), but spending per eligible is slightly lower ($5,285 versus $5,854). States that enact a FCA after 1999 have, on average, slightly higher Medicaid spending per eligible ($5,420).[20] FCA states also have larger MFCU expenditures, both in total (about $4.1 million to $5.3 million compared to $1.8 million) and per Medicaid eligible ($3.32 to $3.39 versus $2.53). This is consistent with states who pass a FCA having a stronger stance on Medicaid fraud control and may indicate that FCA legislation and MFCU spending are complements in state fraud control efforts. States with FCAs have more eligibles enrolled in managed care, have a higher percentage of black population and slightly more Democrats in the state Senate and House.

Notably, states with a FCA enacted typically have a lower FMAP on average (56.2 to 58.1 versus 63.3). This could reflect relatively richer states, which consequently have lower FMAPs, enacting FCAs and using a greater pool of resources to combat fraud. A lower FMAP also means that the state is paying relatively more, dollar for dollar, for its

[19] Simon, Tennyson, and Hudman (2009) perform a similar analysis on aggregate Medicaid prescription drug spending and state Medicaid policies using NPC annual reports.

[20] Medicaid spending measures reflect spending for all service types and groups combined.

Medicaid program and receives less matching from the federal government. Consequently, states with lower FMAPs have a stronger financial incentive to target fraud in their own Medicaid programs. This financial incentive is absent for Medicare. Figure 2.5 explores the relationship between state FMAPs and FCA implementation further. By grouping states into quartiles based on their relative FMAPs in 1991, we see that states with a lower FMAP, which implies less generous matching by the federal government, tend to lead other states in passing FCAs. After about 1999, states with FMAPs below the 25th percentile begin to rapidly enact FCA legislation, and states with FMAPs between the 25th and 50th percentile behave similarly. States with the highest FMAPs and which receive the most generous federal matching for their Medicaid programs lag behind other states in passing FCA legislation, with only 42 percent of states with an FMAP above the 75th percentile passing a FCA by 2016, compared to 92 percent of states in the first quartile and 77 percent in the second quartile of FMAPs.[21] These trends lend some support to the idea that states view anti-fraud enforcement as a money-saving endeavor, through direct recoveries from fraud settlements and judgments and through the deterrence of future fraud.

Table 2.4 shows changes in state prescription drug policies over time. Policies include prior authorization (PA), whether or not the state's Medicaid program requires a co-pay for prescriptions, pharmacy reimbursement formula, prescription limits (as categorized by Lieberman et al. (2016)), and the generic substitution rate, which is the proportion of prescriptions filled with a generic drug in cases where a generic is available. According to Table 2.4, states are increasingly implementing prior authorization policies, requiring co-pays, establishing brand-specific prescription limits and overall prescription limits, and substituting more generics. States are also adopting more complex pharmacy reimbursement formulas which incorporate wholesale acquisition cost (WAC), actual acquisition cost (AAC), or a combination of these and average wholesale price (AWP). By 2012, only 35 percent of states have a pharmacy reimbursement policy that uses AWP as the only benchmark, compared to 88 percent in 1999. This is consistent with evidence from a federal audit in 2000 that

[21] Figure 2.5 looks very similar if instead of calculating FMAP percentiles based on 1991 FMAPs, we use a state's average FMAP from 1991 through 2016.

found AWP benchmark prices to be inflated and thus not a useful benchmark for Medicaid reimbursement (Alpert, Duggan, and Hellerstein, 2013).

Figures 2.7 a and 2.8 present total Medicaid spending and Medicaid spending on prescription drugs, by eligible group.[22] Generally, the disabled and aged groups make up the two largest spending groups. Total spending for all groups, except children, dips after 2005, and then continues to grow at a slightly slower rate. The dip in spending is most dramatic for the aged and disabled groups and is due in large part to the shift of dually eligible individuals to Medicare as Medicare Part D was implemented. Consistent with this program change, spending on prescription drugs exhibits a more dramatic drop post-2005.[23] Over the whole sample period, total prescription drug spending averages about $35 billion per year. Spending hit a peak in 2005 at $55 billion and was about $24 billion in 2012. Figure 2.9 shows how the total number of aged eligibles differentially responds during this period. While the number of eligibles in other groups continues to increase or dips slightly, the number of aged eligibles noticeably drops before returning to a similar rate of growth. Given the Medicare program changes which differentially affected aged eligibles and spending, we suspect that any potential effect of anti-fraud activities on Medicaid spending on aged beneficiaries may be confounded by the Medicare Modernization Act. Although spending for aged and disabled significantly drops, spending for adults and children remains relatively stable, only decreasing slightly after 2011, when certain ACA provisions were implemented which extended drug rebate offers to Medicaid managed care plans and as states shifted drug spending to managed care plans (MACPAC, 2016).

Table 2.5 presents mean statistics for total spending, Medicaid eligibles, and spending per eligible over all states and years 1999 through 2012 by service type and group. For all service categories shown, the disabled represent the single largest group in terms of total spending and spending per eligible. Children represent the largest group in Medicaid eligibles. Spending per eligible for "all services," on average, ranges from just over $2,000

[22] Medicaid prescription drug spending data from the MSIS does not include rebates paid under the federal drug rebate program.

[23] Bruen and Miller, 2008 estimate that Medicaid spending on prescription drugs fell by about 50 percent on average after Medicare Part-D was implemented.

for children to over $16,700 for disabled. Prescription drug spending per eligible ranges from $155 for children to over $2,300 for disabled.

2.6 Empirical Model

2.6.1 Difference-in-Difference Model Specification

We estimate a generalized difference-in-differences model shown in equation (1).

$$log(y_{st}) = \text{fca}_{st}\gamma + log(\text{mfcu}_{st})\phi + x'_{st}\beta + \eta_s + \xi_t + \varepsilon_{st} \tag{2.1}$$

In this specification, the log of Medicaid spending per eligible, y_{st}, for state s in year t, is regressed on an indicator variable for whether the state has enacted a FCA as of year t, the log of state MFCU expenditures per Medicaid eligible, state demographic and Medicaid program controls, and state and year fixed effects. Models are stratified by eligible groups. The coefficients of interest are γ and ϕ on the FCA indicator and (logged) MFCU expenditure per beneficiary. The vector x includes the state's FMAP in year t, unemployment rate, log of gross state product, population controls such as the proportion of the total state population under age 14, over age 65, female age 15 to 44, and proportion black, state welfare program characteristics including the percent of uninsured low income children and minimum wage and Medicaid program controls including age distribution controls, managed care enrollment, and non-dual eligibles interacted with a Medicare part-D dummy (0 prior to 2006 and 1 for 2006 onward), and state government controls including proportion of the state senate and house that is Democrat. Following Howard (2010), state-level demographics are included to control for factors that may influence Medicaid program spending. State welfare and government controls proxy for program generosity and state attitudes towards welfare which likely affect Medicaid spending as well. In models with prescription drug spending as the dependent variable, we also include state prescription drug policies. Policies include indicators for prior authorization, whether or not the state's Medicaid program requires a co-pay for prescriptions, "AWP only" pharmacy reimbursement formula, prescription limits, and the generic substitution rate. Standard errors are clustered at the

state level in all specifications (Bertrand, Duflo, and Mullainathan, 2004).

One may be concerned with selection of states choosing to enact their own FCA. This choice may be due to unobservable characteristics, and it may be inappropriate to compare states which have a FCA statute to states which do not. We can consider two potential scenarios. First, states with the highest spending, and potentially the most fraudulent activity, will enact their own FCA in order to control spending. States with their own FCAs would then be associated with higher spending per beneficiary, as compared to states with no such statute, and the coefficient estimate on the parameters of interest in the naive model would be biased toward zero or positive.

Second, states which enact their own FCA likely choose to do so because they benefit financially from its passage. Although states collect larger payouts if their FCA is harmonized with the federal FCA statute, they may decide to conserve administrative resources and free-ride on federal or other state anti-fraud efforts, Bucy et al. (2010). According to a 2014 OIG report, two-thirds of civil cases prosecuted with MFCU resources, which frequently utilize FCAs, are "global" cases where multiple states are plaintiffs in the suit. This likely induces a type of free-rider behavior where a single state need not enact its own FCA or heavily invest in anti-fraud activity to become plaintiff in a suit and benefit from a group-effort to prosecute defrauders. As a result of free-riding behavior, the deterrent effect of FCAs will be underestimated. We correct for this unobserved heterogeneity by using state-specific fixed effects (Besley and Case, 2010; Galiani, Gertler, and Schargrodsky, 2005). This method will control for any time-invariant characteristics that may influence a state's decision to enact an FCA.

2.6.2 Aggregate Medicaid Expenditure Results

Table 2.6 shows specifications for categories "All services," "Excluding Prescription Drugs," and "Prescription Drugs Only." All regressions include year and state fixed effects, as well as group compositional controls in models where multiple eligibility groups are included. In each table, the first column presents results for all Medicaid eligibility groups (except aged). The next columns examine the effect of state anti-fraud activity and legislation on spending for children, adults, and the disabled separately, then all groups

combined (including aged), and finally aged alone. The first column omits the aged group because this group may exhibit differential Medicaid program participation trends due to passage of the Medicare Modernization Act.[24]

Panel 1 of Table 2.6 (all services) shows that generally, there is no effect of state FCAs or MFCU expenditures on aggregate Medicaid spending per eligible.[25] There is a positive and significant (10 percent level) of FCA legislation on spending per adult eligible, and a negative 7 percent effect for the disabled.[26] Panel 2 presents results for the "excluding prescription drugs" category. Results for "excluding prescription drugs" are similar to those of all services combined. There is a significant (10 percent level) negative effect of FCA legislation for the disabled and aged groups, and positive effect for adults.

Specifications in Panel 3 include prescription drug spending only. Results indicate much larger (negative) effects of state FCAs. For all groups, controlling for composition effects, there is a 18.3 percent decline in prescription drug spending per eligible (significant at the 5 percent level). This effect is slightly larger for the "all except aged" category, which implies a 20.6 percent decline in prescription drug spending per eligible (significant at the 5 percent level). There is also a significant 17.6 percent decline in spending for the disabled. Across all specifications, the sign and magnitude of the estimated effect of state FCAs is similar, with the aged specification showing the smallest effect and is insignificant. State MFCU expenditures have no significant effect on spending in any specification although the point estimates are negative for all groups except adult and aged. This may reflect the imputation of MFCU dollars in some years.

Panel 4 further includes state prescription drug policy variables. FCA coefficients are

[24] Although we attempt and control for the implementation of Medicare Part D, the magnitude of this policy still likely introduces noise into our model. We should only be concerned with comparing across pre- and post-Medicare Part D years if states which have implemented a FCA exhibit systematically different responses in prescription drug spending than those which have not. Trends in spending for FCA versus non-FCA states do not seem to suggest this type of bias. Limiting the sample to years 2006 and forward does reduce magnitudes slightly. Coefficient estimates on the FCA term maintain a negative sign, but standard errors inflate since we are throwing out approximately half of the identifying variation in state FCA legislation.

[25] See appendix Tables B.1 and B.2 for specifications including additional services and sample periods.

[26] All estimated coefficients except the log of MFCU expenditures have been transformed by $(e^{\beta} - 1) \times 100$ and may be interpreted as a percentage change. The log of MFCU expenditures is interpreted as an elasticity with regard to a 10 percent increase in MFCU expenditures.

extremely similar. Medicaid co-payments have a large and negative effect, but only in the "Child" category. "AWP-only" reimbursement is associated with increased prescription drug spending per eligible. This is consistent with findings from Alpert, Duggan, and Hellerstein (2013) that AWP benchmarks were inflated by manufacturers, and as states moved away from AWP reimbursement benchmarks, drug reimbursements fell.

Results in panels 3 and 4 of Table 2.6 are markedly different than those for all services aggregated and excluding prescription drugs. Although standard errors are relatively large, the responsiveness of prescription drug spending per eligible to state FCAs is much greater than in other categories shown. These results are consistent with incentives contained within state FCA legislation and provide evidence that the presence of state anti-fraud legislation has a substantial negative effect on prescription drug spending. Applying results from the "all (except aged)" specification, state FCA legislation reduces prescription drug spending by $115 per eligible (21.2 percent X $543), on average, resulting in an average annual savings to a state of $107 million. In total, this implies about $5.4 billion in annual savings on Medicaid prescription drug expenditures if all states were to implement an FCA. This savings to the Medicaid program reflects a behavioral response of pharmaceutical manufacturers, pharmacies, and providers and is a savings in addition to any actual recoveries, settlements, and judgments from FCA or other fraud prosecutions. Total federal FCA recoveries where the Department of Health and Human Services was a plaintiff average about $2.6 billion annually between 2010 and 2016, and OIG reports show that at the state level, between one to two-thirds of civil recoveries related to Medicaid Fraud Control Unit activity are associated with prosecution of pharmaceutical manufacturers. The deterrent effect estimated in this paper is large in comparison to actual recoveries in health care fraud cases.

The estimated effects of state FCAs on prescription drug spending are sizable. Estimates of health care fraud suggest that up to 10 percent of total expenditures are fraudulent, implying almost $300 billion in fraud and abuse in 2015. Medicaid and Medicare are identified as being vulnerable populations for fraud and abuse, and fraud enforcement activity suggests that fraudulent activity is not evenly distributed across spending categories (HHS, 2012; Rosenbaum, Lopez, and Stifler, 2009). If MFCU cases target pharmaceutical manufacturers in almost two-thirds of cases, then presumably there is a heightened level of

perceived fraud being perpetrated by pharmaceutical companies. Although off-label prescriptions are not themselves illegal, rates of off-label prescription use averaged 21 percent of all prescriptions in 2001, but for some classes of medicines ranged from 46 percent to 81 percent of prescriptions (Radley, Finkelstein, and Stafford, 2009). In summary, we expect the effects on prescription drug spend to be large.

2.7 Off-Label Usage: State Drug Utilization Data

Our analysis of aggregate state Medicaid spending suggests that state FCAs reduce total prescription drug spending with little effect on other spending categories. We use State Drug Utilization Data (SDUD) from CMS to test whether there is evidence of a behavioral response in prescribing patterns. Alleged off-label marketing forms the basis of FCA liability for pharmaceutical manufacturers in many cases (Qureshi et al., 2011; Kesselheim, Mello, and Studdert, 2011). If FCAs do deter off-label marketing and subsequent prescribing, then we should expect to find a relatively larger effect for drugs which are prone to off-label use versus those that are not.

2.7.1 SDUD

State Drug Utilization Data from CMS includes prescription drug expenditures and utilization for state Medicaid programs beginning in 1991.[27] States report utilization data on covered outpatient prescription drugs in compliance with the federal Medicaid Drug Rebate program. Spending and utilization data are available by state, quarter, and National Drug Code (NDC) which identifies a unique prescription drug product down to the package size. Expenditures in the SDUD are gross of any rebates paid by pharmaceutical manufacturers to state Medicaid programs, and current releases of the data censor state-quarter-NDC observations with 10 or less prescriptions.

We aggregate quarterly observations into annual totals by state and annualize in cases where one or more quarters of data are missing. From 1999 through 2012 there are al-

[27]SDUD has been utilized in numerous previous studies including Duggan and Scott Morton (2006); Kesselheim, Fischer, and Avorn (2006); Fischer, Choudhry, and Winkelmayer (2007); Bruen and Miller (2008); Alpert, Duggan, and Hellerstein (2013); and Bradford and Bradford (2017) among others.

most 5 million state-year-NDC observations. We exclude certain quarters of data where total expenditures and prescriptions are implausibly high or volatile, similar to Bradford and Bradford (2017). Following Alpert, Duggan, and Hellerstein (2013), we omit outliers by comparing spending per prescription for a given NDC.[28] We match each NDC into a therapeutic class (primary and subclass) using Medispan's Generic Product Identifier hierarchical classification system, and aggregate to the state-year-subclass level. Table 2.7 presents therapeutic classes ranked by total prescription volume in the State Drug Utilization Data (SDUD) from 1999 through 2012. Antidepressants make up the largest single category, representing just over 6 percent of prescriptions in the dataset. The top five classes, antidepressants, opioid analgesics, antiasthmatics, anticonvulsants, and antihypertensives make up just over a quarter of total prescriptions, and three-quarters of all prescriptions are represented by the top 24 classes. In some model specifications, we limit the sample to the top 40 therapeutic classes, which make up over 90 percent of prescription volume.[29]

2.7.2 Therapeutic Class and Off-Label Use

To see if there is evidence of a behavioral response of pharmaceutical manufacturers or prescribers to FCA prosecution of off-label promotion, we categorize therapeutic classes as "off-label prone" and "not off-label prone." We base these classifications on previous literature within the medical field which examines off-label use and drug product characteristics.

In an investigative analysis of the top 15 therapeutic classes in terms of spending, cholesterol medications were noted as being rarely prescribed for unapproved treatments while

[28] We omit Arkansas 1991q1 and 2004q4, Colorado 2000q2 and 2001q2, Idaho 2005q1, Indiana 2000q1, 2000q3, and 2012q1, Iowa 1991q1 through 2001q2, Kansas 1999q4 and 2000q1, Kentucky 2012q1 through 2012q4, Maine 2008q1, Maryland 1999q1, 2000q2, 2000q3, 2000q4, Minnesota 2000q1, Missouri 2007q4, Nevada 2002q4, North Dakota 2005q2, Ohio 2010q1 through 2011q3, Pennsylvania 2004q2, Rhode Island 2006q4 and 2007q4 through 2012q4, South Dakota 1991q1 through 2002q3, and 2007q3, Vermont 1999q2 through 1999q4, and 2004q2, and Washington 2003q4, 2006q3, and 2009q3. We exclude Arizona and Tennessee from the sample completely. Data for Arizona is unavailable for many years, since Arizona does not participate in the drug rebate program, and many quarters for TN appear to have poor data quality with large and obvious erroneous outliers. We also trim observations above the 99 percentile of spending per prescription within an NDC across all states and years and limit the sample of spending and prescriptions to Medicaid fee-for-service (FFS) observations omit managed care (MCO) spending and prescription observations which are available only beginning in 2010. Our sample restrictions leave about 96 percent of the FFS state-quarter-NDC observations in the SDUD.

[29] Ranking classes by total spending, rather than prescriptions, results in a very similar ordering of drug classes.

three-quarters of anti-seizure medications, two-thirds of antipsychotics, and one-quarter of antidepressants are prescribed for off-label uses (Adams and Young, 2003). Radley, Finkelstein, and Stafford (2009) analyze physician-patient encounter data and find that off-label use varies widely by therapeutic class. Controlling for other drug-specific characteristics, cardiac therapies, including antianginals, antiarrhythmics, and anticoagulants, are found to be 6.8 times more likely to be prescribed for an off-label indication, relative to analgesics. Other therapeutic classes associated with higher off-label use include anticonvulsants, psychiatric therapies including antidepressants, anxiolytics, and antipsychotics, allergy therapies, antiasthmatics, and ulcer and dyspepsia medications. Off-label usage rates for these classes of drugs range from 30 to 46 percent. Diabetes therapies were found to be associated with very little off-label use with only 1 percent of drug mentions for off-label uses. Off-label use of analgesics, agents to lower lipid levels, hormone therapies, contraception, and antihypertensives were also low, ranging from 6 to 14 percent of drug mentions.

Walton et al. (2008) find evidence of substantial off-label prescribing, despite little evidence of efficacy, for drugs within the therapeutic classes of antidepressants, antipsychotics, and anxiolytic-sedatives. Chen et al. (2005) specifically examine off-label use of anticonvulsants among Medicaid beneficiaries and find that over 70 percent of patients taking an anticonvulsant received a prescription for an off label indication. Lin, Phan, and Lin (2006) document off-label usage of beta-blockers and estimate that on average 52 percent of prescriptions are for off-label uses.

Table 2.8 lists our categorization of therapeutic classes as "off-label prone" versus "not off-label prone" based on reviewed literature. Although only about a quarter of observations fall into the off-label prone or not off-label prone categories, these categories represent about half of total spending and prescriptions. Appendix Table 3A provides extensive detail on how we categorize therapeutic classes into off-label categories. In addition to our review of medical and pharmaceutical literature on off-label use, we incorporate estimated off-label

rates provided by Bradford, Paker, and Williams (2015).[30] We include in our analysis additional model specifications which use a continuous probability of off-label use, which varies by therapeutic class and subclass. Figure 2.10 shows the distribution of average estimated off-label rates. Very few classes have an extremely low or high estimated rate of off-label use; 50 percent of total prescriptions fall within therapeutic classes (and subclasses) with an an average estimated off-label rate between about 30 and 50 percent. The average off-label rate across all drug classes is 43.8 percent. For classes which the medical literature indicates are prone to off-label use, the average estimated off-label rate is 44.0 percent with the Bradford, Paker, and Williams estimates. For classes indicated as not prone the average rate is 22.9 percent.

2.7.3 Model

We construct a triple-difference model which estimates the effect of state FCAs for implementing versus non-implementing states, before and after implementation, for off-label prone classes of drugs versus not off-label prone. Our specification generally follows Hoynes, Schanzenbach, and Almond (2016) who have a similar generalized difference-in-difference model that is extended to a triple-difference model with an additional margin of variation.

$$log(y_{icst}) = \gamma \text{fca}_{st} + \delta(\text{fca}_{st} \cdot \text{off-label}_c) + \phi log(\text{mfcu}_{st}) + x'_{st}\beta + \alpha_i + \eta_s + \xi_t + \varepsilon_{icst} \quad (2.2)$$

The dependent variable is total Medicaid prescription drug spending (or total prescriptions) for state s in year t for primary therapeutic class c and subclass i. State, year, class, and subclass effects are included in all models. We also include state-off-label and year-off-label interaction effects as well as state-year quadratic trends in some specifications. Note that the FCA variable is already a generalized difference-in-difference estimator and that an off-label indicator effect is subsumed by drug class fixed effects. Alternative specifications

[30] Estimates of off-label rates provided by Bradford, Paker, and Williams (2015) are calculated using MEPS data from 2007 through 2011, and vary by generic drug name and year. We aggregate estimates up to the therapeutic class and subclass and weight by prescription volume in the SDUD. Our methodology for incorporating these estimates is discussed further in the appendix.

include interactions of the off-label indicator and state and year fixed effects and state-year linear and quadratic trends.

Figures 2.11 and 2.12 plot total prescription drug spending and number of prescriptions for each therapeutic class within off-label prone and not prone categories. Both groups exhibit similar trends in spending and in number of prescriptions. Antipsychotics are a notable outlier in total spending, compared to all other therapeutic classes. The impact of Medicare Part-D between years 2005 and 2006 is notable. This will confound the measured effect of state FCAs if states which enacted FCAs also witnessed a greater shift of prescription drug spending and utilization from Medicaid to Medicare, and if classes which we categorize as off-label prone were differentially effected by Medicare Part-D. Bruen and Miller (2008) show that despite large changes in total Medicaid prescription drug spending and utilization, many of the largest drug classes, in terms of utilization, ranked similarly before and after Part-D took effect. This means that there was not a systematically different effect of Part-D acro drug classes, at least for many of the larger classes that we include in our analysis.

2.7.4 Results

Panels 1 and 2 of Table 2.9 show our triple difference estimation results for total prescription drug spending and prescription volume. Specifications in columns (1) through (3) of each table use a binary indicator for off-label prone classes based upon the reviewed medical literature. Columns (4) through (6) omit analgesics. Opioid analgesics are more likely affected by FCA legislation through channels other than the targeting of off-label marketing. Health care providers may also be liable under the FCAs for over-prescribing and running "pill mill" operations where prescriptions are written for medically unnecessary reasons. In this case, we may see a reduction in the number of prescriptions or total spending for opioids, but not through the channel of deterred off-label marketing. As such, this may be a poor choice of therapeutic class to include in the comparison group. Consistent with FCAs potentially affecting opioid spending and prescriptions through other channels, coefficients slightly increase when opioids are omitted from the comparison group in columns (4) through (6). Bradford, Paker, and Williams (2015) also omit analgesics

from their analysis and so models with analgesics omitted may be more directly comparable to other model specifications using their provided estimated off-label rates. Columns (7) through (9) further omit classes where there is disagreement between the reviewed medical literature and estimated off-label rates provided by Bradford, Paker and Williams. The FCA $\times$ off-label coefficients are typically larger in these specifications where there is an agreement between both methodologies as to which drug-classes have the highest rate of off-label use. All specifications in table 2.9 restrict the sample to drug-classes observed in every year, within each state.

The effect of state FCAs on prescription drug spending for off-label prone drug categories is consistently negative with a similar magnitude, but loses statistical significance in some specifications where state-time trends are included. Magnitudes for the FCA $\times$ off-label coefficient imply a 10 to 17 percent reduction in Medicaid spending for off-label prone prescription drugs in states with an FCA, after implementation. The effect of FCAs overall is negative in most specifications but insignificant. The coefficient flips sign from negative to positive when state-year quadratic trends are added, which may indicate that the effect of FCAs on spending is slow moving and difficult to disentangle from general time trends. Similarly, the effect of MFCU expenditures is consistently negative, but insignificant. Other prescription drug policy controls are mostly insignificant; AWP reimbursement is associated with 13 to 15 percent higher spending in specifications without state-time trends. This is similar to difference-in-difference results using the MSIS data.

Results for the total number of prescriptions are similar to those for prescription drug spending.[31] FCA $\times$ off-label coefficients are consistently negative and significant at at least the 10 percent level. Magnitudes imply about a 10 to 16 percent reduction in prescription volume for off-label prone drug categories in states with their own FCA. FCA coefficients are negative, but insignificant, except when state-time trends are included and the coefficient flips sign and remains insignificant. The log of MFCU expenditures is negative and significant in columns (7) and (8) with similar magnitudes as in prescription spending specifications. The MFCU coefficients imply a 0.43 percent reduction in the total number of

[31] See Appendix tables B.4 through B.9 for additional model specifications.

prescriptions in response to a 10 percent increase in MFCU expenditures. Estimated coefficients may be more prone to endogeneity than FCA legislation since MFCU expenditures are gradually increased over time, states typically exhaust their annual budget for these programs, and they are only incrementally increased year over year. As such, states hoping to control excess Medicaid spending may increase MFCU expenditures relatively faster than states who perceive less abuse and the estimated coefficient will be attenuated towards zero.

Preferred specifications are columns (2), (5), and (8), which include off-label by state and off-label by year interactions. These specifications imply an 11 to 14 percent reduction in prescription drug spending and a 10 to 14 percent reduction in prescription drug volume for off-label prone drug classes, in states with their own FCA legislation, after implementation.

2.7.5 Robustness

Continuous Measures of Off-Label Usage Rates

Panels 1 and 2 of Table 2.10 present model specifications which do not strictly categorize therapeutic classes as off-label prone versus not, but rather use estimated off-label rates as a continuous margin of variation for the triple-difference model. Columns (1) through (9) are ordered the same as in Table 2.9.[32]

Overall results in Table 2.10 give a similar picture as our "baseline" specifications in Table 2.9. Magnitudes for the FCA $\times$ off-label coefficient are mostly negative and of similar size, but typically just outside of the 10 percent significance cut-off. Only columns 1 and 7 for prescription volume have a positive but insignificant sign. Also similar to Table 2.9, the coefficient estimate for FCA is typically negative, but flips sign when state trends are included. Some issues may limit the usefulness of this robustness check. There is relatively little variation in estimated off-label rates, and we may also be mis-characterizing the true off-label rate for classes where we do not match most of the prescription volume to an estimated off-label rate. Larger standard errors may be in part due to the concentration of estimated rates in the "middle" of the distribution which do not provide enough variation

[32]The sample sizes in Table 2.10 differ from Table 2.9 because some drug classes do not have an estimated off-label rate associated with them. Otherwise, the samples for each specification are the same.

for the triple-difference model (see Figure 2.10).

