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

Riley League*

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The US health care system is rife with administrative burdens, but little is known about their causal effects on provider behavior. Using exogenous changes to the jurisdictions of Medicare Administrative Contractors, I show that the resulting increase in claim denials causes providers to adopt cost-saving technologies, bill more aggressively, and consolidate into larger practices. Despite denying more claims, Medicare spending increases as a result of providers' endogenous responses. I explain this counterintuitive result using a model of firms' investment in billing effort and technology. Estimates from this model show that investment costs amount to $89 billion per year and that increasing administrative burdens reduces providers' profits by 4-6% while raising Medicare spending, thus making both providers and the government worse off. Counterfactual simulations indicate that increased administrative burdens would result in substantial reductions in health care spending were providers unable to adjust investment, highlighting the short-run incentives insurers may have to raise administrative burdens.

*Department of Economics, Duke University

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 administrative burdens, finding that they lead to increased consolidation and higher health care spending.

To identify the impact of administrative burdens 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, Medicare has made exogenous changes in the assignment of jurisdictions to administrators, which allows me to identify each contractor's causal effect on denials and assess how providers react to changes in the burdens they face. This variation allows me to assess the responses of the same providers and the same patients to a new administrative regime and thus provide the first evidence on how entire health care markets react to changes in the burdens they face from claim denials.

Studying the impact of exogenous 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., 2021), 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 consolidation of Medicare administrative jurisdictions over time, with the number of jurisdictions falling from 58 to 12 during my sample period. This consolidation has resulted in providers and patients being exposed to different administrators and, therefore, different administrative burdens. 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%.

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 1% of practices exit the market, with this result being driven by single-provider firms; this leads to a 1.1% increase in the size of the average practice remaining after the transition and the share of providers in solo practice falling by 1.2%. 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 discernable 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 a 4.5% *increase* in total Medicare spending. Although payers typically intend for administrative burdens to curtail health care spending, I find they have the opposite effect.

I explain these counterintuitive results with a model of providers choosing the profit-maximizing level of investment in billing effort and technology meant to increase charges and avoid denials. When faced with a greater 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 outweighs the increase in denials, resulting in a net increase in Medicare spending. With Medicare spending more and practices earning less due to their higher costs, increased administrative burdens ultimately make both parties worse off. 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.

Using indirect inference to estimate a parameterized version of my theoretical model, I find billing costs are over $5,700 per provider per month, or $88.7 billion in total billing costs in 2017. Furthermore, I find raising administrative burdens lowers firm profits by 3.7–4.6% depending on the size of the firm while raising Medicare spending, indicating that on the margin, high levels of administrative burden make both the government and providers worse off.

In counterfactual simulations, I find support 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, claim payouts 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 lowers profits for both providers and insurers.

This study contributes to a burgeoning literature on administrative costs in the health care sector. That the burdens are high is well established: the US spends much more on administrative costs than other rich countries. For example, the US has 76% more non-clinical health care workers per capita than Canada, and US physicians spend 69% more of their time on administrative tasks than Canadian physicians do (Pozen and Cutler, 2010). 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).

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 barriers 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 barriers 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, 2022) 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 and highly salient administrative burdens studied by previous research, however, my results show that claim denials increase overall health care spending as providers invest in billing technology to circumvent this burden.

In this way, my results align with a smaller literature that highlights the negative consequences of administrative burdens beyond their potential to waste scarce resources. Perhaps most related, Dunn et al. (2021) find that providers respond to high Medicaid denial rates by declining to accept Medicaid patients. In different contexts, multiple studies have found administrative ordeals limit enrollment in health and social insurance programs as well (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 administrative burdens.

My research stands apart from existing work on administrative burdens in two key ways. First, this paper studies plausibly exogenous changes in administrative burden, whereas most existing research (e.g., Dunn et al., 2021; Shi, 2022; Ganju et al., 2022) has focused on cross-sectional differences across space because payers rarely alter the administrative costs they impose in a manner large enough to discern a response from providers and providers are rarely assigned to new payers or administrators exogenously like they are in my setting. Second, the shocks to administrative burden that I study are large and felt by nearly all providers. While studies of more narrowly tailored administrative burdens like prior authorization (Eliason et al., 2021; Brot-Goldberg et al., 2022) and automatic claim adjudication (Macambira et al., 2022) are important for understanding how providers react to well-targeted burdens, they have little to say about the broader implications of the high levels of administrative burden endemic to the health care system. By contrast, all medical providers engage in billing and face the threat of claim denials. Furthermore, the administrative burdens imposed by Medicare are especially likely to reflect the broader consequences of administrative costs because Medicare has such a large influence on the health care sector. Traditional Medicare represents the largest single 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). In light of Medicare's outsize influence on the health care system, responses to the administrative burdens it imposes are more likely to reflect the most important consequences of administrative costs, such as changes in market structure.

More narrowly, this paper also advances our understanding of the impact of Medicare's administrative structure on the health care system. 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, my study is the first to document the large differences in overall stringency of Medicare contractors and the consequences of these differences.

My research also provides new evidence on the drivers of consolidation in the health care sector. Although many economists have emphasized that consolidation leads to higher prices and profitability for providers, 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 bear easily (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. A large literature has shown the negative consequences of this consolidation, 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 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). Because I find that administrative burdens are a precursor to consolidation, reducing these burdens for providers could have ancillary benefits for the entire health care system.

This relates closely to the drivers of consolidation more broadly, and in particular how regulations 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). Reducing competition is often an unintended consequence of regulation, but incumbent firms often encourage regulation in order to insulate themselves from competition (Stigler, 1971). I provide novel evidence that regulation also disproportionately favors large firms in health care markets as a result of the administrative burden it imposes on providers.

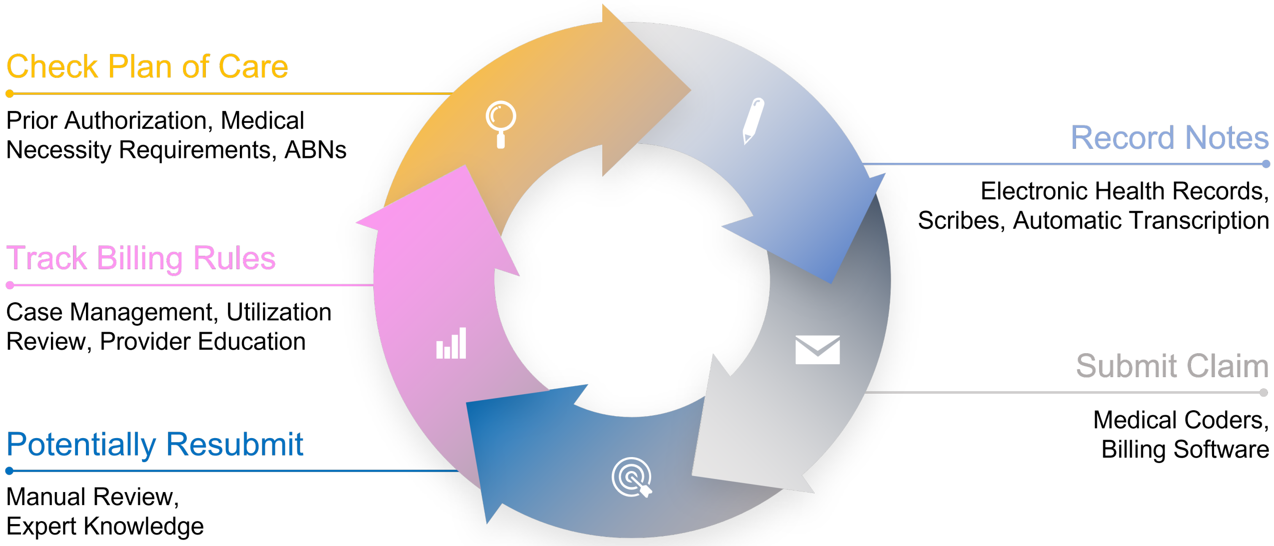
The remainder of this paper is structured as follows. Section 2 describes the health care billing process and provides background on Medicare Administrative Contractors. Section 3 describes the Medicare claims and other sources of data I use in this paper. Section 4 presents evidence that Medicare contractors differ in the administrative burdens they impose on providers and lays out my empirical strategy for using this variation to understand how providers respond to increases in administrative burden. Section 5 presents a theoretical model of investment in billing technology that generates empirical predictions tested in Section 6. Section 7 presents estimates of a parameterized version of my theoretical model. Section 8 concludes.

2 Institutional Context

2.1 Medical Billing Process

The medical billing process is characterized by complexity: multiple insurers with different billing rules, multiple coding systems and forms, and multiple administrative requirements that can be opaque and arbitrary. Figure 1 briefly sketches the costs incurred in a medical practice's billing cycle and the ways that firms can invest in billing technology to overcome administrative burdens. The figure (and my description here) abstract from many sources of administrative costs, including those required for checking a patient's insurance status and collecting payment from patients, along with the difficulties that come from having to bill multiple insurers with diverse requirements. The first step of the cycle requires checking that the care the provider plans to render accords with all the known requirements and sometimes getting explicit permission from insurers or patients before then engaging in extensive documentation of the encounter using a variety of technologies, like electronic health records, voice-to-text technology, or employing staff members called scribes to record these notes. These notes must then get translated

Figure 1: Billing Cycle



Notes: Author's description of a medical practice's billing cycle and the investments in billing technology that can improve the efficiency of the process. Template for graphic is from `https://slidesgo.com/`.

into a claim that will be sent to the insurer to request payment. This is also usually done by administrative staff (called coders), often with the assistance of billing software. Once the claim is submitted the insurer 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 what is essentially an onerous revise and resubmit process that may not ever result in payment. Finally, as this process plays out the administrative staff of the practice try to learn about what works and what doesn't for this one insurer and this one type of patient and enact policies and programs that attempt to avoid denials in the future. This involves educating providers about the billing rules, performing utilization review to identify potential areas of improvement, and implementing case management programs to better guide care throughout the process.

As this process makes clear, claim denials are costly. This breakdown leads to two types of costs. First, denials themselves are costly in terms of foregone revenue and the substantial costs associated with resubmitting a denied claim. 54 billion dollars' worth of claims are denied annually, leading to substantial lost revenue for providers (Gottlieb et al., 2018). In addition, claim denials require substantial additional effort on the part of administrative staff to resolve.[1] The second and more indirect cost of claim denials is the entire billing apparatus of medical practices, which exists to avoid claim denials. Claim denials represent a breakdown of the entire

[1]Dunn et al. (2021) estimate that foregone revenue represents two-thirds of the cost of having a claim denied by Medicare while resubmission costs account for the remaining third.

billing process, meaning that their frequency is an excellent proxy for the broader administrative costs imposed by the onerous and complicated billing system present in health care.

Throughout the billing cycle, providers can make a number of investments to avoid these costly claim denials. These investments can occur at various points in the process and include hiring staff to take notes, submit claims, or review outcomes as well as purchasing IT infrastructure that does the same, like electronic health records and billing software. I refer to these various investments collectively as billing technology, and, as I'll show below, providers increase this investment in response to increased denials.

Denials can occur for countless reasons, but they are often capricious and generally purely administrative. Of the top 6 denial reasons reported by one Medicare contractors, 4 of them are purely about the way care is documented and reported rather than 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 more substantive documentation issues, there is significant uncertainty as to which claims will be paid, with 6.4% of the claims in my sample being denied and CMS reporting that of the claims that get paid, over 6% should not have been.[3] Thus, while there are ways for medical practices to invest in effort to avoid claim denials, their often-arbitrary nature makes some denials inevitable.

2.2 Medicare Administrative Contractors

Traditional Medicare is often thought of as a monolithic, federally-run insurance program (NBPAS, 2021).[4] 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 have distinct regional jurisdictions in which they operate. 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.[5]

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—

[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).

[3] CMS (2020) reports an improper payment rate of 6.27% or $25.74 billion for Traditional Medicare in 2020.

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

[5] According to CMS (2022b), 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 Medicare spending, investment, or market structure.

they must avoid 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). While there are a few examples of the federal government providing more specific guidance on whether certain services meet this standard, in general, these determinations are left to the local contractors.[6] And while some of these coverage rules are stark declarations that a given service will not be reimbursed in any circumstance, it is much more common that these rules delineate the circumstances under which the service will be reimbursed, including the allowed frequency or place of service, permissible indications, or billing or documentation rules. These rules are disseminated to health care providers through direct communication and provider education programs as well as through the administrator posting documents called Local Coverage Determinations and Articles, which are posted online.[7] These coverage rules are generally enforced automatically by checking claims against claim edits, formalized billing rules built into the administrator's claims processing apparatus. Claims are also often reviewed manually by administrators. These processing systems are highly imperfect, featuring claims processing errors as well as significant leeway in how stringently to enforce administrative and billing rules.

Administrators are contracted to provide administrative services for distinct regional jurisdictions determined by the Centers for Medicare and Medicaid Services (CMS). The contract for each jurisdiction is assigned to a contractor using a procurement auction run by the federal government in which bids are scored based on quality and cost. Awarded contracts have a cost-plus structure, meaning that contractors are reimbursed for their costs plus a small bonus incentive contingent on good performance. 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).[8]

Across jurisdictions, the coverage rules implemented by each administrator often vary widely. For example, an inspector general report found that in 2011 35% of procedures were subject to Local Coverage Determinations only in some jurisdictions, while 59% of procedures were subject to an LCD issued by at least one administrator (Levinson, 2014a). These differences in rules

[6]The federal government can specify 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. Analogous to the Local Coverage Determinations (LCDs) issued by the local contractors are the National Coverage Determinations (NCDs) issued by the Centers for Medicare and Medicaid Services. NCDs supersede LCDs and are made when "the service is the subject of substantial controversy" surrounding the item or service (Centers for Medicare and Medicaid Services, 2003). One prominent recent example of this is the NCD limiting coverage of the controversial Alzheimer's drug Aduhelm (Centers for Medicare and Medicaid Services, 2022).

[7]Current Local Coverage Determinations can be found at `https://www.cms.gov/medicare-coverage-database/`.

[8]More details on these contracts are available in Appendix A.

may stem from the large differences in medical practice across jurisdictions, with administrators of some areas reacting to perceived overbilling or accommodating local innovations in their jurisdictions (MedPAC, 2018). However, this variation also likely stems from the idiosyncratic tastes of the administrators and persistent differences in corporate culture or taste for imposition of administrative burdens. To that end, while the use of multiple administrators can encourage more locally tailored coverage rules, the current differentiation of coverage rules is commonly seen as indicative of inefficiency (Levinson, 2014a).

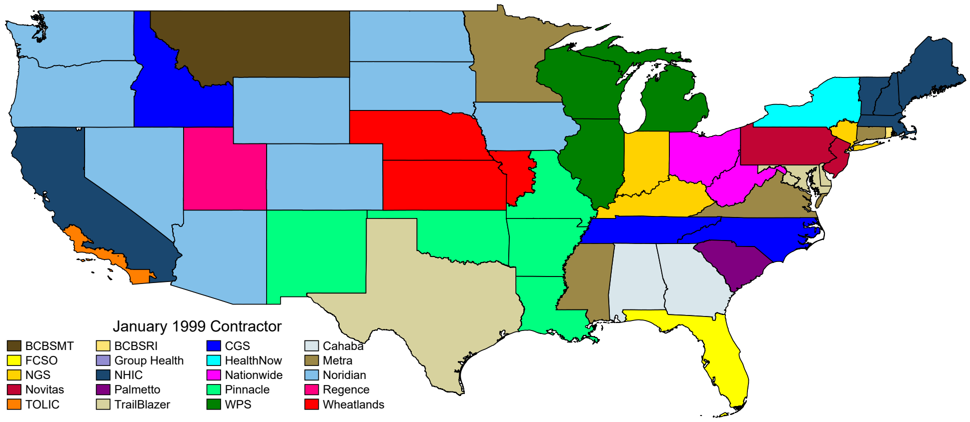
In response to the apparently arbitrary differences in coverage rules across jurisdictions, the federal government reduced the number of contracts and increase their size (Levinson, 2014a). At the beginning of my sample, there were 26 active administrative companies operating in jurisdictions that sometimes spanned state borders (e.g., the Washington, DC area) or were strict subsets of states (e.g., New York). Since the mid-2000s, CMS has gradually reduced the number of jurisdictions, combining multiple states to be under the same contracted jurisdiction. Figure 2 shows that the number of companies administering Traditional Medicare has decreased significantly over the last two decades as CMS reduced the number of jurisdictions from 58 in the early 2000s to 12 today.[9]

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). This means that the recent consolidation in jurisdictions has led to many changes in the coverage rules faced by providers. I observe 59 areas transitioning between contractors during my sample, and these transitions are likely exogenous to the previous denial rates in the local jurisdictions. The original jurisdictional boundaries were set in 1960s and were primarily determined by existing health insurers' ability to quickly implement the then-new Medicare program (Mennemeyer, 1984). The recently consolidated jurisdictions 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). This indicates that the presence of an administrator in a jurisdiction was not determined by the expected impact of that administrator on the denial rate, so examining how the denial rates changes following a change in administrator can plausibly recover the causal effect of the administrator on denials.

