Mechanisms of Hospital Quality Improvement: The Role of Patient Allocation*

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Abstract

This paper asks how hospitals improved the quality of care in response to a Medicare program that penalized excessive readmissions of elderly patients with heart attacks. I document several changes in patient allocation. First, hospitals reallocated heart attack patients towards doctors who, in the pre-program period, had lower readmission and higher survival rates adjusted for patient health, as well as doctors with higher treatment intensities and higher heart attack caseloads. Second, there was an increase in the doctors' specialization in heart attack care and an improvement in the quality of doctor-patient matches. Finally, the changes in the quality of care and patient allocation were greater in hospitals that employed or contracted with physicians compared to hospitals unaffiliated with their physicians. This result highlights that doctor-hospital affiliation affects the hospital's ability to impose changes on physicians and to adjust patient assignments.

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I. Introduction

There is significant variation in the quality of hospital care, leading to substantial differences in patient health outcomes depending on the hospital where a patient is admitted. With this in mind, the US government has implemented various programs that tie hospital payment to their performance, creating incentives for quality improvement. While hospital responses to metrics targeted by these programs have been documented, evidence on the mechanisms of quality improvement remains limited (Chen and Grabowski, 2019; Desai et al., 2016; Gupta, 2021; Gupta et al., 2023; Norton et al., 2018 and others). The knowledge of the mechanisms is crucial for the optimal design of policies aimed at promoting hospital quality.

Doctors' choices are central to many quality responses such as improvements in adherence to clinical guidelines, optimal choice of treatment, and pre-discharge counseling. However, changes in doctor behavior can only occur if hospitals effectively pass down quality incentives to doctors. What hospitals directly control is their patient assignment protocols, which they can use to reallocate patients to high-quality doctors. To the best of my knowledge, this reallocation mechanism for quality improvement has not been previously studied. However, extensive literature documents substantial differences in doctors' treatment styles as well as diagnostic and treatment skills (Abaluck et al., 2016; Currie et al., 2016; Currie and MacLeod, 2017; Chan et al., 2022; Mullainathan and Obermeyer, 2022 and others). My estimates in the sample of elderly Medicare patients with heart attacks imply a 6 percentage points difference in the probability of readmission for observationally similar patients assigned to doctors with high versus low baseline readmissions. This amounts to around a third of the mean readmission rate and highlights a substantial potential benefit from patient reallocation. Moreover, because many doctors in the US are not hospital employees, hospitals may have varying degrees of control over patient assignments and influence on doctors' behavior, depending on the type of the doctor-hospital affiliation.

This paper provides novel evidence on the patient reallocation across doctors as the mechanism of hospital quality improvement, as well as the role of the doctor-hospital affiliation. I study this in the context of the Hospital Readmissions Reduction Program (HRRP), one of the largest US healthcare programs targeting hospital quality. The HRRP penalizes hospitals for excessive readmissions of elderly Medicare patients with select health conditions, including heart attacks that are the focus of this paper. First, I show that there was substantial within-hospital reallocation of patients to different admitting

doctors in response to the HRRP, specifically, to doctors with higher estimated quality, as related to readmission and mortality, higher treatment intensity, and more experience in heart attack treatment. A back of the envelope calculation suggests that around 20 percent of the overall reduction in readmissions can be attributed to reallocating patients from doctors with high baseline readmission rates to those with low rates.[1] The program also led to increased doctors' specialization in heart attack care and an improvement in doctor-patient matches. Second, I document the importance of doctor-hospital affiliations. The findings indicate that both improvements in the quality of care and changes in patient allocation were more pronounced in hospitals affiliated with their physicians compared to hospitals with no affiliation.

I examine hospital responses in the context of the HRRP that started to impose financial penalties on hospitals for excessive unplanned readmissions of Medicare patients in 2012-2013. It is the largest US program targeting healthcare quality and collected around $530 million in hospital penalties in 2017.[2] Readmissions are targeted because they are often considered preventable, and they impose significant costs on both patients and insurers while generating revenue for hospitals from additional hospitalizations. To account for differences in patient health across hospitals, the hospital readmission rate is adjusted for patient risk factors, including demographics and health history. A hospital is penalized if its risk-adjusted readmission exceeds the national average in the measurement period. The readmission metric is based on past hospital performance, implying that current hospital choices only influence future (unknown) penalty status. In the empirical design, I utilize hospital's expectation about exceeding the penalty threshold in the first program year. I focus on quality of care for heart attack patients because this condition is the most suitable for studying the role of patient allocation across doctors. The advantages include the importance of hospital care, a clear distinction between intensive and non-intensive types of treatment, and absence of some gaming responses.[3]

The main data source is inpatient hospital claims for Medicare patients for the period from 2004 to 2015. The data contains a rich set of admission characteristics, including

[1]Specifically, there is a 6 percentage point difference in risk-adjusted readmission between doctors with high versus low baseline readmissions. In an average hospital, 3.7 percent of heart attack patients were reallocated to doctors with low baseline readmission in response to the HRRP. Combined, this results in a 0.24 percentage point decrease in readmissions due to reallocation, which accounts for 21 percent of the total 1.3 percentage point readmission decline.

[2]See https://www.kff.org/medicare/issue-brief/aiming-for-fewer-hospital-u-turns-the-medicare-hospital-readmission-reduction-program/, accessed October 2023.

[3]Because the penalty is assessed individually for each medical condition, I am able to separately analyze the impact on hospital performance for heart attack patients. For detailed discussion, see Section II.

the identifier of an attending physician. While other doctors and healthcare professionals could be involved in a patient's treatment, I focus on the attending physician in the analysis as they hold overall responsibility for patient care and make critical decisions regarding treatments and discharge timing. The analysis is on two main levels: admission-level, to study patient outcomes, and hospital-level, to investigate hospital responses, such as changes in the doctor composition. To differentiate doctors, I consider doctor specialty, experience and pre-reform heart attack caseload. In addition, I define doctor quality and treatment style. These measures are based on the outcomes of heart attack patients treated by a given doctor during the pre-reform period after adjusting the measures for underlying patient health. To adjust for a small number of observations for some doctors, I use empirical Bayes shrinkage methods.

I use a differences-in-differences approach comparing hospitals differetially affected by the HRRP, specifically, hospitals with varying expectation to be penalized in the first program year, before and after the introduction of the program. Hospitals are guided by their expectation of receiving a penalty, since they do not know their future penalty status when deciding how to respond to the program. I compute a non-parametric prediction of the probability to face a penalty in the first program year based on recent readmission performance for each hospital. This measure of hospital expectation is related to the dollar value of the penalty, since both increase in hospital's readmission rate.

In addition, I account for potential mean reversion. For instance, if a hospital had high readmissions not due to its poor quality but because of temporary shocks to patient outcomes or allocation, then after the end of the measurement period and the start of the reform, the hospital is likely to improve as the shock subsides, and not due to the incentives of the HRRP. To address this concern, I use the hospital's historical risk-adjusted readmission rate that precedes the penalty measurement period as an instrument for the expected penalty likelihood. This approach estimates the local treatment effects for hospitals with consistently poor performance on readmission. The identifying assumption is that the outcomes of hospitals with high versus low historical readmission rates would have followed parallel trends in the absence of the penalty. I test this assumption by examining the pre-reform dynamic coefficients on the instrument for the outcomes of interest.

There are two major findings. The first one is that the reform induced substantial reallocation of patients across doctors, as evidenced by three changes in within-hospital allocation. First, I document which types of attending doctors got more involved in the heart attack care. The introduction of the penalty led to a 3 and 4 percentage point

increase, respectively, in the share of heart attack patients treated by attending doctors with high quality in terms of readmission or survival. This corresponds to a 9 and 12 percent increase from the pre-program mean in an average hospital. In addition, around 7 percentage points of patients were reallocated to doctors with high baseline heart attack caseloads. There was no change in patient assignment to cardiologists or doctors with long medical experience, highlighting that hospitals targeted doctors with experience specific to heart attacks in contrast to general experience. Finally, an average hospital had a 7 percentage points increase in the share of heart attack patients assigned to attending doctors with high baseline treatment intensity. This reallocation is related to an increase in the treatment intensity at the patient level as a result of the HRRP, as measured by the use of percutaneous coronary intervention (PCI).

Second, I find changes consistent with increased specialization in heart attack care: there was an 11 percent decline in the number of doctors who work on heart attack cases in an average hospital, and a 6 percent increase in the number of heart attack cases treated by an average doctor. However, compared to an average doctor, there was a much higher increase in per-doctor cases for doctors with high baseline heart attack caseloads and estimated quality. This increase in specialization could in itself be one of the mechanisms of quality improvement if there is learning-by-doing, a phenomena that has been extensively studied in various healthcare contexts, albeit with mixed findings (Červenỳ, 2023; Facchini, 2022; Gaynor et al., 2005; Hentschker and Mennicken, 2018; Tsai et al., 2006; Varabyova et al., 2017).

Third, the reform led to an improvement in the quality of doctor-patient matches. Doctors with high baseline treatment intensity were assigned to patients more appropriate for PCI and experienced a three percent increase in their patients' index of PCI appropriateness. Similar increases were observed for doctors with high baseline quality, high baseline heart attack caseloads, and cardiologists, with no change for an average doctor. It is likely that these doctors are better equipped to assign treatment, perform the procedure, or care for patients who underwent intensive treatment. In contrast, there was no change in doctors' case mixes with respect to the overall health of their patients. Patients appropriate for PCI could be targeted because they are the group with the highest potential to reduce readmissions. It is also possible that sorting patients based on PCI appropriateness, for example, by using any contraindications, is easier than sorting based on general health.

The second major finding is that doctor-hospital affiliation could facilitate quality improvements in response to the HRRP. First, I show that readmission reductions and

treatment changes were higher in hospitals that employ or contract with doctors, compared to hospitals not affiliated with their physicians. Second, there was a corresponding difference in the impact of the reform on patient allocation across physicians, with stronger effects for hospitals affiliated with their doctors. Hospitals unaffiliated with their doctors do not have direct financial relations with physicians and may have weaker non-monetary ties. It may be harder for these hospitals to pass down quality incentives to doctors in order to change treatments and quality. Hospitals without doctor affiliation may also have lower control over patient assignment to doctors.

Additionally, I provide evidence consistent with within-doctor improvements in quality and changes in treatment. I show these responses to the HRRP in admission level analysis in models with doctor-hospital fixed effects. I separately look at continuously working doctors – doctors who treat heart attack patients at a hospital in all years (irrespective of being employed or affiliated with a hospital). This isolates a doctor pool with no change in doctor composition, although it is still affected by patient reallocation. I find an increase in treatment intensity and a decline in readmissions in this sample of continuously working doctors, which is suggestive of within-doctor changes.

There is little evidence of other potential hospital responses. Since reduction in readmissions is associated with increase in treatment intensity, I explore whether hospitals increased investment in a catheterization laboratory (cath lab) which is necessary for intensive treatment and show that there was no change in a cath lab adoption. Compared to other potential mechanisms for quality improvement, patient reallocation offers the advantages of being quickly implementable, accessible to all hospitals, and potentially associated with lower costs. While enhancing doctor-patient assignments might incur higher managerial costs, it does not necessarily require changes in doctor employment and can be confined to adjustments in the composition of shifts and patient assignments within them.