Parallel Trends

Our difference-in-difference and triple-difference estimators rely on the assumption that "but for" the implementation of FCA legislation, prescription drug spending in states which enact a FCA would have continued with a similar trend as in states which never enact legislation. FCA legislation is enacted at various times across states, and so it is difficult to confirm the parallel trends assumption with a simple examination of "pre" and "post" treatment periods. However, we can examine trends in state prescription drug spending prior to FCA implementation for both for states which eventually enact a FCA and for states which do not.[33]

Figures 2.13 and 2.14 plot average prescription drug spending and number of prescriptions for "comparison" states which never enact a FCA and "treatment" states which eventually enact a FCA, but as of 1999, had not. We omit 14 states which had implemented a FCA during or before 1999 and calculate the average annual prescription drug spending and number of prescriptions per state in treatment and comparison groups and for off-label prone and not-off-label prone categories. Both treatment and comparison groups exhibit similar pre-treatment trends in spending and prescriptions. We estimate a model that is similar to our triple-difference equation, except we exclude the FCA treatment variable and instead interact a time-invariant "treatment" indicator with year dummies and an off-label prone indicator. Other state-level control variables are not available for the 1991-1999 period, but state, primary drug class, subclass, class-state and class-year effects are included. We cannot reject the null hypothesis that there is no difference between the coefficients on the treatment and control year dummies, indicating that time trends are similar across FCA and non-FCA states in the pre-treatment period.

[33]This method of checking for pre-treatment parallel trends in outcomes follows Galiani, Gertler, and Schargrodsky (2005).

Event Study

The effects of state FCAs are not necessarily fixed over time. We may expect that if FCAs deter off-label marketing or other fraudulent behavior, that this effect will gradually accumulate over time as the statue is in place longer and used more frequently. We test this theory by augmenting the triple difference model, and estimate an event study-type model which allows the effect of state FCAs to vary over the time since they were enacted:[34]

$$log(y_{icst}) = \sum_{j=-m}^{q} [\gamma_j \text{fca}_{st} D_t^{k+j}] + \sum_{j=-m}^{q} [\delta_j (\text{off-label}_c \cdot \text{fca}_{st}) D_t^{k+j}] + X_{ist}\beta + \alpha_i + \eta_s + \xi_t + \varepsilon_{icst} \tag{2.3}$$

Where, just as before, y is prescription drug spending or alternatively number of prescriptions and X includes state demographics and prescription drug policies. We also include the same set of fixed effects as in previous models, including state, year, subclass, class-state, and class-year effects. In this event study model, m is the number of "leads" prior to FCA implementation, q is the number of lags after, and k denotes the year in which a state enacts a FCA. D_t^j is an indicator function which is set equal to one when $t = k + j$ and zero otherwise. We include FCA "leads" of 4, 3, 2, and 1 years prior to implementation, and lags of 1, 2, 3, and 4 years following, so that m and q are set equal to 4. Estimates of γ_j represent time varying effects of FCA legislation on all drugs (off-label prone and non off-label prone) in relation to the timing of legislation, and the δ_j's are the additional estimated effect for off-label prone drugs only, so that the total effect of FCA legislation on off-label prone drugs is $\gamma_j + \delta_j$.

A test of our identification strategy is to see if the estimated treatment effect in years before FCA implementation is different from zero. Table 2.11 shows these results for prescription spending in column 1 number of prescriptions in 2. Model specifications are comparable to column (5) in Table B.8. Estimated coefficients for δ_j and γ_j are plotted in Figure 2.15 as well. Although the confidence intervals are relatively wide, for off-label

[34] Our model and specification follows Autor (2003) who performs a similar robustness check analyzing the effect of changes in state-level legislation and Courtemanche et al. (2017) who perform a similar check with a triple-difference model analyzing health insurance in Medicaid expansion states.

prone drugs, the point estimates of FCA leads are all statistically non-different than zero (we fail to reject the null hypothesis that all leads are jointly different from zero), and the estimated magnitude becomes negative in implementation year. In years following implementation, the average effect tends to increase in absolute magnitude, and remains steady from 2 through 4 years post-FCA implementation. A joint test of lags shows that we can only reject the null hypothesis that they are jointly equal to 0 at the 11 percent level for spending and 20 percent level for prescriptions. These results are consistent with an accumulating deterrent effect of state FCAs for off-label prone drugs.

2.8 Discussion

This paper systematically documents state FCAs and empirically tests whether or not these anti-fraud statutes, as well as state MFCU expenditures, have any effect on Medicaid spending. Results indicate that state FCAs matter relatively more for prescription drug spending, compared to other service categories. As a result of FCA implementation, Medicaid spending per eligible on prescription drugs drops by about 21 percent. State FCAs do not seem to exhibit any measurable effect on other spending areas. This finding is consistent with observed FCA prosecutions which commonly target pharmaceutical manufacturers for alleged off-label promotion. A typical state FCA statute includes punitive damages up to three-times actual damages plus an additional per-violation penalty. Punitive damages combined with whistleblower provisions make deep-pocketed pharmaceutical companies lucrative targets for FCA prosecution. Per-transaction penalties are more effective in punishing fraudulent behavior that entails a high volume of transactions, such as off-label marketing potentially inducing providers to write excess prescriptions. Whistleblower provisions provide clear incentives for relators to target deep-pocketed defendants such as large pharmaceutical companies.

We further test the hypothesis that FCA legislation has an deterrent effect on prescription drug spending and prescription volume by categorizing therapeutic classes as off-label prone versus not off-label prone. Results indicate that spending and prescriptions for off-label prone classes of drugs are more responsive to FCA legislation. Spending on off-label

prone drugs is about 11 to 14 percent lower for states which have passed FCA legislation, and there is a reductions in prescription volume of 10 to 14 percent. These results provide suggestive evidence that FCAs may be deterring off-label marketing and/or prescribing.

We find no effect of state level MFCU expenditures on aggregate Medicaid spending, and some evidence that MFCU expenditures are associated with fewer prescriptions. First, this is consistent with finding in Becker, Kessler, and McClellan (2005) of no aggregate effect of MFCU expenditures on Medicare spending. Only comparing the effect across different patient and provider groups do the authors find any significant effect of state anti-fraud activities. Medicaid Fraud Control Unit spending may be also be endogenous; states with high levels of fraud likely invest more than low-fraud states. Dollar investments are also relatively easy to adjust from year to year, as opposed to legislation or the implementation of new anti-fraud programs. As Becker, Kessler, and McClellan (2005) discuss, this likely biases the effect towards zero, or positive.

The definition of fraud that we utilize in this paper is based only on the legal language of anti-fraud statutes, and we do not attempt to make any welfare claim as to whether or not these anti-fraud policies are efficient or whether or not prosecuting certain types of fraud is beneficial to society. On one hand, if state FCAs do deter off-label marketing and prescribing, as our findings suggest, then these laws seem to be accomplishing their intended goal of reducing fraud, as the government defines it, and providing savings to state Medicaid programs. On the other hand, this reduction in spending and prescriptions may limit access for some patients who would have benefited from treatment with prescription drugs for an off-label purpose. We are also unable to detect whether the reductions in prescription drugs are offset by substitutions to other drugs or other types of health care service utilization.

Regarding the proposed mechanism where state FCAs deter off-label prescribing, we cannot say, for certain, what type of response is driving the reduction in Medicaid spending per eligible for prescription drugs. It could be that FCAs truly affect pharmaceutical company marketing behavior and/or prescribing physician behavior, and that they exhibit a chilling effect on off-label promotions and prescriptions. However, these laws could also represent a "shakedown" of pharmaceutical companies with deep pockets (Spacapan and Hutchison, 2013), and the decline in spending may be attributable to some other mecha-

nism. The effect of FCAs may be imprecisely measured at the aggregate level because there are numerous behavioral effects. Consider an off-label marketing case where the pharmaceutical manufacturer and prescribing physicians respond by altering behavior and limiting both marketing and new prescriptions. This may decrease costs on one margin, where some patients who might receive relatively little benefit no longer receive the prescriptions. However, for some patient types we may see a switch from a cheaper prescription for an off-label indication to a more expensive substitute.

Table 2.1: State FCA Legislation Enactment Year

State	Year	State	Year
Arkansas	1993	Montana	2005
California	1987	Nebraska	1996
Colorado	2001	Nevada	1999
Connecticut	2009	New Hampshire	2005
Delaware	2000	New Jersey	2008
District of Columbia	1998	New Mexico	2004
Florida	1994	New York	2007
Georgia	2007	North Carolina	1997
Hawaii	2001	Oklahoma	2007
Illinois	1991	Oregon	2009
Indiana	2005	Rhode Island	2007
Iowa	2010	Tennessee	1993
Kansas	2009	Texas	1995
Louisiana	1997	Utah	1981
Maryland	2010	Vermont	2015
Massachusetts	2000	Virginia	2003
Michigan	1977	Washington	2012
Minnesota	2009	Wisconsin*	2007
Missouri	1994		

*Wisconsin repealed their FCA in 2015 and is the only state to do so.

Table 2.2: Summary Statistics: 1999 and 2012

	1999	2012
State pop. (millions)	5.47	6.15
	(8.54)	(9.76)
Medicaid Spending (millions)	3,982.79	7,246.29
	(692.65)	(1,231.57)
Medicaid spending per eligible	5,312.40	5,452.75
	(197.94)	(207.26)
MFCU expenditure (millions)	2.42	4.26
	(7.27)	(10.08)
MFCU expenditure per eligible	3.07	3.08
	(0.32)	(0.28)
% eligibles under age 21	57.30	55.57
	(0.86)	(1.24)
% eligibles age 21 to 64	31.20	35.59
	(0.78)	(1.12)
% eligibles age 65 and over	11.39	8.81
	(0.37)	(0.29)
% eligibles enrolled in MCO plan	57.60	73.49
	(3.99)	(3.19)
% eligibles not dual eligible	73.71	84.77
	(1.66)	(0.56)
FMAP	60.67	59.62
	(1.19)	(1.12)
Unemployment	4.10	7.33
	(0.14)	(0.24)
Female pop age 15-44	21.94	19.75
	(0.12)	(0.18)
Pop age 65 and over	12.55	13.98
	(0.00)	(0.00)
Pop age 14 and under	21.30	19.31
	(0.22)	(0.26)
Pop black	11.39	11.54
	(1.68)	(1.54)
Log gross state product	11.60	12.15
	(0.15)	(0.14)
Percent low inc. children	0.08	0.05
	(0.00)	(0.00)
Personal income per capita	10.20	10.67
	(0.02)	(0.02)
State min wage	5.04	7.39
	(0.11)	(0.10)
% of senate Democrat	51.63	46.63
	(2.28)	(2.76)
% of house Democrat	52.63	46.76
	(2.30)	(2.38)
N	51	51

Table 2.3: Summary Statistics in 2012 for States With and Without a FCA

	Never had FCA	Ever had FCA	Ever had FCA (Post-1998)
State pop. (millions)	3.73	7.16	4.80
	(10.09)	(12.88)	(8.75)
Medicaid Spending (millions)	4,824.45	8,255.40	6,396.86
	(1,420.42)	(1,623.10)	(2,012.94)
Medicaid spending per eligible	5,854.95	5,285.16	5,420.07
	(418.23)	(234.64)	(268.13)
MFCU expenditure (millions)	1.75	5.31	4.11
	(4.68)	(13.84)	(18.00)
MFCU expenditure per eligible	2.53	3.32	3.39
	(0.39)	(0.35)	(0.40)
% eligibles under age 21	55.81	55.47	53.33
	(2.52)	(1.44)	(2.00)
% eligibles age 21 to 64	34.91	35.88	37.69
	(2.12)	(1.34)	(1.81)
% eligibles age 65 and over	9.28	8.61	8.91
	(0.63)	(0.31)	(0.40)
% eligibles enrolled in MCO plan	65.58	76.79	75.70
	(7.75)	(3.09)	(4.32)
% eligibles not dual eligible	82.57	85.69	85.33
	(1.40)	(0.46)	(0.56)
FMAP	63.26	58.10	56.26
	(2.12)	(1.26)	(1.43)
Unemployment	6.89	7.51	7.23
	(0.46)	(0.29)	(0.37)
Female pop age 15-44	19.21	19.98	19.59
	(0.17)	(0.24)	(0.15)
Pop age 65 and over	14.40	13.80	14.13
	(0.00)	(0.00)	(0.00)
Pop age 14 and under	19.23	19.35	18.92
	(0.48)	(0.32)	(0.28)
Pop black	9.57	12.37	9.70
	(3.02)	(1.79)	(1.85)
Log gross state product	11.56	12.40	12.09
	(0.25)	(0.16)	(0.20)
Percent low inc. children	0.06	0.05	0.05
	(0.01)	(0.00)	(0.01)
Personal income per capita	10.61	10.69	10.71
	(0.04)	(0.03)	(0.03)
State min wage	7.30	7.43	7.40
	(0.18)	(0.12)	(0.15)
% of senate Democrat	38.08	50.19	54.08
	(4.85)	(3.21)	(4.18)
% of house Democrat	40.28	49.46	51.88
	(3.79)	(2.90)	(3.75)
N	15	36	23

Table 2.4: Drug Policy Summary Statistics Over Time

	1999	2009	2012
Medicaid co-pay (any)	65.31	81.25	81.63
	(6.87)	(5.69)	(5.59)
Prior authorization	83.67	100.00	100.00
	(5.33)	(.)	(.)
AWP only	87.76	72.92	34.69
	(4.73)	(6.48)	(6.87)
Brand prescription limit	2.04	10.42	12.24
	(2.04)	(4.46)	(4.73)
Overall prescription limit	22.45	31.25	30.61
	(6.02)	(6.76)	(6.65)
Substitution rate	86.21	96.41	
	(0.22)	(0.23)	
N	49	48	49

Substitution rate is missing for Maine in 2009
and all states 2010 though 2012.

Table 2.5: Medicaid Spending and Eligibles by Service and Group

	All	All (Except Aged)	Children	Adult	Disabled	Aged
All Services						
Total spending (millions)	5,950.33	4,272.11	967.46	735.23	2,569.42	1,300.03
	(288.69)	(212.63)	(42.56)	(44.33)	(132.50)	(67.57)
Eligibles (thousands)	1,144.79	1,144.79	1,144.79	1,144.79	1,144.79	1,144.79
	(61.16)	(61.16)	(61.16)	(61.16)	(61.16)	(61.16)
Spending per eligible	5,685.74	4,572.34	1,919.73	3,019.91	15,346.78	14,079.34
	(56.00)	(46.76)	(21.41)	(37.34)	(194.63)	(188.96)
N	714	714	714	714	714	714
Excluding Prescription Drugs						
Total spending (millions)	5,323.54	663.58	892.75	663.58	2,211.76	1,195.28
	(260.67)	(39.24)	(39.36)	(39.24)	(116.22)	(63.62)
Eligibles (thousands)	1,144.79	1,144.79	1,144.79	1,144.79	1,144.79	1,144.79
	(61.16)	(61.16)	(61.16)	(61.16)	(61.16)	(61.16)
Spending per eligible	5,083.01	674.54	1,775.46	2,723.37	13,226.09	12,941.32
	(53.60)	(12.55)	(21.07)	(35.45)	(181.21)	(180.44)
N	714	714	714	714	714	714
Prescription Drugs						
Total spending (millions)	626.78	504.02	74.71	71.65	357.66	104.75
	(32.21)	(26.39)	(4.33)	(6.19)	(18.76)	(6.97)
Eligibles (thousands)	1,144.79	1,144.79	1,144.79	1,144.79	1,144.79	1,144.79
	(61.16)	(61.16)	(61.16)	(61.16)	(61.16)	(61.16)
Spending per eligible	602.73	542.65	144.28	296.54	2,120.69	1,138.02
	(10.44)	(8.79)	(3.88)	(8.32)	(37.18)	(39.35)
N	714	714	714	714	714	714

Standard errors are in parenthesis. Eligible counts reflect total state-year Medicaid eligibles.

Table 2.6: MSIS Aggregate Medicaid Expenditure Results

	All Services					
	All (Except Aged)	Child	Adult	Disabled	All	Aged
FCA	-4.05	-3.30	8.79*	-6.33*	-2.97	-6.35
	(2.99)	(3.30)	(4.94)	(3.15)	(2.44)	(3.72)
Log MFCU expenditure	-0.11	0.03	0.02	-0.04	-0.06	-0.10
	(0.10)	(0.11)	(0.11)	(0.08)	(0.10)	(0.13)
Excluding Prescription Drugs						
FCA	-3.37	-1.67	11.46**	-6.54*	-2.57	-8.12*
	(3.27)	(3.59)	(5.75)	(3.38)	(2.73)	(3.95)
Log MFCU expenditure	-0.08	0.05	0.08	-0.04	-0.02	-0.08
	(0.11)	(0.13)	(0.13)	(0.09)	(0.11)	(0.15)
Prescription Drugs Only						
FCA	-20.55**	-20.50	-19.21	-17.59**	-18.28**	-6.01
	(7.27)	(15.68)	(14.99)	(7.66)	(7.14)	(13.24)
Log MFCU expenditure	-0.17	-0.34	0.05	-0.03	-0.16	0.46
	(0.39)	(0.51)	(0.34)	(0.21)	(0.42)	(0.36)
Prescription Drugs Only - With Policies						
FCA	-21.21**	-19.96	-18.59	-18.74**	-18.70**	-8.03
	(7.24)	(13.53)	(13.21)	(7.55)	(7.15)	(13.19)
Log MFCU expenditure	-0.15	-0.32	0.08	-0.03	-0.15	0.48
	(0.42)	(0.54)	(0.36)	(0.23)	(0.44)	(0.36)
Medicaid co-pay (any)	5.30	-23.48*	-15.08	8.31	6.73	-2.95
	(8.22)	(12.17)	(13.49)	(7.44)	(8.23)	(11.96)
Prior authorization	8.33	9.53	12.34	8.12	6.28	-3.22
	(6.05)	(18.68)	(20.49)	(5.62)	(5.52)	(9.23)
AWP only	16.03**	14.52*	16.30*	16.58**	16.44**	19.51*
	(6.42)	(8.46)	(9.07)	(6.75)	(6.55)	(11.09)
Brand prescription limit	6.12	7.59	3.62	2.48	6.04	3.68
	(9.28)	(18.38)	(18.68)	(8.26)	(8.49)	(15.52)
Overall prescription limit	3.15	33.71	31.08	-2.72	6.58	1.54
	(9.58)	(35.37)	(33.59)	(9.40)	(8.95)	(8.23)
Substitution rate	-0.05	0.22	-0.02	-0.21	-0.02	0.28
	(0.15)	(0.18)	(0.18)	(0.14)	(0.15)	(0.22)

* P<0.1, ** P<0.5, *** P<0.01. Standard errors are in parenthesis and are clustered at the state level. Coefficients have been transformed using $(e^{\beta-1}) * 100$ and are interpreted as a percentage change. MFCU is interpreted as an elasticity for a 10 percent change in MFCU expenditures. All Services and Excluding Prescrition Drug specifications include 686 observations (49 states x 14 years); AZ and TN are excluded. Prescription Drug Only specifications include 685 observations since NM has zero drug beneficiaries in 2012. Year and state effects are included in all specifications as are controls for state population demographics, welfare program characteristics, political controls, Medicaid eligible population controls for age, MCO enrollment and dual eligibility. All and All Except Aged specifications additionally control for relative group composition. Substitution rate is only available through 2009; a missing indicator is included for all missing values.

Table 2.7: Therapeutic Classes by Number of Prescriptions: SDUD 1999 - 2012

Rank	Class	Total Prescriptions	Percent of Total Prescriptions	Cumulative Percent
1	Antidepressants	347,055,936	6.06	6.06
2	Analgesics - Opioid	316,577,408	5.53	11.60
3	Antiasthmatic And Bronchodilator Agents	298,305,504	5.21	16.81
4	Anticonvulsants	261,242,000	4.56	21.37
5	Antihypertensives	249,829,584	4.37	25.74
6	Antipsychotics/Antimanic Agents	236,725,040	4.14	29.87
7	Ulcer Drugs	226,601,616	3.96	33.83
8	Antidiabetics	210,846,240	3.68	37.52
9	Dermatologicals	201,349,248	3.52	41.04
10	Analgesics - Anti-inflammatory	191,016,576	3.34	44.37
11	Antianxiety Agents	188,819,376	3.30	47.67
12	Penicillins	160,177,600	2.80	50.47
13	Antihistamines	159,742,832	2.79	53.26
14	Diuretics	156,017,664	2.73	55.99
15	Antihyperlipidemics	150,042,960	2.62	58.61
16	Cough/Cold/Allergy	140,473,664	2.45	61.07
17	Analgesics - Nonnarcotic	120,272,496	2.10	63.17
18	Beta Blockers	120,141,880	2.10	65.27
19	Calcium Channel Blockers	107,964,544	1.89	67.15
20	Adhd/Anti-narcolepsy/Anti-obesity/Anorexiants	104,011,944	1.82	68.97
21	Ophthalmic Agents	93,571,936	1.64	70.61
22	Minerals & Electrolytes	91,939,888	1.61	72.21
23	Macrolides	82,326,120	1.44	73.65
24	Contraceptives	82,084,096	1.43	75.09
25	Cephalosporins	78,595,096	1.37	76.46
26	Thyroid Agents	74,097,280	1.29	77.75
27	Hematopoietic Agents	73,153,616	1.28	79.03
28	Hypnotics/Sedatives/Sleep Disorder Agents	72,630,496	1.27	80.30
29	Laxatives	70,237,936	1.23	81.53
30	Corticosteroids	67,220,048	1.17	82.70
31	Multivitamins	60,951,756	1.07	83.77
32	Nasal Agents - Systemic And Topical	60,648,692	1.06	84.83
33	Musculoskeletal Therapy Agents	60,110,856	1.05	85.88
34	Anti-infective Agents - Misc.	59,796,952	1.04	86.92
35	Endocrine And Metabolic Agents - Misc.	54,731,484	0.96	87.88
36	Antivirals	48,018,016	0.84	88.72
37	Antianginal Agents	42,347,176	0.74	89.46
38	Anticoagulants	41,868,396	0.73	90.19
39	Antiparkinson Agents	40,119,992	0.70	90.89
40	Fluoroquinolones	38,544,524	0.67	91.56
41	Other	482,803,085	8.44	100.00
Total		5,723,011,553	100.00	

Therapeutic classes are defined using Medispan's Generic Product Identifer (GPI)

Table 2.8: Off-Label "Prone" Classification of Therapeutic Classes

Off-Label Prone	Not Off-Label Prone
Antianginal agents	Analgesics - anti-inflammatory
Antianxiety agents	Analgesics - nonnarcotic
Antiarrhymthmics	Analgesics - opioid
Antiasthmatic and Broncodialator agents	Antidiabetics
Anticoagulants	Antihyperlipidemics
Anticonvulsants	Antihypertensives
Antidepressants	Contraceptives
Antihistamines	
Antiphychotics and Antimanic agents	
Beta-Blockers	
Ulcer drugs	

Therapeutic classes are categorized using Medispan GPI classifications.

Table 2.9: Medical Literature Categorization of Off-label Prone Classes

Prescription Drug Spending									
	Medical Lit. Prone vs. Not			Omit Analgesics			Omit Analgesics; Agree		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
FCA × Off-Label	-16.82***	-9.53	-9.17	-17.33***	-11.00*	-10.22	-17.76**	-14.23**	-12.24**
	(4.99)	(5.40)	(5.42)	(5.67)	(5.86)	(5.79)	(6.33)	(5.59)	(5.68)
FCA	-9.19	-13.72	10.34	-7.30	-11.93	12.93	-5.91	-8.59	16.06
	(9.82)	(10.03)	(12.00)	(9.69)	(10.06)	(12.43)	(9.82)	(10.53)	(11.68)
Log MFCU	-0.28	-0.27	0.09	-0.25	-0.24	0.09	-0.32	-0.32	0.03
	(0.28)	(0.28)	(0.29)	(0.28)	(0.28)	(0.29)	(0.27)	(0.27)	(0.26)
Off-label × year	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Off-label × state	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
State time trend	No	No	Yes	No	No	Yes	No	No	Yes
N	38,253	38,253	38,253	33,387	33,387	33,387	26,633	26,633	26,633
Number of Prescriptions									
	Medical Lit. Prone vs. Not			Omit Analgesics			Omit Analgesics; Agree		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
FCA × Off-Label	-16.27***	-9.99*	-9.64*	-12.74**	-11.45*	-10.71*	-11.57*	-13.73**	-11.82**
	(4.81)	(5.30)	(5.31)	(5.51)	(5.58)	(5.47)	(6.23)	(5.12)	(5.14)
FCA	-9.28	-13.18	9.24	-10.23	-11.16	11.18	-10.33	-8.80	13.50
	(8.63)	(8.95)	(10.66)	(8.12)	(9.07)	(10.87)	(7.99)	(9.44)	(9.89)
Log MFCU	-0.33	-0.33	-0.03	-0.34	-0.33	-0.02	-0.43*	-0.43*	-0.08
	(0.24)	(0.25)	(0.19)	(0.25)	(0.25)	(0.19)	(0.24)	(0.24)	(0.18)
Off-label × year	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Off-label × state	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
State time trend	No	No	Yes	No	No	Yes	No	No	Yes
N	38,253	38,253	38,253	33,387	33,387	33,387	26,633	26,633	26,633

* P<0.1, ** P<0.5, *** P<0.01. Standard errors are in parenthesis and are clustered at the state level. All models include controls for state demographics, Medicaid population composition and number of eligibles, state welfare programs, political party of state government, and prescription drug policies as well as state, year, drug therapeutic class and subclass fixed effects. All coefficient estimates have been transformed by $(e^{\beta}-1)\times 100$ and are interpreted as a percentage change except MFCU which is an elasticity with regard to a 10 percent increase in MFCU expenditures. Sample is limited to drug-class-state observations present in every year.

Table 2.10: Continuous Estimated Off-Label Rate Categorization

Prescription Drug Spending									
	Medical Lit. Prone vs. Not			Omit Analgesics			Omit Analgesics; Agree		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
FCA × Off-Label	-3.65	-19.60*	-12.75	-20.52	-19.33	-15.84	-13.29	-23.88	-19.06
	(13.39)	(10.35)	(11.84)	(12.67)	(12.51)	(13.50)	(13.91)	(13.21)	(15.11)
FCA	-17.92*	-12.03	9.74	-12.07	-12.55	11.67	-13.45	-9.15	14.57
	(8.46)	(10.25)	(12.26)	(9.93)	(11.61)	(13.32)	(10.12)	(12.70)	(14.68)
Log MFCU expenditure	-0.30	-0.30	0.07	-0.27	-0.27	0.07	-0.35	-0.35	0.01
	(0.28)	(0.28)	(0.29)	(0.28)	(0.28)	(0.29)	(0.27)	(0.27)	(0.26)
Off-label × year	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Off-label × state	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
State time trend	No	No	Yes	No	No	Yes	No	No	Yes
N	36,952	36,952	36,952	32,086	32,086	32,086	25,528	25,528	25,528
Number of Prescriptions									
	Medical Lit. Prone vs. Not			Omit Analgesics			Omit Analgesics; Agree		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
FCA × Off-Label	19.81	-20.32*	-14.24	-1.20	-22.53*	-19.45	2.40	-28.33**	-24.21*
	(17.59)	(9.66)	(11.41)	(14.79)	(10.74)	(11.72)	(15.68)	(10.86)	(12.27)
FCA	-24.29***	-11.52	9.29	-18.42**	-10.81	11.59	-18.60**	-7.02	15.51
	(6.98)	(9.90)	(11.03)	(8.08)	(10.99)	(11.73)	(8.27)	(11.69)	(12.57)
Log MFCU expenditure	-0.35	-0.35	-0.05	-0.36	-0.36	-0.05	-0.46*	-0.46*	-0.11
	(0.25)	(0.25)	(0.19)	(0.25)	(0.25)	(0.19)	(0.25)	(0.25)	(0.18)
Off-label × year	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Off-label × state	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
State time trend	No	No	Yes	No	No	Yes	No	No	Yes
N	36,952	36,952	36,952	32,086	32,086	32,086	25,528	25,528	25,528

* P<0.1, ** P<0.5, *** P<0.01. Standard errors are in parenthesis and are clustered at the state level. All models include controls for state demographics, Medicaid population composition and number of eligibles, state welfare programs, political party of state government, and prescription drug policies as well as state, year, drug therapeutic class and subclass fixed effects. All coefficient estimates have been transformed by $(e^{\beta}-1)\times 100$ and are interpreted as a percentage change except MFCU which is an elasticity with regard to a 10 percent increase in MFCU expenditures. Sample is limited to drug-class-state observations present in every year.