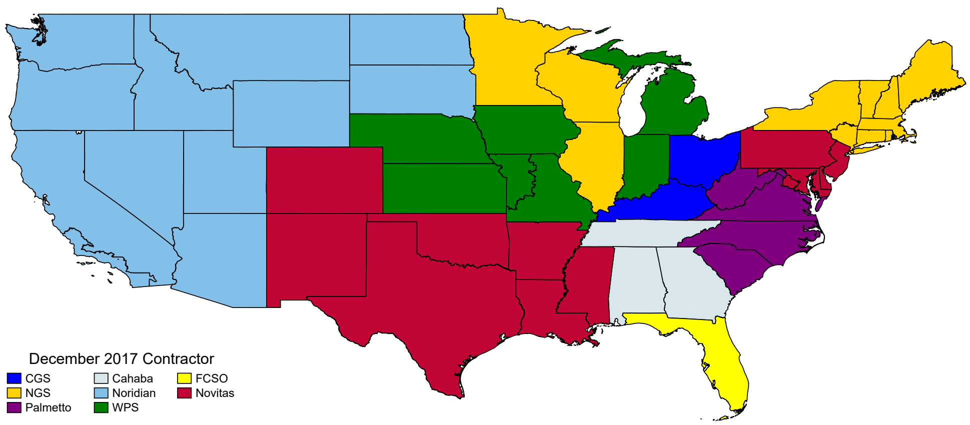
[9]At the beginning of my sample, Medicare Part B claims were processed by entities called "carriers" and Part A claims were processed by "fiscal intermediaries." In addition to consolidating the regional jurisdictions these entities administered, CMS also combined the functions of processing Part A 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 2: Contractor Changes from 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.

3 Data

The primary data used for this project come from a 20% random sample of Medicare claims for physician services (called the carrier file) from 1999–2017. 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., 2021) 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. 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.[10] 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 construct jurisdiction-month-level counts of the number of active TINs.

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 costs relate to EHR adoption. These data report the share of office-based physicians that have adopted basic EHR technology, 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. These data are available from 2010–2015, a period of rapid growth in the adoption of this technology.

Table 1 reports summary statistics for my data at the jurisdiction-month level, including the mean and standard deviation of the outcomes and covariates used in the 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., 2021) that 7.3% 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 3, 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.

Table 2 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

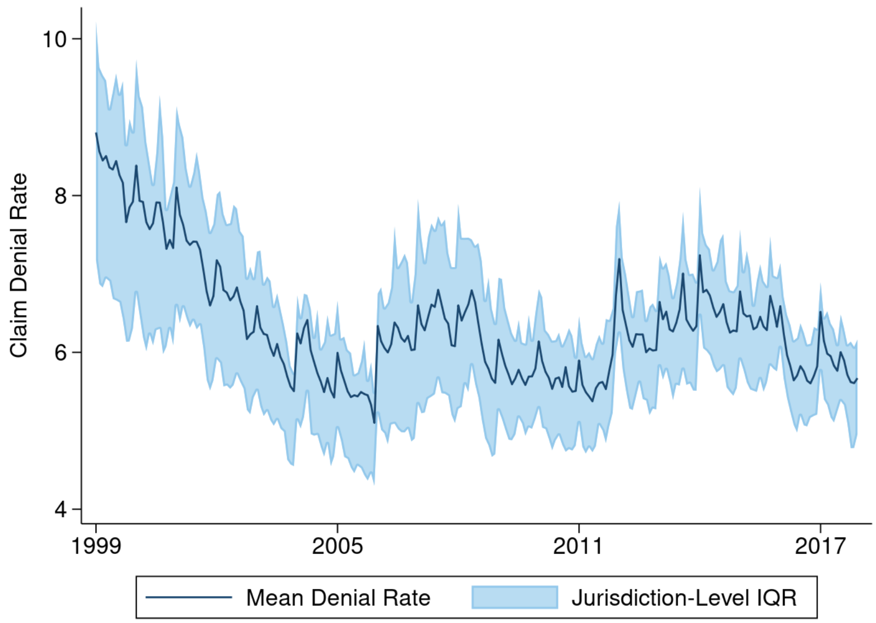
[10] In particular, large group practices may bill under multiple TINs, inflating the apparent number of firms and decreasing their apparent size. Furthermore, when a practice is acquired or merges with another practice or with a hospital, providers may continue to bill under the same TIN.

Table 1: 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	43.00	14.86
Providers per Firm	3.885	1.160
Active Firms	4555	4473
Controls		
Beneficiaries (thousands)	114.4	99.51
Average 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	4.388
Percentage Disabled	16.13	3.974
Observations	12,996	

Notes: Percentage of providers with electronic health records (EHR) is defined at the state-year level from 2010-2015. Providers per firm is the average 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. Both firm-related variables are reported at the jurisdiction-month level and defined starting in 2006. All other variables are reported at the jurisdiction-month level from 1999-2017. ESRD and disabled percentages report the share of Medicare beneficiaries eligible for Medicare due to end-stage renal disease or disability.

Figure 3: Denial Rate Over Time



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

less than 5% for Wheatlands to over 11% for Metra. 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 these changes. 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. This jurisdictional consolidation induced exogenous variation in the areas admin-

Table 2: 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 1999-2017. 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 a different contractor from 1999-2017. Observation count is given by the number of jurisdiction-months the contractor administered from 1999-2017.

istered by each contractor, with 59 jurisdictions transitioning between administrative companies 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,[11] X_{jt} is a vector of observable jurisdiction-level beneficiary characteristics,[12] and γ_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,[13] and ε_{jmt} is a jurisdiction-contractor-month specific error term, which I allow to be arbitrarily correlated within a jurisdiction over time and across jurisdictions within each month. 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) 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

[11] In Appendix B, I use alternative measures of administrative burden including claim line denial rates and the share of 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.

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

[13] In Appendix C, I show that the estimated fixed effects are robust to a more or less flexible jurisdiction-specific time trend.

the event window, which I generally define to be 18 months before and after transition.[14] 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 times (although with different time values). I then estimate

(2)

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

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. These fixed effects account for the fact that control observations may appear more than once in this stacked data set. 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 lower-denial administrators. This comparison is 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. Given the exogenous nature of the assignment of administrators to jurisdictions, I have no reason to believe this is the case.

Similarly, I estimate the transition dynamics regardless of the administrators between which the jurisdiction is transitioning:

$$Y_{jtw} = \sum_{e=-K}^{-2} \beta_e T_{jtw}(e) + \sum_{e=0}^{L} \beta_e T_{jtw}(e) + \Gamma X_{jtw} + \alpha_{jw} + \eta_{tw} + \varepsilon_{jtw}. \tag{3}$$

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

[14] In unreported robustness checks, I have also verified that my results are robust to alternative treatment windows as well as limiting the control group to only jurisdictions that are not administered by either of the contractors involved in the transition of the jurisdiction in question as well as limiting my analysis to the 41 jurisdiction transitions that correspond to the creation of new Medicare Administrative Contractor jurisdictions rather than also including transitions that occur when an incumbent administrator loses a potentially unchanging contract.

denial rate elsewhere, can be attributed to the transition.

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 context considered by Cengiz et al. (2019) to allow for a unit to be treated multiple times. Specifically, I can allow jurisdictions to transition between contractors multiple times.

In addition to understanding how transitions between Medicare contractors affect administrative burden, I can employ the same estimation strategy to understand how provider behavior and market outcomes change following contractor transitions. In Section 6, 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 my 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

$$(4)\quad Y_{sy} = \sum_{e=-3}^{-2} \beta_e T_{sy}(e) + \sum_{e=0}^{4} \beta_e T_{jtw}(e) + \sum_{e=-3}^{-2} \delta_e T_{sy}(e) \times U_s + \sum_{e=0}^{4} \delta_e T_{jtw}(e) \times U_s + \alpha_s + \alpha_y + \varepsilon_{sy}$$

using the traditional two-way fixed effects estimator (i.e., not stacked regression), where Y_{sy} is the share of physicians having adopted basic EHR technology in state s in year y. To address 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 3 gives the estimated effect of each contractor on the share of claims denied.[15] 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 least (TOLIC). This represents a substantial difference given the mean denial rate is only 6.4%. Furthermore, the causal differences are not perfectly reflected in the raw denial rates of each

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

contractor reported in Table 2, 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 of the coefficients reported in Table 3 yields an F-statistic of 278, indicating statistical significance at a confidence level 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 B.

The differences in denial rates manifest themselves immediately upon the transition of a jurisdiction between contractors. Figure 4 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.[16] 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%.

In addition to transitions to higher-denial administrator representing persistent increases in administrative burden, transitions to lower- as well as higher-denial administrators represent acute shocks to administrative burden. Figure 5 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 5c shows that when aggregating across low-to-high and high-to-low 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 9.7% increase from the baseline rate of 6.3%. 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 regime, as documented qualitatively by the Government Accountability Office.[17] This

[16]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. Furthermore, in unreported robustness checks, I show that for transitions between contractors with larger differences in their estimated effect on denial rates, the change in denial rates is larger.

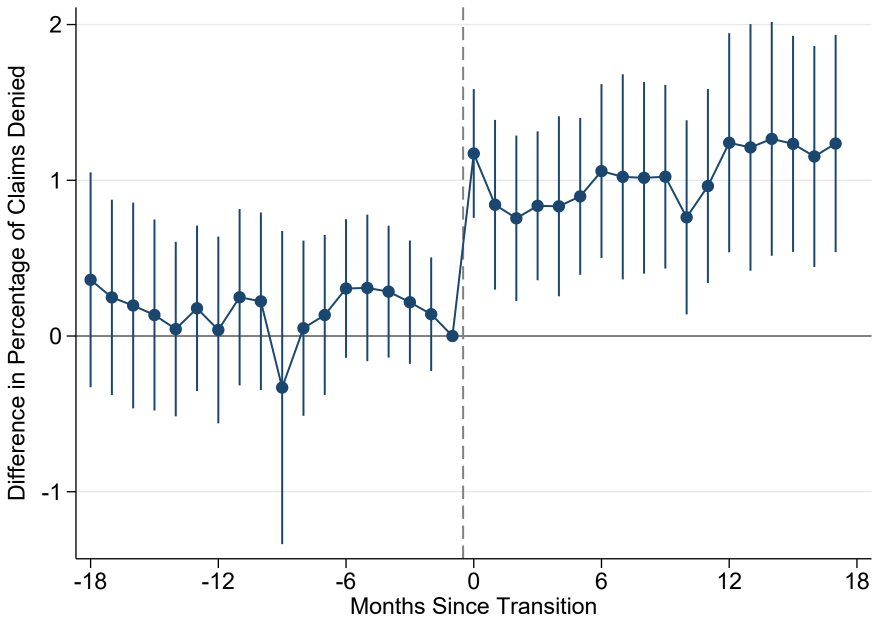
[17]GAO (2015) reports that the government "did not require Medicare Administrative Contractors to make this change (to stricter coverage rules) clear, causing payment denials providers did not anticipate," with provider groups reporting "a lack of clear communication. . . which caused confusion once 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.

Table 3: Estimated Effect of Each Contractor on Denial Rates

	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	6.37	
R^2	0.8037	
Observations	12,996	

Notes: Estimates of γ_m of Equation (1). An observation is a jurisdiction-month. The excluded contractor is Noridian. Dependent variable is the share 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%, 1% and 0.1% level, respectively.

Figure 4: Estimated Effect of Transition to Higher-Denial Administrator on Denial Rates



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

pattern is also reflected other measures of administrative burden analyzed in Appendix B.

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 Theoretical Framework

Changes in administrative burden could lead to a number of different responses by providers. Prior research has highlighted that providers have responded to burden by changing their billing practices (Ganju et al., 2022), the patients they accept (Dunn et al., 2021), the drugs they prescribe (Brot-Goldberg et al., 2022), and even whether they participate in the market at all (Eliason et al., 2021). Shi (2022) 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 final investment channel, generating testable empirical predictions that I will show in Section 6 are borne out in the data.

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

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

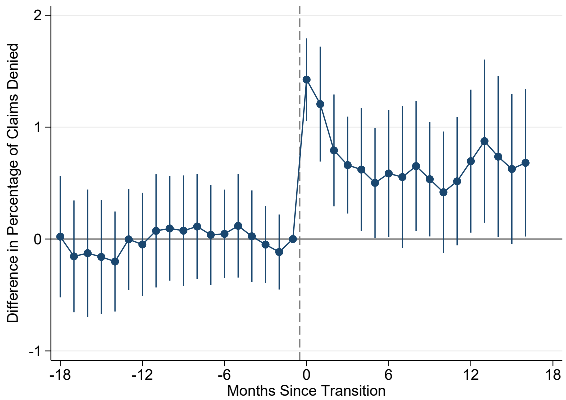
This investment can take many forms, including adopting information technology infrastructure like electronic health records, hiring additional staff to manage the revenue cycle and convert physician notes into medical claims, or other types of effort and investments that make billing easier.

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 I assume 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 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 (Sacarny, 2018; Ganju et al., 2022).[18] For this reason, I assume that the charges per visit net of the cost of care $r(I) \geq 0$ are increasing in investment.[19]

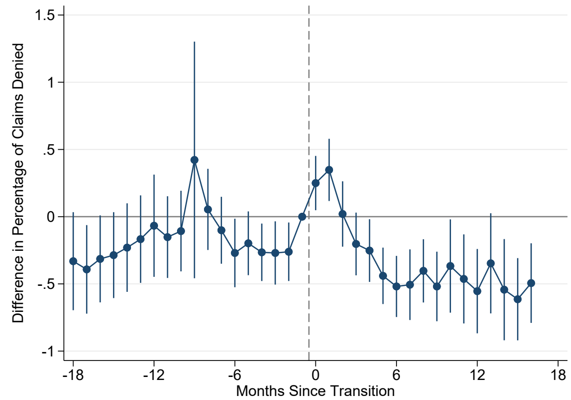
[18]This behavior is often worrying to policymakers (Silverman and Skinner, 2004; Dafny, 2005; Dafny and Dranove, 2009), although it can also represent an improvement in coding accuracy (Gowrisankaran et al., 2016). The model is agnostic on this point.

[19]I also assume that $p(\cdot)$ and $r(\cdot)$ are twice continuously differentiable and that $p(0) = 0$.

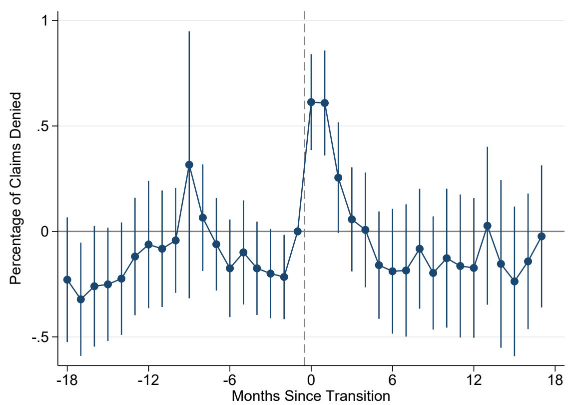
Figure 5: Denial Rate and Transition Dynamics



(a) Transition to Higher-Denial Administrator



(b) Transition to Lower-Denial Administrator



(c) All Transitions

Notes: Estimates of β_e of Equation (3) for $e \in \{-18, \ldots, 17\}$. An observation is a jurisdiction-wave-month. Dependent variables are the share of claims denied, the average number of days from a service being rendered to the final claim being processed, and the churn in charges by diagnosis and procedure from the previous month. 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.

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 technology.

The firm's costs are given by the product of the unit cost of investment c and the quantity of investment $I \geq 0$. 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 7, I relax this assumption.

