Hospital Allocation and the Evolution of Racial Health Disparities: Evidence from Heart Attacks

Amitabh Chandra, Pragya Kakani, Adam Sacarny*

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Abstract

Black patients experience higher mortality and tend to use lower-performing hospitals than white patients in the US. We show that among heart attack patients in Medicare, black patients' use of lower performing hospitals in the 1990s subtracted nearly 1 percentage point off survival rates, but the disparity attenuates by nearly 70% by the 2010s. This development could reflect two forces: reallocation, or relative changes in the use of high-performing hospitals by black versus white patients, and differential performance improvement, or changes in hospital performance that disproportionately occur in hospitals serving black or white patients. We show that the differential performance improvement channel fully accounts for the dynamics. Performance gains at these hospitals were associated with increased returns from a high-cost intervention (cardiac catheterization) and improved adoption of a high-return low-cost input (beta blockers). Our results show that uneven improvements in producer performance can narrow – or exacerbate – racial disparities in health care.

*Chandra: Harvard Kennedy School, Harvard Business School and NBER, mailto:Amitabh_Chandra@harvard.edu; Kakani: Harvard University and NBER, pkakani@g.harvard.edu; Sacarny: Columbia University Mailman School of Public Health and NBER, ajs2102@columbia.edu.

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1 Introduction

African Americans experience considerable disparities in health outcomes in the U.S. relative to other demographic groups. The overall age-adjusted death rate is 20% higher for African Americans than their white peers (Murphy et al., 2017). The causes of this gap are multifactorial and interrelated. They include social determinants of health such as stress, nutrition, drug use, and pollution (Cutler, Deaton and Lleras-Muney, 2006; Currie, Voorheis and Walker, 2020); differences in the use of medical care due to health insurance coverage and trust in providers (Currie, Decker and Lin, 2008; Goodman-Bacon, 2018; Alsan, Garrick and Graziani, 2018; Alsan and Wanamaker, 2018); and the quality and appropriateness of medical treatment due to, for example, physician biases (Smedley, Stith and Nelson, 2003; Chandra and Staiger, 2010).

Another important source of racial disparities in medical outcomes is *market allocation*: the tendency for black and white patients to access different providers, some of which may have much lower (or higher) performance. Indeed, health care for black patients has historically been concentrated among a subset of hospitals with poorer performance as indicated by overall survival rates (Barnato et al., 2005; Skinner et al., 2005; Jha et al., 2007). Similar patterns occur in less emergent settings where patients may have more scope for choice. For example, primary care physicians treating black patients report more limited credentials and more difficulty providing high-quality care than those treating white patients (Bach et al., 2004). These striking and consistent findings point to the role of allocative processes in the disparity. In this way, they recall a large and heretofore distinct literature on the role of allocation in productivity growth in the economy at large (Baily et al., 1991; Olley and Pakes, 1996; Foster, Haltiwanger and Krizan, 2001; Foster, Haltiwanger and Syverson, 2008; Bartelsman, Haltiwanger and Scarpetta, 2013).

In this study, we extend the tools of the productivity literature to the context of race disparities in hospital care, focusing on black and white patients in Medicare experiencing an acute myocardial infarction (AMI), or heart attack, between 1995 and 2014. Taking a decomposition approach, we quantify the role of allocation in race gaps at a point in time. The result, particularly during the 1990s, is that black patients' use of (or access to) lower-performing facilities substantially deteriorates their outcomes relative to white patients. Further augmenting the decomposition to account for geography, we show that most of the disparity is due to where patients live – given the emergent setting, this gap would be difficult to close solely through re-allocating patients.

Surprisingly, however, we find that by the 2010s this gap in the performance of hospitals

used by black and white AMI patients has largely closed. This fact motivates a new, novel decomposition to understand the dynamics of the race gap, isolating the allocative forces that could serve to narrow or widen disparities. It emits two forces. The first is re-allocation, and is the result of black patients increasing their use of facilities that were *ex ante* high performers at a faster (or slower) rate than white patients. The second, which we call differential performance improvement, occurs when performance gains concentrate in facilities that, at baseline, were disproportionately used by black patients relative to white patients (or vice versa). We show essentially the entire closing of the gap results from differential performance improvement.

