Physician Responses to Medicare Reimbursement Rate Changes

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Abstract

I investigate how physicians respond when the Centers for Medicare and Medicaid Services (CMS) change Medicare reimbursement rates. In 2011 the Affordable Care Act increased reimbursement rates in four states differentially across physicians. I use this relatively recent and plausibly exogenous variation to conduct a difference-in-difference analysis comparing physicians with higher reimbursement increases to those with lower increases. I focus on office-based physicians because they had the largest reimbursement rate increases and are more likely to have their income closely tied to Medicare reimbursements (rather than, for example, receiving a wage from a hospital employer). I find that physicians with higher reimbursement rate increases were more likely to continue providing office-based care, while physicians with relatively lower reimbursement were more likely to move all their provision to hospitals and other non-office facilities. Switching practice location to non-office facilities suggests that the physicians have vertically integrated with the facilities, for example, as employees, so my analysis shows a causal link between Medicare reimbursement and the recently increasing vertical integration across the United States. I also find that physicians who remain in office-based care exhibit a positive supply response to the reimbursement increase. My findings suggest that when CMS sets reimbursement rates, it should consider that constraining spending by decreasing rates may limit access. Likewise, it should consider the impacts on vertical integration and such integration’s subsequent impacts on costs and quality, as well as spillovers onto Medicare Advantage and other insurers from changing provider concentration.

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1 Introduction

Medicare reimbursement rates, a key policy lever affecting both spending and access to care, have a theoretically ambiguous impact on healthcare volume, and the empirical literature estimating the impact finds mixed results. Theoretically, reimbursement would positively affect volume if provider substitution effects dominate while the volume-reimbursement relationship could be negative if provider income effects caused the supply curve to bend backwards. The literature empirically investigating the relationship is mixed and the most clearly exogenous variation is from the late 1990s and earlier.

The literature on responses to Medicare reimbursement changes tends to focus on two mechanisms: changes in physician supply of the same types of care and changes in the intensity of care (e.g., switching between x-rays and more intensive MRIs). But a recent phenomenon in US healthcare has been the rise of consolidation, particularly vertical integration between physicians and hospitals—between 2012 and 2018, the share of physician practices owned by hospitals more than doubled from 14% to 31% (Post et al., 2021). A new literature is beginning to look at how Medicare reimbursement differentials across places of service affect vertical integration. But the impacts of reimbursement rates on integration have not been studied in the same settings as the impacts on volume and intensity of care.

This paper estimates the magnitudes and mechanisms of how physicians respond to Medicare reimbursement changes in a relatively modern setting. An Affordable Care Act (ACA) policy increased reimbursement rates in four states in 2011. I use these reimbursement changes, which were plausibly exogenous, to estimate a difference-in-difference (DID) analysis comparing providers within affected states who were more and less exposed to the reimbursement increase. Physicians responded positively to the rate changes along two margins. First, the reimbursement rate change affected practice style—physicians with larger increases were less likely to vertically integrate and stop providing office-based care than physicians with smaller reimbursement increases. And second, for physicians who continued in office-based practice, increased reimbursements increased services provided.

I focus my analysis on office-based care paid through Medicare’s Physician Fee Schedule (PFS). The PFS is large, both as a share of Medicare and in absolute terms. Approximately 38 million of the United States elderly and disabled are covered by traditional fee-for-service Medicare and the PFS sets reimbursements for their office-based and other professional care (Freed et al., 2021). In principle, the relationship could also be negative if demand responses caused by coinsurance linking patient cost-sharing to reimbursement rates dominated. But there is likely excess demand in the market because most patients have supplemental insurance that covers their cost-sharing.

The 38 million people covered by fee-for-service Medicare are the elderly and disabled who choose to enroll in the publicly run Parts A and B—they are 61% of total Medicare beneficiaries and exclude those who choose Part C or Medicare Advantage which is publically funded but privately provided insurance. Medicare Advantage does not
The PFS covers about 10% of total Medicare spending, and in 2018 had a total volume of $70.5 billion (MedPAC [2020]; Cubanski et al. [2019]). The PFS updates reimbursement rates annually, changing rates for some procedures or geographic areas, which makes the impact of the changes continually of policy interest. I focus on office-based PFS care in particular because, office-based care is likely more discretionary than professional care provided in outpatient or inpatient hospitals, and the providers are more likely to have their incomes closely tied to the reimbursement for the procedures they perform, so responses are likely larger.

Most of Medicare’s frequent reimbursement changes are endogenous responses to changing costs, but I leverage a plausibly exogenous ACA policy that raised reimbursements in four states. This policy introduced a binding floor for one of the geographic adjustments that raised rates in Montana, North and South Dakota, and Wyoming in 2011 (Federal Register [2010]). The policy raised rates unequally across procedures generating variation within affected states across physicians providing different bundles of services. Individual physicians specializing in the procedures with larger increases were more exposed to the policy change. The formula Medicare uses to set PFS reimbursements and the ACA policy change interacted such that within states affected by the legislated floor, physicians faced average increases in reimbursement rates ranging from 3% to 15%.

I use this variation to run a DID analysis comparing providers who are more and less affected. The policy change increased rates more for procedures like x-rays and electrocardiograms where a greater share of the input costs come from practice expenses (materials, equipment, and nursing staff) as opposed to physician labor, while services like office visits and psychotherapy that are primarily derived from physician labor received smaller increases. Thus, variation in the types of services across providers generates variation in their average reimbursement change. Psychiatrists who generally face lower reimbursement increases are unlikely to be a good counterfactual for radiologists who generally receive large reimbursement increases. But within a specialty, it seems plausible that family medicine doctors with different practice styles or patient cases mixes and hence different average reimbursement rate changes would have had parallel utilization trends in the absence of the ACA policy. I thus run a DID comparing the more and less affected providers within specialty. A particular strength of this analysis is that I can validate the parallel trends assumption by running an analogous DID in unaffected states—since the treated states are relative outliers I use a covariate matching algorithm to select counties from unaffected states that are most administratively set rates, so these people are excluded from this paper (Freed et al. [2021]).

Physicians can be employed by hospitals, group practices, or other associations and make a purely wage income, they can be sole proprietors whose income changes one-for-one with Medicare reimbursement for their service, or they can be basically anything in between in group practices with varied profit-sharing incentives (Gottlieb et al. [2020]). Since physicians integrated with hospitals change their coding and referral patterns to benefit the hospital, they clearly optimize jointly and hence may respond less strongly to incentives from professional payments or may not be the residual claimant on as large a share of the procedure level reimbursement (Baker et al. [2016]; Sacarny [2018]).
likely similar to the treated states for this placebo test.

The provider level DID estimates a positive provider response along two margins. On the extensive margin, the approximately 3 percentage point spread in reimbursement increases between the 10th and 90th percentile family medicine physicians causes an approximately 8 percentage point increase in the probability of continuing to provide office-based care over the long run. This is almost entirely offset by decreases in provider movement to facility-based care so there is little impact on the provision of any care at all. The estimates for intensive margin changes in service counts conditional on continuing to provide care are likewise positive—the point estimate for all physician is an elasticity of about 5 in the long run, though the standard errors are large. The effect of the ACA reimbursement increase in the affected states seems to have been to increase the number of office-based services provided to Medicare patients and to decrease physician movement out of independent offices and into solely facility based practices and foundation. There is no evidence that the reimbursement increase changed service intensity; i.e., that individual procedures became more resource intensive. This contrasts with [Clemens and Gottlieb (2014)] who found that service intensity drove almost the entirety of the positive response they found.

I extend Clemens and Gottlieb’s (2014) model of physician supply to intuitively describe why the reimbursement increase I study would both decrease vertical integration and for inframarginal physicians increase volume. The positive relationship suggests that the response is a provider driven movement along a supply curve. Medicare mechanically links patient out-of-pocket prices to provider reimbursement with a 20% coinsurance, so demand as well as supply is a function of Medicare reimbursement, but since Medicare administratively sets reimbursement there is no reason to assume the market is anywhere near equilibrium, so I assume the market operates in a disequilibrium along the supply curve. In my model, physicians are the sole decision makers: independent physicians provide more care when their profit margin goes up (offsetting their disutility of effort) and as reimbursement rates rise more physicians decide to practice independently because the increased profit margins make it worth the increased disutility of effort. The two key takeaways from this model are, first, that a reasonable set of physician preferences can induce the intensive and extensive margin physician responses I observe, and, second, that the parameter physicians

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4 The policy applied to “Frontier States” which are defined as states where at least half of the counties have a population per square mile less than six. The affected states were thus more rural and sparsely populated than potential control states, but potential control states have many counties that look similar to the Frontier States.

5 As I discuss later, there are reasons to believe that patient demand may be high or inelastic since many patients have supplemental insurance to cover their cost-sharing.

6 This is consistent with either excess demand and rationing or with excess supply and provider induced demand. I take no stance on which is the case, thought the welfare implication would be quite different. If there were excess demand with reimbursement set below the market clearing rate, the positive response could cause a welcome decrease in rationing as the quantity supplied and demand come closer together. If the positive response were an induced demand response, that would have very different policy implications as Medicare would then being paying more inframarginally and simultaneously inducing inefficient care.
respond to could be the profit margin rather than the reimbursement rate. This last point suggests changing physician costs may have an analogous impact on physician supply as changing Medicare reimbursement rate.

**Related Literature:** This paper contributes to the broad literature evaluating how healthcare provision responds to changes in reimbursement structure. Most specifically, this paper relates to two strands of that literature: first, the literature estimating the utilization response to Medicare reimbursement for outpatient care, and second, the literature investigating how reimbursement impacts vertical integration.

The effects of reimbursement on healthcare provision have been studied quite broadly indeed. Internationally, Norwegian general practitioners provide more visits when the payment increases (Brekke et al., 2017) and Japanese physicians distort their choice between branded and generic drugs to increase profits (Iizuka, 2012). In the United States private insurance incentives affect cesarean section rates (Johnson and Rehavi, 2016) and hospital choice (Ho and Pakes, 2014). Medicaid payments for primary care have been shown to increase appointment availability and utilization for Medicaid patients (Alexander and Schnell, 2019; Cabral et al., 2021; Polsky et al., 2015). The existence of Medicare itself increased the size of the healthcare sector (Finkelstein, 2007), and Medicare’s hospital payments affect how hospital care is provided (Dain, 2005; Einav et al., 2018).

This paper adds to a large literature estimating the utilization response to Medicare reimbursement for outpatient care. The most closely related paper is Clemens and Gottlieb (2014), which studies how an exogenous Medicare policy that changed reimbursement at the geographic level in 1997 affected outpatient utilization. The papers estimating reimbursement elasticities within outpatient Medicare generally use either geographic or procedure level variation in reimbursement, and studies using both types of variation have estimates positive and negative elasticities.

Even the studies using the most clearly exogenous geographic level changes in reimbursement estimate both positive and negative elasticities. Clemens and Gottlieb (2014), Rice (1983), and Rice and McCall (1982) take advantage of geographic reimbursement rate changes that came from Medicare changing the size of the geographic areas at which it determines reimbursement. Clemens and Gottlieb (2014) estimates a positive elasticity, while Rice (1983) and Rice and McCall (1982) estimate negative responses. While the policies generating the variation they study were almost certainly exogenous, the reimbursement rate change was correlated with area characteristics—generally the more rural areas faced reimbursement increases while the urban areas faced decreases. Clemens and Gottlieb (2014) control flexibly for differential trends by urbanicity, but Rice (1983)

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7Slightly more tangentially related, providers who financially benefit from recommending more intensive care by being able to provide it themselves do so to a greater extent for MRIs and cardiac problems (Afendulis and Kessler, 2007; Baker, 2010).
and Rice and McCall (1982) may be biased by differential trends. Other papers using more nuanced strategies to identify the reimbursement-utilization relationship without exogenous policy changes have estimated both positive and negative volume elasticities. Hadley et al. (2009) and Brunt (2015) create a “generosity” measure by subtracting their best estimate of cost from Medicare’s payment rate and assume that time and area fixed effect will account for any unobserved variables that might cause bias, but Hadley et al. (2009) estimates a positive elasticity while Brunt (2015) estimates a negative one. In a more recent, and quite resourceful paper using only public data, Brunt and Hendrickson (2021b) match physician practices with similar characteristics across borders of Medicare payment regions that face different reimbursement rates and estimate a negative elasticity—though this depends on the assumption that no unobserved variables impacting utilization vary discreetly at locality borders, which are often states lines.

Papers estimating the volume response to reimbursement using procedure level variation tend to find positive estimates, with some notable exceptions. Usually procedure-level time series variation is endogenous, but it can be reasonably assumed that the exact timing of large, abrupt changes are exogenous so that short event studies around the changes identify the reimbursement response. Many studies find a positive relationship across a wide range of procedures and time periods including nerve conduction studies, cesarean sections, bladder cancer care, and androgen-deprivation therapy from 2004 to 2015 (Callaghan et al., 2016; Gruber et al., 1999; O’Neil et al., 2016; Shahinian et al., 2010). A few studies looking at similar variation have estimated negative effects (or found no evidence of a positive effect) for intensity modulated radiation therapy, coronary artery bypass grafting, and lung cancer chemotherapy (Jacobson et al., 2010; Howard and Hockenberry, 2021; Yip, 1998).

