Administrative Burden and Consolidation in Health Care: Evidence from Medicare Contractor Transitions*

Riley League†

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The US health care system is characterized by high administrative costs, the effects of which are theoretically ambiguous. Using exogenous changes to the jurisdictions of Medicare Administrative Contractors, I show that increases in a prominent type of administrative burden, claim denials, cause providers to invest in billing and consolidate into larger practices. These endogenous responses by providers fully offset the mechanical reduction in Medicare spending we would expect from the increase in claim denials. I explain this counterintuitive result using a model of firms' investment in billing, estimates of which show that billing costs exhibit substantial economies of scale and amount to $89 billion annually.

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†National Bureau of Economic Research, league@illinois.edu

1 Introduction

A quarter of the $4 trillion of annual health care spending in the United States goes to administrative costs (Sahni et al., 2021; Himmelstein et al., 2020). The consequences of these large administrative burdens are theoretically ambiguous: they could achieve their purpose of reducing total health care spending by discouraging the use of medically unnecessary or low-value services, or they could represent a pure waste of effort and resources while contributing to rising consolidation in the health care sector by increasing the fixed costs of treating patients. In this paper, I provide novel empirical evidence on the consequences of the most common form of administrative burden, claim denials, finding that increases in claim denials lead to higher billing costs, increased consolidation, and no reduction in health care spending.

To identify the impact of claim denials on provider behavior and market outcomes, I use changes in claim denial rates resulting from the decentralized administrative structure of Medicare. Although federally funded, Traditional Medicare is administered regionally by privately-owned companies called Medicare Administrative Contractors, which vary widely in the share of claims they deny. Over time, the government has changed the boundaries of the jurisdictions assigned to each administrator. This not only allows me to identify each contractor's causal effect on denials, but this variation also allows me to assess how provider behavior and health care markets respond to changes in the administrative burdens they face.

Studying the impact of changes in claim denials provides a unique opportunity to understand the broader consequences of administrative costs. Not only are claim denials very costly to health care providers (Dunn et al., 2023), they also represent a breakdown of the larger, very complicated billing system that imposes large burdens on the health care sector. Despite the billions of dollars invested each year in administrative technologies like electronic health records, billing software, and specialized staff, up to $54 billion worth of claims are denied each year (Gottlieb et al., 2018). As such, claim denials serve as useful proxies for the much broader trillion-dollar health care administration apparatus (Sahni et al., 2021), and the responses of providers to changes in denial rates induced by changes in Medicare administrators can be informative about the relationship between this wider system and the administrative burdens imposed by insurers.

For my empirical analysis, I use variation in administrative burdens and claim denial rates induced by the government's combination of Medicare administrative jurisdictions over time, with the number of contracts falling from 58 to 12 during my sample period. This reduction resulted in providers and patients being exposed to different administrators and, therefore, different levels of administrative burden. Comparing the denial rate of jurisdictions as they transition between different administrators, I find large differences across contractors in their propensities to deny claims. The difference between the lowest- and highest-denial administrators is over 5 percentage points, compared to a mean denial rate of 6.4 percent.

After identifying each contractor's causal effect on denial rates, I then show how health care providers respond to changes in administrative burdens. I find that following an increase in administrative burden, providers increase their adoption of electronic health records and increase the charges they submit to Medicare. I also find that 0.9% of practices exit the market immediately following a transition to a higher-denial contractor, with this result being driven by single-provider firms; this leads to a 0.8% increase in the size of the average practice remaining after the transition and the share of providers in solo practice falling by 1.3% immediately after the transition. I find little evidence of improved care, as the use of low-value care is largely unresponsive to claim denials and transitions between administrators have no discernible impact on beneficiary mortality. Finally, despite administrators denying 20% more claims after transitions to higher-denial contractors, providers' responses to the increased burden result in up to a 4.5% *increase* in total Medicare spending. Although payers typically intend for administrative burdens to curtail health care spending, I find they have no such effect.

I explain these counterintuitive results with a model of providers choosing the profit-maximizing level of investment in billing meant to increase charges and avoid denials. When faced with a greater administrative burden, medical practices earn higher returns from adopting billing software, hiring administrative staff, and investing more time in administrative tasks. These investments allow firms to bill Medicare for more charges and better avoid claim denials. My empirical results show that this response fully offsets the increase in denials, resulting in a net increase in Medicare spending after 18 months. Although Medicare spending increases, providers' profits decrease due to their higher billing costs. Furthermore, the model explains the exit and consolidation observed in the data as coming from the high fixed costs of billing technology: small practices do not have a large enough patient volume to justify making the large investments required to handle complex billing rules.

To further support my model billing investment being a key determinant of firm size, I present a number of stylized facts indicating that there exist substantial economies of scale in administrative investments. These include that (1) there is a strong negative relationship between firm size and the share of claims that are denied, (2) physicians in larger firms were more likely to receive payments for the early adoption of health IT, and (3) average administrative costs are declining in firm size for small health clinics and dialysis facilities. These novel results all point to meaningful economies of scale in billing investments, supporting my model's emphasis of this point.

Using indirect inference to estimate a parameterized version of the theoretical model, I find billing costs are over \$5,700 per provider per month, or \$88.7 billion in total billing costs in 2017. I estimate that it costs solo-practitioners \$1.12 in billing investment to raise charges by \$1 per provider, while costing the largest firms less than \$1.07. Because the marginal investment also helps avoid claim denials, increasing investment becomes worthwhile in the face of increased administrative burdens. I find that raising administrative burdens induces administrative investments, lowering firm profits by 3.7–4.6% depending on the size of the firm. At the same time, it also raises Medicare spending, indicating that on the margin increased administrative burden harms both providers and the public fisc.

In counterfactual simulations, I find support for widespread but heretofore empirically unsubstantiated worries about an "administrative arms race" between insurers and providers (Cutler, 2018). I find that were providers unable to increase their investment in response to an increase in administrative burden, Medicare spending would fall by $2.8 billion. This indicates that insurers may have short-run incentives to impose burdens and require more complex billing in an attempt to reduce payments to providers. However, providers respond to these additional burdens by investing in more administrative architecture to claw back this revenue. The competing investments in administrative technologies can result in a race to the bottom that increases insurer spending while lowering provider profits.

This study contributes to a growing literature on administrative costs in the health care sector. That the burdens are high is well established: the US spends nearly a trillion dollars annually on administrative costs in health care (Sahni et al., 2021; Himmelstein et al., 2020). Physicians spend at least 7 hours per week on administrative tasks (Remler et al., 2000; Sinsky et al., 2016), while these tasks consume over a third of nurse time (Hendrich et al., 2008; Casalino et al., 2009). Hospitals even have 50% more administrative workers than beds, and there are 2.2 administrative workers for every office-based physician (Cutler and Ly, 2011). This makes the US an outlier among similar countries, with 76% more non-clinical health care workers per capita than Canada and US physicians spending 69% more of their time on administrative tasks than Canadian physicians do (Pozen and Cutler, 2010).

Although much of this administrative burden is certainly wasteful—Sahni et al. (2021) argue $265 billion per year could be saved by reducing unnecessary administrative costs—which administrative barriers are worthwhile is an open question (Chernew and Mintz, 2021). One hope for administrative burdens is that they act as efficient ordeals, screening out low-value uses of expensive procedures (Nichols and Zeckhauser, 1982; Zeckhauser, 2021). Previous research has often supported this view, finding that some administrative burdens can result in lower health care spending without adversely impacting patient health. For example, prior authorization can be used to steer patients to lower cost prescription medications (Brot-Goldberg et al., 2022) or to combat fraud (Eliason et al., 2021); audits can reduce the provision of medically unnecessary care (Shi, 2024) and upcoding (Ganju et al., 2022); and real-time claim denials can induce pharmacies to dispense cheaper medications (Macambira et al., 2022). In contrast to the narrowly tailored administrative burdens studied by previous research, however, my results show that claim denials increase overall health care spending as providers invest in billing to circumvent this burden.

In this way, my results align with a smaller literature that highlights the negative consequences of more diffuse forms of administrative burden. Perhaps most related, Dunn et al. (2023) find that providers respond to high Medicaid denial rates by declining to accept Medicaid patients. And while I study provider-facing administrative burdens, multiple studies have found that imposing administrative ordeals on potential beneficiaries of social programs can hinder takeup (Arbogast et al., 2022; Shepard and Wagner, 2021; Homonoff and Somerville, 2021; Finkelstein and Notowidigdo, 2019; Deshpande and Li, 2019). My findings of greater exit, consolidation, and spending add to the growing evidence of the negative consequences of certain administrative burdens.

More narrowly, this paper also advances our understanding of the impact of Medicare's administrative structure on the health care system. Given that Traditional Medicare is the single largest health insurance plan in the country, insuring almost 40 million people (CMS, 2022a) and being accepted by 99% of non-pediatric physicians (Ochieng et al., 2020), understanding how its structure impacts the health care system is of independent interest. A few studies have noted the high level of variation in posted rules about coverage across Medicare Administrative Contractors (Foote and Town, 2007; Levinson, 2014a), while others have highlighted discrete cases where differences in these rules may lead to differences in medical practice (Wilk et al., 2018; Carlson et al., 2009; Foote et al., 2008). Although League (2022) shows that differences in administrator policies greatly impact the adoption of new medical procedures, this study is the first to document the large differences in overall stringency of Medicare contractors and the consequences of these differences.

This paper also provides new evidence on the drivers of consolidation in the health care sector. Although many economists have emphasized the negative consequences of consolidation, providers and their defenders often contend that policy changes are increasing costs in a way that necessitates consolidation (Smidt, 2015; Daly, 2018; Gold, 2021). Adoption of expensive billing software, for example, has very high fixed costs that only large practices can reasonably bear (Fleming et al., 2011; Dranove et al., 2014; Bronsoler et al., 2022), and increased scrutiny of claims by insurers may necessitate hiring additional coding staff, which also may not be feasible for small practices. If administrative investments exhibit economies of scale—as found by Andreyeva et al. (2022)—increased administrative burden can cause the efficient firm size to increase. Given the large literature showing negative consequences of consolidation in health care, including higher prices (Gaynor and Vogt, 2003; Dafny, 2009; Gowrisankaran et al., 2015; Cooper et al., 2019), less access to care (Town et al., 2006, 2007), lower nurse wages (Prager and Schmitt, 2021), and few improvements in health outcomes (Cutler et al., 2010; Gaynor et al., 2013; Bloom et al., 2015; Eliason et al., 2020), my finding that imposing administrative burdens can contribute to these changes in market structure is relevant for the competitiveness of health care markets.

This study relates closely to the causes of consolidation more broadly, particularly how regulations and the adoption of intangible capital can increase fixed costs and alter market structure. Regulation has been found to increase concentration in markets as diverse as cement (Ryan, 2012; Fowlie et al., 2016), abortion (Beauchamp, 2015), hotels (Suzuki, 2013), pharmaceuticals (Thomas, 1990), and television (Nishida and Gil, 2014). Furthermore, cross-industry comparisons generally corroborate these results, with regulations serving to reduce the number of firms and increase their size (Klapper et al., 2006; Bailey and Thomas, 2017). Relatedly, intangible capital generally and information technology specifically has been repeatedly shown to exhibit economies of scale, being linked to economy-wide increases in market concentration (Crouzet and Eberly, 2019; Bessen, 2020; Hsieh and Rossi-Hansberg, 2023; De Ridder, 2024; Lashkari et al., 2024). I provide novel empirical evidence that this is also the case in health care markets, meaning that regulations that induce these investments favor larger health care firms over smaller ones.

2 Institutional Context

2.1 Claim Denials

The medical billing process is characterized by complexity: multiple insurers with different billing rules, various coding systems and forms, and countless administrative requirements that can be opaque and arbitrary. To navigate this complex process, providers invest in billing and health care administration in order to receive as much compensation for their services as possible and avoid running afoul of the many administrative rules they face.

After a patient receives treatment from a health care provider, the health care provider (or more likely, an administrative worker from the provider's practice) submits a claim to the patient's insurer detailing the care that was rendered and its justification. The insurer then reviews the claim and decides to either pay or reject it for any number of reasons, including patient enrollment status, medical necessity requirements, or more technical administrative reasons. If the claim is rejected, it begins a costly back-and-forth process that may not ever result in payment. A claim denial occurs when the insurer ultimately declines to pay for the service and the provider does not recieve payment.[1]

Denials can occur for many reasons, but they are often administrative and commonly up to the judgement of the entity processing the claim. For example, all of the top 6 denial reasons reported by one Medicare contractor relate to the way care is documented, reported, and billed, and none of them deal exclusively with what care is actually rendered.[2] In fact, the second most common reason is that parts of the claim are illegible. Even among denials that engage with issues more substantive than legibility, there is significant uncertainty as to which claims will be paid, with 6.4% of the claims in my sample being denied and the Centers for Medicare and Medicaid Services (CMS) reporting that 7.5% of claims are paid in error (CMS, 2022b). Thus, medical practices can invest in administrative staff and information technology to avoid claim denials by improving their documentation and billing, but denials' often-arbitrary nature makes some level of denials inevitable.

[1]While the initial decision of the insurer to decline to pay for a service is also often called a claim denial, I reserve this term for a fully-adjudicated claim that goes unpaid.

[2]These reasons are, in order, "missing patient medical record for this service," "information provided was illegible," "the supporting documentation does not match the claim," "claim must be submitted by the provider who rendered the service," "duplicate of a claim processed, or to be processed, as a crossover claim," and "this claim was chosen for medical record review and was denied after reviewing the medical records" (Novitas, 2022).

Claim denials are a particularly important form of administrative burden to study for a few reasons. First, they are much more common than other forms of administrative burden whose causal effects have been studied. For example, while Traditional Medicare requires prior authorization for only 9 services (CMS, 2023), all claims submitted to insurers face the prospect of being denied. Indeed, 54 billion dollars' worth of claims are denied annually, (Gottlieb et al., 2018).

Due to the ever-present threat of claim denials, providers devote significant resources to billing. Because claim denials represent a breakdown of providers' billing processes, their frequency is an excellent proxy for the broader administrative costs imposed by the onerous and complicated billing system present in health care. This makes claim denials more representative of the complex web of billing rules and regulations facing providers than more straightforward and more commonly studied forms of administrative burden like prior authorization.

2.2 Medicare Administrative Contractors

Traditional Medicare is often thought of as a monolithic, federally-run insurance program.[3] But while the government bears all actuarial risk, sets prices for each procedure, and determines the vast majority of Medicare policy, the day-to-day administrative operations are performed by private contractors called Medicare Administrative Contractors, or MACs, who operate in distinct geographic jurisdictions. The administrative tasks performed by these contractors include processing medical claims and prior authorization requests, determining the conditions under which Medicare will reimburse providers for various health care services, and educating providers about these billing rules.[4]

Although statutory guidelines dictate the type of medical services Medicare is intended to pay for, administrators have wide discretion over how to implement these broad standards.[5] Reflecting this discretion, an inspector general report found that while 59% of procedures were subject to coverage and billing rules by at least one contractor, only 41% of these were regulated by all contractors (Levinson, 2014a). Furthermore, differences in the claims processing apparatuses across contractors may further compound the differences in administrative burden. Billing rules are generally enforced automatically by checking claims against formalized billing rules built into the administrator's claims processing apparatus (called claim edits) as well as through manual review by administrators. These claims processing systems are highly imperfect, featuring claims processing errors as well as significant leeway in how stringently to enforce administrative and billing rules (CMS, 2022b). While CMS hopes that this discretion allows administrators to react to local trends in overbilling or innovation in their jurisdictions (MedPAC, 2018), much of this

[3] Medicare's own website says, "Original Medicare is coverage managed by the federal government" (Medicare.gov, 2022).

[4] According to CMS (2022c), Medicare Administrative Contractors perform 10 tasks, 7 of which relate to claims processing and creating billing rules. This entire list is reported in Appendix A. Importantly, none of the three remaining tasks could plausibly affect investment, market structure, or Medicare spending.

[5] Appendix A gives more detail on the federal coverage rules.

variation also likely stems from differences in corporate culture and idiosyncratic taste for imposing administrative burdens and so is commonly seen as indicative of inefficiency (Levinson, 2014a).

Administrators are contracted to provide administrative services for distinct regional jurisdictions determined by CMS. The contracts governing which contractors administer each jurisdiction are assigned using procurement auctions run by the federal government in which bids are scored based on quality and cost.[6] Awarded contracts have a cost-plus structure where contractors are reimbursed for their costs plus a small bonus incentive contingent on good performance.[7] Importantly, contractors bear no actuarial risk and so have no direct financial incentive to deny claims and impose burdens to restrain costs. In fact, contractors are often seen as generally prioritizing claims processing efficiency over implementing programs to reduce overall spending, including fraud-detection programs (Sparrow, 2000).

In response to the apparently arbitrary differences in coverage rules across jurisdictions, the federal government reduced the number of contracts and increased their size (Levinson, 2014a). At the beginning of my sample, there were 26 active administrative companies operating in jurisdictions that had not been changed since Medicare was created in the 1960s.[8] These jurisdictions sometimes spanned state borders (e.g., the Washington, DC area) or were strict subsets of states (e.g., New York). As a result of the Medicare Modernization Act of 2003, since the mid-2000s CMS has gradually reduced the number of contracts, combining multiple jurisdictions to be under the same contractor. Figure 1 shows that the number of contractors administering Traditional Medicare has decreased significantly over the last two decades as CMS reduced the number of contracts from 58 in the early 2000s to 12 today.[9] Because the new contract areas were "designed to reasonably balance distributions of FFS beneficiaries, practitioners and claims volumes" rather than to match jurisdictions with contractors that would impact claim denials in a certain way (CMS, 2005), these changes represent plausibly exogenous shocks to the contractor processing claims in a given area.

Furthermore, these contract changes represent an excellent context in which to study the impact of administrative burden because they entail potentially large changes to the claims processing apparatus claims are routed through. When a jurisdiction changes Medicare contractors, the coverage rules are updated to harmonize coverage for all providers whose claims are processed by the administrator (GAO, 2015) and the claims become routed through new claims process-

[6] As shown in Appendix C, these contract awards are uncorrelated with claims denials.

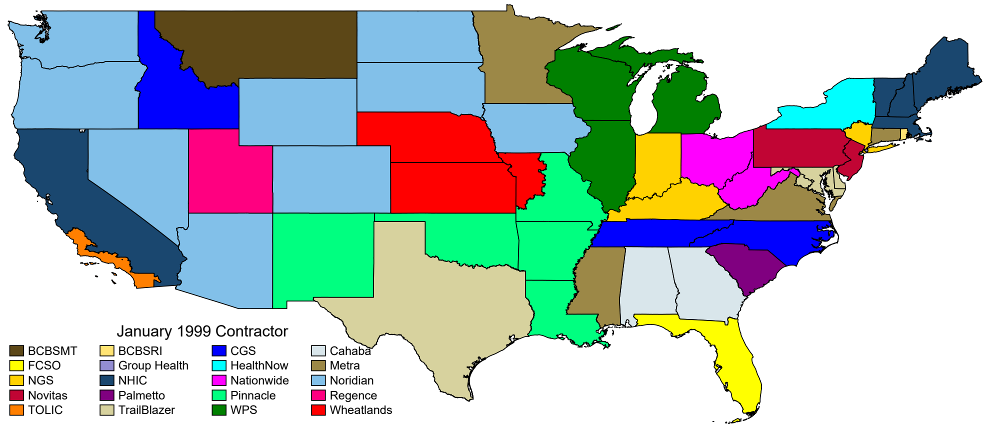
[7] Appendix A gives details on these incentive payments, of which only 1.4% depend on claims processing accuracy.

[8] The original jurisdictions were primarily determined by existing health insurers' ability to quickly implement the then-new Medicare program (Mennemeyer, 1984).

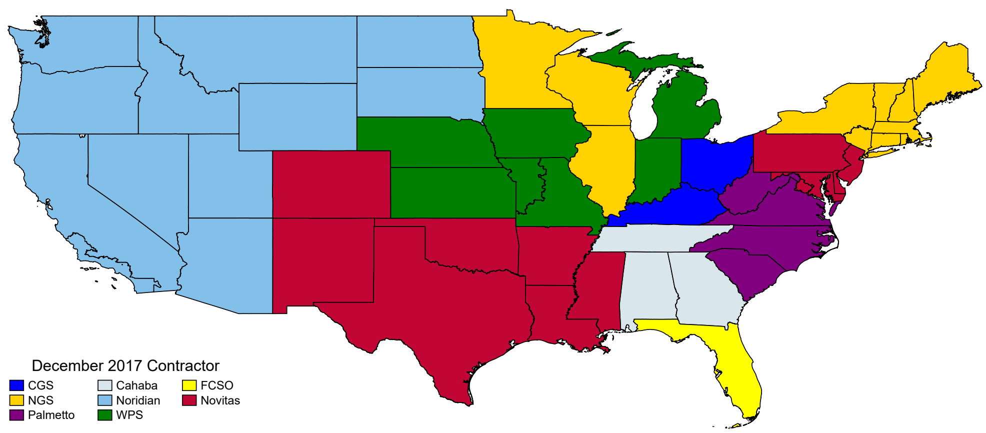
[9] At the beginning of my sample, Medicare Part B claims were processed by entities called "carriers" and Part A claims were processed by "fiscal intermediaries." In addition to combining jurisdictions geographically, CMS also combined the functions of processing Part A and B claims to be performed by a single contractor for a jurisdiction, newly called a Medicare Administrative Contractor. In this paper, I consider only Part B physician services and so refer to carriers and Medicare Administrative Contractors interchangeably.

Figure 1: Contractor Changes 1999–2017

(a) Contractors in 1999



(b) Contractors in 2017



Notes: Each panel reports the administrative company responsible for processing Medicare Part B claims in each jurisdiction of the continental United States in the relevant month. Panel (a) reports this data for January 1999 while panel (b) reports data for December 2017.

ing infrastructure, both automated and manual.[10] The combination of different coverage rules, different automated claim edits, and different personnel manually reviewing claims means that the reshuffling of jurisdictions I study has led to many changes in the potential denials faced by providers. Combined with the plausible exogeneity of the jurisdiction transitions, this represents is the perfect context in which to study causal effects of administrative burden.

[10]Transition plans of incoming contractors indicate that transitions generally involve both recruitment of new employees to review and process claims as well as expanding existing infrastructure to route the new claims workload through the incoming contractor's claims review process. Transition plans and meeting notes for several transitions obtained through FOIA requests are available at `https://www.dropbox.com/scl/fi/11jm7nhwuxj0qxqaynmug/Transition_Plans.zip?rlkey=qv2jru5l8f12ghxmmkotf52nv&dl=0`.

3 Data

The primary data used for this project come from a 20% random sample of Medicare claims for physician services billed to Medicare Part B (called the carrier file) from 1999 to 2017. This data set includes encounter-level information on patient diagnoses, procedures performed, payments made by the patient and insurer, and various claims processing information including the contractor that processed it and whether it was denied. These data represent fully adjudicated claims, meaning that I do not observe claims that are initially denied before being successfully appealed by the provider. This means that the advantage of my data set comes from its size and scope—Medicare is the single largest insurer in the country and other insurers often follow its actions (Clemens and Gottlieb, 2017)—rather than the detail provided on the back-and-forth between providers and insurers (Dunn et al., 2023) or the reasons for denial (Schwartz et al., 2022). Furthermore, using Medicare claims data allows me to identify the administrative contractor processing the claim, which then allows me to identify the responses of providers to being exposed to contractors with different denial rates.

Another important piece of information contained in the Medicare claims data is the Taxpayer Identification Number (TIN) of the entity billing Medicare.[11] This allows me to construct firm-level information such as the number of providers in the firm and whether the firm is active. Although using TINs to define firms is common in the literature on horizontal and vertical integration in health care (e.g., Capps et al., 2018; Austin and Baker, 2015; Welch et al., 2013), this definition has well-known measurement error.[12] Because TINs are assigned by the Internal Revenue Service and are reported on claims for tax compliance purposes, rather than being assigned or reported by Medicare Administrative Contractors, I have no reason to believe that this measurement error would differ by contractor or be correlated with the timing of contractor transitions. I construct firm-month level data on the number of unique providers billing under the same TIN in the same jurisdiction, as well as firm-month-level data on denials, charges, and payments. Finally, I also aggregate this information to create jurisdiction-month-level data on aggregate outcomes like the number of active TINs, average firm size, and total Medicare spending.

I also use state-year-level data from the Office of the National Coordinator for Health Information Technology on physicians' adoption of electronic health record (EHR) technology to understand how administrative burden relates to investment in billing technology. These data report the share of office-based physicians that have adopted basic EHR technology, one particularly

[11] TINs are only reliably in the Medicare data starting in 2006. For this reason, I limit analyses using this variable to data from 2006–2017. In Appendix **APPENDIX**, I show that MAC transitions during this period resulted in similar changes in the denial rate as those estimated for the entire sample.

[12] In particular, large group practices may bill under multiple TINs, inflating the apparent number of firms and decreasing their apparent size. Furthermore, when a practice is acquired or merges with another practice or with a hospital, providers may continue to bill under the same TIN.

important form of investment in billing.[13] These data are available from 2010 to 2015, a period of rapid growth in the adoption of this technology.[14]

I supplement this state-year-level data on EHR adoption with cross-sectional physician-level data on the receipt of payments for the meaningful use of EHR from 2011. Physicians received these subsidy payments as part of the HITECH Act of 2009 after attesting to the meaningful use of EHR. While using subsidy payment data may be an imperfect measure of physicians true EHR adoption behavior, it can still be informative about the cross-sectional relationship between billing investments and firm size.

Finally, I also administrative cost data that is broader than EHR use to understand the relationship between billing investments and firm size. Specifically, I use the Healthcare Provider Cost Reporting Information System (HCRIS) data that contains the cost reports submitted to Medicare by rural health clinics (RHCs), federally qualified health centers (FQHCs), and dialysis facilities.[15] These cost reports contain information reported annually by the facility on, among many other things, it's costs, including administrative and overhead costs, and its patient volume. These variables allow me to construct the average reported administrative cost at the facility and (for dialysis facilities) chain levels to assess the relationship between firm size and average costs. These data are available for 2009–2018 for RHCs and FQHCs and 1998–2022 for dialysis facilities.[16]

Table 1 reports summary statistics on each Medicare Administrative Contractor in my data. In the cross-section, there is wide variation in the denial rates across contractors, ranging from less than 5% for Wheatlands to over 11% for Metra. This is variation is quite wide, given 6.36% of claims are denied overall, as reported in Appendix Table A2 in Appendix B. As will be critical for my empirical strategy, every contractor has at least one jurisdiction transition to or from being administered by that company, meaning that I can identify the causal effect of every administrator.

4 Empirical Strategy

To understand how providers respond to administrative burden, I will compare the outcomes in jurisdictions that transition between administrative contractors that impose different levels of burden. For this to be a valid empirical strategy, two main conditions must be met. First, these transitions must cause the level of administrative burden imposed on providers to change. Second, any changes observed in the outcomes I study must be attributable to these changes.

[13] Basic EHR technology is defined as computerized systems that record clinician notes and orders, patient demographics and medication and problem lists, and allow for the viewing of laboratory and imaging results.

[14] In Appendix **APPENDIX**, I show that MAC transitions during this period resulted in similar changes in the denial rate as those estimated for the entire sample.

[15] I limit my analysis to these facilities because unlike other facilities submitting cost reports to Medicare, these are primarily outpatient facilities billing the Part B contractors I study.

[16] Due to concerns with changes in reporting over time, and given the role of contractors in auditing and affirming cost reports, I do not assess how reported costs change following contractor changes.

Table 1: Contractor Summary Statistics

Contractor	Denial Rate	Exit Year	Transition Source	Transition Destination	Obs.
Metra	11.03	2000	4	0	80
Group Health	10.84	2008	1	0	114
BCBSRI	9.04	2003	1	0	60
TOLIC	7.73	2000	1	0	22
Regence	7.36	2005	1	0	83
Nationwide	6.94	2002	2	0	82
HealthNow	6.93	2008	1	0	116
Noridian	6.87	-	4	7	2602
CGS	6.54	-	3	2	591
TrailBlazer	6.50	2012	9	4	918
NGS	6.48	-	3	12	1404
Pinnacle	6.40	2012	6	1	719
FCSO	6.15	-	1	2	430
Novitas	6.14	-	1	12	1236
NHIC	6.11	2013	7	2	971
Cahaba	6.00	2018	1	2	702
BCBSMT	5.96	2006	1	0	94
Palmetto	5.85	-	5	8	931
Triple-S	5.73	2009	1	0	121
WPS	5.58	-	3	7	1393
Wheatlands	4.90	2008	3	0	327

Notes: Denial rate is the percentage of claims denied in jurisdictions administered by the contractor from 1999 to 2017. Exit year reports the last year the contractor administered any jurisdiction and is missing if the contractor is currently administering at least one jurisdiction. Transition source and destination report the number of jurisdictions that transition from or to this contractor from 1999 to 2017. Observation count is the number of jurisdiction-months the contractor administered from 1999 to 2017.

As discussed in Section 2, the exogeneity needed to satisfy the second requirement is likely met due to the institutional process that consolidated administrative jurisdictions. Therefore, in this section I will focus on presenting evidence that administrative contractors differ in the levels of administrative burden they impose while also describing the empirical strategy I use to assess the responses of providers to administrator transitions more broadly.

The jurisdictions that Medicare Administrative Contractors administer are determined by government regulation, and the number of these regions has decreased over time, from 58 in 1999 to 12 in 2017. As a result, I observe 59 jurisdictions transitioning between administrators during my sample. Using a two-way fixed effects model, I use this variation to identify the causal effect of each contractor on the administrative burden faced by providers, holding constant time-invariant characteristics of each jurisdiction as well as national trends. I validate this model by examining the window immediately surrounding transitions of jurisdictions between contractors using dynamic difference-in-differences methods. The model I use to identify the impact of each administrator is

$$Y_{jmt} = \mu_m + \Gamma X_{jt} + \alpha_{0j} + \alpha_{1j}t + \eta_t + \varepsilon_{jmt}, \tag{1}$$

where Y_{jmt} is the share of claims denied in jurisdiction j administered by Medicare Administrative Contractor m in month t,[17] X_{jt} is a vector of observable jurisdiction-level beneficiary characteristics,[18] and μ_m, α_{0j}, and η_t are administrator, jurisdiction, and time period fixed effects, respectively. Including $\alpha_{1j}t$ allows for jurisdiction-specific time trends,[19] and ε_{jmt} is a jurisdiction-contractor-month specific error term, which I allow to be arbitrarily correlated within a jurisdiction over time.[20] μ_m is the object of interest: the impact of each contractor on the denial rate.

This empirical strategy isolates differences in denial rates attributable to differences in the administrator rather than other drivers of administrative burden that may vary geographically or over time. Because jurisdictions transition between different administrators, I am able to compare the denial rates for the same beneficiary population and provider community. Given the wide geographic variation in both the values and health status of the patient population as well as the beliefs, norms, and culture of health care providers (Fisher et al., 2003a,b; Finkelstein et al., 2016), these transitions are necessary to identify the contribution of each contractor to differences in denial rates.

To validate that I am capturing a causal effect of each administrative company rather than misattributing the impact of residual trends, I examine transition events between contractors with high or low estimated effects on denials. To do this, I follow Cengiz et al. (2019) and Deshpande and Li (2019) in creating a stacked data set to construct appropriate control groups for each transition. To implement this method, I create separate data sets for each transition w (for wave) consisting of the jurisdiction that transitions at time g and control jurisdictions that do not also experience a transition during the event window, which I generally define to be 18 months before and after transition. Each of these data sets is appended (or "stacked") such that each transitioning jurisdiction appears once while each jurisdiction may appear as a control multiple

[17] In Appendix D.1, I use alternative measures of administrative burden including the share of claim lines (rather than complete claims) and charges denied as the dependent variable, showing that my results are robust to these alternative definitions and indicating that I am assessing a robust measure of administrative burden.

[18] These include a quadratic function of the number of beneficiaries, the average age of beneficiaries, the shares of beneficiaries that are eligible due to end-stage renal disease, eligible due to disability, white, black, and eligible for Medicaid.

[19] In Appendix D.2, I show that the estimated fixed effects are robust to alternative jurisdiction-specific time trend specifications.

[20] In the main text, I report standard errors clustered at the jurisdiction-level unless otherwise noted. In Appendix D.3, I report standard errors bootstrapped at the jurisdiction level.

times (although with different time values). I then estimate

$$(2)\quad Y_{jtw} = \sum_{e=-K}^{-2} \beta_e T_{jtw}(e) + \sum_{e=0}^{L} \beta_e T_{jtw}(e) + \sum_{e=-K}^{-2} \delta_e T_{jtw}(e) \times U_w + \sum_{e=0}^{L} \delta_e T_{jtw}(e) \times U_w + \Gamma X_{jtw} + \alpha_{jw} + \alpha_{tw} + \varepsilon_{jtw},$$

where K and L give the size of the treatment window, $T_{jtw}(e)$ is an indicator for being the transitioning jurisdiction e months from transition (where e denotes event time: $e \equiv t - w$), U_w is an indicator for whether the transition is from a contractor with a lower estimated effect on denials to a higher one, α_{jw} and α_{tw} are jurisdiction-by-wave and time-by-wave fixed effects.[21] δ_e is the object of interest and reports the differential change in denial rates in jurisdictions that transition to higher-denial administrators relative to those that transition to lower-denial administrators. These comparisons are relative to jurisdictions that do not change administrators during the event window and therefore can be thought of as a dynamic triple-differences specification. The key identifying assumption is that the only differential change between high-denial and low-denial contractors at the time of transition that would impact the denial rate is the transition itself. This would be violated if, for example, low-denial rate jurisdictions whose denial rates would naturally rise due to reversion to the mean were disproportionately assigned to high-denial administrators. In Appendix C, I present several pieces of evidence that this is unlikely to be the case and in support of my identifying assumption. These include showing a lack of correlation between the estimated impact of the incoming administrator and the outgoing administrator or the previous denial rate in the jurisdiction, the estimated impact of the administrator having no correlation with the probability of winning a contract, and the lack of changes in beneficiary population characteristics following contractor transitions.

In order to recover a summary parameter of the consequences of a transition to a higher-denial contractor over the entire post-transition window, I also estimate

$$(3)\quad Y_{jtw} = \sum_{e=-K}^{-2} \beta_e T_{jtw}(e) + \beta_{post} \sum_{e=0}^{L} T_{jtw}(e) + \sum_{e=-K}^{-2} \delta_e T_{jtw}(e) \times U_w + \delta_{post} \sum_{e=0}^{L} T_{jtw}(e) \times U_w + \Gamma X_{jtw} + \alpha_{jw} + \eta_{tw} + \varepsilon_{jtw},$$

where the coefficient of interest is δ_{post}, the static effect of the transition to a higher denial contractor over the L months after the transition.