Table 2.11: Dynamic Effects

	(1)	(2)
Off-label × 4 years pre	4.89	3.57
	(4.87)	(3.95)
Off-label × 3 years pre	6.59	4.86
	(6.09)	(5.47)
Off-label × 2 years pre	4.64	4.29
	(6.25)	(6.20)
Off-label × 1 year pre	0.52	-0.75
	(6.31)	(6.48)
Off-label × Implementation year	-2.71	-1.68
	(6.69)	(7.04)
Off-label × 1 year post	-1.69	-0.57
	(6.94)	(7.59)
Off-label × 2 years post	-7.45	-6.89
	(5.85)	(6.28)
Off-label × 3 years post	-6.21	-7.29
	(5.43)	(5.74)
Off-label × 4 years post	-5.88	-5.91
	(5.10)	(4.89)
4 years pre	12.37	9.67
	(9.96)	(8.46)
3 years pre	8.23	6.43
	(11.05)	(9.89)
2 years pre	3.49	3.29
	(11.36)	(10.44)
1 year pre	7.45	7.51
	(11.77)	(10.99)
Implementation year	2.71	3.20
	(12.09)	(11.23)
1 year post	-1.53	-0.82
	(11.07)	(10.60)
2 years post	3.34	3.95
	(11.59)	(11.12)
3 years post	-2.78	-1.59
	(9.92)	(9.46)
4 years post	-9.16	-5.71
	(9.39)	(9.07)
$H_0 : \delta_{-4}...\delta_{-1} = 0$	0.4520	0.3141
$H_0 : \gamma_{-4}...\gamma_{-1} = 0$	0.4232	0.5052
$H_0 : \delta_0...\delta_4 = 0$	0.1111	0.2008
$H_0 : \gamma_0...\gamma_4 = 0$	0.6884	0.7794
N	48,580	48,580

* P<0.1, ** P<0.5, *** P<0.01. Standard errors are in parenthesis and are clustered at the state level. All models include state, year, subclass, off-label-state, and off-label-year fixed effects. All coefficient estimates have been transformed by $(e^{\beta} - 1) \times 100$ interpreted as a percent change.

Figure 2.1: FCA Referrals, Investigations, and Actions

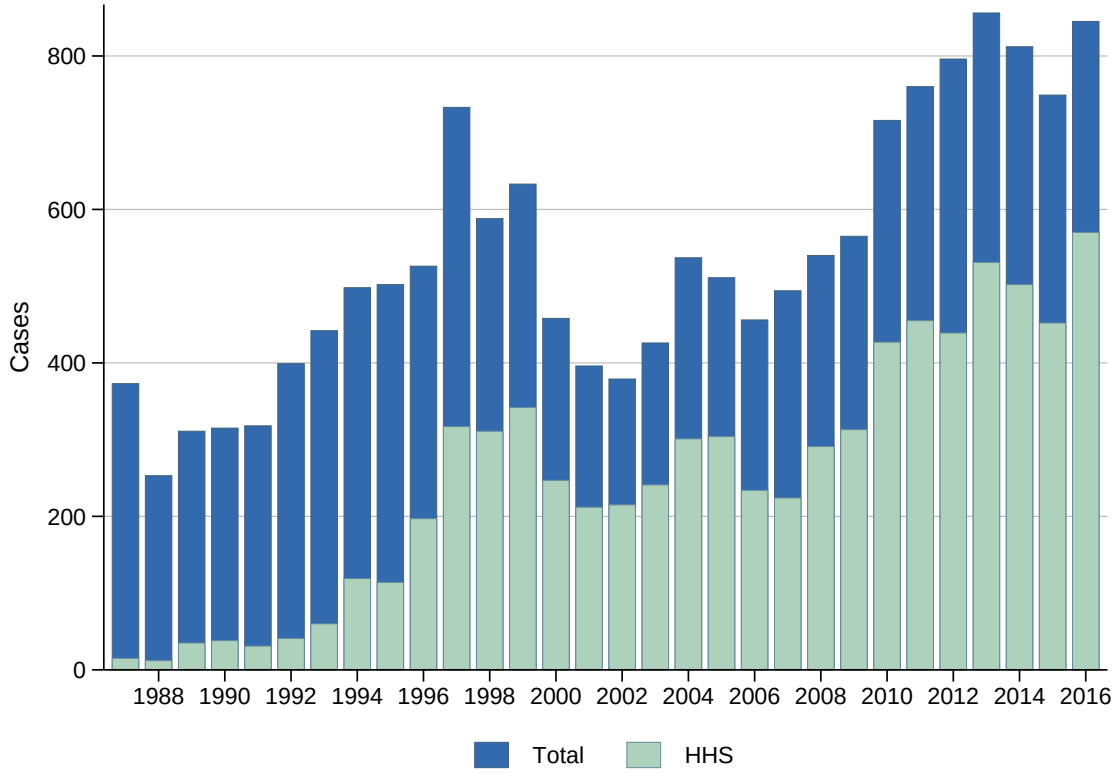


Figure 2.2: FCA Settlements and Judgments

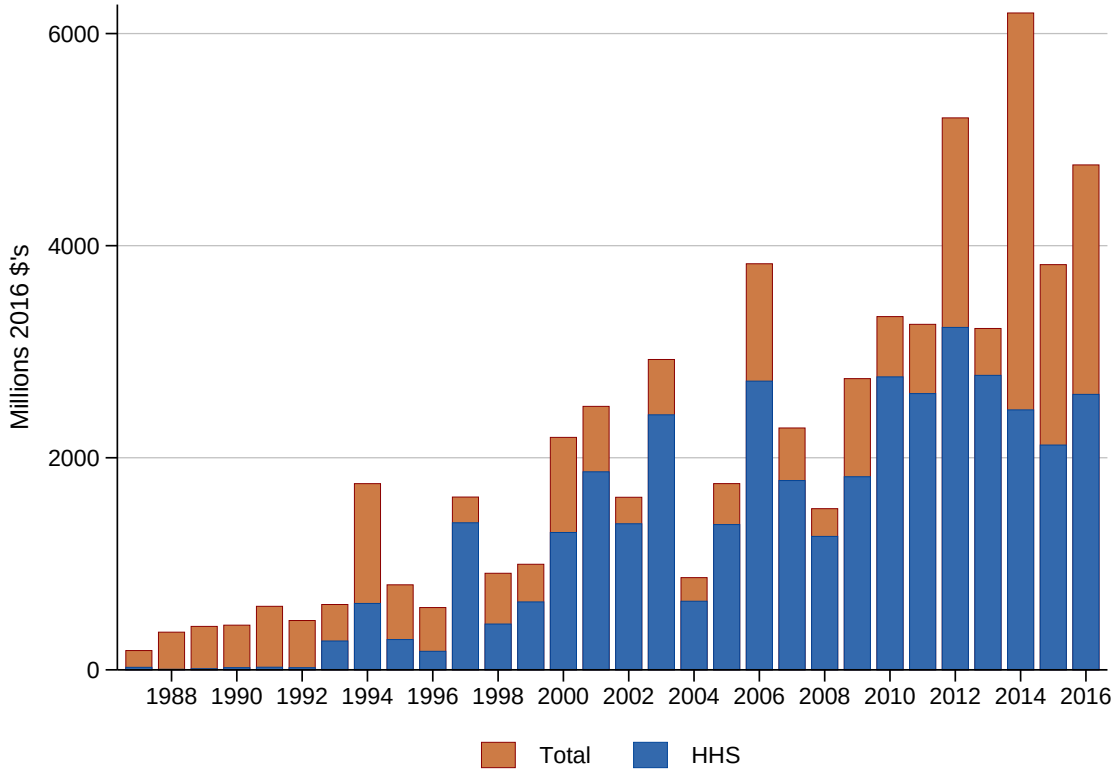
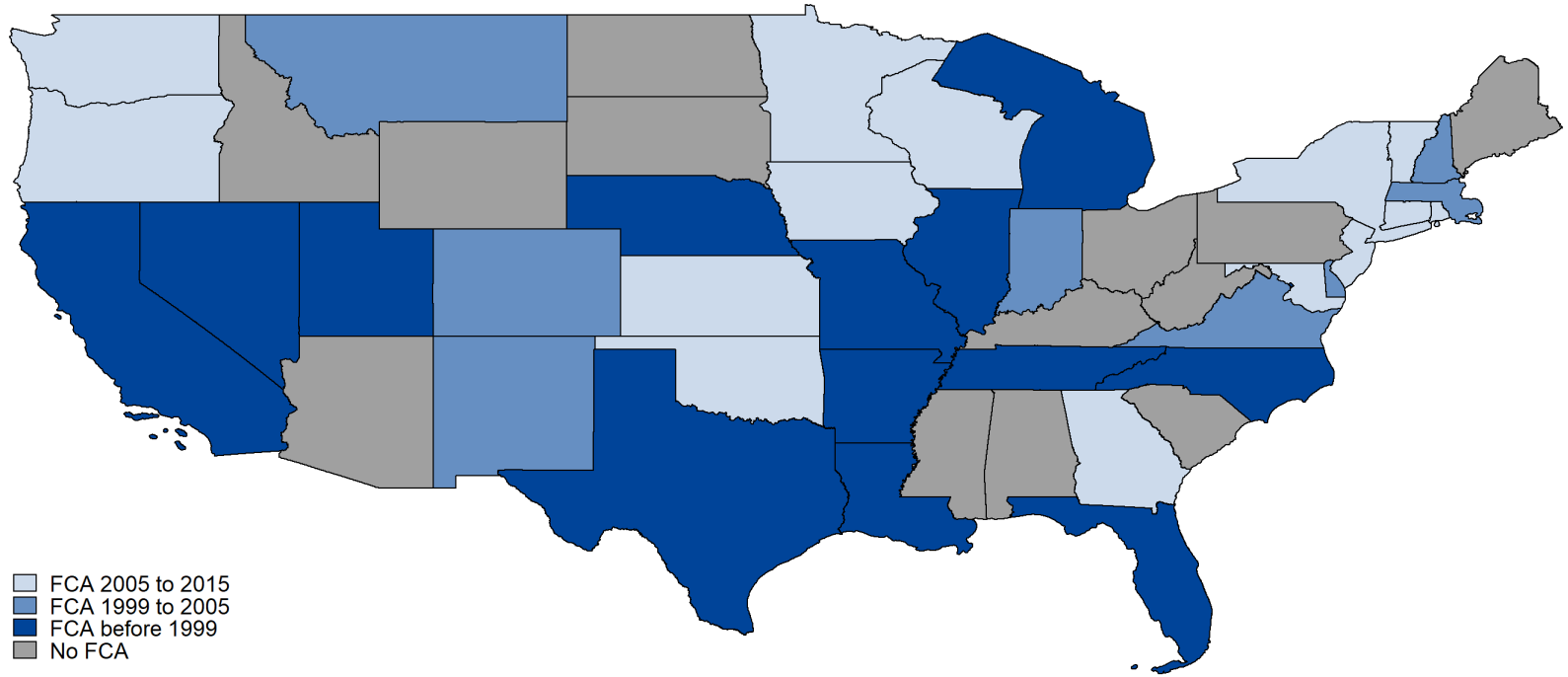


Figure 2.3: State FCA Implementation



Note: Alaska and Hawaii are omitted from this map. Alaska does not have a state FCA, and Hawaii enacted a FCA in 2001.

Figure 2.4: State FCA Implementation by Type

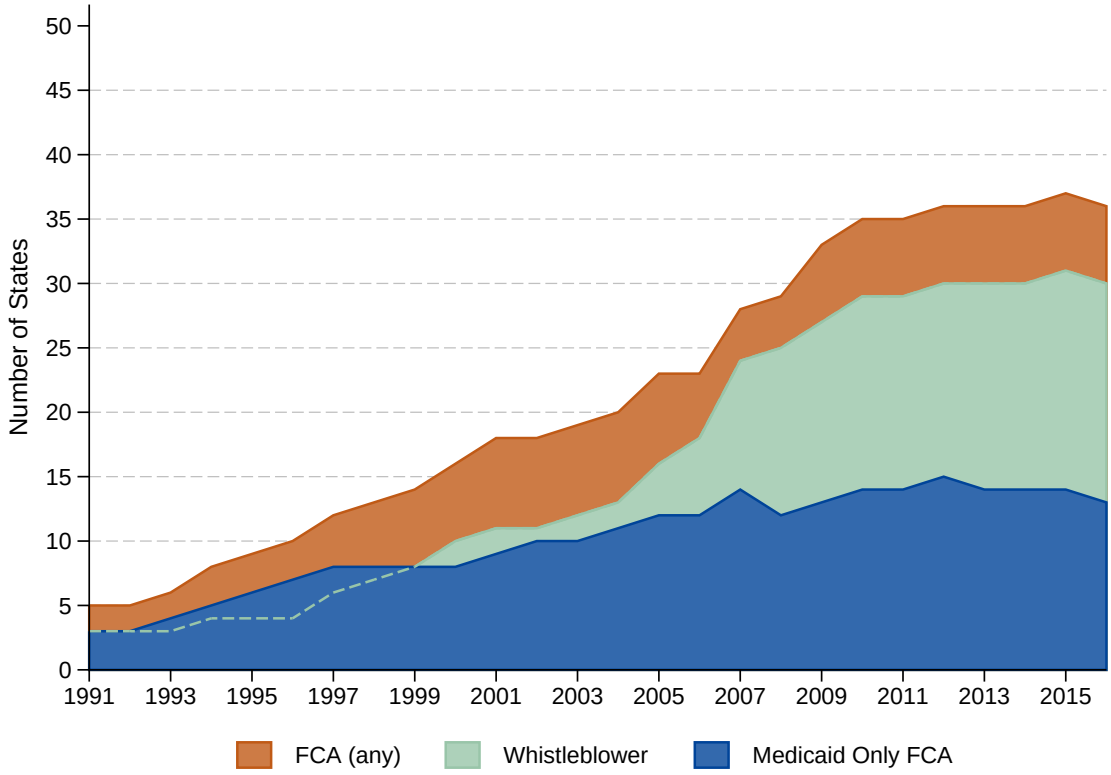
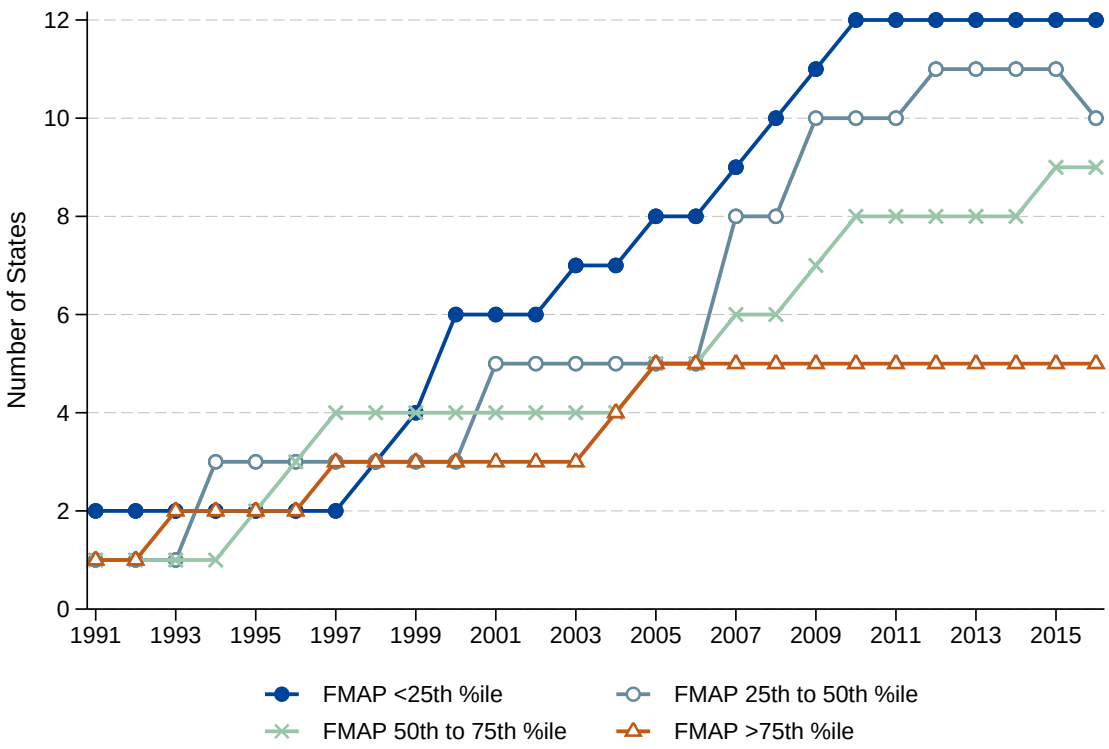


Figure 2.5: State FCA Implementation by Federal Medical Assistance Percentage



FMAP percentiles are based on the distribution of FMAPs in 1991.

Figure 2.6: Medicaid Fraud Control Unit Expenditures

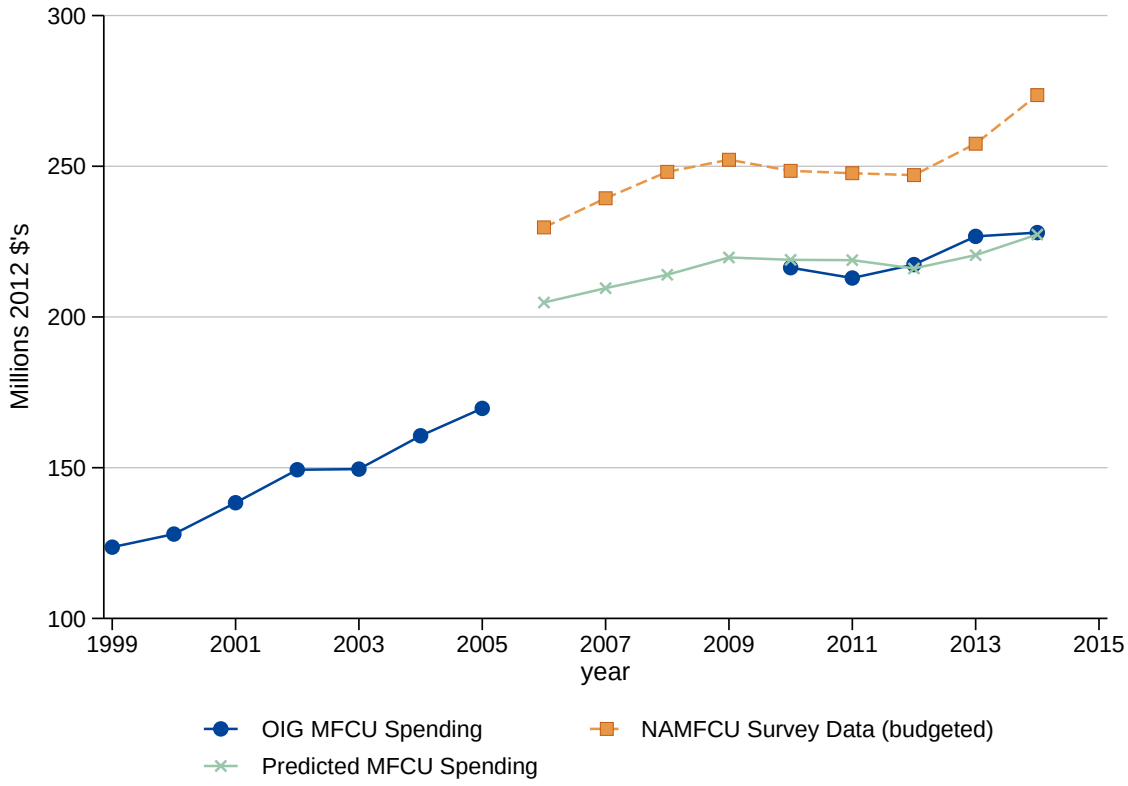


Figure 2.7: Total Medicaid Spending for All Services

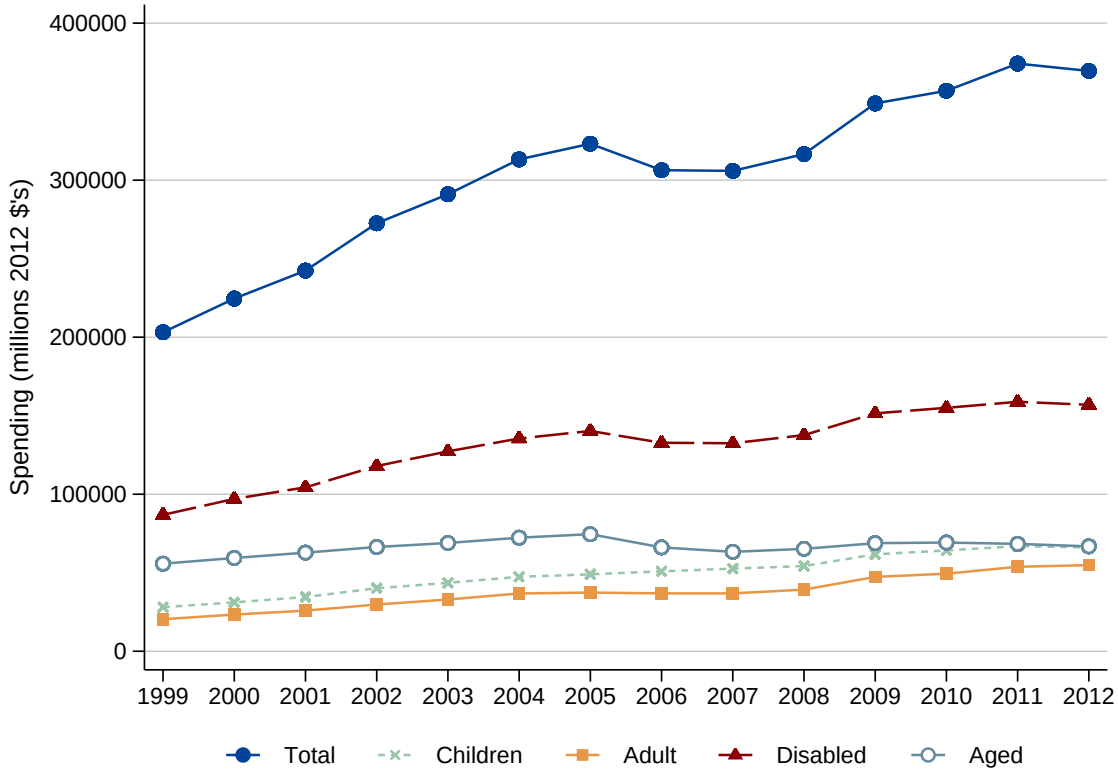


Figure 2.8: Total Medicaid Spending for Prescription Drugs

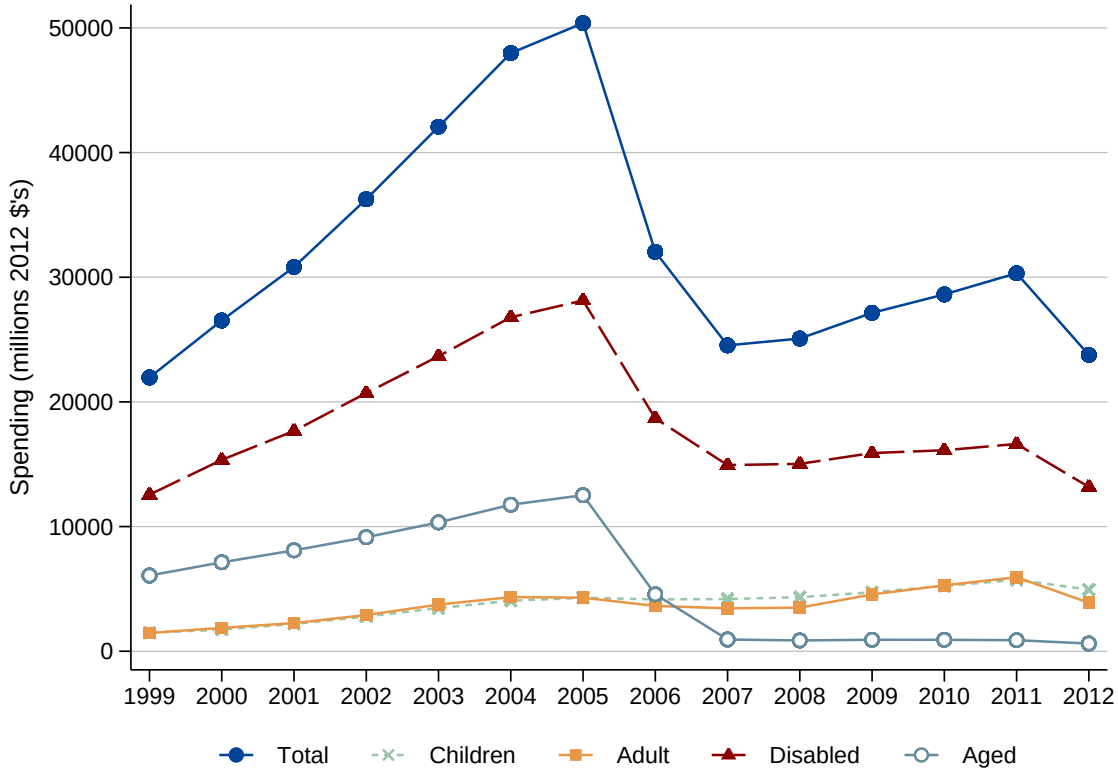


Figure 2.9: Total Number of Medicaid Eligibles

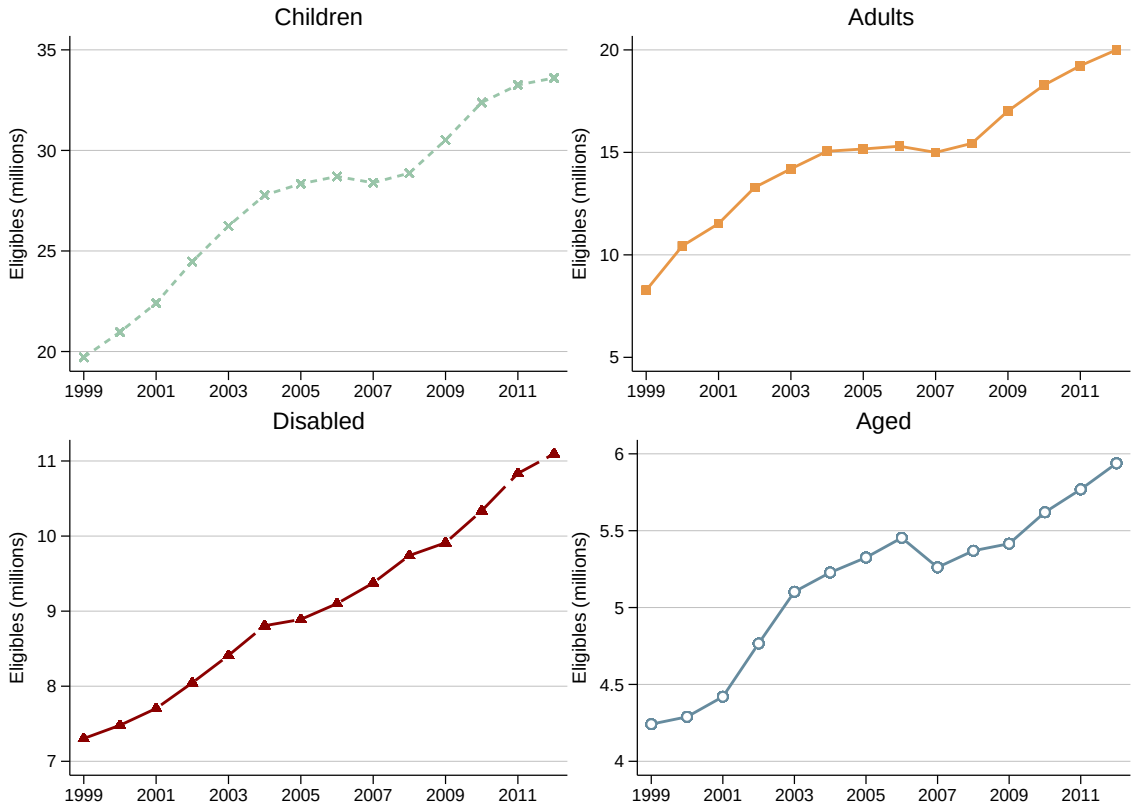
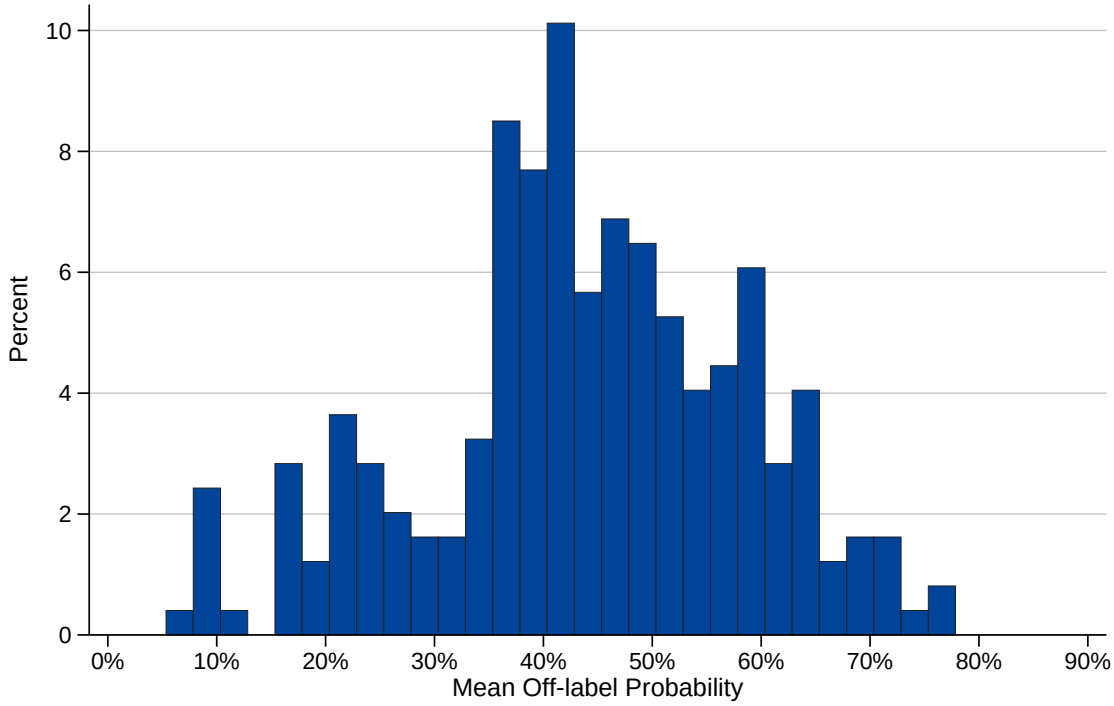


Figure 2.10: Distribution of Estimated Off-Label Usage Probabilities



Off-label probabilities derived from estimates provided by Bradford, Paker, & Williams.
We aggregate NDC-level probabilities up to the drug-class level, identified by class and subclass, and weight by the volume of prescriptions for each NDC. Analgesics are excluded.