My paper contributes to the literature on responses to Medicare reimbursement by analyzing a relatively recent exogenous change. My finding of a positive reimbursement-utilization relationship strengthens the growing consensus across countries, insurance providers, and types of care that providers respond positively to reimbursements. Another contribution is my finding that extensive margin provider participation is a mechanism in the response. That provider financial incentives shape volumes is well established, but within Medicare the typical mechanism is via service intensity—Clemens and Gottlieb (2014) find no response for the number of services or providers, and their entire positive results is driven by service intensity. Though the extensive margin response that I find is not surprising given Clemens et al. (2021) finding that higher reimbursement rates cause providers to engage in capacity building.

This paper also relates to the literature investigating how Medicare reimbursement impacts ver-

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8 A related paper, Brunt and Hendrickson (2021a) uses reimbursement variation at the provider level to estimate a negative elasticity. This is more similar to the geographic level studies than it is to the procedure level studies since the variation is in the total amount that the physician’s Medicare income changes rather than only a subset.

9 Brunt (2015) also finds a response driven by intensity, but his results have the opposite sign.
tical integration. The most closely related paper in that literature is Dranove and Ody (2019) which investigates a 2010 reimbursement rate change in the PFS that differentially changed the facility versus non-facility rate for various Medicare procedures. They find that physicians who provided procedure mixes with a higher relative price in facilities were more likely to vertically integrate and that procedures with higher relative Medicare reimbursement in facilities shifted their locations to facilities. Since they did not have Medicare microdata they were unable to investigate the impact of the reimbursement rate changes on Medicare provision by individual physicians. A similar closely related paper Post et al. (2021) investigates how the disparity between the office and facility payment that Medicare would pay for a physician’s procedures affects the rate at which the physician consolidates with healthcare systems. They find that financial incentives strongly and positively influence consolidation for primary care physicians and medical specialists, but have no impact for surgeons—though Post et al. (2021) do not have exogenous variation in reimbursement rates.

Other papers in the literature looking at the impact of reimbursement on consolidation focus on specific specialties. Post (2021) looks at the impacts of reimbursement policy on primary care integration and finds that the impacts are quite heterogeneous across physicians (by market characteristics and physician volume). Sloan et al. (2021) finds that the introduction of the Medicare prospective payment system for end stage renal disease which decreased reimbursement increased integration of small chain and independent dialysis facilities. Song et al. (2015) and Masoudi et al. (2019) both find that reimbursement rate cuts to office-based cardiology services (for example, echocardiograms and electrocardiograms) both affected care locations. However, Alpert et al. (2017) finds that there is little to no impact of two Medicare payment reforms on vertical integration for oncology.

This paper contributes to the literature on the relationship between vertical integration and reimbursement in two main ways. First, by looking at the response to absolute changes in reimbursement for non-consolidated care. While it is sensible to consider the independent/integrated differential as Dranove and Ody (2019) and Post et al. (2021) do given the concepts of outside options and bargaining power, given that physicians are often viewed as altruistic it is possible that they respond not so much to outside options as to the feasibility of maintaining a practice with reasonable net income (Arrow, 1963). And second, it ties this literature to the literature on volume responses to reimbursement rates by evaluating integration as a mechanism for volume responses.

This paper is also related to the literature on access to care for Medicare patients (and given my setting, to rural access in particular). Cross-sectional evidence from Brunt and Jensen (2014, 2013) and Gillis and Lee (1997) show that higher Medicare rates are associated with more providers accepting new Medicare patients and Medicare patients reporting better access to care. And in rural areas, these concerns are amplified by already poorer access—Chan et al. (2006) finds that Medicare beneficiaries generally have to travel further for their care, and Johnston et al. (2019) finds that
rural Medicare patients lack access to specialists and that this is associated with preventable hospitalizations and mortality. This paper contributes to that literature by suggesting that reimbursements have an inverse relationship with provider participation in office-based care and volume.

The rest of my paper proceeds as follows. Section 2 discusses describes background information on the Physician Fee Schedule, the ACA policy change, and how to think about equilibrium in the PFS market. Section 3 describes the data and some measurement issues. Section 4 presents the provider level DID strategy and results. Section 5 explores heterogeneity across provider characteristics. Section 6 introduces a model to build intuition explaining the results. And section 7 presents policy implication and concludes.

2 Background: the Physician Fee Schedule and Reimbursement Rate Variation

The PFS covers professional care within Fee-for-Service Medicare and is a large subset of total Medicare spending. An ACA policy increased reimbursement in four states in 2011, but did so with differential impact across procedures and providers within those four states.

PFS spending accounts for 10% of total Medicare spending (MedPAC 2020). Medicare as a whole includes traditional Fee-for-Service health insurance, the privately provide Medicare Advantage health insurance, and Part D insurance for prescription drugs. Fee-for-Service Medicare covers institutional care through Part A and professional and other outpatient care through Part B. Part B is itself composed of many payment systems of which the PFS is a relatively large component; other examples of payment systems are the Outpatient Prospective Payment System and the Ambulatory Surgery Center Payment System.

The professional care covered by the PFS includes payments to physicians and other professionals. The types of services paid via the PFS range from office visits to surgical procedures to diagnostic and therapeutic services. These services can be performed in physician offices or in facilities like inpatient or outpatient hospitals, skilled nursing facility, or ambulatory surgical centers. In non-facilities (primarily offices) the PFS payment covers the full cost of care, while in facilities the PFS covers only the professional component and another Medicare program makes a separate payment to the facility.

The PFS sets a total reimbursement rate for each procedure, which is paid to the provider by the patient’s cost-sharing (deductible and coinsurance) and Medicare’s payment. Patients have a 20% coinsurance rate and a deductible that applies to all Part B care—in 2011 the deductible was $162

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10 Other professionals include physicians assistants, nurse practitioners, and physical therapists who can provide professional care, though the non-physicians only file a separate claim if they are providing care independently, most non-physician work is included in the payment to the physician).
and it increases slightly each year. The deductible and 20% coinsurance mechanically link patient and provider prices. Though patients may have supplemental insurance (for example Medigap) that covers this cost-sharing.

The PFS is a good setting for my study because it is large, it has frequent reimbursement variation, and it is paid at a particularly granular level. It is large enough and affects enough peoples’ health care that it is worth studying for its own sake. Its frequent reimbursement changes both make understanding the volume response an important policy question and generate variation to estimate the volume response. And finally, the PFS pays for care at the procedure level—these granular payments means that there is more scope for patients and providers to finely vary utilization than there is in other payment systems where reimbursements are bundled.

2.1 Physician Fee Schedule Reimbursement Rate Setting

The PFS pays for care at the procedure level and sets reimbursement for each procedure at the area, time level. It sets this reimbursement based on procedures’ input costs and adjusts for geographic variation in these costs.

The PFS pays separately for each individual service or procedure according to its Current Procedural Terminology (CPT) classification. With physician input, CMS sets relative value units (RVUs) which describe the input costs for each CPT code. This is done separately for three types of inputs: provider work, practice expenses (materials, employee costs, and office rental), and malpractice liability insurance. Thus, each procedure has three RVUs.

Each of a procedures three RVUS are separately adjusted for geographic variation in cost for that input by multiplying the RVUs by an area, input specific geographic practice cost index (GPCI). These GPCIs describe how the costs of provider work, practice expenses, and malpractice liability insurance vary across areas. The geographic area that CMS adjusts costs at are localities. There are 89 localities in the United States—some are states (eg, New Hampshire), some are metropolitan areas (eg, Boston Metropolitan Area), and some are the rest of states with metropolitan areas excluded (eg, Rest of Massachusetts). Medicare combines the RVUs and GPCIs with an annually set conversion factor that scales the RVU measure of relative cost into dollars.

A simplified version of the formula Medicare uses to combine the RVUs and GPCIs into procedure by area reimbursement rates is below. This omits malpractice liability insurance costs and a few other minor adjustments, which are not critical for understanding the reimbursement vacation my identification strategies use—see the appendix for a more complete discussion of how reimbursement rates are set.
Reimbursement$_{pj} \approx ConversionFactor \ast \left[ RVU_p(work) \ast GPCI_j(work) \\
+ RVU_p(practice\ expense) \ast GPCI_j(practice\ expense) \right]$

Where $p$ indexes procedure and $j$ indexes locality. The parameters change over time, so there is an implicit time subscript. The policy variation I exploit was an exogenous change in the practice expense GPCI in four states, so the important takeaway is that this only affects reimbursement in those four states and affects reimbursement more for procedures with larger practice expense RVUs.

2.2 ACA Floor on Practice Expense Geographic Practice Cost Index:

The ACA mandated a permanent floor for practice expense (PE) GPCIs in Frontier States. Frontier States are defined as states where at least fifty percent of the counties have a population per square mile of less than six \footnote{\textit{Federal Register} 2010}. The five Frontier States in 2011 were Montana, Nevada, North and South Dakota, and Wyoming, but the GPCI floor did not bind in Nevada. Hence the GPCI Floor increased reimbursement from 2011 on in Montana, North and South Dakota, and Wyoming. I call these four states the treated states.

Figure 1 shows the PE GPCI over time in the four treatment states and the surrounding states from which I select counties to use as a falsification test for my analysis—note that from 2011 on the treatment states have a GPCI of 1, which is much higher than their pre-2010 level. There was also a smaller increase in PE GPCI in the treatment and some of the control states in 2010 and 2011—this is a temporary ACA provision, which I treat as noise that just dilutes some of my variation.\footnote{This was the result of a policy that only applied in 2010 and 2011 that limited the incorporation of below average costs into GPCIs—for localities with costs below average, it reduced the deviation from average by a constant percentage.} The bottom panel of figure 1 shows that the increase in PE GPCIs in the treated states translated into an increase in reimbursement per RVU, while there was a much smaller increase in neighboring states over the same period.

The ACA included two other provisions intended to protect access to care in Frontier States. First, it established an area wage index floor for hospitals at 1.00, and second, it established an area wage adjustment factor for hospital outpatient department services at 1.00. \footnote{11th Congress, 2010} These are potential confounders. They do not affect office-based care directly, but to the extent that office-based care is a substitute or complement for hospital care, this could affect care. I focus on office-based physicians in my analysis because it seem reasonable to assume that the facility rate changes affects office-based physicians equally as a change in outside option.
Variation Induced by the 2011 PE GPCI Floor: The PFS’s formula along with the PE GPCI floor creates differential reimbursement changes across procedures, areas, and providers.

Since the PE GPCI multiplies only the PE RVU in the reimbursement formula the increase in reimbursement is larger for procedures with a larger share of RVUs from practice expenses. Comparing two procedures with very different PE shares exemplifies this distinction. Psychotherapy has a PE share of 0.23, while eye exams have a PE share of 0.75. For psychotherapy, a 0.15 increase in the PE GPCI would increase reimbursement by 4% since only 23% of the total RVUs are subject to the increased GPCI, while for eye exams the same 0.15 PE GPCI increase would increase reimbursement by almost 13% since 75% of the RVUs are subjected to the increased GPCI.

Table 1 shows the psychotherapy and eye exam example in panels A and B. Panel A lists the GPCIs for Montana in 2009 and 2011—there was a 0.153 increase in the PE GPCI. Panel B shows the RVUs for psychotherapy and eye exams in 2009 and 2011 in columns 1 though 4—three key points about the RVUs are that (1) psychotherapy is more intensive since the sum of its RVUs is higher, (2) psychotherapy has a lower PE share, and (3) eye exams had their PE RVUs updated between 2009 and 2011. Column 5 shows the GPCI-adjusted sum of RVUs in 2009—this is proportional to reimbursement, which is simply total adjusted RVUs multiplied by a conversion factor. Column 6 shows the 2011 GPCI-adjusted total RVUs, for psychotherapy this is just the same RVUs multiplied by the new 2011 GPCIs. But for eye exams, the PE RVUs also changed between 2009 and 2011 (compare columns (2) and (4))—thus the difference in GPCI-adjusted total RVUs incorporates both the change in GPCIs (which I am assuming was exogenous) and the endogenous change in PE RVUS. Column (7) shows the GPCI-adjusted total RVUs using the new 2011 GPCI rates, but the old 2009 RVUs, the difference between this and the 2009 GPCI-adjusted total RVUs is only due to the exogenous change in GPCI rates. Columns 8 and 9 show the percent changes in GPCI-adjusted total RVUs (and reimbursement) for the actual change and the change induced by the exogenous GPCI floor holding RVUs fixed.