Similarly, I estimate the transition dynamics regardless of the administrators between which

[21]In Appendix D.4, I replace the U_w indicator with a continuous measure of the difference in estimated denial rate effects between the source and destination contractor, akin to the estimates obtained using the movers designs of Finkelstein et al. (2016), Molitor (2018), Cutler et al. (2019), and Badinski et al. (2023).

the jurisdiction is transitioning:

$$(4) \qquad Y_{jtw} = \sum_{e=-K}^{-2} \beta_e T_{jtw}(e) + \sum_{e=0}^{L} \beta_e T_{jtw}(e) + \Gamma X_{jtw} + \alpha_{jw} + \eta_{tw} + \varepsilon_{jtw}.$$

This equation is also estimated using stacked regression, but rather than comparing transitions between high- and low-denial administrators in a triple-difference framework, compares jurisdictions that transition to any administrator to those that do not transition at the same time. The identification of β_e relies primarily on the standard difference-in-differences assumption that any changes in the denial rate for jurisdictions that change administrators, relative to changes in the denial rate elsewhere, can be attributed to the transition. Where the triple-difference framework nets out any disruptions associated with changing contractors that would be present even for transitions that decrease administrative burden in order to focus on the effects of a permanent increase in administrative burden, the specification in Equation (4) identifies these potential short-term disruptions.

Using the stacked regression method is particularly appealing in this setting because, by assuming that any dynamic treatment effects stabilize at some point after a transition (at most K months prior to the next transition), I am able to extend the method beyond the contexts considered by Cengiz et al. (2019) and Deshpande and Li (2019) to allow for a unit to be treated multiple times. Specifically, I can allow jurisdictions to transition between contractors multiple times.[22]

In addition to understanding how transitions between Medicare contractors affect the denial rate, I can employ the same estimation strategy to understand how provider behavior and market outcomes change following contractor transitions. In Section 5, I estimate the same equations with various other outcomes, including Medicare spending and charges as well as measures of market concentration. For these outcomes, the identification assumption is that the only differential change experienced by providers transitioning to a higher-denial administrator is an increase in the administrative burden they face.

Due to the limited time period for which I have data on EHR adoption, I must slightly alter my estimation strategy for that part of the analysis. For this, I employ closely related standard difference-in-differences techniques to compare the rate of adoption following transitions of jurisdictions to higher- or lower-denial administrators. In particular, I estimate

$$(5) \quad Y_{jt} = \sum_{e=-3}^{-2} \beta_e T_{jt}(e) + \sum_{e=0}^{4} \beta_e T_{jt}(e) + \sum_{e=-3}^{-2} \delta_e T_{jt}(e) \times U_j + \sum_{e=0}^{4} \delta_e T_{jt}(e) \times U_j + \Gamma X_{jt} + \alpha_j + \alpha_t + \varepsilon_{jt}$$

using the traditional two-way fixed effects estimator (i.e., not stacked regression), where Y_{jt} is the share of physicians having adopted basic EHR technology in jurisdiction j at time t. To address

[22] From 1999 to 2017, 12 jurisdictions transition between administrators twice while 2 transition three times.

concerns about aggregation across different waves of treatment (Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021), I present estimates for transitions that occur in 2011, 2012, and 2013 separately as well.

4.1 Effect of Contractor Transitions on Administrative Burden

Using the methods described in the previous subsection, I find that Medicare Administrative Contractors vary widely in the administrative burdens they impose and their causal effects on denial rates. Table 2 gives the estimated effect of each contractor on the share of claims denied.[23] These estimates indicate a wide range of effects, with the administrator that denies the most claims (Metra) denying 5.4 percentage points more claims than that which denies the fewest (TOLIC). This represents a substantial difference given the mean denial rate is only 6.4 percent. Furthermore, the causal differences are not perfectly reflected in the raw denial rates of each contractor reported in Table 1, indicating important differences over time and across jurisdictions in the way providers bill regardless of the administrator processing the claims. A joint significance test of the equality of all the coefficients reported in Table 2 yields an F-statistic of 278, indicating a p-value of less than 0.001. In addition, the estimated causal effect of each contractor on the share of claims denied is reflected in their effects on other measures of administrative burden as well, as shown in Appendix D.1.

The differences in denial rates emerge immediately upon the transition of a jurisdiction between contractors. Figure 2 reports estimates of the differential change in the denial rate when a jurisdiction transitions from a less to more stringent contractor relative to a transition to one that imposes a lower denial rate.[24] After not having differential trends in denial rates prior to the transition, the denial rates change immediately upon transition depending on whether the transition is to a more or less stringent contractor. This difference is constant between 0.8 and 1.3 and is statistically significant for each of the 18 months following the transition. After 18 months, the estimated difference in the denial rate is 1.24 percentage points higher, indicating a nearly 20% increase relative to the mean denial rate of 6.4 percent.

In addition to a transition to higher-denial administrator representing a persistent increase in administrative burden, transitions to lower- as well as higher-denial administrators represent acute shocks to administrative burden. Figure 3 shows that for transitions of both types, the denial rate spikes immediately following the transition. Even for a transition to a lower-denial administrator, transitions between contractors result in changes in coverage rules and so may be disruptive to providers. Figure 3c shows that when aggregating across low-to-high and high-to-low

[23]The estimates are given relative to a large contractor called Noridian that current administers Medicare for much of the Mountain and Pacific West.

[24]Note that this result was not guaranteed ex ante. Whether the transition was from a lower- to higher-denial administrator or vice versa is determined by the estimates of the contractor's fixed effect in Equation (1), rather than the estimated change in the window surrounding transitions. Indeed, in Appendix D.4, I show that the denial rate does not immediately adjust to match the estimated effect of the incoming contractor.

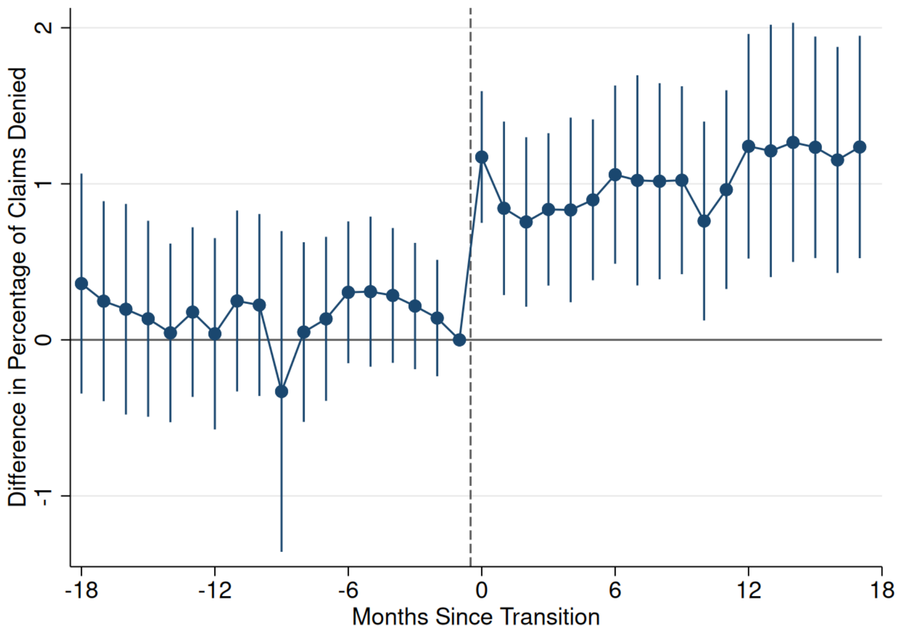
Table 2: Estimated Effect of Each Contractor on Denial Rate

	Denial Rate	Std. Error
Metra	1.859***	0.661
Nationwide	1.114**	0.431
Group Health	0.668	0.543
Triple-S	0.576	0.502
Pinnacle	0.410	0.518
BCBSRI	0.398	0.642
Wheatlands	0.350	0.512
TrailBlazer	0.342	0.459
NHIC	0.236	0.457
NGS	0.164	0.481
Novitas	-0.0161	0.532
WPS	-0.0928	0.452
Palmetto	-0.186	0.230
HealthNow	-0.356	0.521
FCSO	-0.659	0.453
Cahaba	-0.761	0.906
CGS	-1.061**	0.463
BCBSMT	-1.506***	0.167
Regence	-2.091***	0.251
TOLIC	-3.518***	0.699
Demographic Controls	Yes	
Month Fixed Effects	Yes	
Jurisdiction Fixed Effects	Yes	
Jurisdiction-Specific Trend	Yes	
Dep. Var. Mean	6.360	
R^2	0.8037	
Observations	12,996	

Notes: Estimates of μ_m of Equation (1). An observation is a jurisdiction-month. The excluded contractor is Noridian. Dependent variable is denial rate. Denial rate is the percentage of claims denied. Standard errors are reported to the right of the point estimates and clustered by jurisdiction. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

transitions, the denial rate spikes sharply in the month of transition. I estimate that the denial rate in the month of transition is 0.613 percentage points higher in the month of transition than the month before, a 9.6% increase from average denial rate during my sample, 6.4 percent. After the initial spike, however, the denial rate gradually recovers to its pre-transition average (again, pooling transitions to higher- and lower-denial administrators) within 6 months. This denial rate behavior is consistent with providers having difficulty navigating the coverage and billing rules of the new administrator before gradually changing their behavior in response to the new coverage

Figure 2: Effect of Transition to Higher-Denial Administrator on Denial Rate



Notes: Estimates of δ_e of Equation (2) for $e \in \{-18, \ldots, 17\}$ with $K = 18$ and $L = 17$. An observation is a jurisdiction-wave-month. Dependent variable is denial rate. Denial rate is the percentage of claims denied. Error bars give the 95% confidence interval for each estimate. Standard errors are clustered by jurisdiction.

regime, as documented qualitatively by the Government Accountability Office.[25]

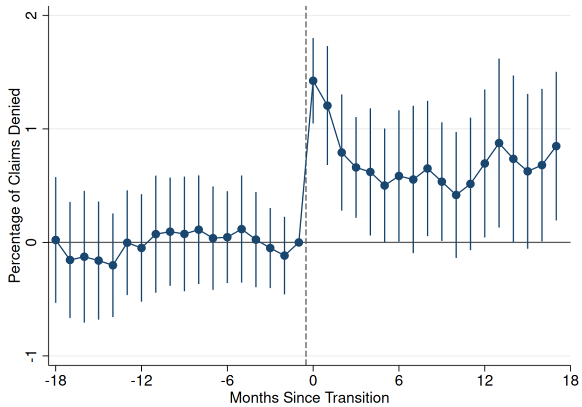
Transitions between administrators represent meaningful changes in the administrative burdens faced by providers, both because administrators differ in the administrative burdens they impose and because the transitions themselves are disruptive. Thus, by analyzing the way that providers alter their behavior following transitions between administrators, we can learn about the consequences of administrative burdens more generally.

5 Effects of Increased Burden

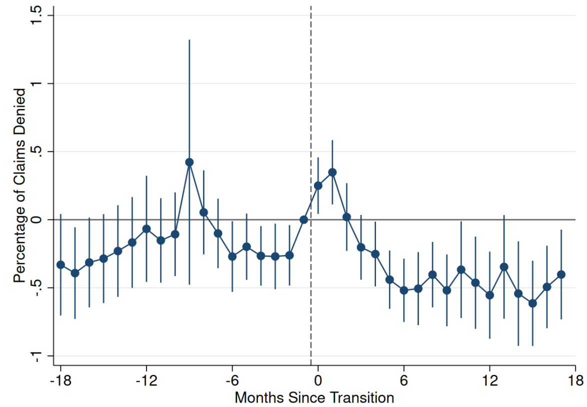
In this section, I present evidence that exposing providers to increased claim denials leads them to make billing investments and increase charges with little evidence of changes in patient care. I also find that increased administrative burden alters market structure and, counterintuitively,

[25]GAO (2015) reports that the government "did not require Medicare Administrative Contractors to make this change (to stricter coverage rules) clear, causing payment denials providers did not anticipate," with provider groups reporting "a lack of clear communication... which caused confusion once the local coverage determinations were finalized and claims were rejected." This confusion is understandable given the extensive coverage rules contractors impose and the potential difficulty in changing medical and billing practices in light of them. As noted by the GAO report, the transitions involve hundreds of new rules being put out for public comment, which physicians reported being unable to review in a timely manner.

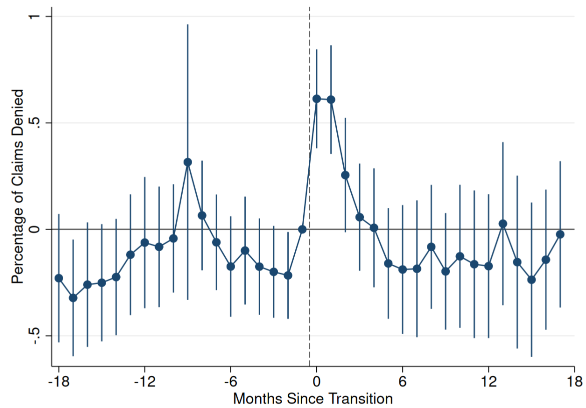
Figure 3: Denial Rate and Transition Dynamics



(a) Transition to Higher-Denial Administrator



(b) Transition to Lower-Denial Administrator



(c) All Transitions

Notes: Estimates of β_e of Equation (4) for $e \in \{-18, \ldots, 17\}$ with $K = 18$ and $L = 17$. An observation is a jurisdiction-wave-month. Dependent variable is denial rate. Denial rate is the percentage of claims denied. Error bars give the 95% confidence interval for each estimate. Standard errors are clustered by jurisdiction. Panel (a) reports estimates using only transitions of a jurisdiction to an administrator with a higher estimated effect on denial rates, while panel (b) is limited to transitions to lower-denial administrators. Panel (c) reports estimates for all transitions.

that increased denials do not reduce Medicare spending.

5.1 Effect on Spending and Care

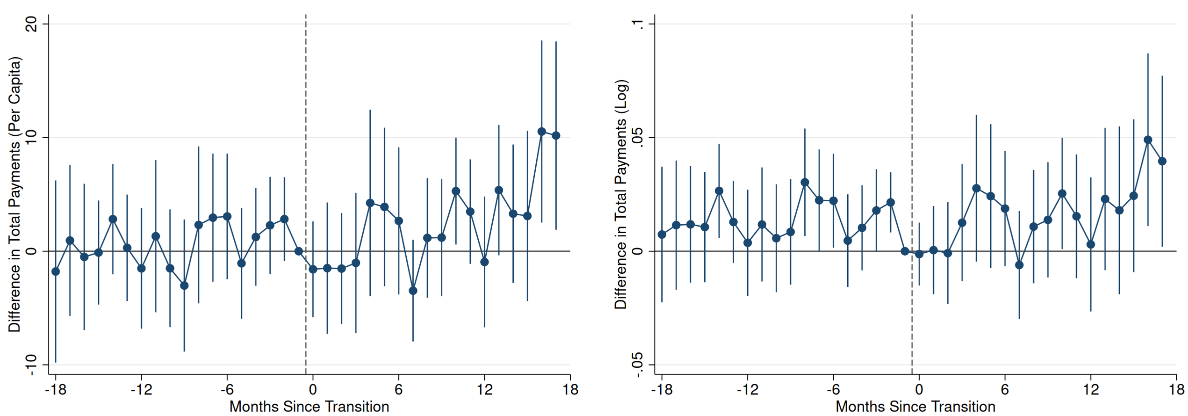
The effect of increased claim denials on spending is not obvious ex ante, as the mechanical effect of denying more claims could be either offset or enhanced by endogenous responses on the part of providers. As shown by Figure 4 and Table 3, following a transition to a higher-denial contractor, Medicare spending does not fall at all and after 18 months is estimated to be \$10 per beneficiary and 0.04 log points, or 4.0–4.5% higher. Because claim denials increase following a transition to a higher-denial contractor, we would expect spending to fall by 1.1% in the absence of changes to provider behavior and billing, which we can rule out at $p < 0.05$ over the entire post-period and at $p < 0.01$ after 18 months. Appendix Figure A23 shows the implied level of spending under only a mechanical response along with the estimates presented here. This figure shows that in the months immediately following the transition, there is little difference between these two values the true estimated level of spending increases while the implied mechanical level of spending says reduced. These results indicate that the endogenous responses of providers fully offset the mechanical reduction in spending that would occur as a result of increased claim denials.

Table 3: Effect of Transition to Higher-Denial Administrator on Medicare Spending

	End of Post-Period		All of Post-Period	
	(1) Payments (per capita)	(2) Payments (log)	(3) Payments (per capita)	(4) Payments (log)
Increase in Denials	10.18**	0.0396**	2.465	0.0165
	(4.137)	(0.0188)	(2.112)	(0.0109)
Dep. Var. Mean	227.5	16.61	227.5	16.61
Observations	70,164	70,164	70,164	70,164

Notes: Columns (1) and (2) report estimates of δ_{17} of Equation (2) with $K = 18$ and $L = 17$, and columns (3) and (4) report estimates of δ_{post} of Equation (3) with $K = 18$ and $L = 17$. An observation is a jurisdiction-wave-month. Dependent variables are total Medicare payments measured per Medicare beneficiary and in logs. Standard errors are clustered by jurisdiction. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Figure 4: Effect of Transition to Higher-Denial Administrator on Medicare Spending



(a) Payments Per Capita

(b) Log Payments

Notes: Estimates of δ_e of Equation (2) for $e \in \{-18, \ldots, 17\}$ with $K = 18$ and $L = 17$. An observation is a jurisdiction-wave-month. Dependent variables are total Medicare payments measured per Medicare beneficiary and in logs. Error bars give the 95% confidence interval for each estimate. Standard errors are clustered by jurisdiction.

Despite failing to achieve their putative aim of reducing health care spending, administrative burdens may improve patient care. Although administrative burdens are generally targeted toward combating waste and inefficiency, they can also be used to protect patients and encourage higher-value, more-effective care. Examples of these types of burdens include real-time denials for prescription drugs that may have dangerous interactions with one another as well as claim denials for care known to be wasteful. In Appendix F.3, I show that differences between administrators in the treatment of claims for low-value care can potentially induce providers to change their provision of these services, but that this is the case only for changes in denials that are *much* larger than those experienced by most procedures. This indicates that while large, clear burdens can alter care provision—as is the case with prior authorization, for example (Eliason et al., 2021; Brot-Goldberg et al., 2022)—subtle differences in billing rules are unlikely to have a material impact on the provision of care. This result is consistent with the evidence of Dunn et al. (2023) that differences across payers in denial probability are unrelated to treatment intensity, while Macambira et al. (2022) highlight the impotence of after-the-fact denials to alter medical care when compared to automatic claim adjudication.

Consistent with no change in the provision of care, I also find no change in aggregate beneficiary mortality following a transition to a higher-denial administrator, as shown in Figure A26 in Appendix F.4. The estimated change in mortality after a transition is close to zero but is somewhat imprecise.[26] Although I cannot rule out changes in mortality for all patients, previous research in settings where administrative burdens clearly alter the provision of care generally fails to find evidence of changes in patient outcomes (Eliason et al., 2021; Brot-Goldberg et al., 2022; Macambira et al., 2022). In my context, there is little evidence that claim denials lead to large changes in the actual provision of care and, accordingly, little change in outcomes for patients.

5.2 Effect on Billing Investments

Next, I turn to assessing how billing investments change following a transition to a higher-denial contractor. First, I assess the effect on the adoption of electronic health record (EHR) technology, a bundle of services that promise to make billing easier and more effective by automating more of the process. Previous research has shown that EHR adoption by hospitals is associated with increased charges (Agha, 2014), revenues (Ganju et al., 2022), and compliance with billing rules (Sacarny, 2018; Shi, 2024) as well as lower costs of billing (Gowrisankaran et al., 2019). Figure 5 presents estimates of the difference in EHR adoption rates in jurisdictions that transition from lower-denial to higher-denial administrators between 2010 and 2015, both aggregated across years as well as broken out by the year of the transition. Across all years, the rate of EHR adoption increases following a transition to a higher-denial administrator, although this difference is consistently statistically significant only following transitions that occurred in 2011. Aggregating across all years of transition, I find that jurisdictions that face an increase in administrative burden have EHR adoption rates 7.7 percentage points higher after 4 years and 5.1 percentage points higher

[26] I cannot rule out increases or decreases in mortality of up to 1.9% at the 95% confidence level.

over the entire post-period, as shown in Table 4.

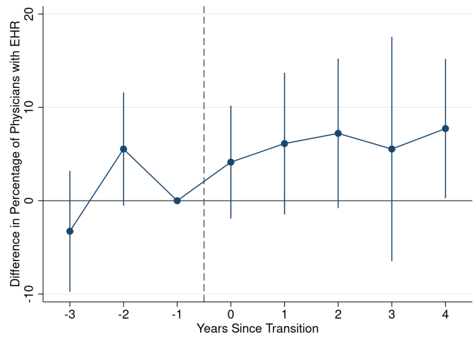
Table 4: Effect of Transition to Higher-Denial Administrator on EHR Adoption and Charges

	End of Post-Period			All of Post-Period		
	(1) Share Adopt EHR	(2) Charges (per capita)	(3) Charges (log)	(4) Share Adopt EHR	(5) Charges (per capita)	(6) Charges (log)
Increase in Denials	7.729**	46.74**	0.0595**	5.130*	20.64**	0.0324**
	(3.721)	(20.73)	(0.0260)	(2.963)	(9.220)	(0.0135)
Dep. Var. Mean	42.85	617.2	17.58	42.85	617.2	17.58
Observations	3,948	70,164	70,164	3,948	70,164	70,164

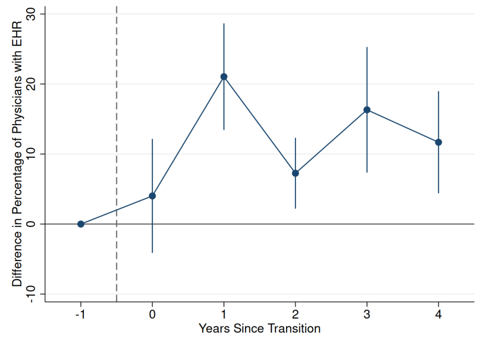
Notes: Column (1) reports the estimate of δ_4 of Equation (5), columns (2) and (3) report estimates of δ_{17} of Equation (2) with $K = 18$ and $L = 17$, column (4) reports the estimate of δ_{post} in a variation of Equation (5) where $\beta_{post} \sum_{e=0}^{4} T_{jt}(e)$ replaces $\sum_{e=0}^{4} \beta_e T_{jt}(e)$ and $\delta_{post} \sum_{e=0}^{4} T_{jt}(e) \times U_j$ replaces $\sum_{e=0}^{4} \delta_e T_{jt}(e) \times U_j$, and columns (5) and (6) report estimates of δ_{post} of Equation (3) with $K = 18$ and $L = 17$. In columns (1) and (4), an observation is a jurisdiction-month and the sample is limited to 2010–2015. In columns (2), (3), (5), and (6), an observation is a jurisdiction-wave-month. Dependent variables are the share of practices that have adopted electronic health records and the total charges billed to Medicare per beneficiary and in logs. Standard errors are clustered by jurisdiction. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

In line with this result, I see that the charges submitted by providers to Medicare also increase following transitions to higher-denial administrators. Figure 6 shows that over time, transitions to contractors that are more aggressive with claim denials result in providers submitting more charges. This response is not immediate and instead gradually accumulates over time. As reported in Table 4, charges are $47 per capita and 0.06 log points higher 18 months after transitioning to a higher-denial contractor, an increase of 6.1–7.6 percent. This increase in charges is consistent with firms investing more in billing and expending effort to extract more charges from each visit.

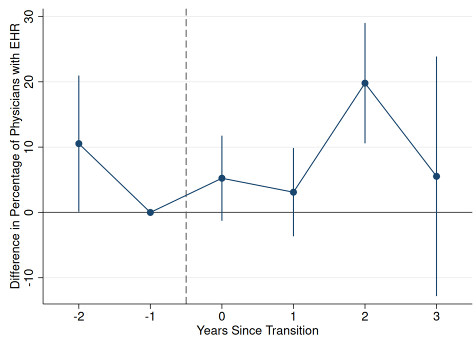
Figure 5: Effect of Transition to Higher-Denial Administrator on EHR Adoption



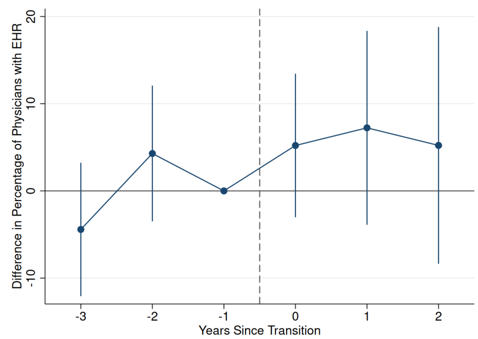
(a) All Years



(b) 2011 Transitions



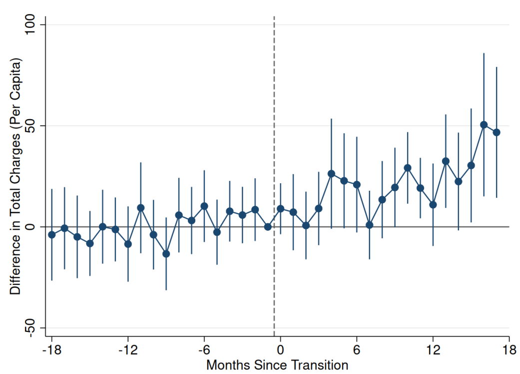
(c) 2012 Transitions



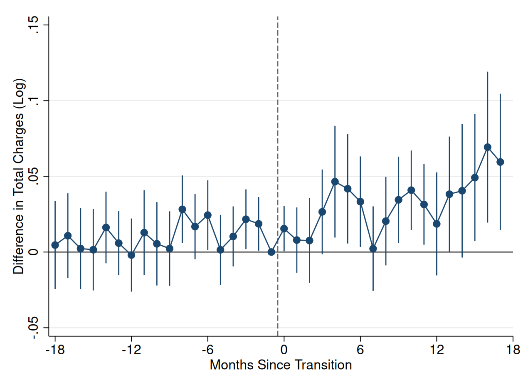
(d) 2013 Transitions

Notes: Estimates of δ_e of Equation (5) for $e \in \{-3, \ldots, 4\}$. An observation is a jurisdiction-month. Dependent variable is the share of office-based physician practices that have adopted basic EHR technology. Panels (b), (c), and (d) limit the sample to jurisdictions subject to a transition in the year noted in the subfigure title and jurisdictions not subject to a transition in 2010–2015. Sample is limited to 2010–2015. Error bars give the 95% confidence interval for each estimate. Standard errors are clustered by jurisdiction.

Figure 6: Effect of Transition to Higher-Denial Administrator on Charges



(a) Charges Per Capita



(b) Log Charges

Notes: Estimates of δ_e of Equation (2) for $e \in \{-18, \ldots, 17\}$ with $K = 18$ and $L = 17$. An observation is a jurisdiction-wave-month. Dependent variables are total charges billed measured per Medicare beneficiary or in logs. Error bars give the 95% confidence interval for each estimate. Standard errors are clustered by jurisdiction.

5.3 Effect on Market Structure

Next, I assess the impact of contractor transitions on market structure. As Figure 7a shows, increases in administrative burden lead to firm exit, particularly among the smalled firms. Transitions to higher-denial administrators result in 0.9% fewer firms operating in the month after the transition relative to the month before (as shown by column (1) of Table 5) and the number of firms remaining well below trend thereafter. Furthermore, I find that exit is driven by the smallest firms while undetectable for larger firms. Immediately following a transition to a higher-denial administrator, the number of single-provider firms drops by 1.4%,[27] leading to an immediate change in the size distribution of firms. The share of providers in solo practice drops 0.2 percentage points (1.3%) and the average number of providers per firm increases 0.03 providers (0.8%) in the month following a transition to a higher-denial administrator. These results indicate that increasing administrative burdens effects not only provider billing investments but also market structure.

Table 5: Effect of Transition to Higher-Denial Administrator on Market Structure

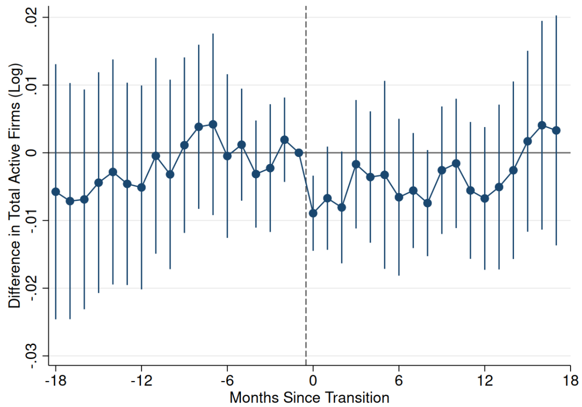
	(1) Active Firms (Log)	(2) Active Single-Provider Firms (Log)	(3) Share of Providers in Solo Practice	(4) Providers Per Firm
Increase in Denials	-0.00893***	-0.0138***	-0.00239**	0.0303**
	(0.00277)	(0.00507)	(0.00102)	(0.0132)
Dep. Var. Mean	8.004	7.556	0.188	3.754
Observations	53,208	53,208	53,208	53,208

Notes: Estimates of δ_0 of Equation (2) with $K = 18$ and $L = 17$. An observation is a jurisdiction-wave-month. Dependent variables are the number of active firms and the number of single-provider active firms (both in logs), the share of providers affiliated with single-provider firms, and the firm-level average number of providers per firm. Active firms is the number of unique tax identification numbers under which a claim is submitted. Providers per firm is the average number of unique providers in a jurisdiction billing under the same tax identification number. Sample is limited to 2006–2017. Standard errors are clustered by jurisdiction. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

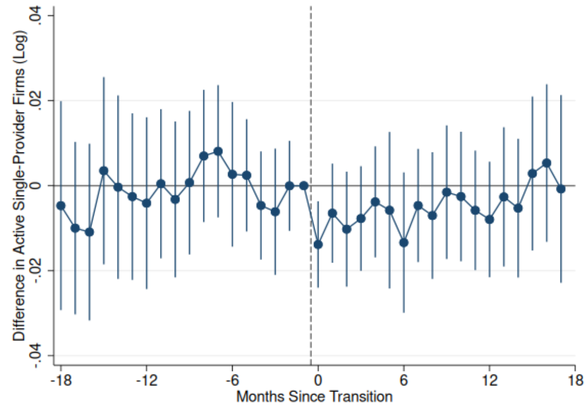
In Appendix F.2, I present additional results that indicate that these changes in market structure are not driven by changes in the number of active providers but rather only in the number and composition of firms. This means that while administrative burdens may lead solo practitioners to sell their practices and affiliate with larger firms, it does not appear to induce solo practitioners to stop practicing entirely. While this consolidation may not be as disruptive to patients' access to care as if increased administrative burden led providers to stop caring for patients en masse, the change in market structure likely has important implications for the competitiveness of health care markets.

[27] In Appendix F.2, I show that there is little change in the number of larger firms.

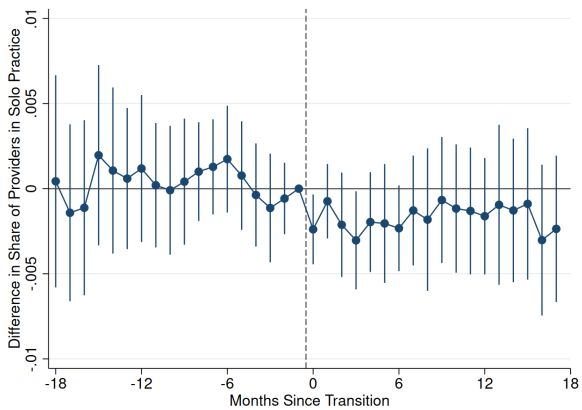
Figure 7: Effect of Transition to Higher-Denial Administrator on Market Structure



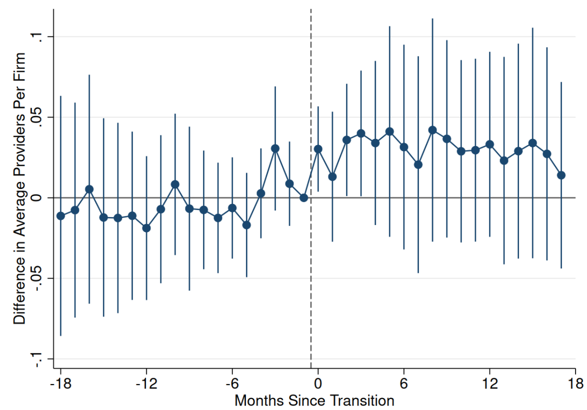
(a) Active Firms



(b) Active Single-Provider Firms



(c) Share of Providers in Solo Practice



(d) Average Providers per Firm

Notes: Estimates of δ_e of Equation (2) for $e \in \{-18, \ldots, 17\}$ with $K = 18$ and $L = 17$. An observation is a jurisdiction-wave-month. Dependent variables are the number of active firms and the number of single-provider active firms (both in logs), the share of providers affiliated with single-provider firms, and the firm-level average number of providers per firm. Active firms is the number of unique tax identification numbers under which a claim is submitted. Providers per firm is the average number of unique providers in a jurisdiction billing under the same tax identification number. Sample is limited to 2006–2017. Error bars give the 95% confidence interval for each estimate. Standard errors are clustered by jurisdiction.

6 Theoretical Framework

In order to interpret the empirical results presented above, in this section I present a theoretical framework emphasizing the role of billing investments in shaping providers' responses to administrative burden. The model developed here, as I will show, explains the results presented in the previous section and is supported by a number of key stylized facts presented later in this section. That said, changes in administrative burden could lead to a number of different responses by providers. Prior research has highlighted that providers have responded to administrative burden by changing their billing practices (Ganju et al., 2022), the patients they accept (Dunn et al., 2023), the drugs they prescribe (Brot-Goldberg et al., 2022), and even whether they participate in the market at all (Eliason et al., 2021). Shi (2024) highlights that in response to increased audits of their admissions practices, hospitals adopt software that helps them abide by medical necessity requirements. The theoretical framework I outline below emphasizes this last channel of provider investment, but highlights the important role of economies of scale in these investments in determining the optimal firm size. Mathematical details on the model and the predictions it generates are given in Appendix E.

Provider practices, or firms more generally, choose their level of investment in billing I to maximize profits:

$$\max_I \Pi(I) = p(I)r(I)v - cI. \tag{6}$$

This investment can take many forms, including adopting information technology infrastructure like electronic health records, hiring additional staff to manage the revenue cycle and convert physician notes into medical claims, or other types of effort and investments that increase the efficacy of the practice's billing apparatus.[28]

Investment has two benefits to the firm in this model. First, it lowers the denial rate and increases the likelihood that a claim is paid in full. The function $p(I) \in [0, 1]$, which is increasing, captures how the payment rate responds to this investment. Second, it makes firms able to extract more charges from the same patient encounter. This can entail reporting diagnoses or claim modifiers that indicate a more severe condition for the patient or reporting that the provider rendered more (or more expensive) care. This behavior is called upcoding and has previously been shown to respond to investment in billing technology like electronic medical records (Abelson et al., 2012; Sacarny, 2018; Ganju et al., 2022).[29] For this reason, I assume that the charges per visit net of the cost of care $r(I)$ are increasing in investment.