A potential concern about the patient reallocation result is that high-quality doctors are reassigned away from patients with other health conditions and to patients with heart attacks. This could hurt the quality of care for non-targeted patients. However, prior studies of the HRRP find no change or decline in readmissions for non-targeted groups, with improvements observed for similar health conditions that are treated by doctors who also treat heart attacks (Batt et al., 2020; Chen and Grabowski, 2019; Gupta, 2021). It is possible that doctor quality is specific to a health condition, and hospitals were able to improve doctor-patient matches across different conditions. Similarly, if there was an increase in the number of per-doctor cases and specialization not only for heart attacks but

also for other conditions, this could have promoted learning-by-doing across the board. In addition, heart attack is one of the most severe conditions and could be more sensitive to doctor quality compared to other diseases.

This paper contributes to two main strands of literature. First, it is related to the extensive literature on the effect of programs targeting hospital quality. The most related are studies that examine the effect of the HRRP on quality of care and potential gaming responses (Carey and Lin, 2016; Chen and Grabowski, 2019; Chhabra et al., 2019; Desai et al., 2016; Gupta, 2021; Mellor et al., 2017).[4] There is also evidence on hospital responses potentially related to quality improvement such as increased treatment intensity and improved coordination with post-acute care providers (Gupta, 2021; Gupta et al., 2023). Norton et al. (2018) study another pay-for-performance program that targets a range of quality measures, the Hospital Value-Based Purchasing (HVBP) Program, and show improved hospital performance in response to the program. Multiple studies explore whether public reports of hospital and surgeon quality induce quality improvements, and provide mixed evidence while documenting gaming responses such as patient selection to the targeted procedure (Cutler et al. (2004); Dranove et al. (2003); Dranove and Sfekas (2008); Mukamel et al. (2004); Yoon (2020) and others). I contribute to this literature by providing novel evidence on patient reallocation across physicians as a hospital's response to quality incentives. This finding points to a potential benefit from policies promoting within-hospital patient reallocation, for instance, providing hospitals with information on doctor quality in order to facilitate efficient patient assignments. It could also inform policymakers on the benefits of imposing quality incentives on hospitals or other organizations instead of individual doctors.[5]

Second, this study contributes to the literature examining the role of doctor-hospital affiliation in healthcare delivery. This topic is particularly relevant given the increasing prevalence of doctor-hospital affiliations in the United States over the past decades (Nikpay et al., 2018; Scott et al., 2017). Research in this area largely indicates that vertical integration or the employment of doctors by hospitals is associated with higher prices, increased hospital utilization, and greater healthcare spending (Baker et al., 2014; Capps et al., 2018; Lin et al., 2021; Post et al., 2023; Whaley et al., 2021) and with related re-

[4]Prior studies document distortionary responses, such as lower admissions of patients returning to a hospital or upcoding (Gupta, 2021; Ody et al., 2019). Gupta (2021) estimates that the majority of the readmission decline is due to a decrease in patient returns rather than selective readmissions and thus represents true quality improvements despite gaming responses. The goal of this paper is to study the mechanisms behind these true quality improvements.

[5]An example of a pay-for-performance program targeting individual doctors is the Merit-Based Incentive Payment System.

sponses such as overuse of care and upcoding (Post et al., 2022; Young et al., 2021). Prior studies find no effect of increased doctor-hospital affiliation on quality measures (Koch et al., 2021; Scott et al., 2017). I add to this literature by showing that doctor-hospital affiliation might enhance the effectiveness of hospital quality programs. Even if affiliation does not lead to better hospital quality alone, it might allow for easier alignment of incentives and better control of the physician workforce in response to external quality incentives. This evidence can be one of the inputs into policy evaluations and regulation of doctor-hospital affiliation.

The rest of the paper proceeds as follows. Section II provides background on potential mechanisms of hospital quality improvement and the setting of the HRRP. Section III describes the data, followed by the empirical framework introduced in Section IV. Section V presents and discussed the results, and Section VI concludes.

II. Background

Acute myocardial infarction (AMI), or heart attack, is a sudden condition and typically requires immediate hospital care. Heart attack happens when there is a blockage in one of the coronary arteries that supply blood flow to the heart. It is usually caused by a blood clot and results in insufficient supply of oxygen to the heart muscle. Heart attack patients are treated with reperfusion which is the restoration of the blood flow to the heart. Reperfusion can be performed using invasive procedures or medication, specifically thrombolytics – drugs that help dissolve blood clots. Procedures include percutaneous coronary intervention (PCI) that inserts a stent (a permanent metal tube) to a blocked coronary artery restoring the blood flow. Rarely reperfusion is achieved with bypassing the blockage through open-heart surgery (coronary artery bypass graft, or CABG).

Mechanisms of quality improvement

There are several ways how hospitals can improve their readmission performance and quality of care in general. Examples include better adherence to clinical guidelines, improvement in correct diagnosis and choice of treatment, and reduction in hospital-acquired infections. Other changes relate to preparing patients for discharge that could be especially important for readmission reduction, for instance, pre-discharge counseling and better coordination with post-acute care providers or outpatient physicians. Some of the quality improvements can be implemented by hospital administrative staff, nurses and other personnel, for example, an introduction of electronic health records or a decrease

in hospital-acquired infections. However, many changes involve physician care and are related to optimal choice of treatment.

Similar to other hospitalized patients, heart attack patients can be treated by several doctors. First, they can be stabilized by doctors or other medical professionals in the ER or ambulance. After being admitted to the hospital, a patient is assigned an attending physician who is responsible for the patient care, including the choice of treatments and other decisions such as when to discharge a patient. Most heart attack patients have an attending physician who is a cardiologist or an internal medicine doctor. If attending physician who is an internal medicine doctor prescribes a PCI (but cannot perform it), another doctor who is a cardiologist performs the procedure. In my data, I observe the attending physician for all patients and operating physician for patients that underwent a procedure or surgery. When studying the effect of the reform on doctor composition and its relation to improvements in quality, I focus on the attending physician as a doctor who is responsible for patient care and has a major impact on the quality of care.

As described in details below, the HRRP targeted several health conditions, which at the time of its introduction were heart attack, heart failure and pneumonia. I limit my analysis to heart attack for the following reasons. First, because of the highly acute nature of heart attack, patient health outcomes are highly dependent on quality of hospital care compared to chronic conditions for which ongoing (including post-discharge) treatment plays an important role. Second, heart attack has a well-defined and extensively studied choice of treatment between intensive and non-intensive care, which I use to differentiate between physicians with different treatment styles. In addition, because heart attack patients have emergency admissions and not planned admissions, this rules out a response documented by Alexander (2020) in the context of voluntary cost-reduction program: doctors working in more than one hospital shifted their referrals and admissions so that healthier patients were admitted to participating hospitals.

In contrast to other hospital personnel, such as nurses or orderlies, a substantial fraction of doctors are not hospital employees. Non-employed physicians can only practice in hospitals where they have admitting privileges, which are the rights granted to a physician by a hospital to admit patients to that hospital. The affiliation between doctors and hospitals can take various forms, which can affect the hospital's ability to pass down quality incentives to doctors. In 2012, 42 percent of hospitals employed at least a portion of their physician workforce, while 19 percent of hospitals engaged in contractual affiliations, leaving the remaining 38 percent with no affiliation with their physicians (Scott et al., 2017). Contractual non-employment affiliation could take the form of compensating

non-employed physicians for specific services, such as working shifts in the ER. Another example includes joint ventures or the creation of a firm that offers services to physicians, such as IT services, equipment leasing, or negotiation of insurance contracts (MedPAC 2007).

One potential mechanism for hospital quality improvement is reallocation of patients to high quality doctors. There are different ways how a hospital can achieve this reallocation. Consider a case of employed physicians who work in shifts at a hospital. Typically, admitted patients are assigned to doctors based on the physician's specialty and the number of active cases handled by the doctor. Hospitals may adjust their assignment protocols to enhance the alignment between a doctor's expertise and a patient's diagnosis and severity. Additionally, hospitals may modify the composition of doctors on duty at any given time. In extreme and unlikely cases, employed physicians may face termination, while non-employed physicians may have their admitting privileges revoked. The loss of privileges is unlikely due to the importance of referrals and admissions initiated by physicians with privileges, which represent a significant source of hospital admissions. Moreover, hospitals may be sued by doctors for loss of privileges. Given that, in the case of no affiliation between a hospital and its physicians, a hospital can be limited in its ability to influence the allocation of cases or physician behavior.

Another hospital response to quality incentives could involve changes in capital investments. If hospitals believe that providing intensive treatment is essential to improve quality of care for certain patients, they may consider investing in a catheterization laboratory, often referred to as a cath lab. A cath lab is equipped with imaging equipment used for performing intensive cardiac procedures such as PCI. Hospitals that do not have a cath lab may transfer appropriate patients to another hospital that has a cath lab to receive intensive treatment. Cath lab adoption may be beneficial or harmful for patient health since hospitals have varying quality not only in overall treatment but also in performing intensive procedures (Chandra and Staiger, 2007; Chandra and Staiger, 2020 and others). If a hospital considering cath lab adoption has a low expected quality of intensive treatment, it might be better not to adopt a cath lab and continue to transfer patients to a higher-quality hospital for treatment (taking into account other factors such as the time lost during transfer).

The Hospital Readmissions Reduction Program (HRRP)

The HRRP was created as a part of the Affordable Care Act (ACA) that passed in 2010, alongside other healthcare quality improvement programs. It targets hospital readmis-

sions, which are hospital stays that occur within a month of another hospitalization. Readmissions are common and costly; moreover, it is widely considered that a large fraction of readmissions are unnecessary and preventable (MedPAC 2007). Since hospitals receive reimbursements from Medicare for each admission, before the HRRP, they benefited financially from patient readmissions. In 2011, it cost Medicare 24 billion dollars to pay for 1.8 million hospital readmissions (Hines et al., 2014). The HRRP aims to motivate hospitals to reduce unplanned preventable readmissions in order to cut costs and improve patient health. Penalties for hospitals with excessive readmissions for Medicare patients went into effect in October 2012. Details of the program were shared with hospitals in August 2011. By then, hospitals had an incentive to improve quality and reduce readmissions because the penalty is based on past performance. In addition, hospitals had an expectation of their penalty status in 2012, so that hospital responses are expected at least a year before the first penalty was paid.[6]

Initially, the program targeted fee-for-service Medicare patients with heart attack, heart failure, and pneumonia, expanding to cover other conditions and procedures after three years. The penalty imposed in year t is based on risk-adjusted readmission rate for admissions in years $(t-4, t-2)$ and is determined separately for each condition. For both computation and application of penalty, CMS uses years starting in July, and I correspondingly define years as starting in July in my analysis. Readmissions are measured for index admissions that occur at least 30 days after a previous hospitalization with the same condition and in which the patient is discharged alive. Readmission is a hospitalization in any hospital with any diagnosis within 30 days of discharge from an index admission. Hospital readmission rate is risk adjusted to account for differences in underlying patient health across hospitals (hospital case mix). Patient risk factors include age, gender, comorbidities, and a history of health conditions and procedures within one year of admission. The risk-adjusted readmission rate is then normalized by the national average. If this value is greater than one (the difference is called excess readmission rate), it indicates excessive readmissions and lower quality, resulting in a hospital receiving a penalty in year t. Higher quality hospitals with below average risk-adjusted readmission do not get neither penalty nor reward payments.