The variation in reimbursement changes across procedures with different PE shares translates into variation in reimbursement changes across areas which provide different mixes of procedures. Areas with more high PE share procedures received larger average reimbursement changes than those where the average PE share was lower. Panel C of table provides an example of this type of variation using two fictitious counties. In both counties the Medicare patients get 100 eye exams (column 2), but in the sad county the patients receive 100 psychotherapy visits while in the happy county they only require 10 (column 1). Multiplying these volumes by the GPCI-adjusted total RVUs yields the county aggregate adjusted RVUs (which is proportional to total Medicare

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12 This example is simplified to only include work and PE inputs (i.e., it ignores liability insurance inputs—these are small and would increase complexity with no value added). In the empirical application insurance inputs are treated analogously to work input. Also note that there are multiple types of psychotherapy and eye exams, the listed values are for CPT codes 90806 and 92250 respectively.
—these numbers are shown in columns 3 and 4. Column 5 then shows that the percent change in aggregate adjusted RVUs is larger in the happy county where a great share of the revenue comes from the high PE eye exams. This example shows how the GPCI change caused differential reimbursement changes across counties.

A parallel logic applies to individual providers who provide different mixes of procedures. Obviously, there are probably few providers who provide both eye exams and psychotherapy, but there are family medicine physicians who provide more or fewer high PE share tests like EKGs and x-rays relative to the number of relatively low PE office visits they perform. I exploit this across provider variation in my second identification strategy.

2.3 Possible Disequilibrium in the market for PFS Care

The administratively set prices mean that the market for PFS care may not be in equilibrium. If the market operated on the supply curve, provider decisions would determine aggregate care, while if it operated on the demand curve, patient decisions would determine volume. In theory, a reimbursement change could cause the realized disequilibrium to move along an upward sloping supply curve causing a positive utilization-reimbursement relationship. Or the realized disequilibrium may move along either a downward sloping demand curve or a backward bending supply curve causing a negative utilization-reimbursement relationship.13

Patient demand is a function of provider reimbursement rates because Medicare mechanically links patient out-of-pocket prices to provider reimbursements via a deductible and a 20% coinsurance rate, so when provider reimbursement changes, so does patient price. The RAND Health Insurance Experiment tells us that patients indeed respond to their cost-sharing (Manning et al., 1987). It is likely that within Medicare demand is high or inelastic because many patients have supplemental insurance like Medigap. Supplemental insurance often breaks the mechanical link

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13In principle, provider supply curves may slope backwards. Generally, substitution effects are assumed to dominate income effects in labor supply, but several aspects of healthcare make it plausible that income effects could dominate. The training to become a doctor is costly and long, so entry in response to increased reimbursements may only increase supply in the long term, while income effects cause current providers to work less. Fixed costs are also high (as are transaction costs to exit from provision or sell equipment for certain procedures). Thus when reimbursement rates decrease, in the short run, providers may increase care to cover fixed costs or meet behavioral income targets until exit or other substitution forces decrease provision. One final reason income effects are particularly plausible in response to Medicare reimbursement changes is that other payers often base their payments on Medicare’s rates so even rates for non-Medicare patients could be affected magnifying the shock to income (Clemens and Gottlieb, 2016). In the appendix in figure A.1, I show examples of Medicare reimbursement rates associated with a backward bending supply curve—in this case there could either be excess demand (panel A.1a) or provider induced demand (panel A.1b) allowing the market to move along the downward sloping supply curve. In either case, there is a negative relationship between reimbursement and volume that is driven by providers. The slope of the supply curve depends on whether substitution or income effects dominate. In the short run it is plausible that income effects may dominate, but in the long run substitution effects are generally assumed to dominate (McGuire and Pauly, 1991). Entry and exit over time would relieve pressure to cover fixed costs and reach target incomes.
between patient and provider prices by replacing the coinsurance with a copayment that does not vary with provider reimbursement. Most patients have some form of supplemental insurance—specifically, as of 2014, in affected states only 15% to 24% of Medicare enrollees had no supplemental insurance. And inattentive patients or the general difficulty understanding health care prices would likewise make patient demand high or inelastic. Since I find positive responses to the reimbursement rate increases, I assume that the market for PFS care is not constrained by demand.

Figure 2 shows examples of disequilibrium outcomes in the PFS market. Panel 2a shows two possible disequilibrium states depending on which price level Medicare sets. At \( P_1 \) there is excess demand, so the market would be constrained by the available supply and end up at the disequilibrium indicated by point 1 on the graph with providers somehow rationing care. Then when Medicare increased prices, the disequilibrium would move up along the supply curve. If Medicare set a high enough reimbursement rate, there could be excess supply in the market as shown in panel 2a by reimbursement rate \( P_2 \)—in this case a price increase would cause a decrease in volume as the disequilibrium moved along the demand curve, though my positive finding suggests this is not the case.

Because there is asymmetric information in health care markets, when there is excess supply, instead of the market operating on the demand curve, providers may induce demand (Chandra et al., 2011; McGuire and Pauly, 1991). In health care, providers both provide care and serve as agents to help patients decide what care they need or want. Thus, providers may change the information they provide to patients to shift the demand curve—Chandra et al. (2011) defines provider induced demand as “provision of care that a fully informed patient would not choose for himself.” Panel 2b of Figure 2 shows that when there is excess supply, providers may create an inflated demand curve by inducing demand so that the market operates on the supply curve and the relationship between reimbursements and volume is again positive. Here when Medicare increases price, providers induce additional demand and move along their supply curve. My result of a positive relationship between reimbursement and volume does not distinguish induced demand and excess demand.

3 Data

For my analysis, I need data on the volume and types of procedures provided and the reimbursement rates. I use the Medicare Claims data to measure utilization and actual paid reimbursement rates and the Physician Fee-for-Service RVU files from CMS to measure statutory reimbursement. I also use supplemental data on area characteristics match control counties likely to fulfill the parallel

14 Based off the 2014 Survey of Income and Program Participation data—supplemental coverage includes Medigap, Medicare Advantage, retiree plans, or private plans.

15 Ji (2021) suggests there are at least some segments within Medicare where demand is binding.
trends assumption.

**Restricting to Office-Based Care:** I restrict to office-based care in my analysis. Office-based care generally faced larger reimbursement increases than facility based care this is because the practice expenses of operating a office are included in the reimbursements. For example, CPT “99213” the most common established patient office visits is 0.44 practice expenses in a private physician’s office, but 0.23 in a facility (so a 10% increase in PE GPCI would increase office reimbursement by 4.4% but facility reimbursement only by 2.3%). Office-based care is more likely to be discretionary, since professional payments in facilities include payments to emergency room doctors treating patients and the physicians caring for hospital inpatients. Providers may have more room to self-refer and induce volume if they so desire in office-based settings. And lastly, office-based care is more likely to be provided by independent providers or those in smaller group practices where the provider’s income is more closely linked to the Medicare reimbursement their procedures accrue.

A down-side of restricting to office-based care is that it means that this analysis will not be able to measure any potential changes that the reimbursement rates changes may have had on where care is performed.

**Measuring Reimbursement:** I calculate the statutory reimbursement rates from parameters in the CMS Physician Fee-for-Service RVU files. These contain RVUs, GCPIs, and the annual conversion factor necessary to calculate the statutory reimbursements for each procedure in each locality each year. I select the most revised January publication each year, and run the inputs through the formula listed in annual documentation accounting for any special adjustments that apply in any given year to calculate procedure, locality, year level rates. Additionally, some modifier codes affect the payment, the ones that occur most often are modifier “26” and “TC” for the professional and technical component only, I account for these in my analysis. And some procedure’s have a payment cap at the level they would be paid were they paid via the Outpatient Prospective Payment System, which I account for.

These files also list the counties in each locality. For the states in my setting localities and states map one-to-one.

Some procedures can be done in either a facility (outpatient hospital, emergency room, or ambulatory surgery center) or non-facility setting (physician’s office), and these have different sets of RVUs that apply in the respective settings. Medicare pays different statutory rates for the same procedures. In 2010 I use the July publication because it includes a change to the January rates that applied retroactively, so the January rates were never the actual rates paid. Also, note that in some years there are slight adjustments to the formula—some year multiply some types of RVUs by budget neutrality adjusters (for example in 2008, work RVUs were paid at only 88.06 there normal rate), sometimes there are special adjustments for mental health care, and some procedures have their rates capped at a level based on the Outpatient Prospective Payment amount—I checked the annual formula adjustment and applied these.
procedures depending on whether they are performed in facilities or non-facilities because they also pay a separate facility fee for care performed in facilities. I only consider the non-facility fees because I focus on office-based care in this paper. In the RVU file Medicare notes procedures that are only performed in facilities (and does not provide non-facility RVUs for these procedures)—I drop any procedure that Medicare does not provide a reimbursement rate for in non-facilities.

There are a few payment adjustment that I do not account for. Probably the most important element that I ignore for simplicity is the reduction for multiple units of the same service to one patient on any given day. I also ignore the payment reduction for procedures performed by nurse practitioners and physicians assistants instead of physicians. And finally I ignore the payment increase for procedures performed in Health Provider Shortage Areas.

Measuring Utilization: The general term “utilization” describes both the service count of procedures performed and the intensity of the procedures. For example, doubling the number of office visits would increase utilization, but holding the number of office visits constant and making all short office visits into long office visits would also be an increase in utilization. Measuring the impact on service counts simply entails running the main regression on log service counts. To incorporate intensity changes as well, I follow the standard practice of using log RVUs as an outcome. RVUs are designed by Medicare to measure the relative input costs across procedures, so to the extent Medicare succeeds in this endeavor, RVUs are an apples-to-apples comparison across procedures. This solves the problem that while short and long office visits have an obvious intensity ranking, for most procedures, even the ordinal ranking is not clear (for example, for a twisted ankle, is an x-ray and a physical therapy visit more intensive?)

To measure utilization paid through the PFS, I use Part B claims data for a 20% sample of Medicare beneficiaries. The PFS claims are a subset of the claims in the Carrier file—I assume that all claims in the Carrier file for procedures (defined by Current Procedure Terminology (CPT) codes) that the PFS covers were paid through the PFS. I drop claims to people not enrolled in FFS Medicare that month because they are likely to be erroneous. I drop claims that were denied or assigned zero payment, assuming that these are duplicate or other erroneous claims. I restrict to office-based care by including only claims with place of service code “11”. I exclude procedures that CMS declares are never or rarely performed in non-facilities and does not provide a reimbursement rate for in non-facilities—these are ones with a “NA” in the PE RVU indicator field for that pos

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17 Increasing the intensity of any given procedure could be “upcoding” where the same procedure occurs but is coded differently so that reimbursement is higher, or it could be an actual change in the care provided. Dafny (2005) suggests that in the inpatient setting can be purely a relabeling without affecting care provided. I remain agnostic to whether the increased intensity is real or nominal.

18 I include any CPT codes that has a PFS status code of “A”, or “T” in the CMS Physician Fee-for-Service RVU files—these identify active codes paid separately under the PFS and injections that are only paid if there are no other PFS services billed by the same provider that day.
type. And I similarly drop claims where the listed provider zip code is not one of the counties included in the locality that the claim is listed as having being paid under (if these claims have two non-compatible locations listed I can’t be sure where they occurred).

For each of the claims I record the procedure type (CPT code and payment relevant modifiers), the number of units of service provided, the actual reimbursement made, and the provider zip code. I crosswalk the provider zip code to the provider county in order to run the analysis at the county level since reimbursement is defined based on the provider’s location. I also crosswalk on the total RVUs to use as a measure of service intensity.

**Defining Provider Level \( \Delta \text{Reimbursement} \):** The RVU files provide the locality, year, procedure level reimbursement rates. These change over time as RVUs, GPCIs, and other adjustment change. The frontier state PE GPCI floor plausibly provides an exogenous change in some reimbursement rates. To isolate the exogenous change in reimbursement rates from the GPCI floor, I calculate the counterfactual change in reimbursement rates that would have occurred had only the GPCIs changed, but the RVUs and procedure mix had remained constant. This follows the logic described in the background section and demonstrated in table 1 with psychotherapy and eye exams—I extend that logic to all procedures and calculate the change induced only by the exogenous GPCI changes.

I define counterfactual reimbursement rates for each procedure based on 2009 RVUs and 2011 GPCIs. Then I apply the true 2009 rates and the counterfactual rates to the same set of pre-period claims, aggregate the total amounts to the provider level, and take the percentage difference between the total based on the two rates as the provider level percent change in reimbursement rate. For the pre-period claims, I use all available claims from 2008 and 2009 in order to have a less noisy measure since some of the providers had only a small volume of claims, and I only have a 20% sample of claims. I do not use 2010 because there was a small increase in GPCIs in the treated and some control states that may have impacted quantities. This definition of the reimbursement change only includes variation from the GPCI floor so is as exogenous as the policy.

Table 2 shows the reimbursement rate changes that the providers in the Frontier states faced. Within most specialties there are a few percentage points of variation in the rate changes. For example, for family medicine (FM) physicians (the most common specialty) the 10th percentile reimbursement increase was 7% and the 90th percentile was 9.7%. This variation not huge, but it is reassuring that FM providers are a relatively homogeneous group to make the parallel trends assumption more plausible.