Figure 2.11: Spending and Prescription Volume - Off-Label Prone Drug Classes

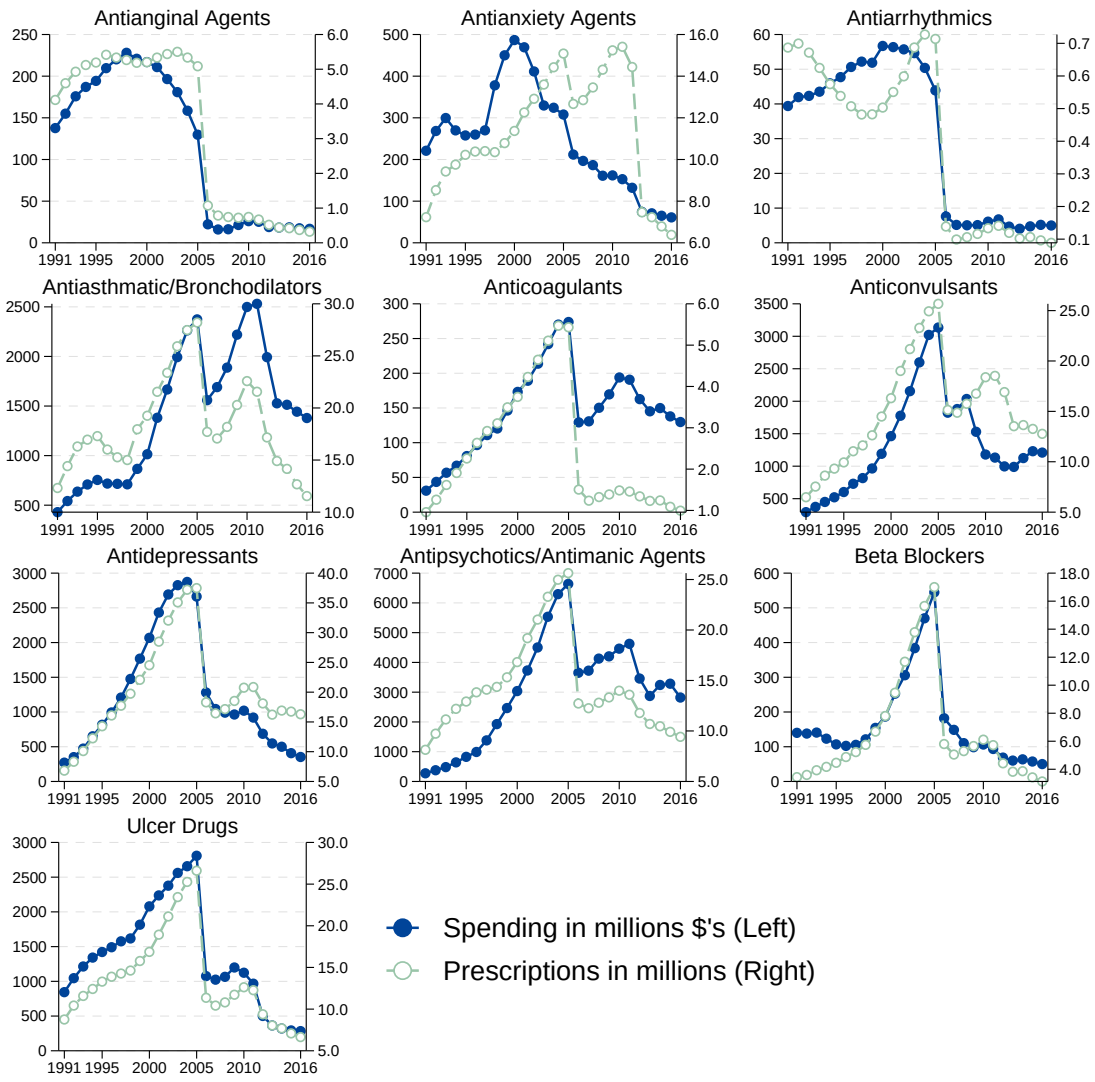


Figure 2.12: Spending and Prescription Volume - Not Off-Label Prone Drug Classes

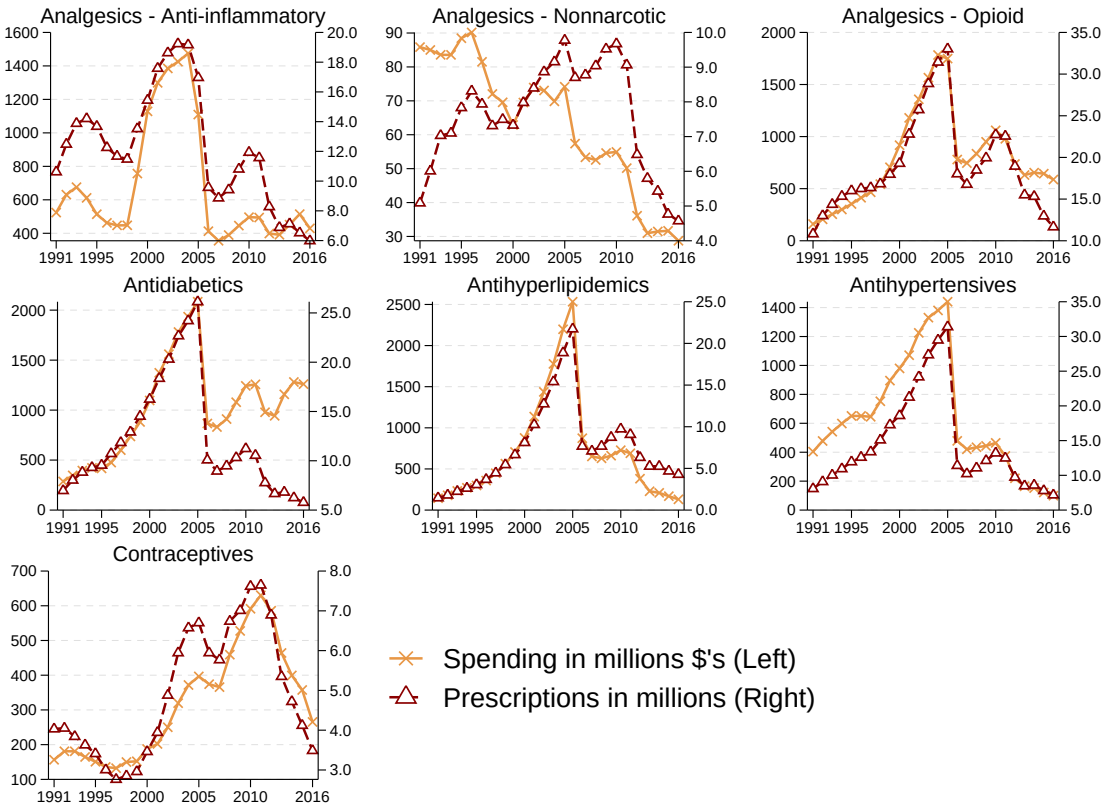
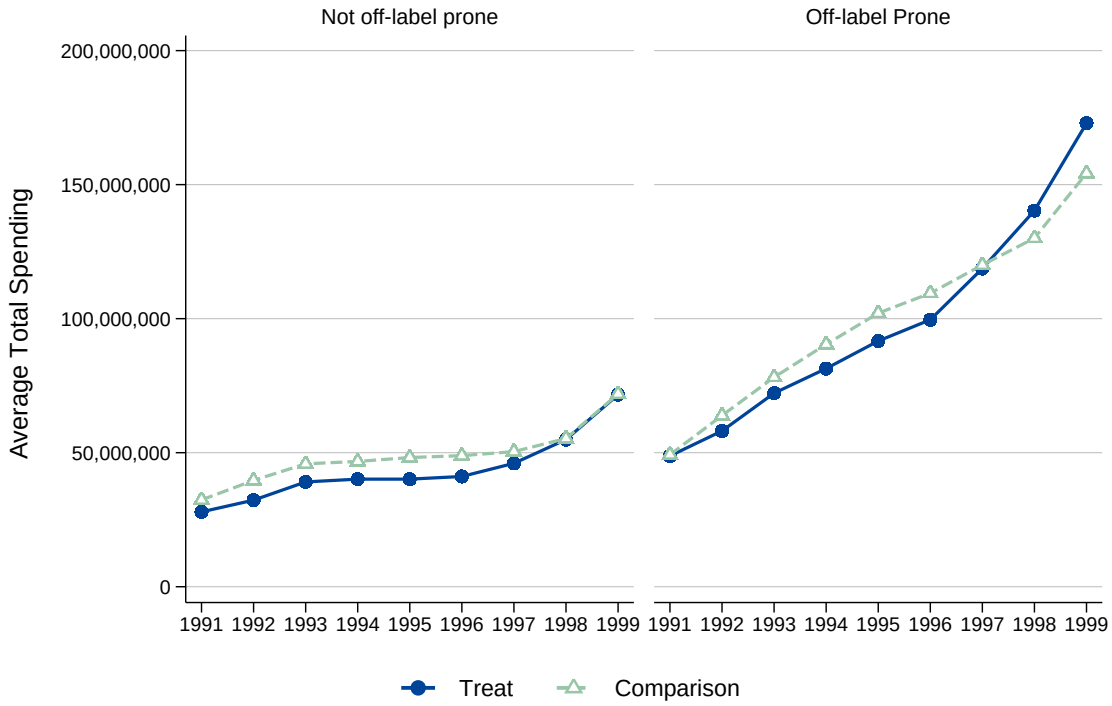
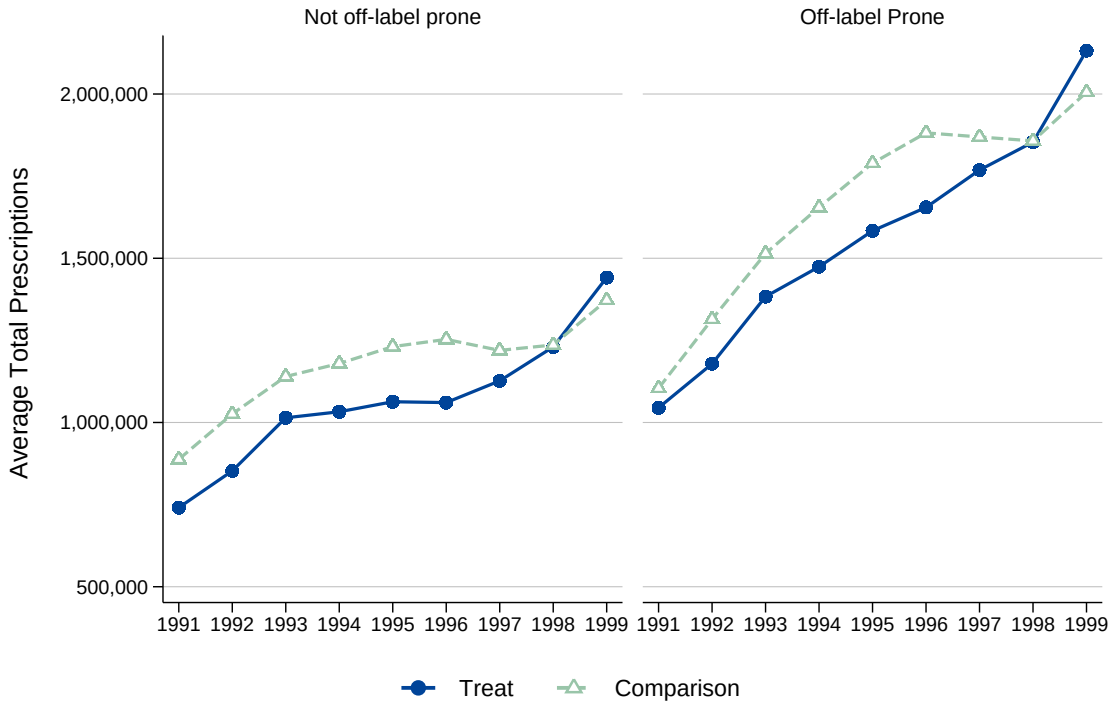


Figure 2.13: Pre-Treatment Prescription Drug Spending



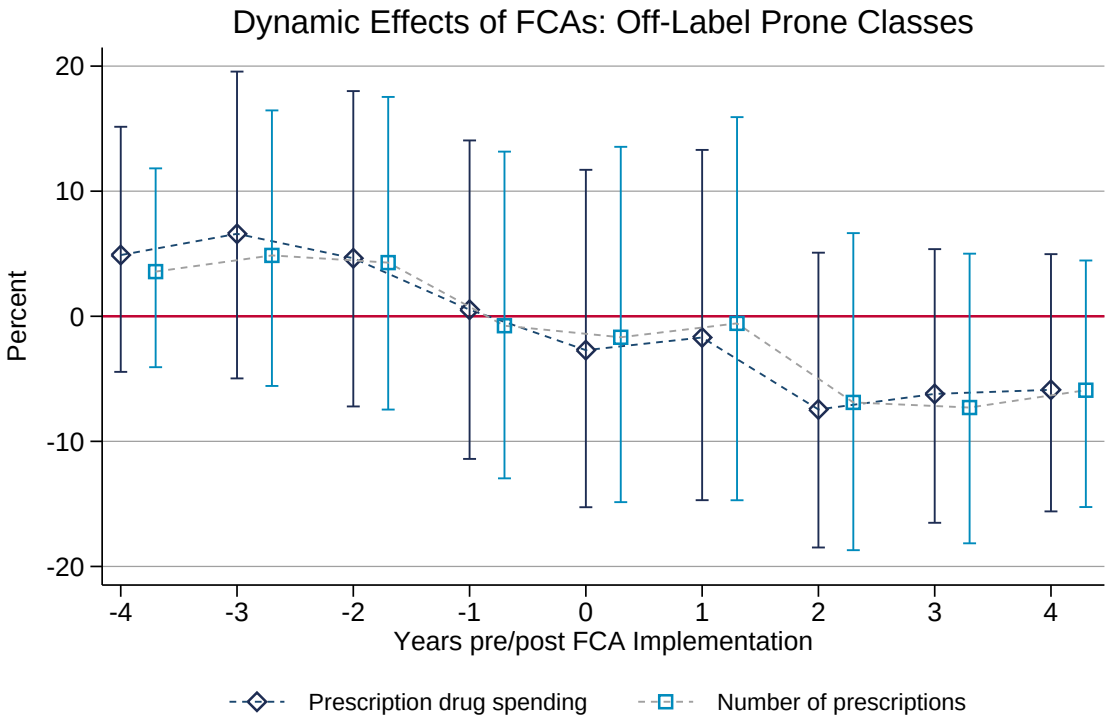
Average total annual prescription drug spending by state across states which eventually enact a FCA versus not. Treat includes only states with a FCA enacted after 1999. Spending in 2012 $'s.

Figure 2.14: Pre-Treatment Prescription Drug Volume



Average annual total number of prescriptions by state across states which eventually enact a FCA versus not. Treat includes only states with a FCA enacted after 1999.

Figure 2.15: Dynamic Effects of FCAs - Off-Label Prone Drug Classes



Coefficients for interaction of off-label prone and FCA timing, δ_l, are estimated from a model with state-level controls, prescription drug polices, state, year, drug class and subclass, off-label-state, and off-label-year effects.

Chapter A: Chapter 1 Appendix

A.1 Treatment of Standard Errors in Regression Analyses

The regression models in Chapter 1 employ heteroscedastic-robust standard errors for the purposes of inference and statistical testing. Alternatively clustering standard errors at the physician specialty level, to allow for intra-specialty correlation of error terms, does not substantially effect the standard error estimates. Cameron and Miller (2015) note that in the presence of "few" clusters, even allowing for clustered error terms may still underestimate standard error magnitudes and over-reject the null hypothesis. I cluster over physician specialties, since this is the group over which the "treatment" variable, relative Medicare reimbursement rates, varies. I am using twelve physician specialties from the NAMCS data, and so there are twelve clusters, which falls in the range where we may be concerned that there are too few groups. To address this issue, I employ a paired bootstrap procedure which resamples from the original data by cluster (specialty), reruns the regression specification, and computes a wald test statistic which tests that the estimated bootstrapped parameter is different than the analogous parameter from the original data and model for each replication. Alternatively, a wild cluster bootstrap is used. Both of these methods are discussed in Cameron and Miller (2015). Figure A.1 shows the paired bootstrapped distribution of t-statistics for the three parameters of interest, the interaction of relative Medicare reimbursement rates and Medical Care, Surgical Care, and Primary Care specialty indicators. Figure A.2 shows t-statistic distributions derived from a wild bootstrap procedure, run with an unrestricted model. P-values obtained from the paired and wild bootstrap procedure are slightly larger than those reported in Table 1.4 (column 4), but still maintain statistical significance at conventional levels for Medical Care and Primary Care specialties. As such, adjusting the standard errors to account for the presence of few clusters does not significantly effect inference or interpretation of the main results in this paper.

A.2 Additional Regression Model Specifications

Tables A.1 through A.5 provide additional model specifications similar to those presented in Table 1.4. Table A.1 presents models including psychiatry, with no survey weighting. Table A.2 includes psychiatry and weights using the NAMCS physician-level weights. Table A.3 excludes psychiatry, with no survey weighting. Table A.4 Omits both Obstetrics/Gynecologists and Pediatricians. Table A.5 omits the last two years of the sample, 2014 and 2015.

Table A.6 presents model specifications identical to that of Table 1.4, column 5, but excludes one specialty from each column. This is to check the sensitivity of results to excluding each specialty one-by-one and determine if any particular specialty is driving the results. When cardiology is excluded (column 1), the effect of Medicare fee differentials becomes negative and insignificant for Medical care specialties. This is likely because cardiologists witnessed a large change in the Medicare fee gap between hospital-based and office-based reimbursement rates, and this variation is driving the result among the Medical care specialty category.

The empirical model specification used in this paper is a generalized difference-in-difference model with a continuous treatment variable measuring the intensity of exposure to Medicare reimbursement rate differentials for each physician specialty over time. Using the continuous treatment measure, there is no clear treatment and comparison group nor is there a well-defined pre- and post-treatment period. However, the identification of the effect of Medicare fee differentials relies partially on two methodological changes that the Centers for Medicare and Medicaid (CMS) implemented in 2007 and 2010. Both of these changes altered the method used by CMS to estimate costs for services, and much of the changes observed in the Medicare reimbursement rate differentials from 2005 through 2015 do occur after 2007. Using a similar grouping as when I test the "parallel trends assumption," I sort four, and alternatively six, specialties into "treatment" and "comparison" groups, and impose pre- and post-treatment periods using both 2007 and 2010 treatment start dates. Using this framework, I can fit the analysis into a more typical difference-in difference framework with a clearly defined treatment and comparison group and pre- and

post-treatment periods.

Table A.7, panels A through D show results across different model specifications and treatment groups and timing. Column 1 in each panel uses NAMCS data from 2000 through 2015 and only includes treatment group and period interactions, and specialty and year fixed effects. Column 2 limits the sample to 2005 through 2015, consistent with the sample period used in the baseline analysis in the paper. Column 3 includes additional controls, identical to those used in the baseline models, and column 4 weights regressions using the NAMCS physician-level survey weights. Panels A and B include cardiology and urology in the treatment group and dermatology and general and family practice in the comparison group and alternatively uses 2007 and 2010 as the treatment date. Panels C and D include additional specialties in the treatment and comparison groups; orthopedic surgery is included in the treatment group and internal medicine in the comparison group.

Across both treatment periods and both categorizations of treatment and comparison groups, results are similar in magnitude. The treated specialties typically see about 3.5 to 5.0 percentage point higher rates of hospital ownership over the comparison group, in the post treatment period. I do not attempt to estimate a heterogeneous effect across specialty subgroups due to the small sample size.

A.3 Medicare Patient Share

Tables 1.5 and 1.6 present specifications where the effect of relative Medicare Reimbursement rates are allowed to vary over a physician's share of patients where Medicare is the primary payer. This methodology generally follows Alpert, Hsi, and Jacobson (2017) who use geographic variation in Medicare patient shares to identify the effect of Medicare payment reforms on the vertical integration of oncologists. I follow this general methodology by interacting the share of physicians' Medicare patients with the measure of Medicare relative reimbursement rates. Figure A.3 shows the variation in Medicare patient share within and across physician specialties. There is notable variation in the share of Medicare patients seen by physicians within specialties; the 25th percentile to 75th percentile typically spans 20 to 30 percentage points. However, there is a very clear relationship between physician

specialty and the average number of Medicare patients seen by a physician. For specialties such as pediatrics and Obstetrics and gynecology, Medicare patients typically make up less than 10 percent of a physician's total patients. Ophthalmologists and cardiologists practices depend more heavily on Medicare patients who make up almost 50 percent of a physician's practice.

Table A.8 presents a specification similar to 1.5, except that an indicator for whether a physician has a Medicare patient share greater than the median is used, instead of a continuous measure of Medicare patient share. This binary indicator sacrifices some of the variation in patient mix across providers, but allows easier interpretation of the interaction term. In columns 1 through 3 of Table A.8 both coefficients on the relative Medicare rate and the interaction term are positive, but insignificant. However, when calculating the "total effect" for a 10 percent increase in the relative Medicare reimbursement rate, there is a positive and significant increase in hospital ownership for providers who see relatively more Medicare patients. Columns 4 and 5 show the main and interaction effects broken out across specialty groups. There is a positive and significant increase in hospital ownership for providers in Medical Care specialties who see relatively more Medicare patients (see "Medical Care Total Effect" and associated p-values in Table A.8.

A.4 Relative Prices and Provider Exposure to Provider-Based Billing

The variable of interest in this paper is the "exposure" of physicians to the relative Medicare reimbursement rates paid to integrated versus non-integrated physicians. Relative prices vary by service and over time, but since the NAMCS data does not contain CPT/HCPCS codes, this measure is constructed at the specialty-year level. This assumes that, on average, the types of services provided by a particular physician in a given specialty can be characterized as that of a representative physician for each specialty. The exposure to relative prices is constructed using aggregate Medicare utilization data from years 2003 and 2007 through 2015. The relative price for each service is weighted by the percent of total revenue generated within an office setting.

Provider-level Medicare utilization data for Medicare Part B services is available for

years 2012 through 2015 through the CMS Provider Utilization and Payment public-use file. This data allows me to construct a provider-level measure of exposure to relative prices generated by Medicare's provider-based billing and compare the provider-specific measure to a specialty average reflecting a representative provider for that specialty. This comparison provides evidence whether a representative physician's exposure to relative prices is a reasonable approximation of the reimbursement rate premium faced by individual physicians.

Figure A.4 presents a summary of the distribution of provider-level relative price exposure centered at the specialty-average relative price for each specialty and year. If the aggregate, specialty-level relative price measure accurately represents the exposure of each provider to relative Medicare reimbursement rates, then there should be a clustering around zero, indicating that there is no difference in the provider-level and specialty-level measures. As expected, there is some variation in the exposure of individual providers within a single specialty to relative price differences in Medicare reimbursement rates. However, across all specialties, the relative price faced by most providers does fall close to the specialty-average relative price. For about half of all provider-year observations, the difference in aggregate and individual relative prices falls within about plus or minus 0.2, as indicated by the interquartile range of each box plot. Opthalmology and orthopedic surgery have the widest spread in relative prices between the 25th and 75th percentile. About 90 percent of provider-year observations have relative prices within plus or minus 0.5 (contained within the span of the whiskers), with the exception of neurology, ophthalmology, and pediatric medicine. Figure A.4 provides evidence that the aggregate, specialty-level measure of exposure to Medicare's provider-based billing rates is a reasonable approximation in the absence of provider-level measures.

Table A.1: Hospital Ownership of Physician Practices - Unweighted Including All Specialties

	(1)	(2)	(3)	(4)	(5)
ln(HOPD/PO)	0.37	0.27	0.28		
	(0.40)	(0.40)	(0.39)		
Primary care × ln(HOPD/PO)				-2.11***	-1.96**
				(0.63)	(0.90)
Surgical care × ln(HOPD/PO)				0.12	0.18
				(0.58)	(0.56)
Medical care × ln(HOPD/PO)				1.31***	1.21**
				(0.48)	(0.49)
Region effects	No	Yes	Yes	Yes	Yes
Other controls	No	Yes	Yes	Yes	Yes
Specialty category	No	No	Yes	No	Yes
N	14,063	14,063	14,063	14,063	14,063

Source: NAMCS Public-Use file 2005 - 2015. * P<0.1, ** P<0.5, *** P<0.01. Robust standard errors are presented in parenthesis. Dependent variable is a binary indicator for hospital ownership. Coefficients have been multiplied by 100 and are interpreted as a percentage point in hospital ownership given a 10 percent increase in HOPD/PO. Year and specialty fixed effects are included in all specifications. Controls include an MSA/Non-MSA indicator, census region, solo versus group practice, percent of visits where the physician is the primary care provider, percent visits where the patient is referred to another physicians, percent Medicare and privately insured patient visits, and and average patient age, sex, and race.

Table A.2: Hospital Ownership of Physician Practices - All Specialties

	(1)	(2)	(3)	(4)	(5)
ln(HOPD/PO)	0.42	0.35	0.36		
	(0.51)	(0.49)	(0.49)		
Primary care × ln(HOPD/PO)				-1.58**	-1.50
				(0.75)	(0.99)
Surgical care × ln(HOPD/PO)				0.55	0.41
				(0.71)	(0.73)
Medical care × ln(HOPD/PO)				1.05*	1.10*
				(0.60)	(0.60)
Region effects	No	Yes	Yes	Yes	Yes
Other controls	No	Yes	Yes	Yes	Yes
Specialty category	No	No	Yes	No	Yes
N	14,063	14,063	14,063	14,063	14,063

Source: NAMCS Public-Use file 2005 - 2015. * P<0.1, ** P<0.5, *** P<0.01. Robust standard errors are presented in parenthesis. Dependent variable is a binary indicator for hospital ownership. Coefficients have been multiplied by 100 and are interpreted as a percentage point in hospital ownership given a 10 percent increase in HOPD/PO. Year and specialty fixed effects are included in all specifications. Controls include an MSA/Non-MSA indicator, census region, solo versus group practice, percent of visits where the physician is the primary care provider, percent visits where the patient is referred to another physicians, percent Medicare and privately insured patient visits, and and average patient age, sex, and race. Models are weighted using physician-level survey weights.