The penalty is implemented through a reduction in reimbursement for treatment of

[6]Hospitals were aware of their raw and risk-adjusted readmission rates for several years before the program started. CMS started to send each hospital a yearly report for each condition with its risk-adjusted readmission and the national rate as a benchmark in 2009 (Desai et al., 2016). In addition, the public reporting of the hospital risk-adjusted readmission started on the Hospital Compare website in 2009.

fee-for-service Medicare patients that hospitals receive from the Centers for Medicare and Medicaid Services (CMS). CMS is the federal agency responsible for administering government insurance programs, including Medicare, and plays a central role in overseeing healthcare policies, including the HRRP. CMS compensates hospitals for the treatment of fee-for-service Medicare beneficiaries using the Prospective Payment System, which provides a fixed payment for each hospital admission. In penalized hospitals, CMS reduced hospital's total Medicare payments up to 1 percent in the first year, and the cap increased to 3 percent in 2015. The reduction is proportional to hospital excess rate of readmissions. In the first year, 64% of hospitals were penalized, resulting in a total penalty of 290 million dollars (Boccuti and Casillas, 2015). Since around one-third of hospital revenue comes from Medicare patients, and a substantial number of hospitals already have low or negative margins, penalized hospitals have a strong incentive to avoid these penalties. Moreover, the marginal penalty, by design, greatly exceeds the revenue from a potential future readmission (MedPAC, 2018). The penalty only affects hospital payments and not physician reimbursements, so any incentive for physicians to improve quality would come through the hospital.

Penalty status and amount is determined separately for each medical condition. The rationale is to motivate hospitals to improve readmissions for patients with each condition. This feature allows me to isolate the effect of heart attack penalty on hospital performance for heart attack patients. The penalty is based on past performance, specifically, the penalty in the first year of July 2012-June 2013 was computed based on admissions occurring from July 2008 to June 2011. Importantly, this measurement period end before August 2011 when hospitals learned the program details. Consequently, hospitals could not influence the penalty only for the first program year. However, readmission rates and penalty status in subsequent years were affected by the introduction of the HRRP. As a result, I rely solely on the first-year penalty status and excess readmission rate to construct the measure of the HRRP incentives in all post-reform years.

III. Data

The primary data source consists of all Medicare fee-for-service inpatient claims in the period from 2004 to 2015. Medicare is a government health insurance program for people who are 65 and older as well as younger people with certain disabilities. The inpatient claims data contains all claims that inpatient providers, including hospitals, submit to CMS for reimbursement of treatment of Medicare beneficiaries. In addition to payment

details, claims document patient's diagnoses, procedures performed, admission and discharge dates, and various other characteristics of an inpatient stay. Importantly, claims also include physician identifier of attending physician. If applicable, they also include operating physician, who is responsible for performing procedures or surgeries, and other physician, for example, an anesthesiologist. As discussed in Section II, when studying doctor composition, I focus on attending doctor because this doctor is responsible for the overall patient treatment.

To construct certain variables, I supplement this data with outpatient claims data that are submitted by physicians, hospital outpatient departments and other outpatient providers.[7] Detailed information on patients is available from the Medicare Master Beneficiary Summary Files (MBSF) and its segments. This data contains patient's demographic characteristics, chronic conditions, and summary of utilization of medical care and spending.

I get hospital characteristics from the American Hospital Association survey. Data on risk-adjusted readmission rates and the penalty status is available from the CMS website. Physician characteristics such as specialty and graduation year are available from CMS Physician Compare data.

I study the sample of Medicare beneficiaries who had a hospital admission for heart attack in 2008-2015 (July 2007 - June 2015). As discussed in Section II, CMS uses year ending in June for the penalty assignment, and in the subsequent analysis, I refer to year as ending in June. I restrict the sample to patients who are at least 65 years old. Furthermore, I restrict the sample to short-term care hospitals, excluding critical access or specialty hospitals that were not included in the program. I exclude small hospitals that are not subject to penalty in at least one year due to CMS restriction that risk-adjusted readmission is computed and the penalty is assigned only if a hospital has at least 25 patients with a relevant condition over a rolling 3 year window used for computation.

For the analysis of readmission, I limit the sample to index admissions for which CMS computes readmission rates and that are the target of the penalty. Index admissions are heart attack admissions that satisfy the following criteria. Index admissions cannot happen within 30 days of discharge for another heart attack admission. This implies that subsequent readmissions after the initial readmission are not counted for the readmission measure. In addition, index admissions only include admissions for which a patient is

[7] I have access to a 100% sample of outpatient claims and a 20% sample of Carrier claims. Outpatient claims cover hospital outpatient departments and other outpatient institutional providers. Carrier claims are submitted by physicians for services they perform in both outpatient and inpatient settings, as well as by other non-institutional providers.

discharged alive, with the rationale that there needs to be a possibility of readmission.[8] In addition, an admission is excluded from index admissions if a patient is discharged from a hospital on the same day as admitted or if transferred to another hospital. Around 80 percent of heart attack admissions in the study period are index admissions. Readmission outcome is admission in any hospital with any diagnosis within 30 days of discharge for index admission. I look at treatment for index admissions, but study survival for all admissions to account for potential changes in in-hospital survival that are by definition zero for all index admission.

In order to study the composition of doctors who treat heart attack cases, I differentiate doctors using several types. Some types are based on doctor characteristics such as specialty and experience (defined as time since graduation) that are available from the Physician Compare data. Other types are constructed from the inpatient claims data to proxy doctor's quality. I define 'baseline' doctor types using data in 2008-2010, which precedes the introduction of quality incentives (both the announcement of the program and the passage of the ACA that marks potential anticipatory responses). First, I divide doctors by heart attack caseload which is the number of heart attack cases in the baseline period, with high type including doctors with more than 15 heart attack cases during the baseline period.[9]

In addition, I define doctor's effect on PCI use, 30-day survival and readmission for all heart attack cases treated by a physician in any hospital in the baseline period. To account for differences in case mix across physicians (i.e. different underlying patient health), I risk-adjust patient outcomes using patient risk factors that include patient demographics, chronic conditions, comorbidities and the type of heart attack. Specifically, I estimate a random-effect logit regression of a patient outcome or treatment - PCI, survival and readmission - on patient risk factors and physician random effect.[10] I use empirical Bayes shrinkage estimates of the random logit effects to define variation in patient outcomes

[8] In principle, hospitals with high in-hospital mortality could have low readmission rates because of this restriction, even after risk-adjustment. In addition to risk adjusted readmission, CMS also computes hospital risk adjusted 30-day mortality, and the two measures are expected to complement each other in assessment of hospital quality. Risk adjusted mortality is publicly reported alongside with risk adjusted readmission and is one of the targets in another quality program - Hospital Value Based Purchasing program (HVBP).

[9] My sample only includes FFS Medicare patients, so the total number of heart attack patients for each doctor is higher and also includes privately insured, patients with Medicare Advantage and other types of health insurance.

[10] The results are robust to an alternative definition of doctor type that uses physician fixed effect from a linear regression of patient patient outcome or treatment on patient risk factors and physician fixed effect.

across physicians for observationally similar patients. Empirical Bayes estimates decrease the estimation error by shrinking the physician effects toward 0, especially for physicians with small number of cases in the baseline period. This adjustment is important in this setting as many doctors work on low number of admissions. The physician effect is not defined for doctors who did not treat any heart attack patients in 2008-2010. In addition, I exclude doctors with less than 5 heart attack cases in the baseline period from the estimation of doctor type because of the noisy estimates. I classify a doctor as a high type separately for each measure if a doctor is above the median of this measure among doctors in the baseline estimation sample. While physician effect on patient outcomes is directly related to doctor quality, other types such as specialty, caseload or treatment intensity are more easily observed by hospitals and could serve as proxies for quality.

To explore the role of intensive treatment in quality improvements and patient reallocation, I create a measure of clinical appropriateness to receive PCI for each patient. In practice, patient appropriateness depends on the characteristics of a heart attack, as well as other medical conditions and overall patient health. For example, clinical guidelines state that very old and frail patients should not receive PCI due to the challenges of recovery from an invasive procedure. Using admissions in pre-period (spanning 2008-2010) in high-quality hospitals, I run a regression of PCI use on detailed patient characteristics and hospital fixed effect. I use the estimates for patient risk factors to predict individual PCI appropriateness for all patients in the sample. I focus on high-quality hospitals to better approximate the optimal choice of treatment for patients with different underlying health conditions.[11]

To investigate how the impact of the HRRP varies based on the type of doctor-hospital relationship, I utilize data from the American Hospital Association (AHA). A limitation of the AHA data is that it only indicates whether a hospital has a specific type of affiliation with some physicians practicing in the hospital, but it does not provide information on the number of physicians under each arrangement. I divide hospitals into two groups: hospitals with any affiliation with some of its physicians (56 percent of hospitals) versus no affiliation or missing data in 2010 (44 percent of hospitals).

Table 1 presents characteristics of heart attack admissions in Columns (1)-(3) and characteristics of attending physicians in Column (4). Column (1) shows characteristics of admissions in hospitals with high penalty risk in the first program year, defined as

[11]To define high-quality hospitals, I assign a rank to each hospital for each year separately based on risk-adjusted mortality and readmission rates in the period preceding the reform (2006-2010). I then average the ranks across years and outcomes and select the top 200 hospitals based on this average rank.

expected probability to receive a penalty in 2013 being greater than 0.5. I describe this measure in Section IV. Column (2) presents a summary for admissions in low penalty risk hospitals, and Column (3) – in all hospitals. There are around 1.4 million heart attack admissions in the sample and 87 percent of them are index admissions - the type of admissions that CMS uses to compute the readmission measure. As expected, the probability of readmission is substantially higher in high penalty risk hospitals, equal to 21 percent, compared to 16 percent in low penalty risk hospitals. In addition, high penalty risk hospitals have a slightly lower survival rate, with an 85 percent probability compared to 86 percent in low penalty risk hospitals. The intensity of treatment is higher in low penalty risk hospitals, with 42 percent of patients receiving PCI as treatment compared to 33 percent in high penalty risk hospitals.

There were substantial differences in patient characteristics between high and low penalty risk hospitals. In hospitals with low penalty risk, white patients had a relatively higher likelihood of admission compared to non-white patients. Specifically, in high penalty risk hospitals, 15 percent of heart attack patients were non-white, contrasting with 9 percent in low penalty risk hospitals. One proxy for proxy for low socioeconomic status (SES) is dual eligibility for Medicare and Medicaid. The eligibility criteria for dual enrollment vary by state and include maximum income and asset requirements. Dual eligible patients constituted 25 percent of patients in high penalty risk hospitals, while only amounting to 18 percent in low penalty risk hospitals. These patterns suggest that one of the factors in existing health disparities is the lower quality of hospitals admitting non-white and low SES patients. Low penalty risk hospitals had more male and younger patients compared to high penalty risk hospitals, as well as patients with better health. To define patient health, I use an approximation of a Charlson Comorbidity index (CCI), a common measure of chronic conditions in elderly patients.

Panel B shows that the majority of patients are treated by doctors with over 10 heart attack cases in 2008-2010, and 33 percent of patients are treated by doctors with more than 50 cases. However, at the doctor level, only 44 percent of doctors treated more than 10 heart attack admissions in the baseline period. Cardiologists and internal medicine doctors together care for around 90 percent of heart attack patients, with a higher concentration of cardiologists in low penalty risk hospitals. Cardiologists work as attending physicians for 45 percent of heart attack admissions but constitute just 22 percent of the heart attack physician pool, as they have a greater number of cases per doctor than internal medicine doctors.

Baseline doctor types are defined based on heart attack admissions from 2008 to

2010, and there are doctors who treat less than 5 heart attack patients before 2011 with undefined baseline types. They treat 26 percent of all admissions and account for 63 percent of doctors in the sample. The remaining 37 percent are equally split between low and high types for each measure. Doctors with high and low types with respect to baseline readmission treat a similar total number of cases; however, higher-intensity and higher-survival doctors treat substantially more patients than the respective low types. Compared to low penalty risk hospitals, heart attack patients in high penalty risk hospitals are more often treated by doctors with poor readmission performance and low intensity, while the probability of being treated by a low-survival physician is similar.