Our research augments and expands upon an array of work studying black-white disparities in health care and health outcomes. Much of the prior literature analyzes point-in-time, or static, disparities and identifies a host of potential causes albeit with a less clear accounting of the relative importance of each. Our static decomposition provides such an accounting; we further show how the disparity evolves through our dynamic decomposition.

A common thread of the research is the role of geography – compared to whites, African Americans generally live in parts of the country with lower average levels of provider performance across many measures (Baicker, Chandra and Skinner, 2005; Bach et al., 2004; Skinner, James N. Weinstein and Wennberg, 2003; Jha, Orav and Epstein, 2011). Given the emergent nature of much of health care, patient location places a significant constraint on the ability of patients to allocate to high-performance providers. Relatedly, segregation within a market can lead to black-white gaps in access to high-performing providers. For example Sarrazin, Campbell and Rosenthal (2009) show that black AMI patients living in segregated neighborhoods are much more likely to use poorly performing hospitals than their white counterparts in the same neighborhoods, suggesting that local geography may influence provider choice. Preferences over providers may also play a role, and black patients or their agents, including referring physicians, may seek out different providers compared to white patients. Potential drivers include differences in perceived quality, preferences over factors such as provider race or safety net status, or willingness or ability to travel for care. For example, black patients are more likely to follow recommendations from black physicians, suggesting that patients may indeed differ in taste for – and potentially benefit from – providers by race (Alsan, Garrick and Graziani, 2018).

Turning to dynamics, we note a significant gap in the literature on how racial disparities in hospital allocation have evolved over time. Motivating our over-time analysis is the core fact that, in some arenas, the U.S. health care system's performance has improved dramatically in

recent years. For example, gains in hospital performance improved one month survival in acute myocardial infarction, heart failure, and pneumonia by 1-3 percentage points over the last two decades (Chandra et al., 2016). If hospital performance improvements correlate with hospitals' focus on treating black patients, disparities will expand or contract even if patients do not change the providers they use – for this reason, we call this channel differential performance improvement. Yet prior work also finds signs that patients re-allocate towards higher performing hospitals over time (Chandra et al., 2016). Re-allocation could occur if patients or agents acting on their behalf can observe provider performance or correlates thereof (including marketing, amenities, or technology) and in response they shift towards higher performing providers. Indeed, patients and their providers appear to respond to signals like hospital report cards, online physician ratings, and unexpected adverse events (Pope, 2009; Luca and Vats, 2013; Barnett et al., 2012; Forrest et al., 2006; Kinchen et al., 2004; Sarsons, 2017). If re-allocation to higher performance hospitals occurs at differing rates for black and white patients, disparities would rise or fall over over time.

In this paper, we seek to characterize the determinants and evolution of black-white disparities in hospital performance. We focus on black and white AMI patients in fee-for-service Medicare. This setting has the key advantage of essentially removing insurance coverage as a determinant of allocation. Specifically, patients in Medicare have access to the vast majority of hospitals and for most patients, there is no difference in the cost of going to a different hospital. Furthermore, AMI has well-validated hospital quality measures (Hull, 2018; Doyle, Graves and Gruber, 2018) and observable measures of technology use that allow us to probe the mechanisms underlying changes in hospital performance. Partly for these reasons, there is also a rich existing literature on disparities in AMI, upon which our work builds. Our main empirical analysis uses re-weighting and decomposition methods to characterize the factors contributing to black-white disparities in hospital performance at a point-in-time – the static decomposition – and over time – the dynamic decomposition.