Table A.3: Hospital Ownership of Physician Practices - Unweighted and Exclude Psychiatry

	(1)	(2)	(3)	(4)	(5)
ln(HOPD/PO)	0.67	0.58	0.59		
	(0.45)	(0.44)	(0.44)		
Primary care × ln(HOPD/PO)				-1.64**	-1.69*
				(0.66)	(0.92)
Surgical care × ln(HOPD/PO)				0.37	0.38
				(0.60)	(0.58)
Medical care × ln(HOPD/PO)				1.93***	1.95***
				(0.54)	(0.54)
Region effects	No	Yes	Yes	Yes	Yes
Other controls	No	Yes	Yes	Yes	Yes
Specialty category	No	No	Yes	No	Yes
N	13,070	13,070	13,070	13,070	13,070

Source: NAMCS Public-Use file 2005 - 2015. * P<0.1, ** P<0.5, *** P<0.01. Robust standard errors are presented in parenthesis. Dependent variable is a binary indicator for hospital ownership. Coefficients have been multiplied by 100 and are interpreted as a percentage point in hospital ownership given a 10 percent increase in HOPD/PO. Year and specialty fixed effects are included in all specifications. Controls include an MSA/Non-MSA indicator, census region, solo versus group practice, percent of visits where the physician is the primary care provider, percent visits where the patient is referred to another physicians, percent Medicare and privately insured patient visits, and and average patient age, sex, and race. Psychiatry is excluded.

Table A.4: Hospital Ownership of Physician Practices - Omit Obstetrics/Gynecology and Pediatrics

	(1)	(2)	(3)	(4)	(5)
ln(HOPD/PO)	0.69	0.69	0.69		
	(0.56)	(0.54)	(0.54)		
Primary care × ln(HOPD/PO)				0.36	0.01
				(1.34)	(1.46)
Surgical care × ln(HOPD/PO)				-0.25	-0.24
				(0.83)	(0.83)
Medical care × ln(HOPD/PO)				1.52**	1.63**
				(0.64)	(0.65)
Region effects	No	Yes	Yes	Yes	Yes
Other controls	No	Yes	Yes	Yes	Yes
Specialty category	No	No	Yes	No	Yes
N	10,421	10,421	10,421	10,421	10,421

Source: NAMCS Public-Use file 2005 - 2015. * P<0.1, ** P<0.5, *** P<0.01. Robust standard errors are presented in parenthesis. Dependent variable is a binary indicator for hospital ownership. Coefficients have been multiplied by 100 and are interpreted as percentage point changes. HOPD/PO has been normalized to be mean 0 and have standard deviation of 1. Year and specialty fixed effects are included in all specifications. Controls include an MSA/Non-MSA indicator, census region, solo versus group practice, percent of visits where the provider is the primary care provider, percent visits where the patient is referred to another physicians, and average patient age, sex, and race. Models are weighted using physician-level survey weights. Obstetrics and Gynecology, Pediatrics, and Psychiatry are excluded.

Table A.5: Hospital Ownership of Physician Practices - 2005 - 2013

	(1)	(2)	(3)	(4)	(5)
ln(HOPD/PO)	1.22*	1.26*	1.29*		
	(0.67)	(0.66)	(0.66)		
Primary care × ln(HOPD/PO)				-0.70	-1.12
				(0.94)	(1.61)
Surgical care × ln(HOPD/PO)				1.47	1.24
				(0.98)	(1.04)
Medical care × ln(HOPD/PO)				1.25*	1.37**
				(0.69)	(0.66)
Region effects	No	Yes	Yes	Yes	Yes
Other controls	No	Yes	Yes	Yes	Yes
Specialty category	No	No	Yes	No	Yes
N	10,354	10,354	10,354	10,354	10,354

Source: NAMCS Public-Use file 2005 - 2015. * P<0.1, ** P<0.5, *** P<0.01. Robust standard errors are presented in parenthesis. Dependent variable is a binary indicator for hospital ownership. Coefficients are interpreted as a percentage point increase in hospital ownership given a 10 percent increase in HOPD/PO. Year and specialty fixed effects are included in all specifications. Controls include an MSA/Non-MSA indicator, census region, solo versus group practice, percent of visits where the physician is the primary care provider, percent visits where the patient is referred to another physicians, percent Medicare and privately insured patient visits, and and average patient age, sex, and race. Years 2014 and 2015 are excluded.

Table A.6: Hospital Ownership of Physician Practices - Exclude Each Specialty

	(1)	(2)	(3)	(4)	(5)	(6)
Primary care × ln(HOPD/PO)	-1.24	-1.02	-1.05	-1.29	-1.17	-1.02
	(1.03)	(1.04)	(1.13)	(1.03)	(1.09)	(1.01)
Surgical care × ln(HOPD/PO)	0.60	0.53	1.22	0.19	0.76	0.70
	(0.76)	(0.77)	(0.80)	(0.79)	(0.81)	(0.76)
Medical care × ln(HOPD/PO)	-0.11	1.90***	2.33***	1.90***	1.93***	2.03***
	(1.80)	(0.67)	(0.65)	(0.64)	(0.66)	(0.66)
Region effects	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Specialty category	Yes	Yes	Yes	Yes	Yes	Yes
N	12,164	12,405	10,498	12,216	11,752	12,272
	(7)	(8)	(9)	(10)	(11)	(12)
Primary care × ln(HOPD/PO)	-0.80	-0.96	-0.91	-1.03	-1.06	-0.95
	(1.32)	(1.06)	(1.07)	(1.03)	(1.06)	(1.03)
Surgical care × ln(HOPD/PO)	0.45	1.41	0.99	0.57	0.04	0.04
	(0.78)	(0.86)	(0.88)	(0.77)	(0.79)	(0.78)
Medical care × ln(HOPD/PO)	1.80***	1.94***	1.97***	1.92***	1.80***	1.91***
	(0.65)	(0.65)	(0.65)	(0.64)	(0.64)	(0.64)
Region effects	Yes	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Specialty category	Yes	Yes	Yes	Yes	Yes	Yes
N	11,988	12,165	12,090	12,393	11,503	12,324

Source: NAMCS Public-Use file 2005 - 2015. * P<0.1, ** P<0.5, *** P<0.01. Robust standard errors are presented in parenthesis. Dependent variable is a binary indicator for hospital ownership. Coefficients are interpreted as a percentage point increase in hospital ownership given a 10 percent increase in HOPD/PO. Year and specialty fixed effects are included in all specifications. Controls include an MSA/Non-MSA indicator, census region, solo versus group practice, percent of visits where the physician is the primary care provider, percent visits where the patient is referred to another physicians, percent Medicare and privately insured patient visits, and and average patient age, sex, and race. Specialties excluded by column are: 1 Cardiology, 2 Dermatology, 3 General/Family practice, 4 General surgery, 5 Internal Medicine, 6 Neurology, 7 Ob/Gyn, 8 Ophthalmology, 9 Orthopedic Surgery, 10 Otolaryngology, 11 Pediatrics, and 12 Urology.

Table A.7: Difference-in-Difference Specifications with Binary Treatment

Panel A: Four Specialties and 2007 Treatment Year				
	(1)	(2)	(3)	(4)
Treat × Post 2007	4.30***	5.19***	5.04***	3.67*
	(1.23)	(1.77)	(1.78)	(2.22)
Region effects	No	No	Yes	Yes
Other controls	No	No	Yes	Yes
N	6,776	4,954	4,889	4,889
Panel B: Four Specialties and 2010 Treatment Year				
	(1)	(2)	(3)	(4)
Treat × Post 2010	5.11***	5.00***	4.91***	5.24**
	(1.42)	(1.62)	(1.60)	(2.06)
Region effects	No	No	Yes	Yes
Other controls	No	No	Yes	Yes
N	6,776	4,954	4,889	4,889
Panel C: Six Specialties and 2007 Treatment Year				
	(1)	(2)	(3)	(4)
Treat × Post 2010	3.18***	3.45**	3.64**	1.95
	(1.00)	(1.53)	(1.53)	(1.77)
Region effects	No	No	Yes	Yes
Other controls	No	No	Yes	Yes
N	9,847	7,285	7,187	7,187
Panel D: Six Specialties and 2010 Treatment Year				
	(1)	(2)	(3)	(4)
Treat × Post 2010	3.75***	3.61***	3.89***	3.96***
	(1.09)	(1.27)	(1.27)	(1.52)
Region effects	No	No	Yes	Yes
Other controls	No	No	Yes	Yes
N	9,847	7,285	7,187	7,187

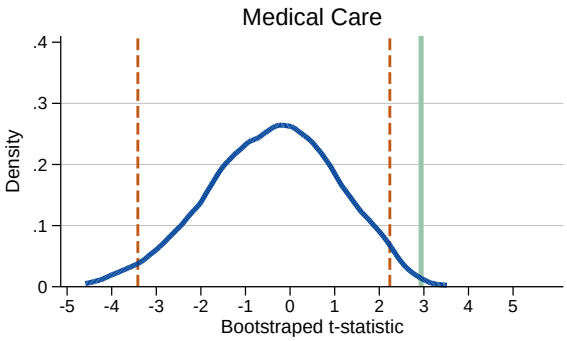
Source: NAMCS Public-Use file 2005 - 2015. * P<0.1, ** P<0.5, *** P<0.01. Robust standard errors are presented in parenthesis. Dependent variable is a binary indicator for hospital ownership. Coefficients are interpreted as a percentage point increase in hospital ownership. Year and specialty fixed effects are included in all specifications. Controls include an MSA/Non-MSA indicator, census region, solo versus group practice, percent of visits where the provider is the primary care provider, percent Medicare and private patient visits, and average patient age, sex, and race. Specialties in the treatment group include cardiology urology, and alternatively, orthopedic surgery. The comparison group includes dermatology, general and family practice, and alternatively, internal medicine.

Table A.8: Hospital Ownership of Physician Practices - Medicare Patient Share Interactions

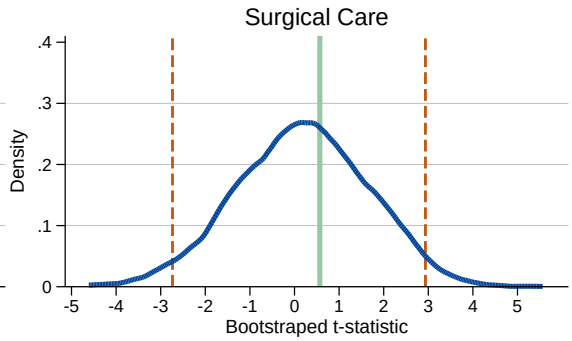
	(1)	(2)	(3)	(4)	(5)
ln(HOPD/PO)	0.50	0.59	0.57		
	(0.70)	(0.68)	(0.68)		
> Median % Medicare×ln(HOPD/PO)	0.59	0.35	0.39		
	(0.58)	(0.57)	(0.57)		
Primary care × ln(HOPD/PO)				-0.89	-1.12
				(1.13)	(1.10)
Surgical care × ln(HOPD/PO)				0.50	0.80
				(0.87)	(0.86)
Medical care × ln(HOPD/PO)				1.54	1.25
				(1.79)	(1.70)
> Median % Medicare×Primary care×ln(HOPD/PO)				0.33	0.34
				(1.81)	(1.80)
> Median % Medicare×Surgical care×ln(HOPD/PO)				0.14	-0.17
				(0.83)	(0.82)
> Median % Medicare×Medical care×ln(HOPD/PO)				0.67	0.89
				(1.69)	(1.62)
Region effects	No	Yes	Yes	No	Yes
Other controls	No	Yes	Yes	No	Yes
Specialty category	No	No	Yes	Yes	Yes
Total Effect	1.09	0.94	0.96		
P-value	0.0479	0.0807	0.0736		
Primary Care Total Effect				-0.55	-0.79
P-Value				0.7467	0.6393
Surgical Care Total Effect				0.64	0.63
P-Value				0.4595	0.4576
Medical Care Total Effect				2.21	2.14
P-Value				0.0002	0.0003
N	13,070	13,070	13,070	13,070	13,070

Source: NAMCS Public-Use file 2005 - 2015. * P<0.1, ** P<0.5, *** P<0.01. Robust standard errors are presented in parenthesis. Dependent variable is a binary indicator for hospital ownership. Coefficients have been multiplied by 100 and are interpreted as a percentage point in hospital ownership given a 10 percent increase in HOPD/PO. Year and specialty fixed effects are included in all specifications. Controls include an MSA/Non-MSA indicator, census region, solo versus group practice, percent of visits where the physician is the primary care provider, percent visits where the patient is referred to another physicians, percent Medicare and privately insured patient visits, and and average patient age, sex, and race. Models are weighted using physician-level survey weights. Psychiatry is excluded.

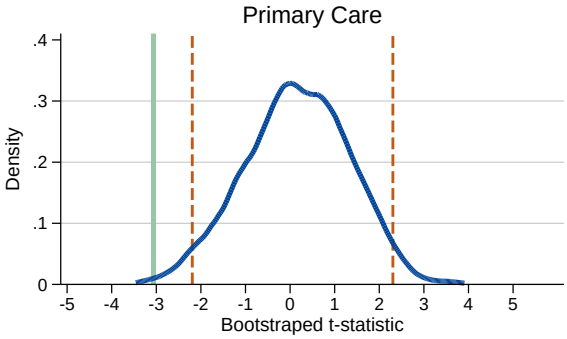
Figure A.1: Pair Bootstrap T-Statistic Distributions by Specialty Category



P-value from a 2-tailed symmetric test is 0.047.



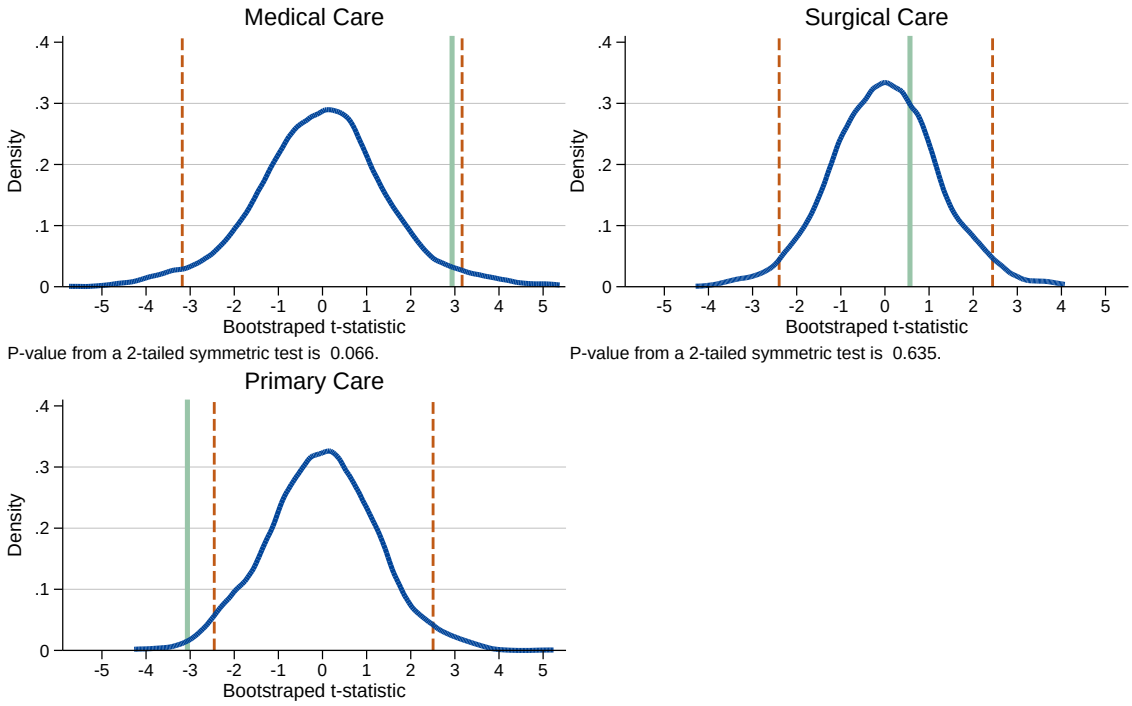
P-value from a 2-tailed symmetric test is 0.703.



P-value from a 2-tailed symmetric test is 0.007.

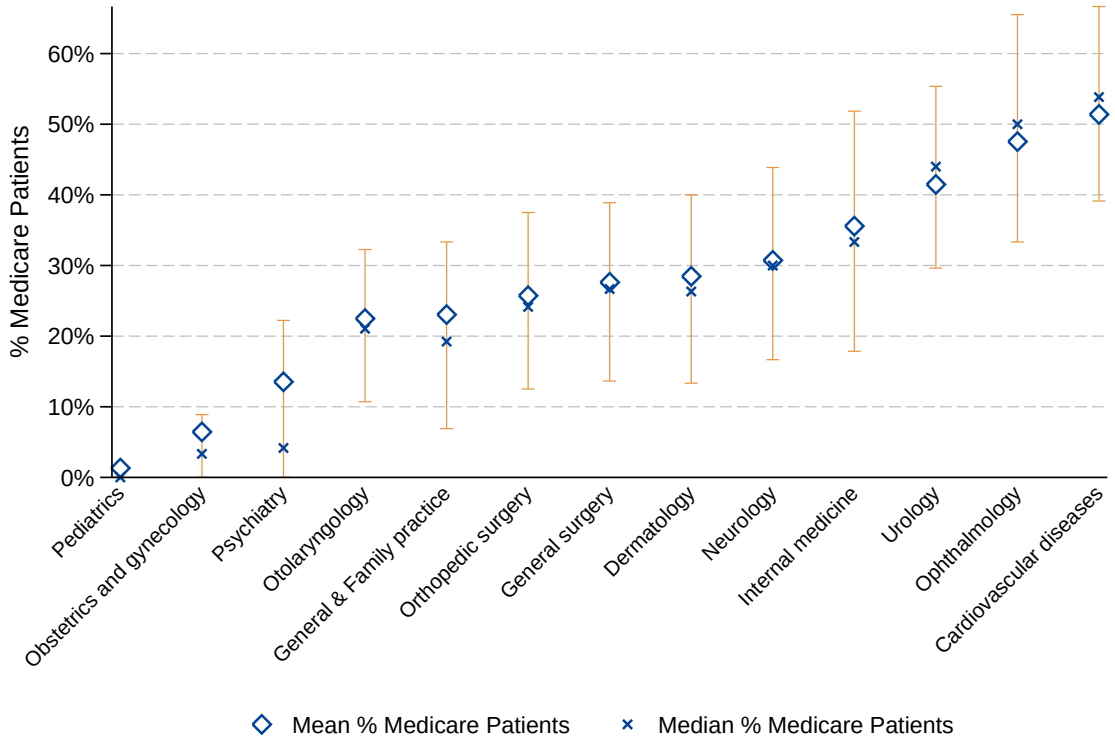
*Dashed lines represent the 2.5th and 97.5th percentiles of the t-statistic distribution generated by a paired bootstrap procedure over clusters with successful replications. The solid line is the t-statistic from the original model.

Figure A.2: Wild Bootstrap T-Statistic Distributions by Specialty Category



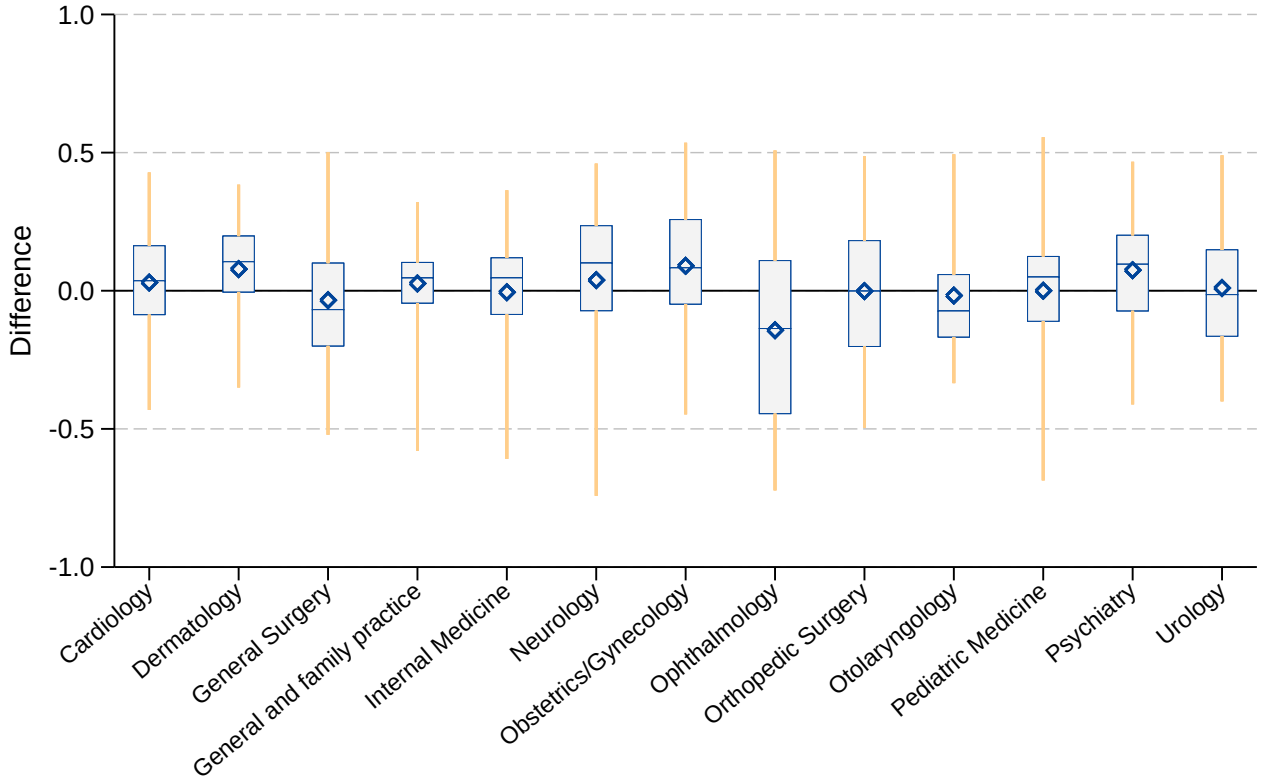
*Dashed lines represent the 2.5th and 97.5th percentiles of the t-statistic distribution generated by a wild bootstrap procedure over clusters with 1999 replications. The solid line is the t-statistic from the original model.

Figure A.3: Medicare Patient Share by Specialty



Source: NAMCS Public-Use file 2005-2015. Lines span the 25th to 75th percentile.

Figure A.4: Distribution of Provider-Specific Relative Reimbursement by Specialty



Source: 2012 - 2015 CMS Medicare Provider Payment and Utilization Data for physicians and other providers. Statistics are calculated as the difference in a provider's annual relative-price measure and the average relative price across all providers within the same specialty for that year. Boxes span the 25 to 75th percentile, and whiskers span the 5th to 95th percentile. Mean and median indicated by a diamond and horizontal line, respectively.

Chapter B: Chapter 2 Appendix

B.1 Additional Specifications for Aggregate Medicaid Expenditure Models

Table B.1 shows additional model specifications comparable to Table 2.6. These specifications include other spending categories in the MSIS data. Overall estimated magnitudes on the FCA coefficient are smaller (in absolute value) than those in the prescription drug specifications and are mostly insignificant. Note that for some spending categories, there are small cell sizes, particularly for children in the nursing home and home health service spending categories. There is a statistically significant and unreasonably large negative effect of FCA legislation on home health expenditures for children and adults, however we are cautious in the interpretation of this result since over 95 percent of spending and eligibles in the home health service category are disabled and aged, and in many state-year cells home health spending on children and adults is zero or very small.

Table B.2 shows model specifications which split the sample into pre- and post-Medicare Part D periods, as well as include state-Part D interactions and state linear time trends. Since Medicare Part D had such a large impact on prescription drug utilization and spending among dually eligible individuals, we may be concerned that this program adds extra noise to our model or potentially results in biased estimates if states with a FCA respond in a systematically different way than those without. Examining aggregate Medicaid expenditures on prescription drugs in both pre- and post-Medicare Part D periods does not significantly affect coefficient estimates for the FCA term. Coefficient estimates are slightly smaller, and standard errors inflate some, especially in the 2006 through 2012 period. This is not surprising since these specifications eliminate roughly half of the identifying variation in FCA implementation. Including state-specific part-D interactions (a binary variable equal to 1 in years 2006 through 2012 and 0 otherwise) decreases coefficient magnitudes on the FCA term. Statistical significance disappears when state linear trends are included. This could occur if the effects of FCA legislation accumulate relatively slowly over time and are difficult to disentangle from other state-specific trends.

Table B.1: MSIS Aggregate Medicaid Expenditure Results

	All (Except Aged)	Child	Adult	Disabled	All	Aged
Nursing Facility						
FCA	-6.80	-18.30	-2.77	-7.75	-9.30	-5.84
	(7.35)	(38.68)	(28.16)	(7.06)	(6.57)	(7.89)
Log MFCU	0.43	-2.58*	0.58	0.15	0.21	0.30
	(0.59)	(1.44)	(0.92)	(0.35)	(0.49)	(0.45)
N	686	506	658	686	686	686
Inpatient Hospital						
FCA	-4.18	-4.41	3.63	-0.60	-2.67	1.50
	(6.41)	(9.58)	(12.45)	(6.81)	(6.67)	(9.32)
Log MFCU	0.06	-0.05	0.24	0.15	0.17	0.51**
	(0.37)	(0.48)	(0.34)	(0.19)	(0.29)	(0.25)
N	686	686	686	686	686	685
Outpatient Hospital						
FCA	-8.88	-11.42	0.36	-4.73	-7.03	-0.59
	(9.98)	(16.77)	(16.56)	(9.06)	(10.11)	(19.44)
Log MFCU	-0.72	-0.36	-0.03	-0.40	-0.69	-0.06
	(0.68)	(0.78)	(0.49)	(0.49)	(0.63)	(0.56)
N	686	686	686	686	686	685
Physician						
FCA	-12.28	-9.62	-8.12	-8.45	-9.87	-16.30
	(9.14)	(15.39)	(16.86)	(9.73)	(9.87)	(14.24)
Log MFCU	-0.17	-0.09	0.17	0.25	0.01	0.15
	(0.52)	(0.56)	(0.41)	(0.34)	(0.50)	(0.49)
N	686	686	686	686	686	683
Home Health						
FCA	9.16	-52.45**	-35.60*	22.60	11.38	-2.01
	(30.97)	(14.24)	(15.01)	(37.45)	(34.16)	(30.64)
Log MFCU	0.56	-0.09	0.94**	0.51	0.50	0.72
	(0.90)	(0.86)	(0.47)	(0.54)	(0.94)	(0.57)
N	681	679	680	682	682	676

* P<0.1, ** P<0.5, *** P<0.01. Standard errors are in parenthesis and are clustered at the state level. Coefficients have been transformed using $(e^{\beta-1}) * 100$ and are interpreted as a percentage change. MFCU is interpreted as an elasticity for a 10 percent change in MFCU expenditures. AZ and TN are excluded from all specifications. Year and state effects are included in all specifications as are controls for state population demographics, welfare program characteristics, political controls, Medicaid eligible population controls for age, MCO enrollment and dual eligibility. All and All Except Aged specifications additionally control for relative group composition.