**Supplemental Data:** I get county characteristics for my propensity score matching algorithm from the Agency for Healthcare Research and Quality. This has county level data on county demographics and health care provider density.
Finally, I use the Master Beneficiary Summary File to measure fee-for-service enrollment in each county.

4 Provider Level Analysis

I run a provider level DID that compares providers only within treated states who receive smaller and larger reimbursement changes. Providers who receive larger reimbursement rate increases are more likely to continue providing office-based care though this increase is offset by decreased facility-based provision. There is weaker evidence that the offset is incomplete, meaning there is an increase in total active providers, and that among providers who continue providing office-based care, higher reimbursement drives an increase in the number of services. However, my estimates for the impact on total care across all settings are noisier and less-clearly well-identified.

Within treated states, providers have different reimbursement rate changes because procedure rates changed deferentially, and providers have different mixes of procedures. The procedures with higher reimbursement rate increases were those with higher PE shares—typically things like imaging and testing. The mix of procedures and hence reimbursement rate change varies across procedures because they have different mixes of patient with different needs, because the providers have different practice styles, and because the providers focus on treating different types of conditions. For example, psychiatrists tend to provide less PE intensive care and hence have lower reimbursement increases than cardiologists who do more imaging and testing.

For the provider analysis, I assume that physicians are on parallel trends only within specialty, not across specialties. For example, it seems plausible that family medicine physicians with different typical mixes of office visits, x-rays, and electrocardiograms would have been on parallel trends in the absence of the policy change. But it seems slightly less plausible that the psychiatrists and cardiologists would have been on parallel trends. There is a concern that cardiologists, for example, that provide more PE intensive care and hence have higher reimbursement changes may not have been on parallel trends, but this can to some extent be evaluated by checking whether there are pre-trends or whether the falsification test in control areas shows a response.

The specification for the provider level analysis is the following:

\[ Y_{ist} = \sum_{\tau} \beta_{\tau} \mathbb{1}(\tau = t) \Delta Reimbursement_i + \gamma_{ist} + \gamma_i + \varepsilon_{ist} \]  

(1)

Where \( i \) represents providers, \( s \) specialty, and \( t \), year. \( \Delta Reimbursement_i \) is the provider level reimbursement change, \( \gamma_i \) are provider fixed effect, and \( \gamma_{ist} \) are specialty by year fixed effects. The individual provider fixed effects implicitly include specialty since that is a provider level attribute.
cluster my standard errors at the provider level. This accounts for any serial correlation in provider outcomes that is not absorbed by the provider fixed effects. And I weight the providers equally in the baseline specification—though I consider the alternative of weighting them by their total Medicare revenue.

**Identification Assumption and Falsification**  The identification assumption is that within specialty physicians with higher and lower reimbursement rate changes would have been on parallel trends had they been treated identically by the policy change. This is subtly different than the standard DID identification assumption that they would have been on parallel trends in the absence of the policy change because the “control group” in my analysis is not untreated by the policy change, but rather is treated to a lesser degree.

The easiest model of physician behavior that satisfies the identifying assumption is that physicians have a homogeneous response to each unit of reimbursement rate change. Then the more treated physicians would have looked just like the less treated physicians if they had been treated to a lesser degree. More flexibly, one could assume that the treatment effect of each unit of reimbursement rate increase is not the same, but that all providers reacted identically to the lowest increase, they would have behaved similarly to the physicians who only received that increase.

The parallel trends assumption would be violated if the treatment effect were correlated with the treatment level. A possible violation of my identifying assumption that exemplifies how it is different from the standard DID identifying assumption when the “control group” is untreated would be if treatment effects and treatment levels were correlated. For example, physicians with lower PE shares (and lower reimbursement rate changes) could be more elastic to reimbursement rate changes than physicians with higher PE shares (and higher reimbursement rate changes). This would mean that in the absence of any changes the two groups would be on parallel trends. But if reimbursement rates went up the same amount for both groups, the lower PE share providers would respond more strongly, and if reimbursement rates went up more for higher PE share physicians (as they did) the different response could be due to both a different elasticity and a different reimbursement rate change. This could in principle even yield a spurious negative elasticity.

To some extent the parallel trends assumption can be tested by running a falsification analysis on providers in areas unaffected by the GPCI floor policy. I use a covariate matching algorithm described in detail in the appendix to select counties in neighboring states that are similar to the counties in the treated states. For providers in the matched control counties, I define the counterfactual reimbursement rate changes they would have faced if they had practiced in the treated states—the distribution of counterfactual reimbursement rate changes is quite similar to the distribution of changes the treated physicians faced suggesting that the groups are comparable. One concern is that there were smaller reimbursement increases in the control states but these were not
correlated with the PE share, so the actual and counterfactual reimbursement rate changes were not particularly correlated—see figure A.2 in the appendix.

I then run exactly the same DID specification on these control physicians in the unaffected states as a falsification. If the providers with different PE shares had different trends in control states in the absence of any policy change, it would not be reassuring that the providers in the treated states would have had parallel trends. This falsification check only tests that the providers would have had parallel trends in the absence of the policy change. It does not test the additional more subtle assumption that the treatment effects for the lower and higher PE share providers were similar and thus that the higher PE share physicians would have had parallel trends to the lower PE physicians if they had had similar reimbursement rate changes.

**Provider Classification and Sample** The sample included in the aggregate provider analysis includes all physicians. The distribution of types of specialties and the number of providers and their Medicare revenue is shown in table 2. The claims data include HCFA specialty codes which are very precise. I group all medical doctors into primary care, medical specialties, surgical specialties, and other specialties following Machado et al. (2021), and within these categories define narrower groups to match the list of main specialties that Chan and Dickstein (2019) uses in their paper. Appendix table C.2 lists how I group HCFA code for my analysis. I drop all providers whose HCFA code does not match one of the main specialties.

There are also many claims to non-physicians, for example, physical therapists, optometrists, and chiropractors. I do not include these in the main analysis.

I drop outlier providers. Very small providers will have noisy estimates of the reimbursement rate change. Very large providers are unusual in some respect. I drop physicians whose Medicare revenue in 2008 and 2009 is below the 5th percentile or above the 95th percentile among their specialty in treated states. Dropping 5% of outliers is a rather large amount, but the physicians at the bottom of the distribution are very low volume indeed, and I check for robustness to dropping only the top 1% of outliers. For the falsification regressions I drop providers whose total 2008 and 2009 Medicare revenue was outside the middle 90% of physicians in treated states to get a more comparable sample.

I also restrict to physicians who were primarily office-based by including only those who received at least 60% of their revenue from office-base care. These physicians are the most affected, the most likely to have their income tightly tied to their reimbursement rates. And they are also likely to have facilities only as an outside option, and hence all be equally a affected by the Medicare reimbursement rate changes in facilities.
4.1 Results for All Physicians

The main result is that providers with larger reimbursement increases have both extensive and intensive increases in provision, though the extensive margin responses are offset by decreases in movement to facility-only provision—I interpret moving all care to facilities as vertical integration following [Neprash et al. (2015)]. There is weaker evidence suggestive that there was an intensive margin increase in care among physicians who remained in office-based care.

I first investigate the response of office-based care to the reimbursement changes. These results from equation 1 are shown in figure 3. The blue squares are the DID estimates in the treated states, and the red circles show the falsification results. These results are also shown in table 3 for a DID with a short-run impact in the first two years and a longer-run impact in the subsequent 3 years.

I investigate the extensive margin response by looking at outcomes of indicators for office-based care. Panel (a) shows that physicians with higher reimbursement increases were more likely to continue providing care. The magnitude for this extensive margin participation result is interpreted as the impact on probability of participation from a 100% reimbursement increase—so given the approximately 3 percentage point variation most specialties have between 10th percentile and 90th percentile physicians (see table 2) an impact of 2.6 (the average long run impact in year 3 to 5) means that moving a physicians from the 10th percentile to the 90th percentile increase would increase participation by about 0.078.\[0.078=3\text{ percentage points times 2.6 probability change per 100 percentage points.}\]

The falsification results in unaffected states show that the types of physicians with lower and higher reimbursement rate changes were not exactly on parallel trends, but the magnitude is quite small—I discuss below the assumptions necessary to difference that trend in control states out in a triple difference.

Panel (b) of figure 3 shows that there is some evidence that the reimbursement change increased office-based volume on the intensive margin. I investigate the intensive margin by looking at RVUs provided—to include both increases in the number of procedures and services and increases in the intensity of individuals services (for example converting short office visits to long ones). Panel (b) shows that the in the short run, physicians do not respond to the reimbursement increase, but in the longer run (3 to 5 years later) the number of services increases for physicians with larger reimbursement increases—the long run elasticity point estimate is 4.1, but while significantly above zero at conventional level is rather noisily estimated. But there are some large but insignificant pre-trends which raise concern about identification. The intensive margin analyses restrict to a balanced panel of physicians who filed office-based claims every year. This makes the results easier to interpret since there is no selection into or out of the panel. But it does not particularly change the results—analogue results for the full sample of physicians are shown in figure A.6 in the appendix and are quite similar. Likewise, I could have measured volume by the number of services or procedures
rather than by RVUs—those results are shown in figure A.3 in the appendix and are also quite similar. Finally for office-based care I investigate change in intensity of care in panel (c)—I measure this by looking at RVUs per service, and find no evidence of any impact. This is interesting because Clemens and Gottlieb (2014); Brunt (2015) and other papers tend to find that intensity of care plays a large role in any volume response to reimbursement rate changes.

I next investigate the extent to which these increases in office-based care are offset by decreases in movement to facility-based care and the impacts on total care. The main finding here is that there is a large offsetting decrease in movements to facility-based provision (suggesting a decrease in vertical integration) and little evidence of any impact of total volume. Since many office-based providers provide occasional facility-based claims (for example visiting their patients in the hospital) the impact of an indicator for any facility-based claims does not measure substitution to facilities very well. Rather I use an indicator for facility-based claims and no office-based claims indicating that the physician has completely changed his practice leaving office-based care (for example by joining a foundation or hospital system as an employee)—these results are shown in panel (a) of figure 4. Here the falsification test does not provide any evidence for a failed parallel trends assumption. The estimates for only facility-based care almost exactly offset the increases in office-based care though the point estimates are somewhat smaller than the increases in office-based participation suggesting that there may be some overall effect.

My analysis does not provide conclusive results for how the reimbursement change for these office-based providers impacts the total care they provide in any place of service, though it does rule out very large impacts. Panel (b) of figure 4 explores the overall effect and shows that it is somewhere between small and an artifact of a failed parallel trends assumption (the increase is almost as large in the falsification states)—even if you ignore the falsification test failure, the estimated impact on total participation would be quite small, the long run point estimate of 1.1 means that the typical 90th percentile physician is only about 3 percentage points more likely to be practicing 3 to 5 years after the reimbursement increase than a 10th percentile one. I also measure total volume by looking at the total number of services or procedures that active physicians provide (panel (c)). The estimates are noisy and the event study has large pre-trends. Another complication with interpreting the results on total volume is that the level of intensity of the services may change between facilities and offices. The PFS only pays for the professional component of facility-based care, while it pays for the entirety of office-based care. This means that I cannot use RVUs as an intensity weighted measure of volume because it would be excluding a large share of the input costs. So even if rate increases for office-based PFS care increase volume and spending for all PFS care there could be offsets on Medicare spending through other payment systems. For example, if care is kept in offices rather than moving to outpatient hospitals, CMS would not need to pay facility fees through the Outpatient Perspective Payment System.
**Triple Difference:** Rather than using the physicians in control states as a falsification to check the plausibility of the parallel trends assumption, one could assume that the trend would have been the counterfactual trend for physicians in the treated states absent the reimbursement change. Under this assumption, a triple difference regression would yield the treatment effect of the reimbursement rate change on physicians. I thus run the following triple difference regression:

\[
Y_{ijst} = \sum_{\tau} \beta_{\tau} \mathbbm{1}(\tau = t) \Delta Reimbursement_i \mathbbm{1}(Treated_i) + \gamma_{jst} + \gamma_i + \varepsilon_{ijst}
\]  

(2)

Where things are defined as before with the addition that \(j\) indexes area (treated or control), so \(\gamma_{jst}\) are separate specialty by year fixed effects for treated and control areas.

In this specification, the series of \(\beta_{\tau}\) can be interpreted as the causal effect of the reimbursement rate change under the assumption that the relative trends between physicians with higher versus reimbursement rate changes would have been parallel across states. Since the impact of the GPCI floor in reimbursement is proportional to the PE share of a physicians RVUs, this amounts to assuming that within specialty, physicians across the distribution of PE shares are moving in parallel across treatment and control states.

The triple difference specification makes it clear that the increase in office-based claims and the offset in facility-only provision very clear. It shows that there is noisy evidence of an increase in total active physicians. And it shows that the intensive margin responses for office-based care and all care are marginally significant, but the pre-trends are exacerbated in the triple difference. See figure A.7 in the appendix.