The product of (i) the payment rate $p(I)$, (ii) the net charges per visit $r(I)$, and (iii) the volume of visits v gives the expected variable profit of the firm. To emphasize the role that firm size plays in investment decisions and the effects of administrative burdens, I stipulate that patient volume v is exogenous and does not depend on investment in billing.[30]

The firm's costs are given by the product of the unit cost of investment c and the quantity of investment I. For illustrative purposes, I assume that the cost of investment is entirely fixed with respect to patient volume, although in my empirical implementation of the model in Section 6.3,

[28] I model the firm's decision as a static one in which the level of investment is chosen each period. In Appendix F.1, I present evidence that this assumption is acceptable in my context.

[29] This behavior is often worrying to policymakers (Silverman and Skinner, 2004; Dafny, 2005; Dafny and Dranove, 2009), although it can also represent an improvement in coding accuracy (Gowrisankaran et al., 2016). The model is agnostic on the accuracy of any changes in coding.

[30] This assumption is consistent with the data. In Appendix F.4, I show that there is no evidence patient volume responds to contractor changes.

I relax this assumption.

This model can be used to generate predictions about how firms will respond to changes in the administrative burden they face. We can think of an increase in administrative burden as operating in two places in this model. The most straightforward is that it increases the denial rate for all levels of investment ($p_1(I) \leq p_0(I)$), meaning that it is more difficult to extract payment from insurers with a given level of billing investment. The second, more subtle way that increased administrative burden may operate in this model is by improving the ability of billing investment to reduce denials ($\frac{\partial p_1}{\partial I} \geq \frac{\partial p_0}{\partial I}$). This channel would be activated by making the billing process more complicated such that the return to investing in technology to combat this burden is higher, for example. Claim denials arise because complicated billing rules are not followed, so those rules becoming more complicated increases the return to investing in ways to navigate the billing process. Indeed, previous research has indicated that billing technology can allow providers to better adapt to and incorporate new billing rules (Sacarny, 2018).

Each of these two channels pushes the equilibrium level of investment in a different direction. The first "more denials" channel serves to lower the equilibrium investment because investing in raising charges becomes less attractive when the probability that each charge is paid falls. By contrast, the second "return to billing" channel serves to raise the equilibrium level of investment because it increases the marginal benefit of investing in terms of avoiding claim denials. Which of these two effects dominates is theoretically ambiguous. If billing investments are not able to effectively avoid the new denials and the denial rate rises dramatically, then the profit-maximizing level of investment will fall in the face of increased administrative burden. On the other hand, if investment can easily overcome the new billing rules and the denial rate does not greatly change, increased administrative burden will lead to increased investment.

This model has a number of implications that are closely related to the empirical results presented in Section 5. First, in the model, increased investment leads to increased charges, so these variables should co-move. Indeed, I find that following a transition to a higher-denial contractor, both EHR adoption and charges increase, as predicted by the model. This result is also consistent with the "return to billing" channel dominating the "more denials" channel and increased administrative burden causing billing investment to increase.

Second, the model implies that

Even beyond the impact on market structure, investment would still be socially wasteful in the context of the model. It serves to only determine transfers between the government and health care providers, but at a real cost. This is consistent with the idea of an "administrative arms race" (Cutler, 2018), where insurers impose burdens and require more complex billing in an attempt to reduce payments to providers, but providers respond by investing in more administrative architecture to claw back this revenue. This in turn leads insurers to impose yet higher burdens that providers then attempt to circumvent. Such a prisoners' dilemma is socially wasteful and highlights the benefits that could come from imposing fewer administrative burdens.

Outside of the model, though, investment in billing technology can potentially have benefits for patients and payers. For example, insurers may value the improved accuracy of billing leading to fewer worries about fraud and improper payments while policymakers have touted the potential for health IT to improve coordination of care across providers and transparency to consumers (Gowrisankaran et al., 2019; Miller and Tucker, 2011; Atasoy et al., 2018). However, existing evidence indicates that the effect of health IT adoption on patient outcomes is likely modest (Agha, 2014; Bronsoler et al., 2022), and investments in billing technology other than electronic health records, such as hiring scribes and coders, are even less likely to improve patient care. And while I find no evidence of improved care or outcomes following an increase in administrative burden in my setting, I cannot rule out potential uncaptured benefits. To that end, I now turn to estimating a structural model of providers investing in billing in order to quantify the current and counterfactual costs of investment that can be weighed against the potential benefits.

6.1 =======

2. Large firms invest more. I Denials (subsidies) are decreasing (increasing) in firm size. I Larger firms are less disrupted by MAC transitions. 3. Increased burden will lower profits, especially for small firms. I Transitions lead to exit, particularly for small firms. I Increased administrative burden causes increase in average firm size. 4. Investment is privately valuable but socially wasteful. I I see no evidence of changes in care provision. I Model is consistent with "administrative arms race" (Cutler, 2018).

Second, large firms will invest more because the fixed cost of investment does not depend on volume while the benefit of investment does. Third, increasing administrative burden will lower firm profits, particularly among small firms that are closer to the threshold of exit. Finally, the net impact on Medicare spending of the direct effect of increasing administrative burdens combined with providers' endogenous responses is unclear: the responses of providers could lead spending to fall by more than the direct change in denials would predict if investment falls or provider responses could mitigate—either partially or fully—the mechanical response if investment increases.

My results indicate that increased administrative burdens lead to higher Medicare spending and increased consolidation. While these are both widely thought to be negative, unintended outcomes,[31] my results shed light on one particularly contentious issue when these mergers are reviewed by competition authorities: the potential for cost savings and economies of scale. My results support the notion that larger physician groups and health systems are better able to invest in the fixed costs of billing technology, something also consistent with the results of Andreyeva

[31]For example, previous research has documented extensive harms that come from consolidation in the health care system, including increased prices (Gaynor and Vogt, 2003; Dafny, 2009; Gowrisankaran et al., 2015; Cooper et al., 2019) and lower nurse wages (Prager and Schmitt, 2021), along with restricted access to care (Town et al., 2006, 2007) and few gains in patient health (Cutler et al., 2010; Gaynor et al., 2013; Bloom et al., 2015; Eliason et al., 2020).

et al. (2022), who find that larger hospital systems are able to reduce administrative expenses, Clemens et al. (2023), who find that physician groups are able to adopt new billing codes more quickly than solo practitioners, and Dunn et al. (2023), who find that small practices lose 38% more Medicare revenue to claim denials and resubmission costs than larger practices. Furthermore, a recent survey of financial executives involved in hospital mergers found that investments in health IT such as electronic medical records and billing software were the most common use of new capital generated by the merger (Knapp et al., 2017). Importantly though, my results indicate not only that consolidation can potentially generate efficiencies but also that one driver of the consolidation that policymakers often worry about is that administrative burdens cause fixed costs to increase in ways that necessitate larger firms.

Industry watchers have long warned about this result. For example, Daly (2018) argues that "smaller hospitals lack the capital to... make necessary investments in information technology and clinical systems that are required in order to operate efficiently and effectively in the current environment," and Smidt (2015) argues the "complex and far reaching" regulatory environment is "leading hospitals to increase their IT know-how and equipment capabilities through mergers and acquisitions." Despite these widespread worries, to my knowledge there have been no studies investigating the link between market structure and claim denials, billing complexity, and administrative burden.

6.2 Stylized Facts About Economies of Scale in Billing

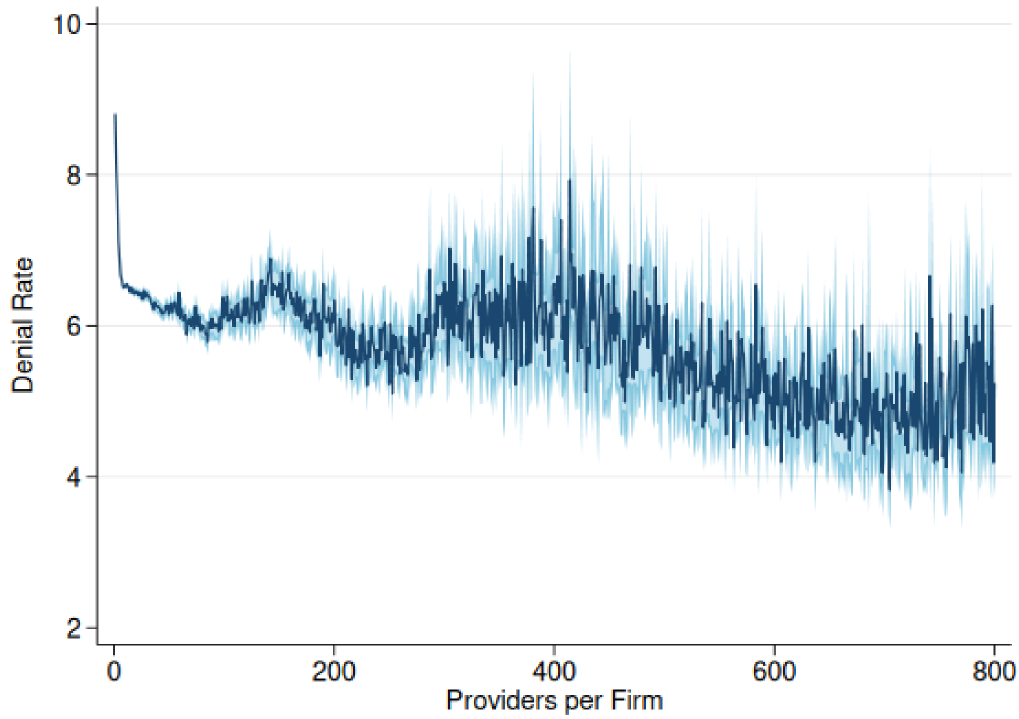
Fact 1: Denials are Decreasing in Firm Size

Next, I show evidence consistent with larger firms investing more in billing. First, larger firms have a smaller share of their claims denied. Figure 8 shows the share of claims denied by the number of providers billing Medicare under a single tax identification number. We see that while solo practitioners face an average denial rate of almost 9%, only 5% of claims are denied for the largest physician groups. This strong negative relationship between firm size and denials is consistent with larger firms investing more in billing to avoid claim denials that smaller firms experience.

Fact 2: Larger Firms Experience Smaller Denial Rate Changes Around Contractor Transitions

In addition to having lower denial rates on average, larger firms also experience smaller changes to their denial rates following contractor transitions. GAO (2015) has documented extensive evidence of confusion on the part of providers about new billing rules when a jurisdiction changes administrators, and as shown in Section 4.1, denial rates tend to spike in the months following a transition. Breaking the sample into quintiles based on the number of providers associated with

Figure 8: Relationship Between Firm Size and Denial Rate



Notes: Figure reports the average denial rate by firm size for firms with up to 800 providers. Denial rate is the percentage of claims denied. An observation is a firm-month. Providers per firm is the number of unique providers in a jurisdiction billing under the same tax identification number. Sample is limited to 2006–2017. 95% confidence interval is given in light blue.

the firm, we see that the magnitude of this spike is decreasing in firm size. Table 6 reports the change in denial rate in the month of transition for firms of various sizes. While one-provider practices see their denials jump by a full percentage point following a contractor change, for the largest firms this spike is only roughly a quarter as large.[32] This result is consistent with larger firms having a larger stock of investment that allows them to more easily detect and respond to changes in billing rules and maintain a low denial rate.

Fact 3: Average Reported Administrative Costs Are Declining or U-Shaped in Volume

Fact 4: Larger Practices Are More Likely To Receive Early Meaningful Use Subsidies

6.3 Empirical Model

Although my results indicate that increasing administrative burdens has unintended consequences in the context I study, my model cannot capture all the potential benefits of adminis-

[32]Event studies showing how the denial rate changes dynamically in the months around transitions are available in Appendix F.4.

Table 6: Effect of Transition on Denial Rate by Firm Size

	(1) Denial Rate	(2) Denial Rate	(3) Denial Rate	(4) Denial Rate	(5) Denial Rate
Month of Transition	1.016***	0.782***	0.463**	0.215	0.284
	(0.164)	(0.161)	(0.179)	(0.176)	(0.237)
Firm-Size Quintile	1	2	3	4	5
Dep. Var. Mean	7.740	6.840	5.893	5.771	5.696
Observations	30,144	30,144	30,144	30,072	28,512

Notes: Estimates of β_0 of Equation (4) with $K = 6$ and $L = 5$. An observation is a jurisdiction-wave-month. Dependent variable is the denial rate for firms of the relevant size. Denial rate is the percentage of claims denied. Providers per firm is the number of unique providers in a jurisdiction billing under the same tax identification number. The cutoffs between the quintiles are 1.5, 5.5, 21.5, and 104.5 providers. Sample is limited to 2006–2017. Standard errors are clustered by jurisdiction. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

trative costs and investment in billing. Because of this limitation, I want to quantify the costs of compliance with billing rules so that policymakers can better judge if these potential benefits are worth the costs I document. To do this, I estimate a parameterized version of the theoretical model presented in Section 6, which will allow me to not only quantify firms' billing costs but also better understand how they would respond to counterfactual policy changes.

To estimate the model, I parameterize the denial rate as depending on the difference of investment and a minimum level of investment $\underline{I}$ divided by the level of investment plus a term a that governs how quickly the returns to investment diminish:

$$p(I) = \begin{cases} \frac{I-\underline{I}}{I+a} & \text{if } I \geq \underline{I} \\ 0 & \text{otherwise} \end{cases}.$$

This functional form means that the payment rate is zero for all levels of investment less than or equal to the minimum level of investment and then asymptotically approaches one as the level of investment increases. I parameterize charges as depending linearly on investment plus a constant that governs the amount of charges a firm would be able to extract from a visit with no investment: $r(I) = I + b$. Note that because I is unit-less, this functional form normalizes one unit of investment to be the amount necessary to raise charges by one dollar.

On the cost side of the equation, I relax the assumption of the theoretical model that investment costs are fixed regardless of patient volume and allow the unit cost of investment to depend linearly on volume such that the cost of investment level I is given by $c(I) = (c + dv) \times I$.

With this parameterization, the profit-maximizing level of investment is

$$I^* = \sqrt{\frac{v(b-a)(a+\underline{I})}{c+(d-1)v}} - a.^{33}$$

While I do not observe investment directly, there are one-to-one mappings between investment and charges and denial rates. This means that the first order condition can be written in terms of these observed variables:

$$r(I^*) = \sqrt{\frac{v(b-a)(a+\underline{I})}{c+(d-1)v}} + b - a$$

$$p(I^*) = 1 - \sqrt{\frac{(a+\underline{I})[c+(d-1)v]}{v(b-a)}}. \tag{7}$$

Finally, I allow each firm i's profits in month t in jurisdiction j to have an idiosyncratic error term ε_{ijt} that I assume is normally distributed with mean zero and an unknown standard deviation σ_π.[34] Thus, firm profits are given by

$$\Pi_{ijt} = p(I_{ijt})r(I_{ijt})v - (c+dv)I_{ijt} + \varepsilon_{\pi,ijt}.$$

This parameterization yields moments that are closely related to the reduced-form results presented earlier. Under the assumption that transitions change only the minimum level of investment $\underline{I}$ (which captures the administrative burden imposed by the Medicare Administrative Contractor), the following three equations report the relationship between the model parameters and the predicted level change in charges, denials, and the number of active firms and the percentage change in denials:

$$\mathbb{E}[\tilde{R}_{ij1}] - \mathbb{E}[\tilde{R}_{ij0}] = \sqrt{\frac{v(b-a)}{c+(d-1)v}}\left(\sqrt{a+\underline{I}_1} - \sqrt{a+\underline{I}_0}\right) \tag{8}$$

$$\mathbb{E}[\tilde{P}_{ij1}] - \mathbb{E}[\tilde{P}_{ij0}] = \sqrt{\frac{c+(d-1)v}{v(b-a)}}\left(\sqrt{a+\underline{I}_0} - \sqrt{a+\underline{I}_1}\right) \tag{9}$$

[33] This is true under the assumptions that $c+(d-1)v>0$, $(c+dv)(\underline{I}+a) < v(\underline{I}+b)$, and that the firm makes non-negative profit at this level of investment.

[34] Note that I assume ε_{ijt} is only incurred if the firm invests at a level $I \geq \underline{I}$. This assumption ensures that all firms with positive profits invest at I^*, while no firm with negative profits invests at all.

$$(10) \qquad \frac{N_{vj1}}{N_{vj0}} = \frac{1-\Phi\left(\frac{-\bar{\Pi}_{vj1}}{\sigma_\pi}\right)}{1-\Phi\left(\frac{-\bar{\Pi}_{vj0}}{\sigma_\pi}\right)},$$

$$(11) \qquad \frac{\left(1-\mathbb{E}[\tilde{P}_{ij1}]\right)-\left(1-\mathbb{E}[\tilde{P}_{ij0}]\right)}{1-\mathbb{E}[\tilde{P}_{ij0}]} = \sqrt{\frac{a+\underline{I}_1}{a+\underline{I}_0}}-1$$

where $\tilde{R}_{ijt} = r(I_{ijt}) + \epsilon_{r,ijt}$ and $\tilde{P}_{ijt} = p(I_{ijt}) + \epsilon_{p,ijt}$ are the observed charges and denial rate that depend on mean-zero measurement error, N_{vjt} is the number of firms of size v operating in jurisdiction j and time t, and $\bar{\Pi}_{vjt}$ is the predicted mean profit for firms of size v in jurisdiction j at time t. The first two moments set the change in average charges and denials equal to the predicted change from the model coming from the reoptimization of the level of investment in light of the change in administrative burden. The third moment is that the change in the ratio of active firms after the transition relative to before is equal to the ratio of the share of firms with positive profits at the two profit-maximizing levels of investment. The fourth moment sets the percentage change in denials equal to that predicted by the model. Notice that the first three moments depend on the size of the firm v, while the fourth moment does not.

These moments are useful because the left-hand side of each of the moments is identified in the reduced form. Estimating the equation

$$(12) \qquad Y_{jtw} = \beta_1 \sum_{e=0}^{L} T_{jtw}(e) + \delta_1 \sum_{e=0}^{L} T_{jtw}(e) \times U_w + \Gamma X_{jtw} + \alpha_{jw} + \eta_{tw} + \varepsilon_{jtw},$$

using the stacked regression estimator discussed in Section 4 limited to firms of size v gives me estimates of the left-hand side of each moment. With the number of active firms as the dependent variable, $\frac{N_{vj1}}{N_{vj0}}$ is given by δ_1 divided by the pre-transition mean number of firms; with charges per provider, $\mathbb{E}[\tilde{R}_{ij1}]-\mathbb{E}[\tilde{R}_{ij0}]$ is given by δ_1;[35] and with the denial rate, $\mathbb{E}[\tilde{P}_{ij1}]-\mathbb{E}[\tilde{P}_{ij0}]$ is given by $-\delta_1$. Without necessarily limiting the sample to firms of a given size and using the natural logarithm of the share of claims denied as the dependent variable, $1+\delta_1$ gives $\frac{\left(1-\mathbb{E}[\tilde{P}_{ij1}]\right)-\left(1-\mathbb{E}[\tilde{P}_{ij0}]\right)}{1-\mathbb{E}[\tilde{P}_{ij0}]}$. Under the identifying assumption that the only differential change in the model parameters in the windows around transitions between low- and high-denial administrators is in the level of administrative burden $\underline{I}$, I can estimate the parameters of the theoretical model using the reduced-form estimates of δ_1 for various outcomes and firm sizes.[36]

I supplement these transition-based moments with two moments that characterize the rela-

[35] Note that charges per provider are scaled by 5 to reflect estimation in the 20% sample of claims.

[36] This assumption may be violated for the number of active firms if the transition changes the number of potential firms of a given size. In Appendix G, I consider an alternative model of firm exit that more explicitly models physician sorting across firms of different sizes, showing that the my results are generally robust to this change.

tionship between denials and firm size. Equation (7) can be rewritten to make it clear that there is a linear relationship between simple transformations of the denial rate and firm size:

$$(1 - p(I^*))^2 = \frac{(a + \underline{I})(d - 1)}{b - a} + \frac{(a + \underline{I})c}{b - a}\frac{1}{v}.$$

Each of these terms can be recovered by estimating the equation

$$SqDeny_v = \beta_0 + \beta_1 \frac{1}{v} + \varepsilon_v, \tag{13}$$

where $SqDeny_v$ is the square of the average denial rate for firms of size v and ε_v is mean-zero measurement error in the average denial rate for firms of size v. This generates two more moments that can be used to estimate the parameters of the model:

$$\beta_0 = \frac{(a + \underline{I})(d - 1)}{b - a} \tag{14}$$

$$\beta_1 = \frac{(a + \underline{I})c}{b - a} \tag{15}$$

I have seven parameters ($\underline{I}_0$, $\underline{I}_1$, a, b, c, d, and σ_π), four transition-based moments (three of which are size-specific), and two moments that characterize the relationship between denials and firm size. I parameterize v as the number of providers associated with the same TIN in a jurisdiction. To improve precision, I group firms of multiple sizes together to estimate the within-size changes in denials, charges, and number of firms. For the moments relating to the changes in denials and charges (represented by Equations (9) and (11) for denials and (8) for charges), I group all firms together because breaking out the response by multiple firm sizes does not contribute additional identifying variation, as discussed in Appendix H.[37] To characterize the change in the number of profitable firms (Equation (10)), I group firms into quintiles by size and use the mean firm size within each quintile as the value of v for that moment to estimate the change in denials. For the moments that characterize the cross-sectional relationship between claim denials and firm size, I parameterize the minimum level of investment to be the average of the pre- and post-transition levels ($\underline{I}_{avg} \equiv \frac{\underline{I}_0 + \underline{I}_1}{2}$). I use indirect inference to estimate parameter values to minimize the weighted sum of squared difference between the left- and right-hand sides of each of these ten moments. To discount less-precisely estimated left-hand side values, I weight each moment by the inverse of the square of the standard error of my estimate of the left-hand side. Estimates of these moments are reported in Table A23 in Appendix J.

[37] In each case, I assign v as the average firm size. Results in the main text weight these means by the number of firms, while in Appendix I I demonstrate the robustness of my results to using the provider-weighted means.

6.4 Estimation Results

Table 7 reports estimates of the parameters of the structural model.[38] Although these parameters are difficult to interpret, they imply that the investment cost of raising total charges by \$1 for a solo practitioner is \$1.12,[39] while the cost of lowering the denial rate by one percentage point is \$731 per month.[40] Thus, investment only increases profit if the resulting reduction in denials is enough to offset the difference between the cost of investment and the amount that investment raises charges.

Table 7: Estimated Parameter Values

Parameter	Estimate
$\underline{I}_0$	401.8
$\underline{I}_1$	505.3
a	0.00118
b	6744.7
c	0.0505
d	1.066
σ_π	40504.6

Notes: Estimates of model parameters.

Furthermore, the estimates indicate that investment costs have substantial components that are both fixed and variable relative to firm size. As shown by Figure 9a, the per-provider unit cost of investment is decreasing in firm size due to the fixed-cost component but never approaches zero due to the non-zero variable cost. Compared to the marginal benefit of a unit of investment in terms of raising charges, the unit cost of investment for a solo practitioner is 65% higher than for a provider in the median-sized firm.[41] This lower per-provider unit cost induces additional investment on the part of large providers, as show in Figure 9b, with the net effect being that equilibrium investment costs per provider are increasing in firm size (Figure 9c). This results in larger firms being more profitable, including on a per-provider basis, as shown by Figure 9d.

The model estimates imply that the costs of compliance with billing rules are high: solo practitioners invest \$5,728 each month in billing while the median provider is in a firm that invests \$77,656 per month. This amounts to 52.9% and 56.8%, respectively, of variable profits from Medicare being absorbed by billing costs. Aggregating these costs across all firms billing

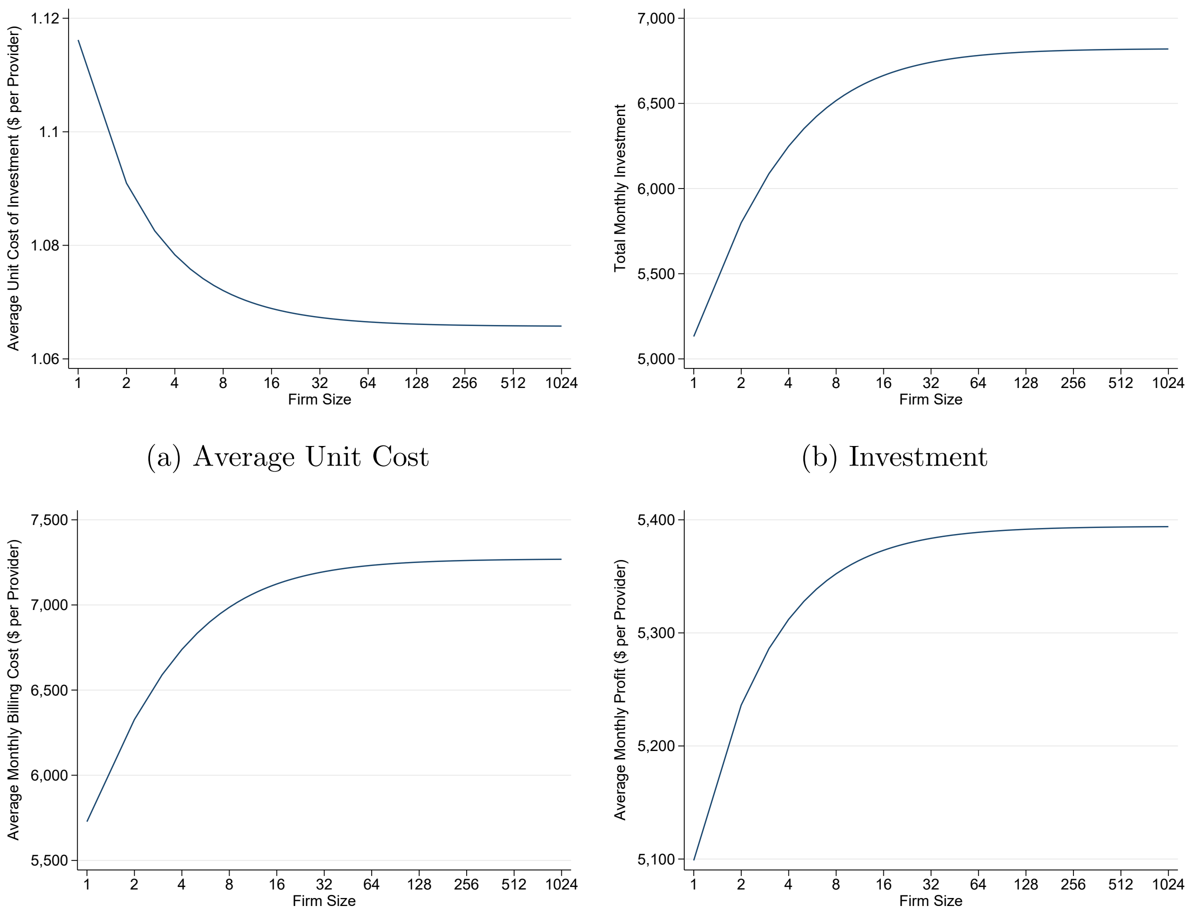
[38] In Appendix J, I present evidence that the estimated model is successful at matching the data. In particular, under the null hypothesis that the estimated model is correct, none of the estimated moments differ in a statistically significant way from the predictions of the model, while I also find that the implied parametric relationship between firm size and denials is remarkably similar to that observed in the data.

[39] This cost is given by $c + d$.

[40] All cross-sectional estimates of billing costs and equilibrium outcomes assume the minimum level of investment is given by $\underline{I}_{avg} \equiv \frac{\underline{I}_0+\underline{I}_1}{2}$.

[41] The median provider is in a firm with 11 total providers.

Figure 9: Equilibrium Outcomes by Firm Size



(a) Average Unit Cost

(b) Investment

(c) Billing Cost per Provider

(d) Profit per Provider

Notes: Equilibrium outcomes implied by parameters presented in Table 7. Panel (a) reports the unit cost of investment divided by the number of providers in the firm. Panel (b) reports the profit-maximizing monthly level of investment. For both of these panels, the units of investment are scaled so that one unit of investment induces a $1 increase in charges per provider. Panel (c) reports the monthly per-provider cost of the profit-maximizing level of investment. Panel (d) reports the equilibrium monthly profit per provider. Note that the horizontal axes of all figures are spaced geometrically.

Medicare in 2017, I find that the total investment costs amount to $88.7 billion.

These cost estimates are consistent with existing estimates of administrative costs, providing reassurance of the model's validity. For example, Sahni et al. (2021) estimate between $49.2 and $182.9 billion in investments in billing in 2019.[42] The typical cost of staff and IT investments appear to be consistent with my estimates as well. For example, the median salary for a medical coder in 2022 is $4,300 per month (Salary.com, 2022), while Fleming et al. (2011) estimate the cost

[42]The bottom end of this range includes only financial transactions ecosystem costs for physician groups, while the top end includes these costs for hospitals as well (including employed physicians) along with costs for industry-specific operational functions and administrative clinical support functions which may also represent investments in billing capabilities.

to maintain an electronic health records system for a five-provider practice to be roughly $7,125 per month. For larger hospitals and physician groups, though, the costs of investments in billing technology can be much larger, as reflected by Partners HealthCare's $1.2 billion upgrade to their electronic health record system (McCluskey, 2015). In line with this, I estimate that billing costs can be over $27 million per month for the largest firms in my data.

In addition to estimating cross-sectional investment costs, the model allows me to quantify the costs of transitioning to a higher-denial administrator. For a solo practitioner, I estimate that raising administrative burdens by the amount of a typical transition to a high-denial contractor induces $655 of additional investment costs each month, lowering profits by 4.6%. For a firm containing the median number of providers, these figures are $8,878 and 4.4%, respectively. For even the largest firms in my data, transitioning to a higher-denial administrator reduces profits by 3.7%. Scaling these estimates up, they imply that imposing a nationwide transition from a low- to high-denial administrator would induce $10 billion in additional billing costs annually and reduce annual industry profits by $3 billion. Furthermore, this change would increase Medicare spending by $7 billion per year.

Including the costs of administration to the insurers would increase the estimates of the costs increasing administrative burdens. CAQH (2014) uses a survey of private insurers to estimate that the cost of receiving and paying a claim manually is $1.40 per claim and $0.47 electronically, indicating a cost of $0.4-1.3 billion to process Medicare claims in 2017. Sahni et al. (2021) estimate administrative costs of $260 billion in 2017 for private and public insurers. Furthermore, each Medicare Administrative Contractor contract is worth $65 million annually on average, with an estimated total cost of $827.5 million in 2022.[43] Increasing administrative burden likely increases the claims processing costs to insurers as well, although these costs are much smaller than those of providers.

6.5 Counterfactual Simulations

Finally, my model allows me to quantify counterfactual changes in Medicare spending and provider profits under different policy regimes. First, I consider how outcomes would change were providers not able to invest in billing in response to a change in administrative burden. This decomposition of costs into mechanical and endogenous responses to changes in administrative burden is important for understanding the incentives of insurers to increase administrative burdens even when doing so may not reduce payments in the long run. In other words, this counterfactual sheds light on the "administrative arms race" aspect of insurers' decisions to impose administrative burdens and providers' decisions to invest in billing.

Were providers not able to change their level of investment following an increase in administrative burdens, I estimate that the denial rate would increase by 25.8% rather than 12.1%,

[43]More details on the contracts awarded by Medicare are available in Appendix A.

Table 8: Decomposition of Mechanical and Endogenous Changes Following Increase in Administrative Burden

	Mechanical Change	Endogenous Response	Equilibrium Change
Medicare Spending	-2.84	+10.23	+7.39
Denial Rate	+25.8%	-13.7%	+12.1%
Investment Cost	0	+10.14	+10.14
Industry Profits	-2.84	+0.09	-2.75

Notes: Estimated change in aggregate outcomes for nationwide transition from low- to high-denial administrator in 2017. Medicare spending, investment costs, and industry profits are given in billions of dollars per year. Denial rate is given in percentage change relative to pre-transition share of claims denied. Mechanical change is given by the changes under increased administrative burden with no change in investment. Equilibrium change allows the level of investment to change to maximize firm profits. Endogenous response gives the difference between these two values.

as shown by Table 8 which decomposes the aggregate change in outcomes into the mechanical changes considered under the counterfactual with the equilibrium changes discussed in the previous subsection. This increase in denial rates would cause Medicare payments to solo practitioners to fall by 2.3% rather than increase by 3.9%, with these reductions occurring across the firm size distribution.[44] This means that a nationwide change from a lower- to higher-denial administrator would reduce Medicare spending by $2.8 billion, in sharp contrast to the $7.4 billion increase that occurs when providers can respond. That the direction of the change in Medicare payments switches once the endogenous responses of providers are ruled out indicates that insurers may have short-run incentives to increase administrative burdens despite the long-run costs of endogenous provider responses.

Were providers unable to respond to changes in administrative burdens, though, firms' profits would fall. The $2.8 billion reduction in Medicare spending would come one-for-one from provider profits. Furthermore, because profits would fall, the increase in administrative burden would induce 3.5% more single-provider firms to exit the market than if they can respond by investing. This indicates that the ability of firms to respond to changes in administrative burden is important for them to maintain their profits and remain in the market.

In Appendix K I consider other counterfactuals, including an investment subsidy similar to that implemented by the HITECH Act of 2009. I show that while this subsidy increases the number of small firms in the market by up to 7%, they are extremely costly, with the investment induced by the subsidy increasing Medicare payouts by more than the cost of the direct subsidy payments. Similarly, I consider using participation subsidies to offset the increases in administrative burden coming from a transition to a higher-denial contractor. Here, I find that the cost of maintaining market structure following a national transition to a higher-denial contractor would be over $1 billion annually, with even perfect firm-level targeting costing nearly $4 million. In short, I find

[44]For the largest firm in my data, payments would fall 1.7% rather than rise 5.1%.

that subsidy payments are a costly way to attempt to avoid potential negative consequences of increased administrative burden.

7 Conclusion

Overall, these results highlight the unintended consequences of administrative burdens in the health care sector. Using exogenous variation in the jurisdictions administered by each Medicare Administrative Contractor, I show that these contractors vary widely in their propensity to deny medical claims, with some administrators imposing much higher administrative burdens on health care providers than others. I then compare the response of providers to transitions between high- and low-denial contractors to show that increased burden leads to increased adoption of electronic health records and higher charges along with exit and consolidation. These responses completely counteract the intended effect of increased denials on overall Medicare spending, with the increased administrative burden leading to no reductions in Medicare spending. These results are consistent with a model of investment in billing technology that I estimate to show that providers spend almost $90 billion annually on billing.

These results have important implications for our understanding of how and why administrative burdens may fail to achieve their goals. While previous research focused on narrowly targeted forms of administrative burdens has often found providers respond by avoiding the targeted service (Eliason et al., 2021; Brot-Goldberg et al., 2022; Shi, 2024), across-the-board increases in claim denials are a much blunter instrument. This additional administrative underbrush does not alter the relative prices of favored or disfavored behaviors and so imposes costs on providers without any benefit in terms of altered provider behavior. While less commonly studied, diffuse administrative burdens are common in health care: from documentation and billing requirements to quality reporting and privacy rules. My results highlight the costs that these ill-targeted administrative burdens may have.