IV. Methods

The penalty timing and structure have important implications for my empirical approach. First, hospitals are penalized based on past readmission performance. This means that when a hospital makes a decision about effort and quality, it does not know whether readmission in this year will be excessive and will be penalized in the future. A hospital has to make decisions based on the expectation of receiving a penalty, and I use expectation as a 'treatment' intensity variable that affects hospital decisions on quality and patient allocation. Note that hospitals just above and below the threshold could have similar expectation to be penalized and similar incentives to improve quality, making the treatment status 'fuzzy'. Moreover, the expectation reflects the intensive margin of the penalty incentive. Hospitals with the highest expectation are almost sure that they will be penalized and have the highest incentive to improve, while hospitals near the threshold are unsure and have lower incentive. To define quality incentives, I only account for an expectation of receiving the penalty and do not use the expectation of its dollar value. Note that conditional on exceeding the readmission threshold, the marginal penalty per additional readmission is constant. Because of that, the magnitude of the excess readmission and the resulting absolute penalty value do not matter for the incentive to avoid a marginal readmission. Moreover, the constructed expectation measure is related to the absolute value of the penalty, since both increase in hospital's readmission rate.

Hospital expectation is unobserved, and I assume that a hospital forms its expectation of excess readmissions based on its past performance: hospitals had information on their readmission rates from CMS reports starting in 2009. Specifically, I assume that the expectation of the probability of being penalized in 2013 (the first year of the program) is predicted from the raw readmission rate in 2009-2011. I construct the corresponding

prediction by a kernel regression of penalty status in 2013 on readmission rate in 2009-2011.[12] Figure 1 plots the hospital penalty expectation for different levels of readmission rate in 2009-2011 as a red line, with true penalty status in the first year depicted by blue dots for each hospital. It illustrates that there was a wide variation in penalty probability for hospitals with medium readmission rates, which created variation in quality incentives.

I study the effect of the HRRP on three levels of analysis: admission, hospital and doctor-hospital level. The analysis of the changes in patient outcomes and treatment is on the admission level, and I study the impact on patient allocation and doctor-patient matches on hospital and doctor-hospital level. On the admission level, I use the following DID model to study the outcome of patient i in hospital h and year t:

$$Y_{iht} = \lambda_h + \lambda_t + \beta Expectation_h \times \mathbf{1}(t \geq 2012)_t + \gamma X_i + \varepsilon_{iht} \tag{1}$$

where Y_{iht} is patient outcome such as readmission, survival or treatment. λ_h are hospital fixed effects that absorb unobserved time-invariant hospital characteristics, including hospital quality that is constant over time and might affect whether the hospital's penalty risk. X_i include patient risk factors and λ_t are year fixed effects. $Expectation_h$ is the expectation of hospital h of receiving the penalty for heart attack readmissions in the first program year, which is interacted with the post-reform period that starts in 2012 (July 2011 - June 2012) after hospitals were notified about the details of the program.[13] I explore the possibility that hospitals started to respond to the program in 2011 when the HRRP was first announced in the dynamic DID graphs described below. The coefficient of interest is β and represents the effect of the HRRP on outcomes in a hospital that expects to be penalized with probability 1 in the post-period of 2012-2015. Standard errors are clustered at the hospital level.

To explore the doctor composition, I look at the share of heart attack cases in a hospital that is assigned to doctors with a certain type, for example, with high or low estimated baseline readmission. For analysis of this and other hospital-level outcomes Y_{ht},

[12] The empirical strategy is similar to Gupta (2021) in using the measure of hospital expectations as well as instrumental variable approach to account for mean reversion.

[13] As discussed in Section II, only the penalty status in the first year is exogenous and is determined before the announcement of the program rules.

I estimate the following model:[14]

$$Y_{ht} = \lambda_h + \lambda_t + \beta Expectation_h \times \mathbf{1}(t \geq 2012)_t + \varepsilon_{ht} \tag{2}$$

In the analysis on doctor-hospital level, I explore the effect of the HRRP incentives on per-doctor number of cases and a case mix of doctor's patients. For that, I estimate the following model on doctor-hospital level, where λ_{dh} is a doctor-hospital fixed effect:

$$Y_{dht} = \lambda_{dh} + \lambda_t + \beta Expectation_h \times \mathbf{1}(t \geq 2012)_t + \varepsilon_{dht} \tag{3}$$

Results from Equations 1-3 could be biased because of mean reversion, especially when the outcome of interest in patient readmission. If a hospital is penalized because of a negative transitory shock on readmission, its future readmission will likely improve after the shock passes. Temporary shocks may include regional factors, such as excessive heat or wildfire smoke, or hospital-level factors, such as an integration with another hospital and a temporary disruption in operations. To deal with this potential bias, $Expectation_h$ is instrumented by Z_h which is a historical risk-adjusted readmission, measured in 2005-2007. The IV estimates provide local treatment effects for hospitals with consistently low performance on readmission. The identifying assumption is that hospitals with high versus low historical readmission performance would have exhibited parallel trends in the absence of the HRRP. To test this assumption, I assess the pre-reform dynamic coefficients β_τ estimated from (or an analogous hospital or doctor-hospital model):

$$Y_{iht} = \lambda_h + \lambda_t + \sum_{\tau \neq 2008} \beta_\tau \mathbf{1}(T_{Z_h} = 1) \times \mathbf{1}(t = \tau)_t + \varepsilon_{iht} \tag{4}$$

where T_{Z_h} is whether hospital h is in the top tercile of the instrument Z_h, meaning the highest historical readmission rates.

Heterogeneity by doctor-hospital affiliation

To study differences in responses to the HRRP by doctor-hospital affiliation, I use a triple-difference approach. For the analysis of patient outcomes, I estimate the following

[14]When studying the share of patients treated by high and low intensity doctors, I include year fixed effects interacted with cath lab status in 2007 to account for differences in the practice environment (since a cath lab is required to perform an intensive treatment). Results on patient allocation to other types of doctors are not sensitive to this specification change.

regression:

$$Y_{iht} = \lambda_h + \lambda_t + \beta_1 Z_h \times \mathbf{1}(t \geq 2012)_t + \beta_2 Affil_h \times \mathbf{1}(t \geq 2012)_t + \beta_3 Z_h \times Affil_h \times \mathbf{1}(t \geq 2012)_t + X_{iht} + \varepsilon_{iht}, \tag{5}$$

where Z_h is the instrument, hospital's historical risk-adjusted readmission, and $Affil_h$ indicates whether a hospital is affiliated with any of its physicians (including employment) in 2010. The magnitude of the estimates is not comparable to the main IV results. β_1 captures the effect of the reform on hospitals without doctor affiliation, with quality incentives measured by Z_h. β_2 represents the change in outcome in the post-reform period for affiliated hospitals with low penalty risk. The coefficient of interest is β_3, the triple-difference estimate, which is the differential response to the same penalty risk for affiliated relative to non-affiliated hospitals after the reform. Standard errors are clustered at the hospital level. For the analysis of patient reallocation, I estimate a similar equation on hospital-year level that excludes patient characteristics. The identifying assumption is that the relative outcome of affiliated and non-affiliated hospitals with high historic readmissions would trend in the same way as the relative outcome of affiliated and non-affiliated hospitals with low historic readmissions in the absence of the program (Olden and Møen, 2022).

V. Results

Effect on patient allocation

Table 2 provides a summary of the effect of the HRRP on patient reallocation. Each result presents the impact of the probability to receive a penalty in the first reform year on the share of heart attack cases treated by attending physicians with certain type. Columns (1)-(2) presents estimates from equation 2 with OLS or IV. Column (3) reports the average value of the outcome of interest in the pre-reform period, from 2008 to 2010. The results suggest that the HRRP quality incentives induced significant reallocation of patients to doctors with high estimated quality in terms of both readmission and survival, to doctors with high baseline treatment intensity and to doctors who treat a high number of heart attack patients before the reform. At a hospital with the highest incentives (expected penalty probability of 1), doctors with low baseline readmission rates gained around 7.4 percentage points of heart attack admissions over 2012-2015. Since around a half of all hospitals are penalized, a change in the average hospital was approximately

3.7 percentage points or a 12 percent increase from the pre-reform mean. In addition, there was a reallocation of heart attack patients to attending doctors with high baseline survival, with an increase in their share of patients in an average hospital of around 2.8 percentage points or 9 percent.

The results for high baseline PCI doctors show consistent patterns of reallocation from low-intensity to high-intensity doctors. In an average hospital, high PCI doctors were allocated around 7 percentage points more heart attack cases post-2011 according to IV estimates. Finally, there was reallocation to doctors more experienced in the care for heart attack patients, specifically, doctors with high number of heart attack cases before the reform. As a result of the HRRP, an average hospital reallocated around 7 percentage points of heart attack patients to these doctors. IV estimates are mostly higher than OLS estimates, which is expected if some hospitals have high penalty risk due to temporary factors rather than low quality and expect lower readmissions as the temporary shock passes without changing their operations. In contrast, the IV approach estimates the effects for hospitals with persistently high readmission rates that would continue to receive penalties if they do not implement quality improvement changes, such as a change in patient allocation.

For doctor types defined by specialty or experience (defined as time since graduation from medical school), there was no effect of the reform on the assignment of heart attack cases. Although there was no change in the share of heart attack cases with a cardiologist serving as an attending doctor, cardiologists increased their overall involvement in the care of heart attack patients because there was an increase in the number of PCI procedures that are performed by cardiologists.

The dynamic effects of the reform on patient allocation are depicted in Figure 2. Each figure plots the dynamic DID coefficients from an analog of equation 4 at the hospital level, where the outcome of interest is the share of heart attack cases allocated to attending doctors with a certain type. The graphs show that the timing of the changes in allocation aligns with the introduction of the HRRP incentives, and there were no differential pre-trends, confirming the identifying assumption. The only exception is the share of cases treated by doctors with high baseline survival, which exhibits a declining pre-trend. Panels (a)-(b) demonstrate that after 2011, hospitals with the highest historical readmission rates experienced an increase in the share of heart attack cases treated by doctors with low baseline readmission rates and with high baseline PCI, increasing by around 2-4 percentage points by 2015. This could have contributed to the decline in readmissions and the increase in PCI observed at the patient level. There was an increase in the share

of heart attack patients allocated to doctors with high baseline survival at high penalty risk hospitals, however, there were differential pre-trends. In addition, hospitals with the highest penalty risk reallocated around 3-4 percentage points of heart attack patient to doctors continuously working in a hospital and doctors with high baseline heart attack caseload by 2015. The dynamic coefficients confirm no change in patient assignment to doctors with different experience or to cardiologists.

Overall, the results indicate that quality incentives led to significant patient reallocation, with hospitals effectively identifying doctors with high quality and relevant experience for heart attack patients, particularly in terms of their baseline heart attack caseload, as opposed to overall medical experience. The effect was stronger for doctors with high treatment intensity and heart attack caseloads compared to doctors with better patient outcomes. Since hospitals do not directly observe doctor's quality, they might use treatment style or experience as proxies for quality.