We first characterize racial disparities in the use of high- and low-performing hospitals at a point-in-time. The basic static decomposition uncovers the gap in average performance of hospitals used by each group. Next, we use a reweighting approach to decompose the relative contribution of three factors to the gap: (1) macro-geography, or differences in where black and white patients reside across large markets in in the U.S., (2) micro-geography, or differences in patient residence by race within markets, and (3) differences in provider choice unexplained by patient residence, which could represent varying preferences of patients or their agents.

Our static analysis reveals that in 1995-1999, black and white AMI patients used hospitals with systematically different levels of performance, subtracting 1 percentage point off survival rates for black patients relative to white patients. By 2010-2014, this gap had attenuated by 70%, yielding a gap of only 0.3 percentage points. Re-weighting white patients to equalize their geographic distribution to that of black patients, we find that in both periods, differences in the geography of patient residence explain half or more of this disparity – though the disparity to explain is, of course, much smaller in the more recent period. Macro-geography is the main explanatory factor during the 1990s, but plays essentially no role in the 2010s, when micro-geography comes to explain the bulk of the extant gap. These results are consistent with two channels: hospitals in disproportionately African American markets improving performance more than other hospitals over this period, or black patients moving towards better performing hospitals at a faster rate than their white peers. The latter mechanism could include moving to markets with better performing hospitals or shifting to higher quality hospitals within markets.

The dynamic decomposition sheds light on the forces underlying the attenuating black-white gap over time. Specifically, it quantifies the relative contribution of two forces: differential performance improvement and re-allocation. We use differential performance improvement to refer to an association between hospital performance improvement over our two decade analysis period and the hospital's relative share of black vs. white patients at baseline. We use re-allocation to refer to a growth over the two decade period in the association between market share and baseline hospital performance for one race group relative to the other.

Nearly all of the disparity closure can be explained by differential performance improvement, with hospitals with higher baseline relative share of black patients experiencing greater performance improvement than others. In contrast, we find only a small role for reallocation in attenuating the disparity over time.

Finally, we investigate two potential mechanisms underlying differential performance improvement over time. First, we use investigate whether technology adoption explains the disparity reducing dynamics of hospital performance. Second, we investigate whether greater improvements in the skill of technology use at hospitals historically treating disproportionately black patients can explain the different rates of performance improvement. This channel could operate if these hospitals improve treatment technique or better select patients appropriate for certain interventions. Of course, both channels also have the potential to exert disparity-expanding effects too.

Our results find a potential role for both technology adoption and skill in technology use

in explaining differential performance improvement. In particular, two developments are consistent with the attenuating black-white gap that we observe. First, growth in use of beta blockers, a key low-cost and effective intervention for AMI, occurred more rapidly at hospitals that disproportionately served black patients. Second, returns to cardiac catheterization, a high-cost yet effective AMI treatment that diffused rapidly during our analysis period, also increased at a faster rate among these hospitals. These results support the hypothesis that increasing proficiency in use of technology may have contributed to differential quality improvement. Yet in other instances, we find signs of capital-intensive technology adoption that may have actually increased racial disparities in hospital performance. Specifically, we find that growth in adoption of capital-intensive technologies, as proxied by cardiac catheterization, cardiac intensive care units, and open heart surgery capabilities, was faster at hospitals disproportionately serving white patients.

Our paper makes several contributions to the literature. First, our findings contribute to a broad literature on the varied and interrelated socioeconomic disparities faced by African Americans including in income (Becker, 1957; Derek and Johnson, 1996; Altonji and Pierret, 1996; Agan and Starr, 2018), criminal justice (Anwar, Bayer and Hjalmarsson, 2012; Arnold, Dobbie and Yang, 2018), and health.

Second, we contribute to the literature on the relative merits of place-based vs. person-based policies, by recognizing hospitals as important component of places (Bartik, 1991; Glaeser and Gottlieb, 2009). The historical importance of across-market geography in explaining disparities in medical outcomes and the importance of differential performance improvement in reducing disparities over time suggest that place-based policies targeted at the hospitals or areas disproportionately serving African Americans may have been efficient for reducing disparities. However, in the most recent period, remaining racial disparities in hospital quality are primarily driven by differences within-market and within-neighborhood. This fact suggests that more local or person-level interventions would be necessary to target the remaining gap. In this regard, our work complements the growing literature recognizing the importance of local areas in impacting many economic outcomes such as educational attainment, intergenerational mobility, and life expectancy (Chetty et al., 2016, 2018).