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Appendix

The following appendices provide additional robustness checks, analyses, and details on the institutional context and data.

Appendix A gives additional detail on the content and allocation of MAC contracts.

Appendix B presents additional summary statistics of the data.

Appendix C provides evidence that supports the plausible exogeneity of the award of MAC contracts.

Appendix D provides evidence of the robustness of my results to alternative specifications and variable definitions.

Appendix E provides mathematical detail on the assumptions and implications of the theoretical framework discussed in Section 6.

Appendix F presents additional results on the impact of contractor transitions not presented in the main text.

Appendix G presents an alternative model of providers sorting into firms of different sizes.

Appendix H proves the identification of the empirical model.

Appendix I provides evidence that the model estimates presented in the main text are robust to alternative weighting schemes.

Appendix J provides evidence that the model estimates match the data well.

Appendix K uses the model estimates to consider outcomes under counterfactual subsidy policies.

A Medicare Administrative Contractor Contracts

Medicare Administrative Contractor contracts are awarded by competitive procurement auctions governed by Federal Acquisition Regulation. These regulations, along with the statutory guidelines for the contracts laid out in the Medicare Prescription Drug Improvement, and Modernization Act (MMA) of 2003 and revised by the Medicare Access and CHIP Reauthorization Act (MACRA) of 2015, stipulate the manner and frequency of contract awards as well as characteristics of the contracts themselves. Table A1 provides details on all Medicare Administrative Contractor contracts awarded under this framework. There have been 33 contracts awarded to 10 unique companies since 2006. The average contract is worth \$364 million and lasts between 5 and 7 years.[45] In total, the government has awarded contracts worth over \$12 billion.

These awards are not without controversy, with 15% of contracts (including 5 of the first 12) being protested by a losing party. In all cases, the contract was eventually awarded to the initial winner.

These contracts have a cost-plus structure where administrators are reimbursed for their realized cost plus a potential bonus payment contingent on good performance. These bonus payments are made based on the contractor's performance relative to the Quality Assurance Surveillance Plan (QASP). For 2018 to 2020 (the only years for which data are available), the median QASP score ranged from 90-97% (CMS, 2021), indicating that these payments are generally made as a matter of course. The QASP entails multiple measures related to 11 performance areas of contractor performance, including customer service, Freedom of Information Act, and Debt Management. Claims processing and medical review are two of these categories. Most of the measures comprising these performance areas relate to timeliness while only one of the 85 measures (medical review of claims and documentation) relates to claim rejection accuracy. This measure states "The contractor shall conduct medical review of claims submitted by providers or suppliers" and comprises only 1.4% of the overall QASP score. Thus, contractors have little direct financial incentive to reject claims for medically unnecessary care.

By contrast, administrators do have a more indirect incentive to ensure that only appropriate care is reimbursed: keeping Medicare happy. Quality is the primary measure on which bids are scored in the procurement auctions that allocate MAC contracts. For example, one procurement request for proposal stipulated, "The Technical Approach evaluation factor and Past Performance evaluation factor are of equal importance. Technical Approach and Past Performance, when combined, are significantly more important than cost or price" (GSA, 2016). Because these contractors are playing a repeated game with the government, they have a strong incentive to pursue the government's goals, which in contrast to the QASP, may depend more heavily on the propriety of the claims paid and the overall financial impact on Medicare. For instance, CMS reported to Congress

[45] The MMA of 2003 stipulated that contracts had to be recompeted at least every 5 years, while MACRA raised this limit to 7 years.

that is goal for the contractors is to "promote the fiscal integrity of Medicare and be accountable stewards of public funds. They will pay claims in a timely, accurate, and reliable manner while promoting cost efficiency and the delivery of maximum value to the customer" (CMS, 2005). Furthermore, CMS has the option to terminate MAC contracts early, although they have never done so as the necessary rebidding and transition process is seen as too costly (Levinson, 2014b).

The tasks that these contracts require of administrators give them little ability to impact the Medicare program outside of administrative burdens. According to Medicare's website these tasks are as follows:

1. "Process Medicare FFS claims
2. Make and account for Medicare FFS payments
3. Enroll providers in the Medicare FFS program
4. Handle provider reimbursement services and audit institutional provider cost reports
5. Handle redetermination requests (1st stage appeals process)
6. Respond to provider inquiries
7. Educate providers about Medicare FFS billing requirements
8. Establish local coverage determinations (LCD's)
9. Review medical records for selected claims
10. Coordinate with CMS and other FFS contractors" (CMS, 2022c).

Notice that tasks 1, 2, 4, 5, and 9 relate to claims processing and tasks 7 and 8 relate to promulgating billing rules enforced by the claims processing system. The remaining tasks are minor and give Medicare Administrative Contractors little discretion to impact the outcomes analyzed in this paper.

While MACs are given wide discretion in determining their local coverage rules, they are constrained by national standards as well. The statutory coverage standard MACs must attempt to meet is avoiding payment for services that "are not reasonable and necessary for the diagnosis or treatment of illness or injury or to improve the functioning of a malformed body member" (Social Security Act, 1965a). The federal government can specify additional coverage rules legislatively or administratively. Legislative rules must go through the normal legislative process and so are uncommon. A rare example of this is regulation on the allowed frequency of various screenings, including mammography and colonoscopy (Social Security Act, 1965b). More common are administratively created rules, including National Coverage Determinations issued by CMS when "the service is the subject of substantial controversy" (Centers for Medicare and Medicaid Services, 2003). One prominent recent example of this is the National Coverage Determination limiting coverage of the controversial Alzheimer's drug Aduhelm (Centers for Medicare and Medicaid Services, 2022). MACs are free to set local coverage rules as they see fit, called Local Coverage Determinations.

Finally, one may wonder why the government contracts with private entities to administer Traditional Medicare rather than processes claims itself. The answer, as it turns out, is politics. When Medicare was created in the 1960s, opposition to perceived government control of doctors was very strong, and allowing private entities to stand between the government and providers was a way to mollify this opposition. In their history of Blue Cross and Blue Shield, Cunningham and Cunningham (1997) note, "Interposing... intermediaries was politically convenient because it insulated providers from direct contact with, and the threat of control by, the dreaded federal bureaucracy," and the more contemporary account of Meyers (1970) argues, "[T]he requirement that it be administered with a third party (carriers) between physicians and the government, arose because of the strong views of the AMA (American Medical Association)... on the grounds that this (claims processing by the government) involved governmental control and was socialized medicine."

Table A1: Medicare Administrative Contractor Contracts

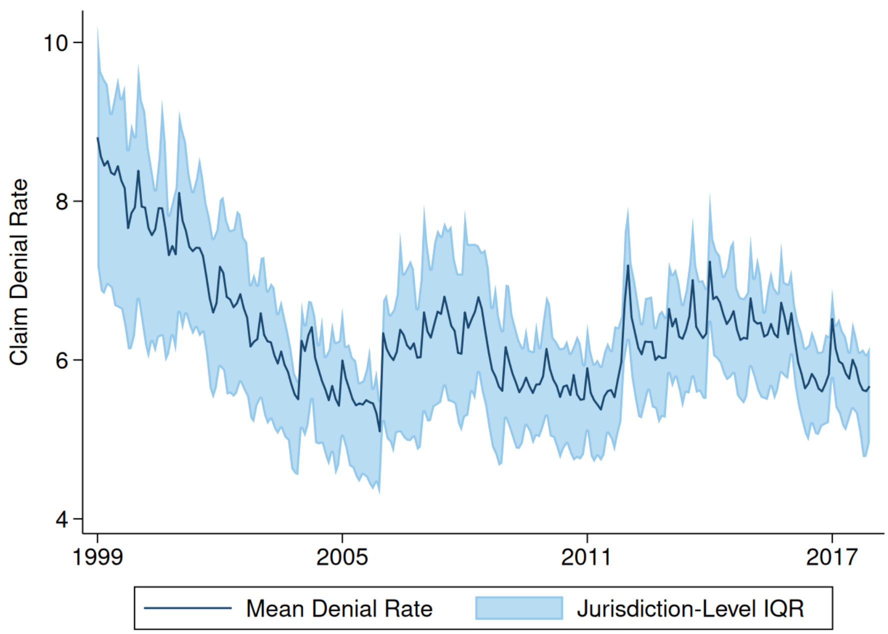
Estimated Value ($millions)	Date Announced	Awardee	Jurisdiction	Length (Years)	Annual Value ($millions)	Protested
192.0	7/31/2006	Noridian	3 (AZ, MT, ND, SD, UT, WY)	5	38.4	No
376.0	8/2/2007	TrailBlazer	4 (CO, NM, OK, TX)	5	75.2	No
225.0	9/5/2007	WPS	5 (IA, KS, MO, NE)	5	45.0	No
466.0	10/24/2007	Novitas	12 (NJ, PA, DE, DC, MD, NoVa)	5	93.2	Yes
358.0	10/25/2007	Palmetto	1 (AS, CA, GU, HI, NV, NMI)	5	71.6	Yes
323.0	3/18/2008	NGS	13 (CT, NY)	5	64.6	No
368.0	9/12/2008	FCSO	9 (FL, VI, PR)	5	73.6	No
176.0	11/19/2008	NHIC	14 (ME, MA, NH, RI, VT)	5	35.2	No
335.0	1/7/2009	Cahaba	J (TN, AL, GA)	5	67.0	No
304.5	5/21/2010	Palmetto	11 (SC, NC, VA, WV)	5	60.9	Yes
243.3	7/8/2010	CGS	15 (KY, OH)	5	48.7	Yes
218.0	8/22/2011	Noridian	F (AK, AZ, ID, MT, ND, OR, SD, UT, WA, WY)	5	43.6	No
218.0	9/30/2011	WPS	8 (IN, MI)	5	43.6	Yes
406.0	11/8/2011	Notivas	H (AR, CO, LA, MS, NM, OK, TX)	5	81.2	No
217.2	7/31/2012	WPS	5 (IA, KS, MO, NE)	5	43.4	No
404.1	9/17/2012	Novitas	L (NJ, PA, DE, DC, MD, NoVa)	5	80.8	No
345.2	9/20/2012	Noridian	E (AS, CA, GU, HI, NV, NMI)	5	69.0	No
318.0	9/27/2012	NGS	6 (IL, MN, WI)	5	63.6	No
493.2	2/22/2013	NGS	K (CT, ME, MA, NH, NY, RI, VT)	5	98.6	No
313.3	2/11/2014	FCSO	N (FL, VI, PR)	5	62.7	No
287.8	9/17/2014	Cahaba	J (TN, AL, GA)	5	57.6	No
394.8	4/1/2015	Palmetto	M (SC, NC, VA, WV)	5	79.0	No
246.3	9/17/2015	CGS	15 (KY, OH)	5	49.3	No
274.6	9/8/2017	Palmetto	J (TN, AL, GA)	5	54.9	No
313.5	7/12/2018	Noridian	F (AK, AZ, ID, MT, ND, OR, SD, UT, WA, WY)	7	44.8	No
282.2	11/1/2018	WPS	8 (IN, MI)	7	40.3	No
842.7	5/30/2019	Novitas	H (AR, CO, LA, MS, NM, OK, TX)	7	120.4	No
302.0	9/30/2019	WPS	5 (IA, KS, MO, NE)	7	43.1	No
432.9	7/15/2020	NGS	6 (IL, MN, WI)	7	61.8	No
556.8	12/18/2020	Noridian	E (AS, CA, GU, HI, NV, NMI)	7	79.5	No
669.3	7/27/2021	Novitas	L (NJ, PA, DE, DC, MD)	7	95.6	No
634.3	12/15/2021	NGS	K (CT, ME, MA, NH, NY, RI, VT)	7	90.6	No
476.5	4/27/2022	FCSO	N (FL, VI, PR)	7	68.1	No

Notes: Data collected from `https://www.cms.gov/Medicare/Medicare-Contracting/Medicare-Administrative-Contractors/Who-are-the-MACs`. Jurisdiction reports the name of the jurisdiction at the time of contract award along with the states that comprise the jurisdiction. Note that claims from northern Virginia, abbreviated "NoVa" in the table, are always processed by the same Medicare Administrative Contractor that processes claims for DC. Length reports the maximum length of the contract when awarded. This always consists of one base year and 4 or 6 option years. Protested indicates the award announcement notes that the contract award was protested by another bidder.

B Additional Summary Statistics

In this appendix, I present additional summary statistics of the data. Table A2 reports summary statistics at the jurisdiction-month level, including the mean and standard deviation of the outcomes and covariates used in my analysis. Note that the mean claim denial rate is 6.4%, indicating that roughly 1 in 15 claims is ultimately unpaid. This estimate is in line with the finding by (Dunn et al., 2023) that 6.7% of Medicare claims were initially denied in the data they use from 2013–2015. Note that there is significant variation across jurisdictions in this rate of denials: the standard deviation is 1.7, or 27% of the mean. Much of this variation in denial rates comes from change over time. As shown in Figure A1, the denial rate fell rapidly over the first few years of my sample before stabilizing around 6%. The variation across jurisdictions also fell modestly over this time, with the inter-quartile range falling from over 3 to less than 1.5.

Figure A1: Denial Rate Over Time



Notes: Jurisdiction-month-level mean share of claims denied along with the denial rates of the 25th and 75th percentile jurisdictions.

Table A2: Summary Statistics

	Mean	Std. Dev.
Outcomes		
Denial Rate	6.360	1.727
Charges (per beneficiary)	601.5	249.6
Payments (per beneficiary)	221.4	72.06
Percentage with EHR	42.85	14.66
Providers per Firm	3.885	1.160
Active Firms	4555	4473
Single-Provider Firms	3068	3249
Share of Providers in Solo Practice	0.191	0.106
Jurisdiction Characteristics		
Beneficiaries (thousands)	114.4	99.51
Average Beneficiary Age	71.67	1.237
Dual-Eligible Percentage	17.93	6.718
Percentage White	84.24	13.76
Percentage Black	8.723	10.59
Percentage Other Race	6.529	10.39
Percentage with ESRD	1.007	0.439
Percentage Disabled	16.13	3.974
Observations	12,996	

Notes: An observation is a jurisdiction-month from 1999 to 2017. Denial rate is the percentage of claims denied. Percentage of providers with electronic health records (EHR) is defined for 2010–2015 and not for Puerto Rico or the jurisdiction covering northern Virginia. Providers per firm is the number of unique providers in a jurisdiction billing under the same tax identification number. Active firms is the number of unique tax identification numbers under which a claim is submitted. All firm-related variables are defined starting in 2006. ESRD and disabled percentages report the share of Medicare beneficiaries eligible for Medicare due to end-stage renal disease or disability.

C Exogeneity of MAC Transitions

The identification of the impact of transitions between Medicare Administrative Contractors relies on the assumption that were the jurisdiction not to transition between contractors, the outcomes I analyze would evolve in the same way as they do in jurisdictions that do not transition between contractors at the same time. In this appendix, I present a number of pieces of evidence in support of this assumption.

First, I show that high-denial contractors are not more or less likely to be awarded contracts nor do they differentially win contracts for jurisdictions that have higher or lower denial rates before the transition. Table A3 reports the estimated correlation between the probability of winning a contract and the estimated causal effect of the contractor, with and without controling for the proximity of the contractors' existing jurisdictions to those covered by the focal contract. In all cases, there is no correlation between the administrative burden imposed by the contractor and the probability of being awarded the contract, indicating that CMS does not select for low- or high-denial contractors—nor for any criteria correlated with denials—in the procurement auctions used to award Medicare Administrative Contractor contracts.

In addition to the estimated effect of the contractor having no relationship with the probability of winning a contract, it also has no relationship with the existing denial rate in jurisdictions that change contractors. The estimated correlation coefficient between the denial rate in the transitioning jurisdiction 12 months before it transitions and the estimated effect of the incoming contractor is 0.0028, while the correlation between the estimated effects of the incoming and outgoing contractors is -0.1389, neither of which are statistically different from zero at the 10% significance level. This lack of correlation further supports the plausibly exogenous nature of the transitions to higher- or lower-denial contractors.

Finally, I demonstrate that there are no changes in beneficiary population characteristics following contractor transitions. Were there to be changes in these outcomes, it may indicate the presence of unobserved shocks correlated with contractor transitions that impact both these characteristics and the outcomes I analyze in the body of the paper. Table A4 shows that none of the nine beneficiary population characteristics used as controls in the analysis in the main text change following contractor transitions in a statistically or economically significant way.

Table A3: Correlation between Estimated Causal Effect of Contractor and Probability of Winning a Contract

	(1) Wins Contract	(2) Wins Contract	(3) Wins Contract
Estimated Causal Effect of Contractor	0.00426	-0.00339	0.00272
	(0.00910)	(0.0111)	(0.00894)
Incumbent or Border		0.168***	
		(0.0383)	
Incumbent			-0.124***
			(0.0222)
Border			0.242***
			(0.0498)
Dep. Var. Mean	0.0663	0.0663	0.0663
R^2	0.00485	0.0823	0.145
Observations	392	392	392

Notes: Estimates of the coefficients of a regression of an indicator for winning a contract on the estimated causal effect of the contractor (μ_m of Equation (1)) along with indicators for being the incumbent contractor in at least one jurisdiction that is part of the contract or of at least one jurisdiction that borders those that are part of the contract. An observation is a contractor-contract pair. The sample is limited to contractors that existed 12 months before the transition of jurisdictions that are part of the contract transitioned. Standard errors are clustered by contract. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Table A4: Estimated Change in Beneficiary Demographics After Transition

	(1) Beneficiaries	(2) Dual-Eligible Share	(3) Average Age	(4) Male Share	(5) White Share	(6) Black Share	(7) Other Race Share	(8) ESRD Share	(9) Disabled Share
Post-Transition	-262.5	-0.000367	0.0189	-0.0000789	0.000137	-0.000183	-0.00000807	-0.0000000101	-0.000548
	(610.3)	(0.00125)	(0.0170)	(0.000264)	(0.000337)	(0.000193)	(0.000271)	(0.0000818)	(0.000572)
Increase in Denials	-781.1	-0.000284	-0.0165	0.000644	-0.0000784	0.000271	-0.0000373	0.000127	0.000829
	(1154.5)	(0.00227)	(0.0268)	(0.000395)	(0.000650)	(0.000326)	(0.000467)	(0.000118)	(0.000989)
Dep. Var. Mean	115952.0	0.175	71.64	0.444	0.858	0.0867	0.0518	0.00995	0.164
Observations	70164	70164	70164	70164	70164	70164	70164	70164	70164

Notes: Estimates of β_{post} and δ_{post} of Equation (3) with $K = 18$ and $L = 17$. An observation is a jurisdiction-wave-month. Dependent variables are reported in the column titles. ESRD and disabled percentages report the share of Medicare beneficiaries eligible for Medicare due to end-stage renal disease or disability. Standard errors are clustered by jurisdiction. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

D Robustness Checks

In this appendix, I present evidence of the robustness of my results to alternative specifications and variable definitions. I first consider alternative measures of administrative burden before estimating the causal effect of each contractor using alternative assumptions on the jurisdiction-specific trends in denials. I then present the results in the main text with bootstrapped standard errors that account for the pre-estimation of the causal effect of each contractor. In the last section of this appendix, I consider a continuous measure of the change in administrative burden after a contractor transition.

D.1 Alternative Measures of Administrative Burden

In this appendix, I report results using alternative measures of administrative burden. The measure used in the main text is the share of claims that are denied. The alternative measures reported here are the share of claim lines that are denied, the share of charges on denied claims, and the share of charges on denied claim lines.

I first report estimates of the causal effect of each administrator on each of these outcomes. The ranking of the administrators using these alternative measures of administrative burden are quite similar to that obtained using my primary measure, as shown in Table A5. The correlation between the estimated effect of each administrator on each of these alternative measures and the estimated effect on the claim denial rate is reported in the table below the point estimates. These correlations range from 0.58 to 0.81, indicating they are all strongly correlated.

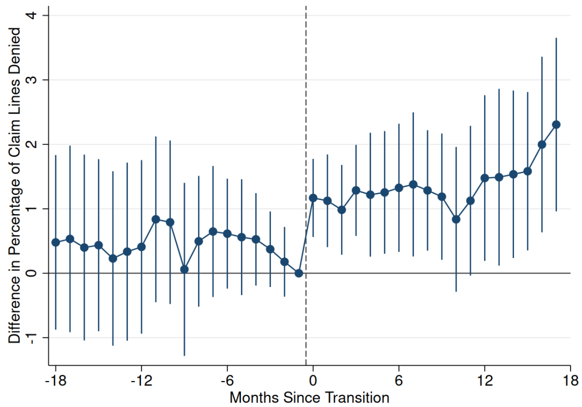
To further validate my measure of administrative burden, I next demonstrate that transitions between low- and high-denial administrators along this measure capture meaningful changes along the alternative measures as well. Figure A2 presents the estimated differential change in each alternative measure of administrative burden following a transition to an administrator with a higher estimated impact on the claim denial rate (the measure used in the main text) relative to a transition to a lower-denial administrator. Across all measures of administrative burden, a transition to an administrator that imposes greater burdens according to my primary measure is associated with a similar increase in the alternative measure of burden, again indicating that I am capturing meaningful differences across administrators in the burdens they impose.

Table A5: Estimated Effect of Each Contractor on Alternative Measures of Administrative Burden

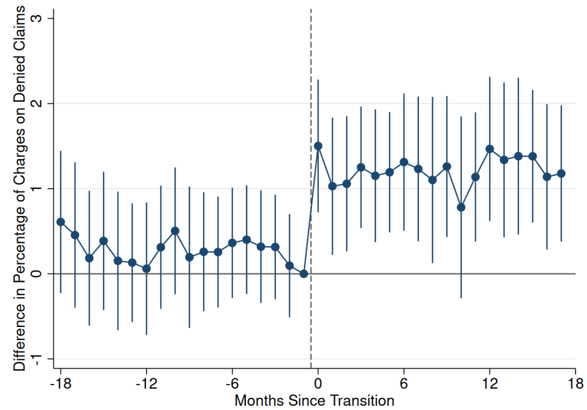
	(1) Line Denial Rate		(2) Share of Charges on Denied Claims		(3) Share of Charges on Denied Claim Lines	
Metra	1.542	1.320	1.779**	0.720	1.532*	0.794
Nationwide	0.147	1.281	1.199**	0.467	0.629	0.532
Group Health	3.447***	1.127	1.244 *	0.627	1.626***	0.573
Triple-S	6.353***	1.284	-2.626***	0.636	-1.185*	0.604
Pinnacle	-0.869	1.338	-0.0910	0.512	-0.552	0.574
BCBSRI	-1.794	1.644	-0.838	0.606	-1.635**	0.684
Wheatlands	0.370	1.614	0.0712	0.493	-0.0766	0.464
TrailBlazer	-0.983	1.263	-0.0162	0.495	-0.281	0.581
NHIC	0.768	1.131	-0.112	0.541	-0.351	0.477
NGS	-1.259	1.088	-0.0301	0.552	-0.458	0.491
Novitas	-1.405	1.389	-0.288	0.541	-0.940	0.606
WPS	0.797	1.238	-0.299	0.486	-0.454	0.468
Palmetto	-1.473*	0.866	-0.321	0.355	-0.649*	0.377
HealthNow	-2.652**	1.157	-0.447	0.580	-0.683	0.537
FCSO	-0.681	1.096	-0.921*	0.531	-1.202**	0.482
Cahaba	-1.704	1.593	-0.923	1.048	-1.475	1.169
CGS	-1.340	1.007	-1.090*	0.581	-1.256**	0.557
BCBSMT	-0.0639	0.400	-2.567***	0.205	-2.348***	0.209
Regence	-2.168***	0.418	-0.887**	0.374	0.00739	0.357
TOLIC	-4.079***	1.496	-4.761***	0.859	-4.312***	0.724
Correlation with Main Estimate	0.5802		0.8052		0.7662	
Demographic Controls	Yes		Yes		Yes	
Month Fixed Effects	Yes		Yes		Yes	
Jurisdiction Fixed Effects	Yes		Yes		Yes	
Jurisdiction-Specific Trend	Yes		Yes		Yes	
Dep. Var. Mean	13.65		6.174		8.078	
R^2	0.906		0.778		0.816	
Observations	12,996		12,996		12,996	

Notes: Estimates of μ_m of Equation (1). Note that coefficient estimates are reported in the same order as in Table 2. An observation is a jurisdiction-month. The excluded contractor is Noridian. Dependent variables are given by the column title. Standard errors are reported to the right of the point estimates and clustered by jurisdiction. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

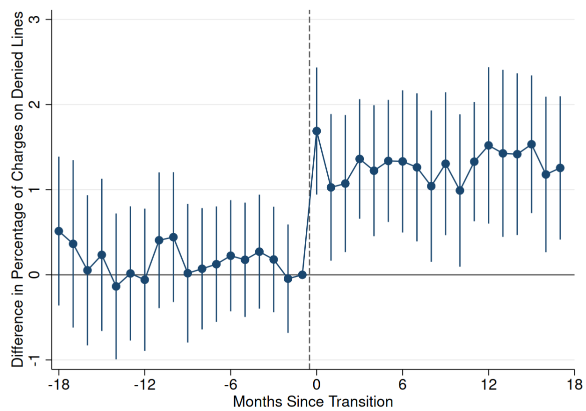
Figure A2: Effect of Transition to Higher-Denial Administrator on Alternative Measures of Administrative Burden



(a) Line Denial Rate



(b) Share of Charges on Denied Claims



(c) Share of Charges on Denied Claim Lines

Notes: Estimates of δ_e of Equation (2) for $e \in \{-18, \ldots, 17\}$ with $K = 18$ and $L = 17$. An observation is a jurisdiction-wave-month. Dependent variables are given by the caption to each subfigure. Error bars give the 95% confidence interval for each estimate. Standard errors are clustered by jurisdiction.

D.2 Estimated Fixed Effects with Alternative Jurisdiction-Specific Trends

In this appendix, I present estimates of the effect of each contractor on the denial rate allowing for more or less flexible jurisdiction-specific trends. The main estimates presented in Table 2 allow each jurisdiction to have an arbitrary mean denial rate and jurisdiction-specific linear trend. In column (1) of Table A6, I present estimates allowing each jurisdiction to have its own mean denial rate but restrict all jurisdictions to have common trends. That is, I estimate the following equation:

$$Y_{jmt} = \mu_m + \Gamma X_{jt} + \alpha_{0j} + \eta_t + \varepsilon_{jmt}, \tag{16}$$

In column (2) I present estimates allowing each jurisdiction to have a quadratic jurisdiction-specific trend, or estimates of the following equation:

$$Y_{jmt} = \mu_m + \Gamma X_{jt} + \alpha_{0j} + \alpha_{1j}t + \alpha_{2j}t^2 + \eta_t + \varepsilon_{jmt}. \tag{17}$$

The correlation of each of these alternative estimates with those presented in Table 2—along with the lack of differential pre-trends shown in Figure 2—indicate that my results are unlikely to be driven by slow-moving, non-linear differential trends across jurisdictions.

Table A6: Estimated Effect of Each Contractor on Denial Rates with Alternative Jurisdiction-Specific Trends

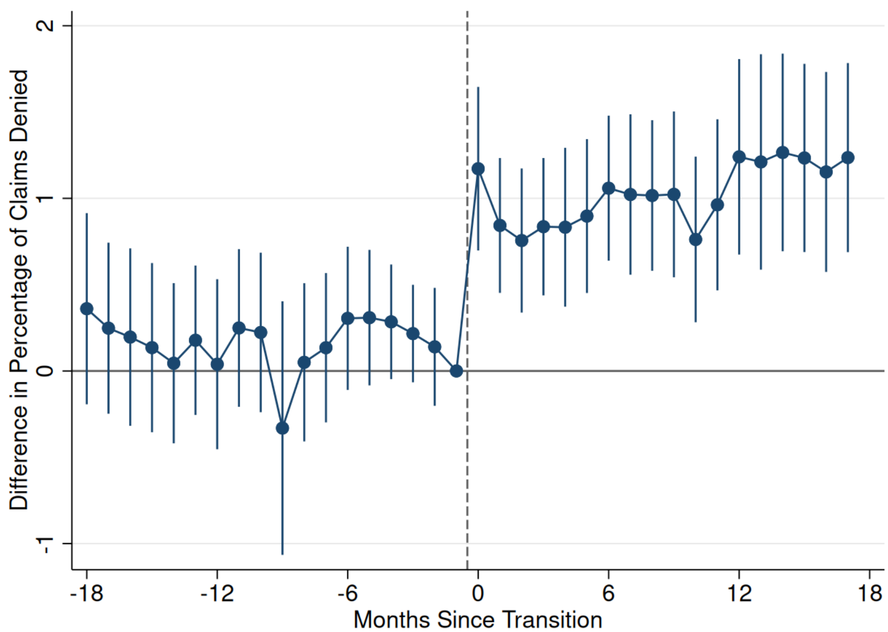
	(1) Denial Rate		(2) Denial Rate	
Metra	2.990***	0.542	0.125	0.618
Nationwide	0.201	0.382	-0.716**	0.349
Group Health	-0.104	0.680	0.677	0.475
Triple-S	1.228	0.761	0.167	0.478
Pinnacle	-0.0836	0.424	0.289	0.421
BCBSRI	1.065**	0.411	-0.654	0.574
Wheatlands	-0.956**	0.395	0.476	0.496
TrailBlazer	-0.152	0.317	0.0741	0.291
NHIC	-0.244	0.418	-0.105	0.349
NGS	-0.630*	0.336	-0.00680	0.383
Novitas	0.228	0.353	0.109	0.325
WPS	-0.160	0.372	-0.0531	0.416
Palmetto	-0.419	0.277	-0.776***	0.215
HealthNow	-0.0298	0.385	-0.427	0.443
FCSO	-0.108	0.436	-0.970**	0.401
Cahaba	-0.216	0.391	-0.364	0.540
CGS	0.250	0.258	-0.956***	0.315
BCBSMT	-0.626***	0.200	-1.758***	0.152
Regence	-1.426***	0.270	-0.413*	0.207
TOLIC	-3.036***	0.557	-2.902***	0.463
Correlation with Main Estimate	0.7974		0.7697	
Demographic Controls	Yes		Yes	
Month Fixed Effects	Yes		Yes	
Jurisdiction Fixed Effects	Yes		Yes	
Jurisdiction-Specific Linear Trend	No		Yes	
Jurisdiction-Specific Quadratic Trend	No		Yes	
Dep. Var. Mean	6.360		6.360	
R^2	0.730		0.844	
Observations	12,996		12,996	

Notes: Estimates of μ_m from Equation (16) are reported in column (1) and Equation (17) are reported in column (2). Note that coefficient estimates are reported in the same order as in Table 2. An observation is a jurisdiction-month. The excluded contractor is Noridian. Dependent variable is the denial rate. Denial rate is the percentage of claims denied. Standard errors are reported to the right of the point estimates and clustered by jurisdiction. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

D.3 Bootstrapped Standard Errors

Much of my estimation relies on previously estimated rankings in the administrative burdens imposed by contractors, but analytical standard errors do not account for the fact that there may be estimation error in these rankings. In order to overcome this issue, in this appendix I report the main results from the text that rely on this previous estimation with bootstrapped standard errors. In particular, I draw a bootstrapped sample of jurisdictions and estimate the causal effect of each contractor using that sample before using these bootstrapped estimates to estimate the consequences of transitioning to a higher-denial contractor in this sample. Thus, any estimation error in my estimate of Equation (1) is carried forward in my estimation of subsequent equations such that the bootstrapped standard errors account for this estimation error. The tables and figures below indicate that my results are extremely robust to using bootstrapped standard errors, with many of the bootstrapped standard errors being smaller than the analytical standard errors reported in the main text.

Figure A3: Estimated Effect of Transition to Higher-Denial Administrator on Denial Rate



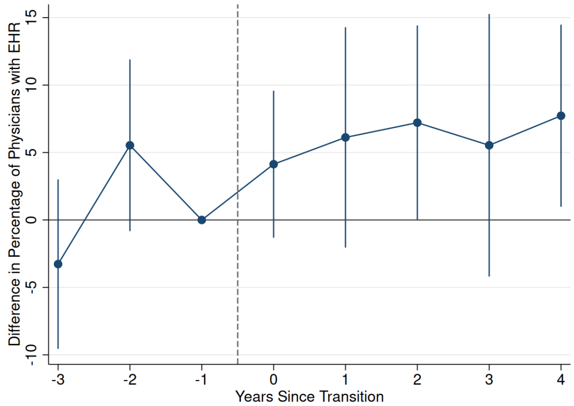
Notes: Estimates of δ_e of Equation (2) for $e \in \{-18, \ldots, 17\}$ with $K = 18$ and $L = 17$. An observation is a jurisdiction-wave-month. Dependent variable is denial rate. Denial rate is the percentage of claims denied. Error bars give the 95% confidence interval for each estimate. Standard errors are bootstrapped by jurisdiction.