**Robustness:** I test robustness for several variations in sample selection and the results are relatively robust. I drop only low volume outliers including all physicians with very high Medicare revenue (appendix figure A.8). I drop the bottom 25% of small volume providers—these have noisier estimates of the reimbursement rate change they face (appendix figure A.9). I include all physicians, even those who are not majority office-based (appendix figure A.10). I restrict to physicians, who receive at least 80% of their Medicare revenue in office-based settings (appendix figure A.11). None of these variation make a big difference in the results.

5 **Heterogeneity**

I examine heterogeneity along three margins: age, specialty, volume, and population density. Age is an important dimension because for older physicians the decision margin may be retirement rather than switching to facility-based care—indeed for physicians who were more than 60 years old in
2011, the offsets from decreased facility-based care were far smaller. Specialty is an important
dimension because different specialties may have different practice cultures and access to care for
all specialties rather than for at least one specialty is important. Provider volume is important
because larger providers have bigger impacts on Medicare spending and care provision. And lastly,
population density helps speak to the external validity of my results.

**Heterogeneity by Age:** Physicians who are close to retirement are likely to be making the choice
of when to retire rather than whether to change their practice style or consolidate with a hospital.
When I restrict to physicians who were at least 60 years old in 2011 when the reimbursement
increase happened, I see a similar extensive margin increase in office-based provision (figure 5
panel (a)). But the offsetting decrease in facility-only provision is muted for these older physicians
and the point estimate for the effect on any provision is larger (figure 5 panel (a) and table 4).
The results are somewhat noisy, but they are suggestive that for at least these older physicians the
reimbursement increase drove extensive margin increases in participation.

**Heterogeneity by Volume:** I explore heterogeneity by provider volume to evaluate the extent to
which the unweighted provider average is representative of the sorts of providers that Medicare
patient see. First, I simply weight the analysis by each providers’ Medicare revenue—these results,
shown in the appendix in figure [A.13] are qualitatively similar, though noisier and the falsification
tests are less reassuring. Next I split providers by whether they have above or below median number
of patients or Medicare revenue (appendix figures [A.14] to [A.17]). The results are again similar
across both of these splits, though again for the larger volume physicians the falsification tests looks
substantially less good. The similarity of the results across different ways to account for provider
volume suggest that small providers who have little practical impact on Medicare do not drive the
results.

The fact that the extensive margin response shows ip for provider with a high number of Medi-
care patients suggests that it si not an artifact of noise from the 20% sample of patients I can observe.

**Heterogeneity by Specialty:** I estimate the provider level analysis separately for the most com-
mon specialties to see how homogeneous the main results are across specialties. I group physicians
broadly into primary care, medical specialists, surgical specialists, and other specialists following
[Machado et al.](#) (2021), and I separately evaluate responses among non-physicians.

The main result for primary care specialties are quite similar for those of physicians in general
with the exception that total volume across places of service increases on the intensive margin as
well. Primary care specialties include family practice, internal medicine, and pediatrics

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20Pediatrics is unsurprisingly quite rare in Medicare.
is a positive extensive margin participation response for office-based care that is somewhat offset by decreased facility-based care (though the facility-response is noisy). These results are shown in table 4 with the event study plots and falsification table in figure A.19 and table A.1 in the appendix.

The key difference between primary care providers and physicians in general is that there is stronger evidence that there is an intensive margin aggregate increase in volume (RVUs) for primary care providers. But this could be an artifact of the PFS only covering professional care in facility and the entirety of care in offices. So this could just be due to the non-professional components of care being paid through other payment systems rather than the PFS.

For medical specialists the results are rather noisy, but overall, it seems that there are minimal if any impacts on extensive margin participation, and the results for intensive marginal responses are too noisy to say much (there are relatively few medical specialists in the affected states). Medical specialties include dermatology, cardiology, medical oncology, neurology, and other smaller specialties listed in the appendix. Since power limits these results to a noisy null, I relegate them to the appendix (figure A.20).

For surgical specialists, it seems like the increased reimbursements increased both extensive margin participation and intensive margin quantities, and to a larger extent than physician on average. These results are shown in figure A.21 (the left column has all surgeons and the right column has only older surgeons because the age differential is particularly striking for surgeons) and the bottom panel of table 4. Surgical specialties include ophthalmology, urology, obstetrics and gynecology, and all specialties with “surgery” in the name. For office-based participation physicians with larger reimbursement increases have increased participation—and the offsets decreased facility based care are smaller, so there is an aggregate increase in participation. And for intensive margin quantities conditional on providing any office based care, reimbursement increases do not seem to cause an increase in provision. Among surgeons, the age differential is particularly striking, the increased office-based participation seems to not be offset to any large extent by moves to facility-only practices.

I also look at the utilization response for other specialties: pathology, radiology, psychiatry, and other specialties listed in the appendix that don’t fit into either medical or surgical specialties. The results for these specialties are quite noisy—possibly because they are a heterogeneous residual rather than a group with any similarities (the results are shown in the appendix in figure A.23). I similarly investigate the response for non-physicians (physical therapists, optometrists, chiropractors, etc listed in the appendix)—the intensive margin results are noisy and the falsification tests fail, but there is some evidence that there is a positive intensive margin response (appendix figure A.24).

**Heterogeneity by Population Density:** One key concern with my analysis is that the setting is four relatively low population, rural states—this raises the question of the extent to which my results...
speak to Medicare as a whole. To investigate this I repeat my analysis restricting the higher population density areas of the treated states. I find that the impact is relatively stable in the subsamples with higher population density.

To graphically summarize how the results change with population density, I run a pre/post DID to get the impact on the various participation, volume, and vertical integration measure in one coefficient. And I repeat the analysis, progressively restricting to higher density areas. These results are shown in figure 6—for all three outcomes of office-based participation, office-based volume, and vertical integration the results are relatively stable with population density though the standard errors blow up as the sample size decreases.

6 Theoretical Framework

My analysis shows that physicians respond positively to their financial incentives along two margins: first they change where they provide care, and second, they change the volumes they provide conditional on place of service. To explain why this might be, I modify Clemens and Gottlieb’s (2014) model where altruistic physicians choose their practice style as well as amount of care to provide. Clemens and Gottlieb (CG) model physicians as choosing between standard and intensive practice styles. Since 1997 when their study was set, the consolidated or integrated practice style has become a significant alternative among physicians (Baker et al., 2018; Capps et al., 2018; Neprash et al., 2015). My simple modification of CG’s model shows that increasing profit margins (either by raising Medicare rates or decreasing marginal costs) makes more physicians choose the non-integrated style. This is consistent with my empirical findings as well at the general trend of decreasing Medicare profit margins and rising consolidation.

CG build a model of physician supply where physicians make marginal decisions to supply more or less care conditional on their practice style, but also make the discrete choice whether to have a standard practice style or to invest in capital equipment or technology to intensify their practice style. In their model, higher productivity physicians invest to have an intensive practice style which entails costly investment but decreases the marginal cost of providing care. Lower productivity physicians operate a standard practice style where marginal costs are higher, but no fixed costs of investment is required. They show that increasing Medicare reimbursement causes a positive supply response through two mechanisms. First conditional on practice style, physicians provide more care when reimbursement is higher. And second, higher reimbursement causes some physicians to switch from standard to intensive styles further increasing their supply. CG show that this mechanism of investment in higher intensity practice styles explains the positive supply response that they find in their analysis of a large 1997 reimbursement rate change.

Since my analysis shows reimbursement rates affects the place where physicians provide care, I
modify CG model to evaluate the choices that physicians make between a independent practice style and a vertically integrated practice style where physicians are employed by facilities or foundations instead of practicing independently. I only include the two choices of vertically-integrated versus non-integrated in my model, but my non-integrated style can be thought of as nesting the standard and intense styles that CG study. CG shows that as reimbursement rate decreases and margins decrease, physicians move towards the standard practice style away from the intensive one. Between my setting in 2011 and their setting in 1997, Medicare margins have fallen significantly, so it seems reasonable that relevant choice of practice styles given market parameters has changed.

I borrow the setup and notation from CG. Physicians can practice medicine using an independent nonintegrated practice style (N) or a vertically integrated style (V). Physicians value their revenue net of costs, patient health benefits due to altruism, and have disutility from effort. Physicians practicing independently are paid \( r \) per unit of care by Medicare and have a variable cost per unit of care, \( c \). Physicians practicing in the consolidated style receive a fixed wage, \( w \), from the facility/foundation that employs them and need pay no marginal costs, which are covered by the facility that employs them. Like CG, I assume that physicians are the decision makers and I can ignore patient demand either due to excess demand or provider induced demand allowing the market to move along a supply curve—since the overall response to reimbursement rates is positive, this seems like a reasonable assumption.

Each physician has some productivity \( \gamma_i \) (distributed according to distribution \( F \))—physicians can produce one unit of care with effort \( 1/\gamma_i \). Producing \( q \) units of care incurs disutility cost \( e \left( \frac{q}{\gamma_i} \right) \) where \( e \) is increasing and convex. Physicians are altruistic and value the patient health benefit of care with weight \( \alpha \). Below, \( b(Q) \) denotes to marginal health benefit of care, where \( Q \) the total health care produced by all physicians is taken as given by individual physicians.

Physicians choose a practice style: \( V \) or \( N \) and a quantity of care \( q \). Assuming quasilinear utility in income and utility, the utility in each practice style is

\[
U_N(q; \gamma_i) = (r - c)q - e \left( \frac{q}{\gamma_i} \right) + \alpha b(Q)q
\]

\[
U_V(q; \gamma_i) = w - e \left( \frac{q}{\gamma_i} \right) + \alpha b(Q)q
\]

The first term in each sum captures the monetary benefit of care, the second term the disutility due to effort, and the third term the benefit from physician altruism for helping their patients.

Under this model, there are three key results about physician supply. First, conditional on practice style physicians with higher productivity provide more care. Second, physicians provide more

21I use “N” and “V” (instead of “I” for integrated) because CG use “I” for intense and “S” for standard and I want to avoid reusing their notation. I see “N” as nesting their “S” and “I”.
care when they are not integrated conditional on their productivity. And third, assuming that \( r > c \)
so that the profit margin of treating patients is positive and that \( w \) is not too high, there is a threshold
\( \gamma^* \) such that providers with productivity above the threshold (\( \gamma_i > \gamma^* \)) practice independently while
those below consolidate.

The relationship between volume and profit margin (\( \pi = r - c \)) is governed by the following
derivative, for which both components are positive—that is as \( \pi \) increases due to either rising \( r \) or
falling \( c \) physicians provide more care and vertically integrate less\(^{22}\)

\[
\frac{\partial Q(r)}{\partial \pi} = \int_{\gamma^*(r)}^{\infty} \frac{\partial q_N^*(\gamma)}{\partial \pi} f(\gamma) d\gamma + \frac{\partial \gamma^*}{\partial \pi} f(\gamma)[q_N^*(\gamma^*) - q_N^*(\gamma^*)]
\]

(4)

Figure 7 shows an example of what quantities of healthcare supplied might look like under this
model and how they would change as profit margins for independent practice change. Higher pro-
ductivity physicians provide more care than low productivity ones—the discrete jump in the func-
tion is when physicians switch from consolidated to independent. Within practice style, provision
increases due to altruism for both style and additionally due to the profit motive for the independent
style. Increasing the profit margin from low to high causes independent style physicians to provide
more care and causes some integrated physicians to become independent and increase their volume
substantially. Inframarginal integrated physicians are unaffected by the profit margin change.

This model can be viewed as an extension of CG model showing what would happen in their
setting if margins were sufficiently low for the lowest productivity physicians. Combining my mod-
ification with their model, physicians would choose whether to consolidate with facilities or prac-
tice independently, and conditional on independent practice would choose between a standard and
intense style. Intuitively in this combined model, the lowest productivity physicians would consol-
date, intermediate ones would operate independently with a standard practice style, and the very
highest productivity physicians would operate independently with an intense style. Then the profit
margin that Medicare reimbursement and marginal costs yield would determine the thresholds. As
profit margins increase, both thresholds would move down so that more physicians would be in-
dependent and conditional on independence more would be intense. Such a more general model
combining mine and CG could reasonably explain the general decrease in Medicare profit margins
since 1997 (when CG was set) and the increase in vertical integration in the United States since
then.

\(^{22}\)CG shows comparative statics for physician choices depend on reimbursement rates, but the same comparative
statics hold for profit margin (reimbursement minus marginal costs), I sow my comparative statics using profit margins
because conversations with doctors suggest that in some areas and specialties the change in margins has been dominated
by changes in costs rather than reimbursement rates.
7 Conclusion

This paper evaluates how utilization responds to Medicare reimbursement changes using a DID analysis and a plausibly exogenous reimbursement change caused by the ACA. Utilization responds positively to reimbursement—some of the positive response to the reimbursement change is caused by providers moving to facility-only provision, which I interpret as vertical integration.