Table B.2: MSIS Additional Specifications

	All (Except Aged)	Child	Adult	Disabled	All	Aged
Years 2006 - 2012						
FCA	-13.53	-18.59	-12.17	-9.16	-10.14	-0.78
	(10.18)	(14.28)	(18.44)	(11.21)	(10.81)	(16.98)
Log MFCU	0.34	0.39	0.57	0.23	0.40	0.79
	(0.62)	(0.72)	(0.44)	(0.48)	(0.61)	(0.66)
N	342	342	342	342	342	342
Years 1999 - 2005						
FCA	-12.19***	-6.55	-19.16	-12.25**	-9.05**	-4.82
	(4.02)	(12.67)	(11.29)	(4.77)	(3.25)	(4.87)
Log MFCU	-0.01	-0.01	0.12	0.07	0.03	0.04
	(0.13)	(0.24)	(0.34)	(0.10)	(0.12)	(0.06)
N	343	343	343	343	343	343
State × Part-D Interaction						
FCA	-11.22*	-9.80	-10.62	-10.66**	-8.45	-3.16
	(5.53)	(13.66)	(14.01)	(4.62)	(5.43)	(6.82)
Log MFCU	0.29	0.07	0.37	0.18	0.33	0.48*
	(0.32)	(0.43)	(0.29)	(0.21)	(0.32)	(0.28)
N	685	685	685	685	685	685
State-Year Linear Trends						
FCA	-1.51	-9.98	-14.24	-0.24	2.17	3.93
	(6.73)	(15.40)	(16.49)	(4.62)	(7.32)	(9.61)
Log MFCU	-0.20	-0.27	-0.24	0.00	-0.17	-0.04
	(0.25)	(0.32)	(0.28)	(0.14)	(0.25)	(0.27)
N	685	685	685	685	685	685

* P<0.1, ** P<0.5, *** P<0.01. Standard errors are in parenthesis and are clustered at the state level. Coefficients have been transformed using $(e^{\beta-1}) * 100$ and are interpreted as a percentage change. MFCU is interpreted as an elasticity for a 10 percent change in MFCU expenditures. AZ and TN are excluded. Year and state effects are included in all specifications as are controls for state population demographics, welfare program characteristics, political controls, Medicaid eligible population controls for age, MCO enrollment and dual eligibility. All and All Except Aged specifications additionally control for relative group composition.

B.2 Continuous Off-label Rates

David Bradford, Meridith Paker, and Jonathan Williams provided us estimates of off-label usage rates, estimated using data from the Medical Expenditure Panel Survey from 2007 to 2011. We were given a list of generic drug names, raw off-label usage rates, and estimated off-label usage rates by year. We linked the generic names provided to NDC's and then match these NDC's to the State Drug Utilization Data and Medispan drug classes.[1] Of the 51,782 NDC-year observations linked to the Bradford, Paker, and Williams data, we match 62% to the State Drug Utilization data from 2007-2011, resulting in 896,160 state-year-NDC observations matched to an estimated off-label rate; this accounts for about 55% of observations in the SDUD and 75% of prescription volume. We further impute off-label rates for NDC's which are not matched to an off-label rate, but share the same drug name in the Medispan data. We then calculate an average off-label usage rate for each drug class in our dataset. This drug class average off-label rate is weighted by the number of prescriptions observed for each NDC from 2007 to 2011, since the estimated off-label rates vary by NDC and year. Although the provided estimated off-label rates vary over time, we collapse the off-label rates into time-invariant averages for two reasons. First, we do not have estimated offlabel rates for most years in the SDUD, and second, this avoids any confounding effect if state FCAs effect both Medicaid expenditure and off-label usage. For all specifications, we limit the sample to the top 40 drug classes in terms of prescriptions and/or spending. These classes comprise over 90% of prescriptions and spending.

B.3 Off-label Prone Categorization

We reviewed numerous studies which examine particular therapeutic classes or drugs and quantify the relative off-label usage rates. Column 3 in Table B.3 summarizes our determination of off-label "prone" versus not based upon this literature. In some instances, the literature is silent on a particular therapeutic class, or it is unclear how the studied

[1] We match about 92% of the provided generic name-year observations to NDC's. Using the same MEPS data, and only our "linked" generic name-year-NDC data, we get very similar estimates of off-label rates by drug class and overall off-label rates.

class related to therapeutic classes included in the Medispan classification system; in these cases we refrain from assigning a classification of prone versus not. Estimates of off-label usage rates provided by Bradford, Paker, and Williams are used as an additional resource to determine which therapeutic classes are more prone to off-label use. Estimated off-label rates provided by Bradford, Paker, and Williams are calculated at the year-drug name level for years 2007 through 2011. We match drug names to NDC's and then aggregate up to the therapeutic class, defined by primary and secondary classes in the Medispan GPI. We weight estimated off-label rates by prescription volume in the SDUD for years 2007 through 2011 to calculate an average off-label rate. Bradford, Paker, and Williams exclude analgesics from their analysis and so we do not included these in our analysis. Column 4 of Table 3A shows the proportion of prescriptions in each therapeutic class that is successfully matched to an estimated off-label probability, and Column 5 presents the average estimated off-label rate. Column 6 combines both the medical literature and estimates provided by Bradford, Paker, and Williams and summarizes whether the sources generally agree or not.

The average off-label rate across all drug classes is 43.8 percent. For classes which the medical literature indicates are prone to off-label use, the average estimated off-label rate is 44.0 percent. For classes indicated as not prone the average rate is 22.9 percent. In general, we determine that there is agreement between the medical literature and the estimated off-label rates if the prone classes are associated with an estimated off-label rate that is high relative to the average rate of about 43 percent and are within the same range as the medical literature. We determine agreement for the not prone classes in the same manner, indicating agreement if the estimated off-label rate is below average and within a similar range as the medical literature. There is disagreement between the estimated off-label rates and medical literature classification for two classes that are categorized as off-label prone: antiasmathics and beta-blockers. Lin, Phan, and Lin (2006) find off-label rates of beta-blockers of 52 percent whereas Bradford, Paker, & Williams find a rate of 30.1 percent, which is below the average estimated off-label rate. There is a larger difference for antiashmathics where Radley, Finkelstein, and Stafford (2009) find off-label rates of 42 percent, Bradford, Paker, & Williams estimate relatively low off-label use of 24 percent. Similarly, in the "not prone" categorization, our sources indicate very different levels of off-label use of contraceptives.

We omit these therapeutic classes from certain model specifications.

Table B.3: Therapeutic Class Prone Vs. Not Categorization and Medical Literature

Therapeutic Class	Medical Literature on Off-Label Use by Drug Class	Medical Literature Prone/Not	Match Rate	Average Off-Label Rate	Agreement
Anticoagulants	Radley, Finkelstein & Stafford (2006) Cardiac therapies [including antianginals antiarrhythmics, and anticoagulants] have off-label usage rate of 46% (pg. 1023 and Table 1).	Prone	97.43	71.85	Yes
Antiarrhythmics	Radley, Finkelstein & Stafford (2006) Cardiac therapies [including antianginals antiarrhythmics, and anticoagulants] have off-label usage rate of 46% (pg. 1023 and Table 1).	Prone	85.54	53.06	Yes
Anticonvulsants	Young & Adams (2003) Three-quarters of anti seizure medications are prescribed off-label. Chen et al. (2005) 71.3% of of anticonvulsant recipients were prescribed at least one off-label anticonvulsant prescription (pg. 633). Radley, Finkelstein & Stafford (2006) Anticonvulsants have off-label usage rate of 46% (pg. 1023 and Table 1). Walton et al. (2008) Ranking the top 25 drugs by volume of off-label use with inadequate evidence, the most prominent classes include anxiolytic sedatives ([including] clonazepam) (pg. 1447 Tables 1 and 2).	Prone	99.09	49.14	Yes

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Table B.3 – continued from previous page

Therapeutic Class	Medical Literature on Off-Label Use by Drug Class	Medical Literature Prone/Not		Average Off-Label Rate	Agreement
Antianxiety Agents	Radley, Finkelstein & Stafford (2006) Psychiatric therapies [including antidepressants, anxiolytics, and antipsychotics] have off-label usage rate of 31% (Table 1). Walton et al. (2008) Ranking the top 25 drugs by volume of off-label use with inadequate evidence, the most prominent classes include anxiolytic sedatives ([including] lorazepam) (pg. 1447 Tables 1 and 2).	Prone	99.89	48.27	Yes

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Table B.3 – continued from previous page

Therapeutic Class	Medical Literature on Off-Label Use by Drug Class	Medical Literature Prone/Not		Average Off-Label Rate	Agreement
Antipsychotics/Antimanic Agents	Young & Adams (2003) Two-thirds of antipsychotics are prescribed off-label. Radley, Finkelstein & Stafford (2006) Psychiatric therapies [including antidepressants, anxiolytics, and antipsychotics] have off-label usage rate of 31% (Table 1). Walton et al. (2008) Ranking the top 25 drugs by volume of off-label use with inadequate evidence, the most prominent classes include antipsychotics(quetiapine and risperidone) (pg. 1447 Tables 1 and 2). Alexander et al. (2011) In 1995, 74% of all antipsychotic treatment visits were for conditions not approved by the FDA [off-label]. By, 2008, 60% were off-label. Off-label use of atypical antipsychotics increased from 50% to 66%; off-label use of typical agents declined from 78% to 67%. The majority of off-label use of antipsychotics is not backed by moderate or good scientific evidence. (pg. 180 and 182 Tables 3 and 4).	Prone	98.80	46.16	Yes
Antianginal Agents	Radley, Finkelstein & Stafford (2006) Cardiac therapies [including antianginals antiarrhythmics, and anticoagulants] have off-label usage rate of 46% (pg. 1023 and Table 1).	Prone	99.87	44.44	Yes

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Table B.3 – continued from previous page

Therapeutic Class	Medical Literature on Off-Label Use by Drug Class	Medical Literature Prone/Not		Average Off-Label Rate	Agreement
Antidepressants	Young & Adams (2003) one-quarter of antidepressants are prescribed off-label. Radley, Finkelstein & Stafford (2006) Psychiatric therapies [including antidepressants, anxiolytics, and antipsychotics] have off-label usage rate of 31% (Table 1). Walton et al. (2008) Ranking the top 25 drugs by volume of off-label use with inadequate evidence, the most prominent classes include antidepressants (escitalopram, trazodone, sertraline, bupropion, amitriptyline, and venlafaxine) (pg. 1447 Tables 1 and 2).	Prone	99.79	39.27	Yes
Ulcer Drugs	Radley, Finkelstein & Stafford (2006) Peptic ulcer and dyspepsia therapies have an off-label usage rate of 30% (pg. 1024 Table 1). Barletta et al. (2015) 63% of gastrointestinal (GI) medication orders in intensive care units were off-label. Proton Pump Inhibitors (PPIs) accounted for most of the off-label use; 99% of PPIs, 99% of Histamin-2-Receptor-Antaganists (H2RA's) and 79% of promotility agents were off-label (pg. 219 and Figure 2).	Prone	98.44	38.84	Yes
Beta Blockers	Lin, Phan, & Lin (2006) 52.0% of all Beta-blocker related visits were prescribed Beta-blockers without approved indications (pg. 1741).	Prone	99.97	30.11	No

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Table B.3 – continued from previous page

Therapeutic Class	Medical Literature on Off-Label Use by Drug Class	Medical Literature Prone/Not		Average Off-Label Rate	Agreement
Antiasthmatic And Bronchodilator Agents	Radley, Finkelstein & Stafford (2006) Antiasthmatics have off-label usage rate of 42% (pg. 1023 and Table 1).	Prone	83.42	24.20	No
Analgesics - Opioid	Radley, Finkelstein & Stafford (2006) Analgesics have off-label usage rate of 6% (pg. 1023 and Table 1).	Not Prone	-	-	-
Analgesics - Nonnarcotic	Radley, Finkelstein & Stafford (2006) Analgesics have off-label usage rate of 6% (pg. 1023 and Table 1).	Not Prone	-	-	-
Analgesics - Anti-inflammatory	Radley, Finkelstein & Stafford (2006) Analgesics have off-label usage rate of 6% (pg. 1023 and Table 1).	Not Prone	-	-	-
Contraceptives	Radley, Finkelstein & Stafford (2006) Womens health therapies [including hormone therapies and oral contraceptives] have off-label usage rate of 11% (Table 1).	Not Prone	29.17	42.77	No
Antihypertensives	Radley, Finkelstein & Stafford (2006) Anthypertensives have off-label usage rate of 14% (pg. 1023 and Table 1).	Not Prone	98.56	23.64	Yes
Antihyperlipidemics	Radley, Finkelstein & Stafford (2006) Medications to lower lipid levels have off-label usage rate of 7% (pg. 1023 and Table 1).	Not Prone	99.87	17.42	Yes
Antidiabetics	Radley, Finkelstein & Stafford (2006) Diabetes therapies [medications for glycemic controlin diabetes mellitus] have off-label usage rate of <1% (pg. 1023 and Table 1).	Not Prone	98.35	11.41	Yes

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Table B.3 – continued from previous page

Therapeutic Class	Medical Literature on Off-Label Use by Drug Class	Medical Literature Prone/Not	Average Off-Label Rate	Agreement
Adhd/Anti-narcolepsy/Anti-obesity/Anorexiants		99.20	67.03	
Musculoskeletal Therapy Agents		98.75	64.51	
Thyroid Agents		99.98	63.36	
Antiparkinson Agents		99.62	60.15	
Antivirals		90.38	55.59	
Anti-infective Agents - Misc.		94.06	47.29	
Fluoroquinolones		99.03	46.93	
Dermatologicals		83.89	44.53	
Ophthalmic Agents		77.91	44.47	
Endocrine And Metabolic Agents - Misc.		91.66	43.22	
Hematopoietic Agents		70.88	41.33	
Diuretics		99.48	40.50	
Corticosteroids		90.16	40.42	
Laxatives		69.50	39.97	
Minerals & Electrolytes		44.10	38.95	

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Table B.3 – continued from previous page

Therapeutic Class	Medical Literature on Off-Label Use by Drug Class	Medical Literature Prone/Not	Average Off-Label Rate	Agreement
Macrolides		98.94	38.77	
Cough/Cold/Allergy		32.43	38.18	
Cephalosporins		96.17	37.88	
Penicillins		99.05	34.95	
Hypnotics/Sedatives/Sleep Disorder Agents	Walton et al. (2008) Ranking the top 25 drugs by volume of off-label use with inadequate evidence, the most prominent classes include anxiolytic sedatives ([including] zolpidem) (pg. 1447 Tables 1 and 2).	97.35	30.87	
Antihistamines		97.46	30.73	
Nasal Agents - Systemic And Topical		99.16	25.10	
Calcium Channel Blockers		54.22	24.54	
Multivitamins		0.00	0.00	

Therapeutic classes are defined using Medispan's Generic Product Identifer (GPI). Bradford, Packer, & Williams limit their sample to non-analgesics, and so there is no estimated off-label probability for these classes. We also include in our categorization of off-label prone drugs Antiarrhythmics, which rank 64 in total prescriptions at 0.09%, and has an predicted off-label probability of 53.06%. No NDC in the Multivitamins therapeutic class is matched to the Bradford, Packer, & Williams dataset.

B.4 Additional Specifications for Models using SDUD

Tables B.4 through B.7 provide additional model specifications using the SDUD. Similar to specifications checks using the MSIS data, we split the sample in half and re-estimate models separately for pre- and post Medicare Part D implementation. Tables B.8 and B.9 relax the restriction of observing each drug subclass in every year during the sample period. Specifications where we use a binary off-label classification exhibit similar magnitudes in the FCA and FCA and off-label interaction terms, but typically with smaller standard errors.

Table B.4: Medical Literature Categorization of Off-label Prone Classes - Pre Medicare Part-D (Years 1999 - 2005)

Prescription Drug Spending									
	Medical Lit. Prone vs. Not			Omit Analgesics			Omit Analgesics; Agree		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
FCA × Off-Label	-11.66**	-1.61	-3.28	-14.48**	0.52	-1.28	-16.70**	3.33	1.59
	(4.59)	(2.42)	(2.36)	(5.30)	(4.11)	(3.98)	(6.63)	(6.84)	(5.77)
FCA	-10.37	-16.07*	9.62*	-7.74	-17.38**	7.09	-7.90	-20.31*	5.14
	(8.56)	(8.04)	(5.97)	(8.53)	(7.63)	(6.64)	(10.32)	(10.42)	(6.43)
Log MFCU	-0.24	-0.24	-0.14	-0.24	-0.23	-0.15	-0.30	-0.29	-0.07
	(0.19)	(0.19)	(0.16)	(0.20)	(0.20)	(0.18)	(0.23)	(0.24)	(0.18)
Off-label × year	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Off-label × state	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
State time trend	No	No	Yes	No	No	Yes	No	No	Yes
N	26,206	26,206	26,206	23,564	23,564	23,564	18,510	18,510	18,510
Number of Prescriptions									
	Medical Lit. Prone vs. Not			Omit Analgesics			Omit Analgesics; Agree		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
FCA × Off-Label	-10.29**	-0.94	-2.19	-12.33**	1.85	0.55	-14.37**	5.67	4.33
	(4.58)	(3.46)	(2.83)	(5.21)	(4.64)	(3.97)	(6.49)	(8.54)	(7.39)
FCA	-10.63	-15.90*	9.93**	-9.49	-18.28**	7.66*	-9.93	-21.77*	3.84
	(7.80)	(8.01)	(4.23)	(7.76)	(7.72)	(4.33)	(9.20)	(10.44)	(5.26)
Log MFCU	-0.15	-0.15	-0.22	-0.17	-0.17	-0.24	-0.22	-0.21	-0.20
	(0.15)	(0.15)	(0.15)	(0.16)	(0.16)	(0.16)	(0.19)	(0.19)	(0.16)
Off-label × year	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Off-label × state	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
State time trend	No	No	Yes	No	No	Yes	No	No	Yes
N	26,206	26,206	26,206	23,564	23,564	23,564	18,510	18,510	18,510

* P<0.1, ** P<0.5, *** P<0.01. Standard errors are in parenthesis and are clustered at the state level. All models include controls for state demographics, Medicaid population composition and number of eligibles, state welfare programs, political party of state government, and prescription drug policies as well as state, year, drug therapeutic class and subclass fixed effects. All coefficient estimates have been transformed by $(e^{\beta}-1)\times 100$ and are interpreted as a percentage change except MFCU which is an elasticity with regard to a 10 percent increase in MFCU expenditures.

Table B.5: Continuous Estimated Off-Label Rate Categorization - Pre Medicare Part-D (Years 1999 - 2005)

Prescription Drug Spending									
	Medical Lit. Prone vs. Not			Omit Analgesics			Omit Analgesics; Agree		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
FCA × Off-Label	-23.07	11.90	8.30	-27.33	14.00	10.47	-28.30*	14.36	9.48
	(13.71)	(19.62)	(16.83)	(14.25)	(22.63)	(19.65)	(13.38)	(22.83)	(18.64)
FCA	-9.42	-21.22*	1.55	-7.70	-21.62*	-0.04	-7.19	-21.83	1.87
	(10.25)	(10.71)	(7.20)	(10.74)	(11.27)	(7.21)	(11.86)	(12.65)	(7.54)
Log MFCU	-0.26	-0.26	-0.14	-0.26	-0.26	-0.13	-0.30	-0.31	-0.08
	(0.19)	(0.19)	(0.19)	(0.20)	(0.20)	(0.19)	(0.23)	(0.23)	(0.18)
Off-label × year	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Off-label × state	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
State time trend	No	No	Yes	No	No	Yes	No	No	Yes
N	24,516	24,516	24,516	21,419	21,419	21,419	17,006	17,006	17,006
Number of Prescriptions									
	Medical Lit. Prone vs. Not			Omit Analgesics			Omit Analgesics; Agree		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
FCA × Off-Label	-13.63	16.65	13.75	-20.03	16.29	13.52	-21.15	16.74	12.84
	(16.37)	(23.09)	(20.16)	(15.17)	(26.33)	(23.40)	(14.28)	(27.28)	(23.23)
FCA	-13.78	-22.86*	0.48	-11.61	-22.83*	0.25	-11.39	-23.27	1.06
	(9.48)	(11.02)	(6.49)	(9.68)	(11.69)	(7.08)	(10.58)	(12.92)	(7.30)
Log MFCU	-0.19	-0.19	-0.21	-0.20	-0.21	-0.20	-0.23	-0.23	-0.17
	(0.15)	(0.15)	(0.16)	(0.17)	(0.17)	(0.16)	(0.19)	(0.19)	(0.16)
Off-label × year	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Off-label × state	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
State time trend	No	No	Yes	No	No	Yes	No	No	Yes
N	24,516	24,516	24,516	21,419	21,419	21,419	17,006	17,006	17,006

* P<0.1, ** P<0.5, *** P<0.01. Standard errors are in parenthesis and are clustered at the state level. All models include controls for state demographics, Medicaid population composition and number of eligibles, state welfare programs, political party of state government, and prescription drug policies as well as state, year, drug therapeutic class and subclass fixed effects. All coefficient estimates have been transformed by $(e^{\beta}-1)\times 100$ and are interpreted as a percentage change except MFCU which is an elasticity with regard to a 10 percent increase in MFCU expenditures.

Table B.6: Medical Literature Categorization of Off-label Prone Classes - Post Medicare Part-D (Years 2006 - 2012)

Prescription Drug Spending									
	Medical Lit. Prone vs. Not			Omit Analgesics			Omit Analgesics; Agree		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
FCA × Off-Label	-7.86	-2.96	-3.17	-8.35	-1.71	-2.15	-9.71	-9.32*	-9.26*
	(6.37)	(6.25)	(6.28)	(6.77)	(6.62)	(6.60)	(7.54)	(5.21)	(5.23)
FCA	-9.36	-11.69	-11.28	-6.18	-10.05	-11.54	-1.57	-2.03	-6.10
	(9.40)	(9.16)	(9.39)	(10.16)	(9.91)	(9.67)	(9.78)	(10.27)	(9.35)
Log MFCU	0.80	0.82	0.42	0.95	0.96	0.36	0.91	0.90	0.27
	(0.61)	(0.61)	(0.51)	(0.71)	(0.71)	(0.52)	(0.66)	(0.66)	(0.41)
Off-label × year	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Off-label × state	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
State time trend	No	No	Yes	No	No	Yes	No	No	Yes
N	27,682	27,682	27,682	25,016	25,016	25,016	19,235	19,235	19,235
Number of Prescriptions									
	Medical Lit. Prone vs. Not			Omit Analgesics			Omit Analgesics; Agree		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
FCA × Off-Label	-6.04	-0.84	-0.99	-4.75	1.09	0.75	-6.56	-4.12	-4.04
	(6.08)	(6.09)	(6.09)	(6.84)	(6.84)	(6.83)	(7.80)	(5.93)	(5.93)
FCA	-5.81	-8.36	-5.81	-4.22	-7.69	-6.72	0.67	-1.17	-2.24
	(9.01)	(8.89)	(8.88)	(9.64)	(9.54)	(9.22)	(9.34)	(9.95)	(8.67)
Log MFCU	0.64	0.65	0.23	0.74	0.74	0.18	0.67	0.65	0.12
	(0.47)	(0.47)	(0.41)	(0.54)	(0.54)	(0.42)	(0.49)	(0.48)	(0.33)
Off-label × year	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Off-label × state	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
State time trend	No	No	Yes	No	No	Yes	No	No	Yes
N	27,682	27,682	27,682	25,016	25,016	25,016	19,235	19,235	19,235

* P<0.1, ** P<0.5, *** P<0.01. Standard errors are in parenthesis and are clustered at the state level. All models include controls for state demographics, Medicaid population composition and number of eligibles, state welfare programs, political party of state government, and prescription drug policies as well as state, year, drug therapeutic class and subclass fixed effects. All coefficient estimates have been transformed by $(e^{\beta}-1)\times 100$ and are interpreted as a percentage change except MFCU which is an elasticity with regard to a 10 percent increase in MFCU expenditures.

Table B.7: Continuous Estimated Off-Label Rate Categorization - Post Medicare Part-D (Years 2006 - 2012)

Prescription Drug Spending									
	Medical Lit. Prone vs. Not			Omit Analgesics			Omit Analgesics; Agree		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
FCA × Off-Label	-1.82	-18.30*	-19.46*	-4.85	-26.48**	-25.79**	-3.44	-25.01**	-25.13**
	(17.42)	(9.25)	(9.17)	(18.18)	(8.87)	(9.02)	(18.88)	(9.47)	(9.55)
FCA	-8.48	-2.39	-6.60	-7.37	1.14	-4.12	-5.47	3.06	-3.09
	(10.04)	(10.65)	(10.24)	(10.22)	(11.34)	(10.46)	(10.52)	(11.07)	(10.44)
Log MFCU	1.14	1.13	0.44	1.12	1.11	0.44	0.99	0.98	0.31
	(0.75)	(0.75)	(0.55)	(0.75)	(0.75)	(0.57)	(0.69)	(0.69)	(0.44)
Off-label × year	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Off-label × state	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
State time trend	No	No	Yes	No	No	Yes	No	No	Yes
N	25,538	25,538	25,538	22,376	22,376	22,376	17,923	17,923	17,923
Number of Prescriptions									
	Medical Lit. Prone vs. Not			Omit Analgesics			Omit Analgesics; Agree		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
FCA × Off-Label	13.78	-10.27	-11.17	6.85	-17.12	-16.39	8.30	-16.71	-16.69
	(21.46)	(10.18)	(10.38)	(19.73)	(9.89)	(9.98)	(20.65)	(10.66)	(10.75)
FCA	-9.68	-1.76	-2.80	-7.38	0.97	-2.01	-5.30	3.57	0.19
	(9.80)	(10.39)	(9.48)	(9.68)	(11.09)	(9.59)	(10.12)	(11.15)	(9.64)
Log MFCU	0.90	0.88	0.19	0.85	0.84	0.20	0.72	0.70	0.12
	(0.59)	(0.58)	(0.46)	(0.56)	(0.56)	(0.46)	(0.52)	(0.51)	(0.36)
Off-label × year	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Off-label × state	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
State time trend	No	No	Yes	No	No	Yes	No	No	Yes
N	25,538	25,538	25,538	22,376	22,376	22,376	17,923	17,923	17,923

* P<0.1, ** P<0.5, *** P<0.01. Standard errors are in parenthesis and are clustered at the state level. All models include controls for state demographics, Medicaid population composition and number of eligibles, state welfare programs, political party of state government, and prescription drug policies as well as state, year, drug therapeutic class and subclass fixed effects. All coefficient estimates have been transformed by $(e^{\beta}-1)\times 100$ and are interpreted as a percentage change except MFCU which is an elasticity with regard to a 10 percent increase in MFCU expenditures.

Table B.8: Medical Literature Categorization of Off-label Prone Classes

Prescription Drug Spending									
	Medical Lit. Prone vs. Not			Omit Analgesics			Omit Analgesics; Agree		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
FCA × Off-Label	-18.22***	-9.33	-8.27	-20.36***	-10.67	-9.73	-17.00**	-12.10*	-10.41
	(4.86)	(5.81)	(5.66)	(5.36)	(6.43)	(6.24)	(5.90)	(5.74)	(5.92)
FCA	-8.83	-14.07	4.01	-5.85	-12.57	6.97	-6.96	-10.56	10.76
	(10.50)	(10.05)	(10.65)	(10.95)	(10.61)	(11.48)	(11.92)	(12.80)	(13.11)
Log MFCU	-0.30	-0.28	-0.09	-0.32	-0.29	-0.10	-0.42	-0.41	-0.23
	(0.30)	(0.30)	(0.25)	(0.30)	(0.30)	(0.26)	(0.29)	(0.29)	(0.24)
Off-label × year	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Off-label × state	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
State time trend	No	No	Yes	No	No	Yes	No	No	Yes
N	55,526	55,526	55,526	48,580	48,580	48,580	37,745	37,745	37,745
Number of Prescriptions									
	Medical Lit. Prone vs. Not			Omit Analgesics			Omit Analgesics; Agree		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
FCA × Off-Label	-15.20***	-6.73	-5.67	-13.96**	-8.52	-7.58	-9.84	-9.26	-7.71
	(4.55)	(5.90)	(5.79)	(5.27)	(6.50)	(6.37)	(5.97)	(6.04)	(6.26)
FCA	-8.39	-13.30	2.85	-7.49	-11.20	5.40	-8.94	-9.56	8.53
	(9.20)	(9.13)	(9.78)	(9.34)	(9.81)	(10.48)	(10.07)	(11.78)	(11.70)
Log MFCU	-0.32	-0.30	-0.14	-0.38	-0.35	-0.16	-0.49*	-0.49*	-0.29
	(0.27)	(0.27)	(0.18)	(0.28)	(0.27)	(0.18)	(0.28)	(0.28)	(0.19)
Off-label × year	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Off-label × state	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
State time trend	No	No	Yes	No	No	Yes	No	No	Yes
N	55,526	55,526	55,526	48,580	48,580	48,580	37,745	37,745	37,745

* P<0.1, ** P<0.5, *** P<0.01. Standard errors are in parenthesis and are clustered at the state level. All models include controls for state demographics, Medicaid population composition and number of eligibles, state welfare programs, political party of state government, and prescription drug policies as well as state, year, drug therapeutic class and subclass fixed effects. All coefficient estimates have been transformed by $(e^{\beta}-1)\times 100$ and are interpreted as a percentage change except MFCU which is an elasticity with regard to a 10 percent increase in MFCU expenditures.