Finally, our work connects and extends two methods, re-weighting and decomposition methodologies, that were previously used separately and to study other aspects of the economy and economic life (Baily et al., 1991; DiNardo, Fortin and Lemieux, 1996; Barsky et al., 2002; Foster, Haltiwanger and Krizan, 2001; Foster, Haltiwanger and Syverson, 2008). By joining these

methods and applying them to this context, we provide new insights on how performance – in the health care sector or outside it – may evolve differently for different groups and drive disparities.

The remainder of the paper proceeds as follows. Section II covers our data and quality measurement approach, Section III explains our main analytic approach for static and dynamic decomposition analyses, Section IV covers our static and dynamic decomposition results, Section V provides evidence on the role of technology in explaining the dynamics of racial disparities in hospital performance, and Section VI concludes.

2 Data and Quality Measurement

We analyze hospital allocation of Medicare beneficiaries with Fee-for-Service (FFS) coverage who experienced an AMI between 1995-2014. For AMI, a primary hospital quality measure used by agencies such as the Centers for Medicare and Medicaid Services (CMS) is 30-day risk-adjusted survival. Thus, for each hospital, we calculate 30-day risk-adjusted survival using administrative data in four 5-year periods (1995-1999, 2000-2004, 2005-2009, 2010-2014) and use this as our primary hospital quality measure.

2.1 Data

We use 100% Medicare Fee-for-Service (FFS) inpatient claims linked to beneficiary information from the Beneficiary Summary File from 1995-2014. Together these data allow us to observe information about patients' hospitalizations (billing codes, provider identifier[1], provider zip code, 30-day survival) and patient characteristics (race, age, gender, and zip code of residence). We then link the patient and provider zip codes to markets, operationalized as health referral regions (HRR), using the Dartmouth Atlas crosswalk. We link claims to data on technology adoption, hospital size, and staffing from the American Hospital Association (AHA) Annual Survey. The cardiac technology adoption variables in the AHA Annual Survey vary by year but include whether the hospital has a diagnostic or interventional catheterization lab, cardiac intensive care, adult cardiac services, adult cardiac electrophysiology, or heart transplant services. We also link claims data to data on hospital beta-blocker and aspirin use at discharge for AMI patients from the Cooperative Cardiovascular Project (CCP) for 1995-1999 and from CMS for 2010-2014. We use different datasets in the endline and baseline periods because the CCP did not collect data from

[1]Provider identifiers in Medicare claims may change over time without a true closure if hospitals convert to critical access hospitals (program for rural hospitals) or merge over time. We thank Jonathan Skinner for kindly sharing the crosswalk necessary to track providers over time.

2010-2014 and CMS did not report these data from 1995-1999. We take care to replicate CMS's exclusion criteria in creating measures of beta-blocker and aspirin use in 1995-1999, with details provided in Appendix Section 3.1.

2.2 Sample

The focus of our analysis is on patients with an initial hospitalization for AMI during the study period and who were not hospitalized for AMI in the year prior to admission. We call such a hospitalization an index event, mimicking Chandra et al. (2016).

We limit to patients who are 66+ at the time of admission in order to assure that we can see admissions and other diagnoses in the year prior to admission. We exclude patients whose claims are not fully observed either because they were not enrolled in both Part A and B of Medicare or were enrolled in Medicare Advantage. We require that patients have this level of coverage for one year prior to the index event and up to death or one year following the index event. We exclude admissions occurring outside the 50 U.S. states or the District of Columbia. We also limit our analysis to patients treated at a short-term acute care hospitals or a critical access hospital, excluding long-term care hospitals. In each period, we limit our analysis to hospitals with 25 or more patients because quality can be reliably estimated in this sample. Finally we limit our main analysis to hospitals meeting all other exclusion criteria in both the first (1995-1999) and final period of analysis (2010-2014). This is done to facilitate longitudinal analyses. This excludes 1277 hospitals in 1995-1999 and 167 hospitals from 2010-2014. We present sensitivity analyses including an unbalanced sample. For analyses of 2000-2004 and 2005-2009, we limit to the subset of hospitals in our main sample that have 25 or more patients in the period.