I explore whether the HRRP led to an increase in specialization in heart attack treatment. Panel A of Table 3 shows that in hospitals with the highest quality incentives, there were approximately four fewer doctors working on heart attack cases after 2011, according to IV estimates. This estimate implies a decline of two doctors in an average hospital, or an 11 percent decrease relative to the pre-reform mean. Panel B explores the change in the number of heart attack patients per doctor estimated from equation 3. The analysis on the doctor-hospital level isolates within-doctor changes in heart attack caseload. The estimated increase in per-doctor cases is approximately 0.4, implying an increase of 0.2 cases per doctor in an average hospital, or a 6 percent change. The effect for an average doctor masks divergent effects by doctor type, as presented in Appendix Table A1. The table presents the effect of the reform on the per-doctor number of heart attack cases separately for each doctor type. There was either no change or a decline in the number of per-doctor cases for doctors with poor patient outcomes, low baseline intensity, or limited experience in heart attack treatment. In contrast, doctors with high baseline quality, intensity, or baseline caseloads experienced an increase of around 1-2 cases per doctor in hospitals with the highest penalty risk over 2012-2015. These findings suggest increased specialization in heart attack treatment. As discussed in Section III, a significant share of doctors only occasionally treat heart attack patients. If hospitals shift their case allocation away from these doctors and instead increase the caseloads of doctors with more experience in heart attack treatment, it may promote a learning-by-doing effect and lead to an improvement in the quality of care.

An increase in the number of cases per doctor for the affected doctors types suggests

reallocation changes on an intensive margin. I show that there were also adjustments on an extensive margin – a change in the composition of doctors who treat at least one heart attack patient, with results presented in Appendix Table A2. Future analysis will explore whether changes in doctor composition are driven by reallocating doctors within a hospital across health conditions or by doctors changing the hospitals they work in.

I test whether the reallocation of patients across doctors involved improvements in doctor-patient matches. To reduce readmissions, hospitals may have assigned high-quality doctors to patients who are most sensitive to the quality of care. In addition, patients appropriate for PCI may have been assigned to doctors with a high baseline treatment intensity if those doctors were more experienced in choosing treatment, performing procedures (if done by the same doctor), or caring for patients after the procedure. To assess this hypothesis, I study an index of propensity to receive PCI for patients treated by each doctor. Table 4 presents estimates from equation 3, exploring changes in patient case mix in terms of PCI appropriateness on a doctor-hospital level. While there was no change in the case mix for an average doctor, doctors with high treatment intensity were assigned to patients more appropriate for PCI. In an average hospital, they experienced around a 3 percent increase in the patients' PCI appropriateness index. There were also increases in PCI appropriateness for patients assigned to attending doctors with low readmission or high survival rates, doctors with high heart attack caseloads, and cardiologists (with no change for other types). In contrast, Appendix Table A3 shows that doctors' case mixes with respect to the overall health of their patients, as defined by the Charlson Comorbidity index (CCI), were not affected by the reform. It is possible that the responsiveness of the patient's readmission outcome is related to overall health in a complex way that the CCI cannot capture.

Effect on patient outcomes

I document the effects of the HRRP on patient outcomes and the quality of care. Figure 3 plots dynamic coefficients estimated from equation 4 for three main outcomes of interest: 30-day readmission and survival, and PCI, an intensive treatment for heart attack patients. Figure 3a shows that 30-day readmissions, which are targeted by the reform, began to decline after the introduction of the HRRP incentives in hospitals with the highest penalty risk. Figure 3b shows that PCI started to increase after 2011. For both outcomes, there were no differential trends before the reform, supporting the identifying assumption. In contrast, there was no change in patient 30-day survival rates, as depicted in Figure 3c. Panel A of Table 5 presents the estimates from equation 1 using OLS (Column 1) and

IV (Column 2). IV estimates imply a 2.4 percentage point decline in readmissions and 3.7 percentage points increase in PCI in the post-reform period in a hospital with the highest quality incentives (expected penalty probability of 1). Because around a half of all hospitals are penalized, in an average hospital, there was a readmission decrease of about 1.3 percentage points and an increase in PCI of about 1.9 percentage point. As expected, the IV estimates for the readmission decline are smaller in magnitude than OLS estimates. OLS estimates include not only improvements due to the HRRP incentives but also effects for hospitals that improve performance only due to mean reversion, as a temporary negative shock on quality passes after the measurement period. In contrast, the OLS estimate for the increase in PCI is smaller than the IV estimate, since hospitals that improve due to mean reversion do not change treatment patterns or other hospital practices.

These results are in line with the previous findings on the impact of the HRRP. Gupta (2021) that is the most closely related study in terms of the empirical approach finds 1.7 percentage point decline in readmissions in an average hospital that is close to my finding of 1.3 percentage points as well as 2.2 percentage points increase in PCI compared to my finding of 1.9 percentage points. In contrast to my results, Gupta (2021) finds around 0.5 percentage point increase in 30-day survival for heart attack patients, which could be driven by differences in methodology. If there was an increase in heart attack survival, my results understate the total improvements in quality of care by only finding the readmissions decline.

I explore the within-doctor changes in treatment and patient outcomes by estimating equation 1 with doctor-hospital fixed effects. The results are presented in Panel B of Table 5 and indicate significant effects on both readmission and PCI. Additionally, I explore changes for patients whose attending doctor is a continuously working doctor, defined as a doctor who treats heart attack cases at a hospital in all years. This clears the sample from changes in the doctor pool (but not changes in patient reallocation). Results in Columns (3)-(4) show that an increase in PCI and a decline in readmissions was also observed in the sample of patients treated by continuously working doctors, additionally supporting the finding of within-doctor changes in patient outcomes.

The role of doctor-hospital affiliation

I investigate whether the type of doctor-hospital affiliation influences a hospital's response to quality incentives. First, I examine heterogeneity in the effect of the HRRP on patient outcomes. Table 6 presents estimates from equation 5, using the triple-difference design.

The results suggest that changes in both readmission and PCI were around 3 times greater in hospitals with doctor affiliation compared to those without affiliation, holding the penalty risk constant (although the difference is only marginally significant). In addition, Appendix Table A4 presents results from equation 1 estimated separately for admissions in hospitals with and without any affiliation with its doctors. The IV estimates indicate greater changes in patient outcomes in hospitals with affiliated physicians compared to hospitals without any affiliation. For a hospital with the highest penalty risk, the reduction in readmissions was around 3 percentage points in hospitals with affiliated physicians compared to 1.3 percentage points in hospitals without any affiliation. Similarly, the increase in the use of PCI was 4.7 and 1.7 percentage points in hospitals with and without affiliation with their doctors.

Next, I estimate differences in patient reallocation response by doctor-hospital affiliation. Table 7 reports the triple-difference results. I find that hospitals with doctor affiliation had substantially higher patient reallocation in response to the reform. This patterns is present for doctors with high estimated quality, high treatment intensity, both heart attack and overall medical experience, and continuously working doctors. For example, the magnitude of the reallocation to doctors with low estimated readmissions was 1.7 times greater in hospitals with doctor affiliation relative to hospitals without affiliation, holding the penalty risk constant. Most estimates are statistically significant. Appendix Table A5 shows the reallocation effects estimated separately for two groups of hospitals and presents qualitatively similar results.

These findings suggest that doctor-hospital affiliation could facilitate responses to quality incentives and improvements in hospital quality. Hospitals that have affiliation with its physicians are in better control of physician assignments as they are better able to implement patient reallocation across physicians. It is also likely that these hospitals are better able to motivate doctors to change their treatment choices and improve quality.

Other responses

Given the observed increases in intensive treatment, the HRRP might have had an effect on hospital investment in a cath lab which is necessary for intensive treatment of heart attacks and other cardiac conditions. Table Appendix Table A6 presents results for the effect of the HRRP incentives on a cath lab adoption. For hospitals without a cath lab in 2007, OLS estimates imply no change in cath lab, while IV estimates show a marginally significant decline in a cath lab adoption due to the HRRP incentives. I interpret these diverging results as no evidence of changes in hospital cath lab investment.

Finally, I explore the heterogeneity in responses to the HRRP by patient race, socioeconomic status, gender and overall health. Appendix Table A7 presents results from equation 1 estimated separately for groups of patients. Panel A shows that the decline in readmissions was higher for non-white patients compared to white patients. The IV estimates indicate a positive effect on survival of non-white patients, although the effect is not statistically significant. Panel B presents the results for patient groups in terms of dual eligibility for Medicare and Medicaid, which serves as a proxy for low socioeconomic status.In response to the HRRP, readmissions declined more for dual eligible patients compared to non-eligible patients. Heterogeneity for patients with better or worse overall health (as defined by low or high Charlson Comorbidity Index, CCI) is presented in Panel C, with the effect on readmissions being more pronounced for sicker patients. Panel D shows similar effects of the HRRP on outcomes of male and female patients. Appendix Table A8 presents results from a triple-difference estimation. The results show similar qualitative patterns, however, most of the triple-difference effects are not statistically significant.

VI. Discussion and conclusions

This paper provides novel evidence on the role of patient allocation across doctors as well as doctor-hospital affiliation for hospital quality improvements. I find that, in response to quality incentives provided by the HRRP, hospitals reallocate heart attack patients to doctors with high estimated quality, high treatment intensity, and high experience in heart attack treatment. There was also an increase in specialization in heart attack treatment and an improvement in doctor-patient matches. Moreover, hospitals with doctor affiliation had higher changes in both patient outcomes and patient reallocation compared to hospitals with no doctor affiliation. These findings can be useful for both the design of quality improvement programs and the regulation of doctor-hospital affiliation.

I study patient allocation only for heart attack patients and there could be similar effects or spillovers for other conditions. The observed patterns of reallocation to doctors with high estimated quality might imply that patients with other conditions are assigned to doctors with lower quality. However, this relies on the assumption that doctor's quality is similar across health conditions. Evidence from prior studies speaks against these negative spillover effects, as they find no change or improvements in quality for non-targeted conditions in response to the HRRP (Batt et al., 2020; Chen and Grabowski, 2019; Gupta, 2021). Several of my findings imply that the reallocation response is not

a zero-sum change, with some patients benefiting while others are harmed. First, I find increased specialization in heart attack care induced by the reform. It is possible that hospitals change patient assignment protocols in such a way as to increase specialization in other conditions as well, which would be beneficial if experience promotes the quality of care. Second, I document improvements in doctor-patient matches for heart attack patients. Similar changes could also be implemented across conditions, with doctors better at treating certain diseases assigned to patients with those conditions. The study of doctor-patient allocation for other health conditions (either targeted or non-targeted by the HRRP) remains for future work.

The findings on changes in doctors' assignment to heart attack patients could be related to broader changes in doctors' practice. Hospitals might adjust the number or timing of doctors' shifts, as well as the composition of doctor teams, which I do not observe. The increase in specialization could be limited to heart attack cases or also present for other conditions. Apart from changes in practice in a hospital, the program might have induced changes in employment or practice across hospitals. All of these adjustments could have significant implications for doctors' welfare, which has been the focus of health policy discussions since the Covid-19 pandemic. Studying potential impacts of quality incentives on doctors' welfare is an area for future research.