Table B.9: Continuous Estimated Off-label Rate Categorization

Prescription Drug Spending									
	Medical Lit. Prone vs. Not			Omit Analgesics			Omit Analgesics; Agree		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
FCA × Off-Label	-9.68	-18.02	-14.11	-23.16	-18.79	-16.58	-20.89	-21.08	-18.40
	(13.21)	(10.33)	(11.54)	(12.52)	(12.52)	(13.10)	(12.93)	(12.89)	(13.62)
FCA	-15.58	-12.52	5.03	-10.35	-12.19	7.04	-10.11	-10.10	10.63
	(10.82)	(12.75)	(13.69)	(11.91)	(13.66)	(14.56)	(12.74)	(14.80)	(15.46)
Log MFCU expenditure	-0.25	-0.25	-0.12	-0.26	-0.26	-0.12	-0.40	-0.40	-0.25
	(0.30)	(0.30)	(0.26)	(0.30)	(0.30)	(0.26)	(0.30)	(0.30)	(0.25)
Off-label × year	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Off-label × state	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
State time trend	No	No	Yes	No	No	Yes	No	No	Yes
N	50,054	50,054	50,054	43,795	43,795	43,795	34,929	34,929	34,929
Number of Prescriptions									
	Medical Lit. Prone vs. Not			Omit Analgesics			Omit Analgesics; Agree		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
FCA × Off-Label	15.31	-14.18	-10.53	-0.08	-14.17	-12.11	-0.32	-17.07	-14.52
	(17.54)	(12.02)	(13.37)	(14.76)	(13.62)	(14.30)	(14.90)	(13.87)	(14.69)
FCA	-20.97**	-11.82	3.81	-15.99	-11.36	4.94	-14.87	-9.09	8.84
	(9.00)	(12.17)	(12.72)	(9.64)	(12.92)	(13.21)	(10.37)	(13.89)	(13.89)
Log MFCU expenditure	-0.31	-0.31	-0.19	-0.34	-0.35	-0.19	-0.49*	-0.49*	-0.31
	(0.27)	(0.27)	(0.19)	(0.28)	(0.28)	(0.19)	(0.28)	(0.28)	(0.20)
Off-label × year	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Off-label × state	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
State time trend	No	No	Yes	No	No	Yes	No	No	Yes
N	50,054	50,054	50,054	43,795	43,795	43,795	34,929	34,929	34,929

* P<0.1, ** P<0.5, *** P<0.01. Standard errors are in parenthesis and are clustered at the state level. All models include controls for state demographics, Medicaid population composition and number of eligibles, state welfare programs, political party of state government, and prescription drug policies as well as state, year, drug therapeutic class and subclass fixed effects. All coefficient estimates have been transformed by $(e^{\beta}-1)\times 100$ and are interpreted as a percentage change except MFCU which is an elasticity with regard to a 10 percent increase in MFCU expenditures.

B.5 State False Claims Act Legislation

This appendix document summarizes the federal and various state False Claims Act (FCA) statutes and tracks amendments to these statutes over time, through July 2015. As of July 2015, 36 states and the District of Columbia have enacted FCA's. Although some state statutes have unique provisions, many generally follow a standard format similar to the federal law. While not all inclusive of every provision, this document attempts to consistently summarize some of the more common features of state FCA's which we believe are important in measuring the relative strength and effect of these laws. These common features include liability and application of the statute, qui tam or whistleblower provisions and rewards, and civil penalties. Each statute summary highlights these features and any changes over time. It is our hope that this summary encourages research into the effect and usefulness of FCA laws and statutes. Example "code" is provided which makes clear any changes in statute features over time.

This summary represents our own work in gathering and analyzing relevant law articles and documentation which are cited below. The Lexis Advance legal database was largely used to track statutes and amendments over time. Any corrections, questions, or comments are welcome.

1 Arkansas

Act

Arkansas Medicaid Fraud False Claims Act State code §20-77-901 to §20-77-911. Enacted April 23, 1993. This act is the civil counterpart to the Arkansas Medicaid Fraud Act.

Liability

§Act is specific to Medicaid. 20-77-902 6(a) and 7(a) anti-kickback provisions.

Penalties

§20-77-903 1(a) Civil penalty of $5,000 to $10,000 per violation plus treble damages and court costs and fees.

Qui Tam

§20-77-911 An individual who provides information leading to the detecting and bringing to trial of a suit may be compensated with no more than a sum of 10% of the damages. April 4, 2011 removed cap of $100,000 in rewards to relator.

Code

SFIPS: 5
FCA: ON April 23, 1993
MEDICAID ONLY: ON April 23, 1993
QUI TAM: OFF

MIN PENALTY: 5,000 April 23, 1993
MAX PENALTY: 10,000 April 23, 1993
TREBLE DAMAGES

2 California

Act

California False Claims Act §12650 to §12656. Effective Sept 30, 1987.

Liability

Applies to all government programs and agencies.

Penalties

§12651 Civil penalty of $5,500 to $11,000 (See 2012 amendment) plus (double) to treble damages and the cost of civil action.

Qui Tam

§12652 (c)(1) allows qui tam suits. §12652 (g)(2) If the state intervenes, plaintiff may receive 15% to 33% of damages. If state does not intervene, plaintiff may receive 25% to 50% of damages.

Amendments

2012 (effective Jan 1, 2013) increased civil penalty from $5,000-$10,000 to $5,500-$11,000. Added anti-retaliation section §12653.

Code

SFIPS: 6
FCA: ON September 30, 1987
MEDICAID ONLY: OFF
QUI TAM: ON September 30, 1987
MIN PENALTY: 5,000 September 30, 1987 to Dec 31, 2012; 5,500 January 1, 2013
MAX PENALTY: 10,000 September 30, 1987 to Dec 31, 2012; 11,000 January 1, 2013
TREBLE DAMAGES

3 Colorado

Act

Colorado Medicaid False Claims Act §25.5-4-303.5 to §25.5-4-310. Enacted May 26, 2010 by S.B. 167. *Originally enacted as §26-4-1103 on April 12, 2001 (effective July 1, 2001). The 2010 amendment altered the Colorado Medical Assistance Act and created the state FCA in order to be more consistent with the Federal FCA and comply with the federal DRA (Deficit Reduction Act) of 2005. §25.5-4-310. State attorney general must issue annual reports of number of actions, who filed, and amounts recovered, starting January 15, 2015.

Liability

Medicaid program only.

Penalties

Civil penalty of $5,000 to $10,000 per violation plus treble damages. See 2006 Amendment.

Qui Tam

§25.5-4-306 allows for Qui Tam suits. Relator may proceed with case if the state intervenes as well as if the state declines. If the state intervenes the relator may receive 15% to 25% of the proceeds plus reasonable expenses. If the state does not intervene, the relator may receive 25% to 30% of the proceeds. §25.5-4-306. (13)(7) has anti-retaliation provisions for relators.

Amendments

Amended and relocated in 2006; May 26, 2010.

Code

SFIPS: 8
FCA: ON July 1, 2001
MEDICAID ONLY: ON
QUI TAM: ON 2006
MIN PENALTY: 5,000 July 1, 2001 to 2006; 5,000 January 1, 2006
MAX PENALTY: $5,000 per claim; 10,000 January 1, 2006
TREBLE DAMAGES (after 2010)

4 Connecticut

Act

Connecticut Medicaid False Claims Act first passed October 3, 2009 §17b301 to §17b301p. Repealed and replaced by §25.5-4-300.4 to §25.5-4-310 on June 13, 2014.

Liability

Applies to state Medicaid programs only. Joint and several liability if multiple persons are involved.

Penalties

Civil penalties of $5,000 to $10,000 per violation plus treble damages and court costs and fees.

Qui Tam

Section 4b allows for Qui Tam suits. Relator may receive 15% to 25% of civil penalties and damages as well as reasonable fees and expenses if the state intervenes. 6b If the state declines to intervene, the plaintiff may receive 25% to 30% of proceeds. Section 11 anti-retaliation.

Amendments

June 13, 2011 increases civil penalty to $5,500 to $11,000 and includes a provision for penalty to increase in accordance with Civil Penalties Inflation Adjustment Act. June 13, 2014 no substantial changes in FCA, it is just included in new statute.

Code

SFIPS: 9
FCA: ON October 3, 2009
MEDICAID ONLY: ON October 3, 2009
QUI TAM: ON October 3, 2009
MIN PENALTY: 5,000 (and up by inflation) October 3, 2009 to June 13, 2011; 5,500 (and up by inflation) June 13, 2011
MAX PENALTY: 10,000 (and up by inflation) October 3, 2009 to June 13, 2011; 11,000 (and up by inflation) June 13, 2011
TREBLE DAMAGES

5 Delaware

Act

Delaware False Claims and Reporting Act enacted June 30, 2000. §1201 to §1211. §1210 annual reporting starting August 15, 2009.

Liability

Applies to all government programs and agencies.

Penalties

Civil penalties of $5,500 to $11,000 per violation plus treble damages and court costs and fees.

Qui Tam

Allows for Qui Tam suits. §1204 rights of qui tam parties; §1205 awards for qui tam parties. Relator receives 15% to 25% percent if state intervenes and 25% to 30% if the state declines to intervene plus court costs and reasonable expenses. §1208 employee protection.

Amendments

Enacted June 30, 2000; July 16, 2009; July 24, 2013 no substantial revisions.

Code

SFIPS: 10
FCA: ON June 30, 2000
MEDICAID ONLY: OFF
QUI TAM: ON June 30, 2000
MIN PENALTY: 5,500 June 30, 2000
MAX PENALTY: 11,000 June 30, 2000
TREBLE DAMAGES

6 District of Columbia

Act

District of Columbia False Claims Act §2-381.01 to §2-381.10 enacted May 8, 1998.

Liability

Applies to any governmental agency or program in the District of Columbia. §2-381.02(c) Joint and several liability of any violation committed by two or more persons. §2-381.05(b) retroactive to April 12, 1997.

Penalties

§2-381.02 Civil penalties of $5,500 to $11,000 plus treble damages. §2-381.10 penalties updated by inflation at least once every four years according to Federal Civil Penalties Inflation Adjustment Act of 1990.

Qui Tam

§2-381.03(b)(1) allows qui tam suits. Private plaintiff may continue with action if District chooses not to intervene. §2-381.03(f) Relator may receive 15% to 25% of proceeds if District intervenes and 25% to 30% if the District chooses not to intervene plus court costs and fees (see 2010 amendment). §2-381.04 anti-retaliation. Also separate whistleblower protection act §2-223.01.

Amendments

Enacted May 8, 1998. Amended April 20, 1999; March 11, 2010 increased maximum relator reward when District intervenes from 20% to 25%; September 14, 2011; March 19, 2013.

Code

SFIPS: 11
FCA: ON May 8, 1998
MEDICAID ONLY: OFF
QUI TAM: ON May 8, 1998
MIN PENALTY: 5,500 and up by inflation May 8, 1998
MAX PENALTY: 10,000 and up by inflation May 8, 1998
TREBLE DAMAGES

7 Florida

Act

Florida False Claims Act enacted May 31, 1994. §68.081 to §68.0892

Liability

Applies to all government programs and agencies.

Penalties

Civil penalties of $5,500 to $11,000 per violation plus treble damages and court costs and fees.

Qui Tam

§68.083 allows for qui tam suits. Plaintiff Receives 15% to 25% percent if state intervenes and 25% to 30% if the state declines to intervene plus court costs and fees. §68.088 protection for employees filing suits.

Amendments

Enacted May 31, 1994. Amended June 26, 2003; July 1, 2007 shortened statute of limitations 6 years to 5 years for qui tam suits. Increased civil penalty from $5,000 to $10,000 to $5,500 to $11,000; July 1, 2013.

Code

SFIPS: 12
FCA: ON May 31, 1994
MEDICAID ONLY: OFF
QUI TAM: ON May 31, 1994
MIN PENALTY: 5,000 May 31, 1994 to July 1, 2007; 5,500 July 1, 2007
MAX PENALTY: 10,000 May 31, 1994 to July 1, 2007; 11,000 July 1, 2007
TREBLE DAMAGES

8 Georgia

Act

State False Medicaid Claims Act (SFMCA) enacted May 24, 2007 §49-4-168 to §49-4-168.6. Georgia Taxpayer Protection False Claims Act (GTPFCA) §23-3-120 enacted April 16, 2012.

Liability

SFMCA is Medicaid only. GTPFCA covers all government programs and agencies (state and local government). GTPFCA still has actions for Medicaid fraud proceed under SFMCA.

Penalties

SFMCA and GTPFCA: $5,500 to $11,000 per fraudulent claim plus treble damages.

Qui Tam

SFMCA: §49-4-168.2 allows qui tam suits. Relator may receive 15% to 25% if state intervenes or 25% to 30% if state does not. §49-4-168.4 protection of employees. GTPFCA: §23-3-122 same as SFMCA qui tam provisions.

Amendments

State False Medicaid Claims Act enacted May 24, 2007. Amended July 1, 2012 reduced statute of limitations from 4 years to 3 years after facts of case known (6 years after violation in each case); April 24, 2013. Georgia Taxpayer Protection False Claims Act enacted April 16, 2012. Amended April 24, 2013.

Code

SFIPS: 13
FCA: ON May 24, 2007
MEDICAID ONLY: ON May 24, 2007 to April 16, 2012 then OFF.
QUI TAM: ON May 24, 2007
MIN PENALTY: 5,500
MAX PENALTY: 11,000
TREBLE DAMAGES

9 Hawaii

Act

§46-171 to §46-181 "Qui Tam Actions or Recovery of False Claims to the Counties" enacted June 13, 2001

Liability

Covers all government programs and counties. §46-171 Joint and several liability.

Penalties

$5,500 to $11,000 per fraudulent claim plus treble damages (See 2012 Amendment).

Qui Tam

§46-175 allows qui tam suits. §46-177 Relator may receive 15% to 25% if state intervenes or 25% to 30% if state does not, plus court costs and reasonable expenses. §46-180 anti-retaliation effective July 9, 2012.

Amendments

Enacted July 13, 2001, Amended July 9, 2012 increased penalty from $5,000-$10,000 to $5,500 to $11,000.;

Code

SFIPS: 15
FCA: ON June 13, 2001
MEDICAID ONLY: OFF
QUI TAM: ON June 13, 2001
MIN PENALTY: 5,000 June 13, 2001 to July 9, 2012; 5,500 after July 9, 2012
MAX PENALTY: 10,000 June 13, 2001 to July 9, 2012; 11,000 after July 9, 2012
TREBLE DAMAGES

10 Illinois

Act

Illinois False Claims Act (Whistleblower Reward and Protection Act) §740 175/1 to §740 175/8 . Approved and effective September 20, 1991.

Liability

Covers any state agency or municipality.

Penalties

§740 175/3 $5,500 to $11,000 per fraudulent claim plus treble damages (see 2006 amendment).

Qui Tam

§740 175/4 allows qui tam suits. Relator may receive 15% to 25% if state intervenes or 25% to 30% if state does not, plus court costs and reasonable expenses. Separate "Whistleblower Act" §740 174/1 to §740 174/40 passed in 2003 (effective January 1, 2004) to protect employees from retaliation.

Amendments

Approved September 20, 1991. Amended January 1, 1996; January 1, 2001; July 31, 2006 increased penalty from $5,000 to $10,000 to $5,500 to $11,000; January 1, 2008; July 27, 2010 renamed "Whistleblower Reward and Protection Act" to "Illinois False Claims Act."

Code

SFIPS: 17
FCA: ON September 20, 1991
MEDICAID ONLY: OFF
QUI TAM: ON September 20, 1991
MIN PENALTY: 5,000 September 20, 1991 to July 31, 2006; 5,500 after July 31, 2006
MAX PENALTY: 10,000 September 20, 1991 to July 31, 2006; 11,000 after July 31, 2006
TREBLE DAMAGES

11 Indiana

Act

False Claims and Whistleblower Protection §5-11-5.5-1. Enacted in 2005.

Also separate fraud control unit specified under Medicaid program.

Liability

Applies to any state agency (not to Medicaid after June 31, 2014).

Penalties

§5-11-5.5-2 penalties of at least $5,000 and treble damages plus court costs.

Qui Tam

§5-11-5.5-4 allos qui tam suits. §5-11-5.5-6 Relator may receive 15% to 25% if state intervenes or 25% to 30% if state does not, plus court costs and reasonable expenses. §5-11-5.5-8 anti-retaliation.

Amendments

Enacted 2005. Amended January 15, 2007

Code

SFIPS: 18
FCA: ON 2005
MEDICAID ONLY: OFF
QUI TAM: ON 2005
MIN PENALTY: 5,000
MAX PENALTY: not limited
TREBLE DAMAGES

12 Iowa

Act

Iowa False Claims Act §685.1 to §685.7 enacted March 10, 2010.

Liability

Covers all state agencies.

Penalties

§685.2 penalties benchmarked to federal FCA (see 2011 amendment); $5,000 to $10,000 plus treble damages. Adjusted for inflation by federal Civil Penalties Inflation Adjustment Act of 1990, Pub. L. No. 101-410.

Qui Tam

§685.3 qui tam suits. Relator may receive 15% to 25% if state intervenes or 25% to 30% if state does not, plus court costs and reasonable expenses. Subsection 6 anti-retaliation and relief.

Amendments

Enacted March 10, 2010. Amended July 26, 2011

Code

SFIPS: 19
FCA: ON March 10, 2010
MEDICAID ONLY: OFF
QUI TAM: ON March 10, 2010
MIN PENALTY: 5,000 and up by inflation
MAX PENALTY: 10,000 and up by inflation
TREBLE DAMAGES

13 Kansas

Act

Kansas False Claims Act §75-7501 to §75-7511. Enacted April 20, 2009

Liability

Covers all state agencies, municipalities and quasi-municipalities. §75-709 Joint and several liability for violations commited by two or more persons.

Penalties

§75-7503 Civil penalties of $1,000 to $11,000 plus treble damages and court costs and expenses.

Qui Tam

§75-7504 "Except as provided in K.S.A. 2013 Supp. 75-7506, and amendments thereto, nothing in this act shall be construed to create a private cause of action." No qui tam suits allowed. §75-7506 Employees may aid in action and are protected from retaliation, but cannot file private suits or recover an award.

Amendments

Enacted April 20, 2009

Code

SFIPS: 20
FCA: ON April 20, 2009
MEDICAID ONLY: OFF
QUI TAM: OFF
MIN PENALTY: 1,000
MAX PENALTY: 11,000
TREBLE DAMAGES

14 Louisiana

Act

Medical Assistance Programs Integrity Law §46:437.1 to §46:440.16 enacted July 15, 1997, effective August 15, 1997.

Liability

Covers all state medical assistance programs. §46:438.2 anti-kickback clause. §46:438.3 false claims.

Penalties

§46:438.6 Civil penalties outlined in three sections: First violators must pay an amount equal to the actual damages, plus interest from date of violation to date of repayment as governed by R.S. 13:4202. Second a civil fine is imposed. Civil fines differ by the type of violation. Illegal remuneration (kickbacks) are subject to penalties of no more than $10,000 per violation OR three times the amount of illegal remuneration, whichever is greater. False claims are subject to a civil penalty of three times damages. Additional civil monetary penalties may be imposed for any violation. Monetary fines are $5,500 to $11,000 per violation (false claim or kickback) (see 2011 amendment) plus interest on the fine, adjusted by inflation by the Federal Civil Penalties Inflation Adjustment Act of 1990, 28 U.S.C. 2461. Violators must also pay court costs and fees.

Combining the payment of actual damages plus civil fines and civil monetary penalties, an FCA violation may result in payment of damages plus a penalty of treble damages, $5,500 to $11,000 (adjusted by inflation) per violation plus interest on damages and the civil monetary penalty.

Qui Tam

§46:439.1 allows qui tam suits for any type of violation. Subsection 6 anti-retaliation. Additional separate whistleblower protection act §46:440.3. §46:439.4 Relator may receive 15% to 25% if state intervenes or 25% to 30% if state does not (see 2009 and 2011 amendments), plus court costs and reasonable expenses.

Amendments

Effective August 15, 1997. Amended June 18, 2007 increased minimum penalty from $0 to $5,000; August 15, 2009 increased qui tam recovery from damages excluding civil

monetary penalties to total proceeds ; August 15, 2011 increased penalties from $5,000 to $10,000 to $5,500 to $11,000; increased qui tam reward from 10% to 20% to 15% to 25% when state intervenes and guarantees at least 25% when state does not intervene.

Code

SFIPS: 22
FCA: ON August 15, 1997
MEDICAID ONLY: OFF
QUI TAM: ON August 15, 1997
MIN PENALTY: 0 August 15, 1997 to June 18, 2007; 5,000 June 18, 2007 to August 11, 2011; 5,500 August 15, 2011
MAX PENALTY: 10,000 August 15, 1997 to June 18, 2007; 11,000 June 18, 2007
TREBLE DAMAGES

15 Maryland

Act

Maryland False Health Claims Act of 2010 (MFHCA) §2-601 to §2-611 enacted April 23, 2010, and effective October 1, 2010. §2-611 annual reporting. Criminal law regarding Medicaid Fraud §8-517 effective 2002 civil penalties of treble damages for false claims and bribes/kickbacks among other fraud.

Maryland False Claims Act (MFCA) §8-101 to §8-111 effective June 1, 2015.

Liability

MFHCA covers any state health plan or program including Medicaid.

MFCA covers all government agencies and programs, state and county.

Penalties

MFHCA §2-602(b) Civil penalties of no more than $10,000 per violation and treble damages.

MFCA §8-102 Civil penalty of up to $10,000 per violation and treble damages.

Qui Tam

MFHCA §2-604 allows qui tam suits. §2-605 Relator may receive 15% to 25% of proceeds plus court costs and reasonable expenses. §2-604(b)(3 Requires state to intervene. If state declines, then the action is dismissed. §2-607 anti-retaliation.

MFCA §8-104 allows qui tam suits. Relator may receive 15% to 25% of proceeds when state intervenes in case. If the state declines, the case is dismissed and the qui tam plaintiff may not pursue the action alone.

Amendments

MFHCA enacted April 23, 2010 and effective October 1, 2010. Amended July 1, 2014 no substantial changed. MFCA effective June 1, 2015.

Code

SFIPS: 24
FCA: ON October 1, 2010
MEDICAID ONLY: ON October 1, 2010 to June 1, 2015
QUI TAM: ON October 1, 2010
MIN PENALTY: 0 October 1, 2010
MAX PENALTY: 10,000 October 1, 2010
TREBLE DAMAGES

16 Massachusetts

Act

Massachusetts False Claims Act Ch. 12 §5A to §5O enacted July 31, 2000.

Liability

Applies to any government entity, state or local.

Penalties

§5B Civil penalty of $5,500 to $11,000 per violation adjusted by the Federal Civil Penalties Inflation Adjustment Act of 1990 (see 2012 amendment), plus treble damages (including consequential damages) and reasonable fees and court costs.

Qui Tam

§5C allows qui tam suits. §5F Relators receive 15% to 25% if attorney general intervenes and 25% to 30% if the attorney general does not intervene plus fees and court costs. Relator may pursue action if AG does not choose to intervene. §5J employee protection.

Amendments

Enacted July 31, 2000. Amended July 1, 2012 increased civil penalty from $5,000 to $10,000 to $5,500 to $11,000 and up by inflation; July 1, 2013.

Code

SFIPS: 25
FCA: ON July 31, 2000
MEDICAID ONLY: OFF
QUI TAM: ON July 31, 2000
MIN PENALTY: 5,000 July 31, 2000 to July 1, 2012; 5,500 July 1, 2012
MAX PENALTY: 10,000 July 31, 2000 to July 1, 2012; 11,000 July 1, 2012
TREBLE DAMAGES

17 Michigan

Act

Medicaid False Claim Act §400.601 to §400.614 Enacted July 27, 1977.

Liability

Applies to state medical assistance programs. §400.604 includes anti-kickback provision.

Penalties

§400.603 Medicaid fraud punishable by jail time up to four years and a fine up to $50,000. §400.604 anti-kickback punishable by four years jail time and a fine of up to $30,000. §400.605 False statements regarding conditions or operation of an institution punishable by four years jail time and a fine of up to $30,000. §400.606 receiving payment by false claim and defrauding state punishable by 10 years jail time and a fine of up to $50,000. §400.610b attorney general may recover all court costs and fees. §400.612 Civil penalty of $5,000 to $10,000 per violation plus treble damages. (See 2009 Amendment)

Qui Tam

§400.610a allows qui tam suits. (9)(b) Relator receives 15% to 25% of proceeds if state intervenes and 25% to 30% if the state does not. (See 2006 amendment). §400.610c employee protection

Amendments

Enacted July 27, 1977. Amended (effective) December 31, 1982; January 3, 2006 added section §400.610a which allows qui tam suits; January 6, 2009 added penalty of $5,000 to $10,000.

Code

SFIPS: 26
FCA: ON July 27, 1977
MEDICAID ONLY: ON July 27, 1977
QUI TAM: OFF July 27, 1977 to January 3, 2006; ON january 6, 2006
MIN PENALTY: 0 July 27, 1977 to January 6, 2009; 5,000 January 6, 2009
MAX PENALTY: 0 July 27, 1977 to January 6, 2009; 10,000 January 6, 2009
TREBLE DAMAGES

18 Minnesota

Act

Enacted May 16, 2009. §15C.01 to §15C.16. §15C.16 annual reporting.

Liability

Covers all state agencies and programs.

Penalties

§15C.02 Civil penalties of $5,500 to $11,000 per violation plus treble damages and court costs and fees.

Qui Tam

§15C.05 allows qui tam suits. §15C.12 plaintiff rewarded reasonable costs and court fees. §Relator receives 15% to 25% of civil penalty and damages if attorney general does intervene, 25% to 30% if the attorney general does not intervene. §15C.145 anti-retaliation

Amendments

Enacted May 16, 2009. Amended April 23, 2013.

Code

SFIPS: 27
FCA: ON May 16, 2009
MEDICAID ONLY: OFF
QUI TAM: ON May 16, 2009
MIN PENALTY: 5,500
MAX PENALTY: 11,000
TREBLE DAMAGES

19 Mississippi

This is Mississippi's criminal fraud statute, and does not cover civil litigation. Not considered an FCA, but has some similar provisions.

Act

Medicaid Fraud Control Act §43-13-201 to §43-13-233 enacted May 15, 1984.

Liability

Specific to state Medicaid program. §43-13-207 anti-kickback.

Penalties

§43-13-215 criminal penalty: felony punishable by 5 years jail time and a fine of up to $50,000. §43-13-225 civil penalty of treble damages.

Qui Tam

No qui tam or whistleblower provisions.

Amendments

Enacted May 15, 1984. Amended July 1, 1998.

Code

SFIPS: 28
MEDICAID ONLY: ON May 15, 1984
QUI TAM: OFF
MIN PENALTY: 0
MAX PENALTY: 0
TREBLE DAMAGES

20 Missouri

Act

Enacted July 6, 1994. §191.905 to §191.914

Liability

Applies to state medical assistance programs. §191.905 Includes an anti-kickback provision.

Penalties

§191.905(12) Civil penalties of $5,000 to $10,000 per violation plus treble damages.

Qui Tam

§191.907 no qui tam suits allowed. Original source of information may receive 10% of recovery. (see 2007 amendment). §191.908 whistleblower protection.