2.3 Quality measurement

We calculate four risk-adjusted 30-day survival measures for each hospital corresponding to the four 5-year periods (1995-1999, 2000-2004, 2005-2009, 2010-2014). In our main analysis, we calculate a single risk-adjusted survival measure for each hospital that encompasses patients in all race groups. This measure is calculated using index events from all patients including non-black, non-white patients.

To develop our estimate of risk-adjusted survival, we begin with all the index events in our analysis after all exclusions are applied. We calculate risk-adjusted survival for each hospital in each period separately by estimating the following equation:

$$s_{iht} = \beta_{0t} + \beta_{1t} X_{iht} + \beta_{2t} A_{iht} + \gamma_{ht} + \epsilon_{iht} \tag{1}$$

where s_{ih} is 30-day survival following hospital admission for patient i at hospital h in each period t, X_{iht} refers to indicators for comorbidities, or non-AMI diagnoses on recorded in the year prior to the index event, and A_{iht} refers to age/race/sex interactions. This regression is estimated separately in each period using a linear, fixed-effects regression approach.

We then develop a quality measure for each hospital h in each period t ($\hat{q}_{h,t}$) per equation 2, which corresponds to the expected 30-day survival for an AMI patient with no comorbidities recorded in the prior year at hospital h in period t.

$$\hat{q}_{h,t} = \hat{\beta}_{0t} + \hat{\gamma}_{ht} \tag{2}$$

We similarly develop a quality measures reflecting the expected 30-day survival for black and white patients with average comorbidity levels as follows:

$$\hat{q}^B_{h,t} = \hat{\beta}_{0t} + \hat{\gamma}_{ht} + \bar{X}^B \hat{\beta} \tag{3}$$

$$q^W_{h,t} = \beta_{0t} + \gamma_{ht} + \bar{X}^W \beta \tag{4}$$

where $\bar{X}^B$ and $\bar{X}^Y$ refer to the vector of comorbidities corresponding to an average black and white patient respectively.

2.4 Summary statistics

Table 1 presents a basic summary of the patients and hospitals included in our main analysis. Panel A shows patient characteristics for black and white patients in 1995-1999 and 2010-2014. Overall, in both periods, black patients were more likely to be female, had greater level of comorbidities, and were younger. Overall the number of heart attack patients decreased from 66,092 black patients and 1,018,234 white patients in 1995-1999 to 60,204 black patients and 710,068 white patients. This is partly due to patients increasingly opting out of Medicare Fee-for-Service into Medicare Advantage, and partly due to overall reductions in AMI incidence during this period (Jacobson, Damico and Neuman, 2018; Yeh et al., 2010). Black patients also had higher overall survival rates in both pariods than their white counterparts (81.7% vs. 81.2% from 1995-1999 and

86.7% vs. 85.8% from 2010-2014). The reasons underlying this pattern remain unknown, but have been previously well-documented in AMI and other emergent conditions specifically in the above-65 population (Barnato et al., 2005; Polsky et al., 2007, 2008; Thomas et al., 2011; Downing et al., 2018; Huckfeldt et al., 2019).

Panel B shows hospital characteristics in 1995-1999 and 2010-2014 for the 2712 hospitals in our main analysis. Overall there is large variation among hospitals in 30-day risk adjusted survival in both periods, with a standard deviation of approximately 4pp. This is comparable to the total growth in survival over this time period. Notably, the number of black patients per hospital varies considerably with only 2181 hospitals having one or more black patients in 1995-1999 and 2120 hospitals having one or more black patients in 2010-2014.