Under mild conditions,[20] the profit-maximizing level of investment I^* is given by

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

The first of these terms represents the marginal increase in variable profit due to additional investment lowering the share of charges that are denied, the second term represents the marginal increase in variable profit coming from investment increasing charges per visit, and the final term is the marginal cost of investment. Thus, firms must trade off the additional variable profits generated by investment against its cost.

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 may increase the denial rate for all levels of investment ($p_1(I) \leq p_0(I)$ for all I), meaning that it is more difficult to extract payment from insurers with a given technology. The second, more subtle way that increased administrative burden may operate in this model is by improving the ability of billing technology to reduce denials ($\frac{\partial p_1}{\partial I} \geq \frac{\partial p_0}{\partial I}$ in a neighborhood around 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. Claim denials arise because complicating 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).

[20] The first condition is that the profit function is concave at I^*:

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

For this to be true, it must be that investment exhibits diminishing marginal returns in terms of extracting 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. The second condition is that

$$\Pi(I^*) = p(I^*) r(I^*) v - cI^* \geq 0.$$

Otherwise the firm will not invest and will make 0 profit.

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 technology to raise the charges per visit becomes less attractive when the yield rate of those charges goes down. To see this mathematically, note 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.[21] The second "return to billing" channel serves to raise the equilibrium level of investment because it increases the marginal benefit of investing in billing technology. Mathematically, 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 also positive.

Which of these two effects dominates is theoretically ambiguous such that the equilibrium level of investment will increase in response to higher administrative burden only if the marginal profit from investment $f(\cdot)$ using the new denial function $p_2(\cdot)$ at the old equilibrium level of investment I^* is positive:[22]

$$\begin{aligned} f(I^*; p_2(\cdot), r(\cdot), v, c) &> 0 \\ \frac{\partial p_2}{\partial I^*}r(I^*)v + p_2(I^*)\frac{\partial r}{\partial I^*}v - c &> 0 \\ \frac{\partial p_2}{\partial I^*}r(I^*) + p_2(I^*)\frac{\partial r}{\partial I^*} &> \frac{c}{v}. \end{aligned}$$

This model generates a number of empirical predictions that I am able to assess using the changes in administrative burden represented by contractor transitions. First, while a larger burden can cause investment to increase or decrease, it will cause charges to move in the same way as investment.[23] Second, large firms will invest more because the fixed cost of investment does not depend on volume while the benefit of investment does.[24] Finally, increasing administrative burden will lower firm profits, particularly among small firms that are closer to the threshold of exit.[25]

[21] This result is an application of the implicit function theorem. It is positive because charges are increasing in investment $\left(\frac{\partial r}{\partial I} \geq 0\right)$, volume is positive, and $\frac{\partial f}{\partial I^*}$ is negative (because I^* is the profit-maximizing rather than profit-minimizing level of investment)

[22] This condition is also sufficient if combined with the condition that the firm continues to operate in light of the new level of burden: $\Pi(I') > 0$.

[23] This is because of my assumption that $r(\cdot)$ is an increasing function.

[24] To see this, note that $\frac{\partial I^*}{\partial v} = -\frac{\partial f}{\partial I^*}^{-1}\frac{c}{v} > 0$.

[25] On the first point, note that $\frac{\partial \Pi(I^*)}{\partial p} = r(I^*)v > 0$ and $\frac{\partial \Pi(I^*)}{\partial \frac{\partial p}{\partial I^*}} = 0$ by the envelope theorem. On the second, note that small firms are less profitable: $\left(\frac{\partial \Pi(I^*)}{\partial v} = p(I^*)r(I^*) > 0\right)$.

6 Effects of Increased Burden

In this section, I show that providers react to increases in administrative burden by investing in technology that allows them to bill more aggressively and that the predictions of my theoretical model are supported by the data.This leads to my final, counterintuitive finding: increased denials *raise* Medicare spending.

6.1 Increased Burden Spurs Investment

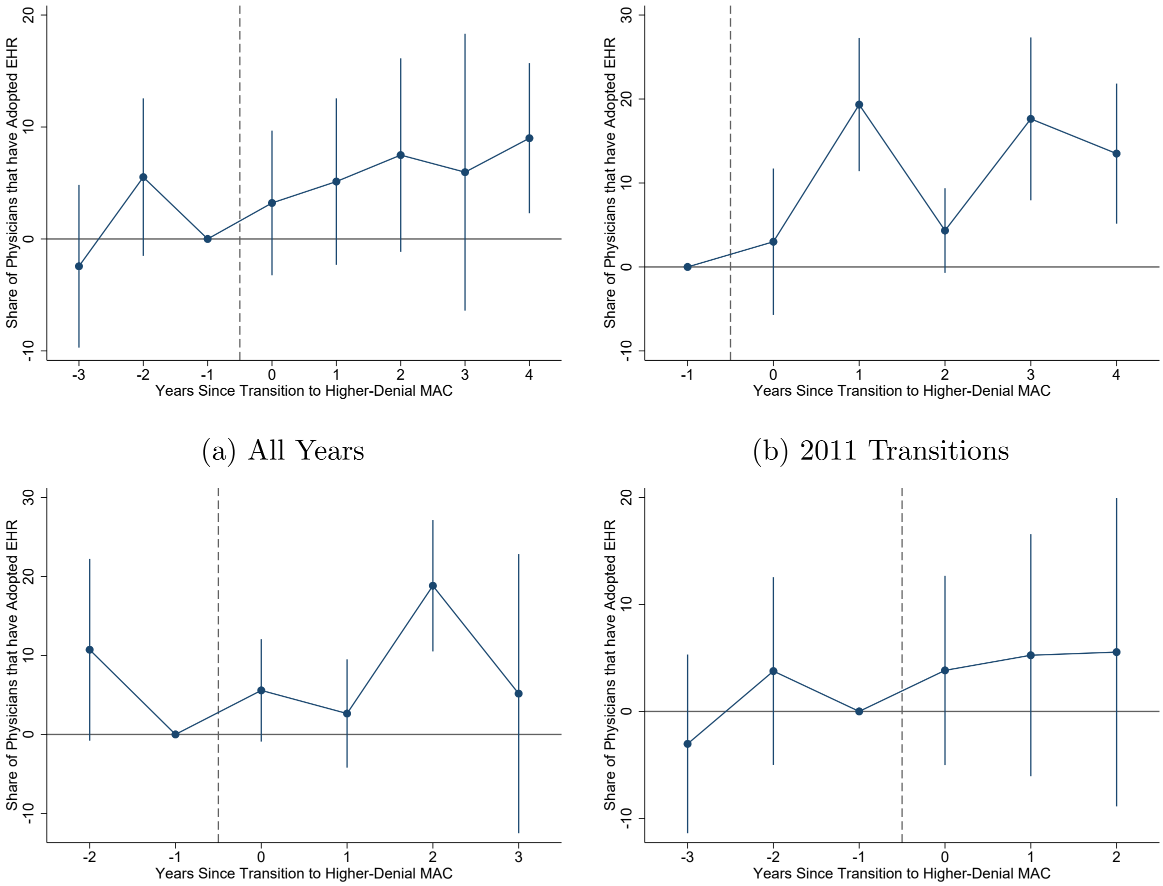
First, I show that investment in billing technology increases following a transition to a higher-denial contractor. Increased administrative burdens may lead providers to adopt electronic health record (EHR) technology, a bundle of services that promise to make billing easier by automating more of the 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, 2022) as well as lower costs of billing (Gowrisankaran et al., 2019). Figure 6 presents estimates of the difference in EHR adoption rates in states 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.

In line with this, I see that the charges submitted by providers to Medicare also increase following transitions to higher-denial administrators. Figure 7 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 7, charges are $47 per capita and 6 log points higher 18 months after transitioning to a higher-denial-rate contractor, an increase of 6.2–7.6%. This increase in charges is consistent with firms investing more in technology and expending more effort to make billing easier and extract more charges from each visit.

6.2 Larger Firms Invest More

Next, I show evidence consistent with larger firms investing more in billing technology. 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. Table 5 reports estimates of the association between firm size and denial rate within jurisdiction-month and with various weighting schemes. Even adjusting for jurisdiction-month specific differences in administrative burden and the standards

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



(a) All Years

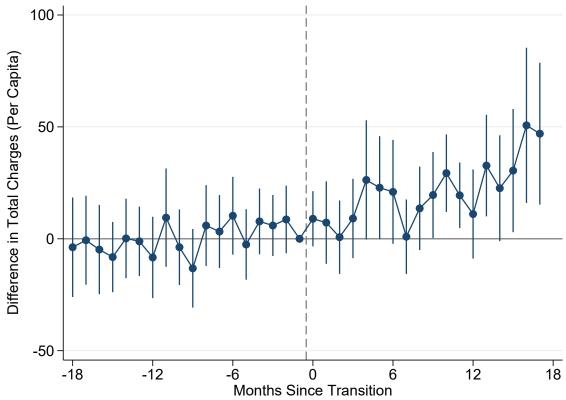
(b) 2011 Transitions

(c) 2012 Transitions

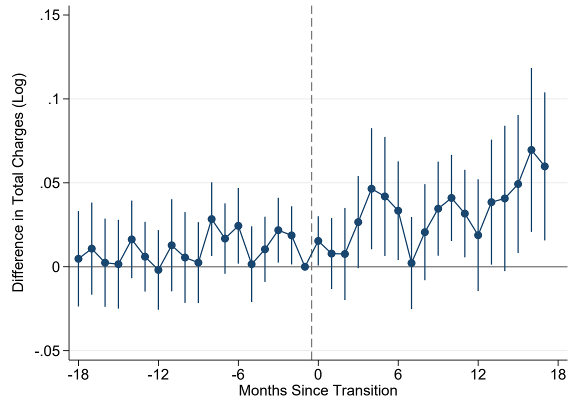
(d) 2013 Transitions

Notes: Estimates of δ_e of Equation (4) for $e \in \{-3, \dots, 4\}$. An observation is a state-year. Dependent variable is the share of office-based physician practices that have adopted basic EHR technology. Error bars give the 95% confidence interval for each estimate. Standard errors are clustered by state.

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



(a) Charges Per Capita



(b) Log Charges

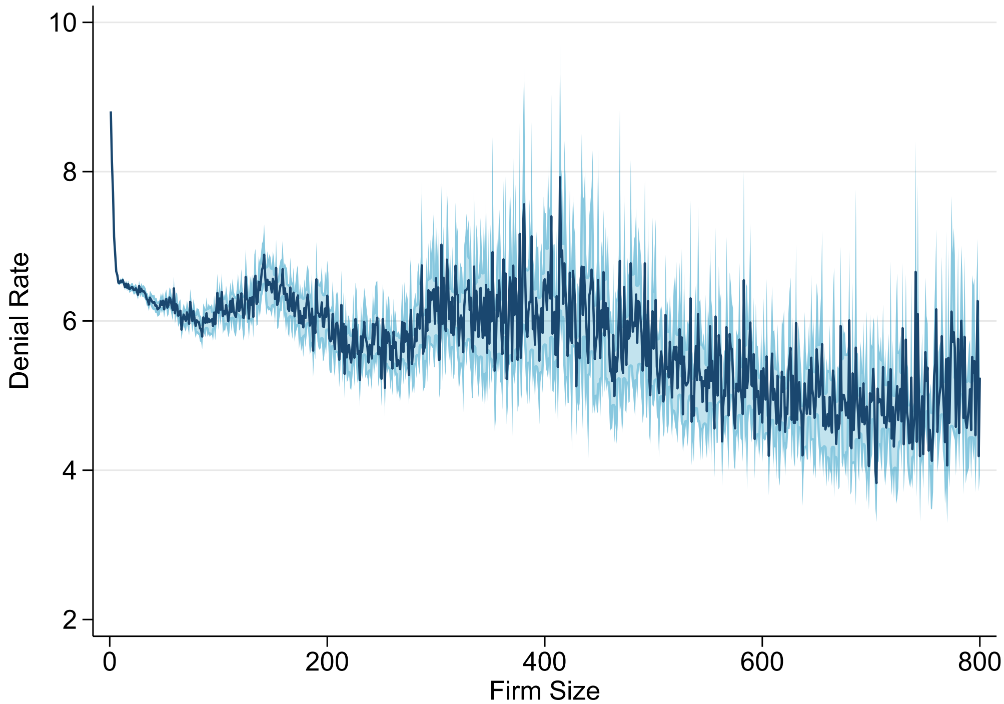
Notes: Estimates of δ_e of Equation (2) for $e \in \{-18, \ldots, 17\}$. An observation is a jurisdiction-wave-month. Dependent variables are total charges billed measured per Medicare beneficiary or in logs. Error bars give the 95% confidence interval for each estimate. Standard errors are clustered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

Table 4: Effect of High-Denial Administrator on EHR Adoption and Charges

	(1) Share Adopt EHR	(2) Charges (per capita)	(3) Charges (log)
Increase in Denials	8.999^{**}	46.97^{**}	0.0598^{**}
	(3.338)	(16.17)	(0.0225)
Dep. Var. Mean	43.00	616.2	17.58
Observations	305	70,164	70,164

Notes: Column (1) reports estimates of δ_4 of Equation (4) where an observation is a state-year. Columns (2) and (3) report estimates of δ_{17} of Equation (2) with $K = 18$ and $L = 17$ where 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 state in column (1) and by jurisdiction in columns (2) and (3). $^{+}$, *, ** and *** indicate significance at the 10%, 5%, 1% and 0.1% level, respectively.

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. 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. 95% confidence interval given in light blue.

of the administrator, the relationship between firm size and the denial rate remains strong, with an additional provider in the practice being associated with an average reduction in denial rate of 0.012 percentage points.

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 the firm, we see that this spike is driven by the smallest firms. Figure 9 reports how the denial rate changes surrounding administrator transitions for firms of various sizes, while Table 6 reports total change in the six months following a transition. While one- or two-provider practices see their denials jump by three-quarters of a percentage point following a contractor change, for the largest firms this spike is only half as large. This result is consistent with larger firms investing more in technology that allows them to more easily detect and respond to changes in billing rules and maintain a low denial rate.

Table 5: Difference in Denial Rate by Firm Size

	(1) Denial Rate	(2) Denial Rate	(3) Denial Rate	(4) Denial Rate
Firm Size	-0.0121***	-0.0121***	-0.00191***	-0.00163***
	(0.000961)	(0.000943)	(0.000323)	(0.000307)
Jurisdiction-Month FEs	0	1	0	1
Weighting	Firms	Firms	Providers	Providers
Dep. Var. Mean	8.397	8.397	7.024	7.024
Observations	61,725,317	61,725,317	199,100,357	199,100,357

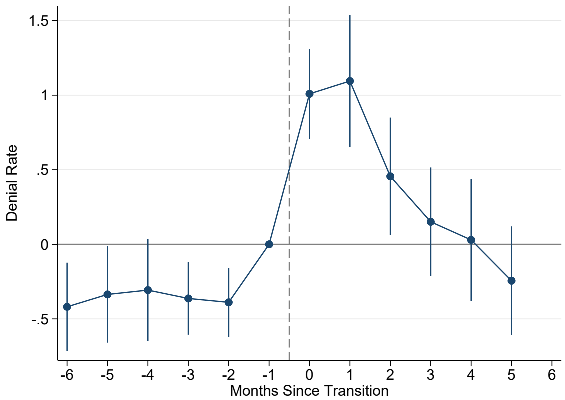
Notes: Estimates from regression of denial rate on firm size. An observation is a firm-month. Firm size is determined by the number of providers in a jurisdiction billing under the same tax identification number. Jurisdiction-month fixed effects are included in columns (2) and (4), and observations are frequency-weighted by the number of providers associated with the firm in columns (3) and (4). Standard errors are clustered by firm. $^{+}$, *, ** and *** indicate significance at the 10%, 5%, 1% and 0.1% level, respectively.