The positive result raises the concern that Medicare must consider access implications when it decreases reimbursement rates. As of 2012, Medicare assumed that 30% of savings from reduced reimbursements would be offset by increased volume, but a panel of academics and actuaries reviewing the Medicare Trustees’ assumptions suggested that the studies and data underlying their assumption were old (Bertko et al., 2012). The 2017 review of the Medicare Trustees’ assumptions expresses particular concern that Medicare access may decline as Medicare rates are projected to fall relative to private rates (Meara et al., 2017). And recently Medicare has been particularly concerned about access in rural areas in particular, due to their lower utilization rates (MedPAC, 2021). My result suggests that to the extent that the response is symmetrical for reimbursement increases and decreases that cutting reimbursement raises serious access concerns as supply falls in response.

The vertical integration response raises all sorts of policy implications and interesting followup questions. Since Medicare makes additional payments for care in outpatient hospitals and other facilities in addition to the PFS payment it makes for the professional component of care, that means that the vertical integration response causes spillovers across Medicare payment systems. The relevant elasticity for Medicare’s budget includes these spillovers—it is insufficient to look only within the PFS. For example, raising PFS rates could reduce Medicare spending even with the positive PFS elasticity I find if the offset in reduced outpatient claims is large enough. Measuring the size of this offset is an important next step.

Additionally the vertical integration response caused by Medicare reimbursement rates implies spillovers on Medicare Advantage and the healthcare system as a whole by increasing provider concentration. The literature on vertical integration tends to find that it causes or is associated with higher spending and lower quality. Baker et al. (2014); Capps et al. (2018); Koch et al. (2017); Neprash et al. (2015); Whaley et al. (2021) all find that vertical integration increases prices or spending. Song et al. (2020) also finds adverse effects on quality. Though Machta et al. (2019) in a review of many observational studies not accounting for selection found that vertical integration was often associated with better quality. This means that fee-for-service Medicare rates have impacts on Medicare Advantage costs, which CMS should internalize.

MedPAC (2021) finds that rural Medicare enrollees have less specialist visits in 2018, for frontier counties utilization was much lower though that may be because enrollees are healthier.
References


Federal Register (2010). Medicare Program; Payment Policies Under the Physician Fee Schedule and Other Revisions to Part B for CY 2011; Final Rule.


8 Figures

Figure 1: Variation in PE GPCI and Reimbursement Rates

(a) Practice Expense GPCIs: Treatment States

(b) Practice Expense GPCIs: States Providing Control Counties

(c) Actual Reimbursements per RVU: Treatment States

(d) Actual Reimbursements per RVU: States Providing Control Counties

Note: The top left panel shows the practice expense GPCIs in the treated states where the 2011 GPCI floor was binding, in these states, the floor increased the GPCIs by about 10 to 15% relative to 2009. The top right panel shows the practice expense GPCIs for neighboring states that I consider as control areas. Note that in many control states and all the treated states, there was a small increase in PE GPCI in 2010—this was the result of a temporary ACA provision. The bottom panels show the actual reimbursement rates Medicare paid per RVU for office-based care in the states affected by the ACA PE GPCI floor and in the set of states I use as potential controls. In treated states there was an approximately 15% increase, while in the control states there were much smaller increases.
Figure 2: Disequilibrium Outcomes

(a) Excess Supply or Excess Demand

(b) Physician Induced Demand

Note: This figure shows some possible disequilibrium outcomes. Panel 2a shows two possible disequilibriums with excess demand and excess supply where the volume transacted is limited by the short side of the market at an administratively set price—when the price increases, the disequilibrium outcome moves along an upward sloping supply curve or a downward sloping demand curve. Panel 2b shows a market with excess supply that still operates on the supply curve because providers induce demand—when the price increases, providers induce more demand (shifting the artificial induced demand curve out) and the disequilibrium outcome moves along the supply curve.
Figure 3: Impacts on Office-Based Care

(a) Indicator for any Office-Based Claims

(b) Log Office RVUs

(c) Log RVUs per Service

Note: This figure has the results from equation 1, the DID model comparing providers based on the percent increase in reimbursement rates—this regresses the outcome on the provider level reimbursement rate change interacted with year dummies and provider and year by specialty fixed effects. The outcomes are indicated in the captions. Providers are weighted equally. Standard errors are clustered at the provider level.
Figure 4: Impacts on Integration and Total Care

(a) Indicator for Only Facility-Based Claims

(b) Indicator for Any Claims

(c) Log Total Services

Note: This figure has the results from equation 1, the DID model comparing providers based on the percent increase in reimbursement rates—this regresses the outcome on the provider level reimbursement rate change interacted with year dummies and provider and year by specialty fixed effects. The outcomes are indicated in the captions. Providers are weighted equally. Standard errors are clustered at the provider level.
Figure 5: Provider Level Event Study (Older Physicians Only)

(a) Indicator for any Office-Based Claims
(b) Log Office RVUs
(c) Indicator for Only Facility-Based Claims
(d) Indicator for any Medicare Claims
(e) Log Total Service Count

Note: This figure has the results from equation 1, the DID model comparing providers based on the percent increase in reimbursement rates—this regresses the outcome on the provider level reimbursement rate change interacted with year dummies and provider and year by specialty fixed effects. The outcomes are indicated in the captions. Providers are weighted equally. Standard errors are clustered at the provider level. The figure restricts to physicians who were at least 60 years old in 2011.
Figure 6: Results by Population Density

(a) Indicator for any Office-Based Claims
(b) Log Office RVUs
(c) Indicator for Only Facility-Based Claims

Note: This figure has the results from equation[1] the DID model comparing providers based on the percent increase in reimbursement rates, except instead of including separate year indicators it just includes a pre/post intervention indicator. This regresses the outcome on the provider level reimbursement rate change interacted with an indicator for years after the increase and provider and year by specialty fixed effects. The outcomes are indicated in the captions. Providers are weighted equally. Each point on the graph is from a separate regression that successively reduces the number of physicians restricting to those from higher population density counties—the leftmost point includes the full sample, the next the top 75%, the top 50%, the top 25%, and the top 10%.
Figure 7: Provider Consolidation and Provision Decisions

Note: This figure shows an example of how physicians in the model change their provision and practice style as the profit margin changes. Note that higher productivity physicians provide more care than low productivity ones—the discrete jump in the function is when physicians switch from consolidated to independent. Within practice style, provision increases due to altruism for both style and additionally due to the profit motive for the independent style. Increasing the profit margin from low to high causes independent style physicians to provide more care and causes some consolidated physicians to become independent and increase their volume substantially. Inframarginal consolidated physicians are unaffected by the margin change.
### 9 Tables

Table 1: Example Reimbursement Variation

#### Panel A: Montana GPCIs

<table>
<thead>
<tr>
<th></th>
<th>2009</th>
<th>2011</th>
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<tr>
<td>Work</td>
<td>1</td>
<td>1</td>
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<tr>
<td>PE</td>
<td>0.847</td>
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#### Panel B: RVUs and Reimbursement Changes for Example Procedures

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<tr>
<th></th>
<th>2009</th>
<th>2011</th>
<th>GPCI-Adjusted Total RVUs</th>
<th>Change (%)</th>
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<tbody>
<tr>
<td></td>
<td>Work</td>
<td>PE</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Psychotherapy</td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>Eye Exams</td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td></td>
<td>Work</td>
<td>PE</td>
<td>Work</td>
<td>PE</td>
</tr>
<tr>
<td>2009</td>
<td>(5)</td>
<td>(6)</td>
<td>2009 + 2011</td>
<td>w/ 09 RVUs</td>
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#### Panel C: Example Physician Reimbursement Changes

<table>
<thead>
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<th>Service Volume</th>
<th>Aggregate Adjusted RVUs</th>
<th>Change (%)</th>
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<tr>
<td>Eye Exams</td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
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<td>Physician A</td>
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<td>100</td>
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<tr>
<td>Physician B</td>
<td>10</td>
<td>100</td>
<td>181.8</td>
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</table>

*Note:* Panel A shows Montana work and PE GPCIs for 2009 and 2011. Panel B shows RVUs for two procedures (psychotherapy and eye exams) in columns 1 through 4. Panel B shows how the RVUs and GPCIs translate into GPCI-adjusted total RVUs, which is proportional to reimbursement. Adjusted Total RVUs = RVU(work) * GPCI(work) + RVU(PE) * GPCI(PE) and are based off the Montana GPCI levels in Panel A. Columns 5 and 6 of Panel B have the 2009 and 2011 adjusted total RVUs. Column 7 has the adjusted total RVUs based on 2009 RVUs and 2011 GPCIs, this shows how the total would have changed if there had been no endogenous RVU changes. Column 8 has the actual percent change in adjusted total RVUs—the percentage difference between columns 5 and 6. Column 9 has the percent change in adjusted total RVUs caused by the exogenous GPCI floor—the percentage difference between columns 5 and 7, which does not include the RVU updates. Panel C shows how there procedures level changes translate into physician level variation in reimbursement for two fictitious physicians—Physicians A provides a lot of psychotherapy and has a smaller total change in aggregate adjusted RVUs since psychotherapy rates do not change as much as eye exam rates. The RVUs for psychotherapy are for current procedural terminology (CPT) code 90806, and eye exam RVUs are for CPT 92250.
Table 2: Providers in Treated States

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>Revenue</th>
<th>PE Share</th>
<th>Mean</th>
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<th>90%-ile</th>
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<td>13.4</td>
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<td><strong>Non-MDs</strong></td>
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<td>7.5</td>
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</tbody>
</table>

Note: This lists the common specialties nested into larger categories (the summary statistic for larger categories includes information on smaller specialties that I omit individual information on). N is the number of distinct providers with office-based care in both 2008 and 2009—this does not restrict to primarily office-based providers as I do in my analysis. Revenue is the sum of all office-based Medicare reimbursements for the 20% sample of patients in 2008 and 2009. The reimbursement changes include only the changes induced by the exogenous GPCI floor—I calculate these by applying 2009 and 2011 GPCIs to 2009 RVUs and case mix.
|                  | Office-Based Care | Integration | Total Care |                  |                   |                   |                   |
|------------------|-------------------|-------------|------------|------------------|-------------------|-------------------|
|                  | (1)               | (2)         | (3)        | (4)              | (5)               | (6)               |
| Treated          | 1                 | Ln(RVUs)    | Ln(RVUs per Srvc) | 1                | 1                 | 1                 |
| 1-2 year         | 0.980**           | -1.016      | 0.937      | 0.0407           | 1.005**           | -1.215            |
|                  | (0.376)           | (1.663)     | (0.496)    | (0.211)          | (0.330)           | (0.899)           |
| 3-5 year         | 2.622***          | 4.148*      | -1.045     | -1.434***        | 1.190**           | -0.380            |
|                  | (0.467)           | (1.940)     | (0.837)    | (0.311)          | (0.414)           | (0.973)           |
| N                | 23931             | 11641       | 11641      | 23931            | 23931             | 15939             |
| N Providers      | 2659              | 1294        | 1294       | 2659             | 2659              | 1771              |
| Falsification    | 1                 | Ln(RVUs)    | Ln(RVUs per Srvc) | 3                | 5                 | 6                 |
| 1-2 year         | 0.419*            | -0.277      | -0.000185  | 0.0495           | 0.458**           | -0.424            |
|                  | (0.182)           | (0.494)     | (0.201)    | (0.0879)         | (0.166)           | (0.384)           |
| 3-5 year         | 0.718**           | -1.039      | 0.0144     | 0.144            | 0.863***          | -1.255*           |
|                  | (0.227)           | (0.668)     | (0.264)    | (0.120)          | (0.209)           | (0.515)           |
| N                | 126522            | 80885       | 80885      | 126522           | 126522            | 90855             |
| N Providers      | 14058             | 8991        | 8991       | 14058            | 14058             | 10095             |

* p < 0.05, ** p < 0.01, *** p < 0.001. Standard errors in parentheses.