Table A7: Estimated Effect of Each Contractor on Denial Rate

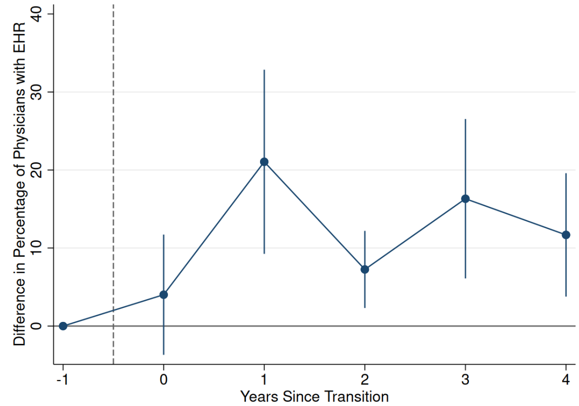
	Denial Rate	Std. Error
Metra	1.859***	0.415
Nationwide	1.114***	0.283
Group Health	0.668*	0.345
Triple-S	0.576	0.355
Pinnacle	0.410	0.404
BCBSRI	0.398	0.509
Wheatlands	0.350	0.325
TrailBlazer	0.342	0.378
NHIC	0.236	0.306
NGS	0.164	0.325
Novitas	-0.0161	0.381
WPS	-0.0928	0.311
Palmetto	-0.186	0.199
HealthNow	-0.356	0.361
FCSO	-0.659**	0.303
Cahaba	-0.761	0.720
CGS	-1.061***	0.320
BCBSMT	-1.506***	0.107
Regence	-2.091***	0.134
TOLIC	-3.518***	0.424
Demographic Controls	Yes	
Month Fixed Effects	Yes	
Jurisdiction Fixed Effects	Yes	
Jurisdiction-Specific Trend	Yes	
Dep. Var. Mean	6.360	
R^2	0.8037	
Observations	12,996	

Notes: Estimates of μ_m of Equation (1). An observation is a jurisdiction-month. The excluded contractor is Noridian. Dependent variable is denial rate. Denial rate is the percentage of claims denied. Standard errors are reported to the right of the point estimates and bootstrapped by jurisdiction. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

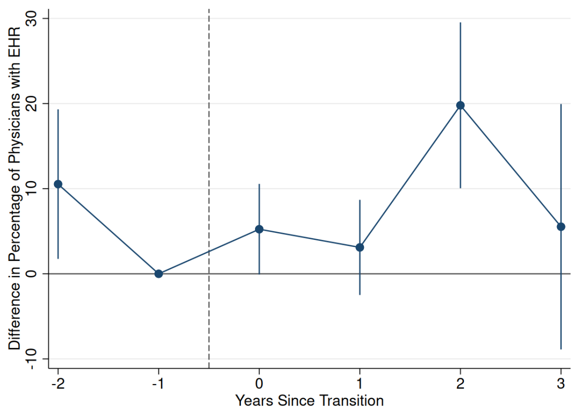
Figure A4: Effect of Transition to Higher-Denial Administrator on EHR Adoption



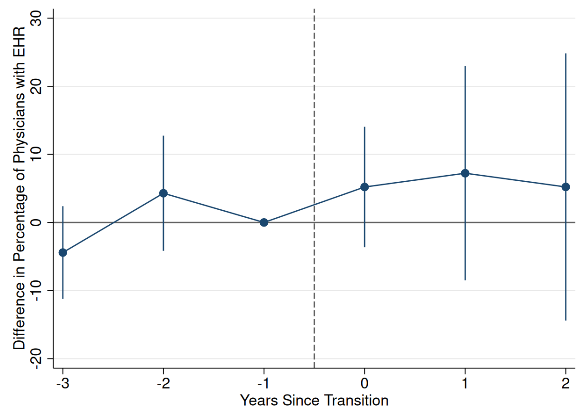
(a) All Years



(b) 2011 Transitions



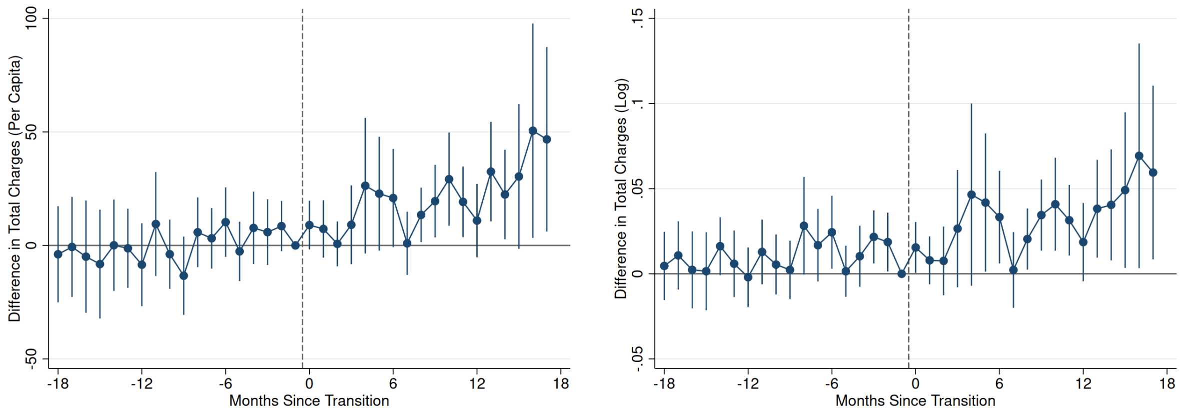
(c) 2012 Transitions



(d) 2013 Transitions

Notes: Estimates of δ_e of Equation (5) for $e \in \{-3, \ldots, 4\}$. An observation is a jurisdiction-month. Dependent variable is the share of office-based physician practices that have adopted basic EHR technology. Panels (b), (c), and (d) limit the sample to jurisdictions subject to a transition in the year noted in the subfigure title and jurisdictions not subject to a transition in 2010–2015. Sample is limited to 2010–2015. Error bars give the 95% confidence interval for each estimate. Standard errors are bootstrapped by jurisdiction.

Figure A5: Effect of Transition to Higher-Denial Administrator on Charges



(a) Charges Per Capita

(b) Log Charges

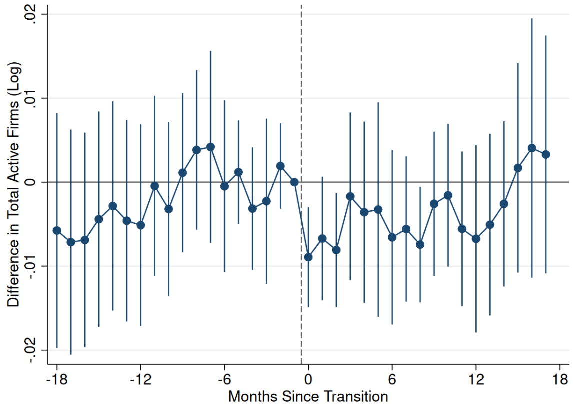
Notes: Estimates of δ_e of Equation (2) for $e \in \{-18, \ldots, 17\}$ with $K = 18$ and $L = 17$. An observation is a jurisdiction-wave-month. Dependent variables are total charges billed measured per Medicare beneficiary or in logs. Error bars give the 95% confidence interval for each estimate. Standard errors are bootstrapped by jurisdiction.

Table A8: Effect of Transition to Higher-Denial Administrator on EHR Adoption and Charges

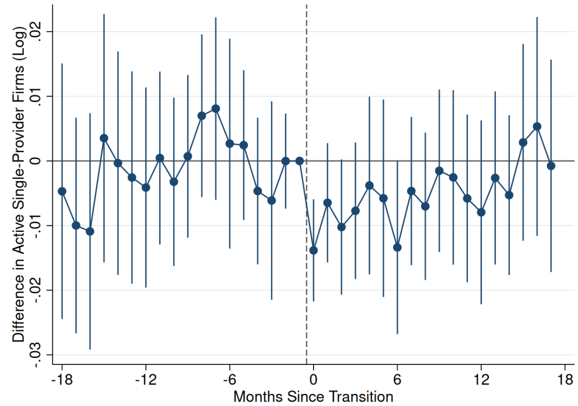
	End of Post-Period			All of Post-Period		
	(1) Share Adopt EHR	(2) Charges (per capita)	(3) Charges (log)	(4) Share Adopt EHR	(5) Charges (per capita)	(6) Charges (log)
Increase in Denials	7.729**	46.74**	0.0595**	5.130	20.64**	0.0324**
	(3.444)	(20.73)	(0.0260)	(3.260)	(9.220)	(0.0135)
Dep. Var. Mean	42.85	617.2	17.58	42.85	617.2	17.58
Observations	3,948	70,164	70,164	3,948	70,164	70,164

Notes: Column (1) reports the estimate of δ_4 of Equation (5), columns (2) and (3) report estimates of δ_{17} of Equation (2) with $K = 18$ and $L = 17$, column (4) reports the estimate of δ_{post} in a variation of Equation (5) where $\beta_{post} \sum_{e=0}^{4} T_{jt}(e)$ replaces $\sum_{e=0}^{4} \beta_e T_{jt}(e)$ and $\delta_{post} \sum_{e=0}^{4} T_{jt}(e) \times U_j$ replaces $\sum_{e=0}^{4} \delta_e T_{jt}(e) \times U_j$, and columns (5) and (6) report estimates of δ_{post} of Equation (3) with $K = 18$ and $L = 17$. In columns (1) and (4), an observation is a jurisdiction-month and the sample is limited to 2010–2015. In columns (2), (3), (5), and (6), an observation is a jurisdiction-wave-month. Dependent variables are the share of practices that have adopted electronic health records and the total charges billed to Medicare per beneficiary and in logs. Standard errors are bootstrapped by jurisdiction. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

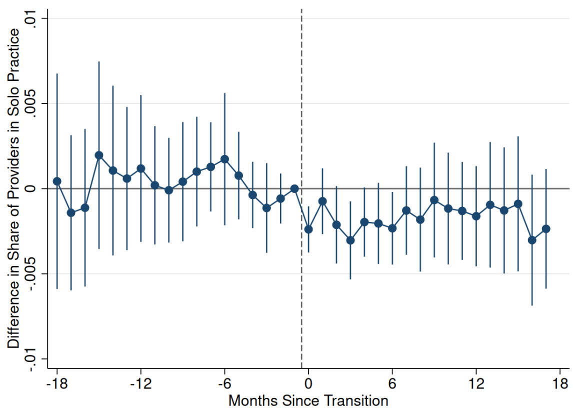
Figure A6: Effect of Transition to Higher-Denial Administrator on Market Structure



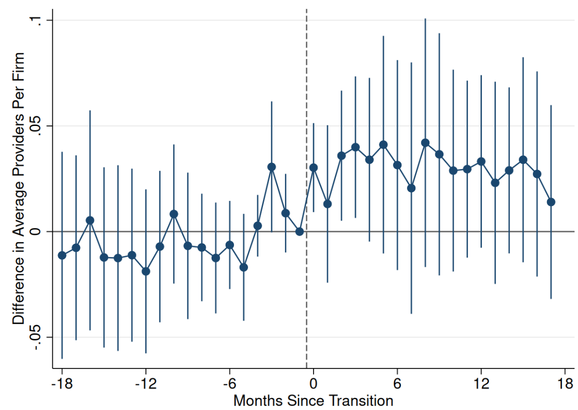
(a) Active Firms



(b) Active Single-Provider Firms



(c) Share of Providers in Solo Practice



(d) Average Firm Size

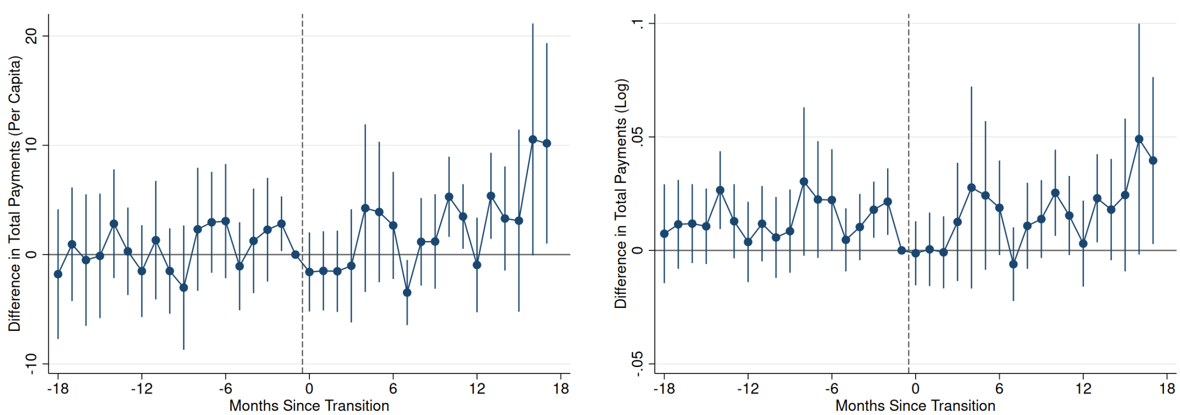
Notes: Estimates of δ_e of Equation (2) for $e \in \{-18, \ldots, 17\}$ with $K = 18$ and $L = 17$. An observation is a jurisdiction-wave-month. Dependent variables are the number of active firms and the number of single-provider active firms (both in logs), the share of providers affiliated with single-provider firms, and the firm-level average number of providers per firm. Active firms is the number of unique tax identification numbers under which a claim is submitted. Providers per firm is the average number of unique providers in a jurisdiction billing under the same tax identification number. Sample is limited to 2006–2017. Error bars give the 95% confidence interval for each estimate. Standard errors are bootstrapped by jurisdiction.

Table A9: Effect of Transition to Higher-Denial Administrator on Market Structure

	(1) Active Firms (Log)	(2) Active Single- Provider Firms (Log)	(3) Share of Providers in Solo Practice	(4) Providers per Firm
Increase in Denials	-0.00893***	-0.0138***	-0.00239***	0.0303***
	(0.00304)	(0.00403)	(0.000692)	(0.0107)
Dep. Var. Mean	8.004	7.556	0.188	3.754
Observations	53,208	53,208	53,208	53,208

Notes: Estimates of δ_0 of Equation (2) with $K = 18$ and $L = 17$. An observation is a jurisdiction-wave-month. Dependent variables are the number of active firms and the number of single-provider active firms (both in logs), the share of providers affiliated with single-provider firms, and the firm-level average number of providers per firm. Active firms is the number of unique tax identification numbers under which a claim is submitted. Providers per firm is the average number of unique providers in a jurisdiction billing under the same tax identification number. Sample is limited to 2006–2017. Standard errors are bootstrapped by jurisdiction. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Figure A7: Effect of Transition to Higher-Denial Administrator on Medicare Spending



(a) Payments Per Capita

(b) Log Payments

Notes: Estimates of δ_e of Equation (2) for $e \in \{-18, \ldots, 17\}$ with $K = 18$ and $L = 17$. An observation is a jurisdiction-wave-month. Dependent variables are total Medicare payments measured per Medicare beneficiary and in logs. Error bars give the 95% confidence interval for each estimate. Standard errors are bootstrapped by jurisdiction.

Table A10: Effect of Transition to Higher-Denial Administrator on Medicare Spending

	End of Post-Period		All of Post-Period	
	(1) Payments (per capita)	(2) Payments (log)	(3) Payments (per capita)	(4) Payments (log)
Increase in Denials	10.18^{**}	0.0396^{**}	2.465	0.0165^{*}
	(4.680)	(0.0188)	(1.763)	(0.00923)
Dep. Var. Mean	227.5	16.61	227.5	16.61
Observations	70,164	70,164	70,164	70,164

Notes: Columns (1) and (2) report estimates of $\delta_1 7$ of Equation (18) with $K = 18$ and $L = 17$, and columns (3) and (4) report estimates of δ_{post} of Equation (19) with $K = 18$ and $L = 17$. An observation is a jurisdiction-wave-month. Dependent variables are total Medicare payments measured per Medicare beneficiary and in logs. Standard errors are bootstrapped by jurisdiction. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

D.4 Continuous Treatment Variable

I'm currently only estimating the effect of transitioning to a higher- or lower-denial contractor, dichotomizing the treatment into facing increased or decreased administrative burden. This approach has the benefit of a straightforward interpretation, but it does not exploit variation in the magnitude of increase or decrease in administrative burden. Indeed, we would expect that contractor changes that cause the equilibrium denial rate to increase by more also elicit stronger reactions on the part of providers. By using a continous measure of treatment intensity, I am able to make use of this variation. Futhermore, using a continuous measure of treatment intensity also allows me to estimate by how much the denial rate in a jurisdiction moves toward the incoming contractor's denial rate analogous to the exercises in Finkelstein et al. (2016), Molitor (2018), Cutler et al. (2019), and Badinski et al. (2023) in the context of geographic variation in care. In this appendix, I do just such an exercise.

In this appendix, I estimate

$$
\begin{aligned}
(18) \quad Y_{jtw} = \sum_{e=-K}^{-2} \beta_e T_{jtw}(e) + \sum_{e=0}^{L} \beta_e T_{jtw}(e) + \sum_{e=-K}^{-2} \delta_e T_{jtw}(e) \times \tilde{U}_w + \sum_{e=0}^{L} \delta_e T_{jtw}(e) \times \tilde{U}_w \\
+ \Gamma X_{jtw} + \alpha_{jw} + \eta_{tw} + \varepsilon_{jtw},
\end{aligned}
$$

which is analgous to Equation (2) but where $\tilde{U}_w$ represents the difference in estimated denial rate effects of the incoming and outgoing contractor, rather than an indicator for whether this difference is positive or negative. Similarly, I also estimate

$$
\begin{aligned}
(19) \quad Y_{jtw} = \sum_{e=-K}^{-2} \beta_e T_{jtw}(e) + \beta_{post} \sum_{e=0}^{L} T_{jtw}(e) + \sum_{e=-K}^{-2} \delta_e T_{jtw}(e) \times \tilde{U}_w + \delta_{post} \sum_{e=0}^{L} T_{jtw}(e) \times \tilde{U}_w \\
+ \Gamma X_{jtw} + \alpha_{jw} + \eta_{tw} + \varepsilon_{jtw},
\end{aligned}
$$

which is analogous to Equation (3). The coefficients of interest are δ_e and δ_{post}, but their interpretations are very subtle. They represent the estimated differential effect of transitioning between contractors that have a more positive difference in their effect on the observed denial rate, with the magnitude representing each percentage point difference.[46]

This difficult interpretation is one of two drawbacks with this approach that lead me to use the binary treatment indicator in the main analysis that I would like to clarify here. First, the difficulty of interpreting estimates using a continous treatment variable is in stark contrast with the interpretation of the estimates in the main analysis. For example, consider the estimate in Table 4 column (3). This coefficient has the straightforward interpretation of indicating that

[46]Estimates with EHR adoption as the dependent variable similarly represent estimates of Equation (5) with $\tilde{U}_j$ substituted for U_j.

Table A11: Effect of Transition to Higher-Denial Administrator on EHR Adoption and Charges

	End of Post-Period			All of Post-Period		
	(1) Share Adopt EHR	(2) Charges (per capita)	(3) Charges (log)	(4) Share Adopt EHR	(5) Charges (per capita)	(6) Charges (log)
Increase in Denials	5.263*	11.46**	0.0203**	4.137*	6.397**	0.0131***
	(2.767)	(5.205)	(0.00774)	(2.096)	(2.841)	(0.00426)
Dep. Var. Mean	42.85	617.2	17.58	42.85	617.2	17.58
Observations	3,948	70,164	70,164	3,948	70,164	70,164

Notes: Column (1) reports the estimate of δ_4 of Equation (5) with $\tilde{U}_j$ substituted for U_j, columns (2) and (3) report estimates of δ_{17} of Equation (18) with $K = 18$ and $L = 17$, column (4) reports the estimate of δ_{post} in a variation of Equation (5) where $\beta_{post} \sum_{e=0}^{4} T_{jt}(e)$ replaces $\sum_{e=0}^{4} \beta_e T_{jt}(e)$ and $\delta_{post} \sum_{e=0}^{4} T_{jt}(e) \times \tilde{U}_j$ replaces $\sum_{e=0}^{4} \delta_e T_{jt}(e) \times U_j$, and columns (5) and (6) report estimates of δ_{post} of Equation (19) with $K = 18$ and $L = 17$. In columns (1) and (4), an observation is a jurisdiction-month and the sample is limited to 2010–2015. In columns (2), (3), (5), and (6), an observation is a jurisdiction-wave-month. Dependent variables are the share of practices that have adopted electronic health records and the total charges billed to Medicare per beneficiary and in logs. Standard errors are clustered by jurisdiction. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

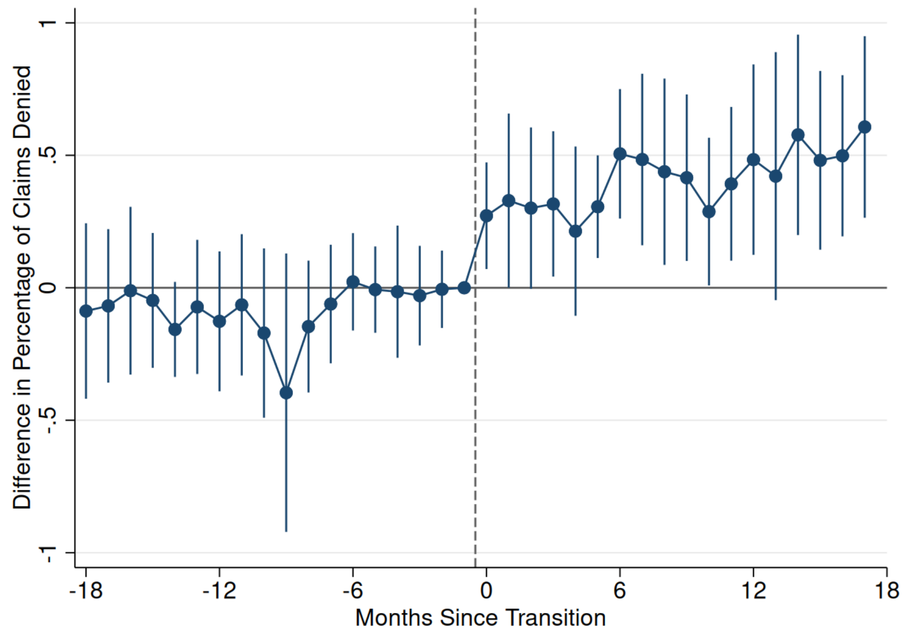
on average, charges increase by 6% 18 months after a transition to a higher-denial contractor. In other words, this is the average effect of increasing administrative burden in this context. However, the interpretation of the same estimate using a continuous treatment variable would be more subtle. Were I to obtain the same estimate, it would indicate that on average, for each percentage point increase in the expected denial rate of the contractor, charges increase 6 percent. The issue that makes this interpretation so subtle is the second main drawback to this approach: it appears to invite treating the denial rate as a treatment variable rather than an equilibrium object. Rather than being a policy lever that contractors control directly, the observed denial rate is the interaction of the administrative burdens imposed by the contractors and the endogenous responses of providers. The equilibrium nature of the denial rate means that the question "What is the causal impact of a one percentage point increase in claim denials?" is ill posed. Using a continuous treatment variable would obscure this point and could lead the estimates to much more easily be interpreted as attempting to answer this malformed question. For these reasons, I eschew using a continuous treatment variable in the main analysis.

Figure A8 presents estimates of Equation (18) with the denial rate as the dependent variable. As in the main analysis, we see that there are no differential pre-trends and there is a discrete jump in the denial rate in the month of transition. The estimate of δ_1 is 0.272, meaning 27% of the estimated effect of the incoming contractor is transferred to the transitioning jurisdiction immediately, while after 18 months, this share increases to 61 percent.[47] Consistent with the discrete increase in denial rates demonstrated in Figure 2 in the main text, these results indicate that denial rates quickly adjust to reflect the administrative burdens imposed by the contractor.

Tables A11–A13 and Figures A8–A12 recreate the results in Section 5 using the continuous measure of the estimated difference in incoming and outgoing contractors. We see that the results are quite similar, although as discussed above, it is difficult to interpret the magnitude of these estimates.

[47] The standard error of the estimate of δ_1 is 0.101, indicating a p-value less than 0.01. The estimate of δ_{18} is 0.607 with a standard error of 0.171, indicating a p-value less than 0.001.

Figure A8: Effect of Transition to Higher-Denial Administrator on Denial Rates



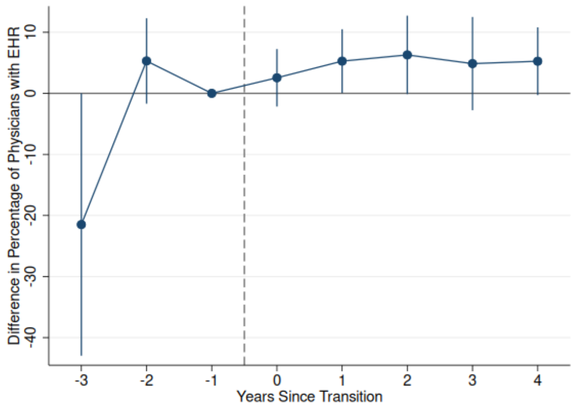
Notes: Estimates of δ_e of Equation (18) for $e \in \{-18, \ldots, 17\}$ with $K = 18$ and $L = 17$. An observation is a jurisdiction-wave-month. Dependent variable is denial rate. Denial rate is the percentage of claims denied. Error bars give the 95% confidence interval for each estimate. Standard errors are clustered by jurisdiction.

Table A12: Effect of Transition to Higher-Denial Administrator on Market Structure

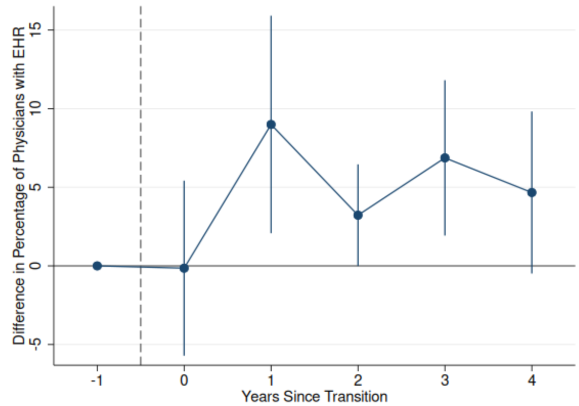
	(1) Active Firms (Log)	(2) Active Single-Provider Firms (Log)	(3) Share of Providers in Solo Practice	(4) Providers per Firm
Increase in Denials	-0.00871***	-0.0122*	-0.00294**	0.0296**
	(0.00305)	(0.00624)	(0.00123)	(0.0121)
Dep. Var. Mean	8.004	7.556	0.188	3.754
Observations	53,208	53,208	53,208	53,208

Notes: Estimates of δ_0 of Equation (18) with $K = 18$ and $L = 17$. An observation is a jurisdiction-wave-month. Dependent variables are the number of active firms and the number of single-provider active firms (both in logs), the share of providers affiliated with single-provider firms, and the firm-level average number of providers per firm. Active firms is the number of unique tax identification numbers under which a claim is submitted. Providers per firm is the number of unique providers in a jurisdiction billing under the same tax identification number. Sample is limited to 2006–2017. Standard errors are clustered by jurisdiction. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

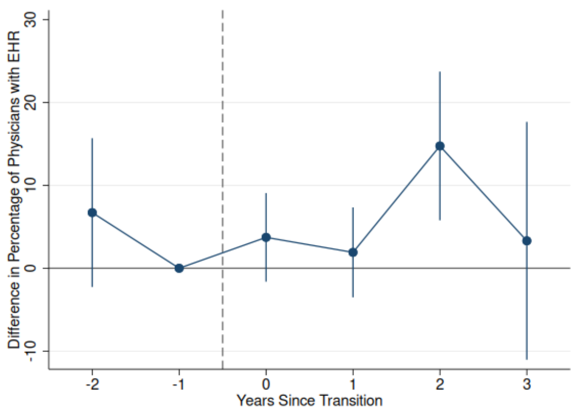
Figure A9: Effect of Transition to Higher-Denial Administrator on EHR Adoption



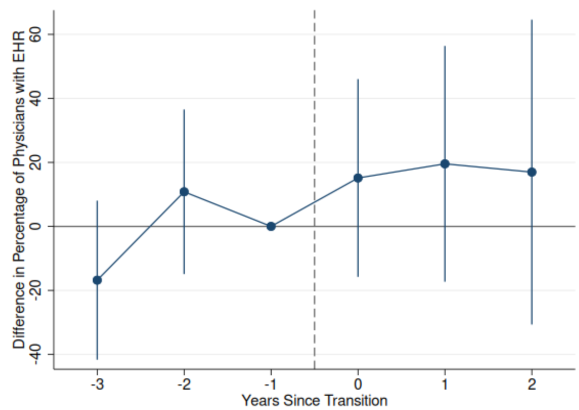
(a) All Years



(b) 2011 Transitions



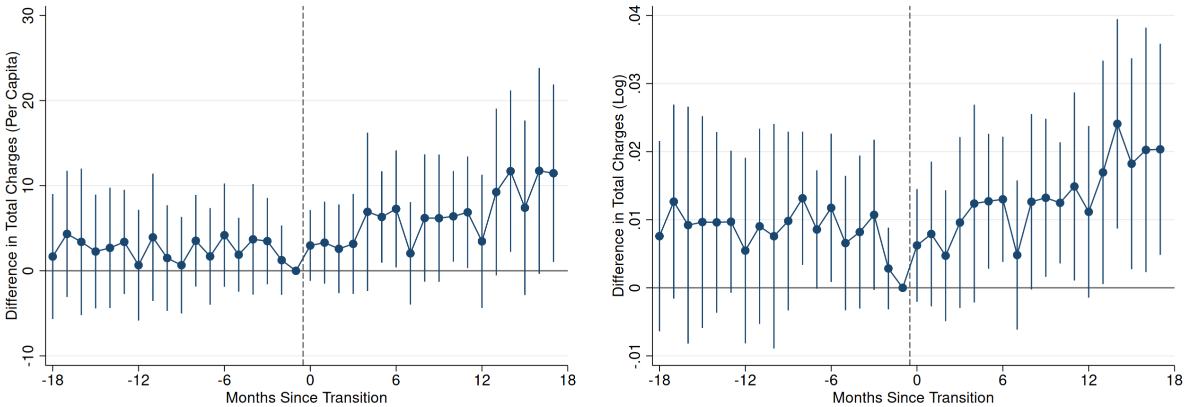
(c) 2012 Transitions



(d) 2013 Transitions

Notes: Estimates of δ_e of Equation (5) for $e \in \{-3, \ldots, 4\}$ with $\tilde{U}_j$ substituted for U_j. An observation is a jurisdiction-month. Dependent variable is the share of office-based physician practices that have adopted basic EHR technology. Panels (b), (c), and (d) limit the sample to jurisdictions subject to a transition in the year noted in the subfigure title and jurisdictions not subject to a transition in 2010–2015. Sample is limited to 2010–2015. Error bars give the 95% confidence interval for each estimate. Standard errors are clustered by jurisdiction.

Figure A10: Effect of Transition to Higher-Denial Administrator on Charges



(a) Charges Per Capita (b) Log Charges

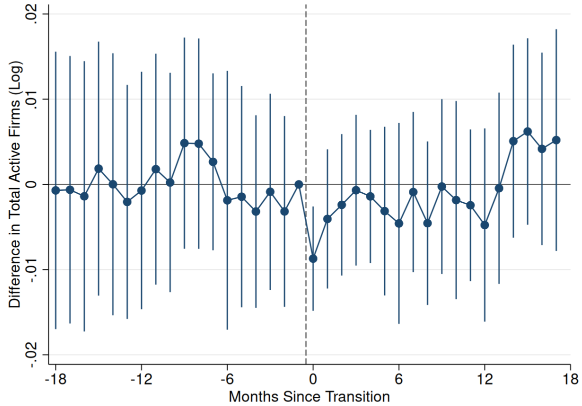
Notes: Estimates of δ_e of Equation (18) for $e \in \{-18, \ldots, 17\}$ with $K = 18$ and $L = 17$. An observation is a jurisdiction-wave-month. Dependent variables are total charges billed measured per Medicare beneficiary or in logs. Error bars give the 95% confidence interval for each estimate. Standard errors are clustered by jurisdiction.

Table A13: Effect of Transition to Higher-Denial Administrator on Medicare Spending

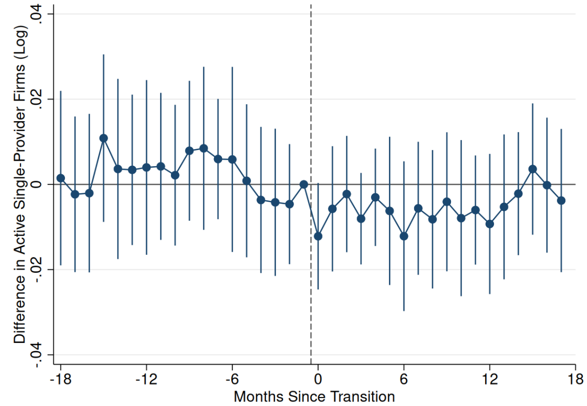
	End of Post-Period		All of Post-Period	
	(1) Payments (per capita)	(2) Payments (log)	(3) Payments (per capita)	(4) Payments (log)
Increase in Denials	3.722**	0.0153*	1.708*	0.00836*
	(1.631)	(0.00849)	(0.964)	(0.00486)
Dep. Var. Mean	227.5	16.61	227.5	16.61
Observations	70,164	70,164	70,164	70,164

Notes: Columns (1) and (2) report estimates of δ_17 of Equation (18) with $K = 18$ and $L = 17$, and columns (3) and (4) report estimates of δ_{post} of Equation (19) with $K = 18$ and $L = 17$. An observation is a jurisdiction-wave-month. Dependent variables are total Medicare payments measured per Medicare beneficiary and in logs. Standard errors are clustered by jurisdiction. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

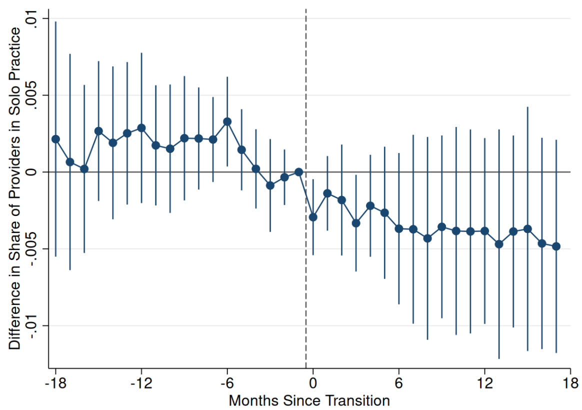
Figure A11: Effect of Transition to Higher-Denial Administrator on Market Structure



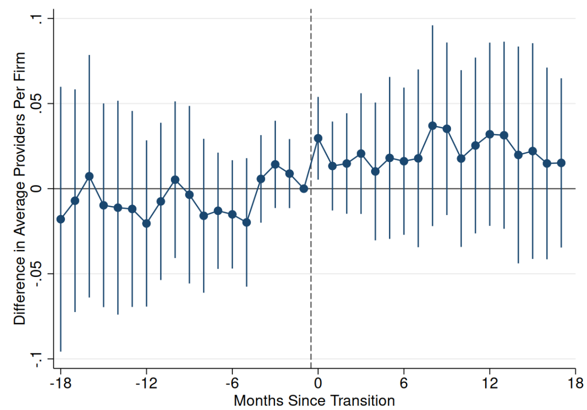
(a) Active Firms



(b) Active Single-Provider Firms



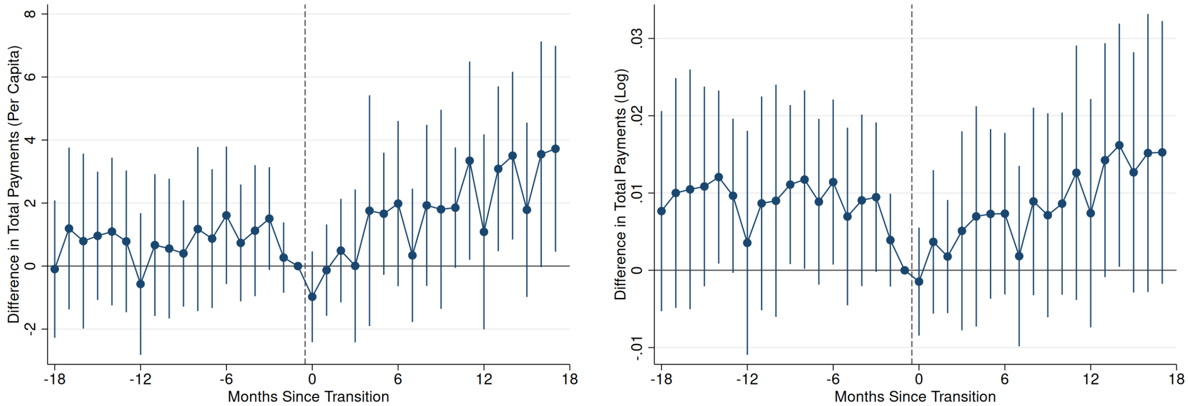
(c) Share of Providers in Solo Practice



(d) Average Firm Size

Notes: Estimates of δ_e of Equation (18) for $e \in \{-18, \ldots, 17\}$ with $K = 18$ and $L = 17$. An observation is a jurisdiction-wave-month. Dependent variables are the number of active firms and the number of single-provider active firms (both in logs), the share of providers affiliated with single-provider firms, and the firm-level average number of providers per firm. Active firms is the number of unique tax identification numbers under which a claim is submitted. Providers per firm is the average number of unique providers in a jurisdiction billing under the same tax identification number. Sample is limited to 2006–2017. Error bars give the 95% confidence interval for each estimate. Standard errors are clustered by jurisdiction.