Table 6: Effect of Transition on Denials by Firm Size

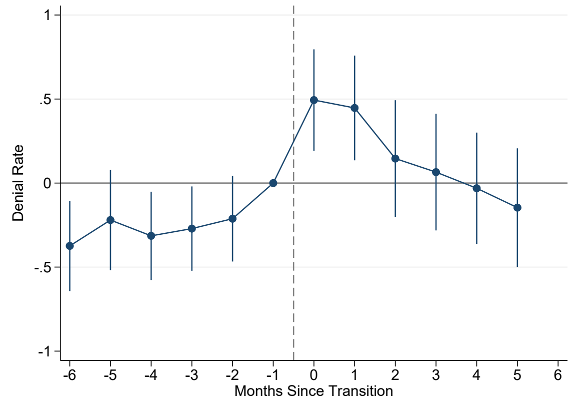
	(1) Denial Rate	(2) Denial Rate	(3) Denial Rate	(4) Denial Rate	(5) Denial Rate
Post-Transition	0.720***	0.395***	-0.00916	0.306^{+}	0.290
	(0.134)	(0.108)	(0.142)	(0.164)	(0.165)
Firm-Size Quintile	1	2	3	4	5
Dep. Var. Mean	7.474	6.232	5.801	6.449	5.354
Observations	30,144	30,144	30,144	30,084	27,768

Notes: Estimates of δ_1 of Equation (10) for $L = 5$. An observation is a jurisdiction-wave-month. Dependent variable is the denial rate for firms of the relevant size. Error bars give the 95% confidence interval for each estimate. Standard errors are clustered by jurisdiction.

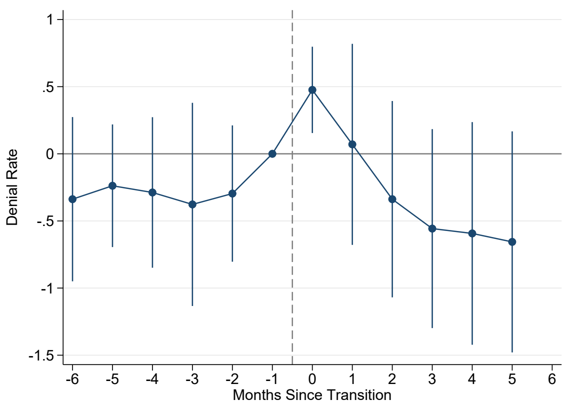
Figure 9: Effect of Transition on Denials by Firm Size



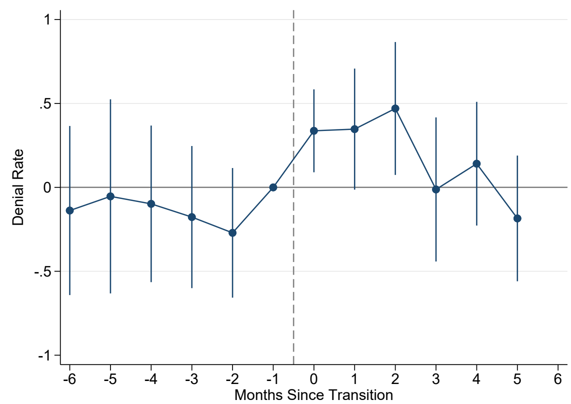
(a) 1-2 Providers



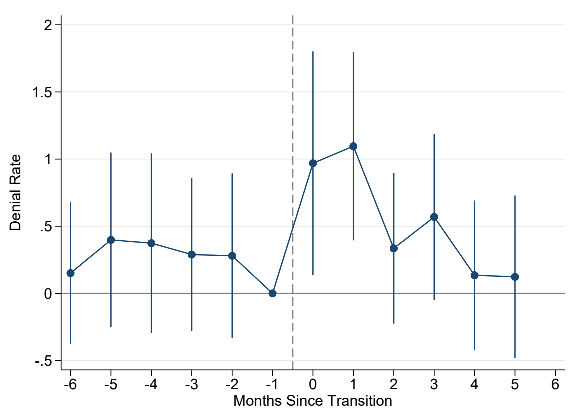
(b) 3-9 Providers



(c) 10-42 Providers



(d) 43-198 Providers



(e) Over 198 Providers

Notes: Estimates of β_e of Equation (3) for $e \in \{-6, \ldots, 5\}$. An observation is a jurisdiction-wave-month. Dependent variable is the denial rate for firms of the relevant size. Error bars give the 95% confidence interval for each estimate. Standard errors are clustered by jurisdiction.

6.3 Increased Burden Lowers Profits and Increases Concentration

The third testable implication of my model is that increasing burdens will reduce firm profits. That is, fewer firms will operate following an increase in administrative burden.[26] As Figure 10a shows, this prediction is supported by the data. Transitions to higher-denial administrators result in roughly 1% fewer firms operating in the three months after the transition relative to the month before and the number of firms remaining well below trend thereafter. As shown by Figures A2 and A3 in Appendix D, even the disruptions associated with transitions to lower-denial administrators induce exit, although much less so than for transitions to higher-denial administrators.

The theoretical model also predicts that exit will be most likely for small practices because these firms will make lower profits and be closer to the threshold of exit. Consistent with this, 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 1.9%,leading to an immediate change in the size distribution of firms. The share of providers in solo practice drops 0.2 percentage points (1.2%) and the average number of providers per firm increases 0.04 (1.1%) in the month following a transition to a higher-denial administrator. These results indicate that increasing administrative burdens advantages larger firms and leads to increased firm size.

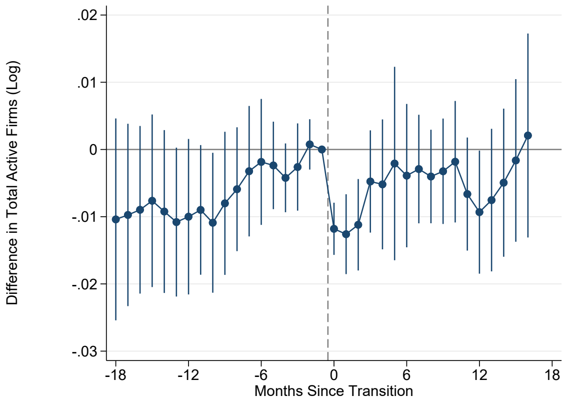
6.4 Other Impacts of Increased Burden

Finally, although the model does not make any prediction on this point, the net effect of the additional investment and consolidation is to increase the overall level of Medicare spending following a transition to a higher-denial administrator. This indicates that all of the additional billing costs imposed on providers that lead to consolidation do not reduce spending for Medicare. Both Medicare and providers would be better off with lower denial rates—Medicare because total spending would be lower and providers because they could avoid inefficient investment costs.

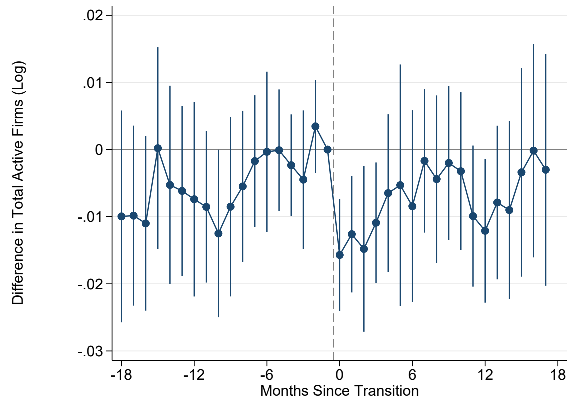
Despite failing to achieve their putative aim of reducing health care spending, administrative burdens may improve patient care. Although administrative burdens are generally targeted toward combating waste and inefficiency, they can also be used to protect patients and encourage higher-value, more-effective 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 E, I show that differences between administrators in the treatment of claims for low-value care can induce providers to change their provision of these services, but that very large changes in denials are necessary. This indicates that while

[26]This is true assuming 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 idosyncratic differences within firm-size bands as I assume in Section 7.

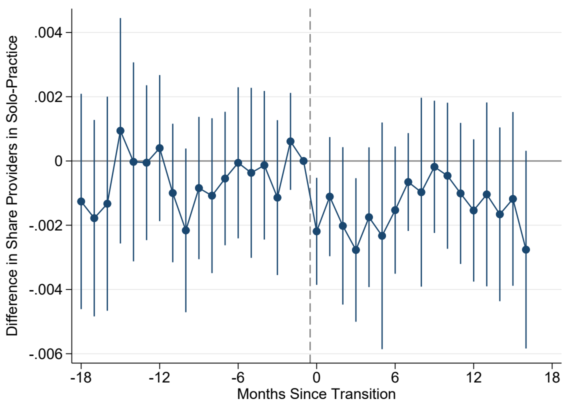
Figure 10: Effect of Transition to Higher-Denial Administrator on Market Structure



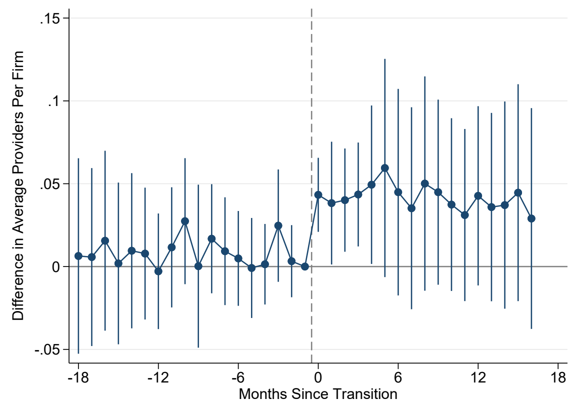
(a) Active Firms



(b) Active Single-Provider Firms



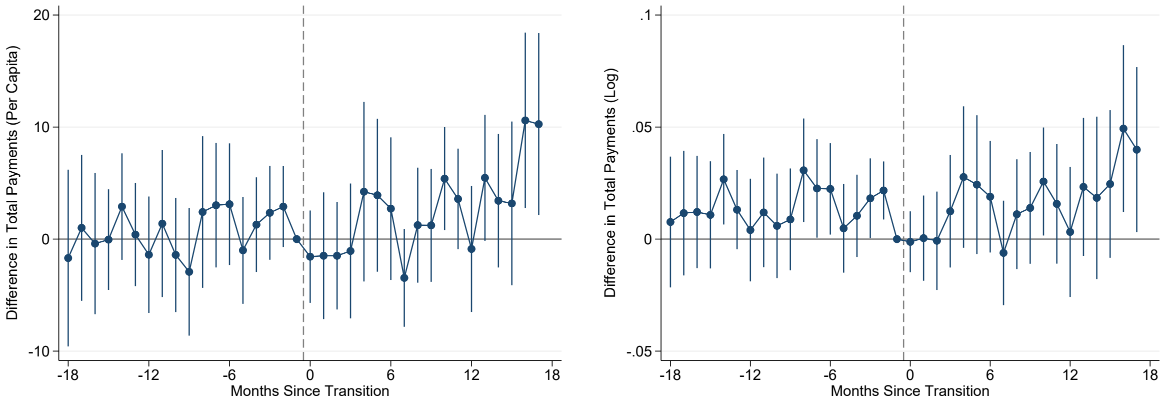
(c) Share of Providers in Solo Practice



(d) Firm Size

Notes: Estimates of β_e of Equation (3) for $e \in \{-18, \ldots, 17\}$. An observation is a jurisdiction-wave-month. The sample is limited to transitions to a higher-denial administrator and appropriate control jurisdictions. 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. Error bars give the 95% confidence interval for each estimate. Standard errors are clustered by jurisdiction.

Figure 11: Effect of Transition to Higher-Denial Administrator on Spending



(a) Payments Per Capita

(b) Log Payments

Notes: Estimates of δ_e of Equation (2) for $e \in \{-18, \ldots, 17\}$. 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.

large, highly salient burdens can alter care provision—as is the case with prior authorization (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. In line with this, I find no change in aggregate beneficiary mortality following a transition to a higher-denial administrator, as shown in Figure A4 in Appendix D. The estimated change in mortality after a transition is close to zero but is somewhat imprecise (I cannot rule out increases or decreases in mortality of up to 1.9% at the 95% confidence level). 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, supporting my focus on investment in billing technology and changes in reporting as the primary responses of providers.

6.5 Discussion

My results indicate that increased administrative burdens lead to higher Medicare spending and increased consolidation, which are both negative, unintended outcomes. Previous research has documented extensive harms that come from consolidation in the health care system, 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 wages (Prager and Schmitt, 2021), and few improvements in health outcomes (Cutler et al., 2010; Gaynor et al., 2013; Bloom et al.,

Table 7: Effect of Higher-Denial Administrator on Medicare Spending

	(1) Payments (per capita)	(2) Payments (log)
18-Months Post-Transition	10.26*	0.0399*
	(4.147)	(0.0188)
Dep. Var. Mean	227.0	16.61
Observations	70,164	70,164

Notes: Estimates of δ_{17} of Equation (2) 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%, 1% and 0.1% level, respectively.

2015; Eliason et al., 2020). My results shed light on one particularly contentious issue when these mergers are reviewed by competition authorities: the potential for cost savings and returns to scale. Indeed, my results are consistent with larger physician groups and health systems being better able to invest in the fixed costs of billing technology. Indeed, 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 also indicate that one driver of this consolidation (and all the ills it often entails) 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.

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 would 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).

These potential benefits seem unlikely to outweigh the costs of raising burdens at the margin, however. As I show, net spending increases following a hike in the denial rate, indicating that any investment did not translate into improved care preventing unnecessary spending. Furthermore, the existing evidence on whether the adoption of electronic health records improves patient health outcomes is mixed (Agha, 2014) with the weight of the evidence indicating only modest effects on patient health (Bronsoler et al., 2022). Furthermore, investments in billing technology other than electronic health records, such as hiring scribes and coders, are even less likely to improve patient care. Finally in Appendix E, I show that denial rate changes are unlikely to shift providers away from known forms of low-value health care, with transitioning between administrators with divergent stances toward 7 types of low value care only reducing the utilization of the treatment subject to the largest (20 percentage point) change in denials. The inability for after-the-fact denials to alter medical care is also highlighted by Macambira et al. (2022). Together, these results indicate that the costs of administrative burdens that I highlight are unlikely to be outweighed by their potential benefits.

7 Empirical Model

Although my results indicate that the costs of administrative burdens are high, my model may not capture all the benefits of administrative costs and investment in billing technology. Because of this limitation, I want to quantify the costs of compliance so that policymakers can better judge if these potential benefits are worth the costs they impose. To do this, I estimate a parameterized version of the theoretical model presented in Section 5, which will allow me to not only quantify firms' compliance costs but also better understand how they would respond to 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

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

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

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

$$p(I^*) = 1 - \sqrt{\frac{(a+\underline{I})[c+(d-1)v]}{v(b-a)}}. \tag{5}$$

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.[27] 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 the only thing that changes immediately around contractor transitions is the minimum level of investment (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,

[27]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.

and the number of active firms and the percentage change in denials:

$$\mathbb{E}[\tilde{R}_{ij1}] - \mathbb{E}[\tilde{R}_{ij0}] = \sqrt{\frac{v(b-a)}{c+(d-1)v}} \left(\sqrt{a+\underline{I}_1} - \sqrt{a+\underline{I}_0}\right) \tag{6}$$

$$\mathbb{E}[\tilde{P}_{ij1}] - \mathbb{E}[\tilde{P}_{ij0}] = \sqrt{\frac{c+(d-1)v}{v(b-a)}} \left(\sqrt{a+\underline{I}_0} - \sqrt{a+\underline{I}_1}\right) \tag{7}$$

$$\frac{N_{vj1}}{N_{vj0}} = \frac{1-\Phi\left(\frac{-\bar{\Pi}_{vj1}}{\sigma_\pi}\right)}{1-\Phi\left(\frac{-\bar{\Pi}_{vj0}}{\sigma_\pi}\right)}, \tag{8}$$

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

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

$$Y_{jtw} = \beta_1 \sum_{e=0}^{L} T_{jtw}(e) + \delta_1 \sum_{e=0}^{L} T_{jtw}(e) \times U_w + \Gamma X_{jtw} + \alpha_{jw} + \eta_{tw} + \varepsilon_{jtw}, \tag{10}$$

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; 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 $\frac{(1-\mathbb{E}[\tilde{P}_{ij1}])-(1-\mathbb{E}[\tilde{P}_{ij0}])}{1-\mathbb{E}[\tilde{P}_{ij0}]}$. 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.[28]

I supplement these transition-based moments with two moments that characterize the relationship between denials and firm size. Equation (5) 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

$$SqDeny_v = \beta_0 + \beta_1 \frac{1}{v} + \varepsilon_v, \tag{11}$$

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.[29] This generates two more moments that can be used to estimate the parameters of the model:

$$\beta_0 = \frac{(a+\underline{I})(d-1)}{b-a} \tag{12}$$

$$\beta_1 = \frac{(a+\underline{I})c}{b-a} \tag{13}$$

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

[28]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 F, I consider an alternative model of firm exit that more explicitly models physician sorting across firms, showing that the my results are generally robust to this change.