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VII. Figures and Tables

Table 1: Summary Statistics

	Admission level, in hospitals with			Doctor level
	High penalty risk	Low penalty risk	All	
	(1)	(2)	(3)	(4)
Expected probability of penalty in 2013	0.84	0.12	0.45	
Panel A. Patient outcomes and characteristics				
30-day readmission	0.21	0.16	0.19	
30-day survival	0.85	0.86	0.86	
PCI	0.33	0.42	0.38	
Index admission	0.85	0.88	0.87	
White	0.85	0.91	0.88	
Dual eligible for Medicaid	0.25	0.18	0.21	
Male	0.49	0.53	0.51	
Age	79.86	78.93	79.37	
CCI approximation (lower is better health)	4.66	4.05	4.33	
Panel B. Attending doctor characteristics				
Total AMI cases: 1-10	0.23	0.20	0.21	0.56
Total AMI cases: 11-50	0.48	0.43	0.45	0.21
Total AMI cases: > 50	0.29	0.37	0.33	0.23
Cardiologist	0.38	0.51	0.45	0.22
Internal medicine	0.52	0.39	0.45	0.58
Experience < 20 years	0.39	0.41	0.40	0.46
Low baseline cases	0.60	0.53	0.56	0.89
High baseline cases	0.40	0.47	0.44	0.11
Baseline doctor types				
Undefined baseline type	0.27	0.25	0.26	0.63
No AMI cases in 2008-2010	0.11	0.11	0.11	0.27
High baseline readmission	0.42	0.32	0.36	0.19
Low baseline readmission	0.32	0.43	0.38	0.18
Low baseline survival	0.32	0.30	0.31	0.18
High baseline survival	0.41	0.45	0.43	0.19
Low baseline PCI	0.32	0.23	0.27	0.18
High baseline PCI	0.41	0.52	0.47	0.19
Observations	643,388	741,338	1,384,726	162,551

Note: The sample is heart attack admissions in 2008-2014 (July 2007–June 2010). Column (1) presents admissions in hospitals with the expected penalty probability in the first program year greater than 0.5, and Column (2) – less than 0.5. Column (4) presents statistics on the doctor-year level. The definition of baseline types is described in Section III and the expected penalty probability is described in Section IV.

Table 2: Effect on patient allocation

	OLS	IV	Y mean in 2008-2010
	(1)	(2)	(3)
***Y* is share of heart attack patients treated by attending doctor with type:**			
Low baseline readmission	0.064	0.074	0.307
	(0.006)	(0.017)	
High baseline PCI (intensive treatment)	0.034	0.143	0.219
	(0.006)	(0.023)	
High baseline survival	0.013	0.056	0.321
	(0.006)	(0.019)	
Continuously working doctor	0.025	0.069	0.158
	(0.004)	(0.014)	
High baseline heart attack caseload	0.037	0.131	0.239
	(0.007)	(0.022)	
Cardiologist	-0.002	0.007	0.163
	(0.005)	(0.017)	
Experience $\geq$20 years	-0.001	-0.005	0.415
	(0.007)	(0.021)	
Observations (hospital-year)	16,278	16,278	

Note: The table presents the effect of the expected probability to receive a penalty in the first program year on the share of heart attack cases treated by each type of doctor, in the post-reform period starting in 2012. Each result presents estimates from a separate regression estimated from equation 3, which includes year and hospital fixed effects. Results are on hospital-year level in 2008-2015. The coefficients present effect for a hospital with expected probability of penalty equal to 1. The likelihood of being penalized for an average hospital is around 0.5. Continuously working doctor is defined as a doctor who works on heart attack cases at a given hospital in each year (irrespective of affiliation with a hospital).

Table 3: Effect on specialization of heart attack treatment

	OLS	IV	Y mean in 2008-2010
	(1)	(2)	(3)
Panel A.			
Number of doctors working with heart attack patients	-1.713	-4.127	18.511
	(0.320)	(1.142)	
Observations (hospital-year)	16,278	16,278	
Panel B.			
Per-doctor heart attack cases	0.080	0.366	3.145
	(0.087)	(0.177)	
Observations (doctor-hospital-year)	333,378	333,378	

Note: The table presents the effect of the expected probability to receive a penalty in the first program year on selected outcomes. Each result presents estimates from a separate regression estimated from equation 3, which includes year and hospital fixed effects. Results are on hospital-year and doctor-hospital level in 2008-2015. The coefficients present effect for a hospital with expected probability of penalty equal to 1. The likelihood of being penalized for an average hospital is around 0.5.

Table 4: Effect on doctor's case mix in terms of PCI appropriateness index

	OLS	IV	Y mean in 2008-2010
	(1)	(2)	(3)
Index of patients' PCI appropriateness	-0.005	0.338	28.789
	(0.216)	(0.519)	
Estimated separately by doctor type			
Low baseline readmission	-0.241	1.250	30.792
	(0.210)	(0.614)	
High baseline readmission	-0.279	0.619	27.940
	(0.184)	(0.547)	
High baseline PCI (intensive treatment)	-0.187	1.836	33.908
	(0.213)	(0.681)	
Low baseline PCI (intensive treatment)	-0.307	0.337	26.519
	(0.185)	(0.541)	
High baseline survival	-0.120	1.696	31.240
	(0.197)	(0.596)	
Low baseline survival	-0.374	0.206	27.653
	(0.190)	(0.566)	
High baseline heart attack caseload	0.115	1.978	34.560
	(0.207)	(0.559)	
Low baseline heart attack caseload	-0.436	0.250	27.290
	(0.181)	(0.568)	
Cardiologist	0.064	2.951	39.376
	(0.238)	(0.779)	
Non-cardiologist	-0.465	-0.268	25.690
	(0.181)	(0.540)	
Experience $\geq$ 20 years	-0.125	0.886	29.989
	(0.189)	(0.528)	
Experience $<$ 20 years	-0.397	0.865	27.911
	(0.202)	(0.632)	
Observations (doctor-hospital-year)	333,378	333,378	

Note: The table presents the effect of the probability to receive a penalty in the first program year on the average index of PCI appropriateness of heart attack patients that a doctor treats in a given year. Each result presents estimates from a separate regression estimated from equation 3, which includes year and doctor-hospital fixed effects. Results are on doctor-hospital-year level in 2008-2015. The coefficients present effects for a hospital with expected probability of penalty equal to 1. The likelihood of being penalized for an average hospital is around 0.5.

Table 5: Effect on patient outcomes: continuously working versus other doctors

	Patients treated by doctors:					
	All		Continuously working		Other	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Analysis with hospital FE						
Readmission	-3.08	-2.45	-2.60	-1.96	-3.30	-2.80
	(0.18)	(0.56)	(0.33)	(1.05)	(0.21)	(0.68)
PCI	1.62	3.73	1.41	2.30	1.31	3.24
	(0.32)	(1.12)	(0.52)	(1.70)	(0.36)	(1.30)
Survival	-0.23	0.11	0.13	0.22	-0.40	-0.04
	(0.15)	(0.46)	(0.27)	(0.78)	(0.18)	(0.57)
Panel B. Analysis with doctor-hospital FE						
Readmission	-2.86	-2.66	-2.60	-2.14	-3.04	-3.14
	(0.22)	(0.68)	(0.34)	(1.05)	(0.28)	(0.93)
PCI	1.08	3.22	1.36	3.79	0.69	1.94
	(0.33)	(1.21)	(0.50)	(1.74)	(0.36)	(1.34)
Survival	-0.13	0.29	0.22	0.71	-0.38	-0.15
	(0.18)	(0.53)	(0.27)	(0.77)	(0.24)	(0.77)
N	1,199,483	1,199,483	355,162	355,162	844,321	844,321

Note: The table presents the effect of the probability to receive a penalty in the first program year on individual outcomes, estimated separately for permanent and other doctors. Permanent doctor works on heart attack cases at a given hospital in each year (irrespective of affiliation with a hospital). Each result presents estimates from a separate regression estimated from equation 1, which includes patient risk factors, year and hospital fixed effects (Panel A) or doctor-hospital fixed effect (Panel B). Results are on admission level in 2008-2015. The coefficients present effect for a hospital with expected probability of penalty equal to 1. The likelihood of being penalized for an average hospital is around 0.5. Continuously working doctor works on heart attack cases at a given hospital in each year (irrespective of affiliation with a hospital). The standard errors are clustered by hospital.

Table 6: Heterogeneity in patient outcomes by doctor-hospital affiliation

	Z_h x After	$Affil_h$ x After	Triple diff
	(1)	(2)	(3)
Readmission	-6.926	-0.357	-11.172
	(6.240)	(0.167)	(7.562)
PCI	8.485	0.293	21.377
	(8.855)	(0.290)	(12.064)
Survival	0.009	-0.173	0.816
	(4.412)	(0.137)	(5.571)

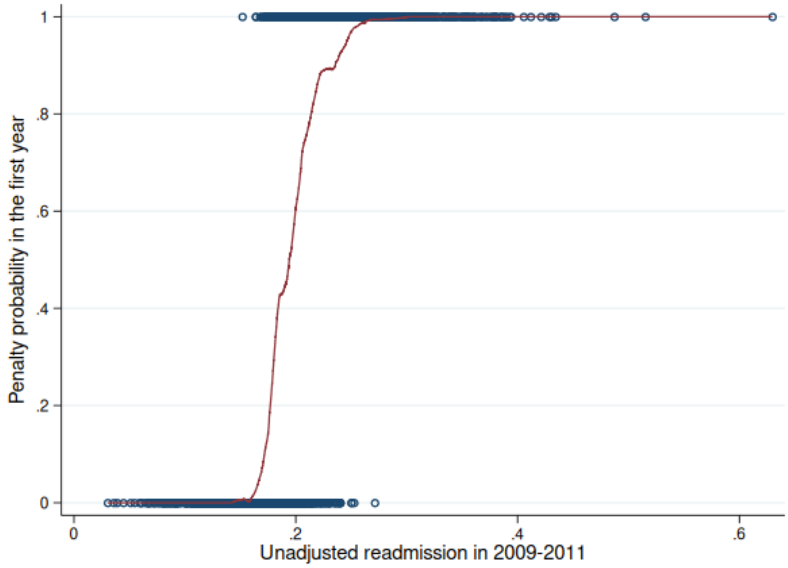
Note: The table presents results from estimating equation 5:
$Y_{iht} = \lambda_h + \lambda_t + \beta_1 Z_h \times \mathbf{1}(t \geq 2012)_t + \beta_2 Affil_h \times \mathbf{1}(t \geq 2012)_t + \beta_3 Z_h \times Affil_h \times \mathbf{1}(t \geq 2012)_t + X_{iht} + \varepsilon_{iht}$,
where Z_h is the instrument, hospital's historical risk-adjusted readmission and $Affil_h$ is whether a hospital is affiliated with any of its physicians in 2010. Each row presents estimates from a separate regression where the outcome of interest is readmission, PCI or survival. The sample is 1,199,483 admissions in 2008-2015. The magnitude of the estimates is not comparable to other results. Column (1) presents β_1, the effect of the reform on hospitals without doctor affiliation (with quality incentives measured by Z_h). Column (2) presents β_2, the change in the post-reform period for affiliated hospitals with low penalty risk. Column (3) presents β_3 or the triple-difference estimate, the differential response to the same penalty risk for affiliated relative to non-affiliated hospitals after the reform. The standard errors are clustered by hospital.