Note: This table has the results from equation 1. Columns 1 though 3 have the results for office-based care—an indicator for any office-based claims, the log RVUs in offices to measure office volume, and the log of RVUs per service to measure office intensity. Column 4 has the results for an indicator for facility only claims, which can be interpreted as vertical integration. And columns 5 and 6 have the results on total care—an indicator for any claims at all and the log of service counts. And the second panel has the analogous results from a similar regression run on providers in control states who did not receive reimbursement increases from the GPCI Floor. I split each DID regression into a short run (1 to 2 year) and long run (3 to 5 year) effect and show coefficients for each of those.
Table 4: Provider DID Heterogeneity

<table>
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<tr>
<th></th>
<th>Office-Based Care</th>
<th>Integration</th>
<th>Total Care</th>
<th></th>
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</thead>
<tbody>
<tr>
<td></td>
<td>(1) Ln(RVUs)</td>
<td>(2) Ln(RVUs per Srvc)</td>
<td>(3)</td>
<td>(4) Ln(Count)</td>
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<td>(0.812)</td>
<td>(3.615)</td>
<td>(1.062)</td>
<td>(0.375)</td>
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<td>3-5 year</td>
<td>2.772**</td>
<td>8.849*</td>
<td>0.201</td>
<td>-0.822</td>
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<td>(4.464)</td>
<td>(1.815)</td>
<td>(0.431)</td>
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<td></td>
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<td>1.991</td>
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<td>(4.060)</td>
<td>(1.123)</td>
<td>(0.525)</td>
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<td>3-5 year</td>
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<td>7.296</td>
<td>2.223</td>
<td>-2.504***</td>
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<td>N Providers</td>
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<td>426</td>
<td>995</td>
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<tr>
<td><strong>Medical Specialists</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>1-2 year</td>
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<td>(0.720)</td>
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<td>3-5 year</td>
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<td>(4.556)</td>
<td>(1.029)</td>
<td>(0.670)</td>
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<td>3726</td>
<td>2085</td>
<td>2085</td>
<td>3726</td>
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<tr>
<td>N Providers</td>
<td>414</td>
<td>232</td>
<td>232</td>
<td>414</td>
</tr>
<tr>
<td><strong>Surgical Specialists</strong></td>
<td></td>
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</tr>
<tr>
<td>1-2 year</td>
<td>1.150</td>
<td>0.572</td>
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<td>(0.748)</td>
<td>(2.172)</td>
<td>(0.917)</td>
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<tr>
<td>3-5 year</td>
<td>4.045***</td>
<td>2.099</td>
<td>-0.707</td>
<td>-2.127**</td>
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<td>(3.712)</td>
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<td>(0.660)</td>
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<td>8226</td>
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<td>4417</td>
<td>8226</td>
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<td>N Providers</td>
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<td>491</td>
<td>491</td>
<td>914</td>
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</table>

* p < 0.05, ** p < 0.01, *** p < 0.001. Standard errors in parentheses.

Note: See table 3. This table has similar results for the treated states for subgroups of physicians. The top panel includes all physicians who were at least 60 years old in 2011. The bottom three panels separate physicians by their specialty group. The falsification results for these specifications are shown in table A.1 in the appendix.
A Extra Tables and Figures

Figure A.1: Backward Bending Supply

Note: This figure shows examples of disequilibrium outcomes on a backward bending supply curve with either excess demand or provider induced demand. Panel A.1a shows excess demand and a backward bending supply curve where a price increase causes the disequilibrium outcomes to move along the backwarding bending supply curve. Panel A.1b has exactly the same supply curve and response to the price change, but the providers must induce demand to operate on their supply curve; in this case, the induced demand curve also shifts out, but I do not show this to avoid crowding the graph.
Figure A.2: Family Medicine Falsification Providers Reimbursement Changes

![Figure A.2: Family Medicine Falsification Providers Reimbursement Changes](image)

**Note:** This figure is a binscatters of the reimbursement rate change that providers in the control states faced actually faced due to GPCI changes between 2009 and 2011 in their state and the reimbursement rate change they would have faced had they faced the average change in GPCIs that the treated states faced. Each provider is weighted by the total Medicare revenue from 2008 and 2009.

Figure A.3: Provider Level Event Study: All Physicians, Service Count Outcomes

**(a) Log Office Service Counts**

![Log Office Service Counts](image)

**(b) Log Total Service Counts**

![Log Total Service Counts](image)

**Note:** This figure has the results from equation 1, the DID model comparing providers based on the percent increase in reimbursement rates—this regresses the outcome on the provider level reimbursement rate change interacted with year dummies and provider and year by specialty fixed effects. The outcomes are indicated in the captions. Each provider is weighted by the total Medicare revenue from 2008 and 2009. Standard errors are clustered at the provider level.
Figure A.4: Impacts on Office-Based Care—Other Volume Measures

Note: This figure has the results from equation [1] the DID model comparing providers based on the percent increase in reimbursement rates—this regresses the outcome on the provider level reimbursement rate change interacted with year dummies and provider and year by specialty fixed effects. The outcomes are indicated in the captions. Providers are weighted equally. Standard errors are clustered at the provider level.
Figure A.5: Impacts on Total Care—Other Volume Measures

(a) Log Total Patient Visits

(b) Log Total Annual Patients

Note: This figure has the results from equation 1, the DID model comparing providers based on the percent increase in reimbursement rates—this regresses the outcome on the provider level reimbursement rate change interacted with year dummies and provider and year by specialty fixed effects. The outcomes are indicated in the captions. Providers are weighted equally. Standard errors are clustered at the provider level.
Figure A.6: Provider Level Event Study: All Physicians, Unbalanced Panel

(a) Log Office RVUs

(b) Log Office Service Counts

(c) Log Office Patient Visits

(d) Log Office Annual Patients

(e) Log RVUs per Service (Office)

Note: This figure has the results from equation 1, the DID model comparing providers based on the percent increase in reimbursement rates—this regresses the outcome on the provider level reimbursement rate change interacted with year dummies and provider and year by specialty fixed effects. The outcomes are indicated in the captions. Each provider is weighted by the total Medicare revenue from 2008 and 2009. Standard errors are clustered at the provider level.
Figure A.7: Provider Level Event Study: All Physicians, Triple Difference

(a) Indicator for any Office-Based Claims
(b) Indicator for Only Facility-Based Claims
(c) Indicator for any Medicare Claims
(d) Log Office RVUs
(e) Log Total RVUs

Note: This figure has the results from equation 2, the triple difference model that compares physicians in treated and control states with higher lower lower exposure to the reimbursement change based on their mix of procedures provided.
Figure A.8: Provider Level Event Study: All Physicians, Not Dropping High Volume Outliers

Note: This figure has results analogous to figures 3 and 4 except that it does not drop physicians whose Medicare revenue was in the top 5% of physicians.
Figure A.9: Provider Level Event Study: All Physicians, Dropping the bottom 25% of Low Volume Physicians

(a) Indicator for any Office-Based Claims
(b) Indicator for Only Facility-Based Claims
(c) Indicator for any Medicare Claims
(d) Log Office RVUs
(e) Log Total RVUs

Note: This figure is analogous to figure 3 and 4 except that it drops the bottom 25% of physicians by Medicare revenue.
Figure A.10: Provider Level Event Study: All Physicians, Including Physicians with Low Office Share

(a) Indicator for any Office-Based Claims

(b) Indicator for Only Facility-Based Claims

(c) Indicator for any Medicare Claims

(d) Log Office RVUs

(e) Log Total RVUs

Note: This figure is analogous to figure 3 and 4 except that it includes physicians who had any office-based claims no matter how small the office-based share.
Figure A.11: Provider Level Event Study: All Physicians, Restricting to 80% Office-Based Share

(a) Indicator for any Office-Based Claims

(b) Indicator for Only Facility-Based Claims

(c) Indicator for any Medicare Claims

(d) Log Office RVUs

(e) Log Total RVUs

Note: This figure is analogous to figures 3 and 4 except that it restricts to physicians who had at least 80% of their Medicare revenue from office-based claims.
Figure A.12: Provider Level Triple Difference Event Study (Older Physicians Only)

(a) Indicator for any Office-Based Claims
(b) Indicator for Only Facility-Based Claims
(c) Indicator for any Medicare Claims
(d) Log Office RVUs
(e) Log Total RVUs

Note: See Figure A.7, this is the same except that it restricts to physicians who were at least 60 years old in 2011.
Figure A.13: Provider Level Event Study: All Physicians, weighting by spending

(a) Indicator for any Office-Based Claims
(b) Indicator for Only Facility-Based Claims
(c) Indicator for any Medicare Claims
(d) Log Office RVUs
(e) Log Total RVUs

Note: This figure has the results from equation 1, the DID model comparing providers based on the percent increase in reimbursement rates—this regresses the outcome on the provider level reimbursement rate change interacted with year dummies and provider and year by specialty fixed effects. The outcomes are indicated in the captions. Each provider is weighted by the total Medicare revenue from 2008 and 2009. Standard errors are clustered at the provider level.
Figure A.14: Provider Level Event Study: All Physicians with Above Median Patient Volume

(a) Indicator for any Office-Based Claims
(b) Indicator for Only Facility-Based Claims
(c) Indicator for any Medicare Claims
(d) Log Office RVUs
(e) Log Total RVUs

Note: This figure has the results from equation 1, the DID model comparing providers based on the percent increase in reimbursement rates—this regresses the outcome on the provider level reimbursement rate change interacted with year dummies and provider and year by specialty fixed effects. The outcomes are indicated in the captions. Providers are weighted equally. Standard errors are clustered at the provider level.
Figure A.15: Provider Level Event Study: All Physicians with Below Median Patient Volume

(a) Indicator for any Office-Based Claims

(b) Indicator for Only Facility-Based Claims

(c) Indicator for any Medicare Claims

(d) Log Office RVUs

(e) Log Total RVUs

Note: This figure has the results from equation 1, the DID model comparing providers based on the percent increase in reimbursement rates—this regresses the outcome on the provider level reimbursement rate change interacted with year dummies and provider and year by specialty fixed effects. The outcomes are indicated in the captions. Providers are weighted equally. Standard errors are clustered at the provider level.
Figure A.16: Provider Level Event Study: All Physicians with Above Median Revenue

(a) Indicator for any Office-Based Claims

(b) Indicator for Only Facility-Based Claims

(c) Indicator for any Medicare Claims

(d) Log Office RVUs

(e) Log Total RVUs

Note: This figure has the results from equation 1, the DID model comparing providers based on the percent increase in reimbursement rates—this regresses the outcome on the provider level reimbursement rate change interacted with year dummies and provider and year by specialty fixed effects. The outcomes are indicated in the captions. Providers are weighted equally. Standard errors are clustered at the provider level.
Figure A.17: Provider Level Event Study: All Physicians with Below Median Revenue

(a) Indicator for any Office-Based Claims
(b) Indicator for Only Facility-Based Claims
(c) Indicator for any Medicare Claims
(d) Log Office RVUs
(e) Log Total RVUs

Note: This figure has the results from equation 1, the DID model comparing providers based on the percent increase in reimbursement rates—this regresses the outcome on the provider level reimbursement rate change interacted with year dummies and provider and year by specialty fixed effects. The outcomes are indicated in the captions. Providers are weighted equally. Standard errors are clustered at the provider level.
Figure A.18: Histogram of Reimbursement Changes by Specialty

(a) Medical Specialists

(b) Surgical Specialists

(c) Primary Care

(d) Other Specialist

Note: This figure shows the histograms of the prices changes faced by different broad specialty groups.
Table A.1: Provider DID Heterogeneity—Falsification

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<th>Office-Based Care</th>
<th>Integration</th>
<th>Total Care</th>
<th></th>
</tr>
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<tr>
<td></td>
<td>(1) Ln(RVUs)</td>
<td>(2) Ln(RVUs per Srvc)</td>
<td>(3)</td>
<td>(4) Ln(Count)</td>
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<td><strong>Primary Care</strong></td>
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<tr>
<td>1-2 year</td>
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<td>1965</td>
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<td>2686</td>
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<td><strong>Surgical Specialists</strong></td>
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<td></td>
<td></td>
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<td>1-2 year</td>
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* p < 0.05, ** p < 0.01, *** p < 0.001. Standard errors in parentheses.

Note: See table 4. This table has similar results for the control states as a falsification.
Figure A.19: Primary Care Provider Level Regressions

(a) Indicator for any Office-Based Claims
(b) Indicator for Only Facility-Based Claims
(c) Indicator for any Medicare Claims
(d) Log Office RVUs
(e) Log Total RVUs

Note: See figure 3 and 4. This figure restrict to primary care specialties: family medicine, internal medicine, pediatrics.
Figure A.20: Medical Specialist Provider Level Regressions

(a) Indicator for any Office-Based Claims
(b) Indicator for Only Facility-Based Claims
(c) Indicator for any Medicare Claims
(d) Log Office RVUs
(e) Log Total RVUs

Note: See figure 3 and 4. This figure restrict to primary care specialties: cardiology, dermatology, gastroenterology, medical oncology, nephrology, neurology, rheumatology, urology, and a few smaller subspecialties, see the appendix.
Figure A.21: Surgical Specialist Provider Level Results

(a) Indicator for any Office-Based Claims

(b) Indicator for any Office-Based Claims (60+ Only)

(c) Indicator for Only Facility-Based Claims

(d) Indicator for Only Facility-Based Claims (60+ Only)

(e) Indicator for any Medicare Claims

(f) Indicator for any Medicare Claims (60+ Only)

Note: This figure has the extensive margin participation results for surgical specialists: cardiac surgery, general surgery, neurosurgery, surgical oncology, orthopedic surgery, plastic surgery, and a few smaller subspecialties, see the appendix. The left column have all surgeons, the right column restricts to surgeons who were at least 60 years old in 2011.
Figure A.22: Provider Level Event Study (Surgeons)—Intensive Margin Outcomes

Note: See figure A.21 This is similar but has the intensive margin responses.
Figure A.23: Provider Level Event Study (Other Specialty Physicians)

(a) Indicator for any Office-Based Claims

(b) Indicator for Only Facility-Based Claims

(c) Indicator for any Medicare Claims

(d) Log Office RVUs

(e) Log Total RVUs

Note: See figure 3 and 4. This figure restrict to other specialist physicians (see appendix).
Figure A.24: Provider Level Event Study (All Non-Physicians)

(a) Histogram of Reimbursement Rate Changes

(b) Indicator for any Office-Based Claims

treated = 2825, falsification = 9030

(c) Indicator for any Medicare Claims

treated = 2825, falsification = 9030

(d) Indicator for Only Facility-Based Claims

treated = 2825, falsification = 9030

(e) Log Office Service Counts

treated = 1585, falsification = 4809

Note: See figure 3 and 4. This figure has the analogous results for non-physicians.
B  More Complete Discussion of the PFS Reimbursement Formula

A more complete version of formula that Medicare uses to set reimbursement rates is below—this includes the Malpractice liability insurance components.

\[ \text{Reimbursement}_{pj} = \text{ConversionFactor} \times \left[ \text{RVU}_p(\text{work}) \times GPCI_j(\text{work}) \\
+ \text{RVU}_p(\text{practice expense}) \times GPCI_j(\text{practice expense}) \\
+ \text{RVU}_p(\text{insurance}) \times GPCI_j(\text{insurance}) \right] \]

Where \( p \) indexes procedure and \( j \) indexes locality. The parameters change over time, so there is an implicit time subscript. There are some adjustments to the formula that factor into reimbursement: place of service (facility and non-facility rates vary), modifier codes, multiple services on the same day.