Amendments

Enacted July 6, 1994. Amended July 11, 2001; July 2, 2007 added relator award and whistleblower protection; Aug 28, 2012 repealed reporting requirement; May 13, 2014

Code

SFIPS: 29
FCA: ON July 6, 1994
MEDICAID ONLY: ON July 6, 1994
QUI TAM: OFF
MIN PENALTY: 5,000
MAX PENALTY: 10,000
TREBLE DAMAGES

21 Montana

Act

Montana False Claims Act §17-8-401 to §17-8-416 enacted October 1, 2005. §17-8-416 annual reporting beginning February 15, 2014.

Liability

Applies to any government agency, program, or subdivision.

Penalties

§17-8-403 Civil penalty of $5,500 to $11,000 per violation plus treble damages which increase by inflation according to the Federal Civil Penalties Inflation Adjustment Act of 1990 (see 2013 amendment) and expenses and court costs.

Qui Tam

§17-8-406 allows qui tam suits. §17-8-410 Relator receives 15% to 25% of the proceeds if the state intervenes and 25% to 30% if the state does not intervene.

Amendments

Enacted October 1, 2005. Amended March 25, 2009 eff. July 1, 2009; May 6, 2013 eff. July 1, 2013 increased civil penalty from $5,000 to $10,000 to $5,500 to $11,000 and increased by inflation and changes to relator awards (was previously 10% to 15% if private citizen elected not to be plaintiff or coplaintiff and 15% to 50% if private citizen elected to be plaintiff or coplaintiff). §17-8-412 anti-retaliation.

Code

SFIPS: 30
FCA: ON October 1, 2005
MEDICAID ONLY: OFF
QUI TAM: ON October 1, 2005
MIN PENALTY: 5,000 October 1, 2005 to July 1, 2009; 5,500 July 1, 2009
MAX PENALTY: 10,000 October 1, 2005 to July 1, 2009; 11,000 July 1, 2009
TREBLE DAMAGES

22 Nebraska

Act

False Medicaid Claims Act §68-934 to §68-947 enacted April 15, 1996.

Liability

Applies to any state medical assistance program. §68-936 joint and several liability for act committed by two or more persons.

Penalties

§68-936 Civil penalties of a fine up to $10,000 per violation and treble damages plus court costs and fees. (See 2004 Amendment).

Qui Tam

No qui tam or whistleblower statutes.

Amendments

Amended June 9, 1997; July 16, 2004 increased civil penalty from up to $5,000 per violation and double damages to up to $10,000 and treble damages; April 14, 2006; July 1, 2007; May 29, 2009; May 7, 2013.

Code

SFIPS: 31
FCA: ON April 15, 1996
MEDICAID ONLY: ON April 15, 1996
QUI TAM: OFF
MIN PENALTY: 0
MAX PENALTY: 5,000 April 15, 1996 to July 16, 2004; 10,000 July 16, 2004
TREBLE DAMAGES (July 16, 2004)

23 Nevada

Act

Nevada False Claims Act §357.010 to §357.250 enacted May 18, 1999.

Liability

Covers all state government agencies and programs and political subdivisions. §357.060 joint and several liability for a violation committed by two or more persons.

Penalties

§357.040 Civil penalties of $5,500 to $11,000 per violation plus treble damages and court costs and fees (see 2007 and 2013 amendments).

Qui Tam

§357.080 allows qui tam suits. §357.110 private plaintiff may continue with suit is attorney general declines to intervene. §357.180 The attorney general or private plaintiff, if successful, may be awarded reasonable court costs and fees. §357.210 Relator receives 15% to 33% of proceeds if the state intervenes and 25% to 50% if the state does not intervene. §357.250 anti-retaliation.

Amendments

Enacted May 18, 1999. Amended June 13, 2007 eff July 1, 2007 increased minimum civil penalty from $2,000 to $5,000; May 24, 2011 eff. July 1, 2011; May 27, 2013 eff. July 1, 2013 increased civil penalty from $5,000 to $10,000 to $5,500 to $11,000.

Code

SFIPS: 32
FCA: ON May 18, 1999
MEDICAID ONLY: OFF

QUI TAM: ON May 18, 1999
MIN PENALTY: 2,000 May 18, 1999 to July 1, 2007; 5,000 July 1, 2007 to July 1, 2011; 5,500 July 1, 2011
MAX PENALTY: 10,000 May 18, 1999 to July 1, 2011; 11,000 July 1, 2011
TREBLE DAMAGES

24 New Hampshire

Act

Medicaid Fraud and False Claims §167:58 enacted in 1981. New Hampshire False Claims Act §167:61-a to §167:61-e enacted and eff. January 1, 2005.

Liability

Covers state health programs. §167:61-a anti-kickback.

Penalties

§167:61-b Civil penalties of $5,000 to $10,000 per violation and treble damages (enacted in 2005).

Qui Tam

§167:61-c allows qui tam suits. §167:61-e Relator receives 15% to 25% if the state intervenes and 25%to 30% if the state does not plus court costs and fees. Separate whistleblower rotection act §275-E1 to §275-E:7

Amendments

FCA enacted January 1, 2005. Amended eff. June 29, 2009; eff. June 14, 2011.

Code

SFIPS: 33
FCA: ON January 1, 2005
MEDICAID ONLY: ON January 1, 2005
QUI TAM: ON January 1, 2005
MIN PENALTY: 5,000
MAX PENALTY: 10,000
TREBLE DAMAGES

25 New Jersey

Act

New Jersey False Claims Act §2A:32C-1 to §2A:32C-17 enacted January 18, 2008 eff. March 13, 2008.

Liability

Covers all state programs and agencies.

Penalties

§2A:32C-3 Civil penalties benchmarked to federal FCA $5,500 to $11,000 per violation and up by inflation according to Federal Civil Penalties Inflation Adjustment Act of 1990 plus treble damages.

Qui Tam

§2A:32C-5(b) allows qui tam suits. §2A:32C-6 private plaintiff may proceed with action if state declines. Relator receives 15% to 25% is the state intervenes and 25% to 30% if the state does not intervene. §2A:32C-8 AG or private plaintiff also awarded court costs and fees. §2A:32C-10 employee protection.

Amendments

Enacted eff. March 13, 2008. Amended eff. Jan. 17, 2010.

Code

SFIPS: 34
FCA: ON March 13, 2008
MEDICAID ONLY: OFF
QUI TAM: ON March 13, 2008
MIN PENALTY: 5,500 and up by inflation March 13, 2008
MAX PENALTY: 11,000 and up by inflation March 13, 2008
TREBLE DAMAGES

26 New Mexico

Act

Medicaid False Claims Act (MFCA) §27-14-1 to §27-14-15 enacted March 3, 2004 eff. May 19, 2004.

Fraud Against Taxpayers Act (FATA) §44-9-1 to §44-9-15 enacted March 13, 2007 eff. July 1, 2007.

Liability

MFCA applies to state Medicaid program. FATA applies to any state program, agency, or subdivision. §44-9-13 Joint and several liability for violation committed by two or more persons.

Penalties

MFCA §27-14-4 Violators liable for treble damages. FATA §44-9-3(c) Civil penalty of $5,000 to $10,000 per violation plus treble damages plus court costs and fees.

Qui Tam

MFCA §27-14-7(b) allows qui tam suits by an "affected" person. §27-14-8(d) Private plaintiff may proceed with action if state does not intervene. §27-14-9 Relators receive 15% to 25% if state intervenes and 25% to 30% if the state doe not intervene plus court costs and fees. §27-14-12 employee protection. FATA §44-9-5 allows qui tam suits. §44-9-6 Private plaintiff may proceed with action if state declines. §44-9-7 Relators receive 15% to 25% if state intervenes and 25% to 30% if the state doe not intervene plus court costs and fees. §44-9-11 anti-retaliation.

Amendments

FATA enacted March 15, 2007 eff July 1, 2007. Amended eff. June 19, 2015.

Code

SFIPS: 35
FCA: ON March 19, 2004
MEDICAID ONLY: ON March 19, 2004 to July 1, 2007; OFF July 1, 2007
QUI TAM: ON ON March 19, 2004
MIN PENALTY: 0 March 19, 2004 to July 1 2007; 5,000 July 1, 2007
MAX PENALTY: 0 March 19, 2004 to July 1, 2007; 10,000 July 1, 2007
TREBLE DAMAGES

27 New York

Act

New York False Claims Act §187 to §enacted April 9, 2007 eff. on and after April 1, 2007.

Liability

Covers any state program, agency, or subdivision. §189(4)(a)Applies to tax violations if net income or sales of person exceeds $1 million in any taxable year subject to violation.

Penalties

§189(1)(h) Civil penalty of $6,000 to $12,000 per violation plus treble damages plus court costs and fees.

Qui Tam

§190(2)(a) allows qui tam suits. §190(2)(f) Private plaintiff may proceed if state declines to intervene. §190(6)(a) Relator receives 15% to 25% if the state intervenes and 25% to 30% if the state does not intervene, plus court costs and fees. §191 anti-retaliation.

Amendments

Enacted eff. April 1, 2007. Amended August 13, 2010 eff. August 27, 2010; March 28, 2013 eff. April 1, 2013.

Code

SFIPS: 36
FCA: ON April 1, 2007
MEDICAID ONLY: OFF
QUI TAM: ON April 1, 2007
MIN PENALTY: 6,000 April 1, 2007
MAX PENALTY: 12,000 April 1, 2007
TREBLE DAMAGES

28 North Carolina

Act

(North Carolina) False Claims Act (FCA) §1-605 to §1-629 enacted August 28, 2009 eff. January 1, 2010. §1-617 annual reporting beginning February 1, 2010.

Medical Assistance Provider False Claims Act (MAPFCA) §108A-70.10 to §108A-70.17 enacted July 25, 1997 eff. December 1, 1997.

Liability

FCA Covers all state government programs, agencies, and subdivisions.
MAPFCA only covers state Medical Assistance programs.

Penalties

FCA §1-607 Civil penalty of $5,500 to $11,000 plus treble damages and court costs and fees.

MAPFCA §108A-70.12 Civil penalty of $5,000 to $10,000 plus treble damages, court costs and fees, and interest on the damage amount.

Qui Tam

§1-608(b) allows qui tam suits. §1-609(f) Private plaintiff may proceed with action if state decides not to intervene. §1-610 Plaintiff receives 15% to 25% if state intervenes and 25% to 30$ if the state does not intervene plus court costs and fees. §1-613 anti-retaliation.

MAPFCA §108A-70.15 employee protection. No qui tam statute in the MAPFCA.

Amendments

FCA enacted eff. January 1, 2007. MAPFCA enacted eff. December 1, 1997; Amended July 5, 2007; August 28, 2009 with FCA (incorporated both statutes under new FCA).

Code

SFIPS: 37
FCA: ON December 1, 1997
MEDICAID ONLY: ON December 1, 1997 to January 1, 2007; OFF January 1, 2007

QUI TAM: OFF until January 1, 2007; ON January 1, 2007
MIN PENALTY: 5,000 December 1, 1997 to January 1, 2007; 5,500 January 1, 2007
MAX PENALTY: 10,000 December 1, 1997 to January 1, 2007; 11,000 January 1, 2007
TREBLE DAMAGES

29 Oklahoma

Act

Oklahoma Medicaid False Claims Act §5053.1 to §5053.7 enacted May 15, 2007, eff. November 1, 2007.

Liability

Applies to state Medicaid program.

Penalties

§5053.1 Civil penalty of $5,000 to $10,000 plus treble damages.

Qui Tam

§5053.2(B)(1) allows qui tam suits. §5053.2(B)(4) private plaintiff may continue with action if the state declines to intervene. §5053.4 Plaintiff may receive 15% to 25% of proceeds if state intervenes and 25% to 30% if the state does not intervene plus court costs and fees.

Amendments

Enacted eff. November 1, 2007. Amended April 13, 2009 eff. November 1, 2009.

Code

SFIPS: 40
FCA: ON November 1, 2007
MEDICAID ONLY: ON November 1, 2007
QUI TAM: ON November 1, 2007
MIN PENALTY: 5,000
MAX PENALTY: 10,000
TREBLE DAMAGES

30 Oregon

Act

Oregon False Claims Act §180.750 to §180.785 enacted June 17, 2009.

Liability

Applies to any government program or agency.

Penalties

§180.760 State is awarded all damages suffered because of violation plus a civil penalty of the greater of either two times damages or $10,000 per violation plus court costs and fees.

Qui Tam

No qui tam or whistleblower provisions.

Amendments

none

Code

SFIPS: 41
FCA: ON June 17, 2009
MEDICAID ONLY: OFF
QUI TAM: OFF
MIN PENALTY: 10,000
MAX PENALTY: 10,000
TREBLE DAMAGES

31 Rhode Island

Act

State False Claims Act §9-1.1-1 to §9-1.1-9 enacted June 21, 2007

Liability

Applies to any state agency, program, or subdivision.

Penalties

§9-1.1-3 Civil penalty of $5,500 to $11,000 plus treble damages plus costs of litigation.

Qui Tam

§9-1.1-4 allows qui tam suits. Plaintiff may continue with action if state declines to intervene. §9-1.1-4(d) Plaintiff may receive 15% to 25% of proceeds if state intervenes and 25% to 30% if the state does not intervene plus court costs and fees.

Amendments

Enacted June 21, 2007. Amended June 13, 15, and 22, 2012 increased civil penalty from $5,000 to $10,000 to $5,500 to $11,000.

Code

SFIPS: 44
FCA: ON June 21, 2007
MEDICAID ONLY: OFF
QUI TAM: ON June 21, 2007
MIN PENALTY: 5,000 June 21, 2007 to June 13, 2012; 5,500 June 13, 2012
MAX PENALTY: 10,000 June 21, 2007 to June 13, 2012; 11,000 June 13 2012
TREBLE DAMAGES

32 Tennessee

Act

Tennessee False Claims Act (TFCA) §4-18-101 to §4-18-108 enacted June 7, 2001.

Tennessee Medicaid False Claims Act (TMFCA) §71-5-182 to §71-5-185 enacted May 17, 1993.

Liability

TFCA applies to all state agencies, programs, and subdivisions. §4-18-108 does not apply to violations covered under the Medicaid False Claims Act.

TMFCA applies only to Tennessee Medicaid program.

Penalties

TFCA §4-18-103 Civil penalty of $2,500 to $10,000 per violation plus treble damages and litigation costs.

TMFCA §71-5-182 Civil penalty of $5,000 to $25,000 per violation adjusted for inflation by the Federal Civil Penalties Inflation Adjustment Act of 1990 plus treble damages and litigation costs.

The attorney general may choose to bring the action as an administrative proceeding where damages are limited to $25,000 (see 2012 amendment), not including a civil penalty of treble damages and a fine of $1,000 to $5,000.

Qui Tam

TFCA §4-18-104(c) allows qui tam suits. The plaintiff may conduct the action even if the state chooses not to intervene. §4-18-104(g) Relator may receive 15% to 33% if the state intervenes and 33% to 50% if the state does not plus court costs and fees. §4-18-105 employee protection.

TMFCA §71-5-183 allows qui tam suits. Plaintiff has right to action if state does not intervene. Plaintiff may receive 15% to 25% of proceeds if state intervenes and 25% to 30% if the state does not intervene plus court costs and fees.

Amendments

FCA enacted June 7, 2001. Amended June 24, 2003; May 24, 2004; May 21, 2012. TMFCA Enacted May 17, 1993. Amended May 17, 2004 annual reporting requirement; April 23, 2012 increased total damages in administrative proceeding from $10,000 to $25,000, April 11, 2013;

Code

SFIPS: 47
*Coding is for Medicaid violations only and only reflects TMFCA since the FCA excludes Medicaid program violations.
FCA: ON May 17, 1993
MEDICAID ONLY: ON May 17, 1993
QUI TAM: ON May 17, 1993
MIN PENALTY: 5,000 and up by inflation May 17, 1993
MAX PENALTY: 25,000 and up by inflation May 17, 1993
TREBLE DAMAGES

33 Texas

Act

Medicaid Fraud Prevention Act §36.001 to §36.132. Enacted June 16, 1995, eff. September 1, 1995.

Liability

Applies only to state Medicaid program.

Penalties

§36.005 §36.132 Provider agreement, professional permit or license may be revoked. §36.007 Attorney general may recover costs of civil litigation. §36.052 Civil penalty of the greater of $5,500 or minimum penalty imposed in Federal FCA to the greater of $15,000 or maximum penalty imposed in Federal FCA per violation if the violation results in injury to a person who is elderly, disabled, or younger than 18. Civil penalty of the greater of $5,500 or minimum penalty imposed in Federal FCA to the greater of $11,000 or the maximum penalty imposed in the Federal FCA per violation for injury to persons not described above. In addition to being held liable for the original payment or value of benefit provided under the Medicaid program, violators are liable to an additional two times the payment or value of benefit (interpreted as treble damages).

Qui Tam

§36.101 allows qui tam suits (see 1997 amendment). §36.104 Private plaintiff may continue with action if state chooses not to intervene (see May 2007 amendment). §36.110 Plaintiff may receive 15% to 25% of proceeds if state intervenes and 25% to 30% if the state does not intervene, plus court costs and fees. §36.115 anti-retaliation.

Amendments

Enacted eff. September 1, 1995. Amended eff. September 1, 1997; September 1, 1999; September 1, 2005; May 4, 2007 plaintiff may continue with action if state chooses not to intervene. Increased minimum plaintiff award from 10% to 15%; September 1, 2007 increased civil penalty from $1,000 to $5,000 for injury to non-elder,disabled, or minor persons; September 1, 2011 increased civil penalty from $5,000 to $5,500 for both injuries to elderly, disabled, and minor, and non elderly disabled, and minor. Increased civil penalty from $10,000 to $11,000 for injury to non elderly, disabled, or minor; September 1, 2013.

Code

SFIPS: 48
FCA: ON September 1, 1995
MEDICAID ONLY: ON September 1, 1995
QUI TAM: ON September 1, 1997
MIN PENALTY: 1,000 September 1, 1995 to September 1, 2007; 5,000 September 1, 2007 to September 1, 2011; 5,500 September 1, 2011
MAX PENALTY *Non-elderly, disabled, minor: 10,000 September 1, 1995 to September 1, 2007; 11,000 September 1, 2007
TREBLE DAMAGES

34 Utah

Act

Utah False Claims Act §26-20-1 to §26-20-15 enacted 1981. Amended in 2007 to expand liability and make penalties consistent with federal False Claims Act.

Liability

Enacted in 1981. Prior to 2007 amendment, applied only to state health programs. Post 2007, applies to any government program. §26-20-4 anti-kickback.

Penalties

§26-20-9.5 Civil penalty of $5,000 to $10,000 per violation plus treble damages and court costs and fees (see 2007 amendment).

Qui Tam

No qui tam or whistleblower provisions.

Amendments

Amended March 16, 2000; March 7, 2007 increased civil penalty from $2,000 to $5,000 to $10,000. Also added statute of limitations and expanded applicability of law; March 25, 2011.

Code

SFIPS: 49
FCA: ON 1981
MEDICAID ONLY: ON 1981 to March 7, 2007; OFF March 7, 2007
QUI TAM: OFF
MIN PENALTY: 0 1981 to March 7, 2007; 5,000 March 7, 2007
MAX PENALTY: 2,000 1981 to March 7, 2007; 10,000 March 7, 2007
TREBLE DAMAGES

35 Vermont

Act

Vermont False Claims Act §32 V.S.A. 630 through §642 enacted May 18, 2015. Effective on passage. https://www.falseclaimsact.com/wp-content/uploads/2015/06/Vermont.pdf

Liability

Applies to all government programs.

Penalties

§631 Civil penalty of $5,500 to $11,000 per claim. Adjusted for inflation using Federal Civil Penalties Inflation Adjustment Act of 1990. Treble damages. Investigation costs.

Quitam

§632 Allows qui tam actions. Relator may proceed if attorney general does not intervene. Relator may receive 15% to 25% of proceeds if the state intervenes and 25% to 30% if the state chooses not to intervene plus court costs and fees. §638 Employee protection from retaliation.

Code

SFIPS: 50
FCA: ON May 18, 2015
MEDICAID ONLY: OFF
QUI TAM: ON May 18, 2015
MIN PENALTY: 5,500 May 18, 2015 on
MAX PENALTY: 11,000 May 18, 2015 on
TREBLE DAMAGES

36 Virginia

Act

Virginia Fraud Against Taxpayers Act §8.01-216.1 to §8.01-216.19 enacted April 17, 2002, eff. January 1, 2003.

Liability

Applies to the commonwealth of Virginia and any government agency, program, or subdivision.

Penalties

§8.01-216.3 Civil penalty of $5,500 to $11,000 per violation plus treble damages and court costs and fees (see 2007 amendment).

Qui Tam

§8.01-216.5allows qui tam suits. §8.01-216.6(f) Private plaintiff may continue with action if commonwealth chooses not to intervene. §8.01-216.7 Relator may receive 15% to 25% of proceeds if the commonwealth intervenes and 25% to 30% if the commonwealth chooses not to intervene plus court costs and fees. §8.01-216.8 employee protection. Also a separate whistleblower protection act §2.2-3010.1.

Amendments

Enacted eff. January 1, 2003. Amended April 12, 2004; March 19, 2007 increased civil penalty from $5,000 to $10,000 to $5,500 to $11,000; March 26, 2011

Code

SFIPS: 51
FCA: ON January 1, 2003
MEDICAID ONLY: OFF
QUI TAM: ON January 1, 2003
MIN PENALTY: 5,000 January 1, 2003 to March 19, 2007; 5,500 March 19, 2007
MAX PENALTY: 10,000 January 1, 2003 to March 19, 2007; 11,000 March 19, 2007
TREBLE DAMAGES

37 Washington

Act

Medicaid Fraud False Claims Act §74.66.005 to §74.66.130 enacted March 30, 2012. §74.66.130 Annual reporting beginning November 15, 2012.

Liability

All Washington state agencies that administer Medicaid funded programs.

Penalties

§74.66.020 Civil penalty of $5,500 to $11,000 plus treble damages. Civil penalties are adjusted annually according to the federal civil penalties inflation adjustment act of 1990 so that they are equal to those imposed by the federal FCA.

Qui Tam

§74.66.050 allows qui tam suits. §74.66.060 Private plaintiff may continue with action if the state chooses not in intervene. §74.66.070 Relator may receive 15% to 25% of proceeds if the state intervenes and 25% to 30% if the state chooses not to intervene plus court costs and fees. §74.66.090 anti-retaliation.

Amendments

Enacted March 30, 2012

Code

SFIPS: 53
FCA: ON March 30, 2012
MEDICAID ONLY: ON March 30. 2012
QUI TAM: ON March 30, 2012
MIN PENALTY: 5,500 and up by inflation March 30, 2012
MAX PENALTY: 11,000 and up by inflation March 30, 2012
TREBLE DAMAGES

38 Wisconsin

Act

False Claims for Medical Assistance §20.931 enacted October 26, 2007.

*Note: Wisconsin repealed its FCA in July, 2015. Reportedly, due to infrequent intervention in suits and the presence of other legislation which allows prosecution of Medicaid fraud. (Chen, 2015) http://www.natlawreview.com/article/wisconsin-repeals-state-false-claims-act)

Liability

Applies to state medical assistance programs including Medicaid. §893.981 10 year statute of limitations and §20.931(15) allows retroactive action as long as it is within this 10 year limit. This means that the act applies to any false claims violations starting October 27, 1997. Retroactivity was held that it did not violate the Ex Post Facto Clause of the Constitution in UNITED STATES OF AMERICA, ex rel. AMY BERGMAN, Relator, v. ABBOT LABORATORIES, Defendant, CIVIL ACTION NO. 09-4264.

Penalties

§20.931(2) Civil penalty of $5,000 to $10,000 plus treble damages.

Qui Tam

§20.931(5)(a) allows qui tam suits. §20.931(8) Private plaintiff may continue with action if the state chooses not to intervene. §20.931(11) Relator may receive 15% to 25% of proceeds if the state intervenes and 25% to 30% if the state does not intervene plus court costs and fees. §20.931(14) anti-retaliation.

Amendments

Enacted October 26, 2007. Amended April 6, 2012

Code

SFIPS: 55
*Using actual enactment and not retroactivity dates
FCA: ON October 27, 2007
MEDICAID ONLY: ON October 27, 2007
QUI TAM: ON October 27, 2007
MIN PENALTY: 5,000 October 27, 2007
MAX PENALTY: 10,000 October 27, 2007
TREBLE DAMAGES
FCA OFF July 14, 2015

39 United States

Act

False Claims Act §3729 to §3733 (focus on most recent amendments; was originally enacted in 1863).

Liability

Any U.S. government agency or program.

Penalties

§3729(G) Civil penalty of $5,000 to $10,000 adjusted by inflation according to the Federal Civil Penalties Inflation Adjustment Act of 1990 plus treble damages.

Qui Tam

§3730 allows qui tam suits. Plaintiff may receive 15% to 25% of proceeds if the government intervenes, or 25% to 30% plus court costs and fees if the government does not proceed.

Amendments

Amended October 2, 1986 civil penalty of $2,000 and double damages.; July 5, 1994 ; May 20, 2009 civil penalty of $5,000 to $10,000 and treble damages. Employee protection.

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Vita

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Education

Masters of Science in Economics,
University of Kentucky, Lexington, KY, December 2014

Bachelors of Business Administration, Economics and Finance. Minor: Mathematics
Marshall University, Huntington, WV, May 2012

Work Experience

Health Economist July 2018 -
RTI International, Health Care Financing and Payment Program — Research Triangle Park, NC

Research Assistant October 2015 - September 2016; Summer 2017
Kentucky Transportation Center - Intelligent Transportation Systems — University of Kentucky, Lexington, KY

Research Consultant Summer 2014, 2015, 2016, and 2017
Brookshire, Barrett, & Associates, LLC — Charleston, WV

Research Associate January 2012 - June 2013
Brookshire, Barrett, & Associates, LLC — Charleston, WV

Teaching Experience

Instructor of Record Summer 2014, Fall 2014, Spring 2015, Fall 2015 (2)
University of Kentucky — Lexington, KY

- Taught Principles of Microeconomics.

Teaching Assistant Spring 2015
University of Kentucky — Lexington, KY

- Taught recitation section of graduate macroeconomics.

Publications & Presentations

Brookshire, Michael L., and Grayson L. Forlines, "Rejoinder: The P Problem Fallacy–A Second Attempt At Obfuscation Also Fails," *The Rehabilitation Professional*, 23(4), pp. 239-241, 2015.

Brookshire, Michael L., and Grayson L. Forlines, "Rejoinder: The Debunking Attempt is Bunkum With No 'De'," *The Rehabilitation Professional*, 23(3), pp. 129-132, 2015.

Brookshire, Michael L., and Grayson L. Forlines, "The P Problem and and the Estimation of Worklife Expectancy Losses In Personal Injury Cases," *The Rehabilitation Professional*, 22(4), pp. 207-216, 2014.

"Drivers of Physician-Hospital Integration: The Role of Medicare Reimbursement"

- Presented at the Southern Economic Association, Graduate Students in Free Enterprise session, Tampa, FL, November 17, 2017.
- Presented at the 18th Annual Southeastern Health Economics Study Group, Nashville, TN, October 13, 2017.
- Presented at Centre College seminar series, Danville, KY, September 29, 2017.

"Outsourcing Fraud Enforcement–Whistleblower Laws and Medicaid Expenditure"

- Accepted for presentation at the American Society of Health Economists Conference, Atlanta, GA, June, 2018.
- Presented at the Southern Economic Association Graduate Student Awards Session, Tampa, FL, November 17, 2017.
- Presented at the conference for the Kentucky Economic Association, Lexington, KY, October 21, 2016.
- Presented at the 2016 Bates White Life Sciences Conference in Washington, D.C., May 24, 2016.

"The P Problem and and the Estimation of Worklife Expectancy Losses In Personal Injury Cases"

- Presented at the National Association of Forensic Economics conference in Tampa, Florida, March 2013.

Awards

BB&T Graduate Fellowship, 2015

Daniel R. Reedy Quality Achievement Award, 2013, 2014, 2015

Gatton Fellowship, 2014

Teaching Assistantship, 2013-2014, 2014-2015, 2015-2016

Schnatter Institute for the Study of Free Enterprise fellowship recipient, Spring 2017, Fall 2017, Spring 2018.