Table 7: Heterogeneity in patient reallocation by doctor-hospital affiliation

	Z_h x After	$Affil_h$ x After	Triple diff
	(1)	(2)	(3)
***Y* is share of heart attack patients treated by attending doctor with type:**			
Low readmission	0.305	-0.001	0.199
	(0.096)	(0.003)	(0.126)
High PCI	0.511	0.004	0.259
	(0.092)	(0.003)	(0.119)
High survival	0.203	-0.002	0.201
	(0.100)	(0.003)	(0.130)
Continuously working	0.270	-0.006	0.207
	(0.077)	(0.002)	(0.100)
High baseline AMI caseload	0.549	-0.006	0.330
	(0.109)	(0.003)	(0.140)
Cardiologist	0.075	0.001	-0.060
	(0.081)	(0.003)	(0.112)
Experience ≥20 years	-0.270	-0.004	0.438
	(0.115)	(0.004)	(0.150)

Note: The table presents results from estimating a hospital-level analog of equation 5: $Y_{ht} = \lambda_h + \lambda_t + \beta_1 Z_h \times \mathbf{1}(t \geq 2012)_t + \beta_2 Affil_h \times \mathbf{1}(t \geq 2012)_t + \beta_3 Z_h \times Affil_h \times \mathbf{1}(t \geq 2012)_t + \varepsilon_{ht}$, where Z_h is the instrument, hospital's historical risk-adjusted readmission and $Affil_h$ is whether a hospital is affiliated with any of its physicians in 2010. Each row presents estimates from a separate regression where the outcome of interest is the share of AMI cases treated by doctors with a certain type. The sample is 16,278 hospital-years in 2008-2015. The magnitude of the estimates is not comparable to other results. Column (1) presents β_1, the effect of the reform on hospitals without doctor affiliation (with quality incentives measured by Z_h). Column (2) presents β_2, the change in the post-reform period for affiliated hospitals with low penalty risk. Column (3) presents β_3 or the triple-difference estimate, the differential response to the same penalty risk for affiliated relative to non-affiliated hospitals after the reform. Continuously working doctor works on heart attack cases at a given hospital in each year (irrespective of affiliation with a hospital).

Figure 1: Expected penalty in the first year



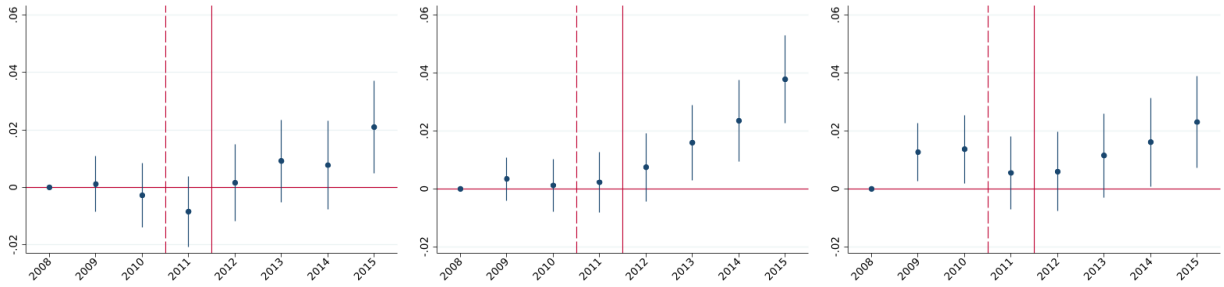
Note: The plot shows $Expectation_h$, the expected probability of receiving the penalty for heart attack readmissions in the first program year (red line). It is a non-parametric prediction of the penalty status in the first year (blue dots) from hospital's unadjusted readmissions in 2009-2011.

Figure 2: Dynamic effect on patient allocation, by type of attending doctor

(a) Low baseline readmission

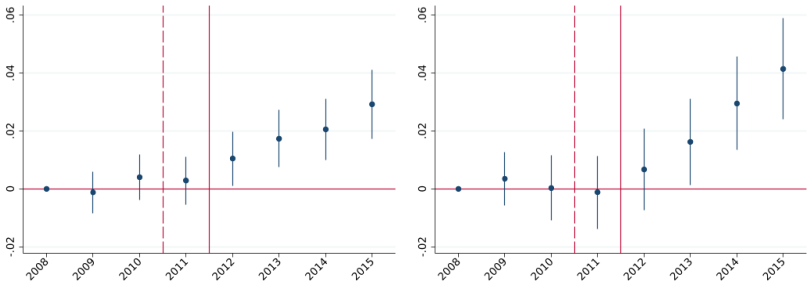
(b) High baseline PCI (intensive treatment)

(c) High baseline survival



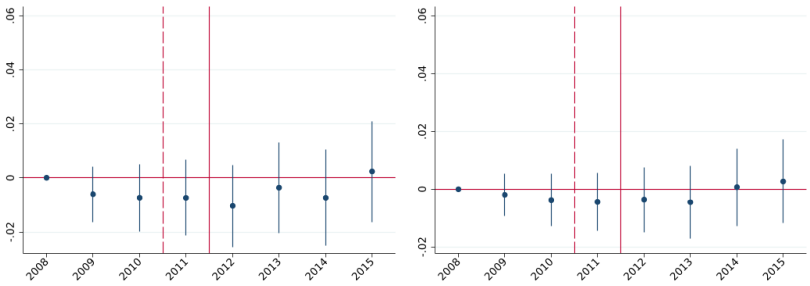
(d) Continuously working

(e) High baseline heart attack caseload



(f) Experience ≥20 years

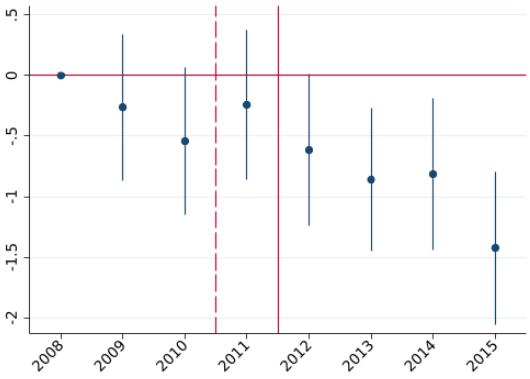
(g) Cardiologist



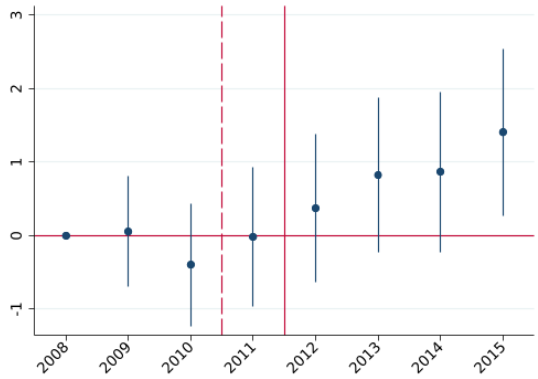
Note: Each plot presents dynamic effects on the share of heart attack cases treated by a certain type of doctor, estimated from equation 4, which includes year and hospital fixed effects. Coefficients are on the dummy for the top tercile of the instrument, implying the highest historical risk-adjusted readmission rates. Results are on hospital-year level, with year starting in July. Solid line marks the announcement of the reform and the first year with expected hospital responses. Dashed line marks the passage of the ACA and the first year of potential anticipatory responses. Continuously working doctor works on heart attack cases at a given hospital in each year (irrespective of affiliation with a hospital).

Figure 3: Effect on patient outcomes

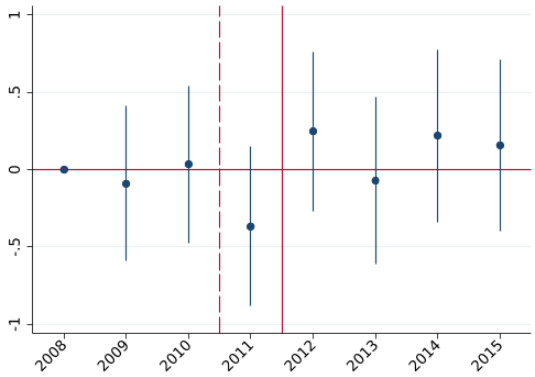
(a) Readmission



(b) PCI



(c) Survival



Note: Each plot presents dynamic effects on patient outcomes, estimated from equation 4, which includes year and hospital fixed effects. Coefficients are on the dummy for the top tercile of the instrument, implying the highest historical risk-adjusted readmission rates. Results are on admission level, with year starting in July. Solid line marks the announcement of the reform and the first year with expected hospital responses. Dashed line marks the passage of the ACA and the first year of potential anticipatory responses.

A. Appendix Figures and Tables

Appendix Table A1: Effect on per-doctor number of cases

	OLS	IV	Y mean in 2008-2010
	(1)	(2)	(3)
Per-doctor cases	0.080	0.366	3.145
	(0.087)	(0.177)	
Estimated separately by doctor type			
Low baseline readmission	0.247	1.208	4.385
	(0.081)	(0.280)	
High baseline readmission	-0.177	0.354	2.619
	(0.048)	(0.181)	
High baseline survival	0.144	1.364	4.600
	(0.087)	(0.305)	
Low baseline survival	-0.053	0.196	2.470
	(0.046)	(0.151)	
High baseline PCI (intensive treatment)	0.081	1.990	4.876
	(0.100)	(0.392)	
Low baseline PCI (intensive treatment)	-0.137	-0.319	2.377
	(0.045)	(0.140)	
High baseline heart attack caseload	-0.066	0.995	7.374
	(0.143)	(0.409)	
Low baseline heart attack caseload	-0.125	-0.283	2.046
	(0.031)	(0.101)	
Cardiologist	0.118	1.434	5.164
	(0.113)	(0.387)	
Non-cardiologist	-0.114	-0.024	2.554
	(0.047)	(0.161)	
Experience $\geq$ 20 years	0.135	1.127	3.388
	(0.063)	(0.204)	
Experience $<$ 20 years	-0.015	0.383	2.966
	(0.059)	(0.220)	
Observations (doctor-hospital-year)	333,378	333,378	

Note: The table presents the effect of the expected probability to receive a penalty in the first program year on the number of per-doctor heart attack cases. Each result presents estimates from a separate regression estimated from equation 3, which includes year and doctor-hospital fixed effects. Results are on doctor-hospital-year level in 2008-2015. The coefficients present effect for a hospital with expected probability of penalty equal to 1. The likelihood of being penalized for an average hospital is around 0.5. Permanent doctor works on heart attack cases at a given hospital in each year (irrespective of affiliation with a hospital).

Appendix Table A2: Effect on doctor composition

	OLS	IV	Y mean in 2008-2010
	(1)	(2)	(3)
***Y* is share of doctors with each type among heart attack attending doctors**			
Low baseline readmission	0.035	0.065	0.236
	(0.004)	(0.013)	
High baseline survival	0.012	0.047	0.239
	(0.004)	(0.013)	
High baseline PCI (intensive treatment)	0.037	0.110	0.165
	(0.004)	(0.015)	
High baseline heart attack caseload	0.017	0.072	0.130
	(0.004)	(0.013)	
Continuously working doctor	0.010	0.026	0.089
	(0.002)	(0.007)	
Cardiologist	-0.011	-0.019	0.120
	(0.004)	(0.012)	
Experience $\geq$20 years	-0.002	-0.014	0.366
	(0.006)	(0.016)	
Observations (hospital-year)	16,278	16,278	

Note: The table presents the effect of the expected probability to receive a penalty in the first program year on the share of each type of doctor in a pool of doctors who treat heart attack cases (this measure is different from the share of cases as it does not account for differences in per-doctor cases). Each result presents estimates from a separate regression estimated from equation 3, which includes year and hospital fixed effects. Results are on hospital-year level in 2008-2015. The coefficients present effect for a hospital with expected probability of penalty equal to 1. The likelihood of being penalized for an average hospital is around 0.5. Permanent doctor works on heart attack cases at a given hospital in each year (irrespective of affiliation with a hospital).