C  Data Notes

C.1  Selecting Control Areas: Covariate Matching

I use covariate matching to select a set of control counties likely to be similar to the treatment counties.

As shown in table C.1 the treated states are far more rural and sparsely populated than the United States as a whole. The treated states lack large metropolitan areas—the one Frontier State (Nevada) with a large metropolitan area (Las Vegas) had a sufficiently high PE GPCI such that the floor did not bind. The fact that the treated states are such outliers makes it hard to find potentially comparable states or even to generate comparable “synthetic” states by aggregating entire state a la Abadie (2021) and Abadie et al. (2010). Thus, I instead look within states for counties that match treated counties so I can, for example, include rural northern Nevada without having to include Las Vegas.

The pool of possible control counties I consider is all the counties in the surrounding states as well as Nevada. To the extent that health care customs, economic conditions, and other factors influencing utilization choices change slowly with geography the surrounding states are likely to have counties on similar trends to the treatment counties. And Nevada is also considered a Frontier State, so many of its counties are likely similar to the counties in the treatment states.

I generate a propensity score for each county in treated and control states by regressing a treatment indicator on covariates and for each treated county select five matched control counties. The covariates used for matching are the 2010 poverty rate, SNAP recipiency rate, share of population living on farms, number of hospital beds per capita, and psychiatrists per capita. These predictors
were selected by regressing the treatment indicator on a standardized index of many county characteristics and choosing the five predictors that were the most significant. This method closely parallels the method used by Diamond et al. (2020).

For each treatment county I include five matched control counties. The five matched control counties are given a total weight equal to the weight of the treatment county and the weight is split among the control counties proportionately to their FFS population. Control counties can match multiple treatment counties, in which case I sum the weight they get from each treatment county. In all regressions, I weight the control counties as described above, and I weight treatment counties by their FFS enrollment. This weighting method has two benefits. First, matching each treated county to several control counties avoids placing too much weight on very small counties in control states which adds noise to my regression. And second, weighting control counties by the enrollment in their matched treatment county avoids placing too much weight on potentially large control counties that match only very small control counties (for example, the Twin Cities in Minnesota receive some weight, but not nearly as much weight as would be proportionate to their population).

Figure C.1 shows that the counties in the treatment and control states have an overlapping distribution of propensity scores. As expected the treatment counties generally have higher propensity scores and there is a left tail of control counties that do not match any treatment counties. Figure C.2 shows the weights placed on the treatment and control counties in the analysis—for treatment counties this is the FFS population, and for control counties this is the sum of the FFS population on the treatment counties they match. Note that the matching algorithm does not place too much weight on the big cities in the control states: Las Vegas has zero weight, while the counties containing Minneapolis, Saint Paul, Denver, and Salt Lake City respectively have weight 441, 321, 939, and 1611. Salt Lake City’s relatively high weight stems from the fact that it matches Missoula’s county, which has over 2000 FFS enrollees.

The full set of variables I initially considered were: 2010 population density; poverty rate, SNAP rate; share living on farms; housing density; rural population share; number of medical generalists, specialists, psychiatrists, and hospital beds per capita; and 2007-2010 trend in facility and office visits. I did not use variables that are related to absolute instead of per capita size since these tended separate treatment and control counties too well (intuition along the lines that an indicator for treatment would be a useless characteristic to base the propensity score on): eg FFS enrollees, population, number of facility or office visits. I also considered matching of the county level counterfactual GPCIs (as opposed to the real locality level ones), which is available in the 2011 County Data File for the 6th GPCI Update, but they do not vary much within states leading me to believe that they are based on many state level approximations (at least for the relevant regions).
Figure C.1: Propensity Scores of Treatment and Control Counties

Note: This figure shows the histogram of propensity scores for each county in the treatment and control states, with counties weighted by population. The propensity score is the fitted value from the regression: \(1(treated_c) = X_c + \epsilon_c\) where \(c\) indexes county and \(X_c\) includes the 2010 poverty rate, SNAP recipiency rate, share of population living on farms, number of hospital beds per capita, and psychiatrists per capita. The key take-away is that the propensity score have substantial overlap.

Figure C.2: Map of Treatment and Matched Control Counties

Note: The treatment states are outlined in blue. The colors show the weight on each county in the treatment and control states. In the treatment states, the weight is the FFS population. In the control states the weight is the FFS population of the matched treatment counties. The key take-away is that the control counties do not place too much weight on a few small counties (which would cause noisy estimates) and do not place too much weight on the big cities in the control states (which would indicate that the matching algorithm did not do well).
Figure C.3: Reimbursement Changes for Treatment and Matched Control Counties

Note: This shows the percent increase in reimbursement rate in treated and control counties caused by the GPCI floor; that is, the change in reimbursement that results from fixing procedure RVUs and procedure case mix at the 2009 levels and then assigning statutory reimbursement rates based on either 2009 or 2011GPCIs. This isolates the most plausibly exogenous change in reimbursement and does not include endogenous changes in reimbursement rates caused by updates to RVUs or changes in the types of care provided in a county.
Table C.1: Characteristics of Treated States and Matched Control Counties

<table>
<thead>
<tr>
<th></th>
<th>Control</th>
<th>Treated</th>
</tr>
</thead>
<tbody>
<tr>
<td>FFS Enrollees</td>
<td>686.8</td>
<td>1338.1</td>
</tr>
<tr>
<td>Percent Persons in Poverty 2010</td>
<td>14.55</td>
<td>13.51</td>
</tr>
<tr>
<td>Food Stamp/SNAP Recipients 2010 per capita</td>
<td>0.103</td>
<td>0.101</td>
</tr>
<tr>
<td>Hospital Beds per Capita</td>
<td>5.786</td>
<td>5.622</td>
</tr>
<tr>
<td>Psychiatrists per Capita</td>
<td>0.0323</td>
<td>0.0677</td>
</tr>
<tr>
<td>Share living on Farms</td>
<td>12.73</td>
<td>6.344</td>
</tr>
<tr>
<td>Annual Office-Based Services per Enrollee</td>
<td>16.92</td>
<td>32.50</td>
</tr>
</tbody>
</table>

Note: This table provides basic summary statistics for the matching variables used to match the treatment and control counties. The treated counties are weighted by their FFS enrollment, and the control counties by the FFS enrollment of their matched treatment county. I also include the average number of office-based services per enrollee to show that it is higher in the treated states.

C.2 Specialty Definitions

I group HCFA specialty codes that are provided in the carrier claims into slightly broader specialties. I categorize these groups to match those in Chan and Dickstein (2019) with the addition of physical therapy, occupational therapy, chiropractic, and psychology. These categorization I made is shown in table C.2. This is the categorization I use for the provider summary statistics in table 2.

I then group these larger specialty groups into primary care, medical specialties, surgical specialties, and other specialties following Machado et al. (2021). This grouping is described in table C.3.
<table>
<thead>
<tr>
<th>Grouped Specialties</th>
<th>HCFA Codes included</th>
</tr>
</thead>
<tbody>
<tr>
<td>Anesthesiology</td>
<td>5, 9, 72</td>
</tr>
<tr>
<td>Cardiac Surgery</td>
<td>78</td>
</tr>
<tr>
<td>Cardiology</td>
<td>C3, 6, 21, 23, 31, 76</td>
</tr>
<tr>
<td>Chiropractic</td>
<td>35</td>
</tr>
<tr>
<td>Clinical Social Worker</td>
<td>80</td>
</tr>
<tr>
<td>Colorectal surgery</td>
<td>28</td>
</tr>
<tr>
<td>Dermatology</td>
<td>7</td>
</tr>
<tr>
<td>Emergency medicine</td>
<td>93</td>
</tr>
<tr>
<td>Family medicine</td>
<td>1, 8, 38</td>
</tr>
<tr>
<td>Gastroenterology</td>
<td>10</td>
</tr>
<tr>
<td>General surgery</td>
<td>2</td>
</tr>
<tr>
<td>Infectious disease</td>
<td>44</td>
</tr>
<tr>
<td>Internal medicine</td>
<td>11</td>
</tr>
<tr>
<td>Internal medicine subspecialties</td>
<td>46, 82</td>
</tr>
<tr>
<td>Nephrology</td>
<td>39</td>
</tr>
<tr>
<td>Neurology</td>
<td>13, 86</td>
</tr>
<tr>
<td>Neurosurgery</td>
<td>14</td>
</tr>
<tr>
<td>Nurse Practitioner</td>
<td>50</td>
</tr>
<tr>
<td>Obstetrics and gynecology</td>
<td>16</td>
</tr>
<tr>
<td>Occupational Therapy</td>
<td>67</td>
</tr>
<tr>
<td>Oncology</td>
<td>83, 90, 91, 98</td>
</tr>
<tr>
<td>Ophthalmology</td>
<td>18</td>
</tr>
<tr>
<td>Optometrist</td>
<td>41</td>
</tr>
<tr>
<td>Orthopedic surgery</td>
<td>20, 40</td>
</tr>
<tr>
<td>Osteopathic manipulative therapy</td>
<td>12</td>
</tr>
<tr>
<td>Other</td>
<td>C0, 17, 25, 84, 79, 81</td>
</tr>
<tr>
<td>Otolaryngology</td>
<td>4</td>
</tr>
<tr>
<td>Pathology</td>
<td>22</td>
</tr>
<tr>
<td>Pediatrics</td>
<td>37</td>
</tr>
<tr>
<td>Physical Therapy</td>
<td>65</td>
</tr>
<tr>
<td>Physicians Assistant</td>
<td>97</td>
</tr>
<tr>
<td>Plastic surgery</td>
<td>24, 85</td>
</tr>
<tr>
<td>Podiatry</td>
<td>48</td>
</tr>
<tr>
<td>Psychiatry</td>
<td>26, 27</td>
</tr>
<tr>
<td>Psychology</td>
<td>62, 68</td>
</tr>
<tr>
<td>Pulmonary medicine</td>
<td>29</td>
</tr>
<tr>
<td>Radiation oncology</td>
<td>92</td>
</tr>
<tr>
<td>Radiology</td>
<td>30, 36, 94</td>
</tr>
<tr>
<td>Rheumatology</td>
<td>3, 66</td>
</tr>
<tr>
<td>Thoracic surgery</td>
<td>33</td>
</tr>
<tr>
<td>Urology</td>
<td>34</td>
</tr>
<tr>
<td>Vascular surgery</td>
<td>77</td>
</tr>
</tbody>
</table>
Table C.3: Categorizing Specialty Codes to Broad Groups

<table>
<thead>
<tr>
<th>Category</th>
<th>Specialties</th>
</tr>
</thead>
<tbody>
<tr>
<td>Primary Care</td>
<td>Family Medicine, Internal Medicine, Pediatrics</td>
</tr>
<tr>
<td>Medical Specialties</td>
<td>Cardiology, Dermatology, Gastroenterology, Endocrinology, Hematology, Nephrology, Neurology, Medical Oncology, Pulmonary Medicine, Rheumatology</td>
</tr>
<tr>
<td>Other Specialties</td>
<td>Anesthesiology, Emergency Medicine, Infectious Disease, Neuropsychiatry, Hospice and Palliative Care, Sports Medicine, Physical Medicine, Preventive Medicine, Critical Care, Sleep Medicine, Pathology, Psychiatry, Psychology, Radiation oncology, Radiology</td>
</tr>
<tr>
<td>Non Physicians</td>
<td>Chiropractic, Clinical Social Worker, Nurse Practitioner, Occupational Therapy, Optometrist, Osteopathic Manipulative Therapy, Physician Assistant, Physical Therapy, Podiatry</td>
</tr>
</tbody>
</table>

*Note:* I group specialties together following [Machado et al. (2021)](Machado et al. [2021]), and using common sense to include non-physicians and specialties that they do not include.