[29]Note that $SqDeny_v$ is the square of the average denial rate rather than the average of the squared denial rate. Were $SqDeny_v$ defined in the latter way, ordinary least-squares would generate biased estimates of β_0 and β_1 in the presence of firm-level measurement error of the denial rate. This is because

$$E\left[\left(1-\tilde{P}_{ijt}\right)^2 |v\right] = \frac{(a+\underline{I})(d-1)}{b-a} + \frac{(a+\underline{I})c}{b-a}\frac{1}{v} + \sigma^2_{\epsilon,v},$$

where $\sigma^2_{\epsilon,v}$ is the variance of the measurement error of denial rates for firms of size v. If this measurement error is non-zero, the OLS estimate of β_0 would be biased upward. If the variance of the measurement error is correlated with firm size, then the OLS estimate of β_1 would be biased in the direction of this correlation.

within-size changes in denials, charges, and number of firms. For the moments relating to the changes in denials and charges (represented by Equations (7) and (9) for denials and (6) 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 G.[30] To characterize the change in the number of profitable firms (Equation (8)), 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 ($\underline{I}_{avg} \equiv \frac{I_0+I_1}{2}$). 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 the ten moments reported in Table 8. To discount less-precisely estimated left-hand side values, I weight each moment by the square of the standard error of my estimate of the left-hand side.

7.1 Estimation Results

Table 8 reports details on the moments used in estimation and estimates for the value of the left-hand side of each moment. Notice that the estimates are consistent with the predictions of the model: there are more denials and charges following a transition to a higher-denial administrator. Furthermore, the estimates are consistent with exit increasing more for smaller firms than larger ones after transitioning to a higher-denial administrator.

More importantly, the values presented in Table 8 identify the parameters of the structural model. Table 9 reports estimates of these parameters. In Appendix I, I present evidence that the estimated model is successful in matching the data. In particular, under the null hypothesis that the estimated model is correct, none of the estimated values reported in Table 8 differ in a statistically significant way from the predictions of the model.

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, while the cost of lowering the denial rate by one percentage point is \$731 per month.[31] Furthermore, the estimates indicate that investment costs have substantial components that are both fixed and variable relative to firm size. As shown by Figure 12a, 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.[32]

[30] 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 H I demonstrate the robustness of my results to using the provider-weighted means.

[31] All cross-sectional estimates of billing costs and equilibrium outcomes assume the minimum level of investment is given by $\underline{I}_{avg} \equiv \frac{I_0+I_1}{2}$.

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

Table 8: Estimated Moments

(1) Moment Equation	(2) Firm Sizes	(3) Estimand	(4) Structural Representation	(5) Estimate
Equation (8)	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
				(0.0153)
Equation (8)	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
				(0.0154)
Equation (8)	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
				(0.0106)
Equation (8)	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
				(0.0260)
Equation (8)	≥ 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
				(0.0397)
Equation (6)	All	$\mathbb{E}[\tilde{R}_{ij1}] - \mathbb{E}[\tilde{R}_{ij0}]$	$-\sqrt{\frac{v(b-a)}{c+(d-1)v}}\left(\sqrt{a+\underline{I}_0} - \sqrt{a+\underline{I}_1}\right)$	701.0
				(353.2)
Equation (7)	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
				(0.00180)
Equation (9)	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
				(0.0245)
Equation (12)	All	β_0	$\frac{(a+\underline{I}_{avg})(d-1)}{b-a}$	44.16
				(2.50)
Equation (13)	All	β_1	$\frac{(a+\underline{I}_{avg})c}{b-a}$	33.91
				(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 (8), column (5) reports estimates of $\delta_1 + 1$ of Equation (10) 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 (7), column (5) reports estimates of $-\delta_1$ of Equation (10) with share of claims denied as the dependent variable. For the moment associated with Equation (6), column (5) reports estimates of δ_1 of Equation (10) 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 (12) and (13), column (5) reports estimates of β_0 and β_1, respectively, of Equation (11). For these estimates, an observation is a firm-month, and the standard errors are reported in parentheses and clustered by firm size.

Table 9: 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.

This lower per-provider unit cost induces additional investment on the part of large providers, as show in Figure 12b, with the net effect being that equilibrium investment costs per provider are increasing in firm size (Figure 12c). This results in larger firms being more profitable, including on a per-provider basis, as shown by Figure 12d.

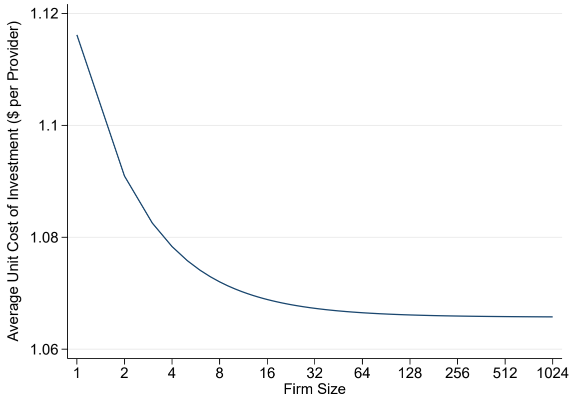
The model estimates imply that the costs of compliance with billing rules are high: solo practitioners invest \$5,728 each month in billing technology while the median provider is in a firm that invests \$77,656 per month. This amounts to 52.9% and 56.8%, respectively, of variable profits from Medicare being absorbed by billing costs. Aggregating these costs across all firms billing 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.[33] 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 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.

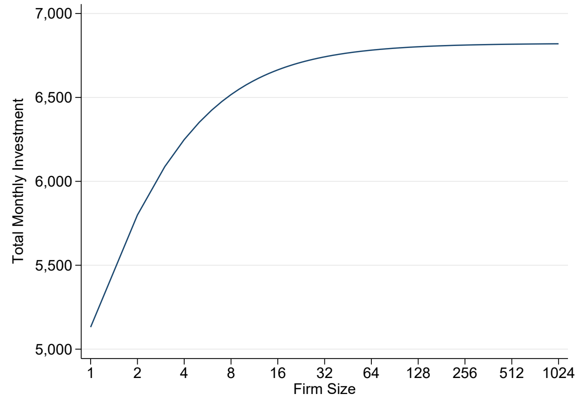
In addition to estimating cross-sectional investment costs, the model allows me to quantify the costs of transitioning to a higher-denial administrator. For a solo practitioner, I estimate that raising administrative burdens induces \$655 of additional investment costs each month, lowering profits by 4.6%. For a firm containing the median number of providers, these figures are \$8,878

[33]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.

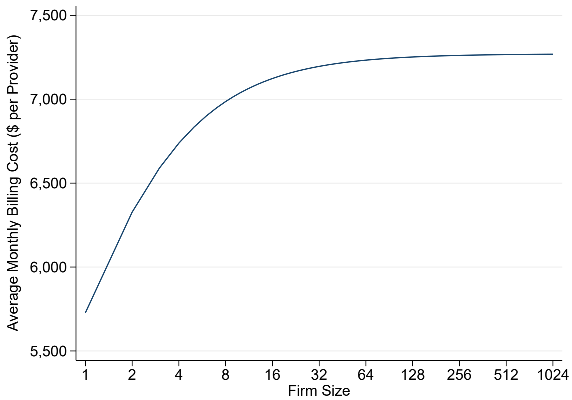
Figure 12: Equilibrium Outcomes by Firm Size



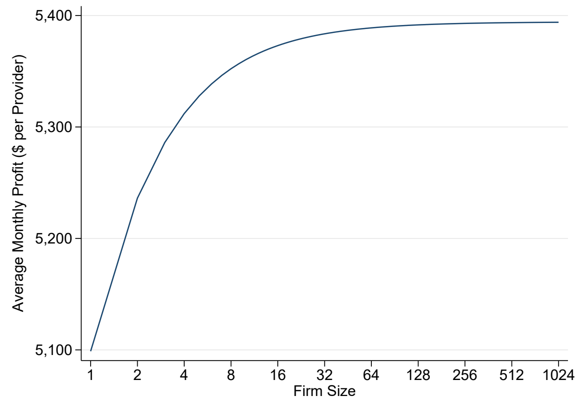
(a) Average Unit Cost



(b) Investment



(c) Billing Cost per Provider



(d) Profit per Provider

Notes: Equilibrium outcomes implied by parameters presented in Table 9. 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.

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 transitioning all providers from low- to high-denial administrators 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.[34] Increasing administrative burden likely increases the costs to insurers as well.

7.2 Counterfactual Simulations

Finally, my model allows me to quantify the counterfactual changes in Medicare spending and provider profits under different states of the world. First, I consider how outcomes would change were providers not able to invest in billing technology 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 technologies. Were providers not able to change their level of investment following to an increase in administrative burdens, I estimate that in response to an increase in administrative burden the denial rate would increase by 25.8% rather than 12.1%, as shown by Table 10 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.[35] This means that a nation-wide change from a lower- to higher-denial administrator would *reduce* Medicare spending by \$2.8 billion rather than increase it by \$7.4 billion because of the endogenous response of providers. 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.

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

[35] For the largest firm in my data, payments would have fallen 1.7% rather than risen 5.1%.

Table 10: 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 nation-wide 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 the 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.

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 exit the market. 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.

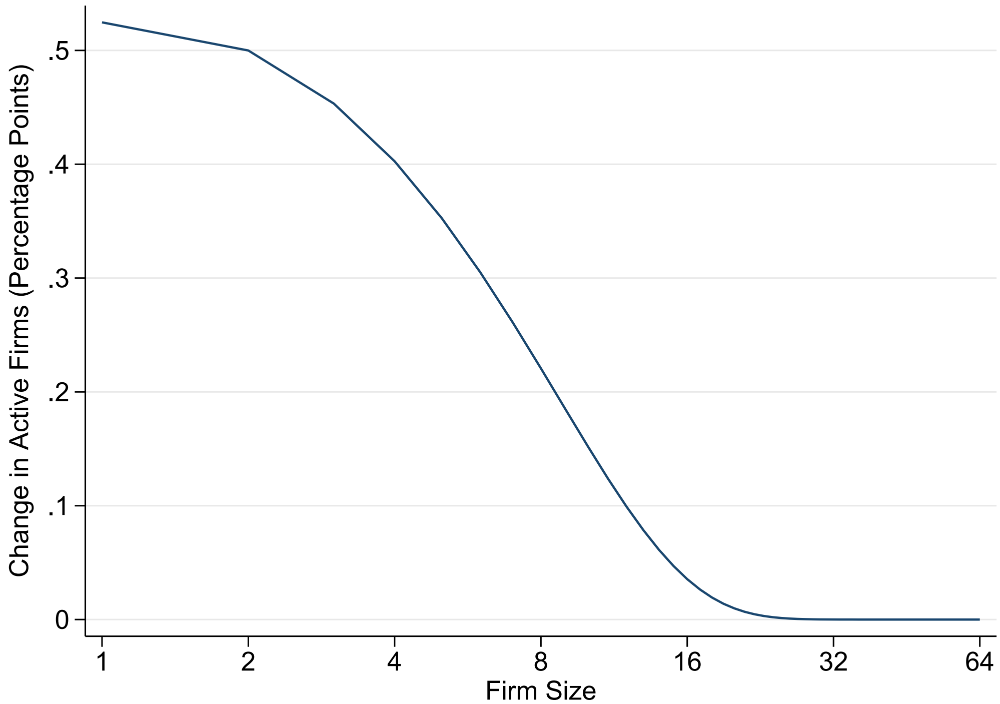
Another important counterfactual policy is the elimination of the fixed component of the investment cost. This counterfactual quantifies the returns to scale coming from investment and could be implemented by an investment subsidy of 5.05 cents per unit of investment. With the fixed portion of costs eliminated, firms of all sizes invest the same amount and have the same level of per-provider investment costs and profits. Because smaller firms make lower profits in the presence of fixed costs, eliminating these costs would alter the firm size distribution, as shown in Figure 13. The number of active single practitioner firms would increase by 0.54% without any increase in the number of firms with more than 36 providers. In aggregate, this change would result in 24.5% more investment with investment costs rising by $4.9 billion annually.[36] This would raise annual industry profits by $866 million and Medicare spending by $5.8 billion.

A closely related counterfactual is testing 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).[37] 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

[36]This assumes the fixed portion of the cost was eliminated. Were it paid for by a subsidy, the subsidy would cost $974 million annually, meaning the total investment cost increase would be $5.9 billion.

[37]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.

Figure 13: Counterfactual Change in Number of Active Firms



Notes: Estimated percent change in the number of active firms by providers per firm were the fixed cost component of the cost of investment eliminated.

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.

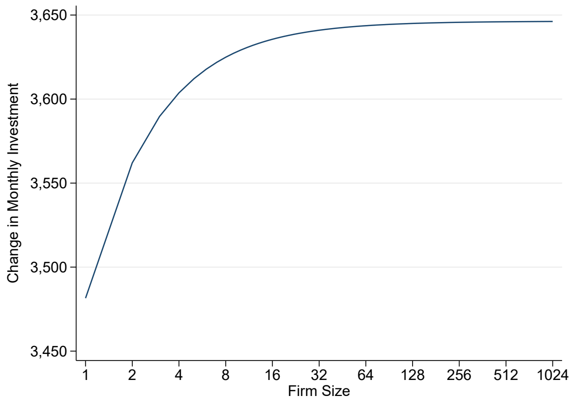
Using my model estimates, I am able to quantify the additional cost to the government of the subsidy program. Fleming et al. (2011) estimate the cost of adopting EHR for small physician practices amounts to $46,659 per physician in the first year, meaning the HITECH Act gave a 38.6% subsidy up to $1,500 of investment per physician per month.[38] 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 14. 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%. These changes are much larger than those that would be induced by eliminating the fixed cost component of investment costs, but the costs of this subsidy program would be much larger as well. As shown by Figure 15, the subsidies necessary to offset the fixed costs of investment are only $344 per *firm*, while the HITECH subsidy is $1500 per *provider*. Furthermore, for both subsidy programs the direct costs to the government of the subsidy are much smaller than the additional 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 aggressively, 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.

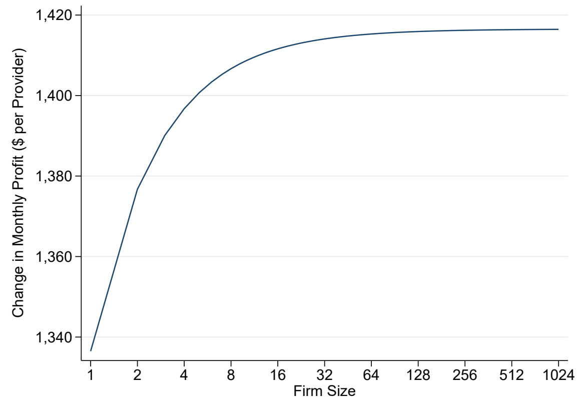
As a final counterfactual, I consider a subsidy regime designed to prevent exit in response to an increase in administrative burden, where the size of the required payment depends on the

[38]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.