Figure A12: Effect of Transition to Higher-Denial Administrator on Medicare Spending



(a) Payments Per Capita

(b) Log Payments

Notes: Estimates of δ_e of Equation (18) for $e \in \{-18, \ldots, 17\}$ with $K = 18$ and $L = 17$. An observation is a jurisdiction-wave-month. Dependent variables are total Medicare payments measured per Medicare beneficiary and in logs. Error bars give the 95% confidence interval for each estimate. Standard errors are clustered by jurisdiction.

E Mathematical Details on Theoretical Framework

In this appendix, I provide detail on the assumptions of the model and formal, mathematical support to the claims made in Section 6 about the implications of the model. As mentioned above, firms choose investment $I \geq 0$ to maximize profits, given by Equation (6), as well as here:

$$\Pi(I) = p(I)r(I)v - cI.$$

It is assumed that $p(\cdot)$ and $r(\cdot)$, the payment probability and net charges functions, are both weakly increasing, twice continuously differentiable, and that $p(I)$ is bounded between zero and one over the domain of I and that $p(0) = 0$. The assumption that $p(0) = 0$ implies that $\Pi(0) = 0$ and that the firm may choose to invest nothing (shut down) if it is unprofitable. I also assume that v and c are strictly positive.

The profit-maximizing level of investment is given by I^*, where I^* is defined such that

$$f(I^*; p(\cdot), r(\cdot), v, c) = \frac{\partial p}{\partial I^*} r(I^*)v + p(I^*)\frac{\partial r}{\partial I^*} v - c = 0, \tag{20}$$

if $\Pi(I^*) \geq 0$ and zero if $\Pi(I^*) < 0$ under the assumption that $\frac{\partial f}{\partial I^*} < 0$, or

$$\frac{\partial^2 p}{\partial I^* \partial I^*} r(I^*) + 2\frac{\partial p}{\partial I^*}\frac{\partial r}{\partial I^*} + p(I^*)\frac{\partial^2 r}{\partial I^* \partial I^*} < 0.$$

For this assumption that the profit function is concave at I^* to be true, it must be that investment exhibits diminishing marginal returns in terms of extracting additional charges or reducing denials or both. Note that because $p(\cdot)$ is monotonic, bounded above, and twice continuously differentiable, it must exhibit diminishing returns at some point. I make the assumption that $\frac{\partial f}{\partial I^*} < 0$, so all firms that invest do so at I^*.

To interpret Equation (20), it indicates that firms trade off the marginal increase in revenue from increasing investment against the costs of that investment. The first term represents the marginal increase in revenue coming from lowering the share of charges that are denied. The second term represents the effect on profits on increased paid charges per visit.

An increase in administrative burden is represented by altering the $p(\cdot)$ function in two ways. The first is increasing the probability of denial for a given level of investment, or having $p_1(I) \leq p_0(I)$ for all I, where p_0 represents the $p(\cdot)$ function under lower administrative burden and $p_1(\cdot)$ represents it under higher burden. The downward shift in the probability of payment serves to lower the equilibrium level of investment as investing in raising charges becomes less attractive when the share of those charges that are paid goes down. Applying the implicit function theorem, we see that

$$\frac{\partial I^*}{\partial p} = -\frac{\partial f}{\partial I^*}^{-1}\frac{\partial f}{\partial p} = -\frac{\partial f}{\partial I^*}^{-1}\frac{\partial r}{\partial I^*}v,$$

which is positive because $\frac{\partial f}{\partial I^*}$ is negative (the profit function is concave) and $\frac{\partial r}{\partial I^*}$ is positive (charges are increasing in investment).

The second change to the $p(\cdot)$ function resulting from an increase in administrative burden is that it becomes steeper in a neighborhood around I^*, or $\frac{\partial p_1}{\partial I} \geq \frac{\partial p_0}{\partial I}$ for I in a neighborhood around I^*. This increases the marginal effect of investment on denials and, consequently, increases the profit-maximizing level of investment. Again applying the implicit function theorem, we see that

$$\frac{\partial I^*}{\partial \frac{\partial p}{\partial I}} = -\frac{\partial f}{\partial I^*}^{-1} \frac{\partial f}{\partial \frac{\partial p}{\partial I}} = -\frac{\partial f}{\partial I^*}^{-1} r(I^*)v,$$

which is positive if and only if $r(I^*)$ is positive. Because the profit-maximizing level of investment is 0 if $r(I^*) < 0$, it must be that $r(I^*)$ and $\frac{\partial I^*}{\partial \frac{\partial p}{\partial I}}$ are both positive, or $r(I^*)$ is negative and the profit-maximizing level of investment is zero.

Which of these two channels dominates is ambiguous. Investment will increase in response to higher administrative burden only if the marginal profit from investment $f(\cdot)$ using the new denial function $p_1(\cdot)$ at the old profit-maximizing level of investment I^* is positive:

$$\begin{aligned}
f(I^*; p_1(\cdot), r(\cdot), v, c) &> 0 \\
\frac{\partial p_1}{\partial I^*} r(I^*)v + p_1(I^*)\frac{\partial r}{\partial I^*}v - c &> 0 \\
\frac{\partial p_1}{\partial I^*} r(I^*) + p_1(I^*)\frac{\partial r}{\partial I^*} &> \frac{\partial p_0}{\partial I^*} r(I^*) + p_0(I^*)\frac{\partial r}{\partial I^*} \\
\left(\frac{\partial p_1}{\partial I^*} - \frac{\partial p_0}{\partial I^*}\right) r(I^*) &> \left(p_0(I^*) - p_1(I^*)\right)\frac{\partial r}{\partial I^*},
\end{aligned}$$

where the third line follows because $f(I^*; p_0(\cdot), r(\cdot), v, c) = 0$. This condition is also sufficient if combined with the condition that the firm makes positive profit at the new level of administrative burden. This series of inequalities makes it clear that I^* will increase when the increase in denial-avoidance returns is large while the level shift in denials is small. An increase in investment following an increase in administrative burden is also more likely when the variable profits of the practice conditional on payment are high (because the increase in the marginal effect of investment on denials is more valuable) but the marginal effect of investment on charges is low (because the level shift in denials will be less important if this channel is already weak). Thus the effect of an increase in administrative burden on investment is ambiguous.

The ambiguity in the response of providers to an increase in administrative burden means that these responses could lead to changes in denials and Medicare spending that are larger, smaller, or even of the opposite sign of the mechanical changes that would come from altering the $p(\cdot)$ function without a change in investment. For example, if an increase in administrative burden leads providers to decrease investment, equilibrium denials will increase by more than the direct change in the denial function, which, along with the resulting decrease in charges, will lead to a larger-than-mechanical decrease in expected practice revenue (which is equal to Medicare spending). By contrast, if increased administrative burden leads to increased investment, the effect on denials will be muted and, as charges increase, spending will not fall by as much as it would in the absence of provider responses. In fact, provider responses could even more-than-offset the direct effect of the increase in administrative burden and lead expected revenue to increase. This could happen if, for example, the change in the slope of $p(\cdot)$ is large while the change in level is small. In the extreme case, suppose the slope increases while the change in the level of denials at I^* approaches zero. Then investment would increase, as would charges and (because of the vanishingly small direct effect of the increase in burden on the denial rate) the probability of payment, increasing expected payment. This ambiguity makes understanding providers' endogenous responses to administrative burden crucial to assessing the consequences of these burdens.

What is not ambiguous is that investment and charges move the same way in the model. This is true by the assumption that charges are increase in investment, i.e. that $r(\cdot)$ is an increasing function. Also unambiguous is the prediction that the profit-maximizing level of investment is increasing in patient volume v. This is because

$$\frac{\partial I^*}{\partial v} = -\frac{\partial f}{\partial I^*}^{-1}\left(\frac{\partial p}{\partial I^*}r(I^*) + p(I^*)\frac{\partial r}{\partial I^*}\right) = -\frac{\partial f}{\partial I^*}^{-1}\frac{c}{v} > 0,$$

where the second equality holds by the first-order condition.

The final implication of the model is that profits are decreasing in administrative burden and volume. To see this first point, note that

$$\frac{\partial \Pi(I^*)}{\partial p} = r(I^*)v,$$

which is positive if the firm makes positive profits, while $\frac{\partial \Pi(I^*)}{\partial \frac{\partial p}{\partial I^*}} = 0$ by the envelope theorem. This means that profits are decreasing in administrative burden. On the second prediction, note that small firms are less profitable:

$$\frac{\partial \Pi(I^*)}{\partial v} = p(I^*)r(I^*),$$

which is positive if the firm makes positive profits. My empirical test of the former result (that increased administrative burden would lead to firm exit) requires the additional assumption that the change in administrative burden represented by the transitions I study move firms of some particular size v from having positive to negative profits. Alternatively, this will also be true if profits are subject to idiosyncratic differences within firm-size bands as I assume in Section 6.3.

F Additional Results on Effect of Contractor Transitions

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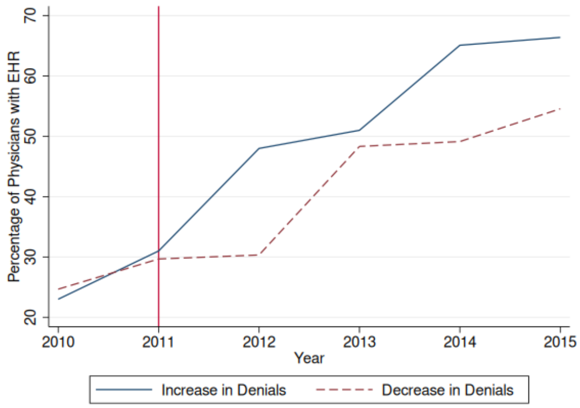
In this appendix, I present additional results on the impact of contractor transitions not presented in the main text. First, I present evidence that charges and spending fall after a jurisdiction transitions to a lower-denial contractor, consistent with billing investments occurring every period rather than being one-time sunk costs. Then, I show additional results related to the effect of contractor transitions on market structure before presenting evidence that large changes in the denial rate for low-value procedures have little impact on their use. Finally, I present additional results discussed in the main text on other consequences of exposing providers to increased claim denials.

F.1 Persistence of Investment

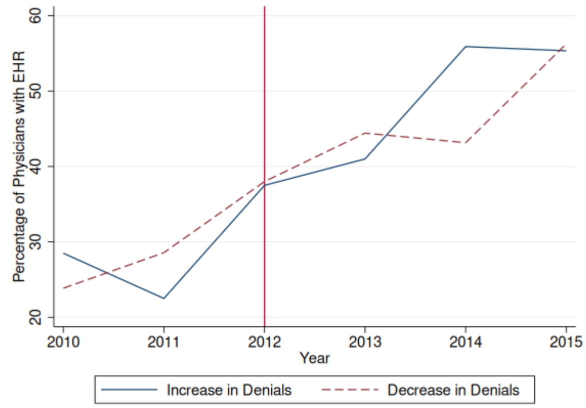
In the model, the investment decision is made each period with no investment stock carried forward from previous periods. This means that the firm's problem is completely static, with investment in one period being unrelated to investment in the next. In reality, much of this investment is personnel costs for administrative and billing staff, but this assumption is still clearly a simplification of reality where some billing investments are persistent over time. Prominent among these is the adoption of electronic health records. While much of the cost of these systems is paid over long time periods (both through depreciation and through maintenance costs), their upfront adoption costs are sunk and so they are not lightly deadopted. Indeed, Figure A13 shows that even in jurisdictions that transitioned to lower-denial contractors, EHR adoption grew substantially from 2010 to 2015, albeit at a slower rate than other jurisdictions.

However, in this appendix I will show that lowering administrative burden leads charges and Medicare spending to fall, consistent with the model's assumption that investment is not sunk and reduced investment leads to less aggressive billing. Figures A14 and A15 limit the sample to transitions to lower-denial contractors and show that compared to jurisdictions that do not transition contractors at the same time, charges and spending fall dramatically in jurisdictions exposed to lower administrative burden. This indicates that lowering administrative burden not only avoids ratcheting up the administrative arms race with providers but can actually lower spending.

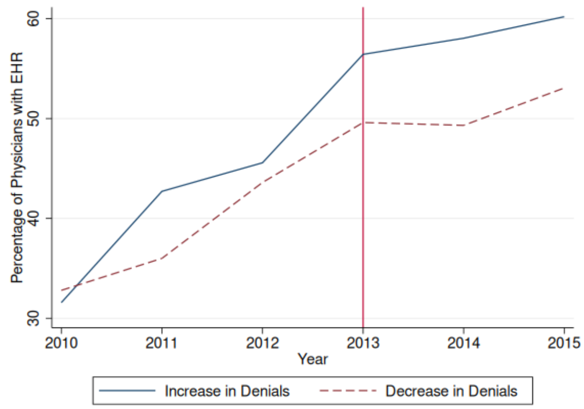
Figure A13: Trends in EHR Adoption



(a) 2011 Transitions



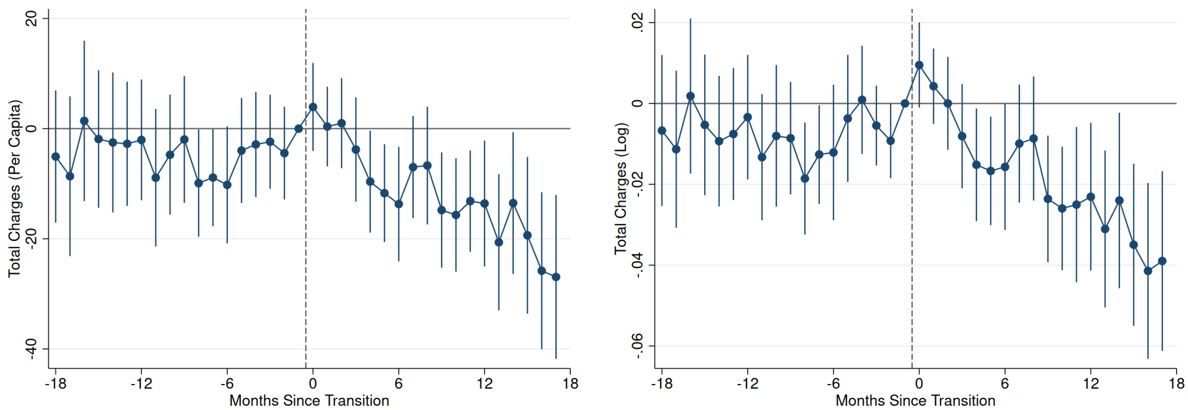
(b) 2012 Transitions



(c) 2013 Transitions

Notes: Figures report the across-jurisdiction average share of providers who have adopted EHR for jurisdictions that transition contractors in the year reported in the subfigure caption. Means are reported separately for jurisdictions that transition to higher- and lower-denial contractors. Sample is limited to 2010–2015.

Figure A14: Effect of Transition to Lower-Denial Administrator on Charges

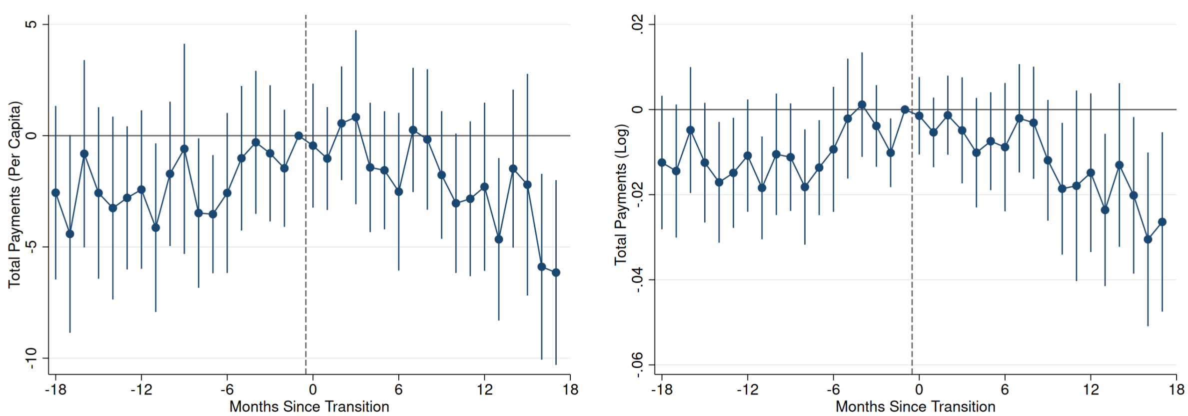


(a) Charges Per Capita

(b) Log Charges

Notes: Estimates of β_e of Equation (4) for $e \in \{-18, \ldots, 17\}$ with $K = 18$ and $L = 17$. An observation is a jurisdiction-wave-month. Dependent variables are total charges billed measured per Medicare beneficiary or in logs. The sample is limited to waves of transitions to a lower-denial contractor. Error bars give the 95% confidence interval for each estimate. Standard errors are clustered by jurisdiction.

Figure A15: Effect of Transition to Lower-Denial Administrator on Medicare Spending



(a) Payments Per Capita

(b) Log Payments

Notes: Estimates of β_e of Equation (4) for $e \in \{-18, \ldots, 17\}$ with $K = 18$ and $L = 17$. An observation is a jurisdiction-wave-month. Dependent variables are total Medicare payments measured per Medicare beneficiary and in logs. The sample is limited to waves of transitions to a lower-denial contractor. Error bars give the 95% confidence interval for each estimate. Standard errors are clustered by jurisdiction.

F.2 Additional Results on the Effect of Transitions on Market Structure

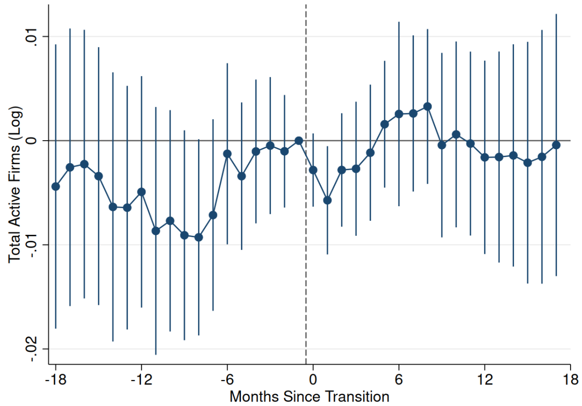
In this appendix, I report additional results on the changes in market structure following Medicare Administrative Contractor transitions. First, while I report estimates of the differential effect of a transition to a higher- relative to lower-denial contractor in the main text, here I show that unlike for changes in EHR adoption, charges, and spending, the effects of transitions on market structure are not symmetric for increases or decreases in administrative burden. In particular, while my results are consistent with investment falling when administrative burdens fall, there is no evidence that lowering administrative burdens induces entry or decreases average firm size. Figure A16 reports how market structure changes following a transition to a lower-denial administrator relative to jurisdictions that at the same time do not change administrators. We see that while there may be disruptive effects of these transitions, there is little evidence of long-term changes in firm size. By contrast, Figure A17 shows that the results reported in the main text are driven by changes induced by transitions to higher-denial administrators, with increases in administrative burden leading to firm exit and increased average firm size.

Second, while Table 5 reports the change in market structure following an increase in administrative burden in the month of transition, Table A14 reports estimates for the entire post-period. The estimates are less precise over this longer horizon, and the estimates lose statistical significance, although they are of the same sign as those reported in the main text.

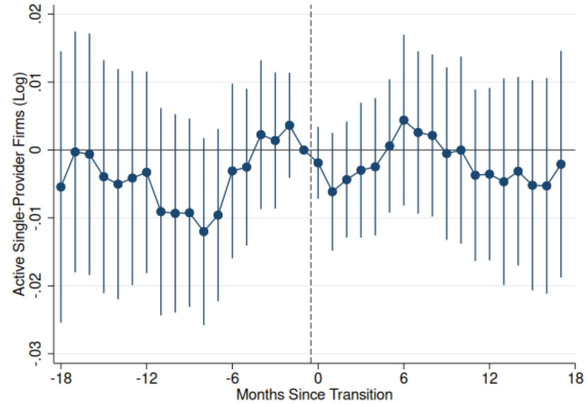
Next, Figure A18 presents estimates of the change in the number of active firms for firms comprised of more than one provider. Breaking these larger firms into the remaining four quintiles of firm size, it is difficult to discern any clear changes in the number of active firms. The number of firms in the highest quintile may increase, but this increase is imprecisely estimated. This indicates that the increases in average firm size are largely driven by exit of the smallest firms rather than large increases in the number of larger firms, although I cannot rule this out.

Finally, Figure A19 reports estimates of the change in the number providers (rather than firms) active in a jurisdiction as well as the frequency of provider exit. These results show there are no meaningful changes in the these variables, indicating that while the firms providers are associated with change, there are few changes in the activity of providers. This is consistent with much of the change in market structure being driven by acquisitions of single-provider firms by larger firms rather than solo practitioners completely quitting the practice of medicine.

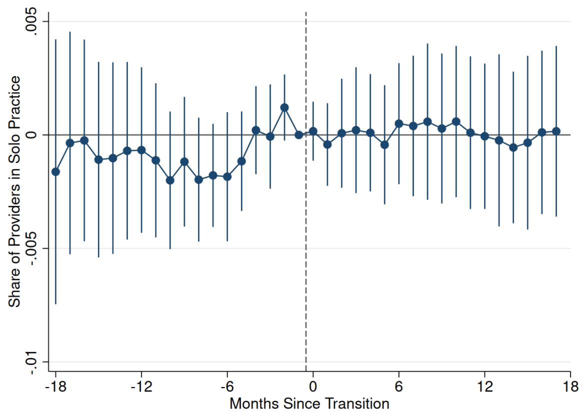
Figure A16: Effect of Transition to Lower-Denial Administrator on Market Structure



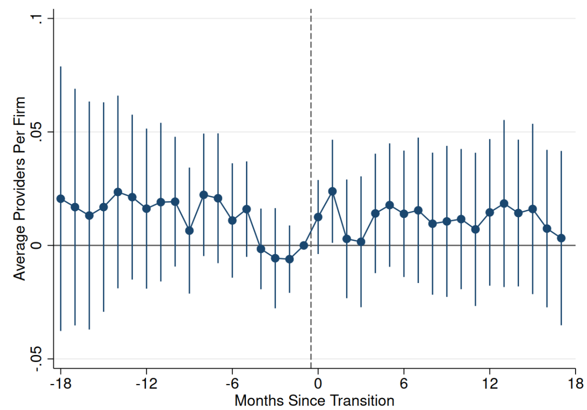
(a) Active Firms



(b) Active Single-Provider Firms



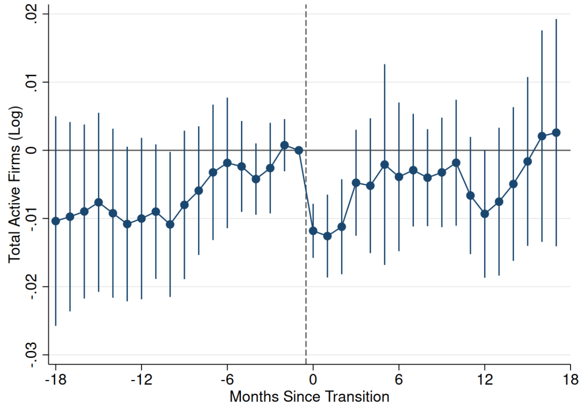
(c) Share of Providers in Solo Practice



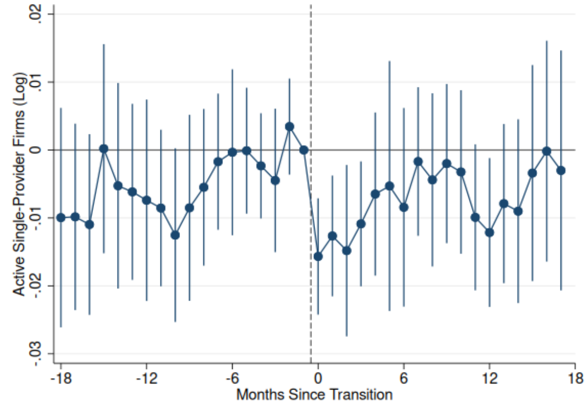
(d) Average Firm Size

Notes: Estimates of β_e of Equation (4) for $e \in \{-18, \ldots, 17\}$ with $K = 18$ and $L = 17$. An observation is a jurisdiction-wave-month. Dependent variables are the number of active firms and the number of single-provider active firms (both in logs), the share of providers affiliated with single-provider firms, and the firm-level average number of providers per firm. Active firms is the number of unique tax identification numbers under which a claim is submitted. Providers per firm is the average number of unique providers in a jurisdiction billing under the same tax identification number. Sample is limited to 2006–2017. The sample is limited to waves of transitions to a lower-denial contractor. Error bars give the 95% confidence interval for each estimate. Standard errors are clustered by jurisdiction.

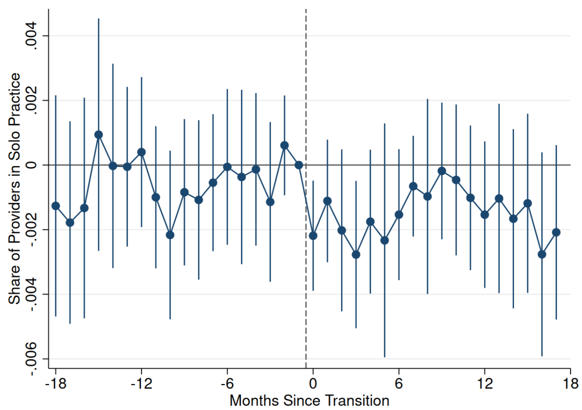
Figure A17: Effect of Transition to Higher-Denial Administrator on Market Structure



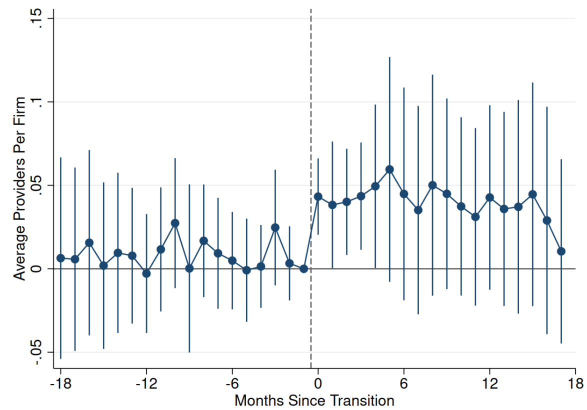
(a) Active Firms



(b) Active Single-Provider Firms



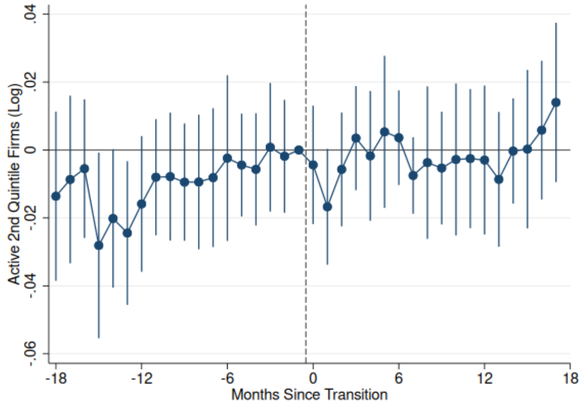
(c) Share of Providers in Solo Practice



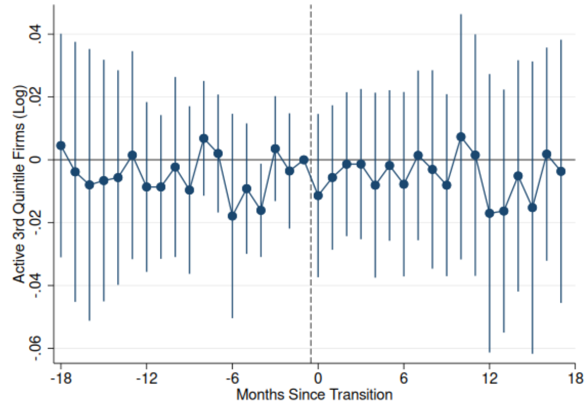
(d) Average Firm Size

Notes: Estimates of β_e of Equation (4) for $e \in \{-18, \ldots, 17\}$ with $K = 18$ and $L = 17$. An observation is a jurisdiction-wave-month. Dependent variables are the number of active firms and the number of single-provider active firms (both in logs), the share of providers affiliated with single-provider firms, and the firm-level average number of providers per firm. Active firms is the number of unique tax identification numbers under which a claim is submitted. Providers per firm is the average number of unique providers in a jurisdiction billing under the same tax identification number. Sample is limited to 2006–2017. The sample is limited to waves of transitions to a higher-denial contractor. Error bars give the 95% confidence interval for each estimate. Standard errors are clustered by jurisdiction.

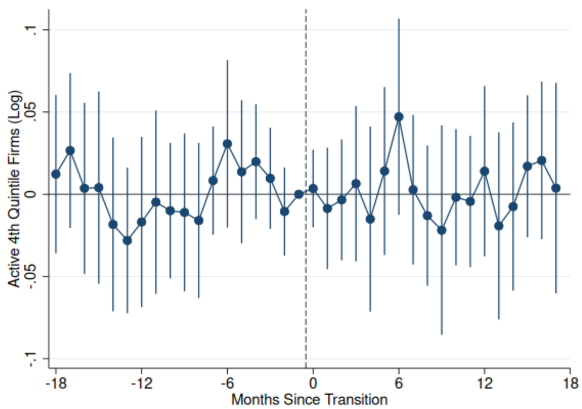
Figure A18: Effect of Transition to Higher-Denial Administrator on Larger Firms



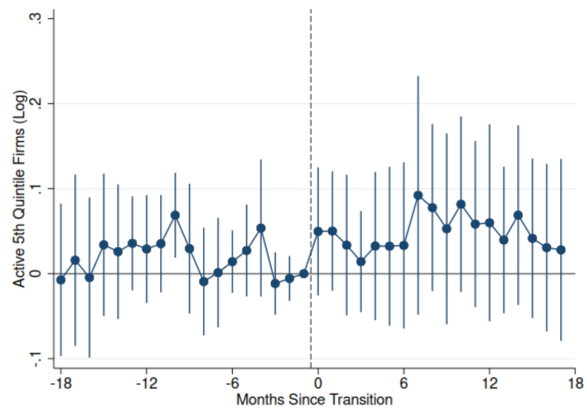
(a) Active Firms Second Quintile Firms



(b) Active Firms Third Quintile Firms



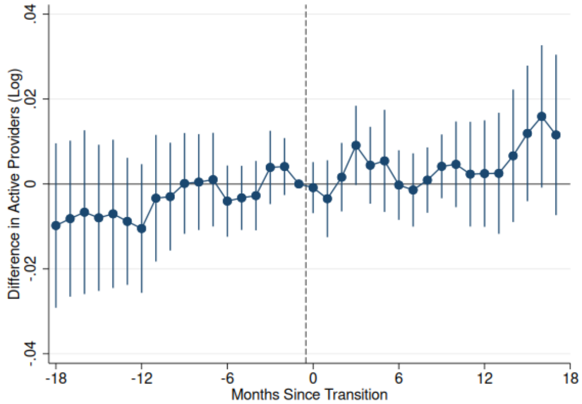
(c) Active Firms Fourth Quintile Firms



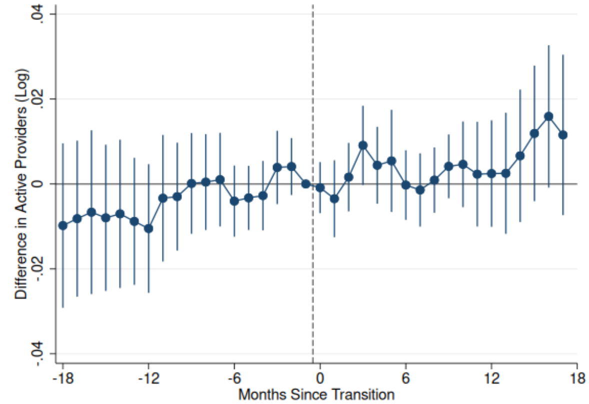
(d) Active Firms Fifth Quintile Firms

Notes: Estimates of δ_e of Equation (2) for $e \in \{-18, \ldots, 17\}$ with $K = 18$ and $L = 17$. An observation is a jurisdiction-wave-month. Dependent variables are the number of active firms of each size. Active firms is the number of unique tax identification numbers under which a claim is submitted. Providers per firm is the number of unique providers in a jurisdiction billing under the same tax identification number. The cutoffs between the quintiles are 1.5, 5.5, 21.5, and 104.5 providers. Sample is limited to 2006–2017. Standard errors are clustered by jurisdiction. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

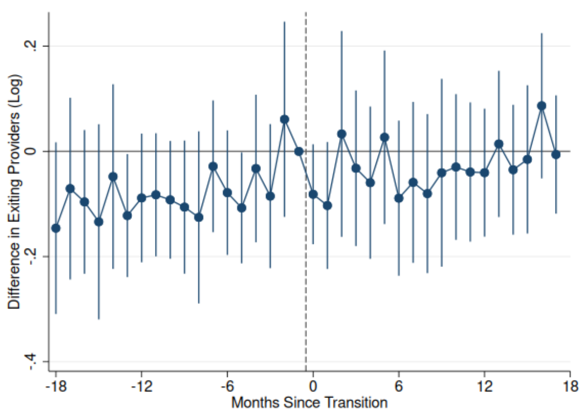
Figure A19: Effect of Transition to Higher-Denial Administrator on Provider Participation



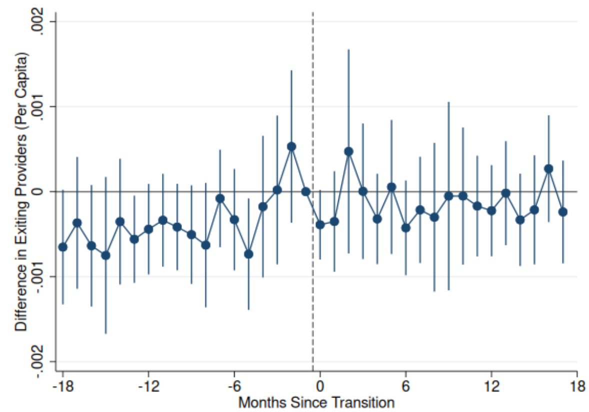
(a) Log Active Providers



(b) Active Providers Per Capita



(c) Log Provider Exits



(d) Provider Exits Per Capita

Notes: Estimates of δ_e of Equation (2) for $e \in \{-18, \ldots, 17\}$ with $K = 18$ and $L = 17$. An observation is a jurisdiction-wave-month. Dependent variables are the number of active providers and the number of providers permanently exiting a jurisdiction (both in logs and per Medicare beneficiary). Sample is limited to 2006–2017. Error bars give the 95% confidence interval for each estimate. Standard errors are clustered by jurisdiction.