Appendix Table A3: Effect on doctor's case mix in terms of CCI

	OLS	IV	Y mean in 2008-2010
Index of patient health (CCI approximation)	0.060	0.095	4.171
	(0.035)	(0.075)	
Estimated separately by doctor type			
Low baseline readmission	0.072	0.076	4.041
	(0.032)	(0.091)	
High baseline readmission	0.006	0.031	4.226
	(0.029)	(0.081)	
High baseline PCI (intensive treatment)	0.051	-0.077	3.857
	(0.032)	(0.094)	
Low baseline PCI (intensive treatment)	0.011	0.101	4.310
	(0.030)	(0.082)	
High baseline survival	0.055	-0.030	4.032
	(0.031)	(0.087)	
Low baseline survival	0.016	0.093	4.235
	(0.029)	(0.081)	
High baseline heart attack caseload	0.028	-0.018	3.788
	(0.032)	(0.082)	
Low baseline heart attack caseload	0.027	0.057	4.271
	(0.028)	(0.082)	
Cardiologist	0.002	-0.245	3.384
	(0.034)	(0.104)	
Non-cardiologist	0.028	0.113	4.401
	(0.028)	(0.080)	
Experience $\geq$ 20 years	0.024	0.035	4.163
	(0.031)	(0.084)	
Experience $<$ 20 years	0.024	0.044	4.177
	(0.034)	(0.096)	
Observations (doctor-hospital-year)	333,378	333,378	

Note: The table presents the effect of the probability to receive a penalty in the first program year on the average Charlson Comorbidity Index (CCI) of heart attack patients that a doctor treats in a given year. Each result presents estimates from a separate regression estimated from equation 3, which includes year and doctor-hospital fixed effects. Results are on doctor-hospital-year level in 2008-2015. The coefficients present effects for a hospital with expected probability of penalty equal to 1. The likelihood of being penalized for an average hospital is around 0.5. CCI is an index designed to predict patient's mortality from age and chronic conditions. I use an approximation of the CCI, described in the Appendix.

Appendix Table A4: Effect on patient outcomes: hospitals with and without doctor affiliation

	Affiliation		No Affiliation	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Readmission	-3.10	-2.99	-3.01	-1.26
	(0.22)	(0.63)	(0.30)	(1.16)
PCI	1.60	4.71	1.63	1.72
	(0.42)	(1.47)	(0.48)	(1.72)
Survival	-0.35	0.13	-0.04	0.02
	(0.19)	(0.56)	(0.26)	(0.84)
Observations	844,884	844,884	540,089	540,089

Note: The table presents the effect of the probability to receive a penalty in the first program year on individual outcomes, estimated separately for hospitals with no affiliation and with employment or contractual affiliation with its doctors. Each result presents estimates from a separate regression estimated from equation 1, which includes patient risk factors, year and hospital fixed effects. Results are on admission level in 2008-2015. The coefficients present effect for a hospital with expected probability of penalty equal to 1. The likelihood of being penalized for an average hospital is around 0.5.

Appendix Table A5: Effect on patient allocation: hospitals with and without doctor affiliation

	Affiliation		No Affiliation		Y mean in 2008
	OLS	IV	OLS	IV	
	(1)	(2)	(3)	(4)	(5)
***Y* is share of heart attack patients treated by attending doctor with type:**					
Low readmission	0.065	0.080	0.058	0.066	0.303
	(0.007)	(0.021)	(0.009)	(0.030)	
High PCI	0.035	0.157	0.039	0.139	0.220
	(0.008)	(0.026)	(0.011)	(0.041)	
High survival	0.021	0.079	0.012	0.054	0.314
	(0.007)	(0.023)	(0.009)	(0.032)	
High baseline AMI caseload	0.028	0.147	0.047	0.110	0.237
	(0.009)	(0.027)	(0.011)	(0.036)	
Continuously working	0.027	0.078	0.022	0.053	0.154
	(0.005)	(0.016)	(0.006)	(0.024)	
Cardiologist	-0.001	0.002	-0.002	0.015	0.162
	(0.007)	(0.022)	(0.008)	(0.027)	
Experience $\geq$20 years	0.001	0.025	-0.005	-0.065	0.383
	(0.009)	(0.026)	(0.011)	(0.037)	
N	9,057	9,057	7,221	7,221	

Note: The table presents the effect of the probability to receive a penalty in the first program year on the share of heart attack cases treated by each type of doctor, estimated separately for hospitals with no affiliation and with employment or contractual affiliation with its doctors. Each result presents estimates from a separate regression estimated from equation 3, which includes year and hospital fixed effects. Results are on admission level in 2008-2015. The coefficients present effect for a hospital with expected probability of penalty equal to 1. The likelihood of being penalized for an average hospital is around 0.5. Continuously working doctor works on heart attack cases at a given hospital in each year (irrespective of affiliation with a hospital).

Appendix Table A6: Effect on cath lab presence in a hospital, by whether a hospital has a cath lab in 2007

	OLS	IV	N
	(1)	(2)	(3)
Hospitals with			
No cath lab in 2007	0.017	-0.125	6,711
	(0.016)	(0.070)	
Cath lab in 2007	0.002	0.014	13,256
	(0.011)	(0.030)	

Note: The table presents the effect of the probability to receive a penalty in the first program year on a dummy for whether a hospital has a cath lab in a given year. Each result presents estimates from a separate regression estimated from equation 3, which includes year and hospital fixed effects. Results are on hospital-year level in 2008-2015. The coefficients present effect for a hospital with expected probability of penalty equal to 1. The likelihood of being penalized for an average hospital is around 0.5. The first line presents results for hospitals that do not have a cath lab in 2007, and the second line – for hospitals with a cath lab in 2007.

Appendix Table A7: Heterogeneity in patient outcomes by patient type

	OLS	IV	Y mean in 2008-2010	OLS	IV	Y mean in 2008-2010
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A	**Non-white**			**White**		
Readmission	-3.33	-3.20	23.35	-3.05	-2.31	19.42
	(0.51)	(1.84)		(0.19)	(0.60)	
PCI	1.66	2.99	30.85	1.62	3.80	38.37
	(0.67)	(2.94)		(0.34)	(1.09)	
Survival	0.17	1.26	85.61	-0.32	-0.10	85.08
	(0.39)	(1.47)		(0.16)	(0.48)	
Panel B	**Dual eligible for Medicaid**			**Not dual eligible for Medicaid**		
Readmission	-4.19	-2.90	24.64	-2.70	-2.16	18.55
	(0.40)	(1.17)		(0.20)	(0.64)	
PCI	0.93	4.64	26.92	1.84	3.43	40.43
	(0.47)	(1.68)		(0.35)	(1.18)	
Survival	-0.21	-0.25	83.48	-0.21	0.32	85.60
	(0.33)	(1.03)		(0.17)	(0.51)	
Panel C	**High CCI (sicker)**			**Low CCI (healthier)**		
Readmission	-3.50	-2.58	24.83	-2.63	-1.95	15.93
	(0.28)	(0.88)		(0.22)	(0.70)	
PCI	0.87	2.02	27.20	1.82	4.16	45.69
	(0.37)	(1.23)		(0.39)	(1.35)	
Survival	-0.62	-0.09	81.57	-0.05	-0.17	88.11
	(0.24)	(0.70)		(0.18)	(0.56)	
Panel D	**Male**			**Female**		
Readmission	-3.07	-2.33	18.57	-3.03	-2.38	21.15
	(0.24)	(0.72)		(0.26)	(0.80)	
PCI	1.80	3.63	42.45	1.54	4.05	32.58
	(0.38)	(1.27)		(0.38)	(1.31)	
Survival	0.06	0.33	86.04	-0.50	-0.16	84.23
	(0.20)	(0.59)		(0.22)	(0.64)	

Note: The table presents the effect of the probability to receive a penalty in the first program year on individual outcomes, estimated separately for patients in each group. Each result presents estimates from a separate regression estimated from equation 1, which includes patient risk factors, year and hospital fixed effects. Results are on admission level in 2008-2015. The coefficients present effect for a hospital with expected probability of penalty equal to 1. The likelihood of being penalized for an average hospital is around 0.5. The standard errors are clustered by hospital.

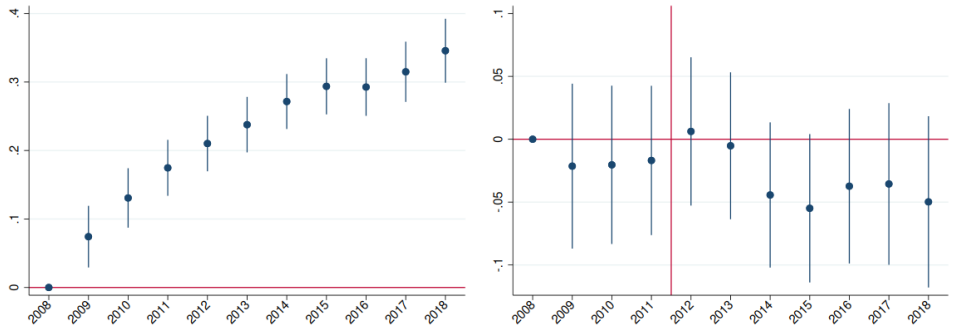
Appendix Table A8: Heterogeneity in patient outcomes by patient type: triple difference approach

	$Z_h \times After$	$Group_i \times After$	Triple diff
	(1)	(2)	(3)
Panel A. Non-white			
Readmission	-13.50	-0.23	-4.93
	(3.72)	(0.24)	(9.72)
PCI	22.60	-0.05	-10.52
	(6.22)	(0.31)	(13.31)
Survival	-0.22	0.01	5.08
	(2.83)	(0.18)	(7.87)
Panel B. Dual eligible for Medicaid			
Readmission	-12.55	-0.51	-4.54
	(3.82)	(0.19)	(7.84)
PCI	20.28	-0.22	5.68
	(6.37)	(0.21)	(8.95)
Survival	2.00	-0.05	-5.39
	(2.88)	(0.16)	(6.70)
Panel C. High CCI (sicker patients)			
Readmission	-11.84	-0.62	-3.21
	(3.96)	(0.15)	(6.24)
PCI	26.37	1.11	-15.67
	(7.00)	(0.17)	(6.89)
Survival	-0.32	0.35	-0.62
	(3.07)	(0.12)	(4.95)
Panel D. Male			
Readmission	-13.71	0.36	-0.44
	(4.90)	(0.14)	(5.72)
PCI	21.32	1.09	2.26
	(7.27)	(0.17)	(7.15)
Survival	-0.90	0.00	3.23
	(3.81)	(0.12)	(4.61)

Note: The table presents results from estimating the following equation:
$Y_{iht} = \lambda_h + \lambda_t + \beta_1 Z_h \times \mathbf{1}(t \geq 2012)_t + \beta_2 Group_i \times \mathbf{1}(t \geq 2012)_t + \beta_3 Z_h \times Group_i \times \mathbf{1}(t \geq 2012)_t + X_{iht} + \varepsilon_{iht}$,
where Z_h is the instrument, hospital's historical risk-adjusted readmission. Each row presents estimates from a separate regression for the outcome of interest and patient characteristic listed in each panel. The sample is 1,199,483 admissions in 2008-2015. The magnitude of the estimates is not comparable to other results. Column (1) presents β_1, the effect of the reform on patients without a listed characteristic (with quality incentives measured by Z_h). Column (2) presents β_2, the change in the post-reform period for patients with a listed characteristic in hospitals with low penalty risk. Column (3) presents β_3 or the triple-difference estimate, the differential response to the same penalty risk for patients with listed characteristic relative to other patients after the reform. The standard errors are clustered by hospital.

A1: Effect on presence of a cath lab

(a) Trend (year FE) (b) Effect of penalty probability



Note: Each plot presents dynamic effects on the presence of a cath lab, estimated from equation 4, which includes year and hospital fixed effects. Coefficients are on the dummy for the top tercile of the instrument, implying the highest historical risk-adjusted readmission rates. Results are on hospital-year level. Solid line marks the announcement of the reform and the first year with expected hospital responses.