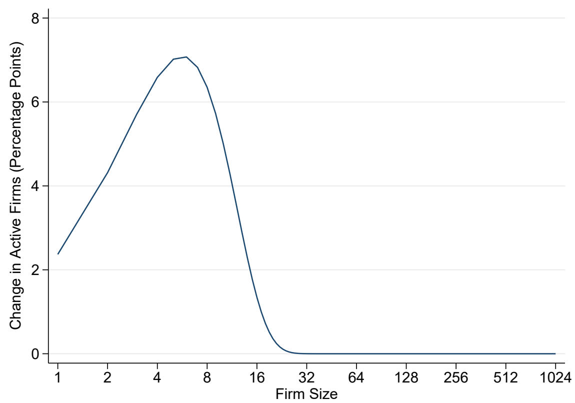
Figure 14: Change in Equilibrium Outcomes by Firm Size with HITECH Subsidy



(a) Investment



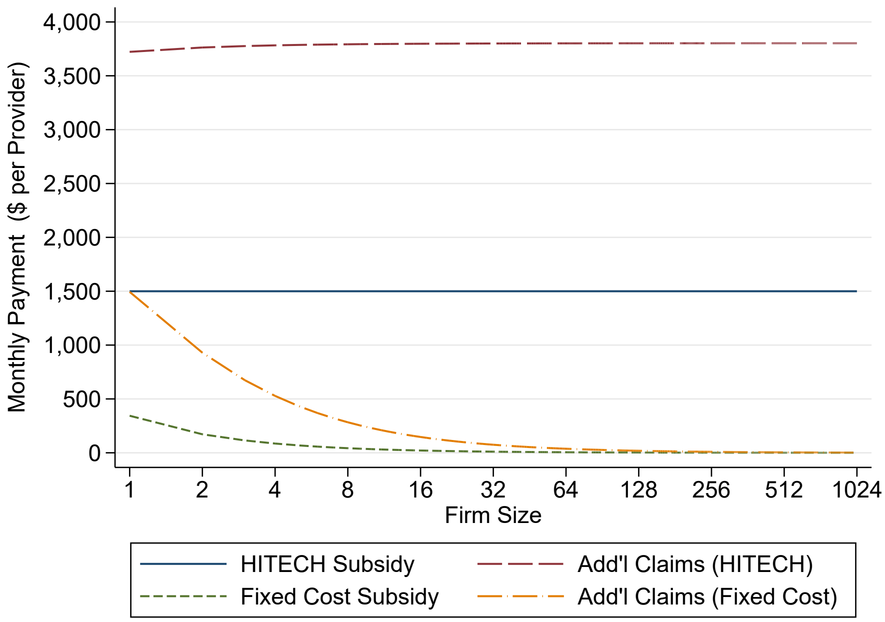
(b) Profit per Provider



(c) Active Firms

Notes: Change from equilibrium outcomes implied by parameters presented in Table 9 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.

Figure 15: Transfers to Firms Through Subsidy Channels



Notes: Additional payments by the government to firms relative to the equilibrium outcomes implied by parameters presented in Table 9 under a 38.6% marginal subsidy up to $1,500 per provider (HITECH subsidy) or a 5.05 cent subsidy per unit of investment (fixed cost subsidy). Additional claim payments are the additional payments made under the HITECH subsidy through the more aggressive billing practices induced by the subsidy. Note that the horizontal axes of all figures are spaced geometrically.

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 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.[39] Thus, with perfect targeting the same market structure could be maintained much more cheaply. Nonetheless, the high cost of imperfectly targeted subsidies indicates that the negative effects of increased administrative burden are difficult to offset.

8 Conclusion

Overall, these results highlight the negative consequences of administrative burdens in the health care sector. Using exogenous variation in the areas 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 negate the effect of more aggressive denials on overall Medicare spending. In fact, more aggressive denials on average promote higher health care spending. These results are consistent with a model of investment in billing technology that I estimate to show that the annual cost of complying with Medicare's billing rules is almost $90 billion. Overall, my results indicate that administrative burdens not only entail massive amounts of waste, but that they have negative consequences for the competitiveness of health care markets. Policymakers need to be cautious when imposing administrative burdens because, as it stands now, administrative burdens do not achieve their goal of reducing health care spending and instead have the unintended consequence of increasing concentration among health care providers, indicating that administrative burdens are a lose-lose for the government, providers, and patients.

[39] The total subsidy payments to firms of size v is given by

$$\tilde{N}_{vj}\sigma_\pi \int_{\frac{\Pi_{vj1}}{\sigma_\pi}}^{\frac{\Pi_{vj0}}{\sigma_\pi}} \left(x - \frac{\Pi_{vj1}}{\sigma_\pi}\right) \frac{\phi(x)}{\Phi\left(\frac{\Pi_{vj0}}{\sigma_\pi}\right) - \Phi\left(\frac{\Pi_{vj0}}{\sigma_\pi}\right)} dx,$$

where $\tilde{N}_{vj}$ is the number of potential firms of size v in jurisdiction j.

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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.[40] 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, meaning that 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 (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 1.3% of the overall QASP score. Thus, contractors have little direct financial incentive to reject claims for medically unnecessary care.

In contrast, administrators do have a more indirect incentive to ensure that only appropriate care is reimbursed: keeping Medicare happy. The contracts are awarded via procurement auction, with quality being the primary measure. 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, depend heavily on the propriety of the claims paid and the

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

overall financial impact on Medicare. For instance, CMS reported to Congress that contractors "will 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, 2022b).

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.

Finally, one may wonder why the government contracts with private entities to administer Traditional Medicare rather than process claims itself. The answer, as it turns out, is largely political. 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,

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 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.

"[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 involved governmental control and was socialized medicine."

B 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 A2. 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.

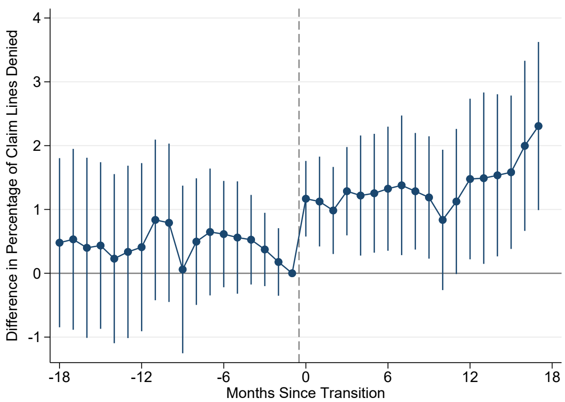
To further validate my measure of administrative burden, I next demonstrate that transitions between low- and high-denial administrators along this measure capture meaningful changes along the alternative measures as well. Figure A1 presents the estimated differential change in each alternative measure of administrative burden following a transition to an administrator with a lower estimated impact on the claim denial rate to one with a lower estimated effect 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 A2: Estimated Effect of Each Contractor on Alternative Measures of Administrative Burden

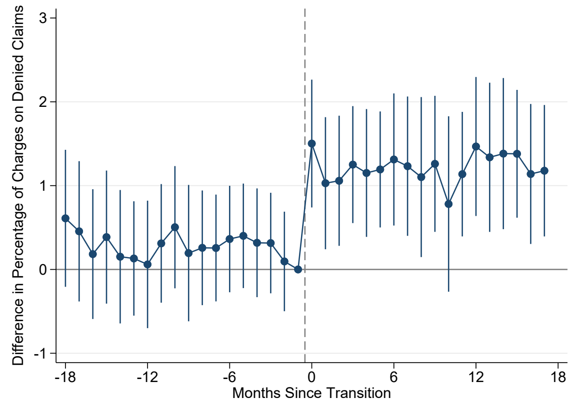
	(1) Line Denial Rate		(2) Share of Charges on Denied Claims		(3) Share of Charges on Denied Claim Lines	
Metra	1.542	1.32	1.779	0.72	1.532	0.794
Nationwide	0.147	1.281	1.199	0.467	0.629	0.532
Group Health	3.447	1.127	1.244	0.627	1.626	0.573
Triple-S	6.353	1.284	-2.626	0.636	-1.185	0.604
Pinnacle	-0.869	1.338	-0.091	0.512	-0.552	0.574
BCBSRI	-1.794	1.644	-0.838	0.606	-1.635	0.684
Wheatlands	0.37	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	-0.94	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	0.58	-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	-1.34	1.007	-1.09	0.581	-1.256	0.557
BCBSMT	-0.0639	0.4	-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 γ_m of Equation (1). Note that coefficient estimates are reported in the same order as in Table 3. 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%, 1% and 0.1% level, respectively.

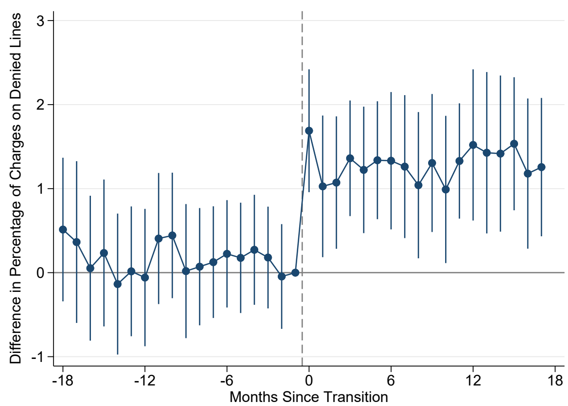
Figure A1: Estimated Effect of Transition on Alternative Measures of Administrative Burden



(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 $e \in \{-18, \ldots, 17\}$. 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.

C 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 3 allow each jurisdiction to have an arbitrary mean denial rate and jurisdiction-specific linear trend. In column (1) of Table A3, 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:

$$Y_{jmt} = \mu_m + \Gamma X_{jt} + \alpha_{0j} + \eta_t + \varepsilon_{jmt}, \tag{14}$$

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

$$Y_{jmt} = \mu_m + \Gamma X_{jt} + \alpha_{0j} + \alpha_{1j} t + \alpha_{2j} t^2 + \eta_t + \varepsilon_{jmt}, \tag{15}$$

The correlation of each of these alternative estimates with those presented in Table 3—along with the lack of differential pre-trends shown in Figure 4—indicate that my results are unlikely to be driven by slow-moving differential trends across jurisdictions.

Table A3: Estimated Effect of Each Contractor on Denial Rates with Alternative Jurisdiction-Specific Trends

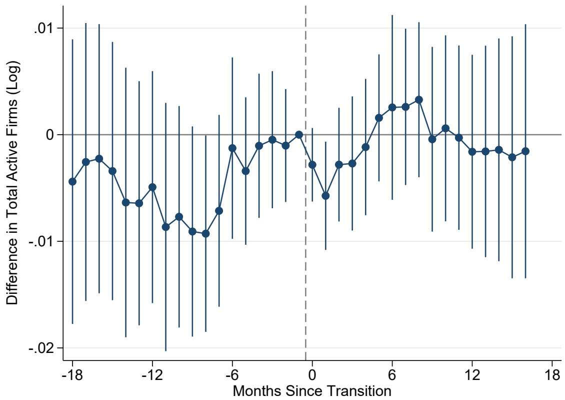
	(1) Denial Rate		(2) Denial Rate	
Metra	2.990***	0.542	0.125	0.618
Nationwide	0.201	0.382	-0.716*	0.349
Group Health	-0.104	0.680	0.677	0.475
Triple-S	1.228	0.761	0.167	0.478
Pinnacle	-0.0836	0.424	0.289	0.421
BCBSRI	1.065**	0.411	-0.654	0.574
Wheatlands	-0.956*	0.395	0.476	0.496
TrailBlazer	-0.152	0.317	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 γ_m from Equation (14) are reported in column (1) and Equation (15) are reported in column (2). Note that coefficient estimates are reported in the same order as in Table 3. An observation is a jurisdiction-month. The excluded Contractor is Noridian. Dependent variable is the share 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%, 1% and 0.1% level, respectively.

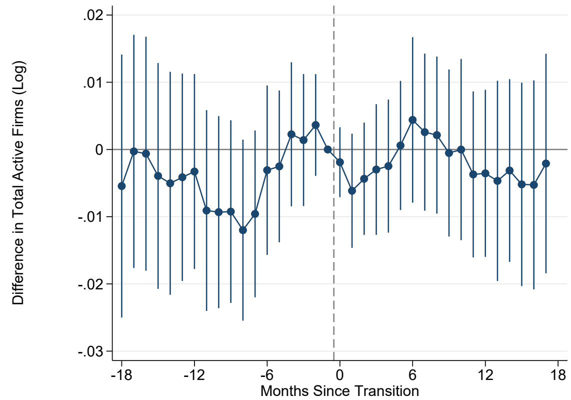
D Other Consequences of Increasing Administrative Burden

In this appendix, I report additional results on the responses of providers to changes in their Medicare Administrative Contractor. Figure A2 reports how market structure changes following a transition to a lower-denial administrator while Figure A3 reports estimates of the triple-difference specification comparing the changes following transitions to higher- and lower-denial administrators. Figure A4 and Table A4 report evidence that beneficiary mortality does not change following transitions.

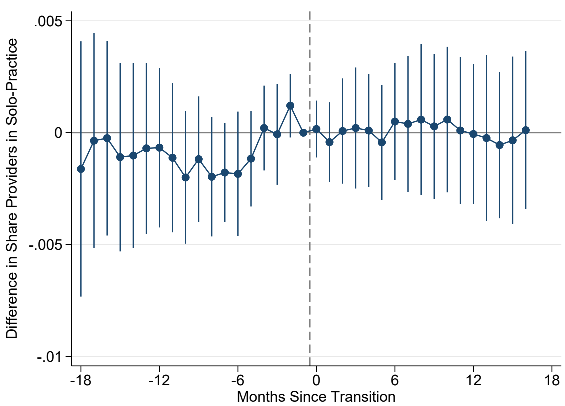
Figure A2: Effect of Transitions to Lower-Denial Administrators on Market Structure



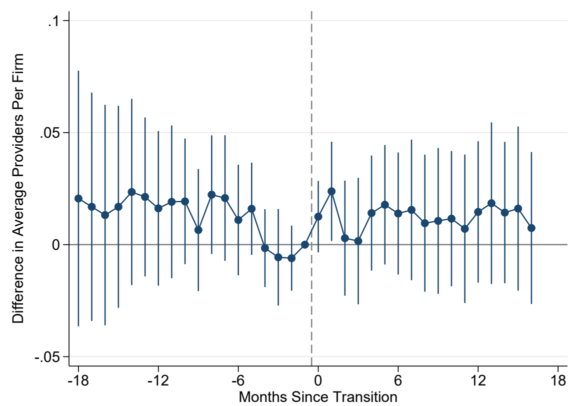
(a) Active Firms



(b) Active Single-Provider Firms



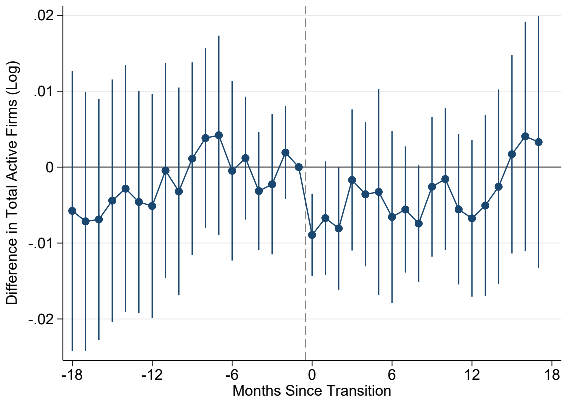
(c) Share of Providers in Solo Practice



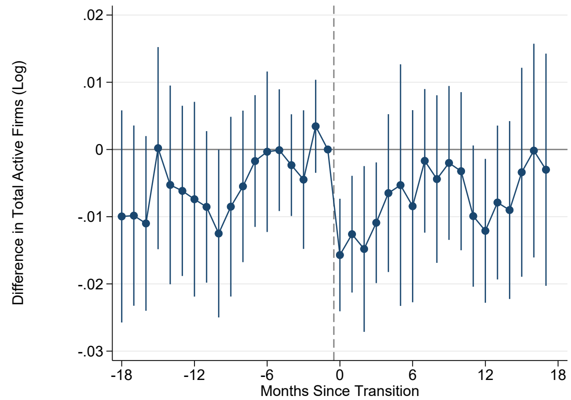
(d) Firm Size

Notes: Estimates of β_e of Equation (3) for $e \in \{-18, \ldots, 17\}$. An observation is a jurisdiction-wave-month. The sample is limited to transitions to a lower-denial administrator and appropriate control jurisdictions. 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. Error bars give the 95% confidence interval for each estimate. Standard errors are clustered by jurisdiction.