Table A14: Effect of Transition to Higher-Denial Administrator on Market Structure

	(1) Active Firms (Log)	(2) Active Single-Provider Firms (Log)	(3) Share of Providers in Solo Practice	(4) Providers per Firm
Increase in Denials	-0.00372	-0.00507	-0.00172	0.0302
	(0.00383)	(0.00560)	(0.00137)	(0.0206)
Dep. Var. Mean	8.004	7.556	0.188	3.754
Observations	53,208	53,208	53,208	53,208

Notes: Estimates of δ_{post} of Equation (3) with $K = 18$ and $L = 17$. An observation is a jurisdiction-wave-month. Dependent variables are the number of active firms and the number of single-provider active firms (both in logs), the share of providers affiliated with single-provider firms, and the firm-level average number of providers per firm. Active firms is the number of unique tax identification numbers under which a claim is submitted. Providers per firm is the average number of unique providers in a jurisdiction billing under the same tax identification number. Sample is limited to 2006–2017. Standard errors are clustered by jurisdiction. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

F.3 Low-Value Care

One area in which providers and claims processors may interact differently are claims for low-value care. Much of the health care provided in the US is thought to be of very low value, with Fisher et al. (2003a,b) estimating roughly 30% Medicare spending results in no improvements in health. This wasteful resource use can come from a variety of sources, including physicians persisting in providing care that is rarely if ever cost-effective (Chandra et al., 2011) or physicians making errors in determining which patients are suitable for which treatments (Mullainathan and Obermeyer, 2022). Utilization of these low-value treatments vary especially widely, with local practice styles differing in their embrace of these treatments (Skinner, 2011). This variation in utilization of potentially low-value treatments has been known for at least 80 years since Glover (1938) highlighted the differences in tonsillectomy rates across Britain.

The geographic variation in the utilization of low-value procedures represents a setting for which the decentralized administrative structure of Medicare may pose an advantage. Indeed, a recent MedPAC report argues that having multiple regional administrators is advantageous for reacting to "regional differences, which the agency considers to be a fundamental characteristic of local coverage" (MedPAC, 2018). Furthermore, while administrative burdens may often impose needless costs, erecting barriers to providers' ability to supply unnecessary and wasteful care can be welfare enhancing (Zeckhauser, 2021).

To assess this possibility I estimate the effect of each contractor on the probability of denying each of 7 different low-value services, and I investigate provider responses to changes in the denial rates for these services. The low-value services I use come from Schwartz et al. (2014) and include cervical and colorectal cancer screenings for elderly patients, carotid artery disease (CAD) screening, prostate-specific antigen (PSA) testing in elderly men, homocysteine testing, carotid endarterectomy, and inferior vena cava (IVC) filter placement. Table A15 reports details on the measurement of each of these treatments, following Schwartz et al. (2014).

Table A16 reports the mean denial and utilization rates for these services in my data, along with the range of estimates of the causal effect of each contractor on the denial rate for these procedures and the correlation of these estimated causal effects with the estimated effect on denial rates reported in Table 2. These results indicate that differences across administrators in their propensity to deny claims for these low-value services vary even more widely than their overall propensity to deny claims. Furthermore, these effects are generally positively correlated with the overall administrator effects on denials, indicating that contractors that impose high administrative burdens in general do the same for low-value care.

The low-value service with the widest range of estimated fixed effects is homocysteine testing, for which the estimated range is over three times the mean denial rate. Figure A20 reports event study estimates for transitions from an administrator with a lower propensity to deny these claims to a higher one. We see that these transitions result in very large and immediate changes in the

Table A15: Classification of Low-Value Care

Service	CPT/HCPCS Codes	Patients Qualifying
Cervical Cancer Screening	G0101 G0123 G0124 G0141 G0144–G0146 G0148 P3000 P3001 Q0091	Women over 65
Colorectal Cancer Screening	45330–45345 45378–45392 82270 G0104–G0106 G0120–G0122 G0328	Patients over 75
PSA Testing	84152–84154 G0103	Men over 75
Homocysteine Testing	82607 82746–82747 83090	All patients
CAD Screening	3100F 36222–36224 70498 70547–70549 93880 93882	All patients
Endarterectomy	35301	All patients
IVC Filter Placement	75940	All patients

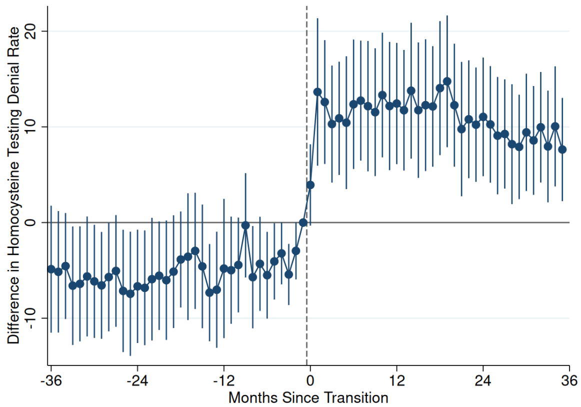
Notes: Codes used for measures of low-value care services. The second column reports the procedure codes indicating that the service has been rendered. The third column reports the patient population for which the procedure is deemed low value. Table follows eTable 1 of Schwartz et al. (2014).

Table A16: Summary Statistics for Low-Value Care

Service	Denial Rate	Utilization Rate	Effect Range	Standard Error	Correlation
Cervical Cancer Screening	26.3	19.6	21.1***	2.12	0.22
Colorectal Cancer Screening	12.0	126.7	23.9***	2.99	-0.17
PSA Testing	18.2	82.2	19.3***	5.65	0.52**
Homocysteine Testing	13.5	9.92	37.7***	5.63	0.37*
CAD Screening	15.2	8.96	24.0***	3.30	0.47**
Endarterectomy	4.37	0.250	11.0***	1.48	0.34
IVC Filter Placement	6.27	0.084	13.2***	3.00	0.39*

Notes: Denial rate reported is the jurisdiction-month-level average percentage of claims for the service denied. Utilization rate reported is the jurisdiction-month-level average number of uses per 1000 eligible beneficiaries. The sample includes claims from 1999 to 2017 for all services except interior vena cava filter placement, for which the sample is limited to 1999–2012. Effect range is the difference between the largest and smallest estimate of μ_m of Equation (1) with the denial rate for the relevant service as the dependent variable. The standard error of this range is given by a T-test of equality of the most extreme coefficients. Correlation reports is the contractor-level correlation between the estimates of μ_m of Equation (1) with the denial rate for the relevant service as the dependent variable and the estimates reported in Table 2. Standard errors are clustered by jurisdiction. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Figure A20: Effect of Transition to Higher-Denial Administrator on Homocysteine Testing



(a) Denials

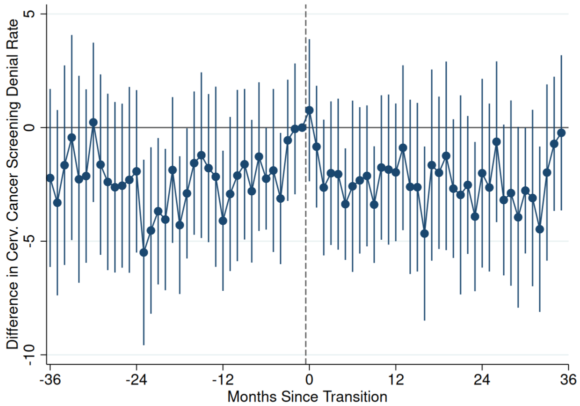
(b) Utilization

Notes: Estimates of δ_e of Equation (2) for $e \in \{-36, \ldots, 35\}$ with $K = 36$ and $L = 35$ where U_w is an indicator for transitioning to a contractor that denies more claims for homocysteine testing. An observation is a jurisdiction-wave-month. Dependent variables are the share of claims for homocysteine testing denied and the number of claims for homocysteine testing per 1,000 beneficiaries. Error bars give the 95% confidence interval for each estimate. Standard errors are clustered by jurisdiction.

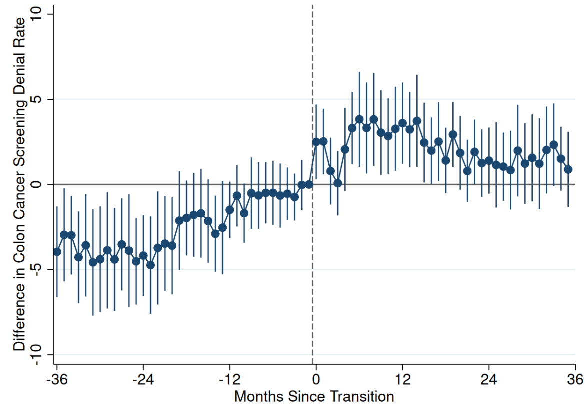
denial rate for this low-value procedure. In contrast with the response to the overall denial rate, the jump in denial rates for this service appears to result in decreased use over time, although this effect is imprecisely estimated.

Figures A21 and A22 report similar event study estimates for the other six types of low-value care. First, we see that for some services transitions resulted in negligible denial rate changes while for others—including colorectal cancer screenings, PSA testing, and CAD screening—the changes were smaller but still notable. Nonetheless, for none of these services does utilization meaningfully decrease. This is consistent with providers only being willing to dramatically change practice patterns for a given procedure in response to a large change in the denial rate. In fact, even relatively large changes in denial rates often represent much smaller changes in provider revenue. For example, while the roughly 20 percentage point change in denial rates observed for homocysteine testing represents a drop in expected revenue of 23% relative to the mean denial rate, the 1.2 percentage point change in overall denial rates reported in Figure 2 represents a 19% change in the denial rate but only a 1% a reduction in revenue. These results indicate that while major changes in the administrative burden imposed on specific practices can effectively shift providers away from that practice (consistent with the results of Brot-Goldberg et al. (2022), Eliason et al. (2021), Shi (2024), and Macambira et al. (2022)), minor changes to the denial rate for a procedure are unlikely to greatly affect the use of that procedure. In this context, this means that the generally small changes to denial rates resulting from contractor transitions are unlikely to have first order effects on the care actually rendered by providers, including for low-value care.

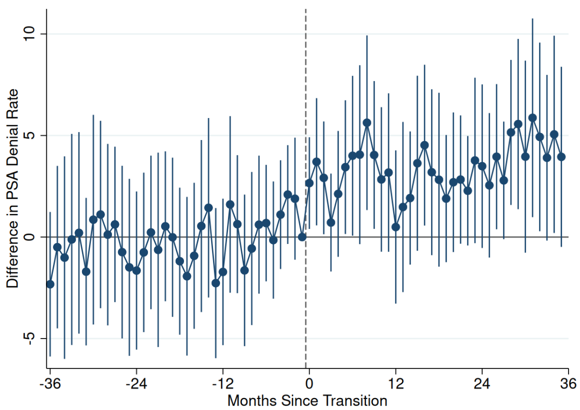
Figure A21: Effect of Transition to Higher-Denial Administrator on Denials of Low-Value Services



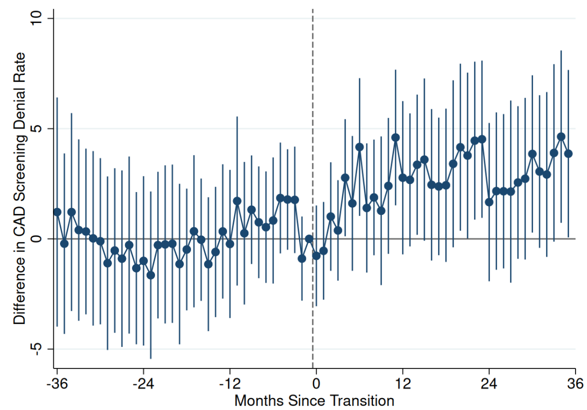
(a) Cervical Cancer Screening



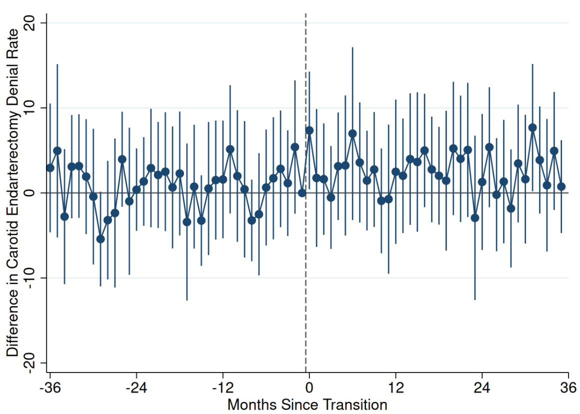
(b) Colorectal Cancer Screening



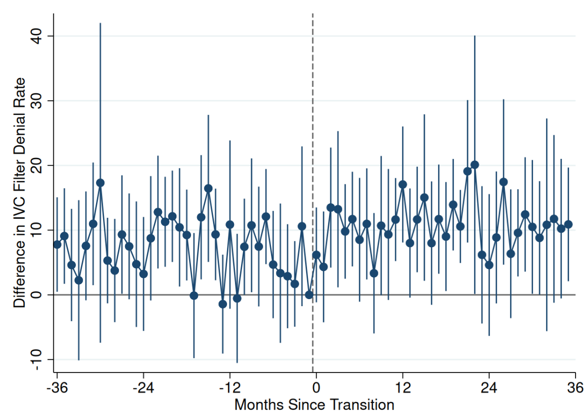
(c) PSA Testing



(d) CAD Screening



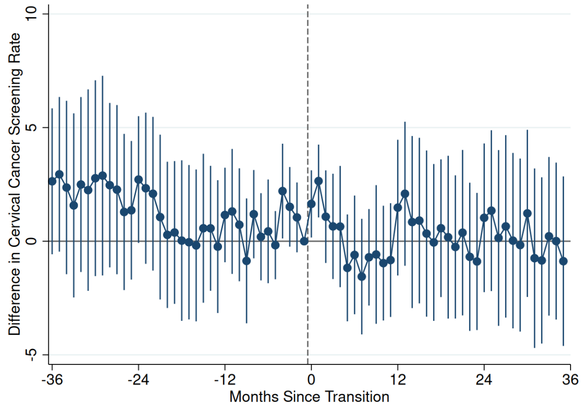
(e) Endarterectomy



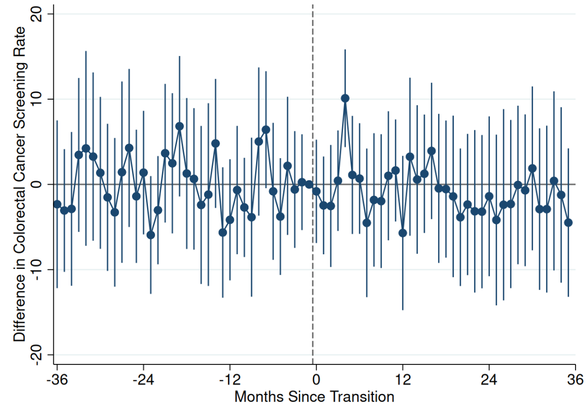
(f) IVC Filter Placement

Notes: Estimates of δ_e of Equation (2) for $e \in \{-36, \ldots, 35\}$ with $K = 36$ and $L = 35$ where U_w is an indicator for transitioning to a contractor that denies more claims for the services noted in the subfigure caption. An observation is a jurisdiction-wave-month. Dependent variables are the share of claims for the services noted in the subfigure caption denied. Error bars give the 95% confidence interval for each estimate. Standard errors are clustered by jurisdiction.

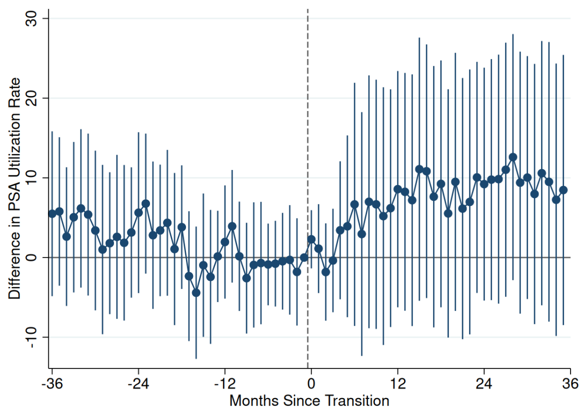
Figure A22: Effect of Transition to Higher-Denial Administrator on Utilization of Low-Value Services



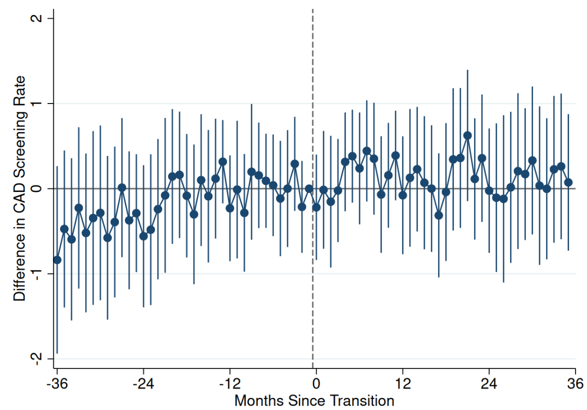
(a) Cervical Cancer Screening



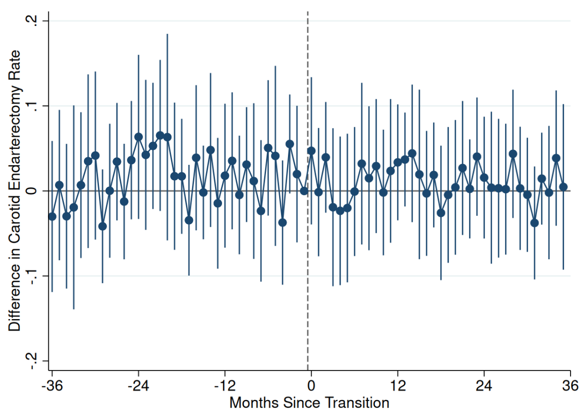
(b) Colorectal Cancer Screening



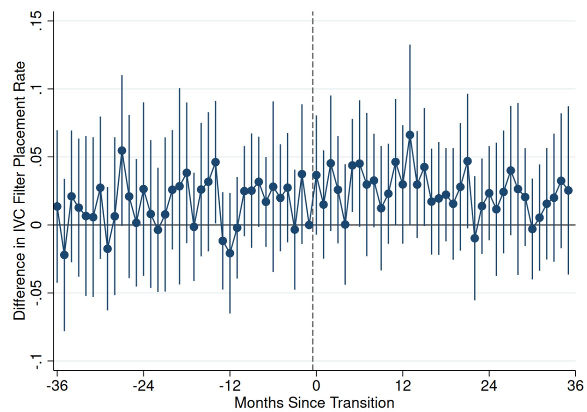
(c) PSA Testing



(d) CAD Screening



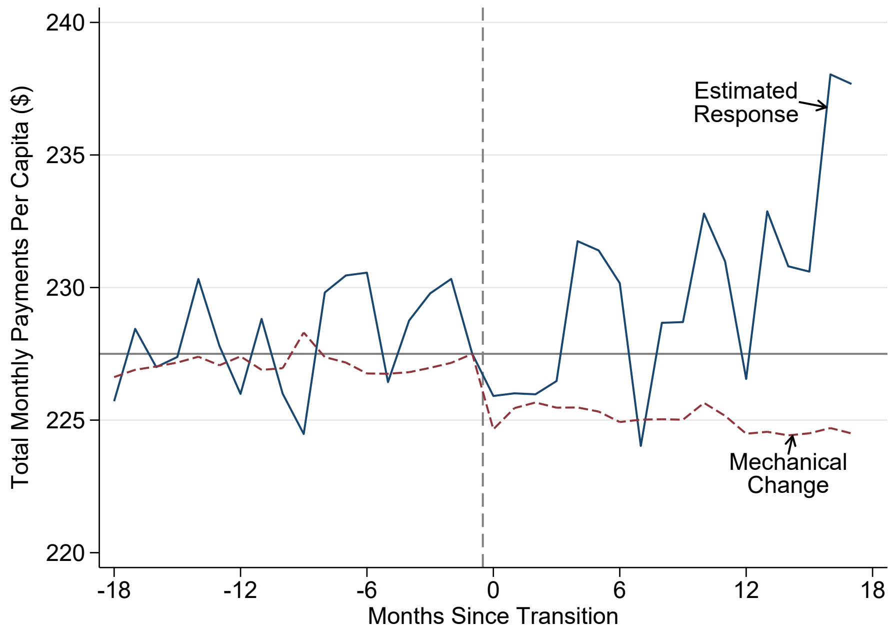
(e) Endarterectomy



(f) IVC Filter Placement

Notes: Estimates of δ_e of Equation (2) for $e \in \{-36, \ldots, 35\}$ with $K = 36$ and $L = 35$ where U_w is an indicator for transitioning to a contractor that denies more claims for the services noted in the subfigure caption. An observation is a jurisdiction-wave-month. Dependent variables are the number of claims for the services noted in the subfigure caption per 1,000 beneficiaries. Error bars give the 95% confidence interval for each estimate. Standard errors are clustered by jurisdiction.

Figure A23: Effect of Transition to Higher-Denial Administrator on Per Capita Spending



Notes: Implied level of per-capita spending using estimates of δ_e of Equation (2) for $e \in \{-18, \ldots, 17\}$ with $K = 18$ and $L = 17$. Mechanical change is calculated using estimates of the change in denial rate. An observation is a jurisdiction-wave-month. Denial rate is the percentage of claims denied.

F.4 Other Consequences of Increasing Administrative Burden

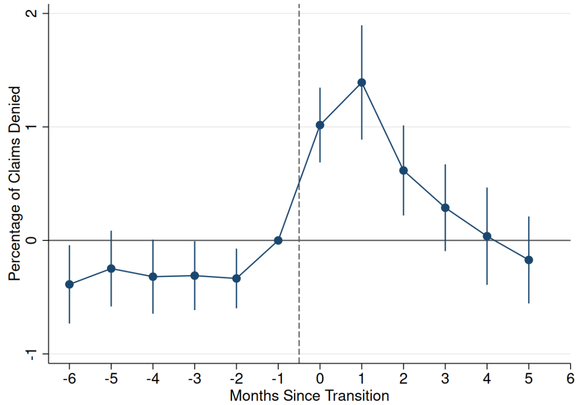
In this appendix, I report additional results on the responses of providers to changes in their Medicare Administrative Contractor. Figure A23 presents the implied level of spending using the estimates presented in Figure 4a adding back in the dependent variable mean along with the level of spending that would have occurred if the only change had been the changes in the denial rate presented in Figure 2. More explicitly, to calculated the mechanical change in spending, I calculate the value of Medicare payments if there had been no denials by dividing the observed mean level of payments by 1 minus the average denial rate. I then calculate the implied mechanical change in spending by assigning this value of would-be spending to each month and multiplying it by 1 minus the average denial rate plus the estimated change in the denial rate in that month (the estimates presented in Figure 2). By doing this, I impose that the level of spending if no claims were denied would be the exact same in each month (ruling out any endogenous changes in billing) and present the mechanical change in spending attributable to just the change in the denial rate. As Figure A23 shows, in the months immediately following the transition, there is little difference between the mechanical and observed levels of spending. However, after approximately three months, the observed level of spending begins to increase while the mechanical level of spending says reduced, resulting in the levels being quite different by the end of the event window.

Figure A24 reports how the denial rate changes surrounding administrator transitions for firms of various sizes. Consistent with the results presented in Table 6, smaller firms are subject to much larger spikes in the share of claims that are denied around a contractor transition than larger firms are.

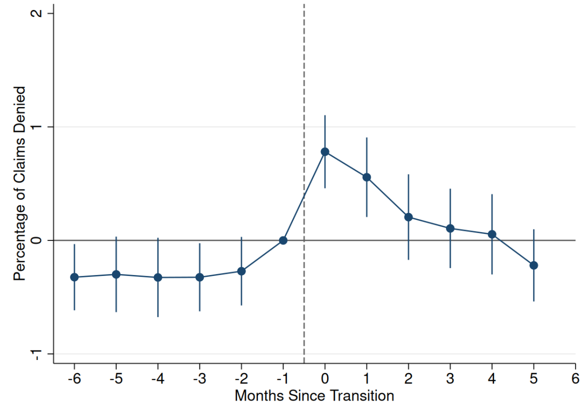
Figure A25 and Table A17 report evidence that provider volumes do not respond to administrative burden. This is true across various measures that capture the volumes of patients treated by each provider, including the number of patients treated at all, the number of patient-days, the number of patient-provider pairs that interact at all during the jurisdiction-month, and the number of patient-provider-day tuples.

Figure A26 and Table A18 report evidence that beneficiary mortality does not change following transitions. The results in the table indicate that there is no meaningful change in mortality following a transition to a lower-denial contractor nor is there a differential effect of transitioning to a higher-denial contractor.

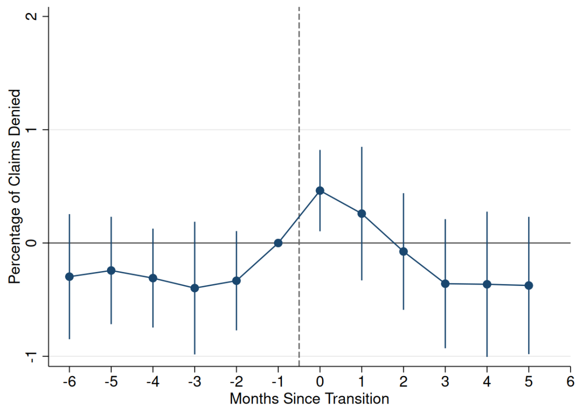
Figure A24: Effect of Transition on Denial Rate by Firm Size



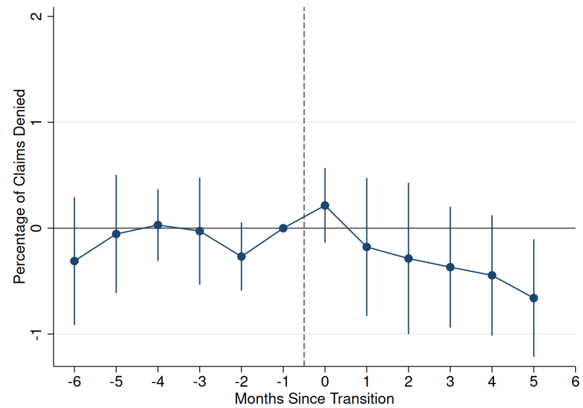
(a) 1 Provider



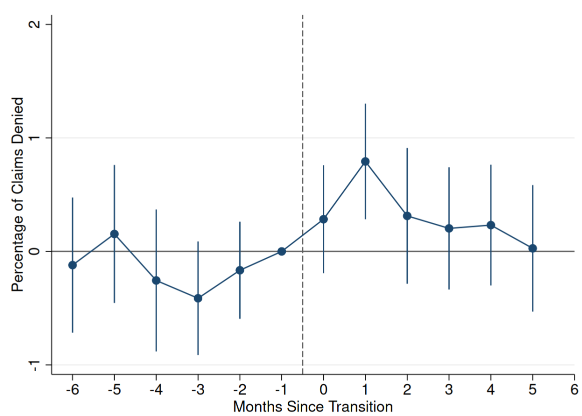
(b) 2–5 Providers



(c) 6–21 Providers



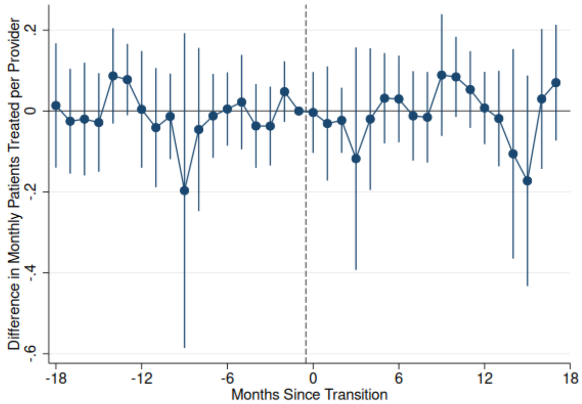
(d) 22–104 Providers



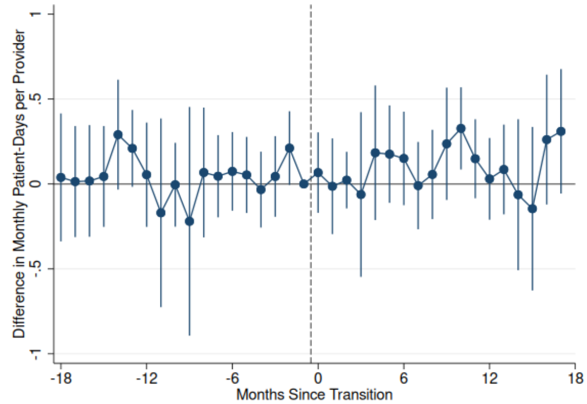
(e) Over 104 Providers

Notes: Estimates of β_e of Equation (4) for $e \in \{-6, \ldots, 5\}$ with $K = 6$ and $L = 5$. An observation is a jurisdiction-wave-month. Dependent variable is the denial rate for firms of the relevant size. Denial rate is the percentage of claims denied. Providers per firm is the number of unique providers in a jurisdiction billing under the same tax identification number. Sample is limited to 2006–2017. Error bars give the 95% confidence interval for each estimate. Standard errors are clustered by jurisdiction.

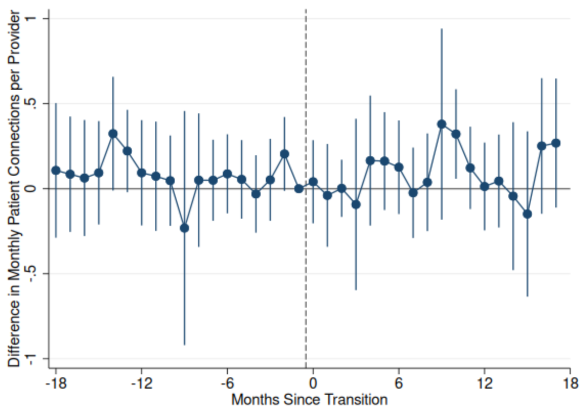
Figure A25: Effect of Transition to Higher-Denial Administrator on Volume of Patients Treated



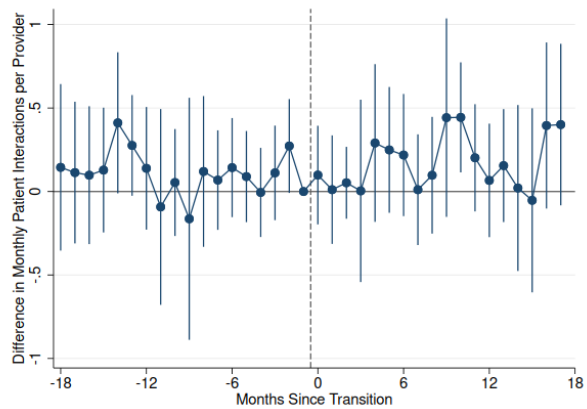
(a) Patients Treated



(b) Patient-Days



(c) Patient Connections



(d) Patient Interactions

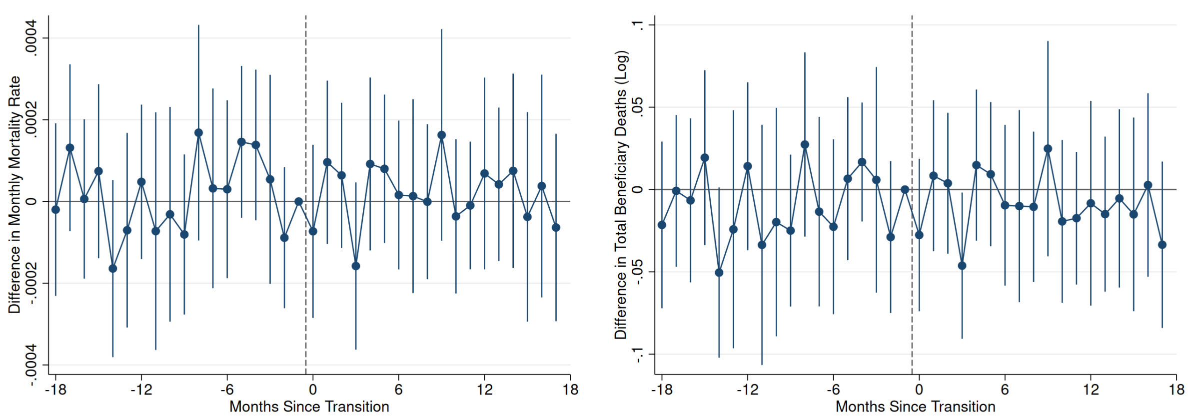
Notes: Estimates of δ_e of Equation (2) for $e \in \{-18, \ldots, 17\}$ with $K = 18$ and $L = 17$. An observation is a jurisdiction-wave-month. Patients treated per provider is the total number of patients treated in a jurisdiction-month divided by the number of active providers. Patient-days per provider is the total number of patient-days in a jurisdiction-month on which a service was provided divided by the number of active providers. Patient connections per provider is the total patient-provider pairs realized in a jurisdiction-month divided by the number of active providers. Patient interactions per provider is the total patient-provider-day tuples realized in a jurisdiction-month divided by the number of active providers. Sample is limited to 2006–2017. Error bars give the 95% confidence interval for each estimate. Standard errors are clustered by jurisdiction.

Table A17: Effect of Transition to Higher-Denial Administrator on Volume of Patients Treated

	(1) Patients Treated per Provider	(2) Patient-Days per Provider	(3) Patient Connections per Provider	(4) Patient Interactions per Provider
Increase in Denials	-0.00687	0.0979	0.0883	0.173
	(0.0426)	(0.101)	(0.104)	(0.133)
Dep. Var. Mean	4.132	10.19	10.78	13.48
Observations	53,208	53,208	53,208	53,208

Notes: Estimates of δ_{post} of Equation (3) with $K = 18$ and $L = 17$. An observation is a jurisdiction-wave-month. Patients treated per provider is the total number of patients treated in a jurisdiction-month divided by the number of active providers. Patient-days per provider is the total number of patient-days in a jurisdiction-month on which a service was provided divided by the number of active providers. Patient connections per provider is the total patient-provider pairs realized in a jurisdiction-month divided by the number of active providers. Patient interactions per provider is the total patient-provider-day tuples realized in a jurisdiction-month divided by the number of active providers. Sample is limited to 2006–2017. Standard errors are clustered by jurisdiction. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Figure A26: Effect of Transition to Higher-Denial Administrator on Mortality



(a) Morality Rate

(b) Log Total Deaths

Notes: Estimates of δ_e of Equation (2) for $e \in \{-18, \ldots, 17\}$ with $K = 18$ and $L = 17$. An observation is a jurisdiction-wave-month. Dependent variables are total monthly deaths of Medicare enrollees per Medicare beneficiary and in logs. Error bars give the 95% confidence interval for each estimate. Standard errors are clustered by jurisdiction.