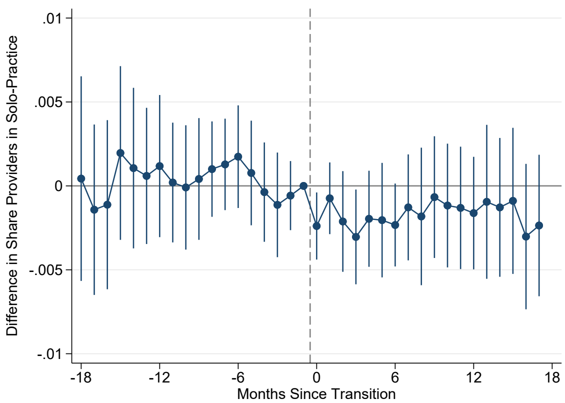
Figure A3: Differential Effect of Transitions to Higher-Denial Administrators on Market Structure



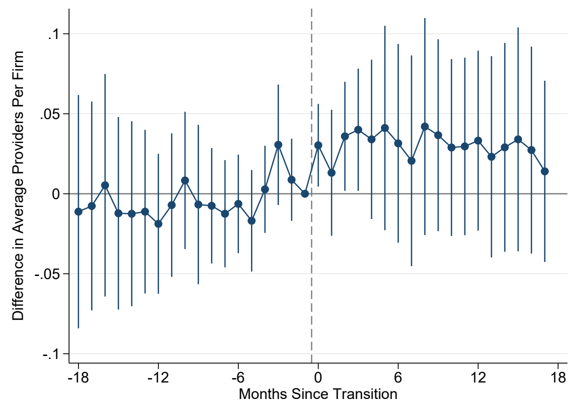
(a) Active Firms



(b) Active Single-Provider Firms



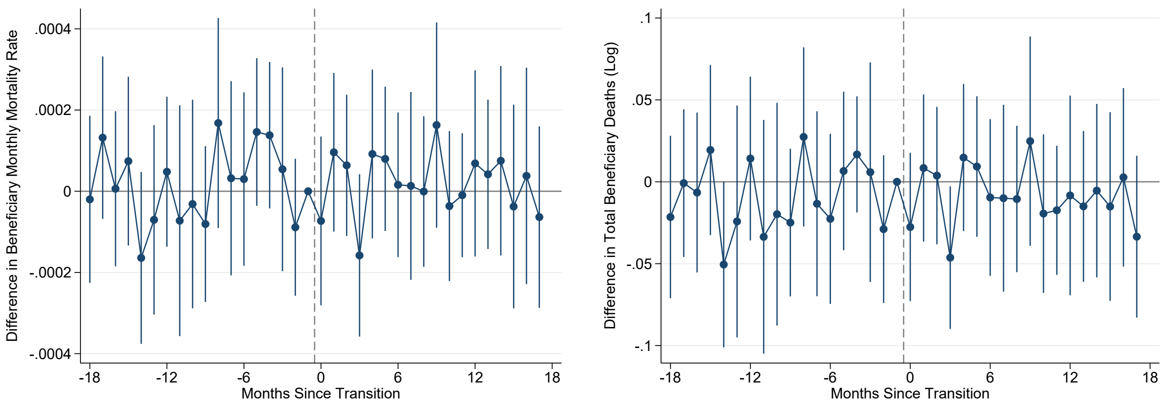
(c) Share of Providers in Solo Practice



(d) Firm Size

Notes: Estimates of δ_e of Equation (2) for $e \in \{-18, \ldots, 17\}$. 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. Error bars give the 95% confidence interval for each estimate. Standard errors are clustered by jurisdiction.

Figure A4: 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 $e \in \{-18, \ldots, 17\}$. 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 A4: Effect of Higher-Denial Administrator on Mortality

	(1) Mortality (per capita)	(2) Mortality (log)
Post-Transition	-0.00000596	-0.00513
	(0.0000234)	(0.00622)
Increase in Denials	0.00000369	0.000137
	(0.0000438)	(0.00985)
Dep. Var. Mean	0.00431	5.741
Observations	70,164	70,164

Notes: Estimates of δ_1 of Equation (10) with $L = 17$. 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%, 1% and 0.1% level, respectively.

E 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 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 screening, prostate-specific antigen testing in elderly men, homocysteine testing, carotid endarterectomy, and inferior vena cava filter placement. In future versions of paper, I hope to incorporate more instances of low-value care, including the 19 other services highlighted by Schwartz et al. (2014).

Table A5 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 3. 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 A5 reports event study estimates for transitions from an administrator with a lower propensity to deny these

Table A5: Summary Statistics for Low-Value Care

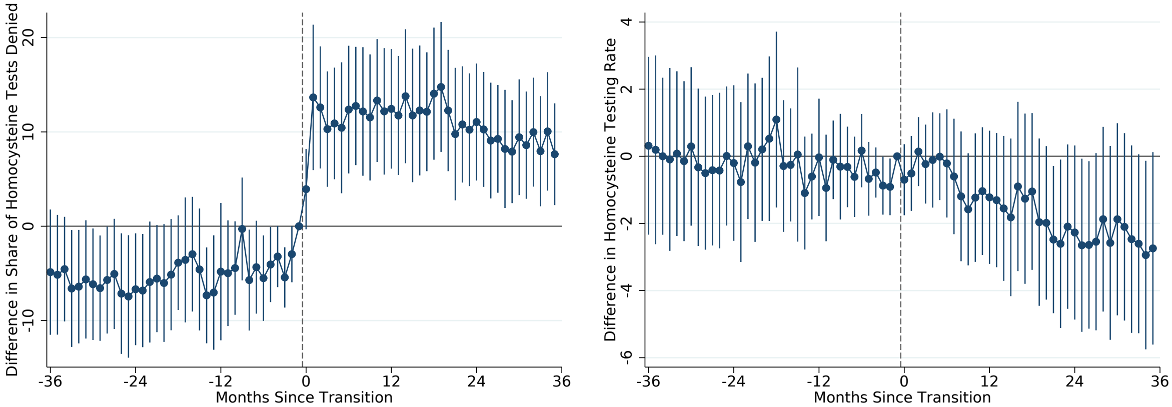
Service	Denial Rate	Utilization Rate	Effect Range	Standard Error	Correlation
Cervical Cancer Screening	26.3	16.9	22.2***	2.75	0.20
Colorectal Cancer Screening	12.0	15.9	22.1***	4.45	-0.20
PSA Testing	18.2	30.0	21.8***	6.35	0.63**
Homocysteine Testing	13.5	9.92	37.7***	9.42	0.37+
CAD Screening	15.1	8.96	24.0***	3.48	0.47*
Endartectomy	4.37	0.250	11.0***	1.91	0.34
IVC Filter Placement	6.27	0.084	13.2***	2.76	0.39+

Notes: Denial rate reported is the jurisdiction-month-level average share of claims for the service denied. Utilization rate reported is the jurisdiction-month-level average number of uses per 1000 eligible beneficiaries. Effect range is the difference between the largest and smallest estimate of γ_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 Z-test of equality of the coefficients. Correlation reports is the contractor-level correlation between the estimates of γ_m of Equation (1) with the denial rate for the relevant service as the dependent variable and the estimates reported in Table 3. Standard errors are clustered by jurisdiction. +, *, ** and *** indicate significance at the 10%, 5%, 1% and 0.1% level, respectively.

claims to a higher one. We see that these transitions result in very large and immediate changes in the 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 results in decreased use over time.

Figures A6 and A7 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 respond. This is consistent with providers only being willing to dramatically change practice patterns for a given procedure in response to large changes 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 percentage point change in overall denial rates reported in Figure 4 represents a 16% change in the denial rate but only a 1% a reduction in revenue. These results indicate that minor changes to the denial rate for a procedure are unlikely to affect the use of that procedure, meaning that denials are unlikely to steer providers toward high-value care.

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

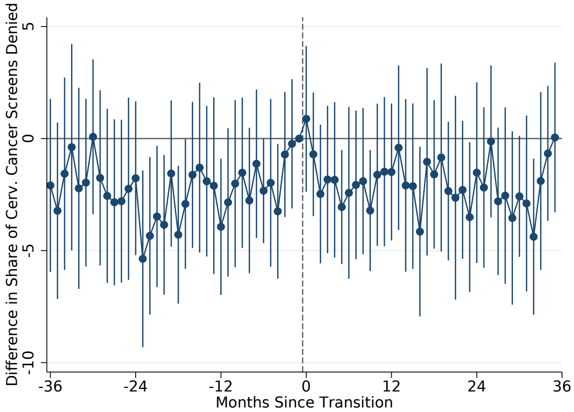


(a) Denials

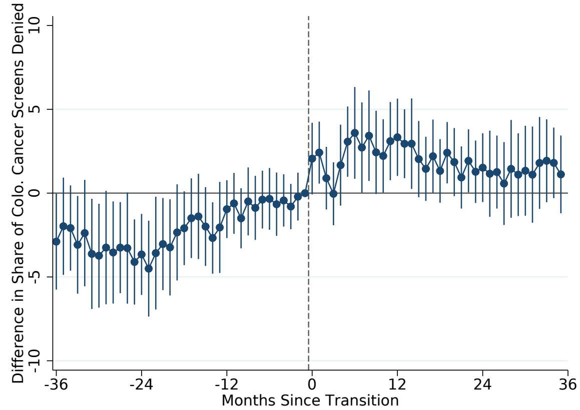
(b) Utilization

Notes: Estimates of β_e of Equation (2) for $e \in \{-36, \ldots, 35\}$. 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.

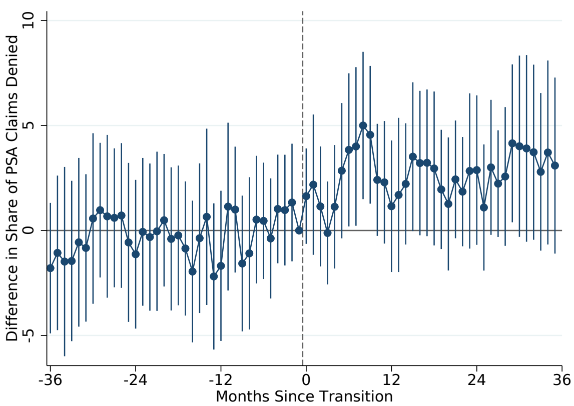
Figure A6: Effect of Transition to Higher-Denial Administrator on Denials of Low-Value Services



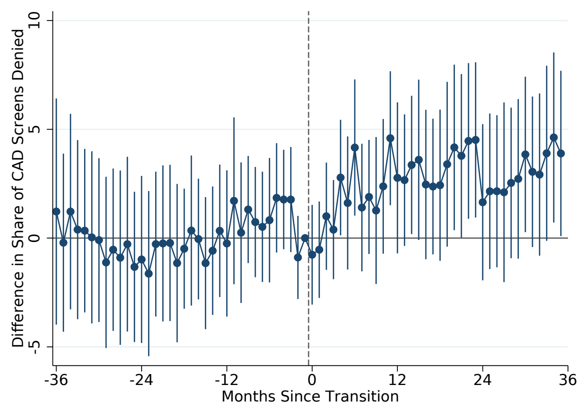
(a) Cervical Cancer Screening



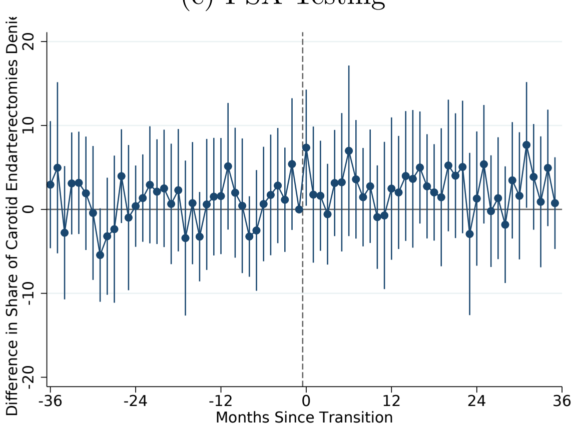
(b) Colorectal Cancer Screening



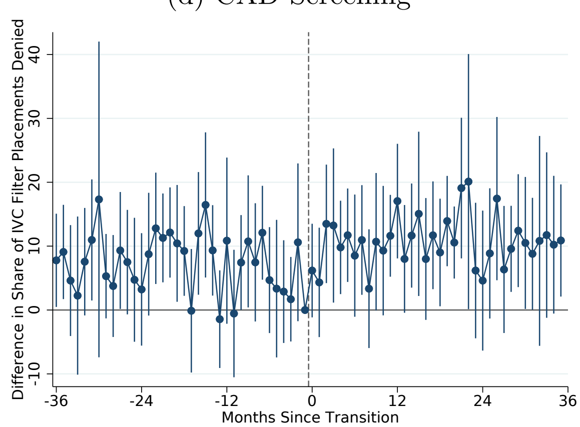
(c) PSA Testing



(d) CAD Screening



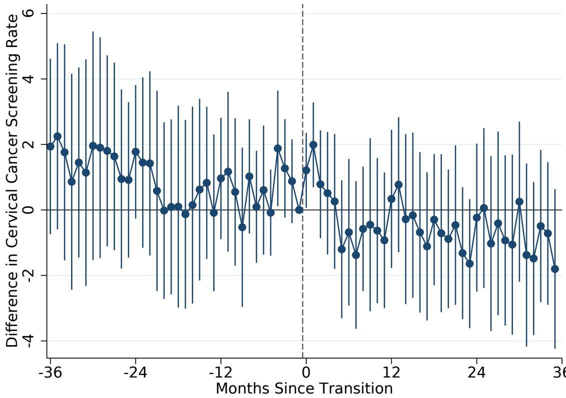
(e) Endartectomy



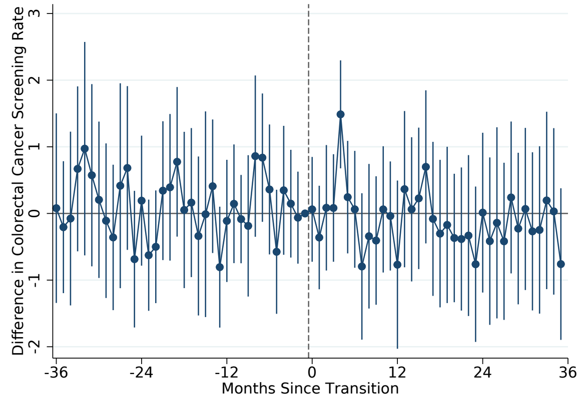
(f) IVC Filter Placement

Notes: Estimates of β_e of Equation (2) for $e \in \{-36, \ldots, 35\}$. An observation is a jurisdiction-wave-month. Dependent variables are the share of claims for various types of low-value care denied. Error bars give the 95% confidence interval for each estimate. Standard errors are clustered by jurisdiction.

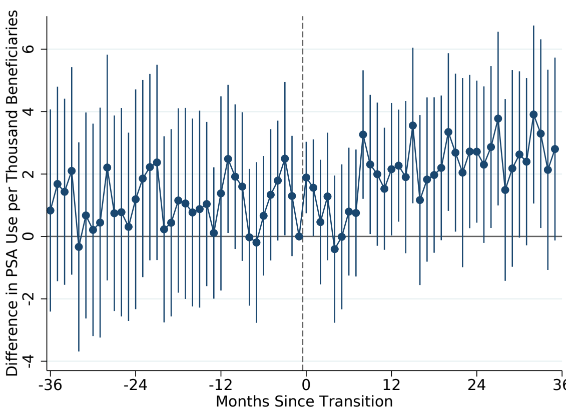
Figure A7: Effect of Transition to Higher-Denial Administrator on Utilization of Low-Value Services



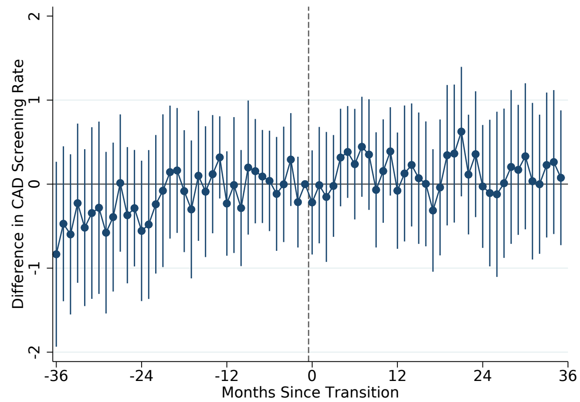
(a) Cervical Cancer Screening



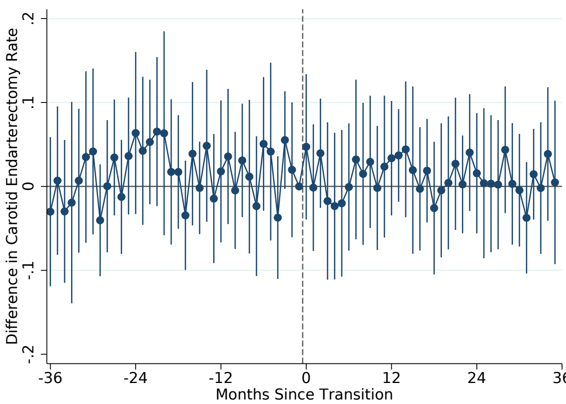
(b) Colorectal Cancer Screening



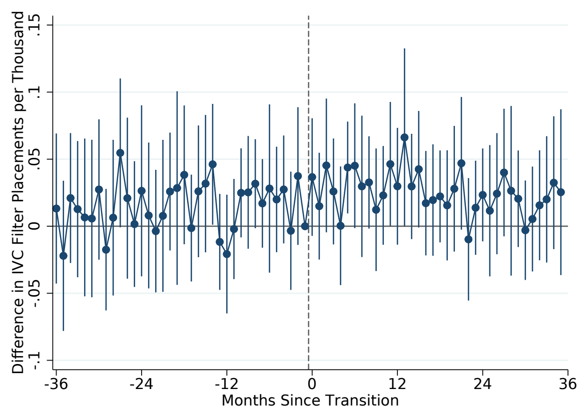
(c) PSA Testing



(d) CAD Screening



(e) Endartectomy



(f) IVC Filter Placement

Notes: Estimates of β_e of Equation (2) for $e \in \{-36, \ldots, 35\}$. An observation is a jurisdiction-wave-month. Dependent variables are the number of claims per 1,000 beneficiaries for various types of low-value care. Error bars give the 95% confidence interval for each estimate. Standard errors are clustered by jurisdiction.

F Alternative Model of Firm Exit

In the main text, I model firms as having idosyncratic 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 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 idosyncratic 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:

(16)

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

Table A6 reports reduced form estimates of these changes for firms of various sizes, analogous to those reported in Table 8 in the main text. Using these moments in estimation rather than those associated with Equation (8), I obtain parameter estimates that imply very similar investment costs to those implied by the model presented in the main text. Figure A8 recreates Figure 12 showing the equilibrium outcomes under the main model and the alternative model considered in this appendix, while Table A7 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 the alternative model. Nonetheless, the robustness of my estimate of the cost of investment to this alternative model lends credence

Table A6: Estimated Alternative Moments

(1) Moment Equation	(2) Firm Sizes	(3) Estimand	(4) Structural Representation	(5) Estimate
Equation (16)	2–5	$\log(P_{v1}) - \log(P_{11}) - (\log(P_{v0}) - \log(P_{10}))$	$\alpha\left(\log\left(\frac{\Pi_{v1}}{v}\right) - \log(\Pi_{11}) - \left(\log\left(\frac{\Pi_{v0}}{v}\right) - \log(\Pi_{10})\right)\right)$	0.0160 (0.0150)
Equation (16)	6–21	$\log(P_{v1}) - \log(P_{11}) - (\log(P_{v0}) - \log(P_{10}))$	$\alpha\left(\log\left(\frac{\Pi_{v1}}{v}\right) - \log(\Pi_{11}) - \left(\log\left(\frac{\Pi_{v0}}{v}\right) - \log(\Pi_{10})\right)\right)$	-0.000600 (0.0181)
Equation (16)	22–104	$\log(P_{v1}) - \log(P_{11}) - (\log(P_{v0}) - \log(P_{10}))$	$\alpha\left(\log\left(\frac{\Pi_{v1}}{v}\right) - \log(\Pi_{11}) - \left(\log\left(\frac{\Pi_{v0}}{v}\right) - \log(\Pi_{10})\right)\right)$	-0.00432 (0.0252)
Equation (16)	≥ 104	$\log(P_{v1}) - \log(P_{11}) - (\log(P_{v0}) - \log(P_{10}))$	$\alpha\left(\log\left(\frac{\Pi_{v1}}{v}\right) - \log(\Pi_{11}) - \left(\log\left(\frac{\Pi_{v0}}{v}\right) - \log(\Pi_{10})\right)\right)$	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 (16), column (5) reports estimates of δ_1 of Equation (10) 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.

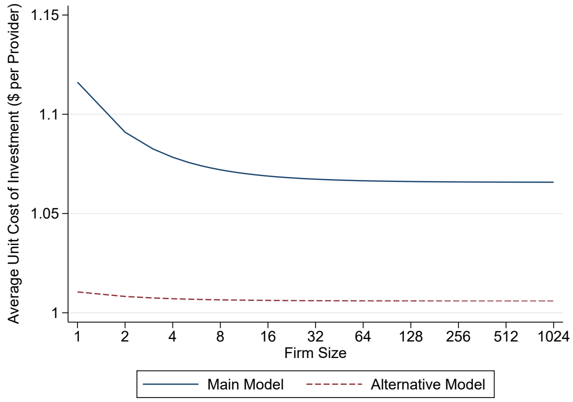
to my estimates.

Table A7: Key Values Under Alternative Provider Allocation Model

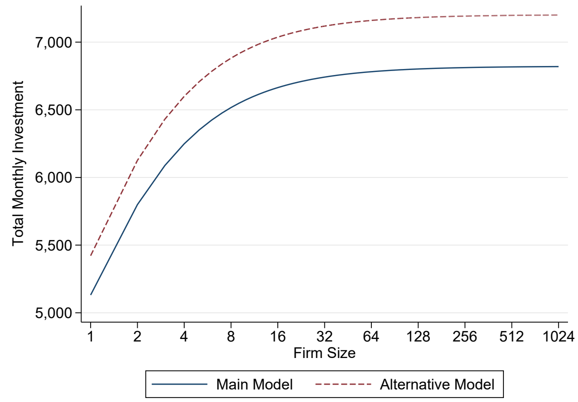
	Main Model	Alternative Model
Total Billing Costs	88.7	87.7
Transition Costs	10	10
Transition Profit Change	-3	-2
Transition Spending Change	7	9
Spending Change Without Response	-2.8	-1.6
Fixed Cost Subsidy Cost Change	4.9	5.6
Fixed Cost Subsidy Profit Change	0.9	0.1
Fixed Cost Subsidy Spending Change	5.8	5.6
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, except targeted transfer costs which is reported in millions.

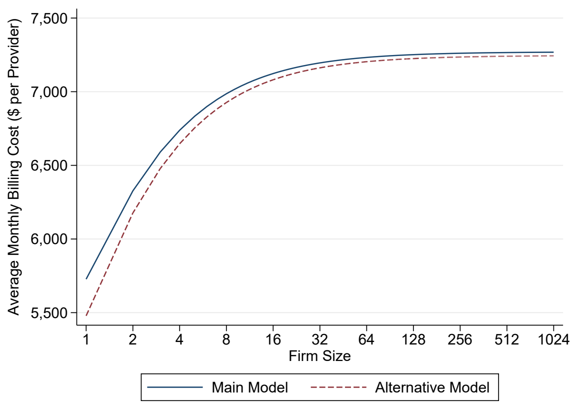
Figure A8: Equilibrium Outcomes by Firm Size Under Alternative Provider Allocation Model



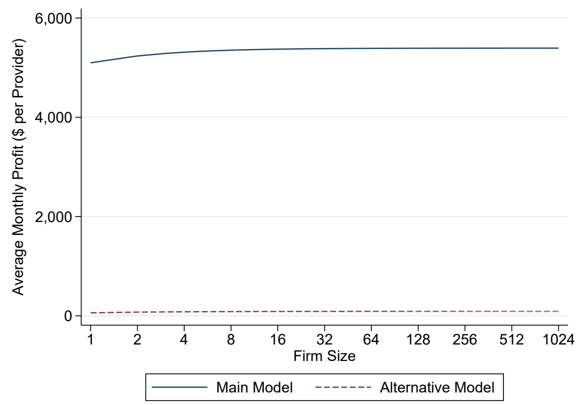
(a) Average Unit Cost



(b) Investment



(c) Billing Cost per Provider



(d) Profit per Provider

Notes: Equilibrium outcomes implied by parameters presented in Table 9 along with those implied by the alternative model presented in Appendix F. 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.

G Proof of Model Identification

In this Appendix, I prove that the model outlined in Section 7 is identified using the moments I employ in estimation.

First, let β_0 and β_1 be defined as Equation (11). 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[41]

$$\frac{\beta_1}{\beta_0} = \frac{c}{d-1} \tag{17}$$

and

$$\sqrt{a+\underline{I}_0} = \frac{2+2\delta+\delta^2}{2\sqrt{-\rho_v\pi_v}}\underline{I}_0 + \frac{\delta(2+\delta)}{2\sqrt{-\rho_v\pi_v}}a + \frac{\sqrt{-\rho_v\pi_v}}{2} \tag{18}$$

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 Π_v in a low-administrative-burden

[41] Note that Equation (18) 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

$$\nu_v = \frac{1 - \Phi\left(-\frac{\Pi_{v0}+\alpha_v}{\sigma_\pi}\right)}{1 - \Phi\left(-\frac{\Pi_{v0}}{\sigma_\pi}\right)}. \tag{19}$$

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 (19) for at least 3 values of v. This system of equations combined with equations (17) and (18) implies unique values for d, a, and $\underline{I}_0$.[42] 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.

[42] Alternatively, including a fourth value of v in the system of equations (19) would also allow a and $\underline{I}_0$ to be separately identified.

H Results on Robustness of Model

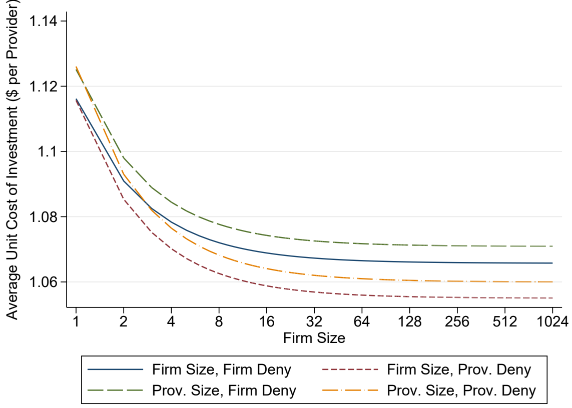
To estimate the model, I group similarly sized firms together to improve precision of the reduced form estimates to be matched. The predicted values from the model, however, rely on specific values of v. In the main text, I obtain these values using firm-weighted averages. In this section, I demonstrate 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 A9 in Appendix I. Table A8 and Figure A9 recreate the key values reported in the main text and in Figure 12 using these alternative weightings. I also report the values from the main text again for comparison.

Table A8: Key Values Under Alternative Weighting Assumptions

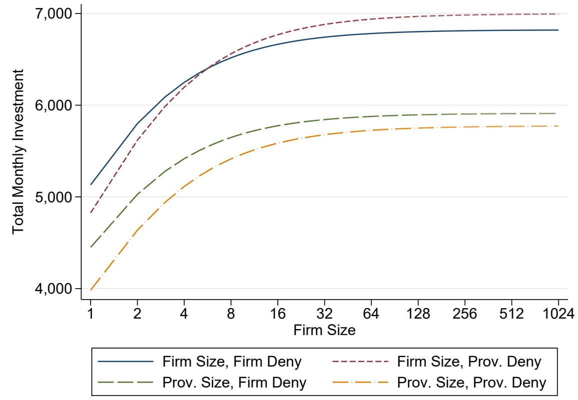
	(1)	(2)	(3)	(4)
Average Size	Firm	Firm	Provider	Provider
Denial-Size Gradient	Firm	Provider	Firm	Provider
Total Billing Costs	88.7	88.5	77.3	73.5
Transition Costs	10	10	9	9
Transition Profit Change	-3	-3	-3	-2
Transition Spending Change	7	8	6	6
Spending Change Without Response	-2.8	-2.6	-2.7	-2.3
Fixed Cost Subsidy Cost Change	4.9	6.6	4.2	5.4
Fixed Cost Subsidy Profit Change	0.9	1.0	0.8	0.9
Fixed Cost Subsidy Spending Change	5.8	7.6	5.0	6.3
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 (11). All values reported in billions of dollars annually, except targeted transfer costs which is reported in millions.

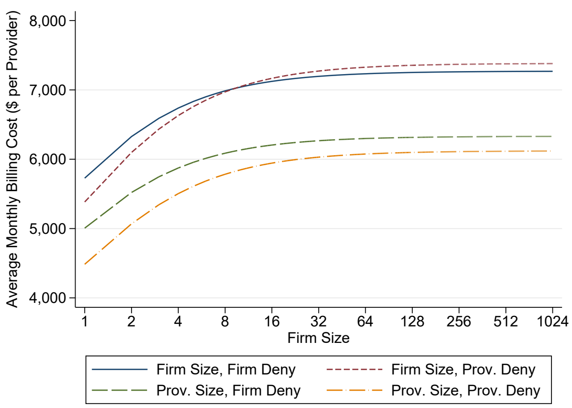
Figure A9: Equilibrium Outcomes by Firm Size with Alternative Weighting Schemes



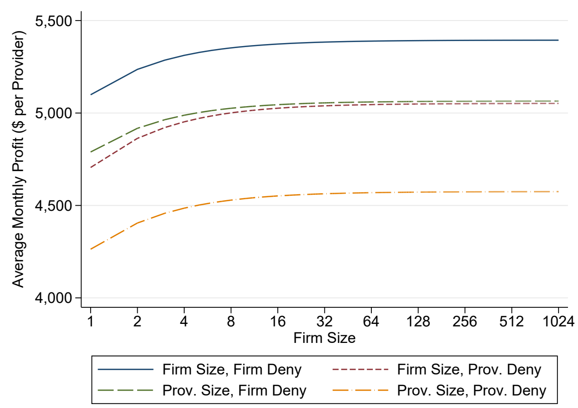
(a) Average Unit Cost



(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 (11) 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.

I 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 observed the relationship between firm size and the denial rate. Table A9 reports estimates of Equation (11) with different weighting schemes along with the values implied by the model estimates reported in Section 7 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 A10 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 A9: 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 (11). 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 9.

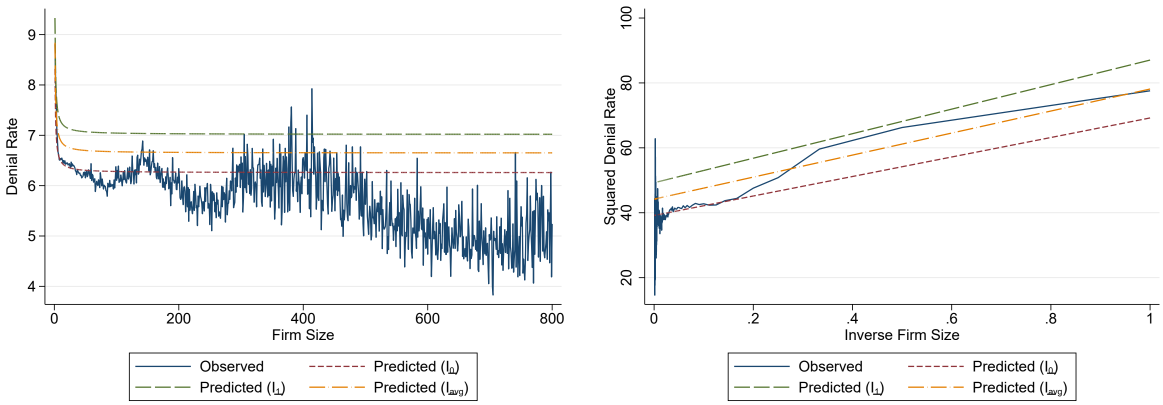
Next, I compare the predicted responses of equilibrium outcomes to a change in administrative burden that come out of the model to those observed in the data. Table A10 presents the estimated and predicted change in charges, denials, and active firms corresponding to the moments used in estimation. Note that columns (1)–(5) of the table are identical to Table 8, 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 A10: 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 (8)	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 (8)	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 (8)	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 (8)	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 (8)	≥ 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 (6)	All	$\mathbb{E}[\tilde{R}_{ij1}]-\mathbb{E}[\tilde{R}_{ij0}]$	$-\sqrt{\frac{v(b-a)}{c+(d-1)v}}\left(\sqrt{a+\underline{I}_0}-\sqrt{a+\underline{I}_1}\right)$	701.0	701.0	1.000
				(353.2)		
Equation (7)	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 (9)	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 (12)	All	β_0	$\frac{(a+\underline{I}_{avg})(d-1)}{b-a}$	44.16	44.20	0.987
				(2.50)		
Equation (13)	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 (8), column (5) reports estimates of δ_1+1 of Equation (10) 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 (7), column (5) reports estimates of $-\delta_1$ of Equation (10) with share of claims denied as the dependent variable. For the moment associated with Equation (6), column (5) reports estimates of δ_1 of Equation (10) 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 (12) and (13), column (5) reports estimates of β_0 and β_1, respectively, of Equation (11). 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 9. 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 A10: 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 9.

Thus 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.