Table A18: Effect of Transition to Higher-Denial Administrator on Mortality

	(1) Mortality (per capita)	(2) Mortality (log)
Post-Transition	-0.0000564	-0.00585
	(0.0000466)	(0.00830)
Increase in Denials	0.0000204	-0.00857
	(0.0000689)	(0.0159)
Dep. Var. Mean	0.00431	5.741
Observations	70,164	70,164

Notes: Estimates of β_{post} and δ_{post} of Equation (3) for $e \in \{-18, \ldots, 17\}$ with $K = 18$ and $L = 17$. An observation is a jurisdiction-wave-month. Dependent variables are total monthly deaths of Medicare enrollees per Medicare beneficiary and in logs. Standard errors are clustered by jurisdiction. *, ** and *** indicate significance at the 10%, 5%, and 1% level, respectively.

G Alternative Model of Firm Exit

In the main text, I model firms as having idiosyncratic differences in their profitability with firm exit resulting from the profit level falling below zero. In this appendix, I present an alternative model of providers endogenously forming firms of different sizes. In this model, providers derive utility from their income (which I assume is given by firm profits divided by the number of providers) and from the size of the firm of which they are a part according to the utility function

$$U_{iv} = f(v) + \alpha \log\left(\frac{\Pi_v}{v}\right) + \varepsilon_{iv},$$

where $f(v)$ is an arbitrary function of firm size v, α gives the subjective value of log income, and ε_{iv} is an idiosyncratic taste shock for firms of size v for provider i. I allow $f(v)$ to be completely arbitrary, meaning that this utility function allows providers to have preferences for smaller or larger firms.

Under the assumption that ε_{iv} is independently and identically distributed type-1 extreme value across providers and firm sizes, the share of providers sorting into firms of size v is given by

$$P_v = \frac{\exp(\delta_v)}{1 + \sum_{v>1} \delta_v},$$

where δ_v is the difference in mean utility for a firm of size v relative to solo practice:

$$\delta_{iv} \equiv f(v) - f(1) + \alpha\left(\log\left(\frac{\Pi_v}{v}\right) - \log\left(\Pi_1\right)\right).$$

This means that the change in the log share of providers of a given firm size following a transition to a higher-denial administrator is informative about both the taste for income relative to firm size α as well as the change in profits:

$$(21)\quad \log(P_{v1}) - \log(P_{11}) - (\log(P_{v0}) - \log(P_{10})) = \alpha\left(\log\left(\frac{\Pi_{v1}}{v}\right) - \log\left(\Pi_{11}\right) - \left(\log\left(\frac{\Pi_{v0}}{v}\right) - \log\left(\Pi_{10}\right)\right)\right).$$

Table A19 reports reduced form estimates of these changes for firms of various sizes. Using these moments in estimation rather than those associated with Equation (10), I obtain parameter estimates that imply very similar investment costs to those implied by the model presented in the main text. Figure A27 recreates Figure 9 showing the equilibrium outcomes under the main model and the alternative model considered in this appendix, while Table A20 compares key values reported in the text. Both the figure and table show that the estimated investment costs are quite similar across the two models, although the estimated profit levels are much lower under

Table A19: Estimated Alternative Moments

(1) Moment Equation	(2) Firm Sizes	(3) Estimand	(4) Structural Representation	(5) Estimate
Equation (21)	2–5	$\log(P_{v1}) - \log(P_{11}) - (\log(P_{v0}) - \log(P_{10}))$	$\alpha\left(\log\left(\frac{\Pi_{v1}}{v}\right) - \log\left(\Pi_{11}\right) - \left(\log\left(\frac{\Pi_{v0}}{v}\right) - \log\left(\Pi_{10}\right)\right)\right)$	0.0160
				(0.0150)
Equation (21)	6–21	$\log(P_{v1}) - \log(P_{11}) - (\log(P_{v0}) - \log(P_{10}))$	$\alpha\left(\log\left(\frac{\Pi_{v1}}{v}\right) - \log\left(\Pi_{11}\right) - \left(\log\left(\frac{\Pi_{v0}}{v}\right) - \log\left(\Pi_{10}\right)\right)\right)$	-0.000600
				(0.0181)
Equation (21)	22–104	$\log(P_{v1}) - \log(P_{11}) - (\log(P_{v0}) - \log(P_{10}))$	$\alpha\left(\log\left(\frac{\Pi_{v1}}{v}\right) - \log\left(\Pi_{11}\right) - \left(\log\left(\frac{\Pi_{v0}}{v}\right) - \log\left(\Pi_{10}\right)\right)\right)$	-0.00432
				(0.0252)
Equation (21)	≥ 104	$\log(P_{v1}) - \log(P_{11}) - (\log(P_{v0}) - \log(P_{10}))$	$\alpha\left(\log\left(\frac{\Pi_{v1}}{v}\right) - \log\left(\Pi_{11}\right) - \left(\log\left(\frac{\Pi_{v0}}{v}\right) - \log\left(\Pi_{10}\right)\right)\right)$	0.0310
				(0.0326)

Notes: Column (1) reports the equation that defines the moment to be estimated. Column (2) reports the number of providers associated with the firms to which the estimation sample is limited. Columns (3) and (4) report the estimand associated with the moment and the combination of structural parameters to which it is equivalent. For the moments associated with Equation (21), column (5) reports estimates of δ_1 of Equation (12) with difference in the log share of providers associated with firms of size v and of size 1 as the dependent variable. An observation is a jurisdiction-wave-month, and the standard errors are reported in parentheses and clustered by jurisdiction.

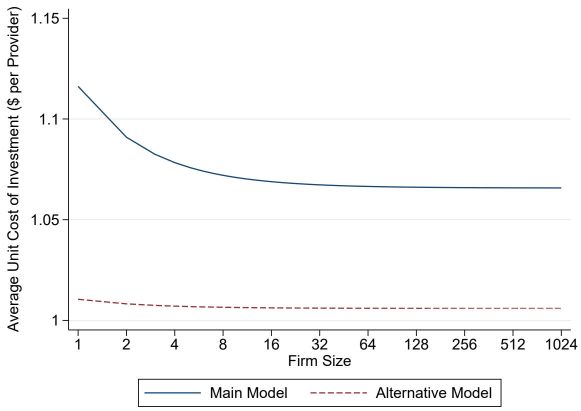
the alternative model. Nonetheless, the robustness of my estimate of the cost of investment to this alternative model lends credence to my estimates.

Table A20: Key Values Under Alternative Provider Allocation Model

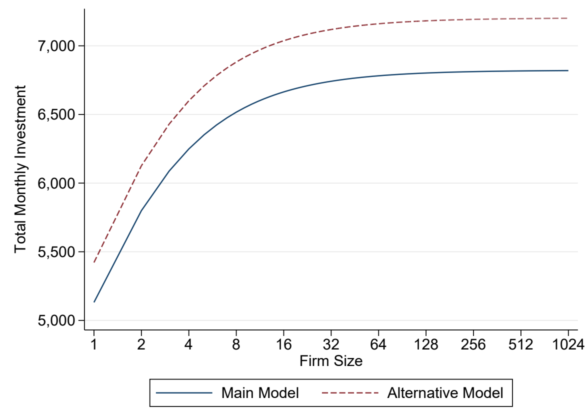
	Main Model	Alternative Model
Total Billing Costs	88.7	87.7
Transition Costs	10	10
Transition Profit Change	-3	-2
Transition Spending Change	7	9
Spending Change Without Response	-2.8	-1.6
HITECH Subsidy Spending Change	49	50

Notes: Estimated value of key figures reported in the main text under alternative modeling assumptions. All values reported in billions of dollars annually.

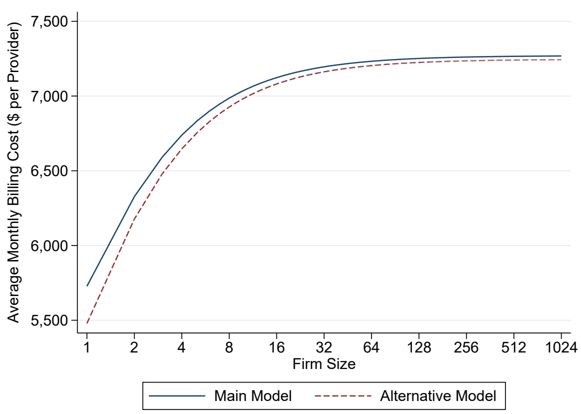
Figure A27: Equilibrium Outcomes by Firm Size Under Alternative Provider Allocation Model



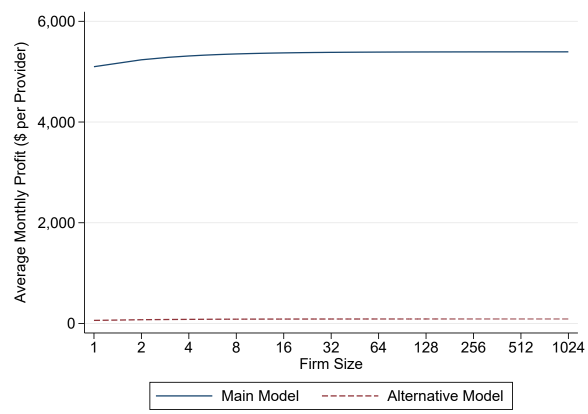
(a) Average Unit Cost



(b) Investment



(c) Billing Cost per Provider



(d) Profit per Provider

Notes: Equilibrium outcomes implied by parameters presented in Table 7 along with those implied by the alternative model presented in Appendix G. Panel (a) reports the unit cost of investment divided by the number of providers in the firm. Panel (b) reports the profit-maximizing monthly level of investment. For both of these panels, the units of investment are scaled so that one unit of investment induces a $1 increase in charges per provider. Panel (c) reports the monthly per-provider cost of the profit-maximizing level of investment. Panel (d) reports the equilibrium monthly profit per provider. Note that the horizontal axes of all figures are spaced geometrically.

H Proof of Model Identification

In this appendix, I prove that the model outlined in Section 6.3 is identified using the moments I employ in estimation.

First, let β_0 and β_1 be defined as in Equation (13). Let δ be the estimated percent change in the denial rate, π_v be the estimated level change in the denial rate for firms of size v, and σ_v be the estimated level change in the charges per provider for firms of size v, all following a transition to a higher denial administrator. With these objects from the data, the model is identified up to the equations[48]

$$\frac{\beta_1}{\beta_0} = \frac{c}{d-1} \tag{22}$$

and

$$\sqrt{a+\underline{I}_0} = \frac{2+2\delta+\delta^2}{2\sqrt{-\rho_v\pi_v}}\underline{I}_0 + \frac{\delta(2+\delta)}{2\sqrt{-\rho_v\pi_v}}a + \frac{\sqrt{-\rho_v\pi_v}}{2} \tag{23}$$

relating c to d and a to $\underline{I}_0$ that when pinned down deliver $\underline{I}_1$ and b by the following equations:

$$\underline{I}_1 = (1+\delta)^2\underline{I}_0 + \delta(2+\delta)a = \rho_v\pi_v + 2\sqrt{a+\underline{I}_0}\sqrt{-\rho_v\pi_v} - \underline{I}_0$$

$$b = a - \frac{\rho_v c(\beta_0+\beta_1 v)}{\pi_v\beta_0 v}$$

The average level of profit for firms of size v, denoted Π_v is given by

$$\Pi_v = \frac{c(\beta_0+\beta_1 v)}{\beta_0}\left(a - \frac{\rho_v}{\pi_v} - 2\sqrt{-\frac{\rho_v}{\pi_v}(a+\underline{I})}\right) - (2a+\underline{I})v,$$

and the change in profits following a transition to a higher denial administrator is given by

$$\alpha_v = -\left(\frac{2c\rho_v(\beta_0+\beta_1 v)}{\beta_0} + \delta(2+\delta)(\underline{I}_0+a)v\right).$$

Denoting the percentage change in the number of active firms of size v following a transition to a higher denial administrator ν_v and the profits of a firm of size v in a low-administrative-burden

[48]Note that Equation (23) is derived from the following two equations:

$$\delta = \sqrt{\frac{a+\underline{I}_1}{a+\underline{I}_0}} - 1$$

$$\pi_v\rho_v = 2\sqrt{(a+\underline{I}_0)(a+\underline{I}_1)} - (\underline{I}_0 + 2a + \underline{I}_1)$$

regime as Π_{v0}, we have

$$\nu_v = \frac{1 - \Phi\left(-\frac{\Pi_{v0}+\alpha_v}{\sigma_\pi}\right)}{1 - \Phi\left(-\frac{\Pi_{v0}}{\sigma_\pi}\right)}. \tag{24}$$

Π_{v0} and α_v are functions of c, a, and $\underline{I}_0$, so σ_π, c, and an equation relating a to $\underline{I}_0$ are fully characterized by the system of equations composed of Equation (24) for at least 3 values of v. This system of equations combined with equations (22) and (23) implies unique values for d, a, and $\underline{I}_0$.[49] Therefore, the model is fully identified by moments relating the observed and predicted values of β_0 and β_1, π_v and ρ_v for at least one value of v, and ν_v for at least three values of v.

[49] Including a fourth value of v in the system of equations (24) is another way to allow a and $\underline{I}_0$ to be separately identified.

I Results on Robustness of Model

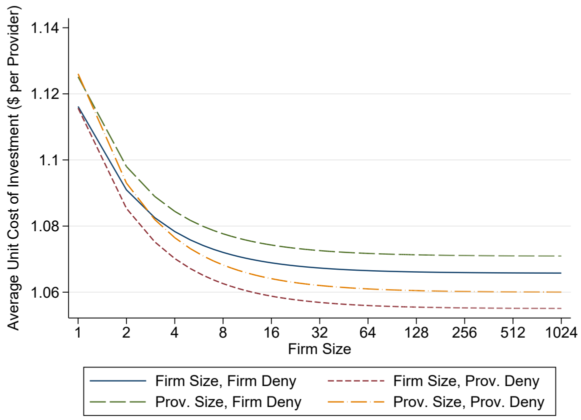
To estimate the model, I group similarly sized firms together to improve precision of the reduced form estimates to be matched. The predicted values from the model, however, rely on specific values of v. In the main text, I obtain these values using firm-weighted averages. In this section, I demonstrate the robustness of my results to weighting by the number of providers. This changes the average number of providers per firm from 3.23 to 116.27. It also alters the estimates of β_1 and β_2 to be those given in Table A22 in Appendix J. Table A21 and Figure A28 recreate the key values reported in the main text and in Figure 9 using these alternative weightings. I also report the values from the main text again for comparison.

Table A21: Key Values Under Alternative Weighting Assumptions

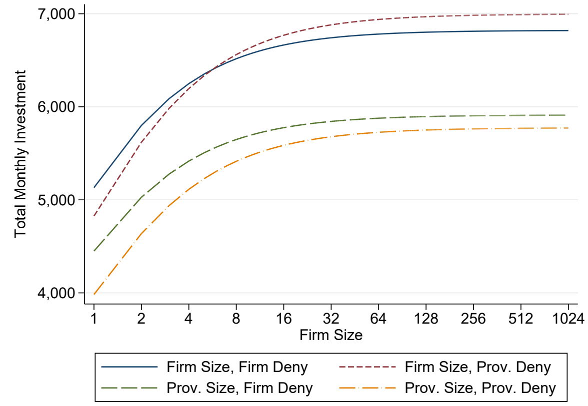
	(1)	(2)	(3)	(4)
Average Size	Firm	Firm	Provider	Provider
Denial-Size Gradient	Firm	Provider	Firm	Provider
Total Billing Costs	88.7	88.5	77.3	73.5
Transition Costs	10	10	9	9
Transition Profit Change	-3	-3	-3	-2
Transition Spending Change	7	8	6	6
Spending Change Without Response	-2.8	-2.6	-2.7	-2.3
HITECH Subsidy Spending Change	49	49	49	49
Untargeted Transfer Cost	1.1	1.1	1.1	1.1
Targeted Transfer Cost	3.8	3.8	3.8	3.6

Notes: Estimated value of key figures reported in the main text under alternative weighting schemes. Average size weighting gives the weighting used to estimate the average firm size used as v. Denial-size gradient weighting gives the weighting used to estimate Equation (13). All values reported in billions of dollars annually, except targeted transfer costs which is reported in millions.

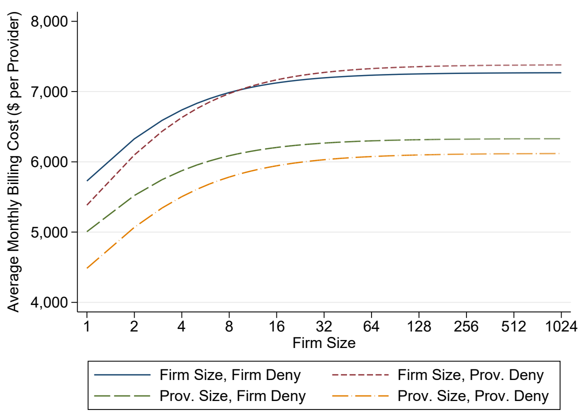
Figure A28: Equilibrium Outcomes by Firm Size under Alternative Weighting Assumptions



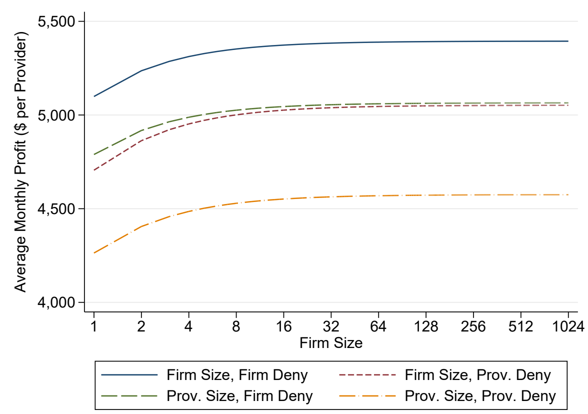
(a) Average Unit Cost



(b) Investment



(c) Billing Cost per Provider



(d) Profit per Provider

Notes: Equilibrium outcomes implied by parameters estimated using various weighting schemes. "Firm Size" and "Prov. Size" indicate the weighting used to estimate the average firm size used as v is firms or providers, respectively. "Firm Deny" and "Prov. Deny" indicate the weighting used to estimate Equation (13) is firms or providers, respectively. Panel (a) reports the unit cost of investment divided by the number of providers in the firm. Panel (b) reports the profit-maximizing monthly level of investment. For both of these panels, the units of investment are scaled so that one unit of investment induces a $1 increase in charges per provider. Panel (c) reports the monthly per-provider cost of the profit-maximizing level of investment. Panel (d) reports the equilibrium monthly profit per provider. Note that the horizontal axes of all figures are spaced geometrically.

J Validating Estimation Results

In this appendix, I provide evidence that my model estimates successfully fit the data well. First, I present evidence that the model is able to closely match the observed relationship between firm size and the denial rate. Table A22 reports estimates of Equation (13) with different weighting schemes along with the values implied by the model estimates reported in Section 6.3 using both the high and low administrative burden estimates of $\underline{I}$ as well as the average level of burden used in the estimation. Notice the concordance between these estimates and those predicted by the model. Figure A29 similarly presents the transformed and untransformed relationships between denial rate and firm size predicted by the model and observed in the data. Both the table and figure indicate that the predictions of the model closely match those of the data.

Table A22: Relationship Between Squared Denial Rate and Inverse Firm Size

	Observed		Predicted		
	(1)	(2)	(3)	(4)	(5)
	Denial Rate^2	Denial Rate^2	Denial Rate^2	Denial Rate^2	Denial Rate^2
Inverse Firm Size	33.91	41.80	30.05	37.80	33.93
	(2.338)	(2.254)			
Constant	44.16	37.91	39.15	49.24	44.20
	(2.495)	(0.5573)			
$\underline{I}$			$\underline{I}_0$	$\underline{I}_1$	$\frac{\underline{I}_0+\underline{I}_1}{2}$
Weighting	Firms	Providers			
Dep. Var. Mean	71.05	50.87			
Observations	61,725,317	199,100,356			

Notes: Estimates of β_0 and β_1 of Equation (13). An observation is a firm-month. Firm size is determined by the number of providers in a jurisdiction billing under the same tax identification number. All estimates are scaled to have the denial rate be between 0 and 100. Observations are frequency-weighted by the number of firms in column (1) and providers associated with the firm in column (2). Standard errors are clustered by firm-size. Columns (3), (4), and (5) report predicted values using the estimates reported in Table 7.

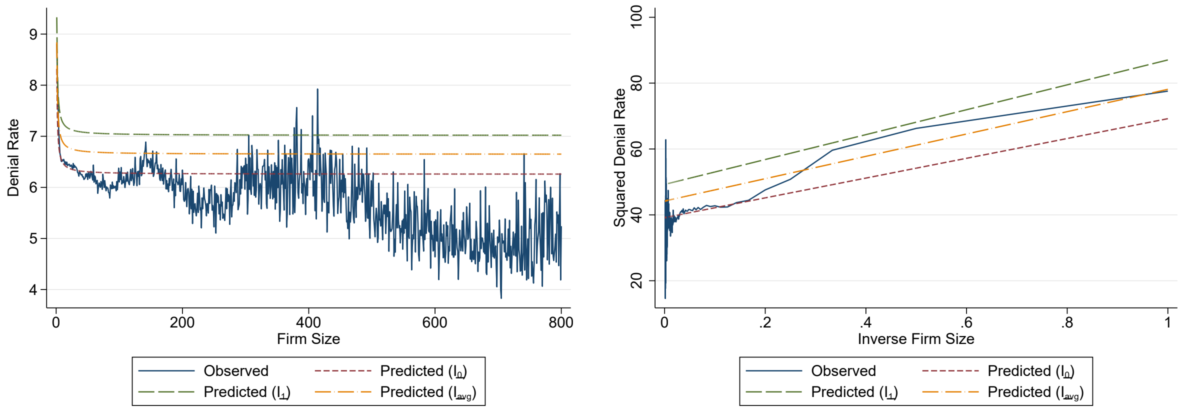
Next, I compare the predicted responses of equilibrium outcomes to a change in administrative burden that come out of the model to those observed in the data. Table A23 presents the estimated and predicted change in charges, denials, and active firms corresponding to the moments used in estimation. Note that column (5) of the table reports the estimate from the data, while column (6) reports the corresponding predictions of the estimated model. As shown in column (7), for none of these moments is the predicted change different from the observed change in a statistically significant way, indicating good model fit.

Table A23: Estimated and Predicted Responses to Changes in Administrative Burden

(1) Moment Equation	(2) Firm Sizes	(3) Estimand	(4) Structural Representation	(5) Estimate	(6) Model Prediction	(7) P-Value
Equation (10)	1	$\frac{N_{vj1}}{N_{vj0}}$	$\frac{1-\Phi\left(\frac{-\bar{\Pi}_{vj1}}{\sigma_\pi}\right)}{1-\Phi\left(\frac{-\bar{\Pi}_{vj0}}{\sigma_\pi}\right)}$	0.989	0.996	0.959
				(0.0153)		
Equation (10)	2–5	$\frac{N_{vj1}}{N_{vj0}}$	$\frac{1-\Phi\left(\frac{-\bar{\Pi}_{vj1}}{\sigma_\pi}\right)}{1-\Phi\left(\frac{-\bar{\Pi}_{vj0}}{\sigma_\pi}\right)}$	0.994	0.991	0.980
				(0.0154)		
Equation (10)	6–21	$\frac{N_{vj1}}{N_{vj0}}$	$\frac{1-\Phi\left(\frac{-\bar{\Pi}_{vj1}}{\sigma_\pi}\right)}{1-\Phi\left(\frac{-\bar{\Pi}_{vj0}}{\sigma_\pi}\right)}$	0.992	0.992	0.998
				(0.0106)		
Equation (10)	22–104	$\frac{N_{vj1}}{N_{vj0}}$	$\frac{1-\Phi\left(\frac{-\bar{\Pi}_{vj1}}{\sigma_\pi}\right)}{1-\Phi\left(\frac{-\bar{\Pi}_{vj0}}{\sigma_\pi}\right)}$	1.012	1.000	0.943
				(0.0260)		
Equation (10)	≥ 104	$\frac{N_{vj1}}{N_{vj0}}$	$\frac{1-\Phi\left(\frac{-\bar{\Pi}_{vj1}}{\sigma_\pi}\right)}{1-\Phi\left(\frac{-\bar{\Pi}_{vj0}}{\sigma_\pi}\right)}$	1.043	1.000	0.830
				(0.0397)		
Equation (8)	All	$\mathbb{E}[\tilde{R}_{ij1}] - \mathbb{E}[\tilde{R}_{ij0}]$	$\sqrt{\frac{v(b-a)}{c+(d-1)v}}\left(\sqrt{a+\underline{I}_1}-\sqrt{a+\underline{I}_0}\right)$	701.0	701.0	1.000
				(353.2)		
Equation (9)	All	$\mathbb{E}[\tilde{P}_{ij1}] - \mathbb{E}[\tilde{P}_{ij0}]$	$\sqrt{\frac{c+(d-1)v}{b-a}}\left(\sqrt{a+\underline{I}_0}-\sqrt{a+\underline{I}_1}\right)$	-0.00874	-0.00846	0.875
				(0.00180)		
Equation (11)	All	$\frac{\left(1-\mathbb{E}[\tilde{P}_{ij1}]\right)-\left(1-\mathbb{E}[\tilde{P}_{ij0}]\right)}{1-\mathbb{E}[\tilde{P}_{ij0}]}$	$\sqrt{\frac{a+\underline{I}_1}{a+\underline{I}_0}}-1$	0.118	0.121	0.887
				(0.0245)		
Equation (14)	All	β_0	$\frac{(a+\underline{I}_{avg})(d-1)}{b-a}$	44.16	44.20	0.987
				(2.50)		
Equation (15)	All	β_1	$\frac{(a+\underline{I}_{avg})c}{b-a}$	33.91	33.93	0.996
				(2.34)		

Notes: Column (1) reports the equation that defines the moment to be estimated. Column (2) reports the number of providers associated with the firms to which the estimation sample is limited. Columns (3) and (4) report the estimand associated with the moment and the combination of structural parameters to which it is equivalent. Note that $\underline{I}_{avg} \equiv \frac{\underline{I}_0+\underline{I}_1}{2}$. For the moments associated with Equation (10), column (5) reports estimates of $\delta_1 + 1$ of Equation (12) with number of active firms as the dependent variable divided by the mean number of firms. For these estimates, an observation is a jurisdiction-wave-month-quintile, and the standard errors are reported in parentheses and clustered by jurisdiction. For the moment associated with Equation (9), column (5) reports estimates of $-\delta_1$ of Equation (12) with share of claims denied as the dependent variable. For the moment associated with Equation (8), column (5) reports estimates of δ_1 of Equation (12) with charges per provider as the dependent variable. Note that charges per provider are scaled by 5 to reflect estimation in the 20% sample. For these estimates, an observation is a jurisdiction-wave-month, and the standard errors are reported in parentheses and clustered by jurisdiction. For the moments associated with Equations (14) and (15), column (5) reports estimates of β_0 and β_1, respectively, of Equation (13). For these estimates, an observation is a firm-month, and the standard errors are reported in parentheses and clustered by firm size. Column (6) reports the predictions of the model using the parameters reported in Table 7. Column (7) reports the p-value of the observed estimate reported in column (5) under the null hypothesis that the model prediction reported in Column (6) is correct.

Figure A29: Relationship Between Firm Size and Denial Rate, Observed and Predicted



(a) Untransformed Variables

(b) Transformed Variables

Notes: Figure reports the observed and predicted average denial rate by firm size for firms with up to 800 providers. An observation is a firm-month. Firm size is determined by the number of providers in a jurisdiction billing under the same tax identification number. Predictions are generating using parameter estimates reported in Table 7.

In sum, comparing the predictions of the model to the observed relationships indicate that the model is matches the data well, lending support to the validity of the model and my estimates.

K Counterfactual Policies

In this appendix, I consider the effects of various counterfactual policy changes. These include assessing the effects of an investment subsidy like the one implemented by the HITECH Act of 2009 and providing participation subsidies to offset the firm exit effects of increased administrative burden.

First, I test the effect of the subsidy provided by the HITECH Act of 2009. This bill gave generous subsidies to health care providers for the meaningful use of electronic health records (EHR). These subsidies totaled up to $44,000 over 5 years for physicians who adopted EHR by 2014 (Wagner, 2009).[50] Previous research has found that this program sped the adoption of EHR, but at a very high cost due to the untargeted nature of the subsidies (Adler-Milstein and Jha, 2017; Dranove et al., 2015). While subsidies often must go to inframarginal agents, this program was particularly poorly targeted because subsidies were given to providers who had adopted EHR prior to the passage of the law. In light of this poor targeting, Dranove et al. (2015) estimate a cost of $48 million in subsidies to induce an additional hospital to adopt EHR for a total cost of $27 billion. This estimate may be a lower bound on the true cost to the government, though, as it ignores the change in health care spending that resulted from the additional investment in billing technology.

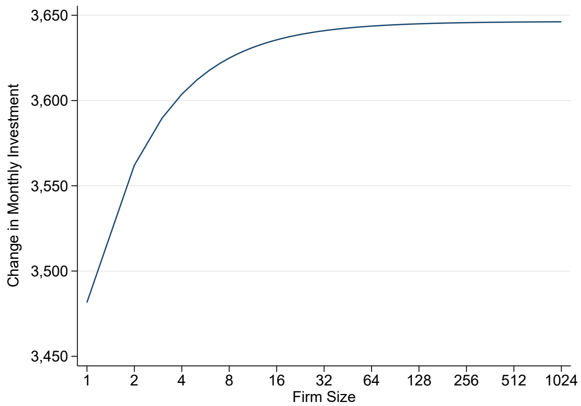
Using my model estimates, I am able to quantify the additional cost to the government of the subsidy program. Fleming et al. (2011) estimate the cost of adopting EHR for small physician practices amounts to $46,659 per physician in the first year, meaning the HITECH Act gave a 38.6% subsidy up to $1,500 of investment per physician per month.[51] The model estimates imply that all providers are induced to invest enough to fully exhaust the subsidy and no more, meaning all firms increase private investment such that the additional cost is $2,386 per provider per month. Because the average unit cost of investment is declining in firm size, this means that larger firms can invest more for the same per-provider cost, as shown by Figure A30. This leads profits to increase for all firms, but more so for larger ones. However, because smaller firms are closer to the exit threshold, this subsidy increases the number of active small- and medium-sized firms, as shown by the figure.

The subsidy program has a sizable effect on market structure, increasing the number of single-provider firms by 2.4% and the number of firms with six providers by over 7%. While this is a meaningful change, it is very costly, entailing direct subsidy payments of $1500 per provider. Furthermore, the direct costs to the government of the subsidy are much smaller than the addi-

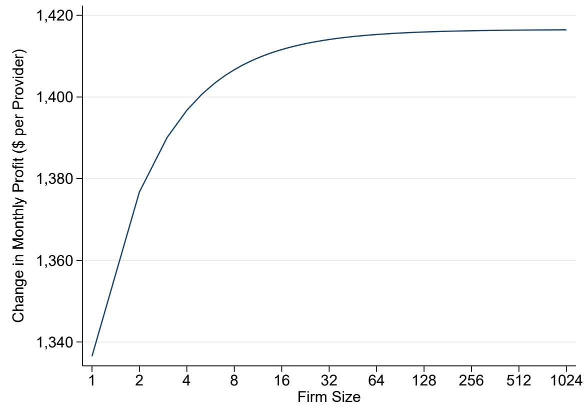
[50] Compounding the incentive to adopt EHR, physicians that had not yet adopted EHR faced a reduction of Medicare payment of 1% in 2016, which grew to 3% by 2018.

[51] Note that I assume the 38.6% subsidy is on the marginal investment. The actual HITECH Act also gave subsidies to entities that had already adopted EHR, may not have subsidized the marginal investment for firms that were far from adopting EHR, and was not continuous in the amount spent on adopting EHR. I abstract from these issues in this counterfactual and instead consider the best-targeted version of this subsidy.

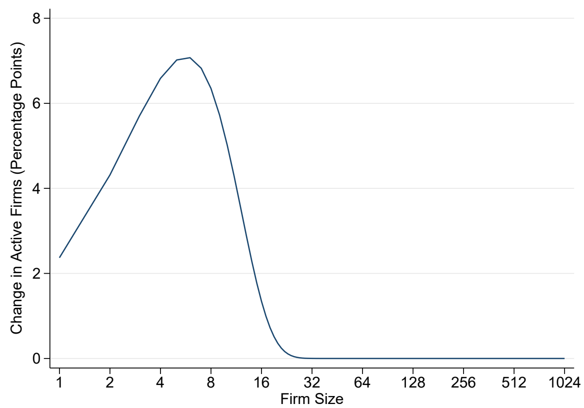
Figure A30: Change in Equilibrium Outcomes by Firm Size with HITECH Subsidy



(a) Investment



(b) Profit per Provider



(c) Active Firms

Notes: Change from equilibrium outcomes implied by parameters presented in Table 7 under 38.6% marginal subsidy up to $1,500 per provider. Panel (a) reports the change in the profit-maximizing monthly level of investment. Units of investment are scaled so that one unit of investment induces a $1 increase in charges per provider. Panel (b) reports the change in the monthly per-provider private cost (net of the subsidy) of the profit-maximizing level of investment. Panel (c) reports the change in the equilibrium monthly profit per provider. Note that the horizontal axes of all figures are spaced geometrically.

tional cost of paying claims that would otherwise have been denied. The HITECH subsidy induces substantial additional investment (as it was intended to), but this additional investment results in providers being able to bill much more efficiently, leading to an increase in Medicare spending of over $3700 per provider per month. This means that direct subsidy payments constitute less than 30% of the total cost of the subsidy program to the government. Aggregating these costs nationally indicates that insofar as the subsidy program induced the additional investment it was intended to, the costs in terms of additional Medicare spending could be as much as $49 billion in addition to the subsidy payments of $19 billion.

As a final counterfactual, I consider a subsidy regime designed to prevent exit in response to an increase in administrative burden, where the size of the required payment depends on the ability of the government to target the subsidies. Suppose first that the government were able to offer subsidies based only on the size of the firm. In order to lower the expected number of exits below one for each firm size, subsidies would have to be offered to firms with up to 23 providers, with the subsidy amounts ranging from \$205 to \$2,884 per firm per month depending on their size. The total cost of such a subsidy program to offset a national transition from a low- to high-denial administrator would be \$1.1 billion per year. By contrast, the cost of the subsidy program could be greatly curtailed with better—albeit unrealistically precise—targeting. If subsidies were given only to those firms that would otherwise exit and each firm received a subsidy amount that made them indifferent between exiting and remaining in the market, the total cost would be only \$3.8 million. Thus, with perfect targeting the same market structure could be maintained much more cheaply, although this represents a lower bound on the cost. Nonetheless, the high cost of imperfectly targeted subsidies indicates that the negative effects of increased administrative burden would likely be difficult to offset.