3 Analytical Approach: Static and Dynamic Decompositions

Our main empirical analysis links reweighting and decomposition methods to characterize the factors contributing to black-white disparities in hospital performance at a point-in-time ("static decomposition") and over time ("dynamic decomposition"). Re-weighting methods have been used in many contexts including to decompose the black-white wage gap (Barsky et al., 2002) and identify the contribution of worker demographics, union density, and the minimum wage on wage inequality (DiNardo, Fortin and Lemieux, 1996). Similar decompositions methods have also been previously employed to study the firm-level drivers of aggregate productivity growth (Foster, Haltiwanger and Krizan, 2001; Foster, Haltiwanger and Syverson, 2008; Baily et al., 1991).

3.1 Static decomposition

In the static decomposition analysis, we quantify the degree to which black patients' use of lower performing hospitals lowers their average 30-day survival relative to white patients following AMI in each 5-year period from 1995-2014 (1995-1999, 2000-2004, 2005-2009, 2010-2014). We then decompose this difference into the share fully explained by differences in the geographic distribution of black and white patients across markets, operationalized as 306 Health Referral Regions (HRRs) nationwide, and within markets but across zip codes.

To motivate our analysis, we begin by expressing the total difference in 30-day survival rates between black and white patients as follows:

$$\begin{aligned}\bar{q}_t^B - \bar{q}_t^W &= \sum_{h \in H_t} \theta_{h,t}^B q_{h,t}^B - \sum_{h \in H_t} \theta_{h,t}^W q_{h,t}^W \\ &= \underbrace{\sum_{h \in H_t} \theta_{h,t}^W (q_{h,t}^B - q_{h,t}^W)}_{\text{Within}} + \underbrace{\sum_{h \in H_t} (\theta_{h,t}^B - \theta_{h,t}^W) q_{h,t}^B}_{\text{Between}}\end{aligned} \tag{5}$$

where $\bar{q}_t^B$ and $\bar{q}_t^W$ are the average 30-day survival of black and white patients in period t, $q_{h,t}^B$ and $q_{h,t}^W$ are the 30-day risk-adjusted survival at hospital h in period t for a black patient of average comorbidity levels and a white patient of average comorbidity levels, $\theta_{h,t}^B$ and $\theta_{h,t}^W$ are the national market share of hospital h in period t among black and white patients, and H_t is the set of hospitals open in period t.

Equation 5 illustrates that the total difference 30-day in survival rates can be divided into two conceptually distinct components. The *within* refers to the difference in survival between black and white patients resulting from disparities in the outcomes each provider achieves for their black versus white patients. These can arise for due to a variety of factors including differing underlying risk factors or treatment efficacy or biases or racism by providers. The *between* term refers to the difference in survival between black and white patients resulting from black patients' use of lower or higher performing hospitals. This is equivalently the average difference in performance between hospitals used by black and white patients.

Our analysis focuses specifically on the characterizing the *between* component of racial differences in 30-day survival rates following AMI, which we also term the "racial disparity in hospital allocation". For clarity, we can re-express and estimate the magnitude of this disparity as follows:

$$\underbrace{\hat{S}_{b,t} - \hat{S}_{w,t}}_{\substack{\text{Racial disparity in} \\ \text{hospital allocation}}} = \sum_{h \in H_t} \theta_{h,t}^B \hat{q}_{h,t}^B - \sum_{h \in H_t} \theta_{h,t}^W \hat{q}_{h,t}^B = \sum_{h \in H_t} \theta_{h,t}^B \hat{q}_{h,t} - \sum_{h \in H_t} \theta_{h,t}^W \hat{q}_{h,t} \tag{6}$$

where $\hat{S}_{b,t}$ and $\hat{S}_{w,t}$ are the average performance of hospitals used by black and white patients respectively. Notably, our main analysis is insensitive to the reference population used as $\hat{q}_{h,t}^B$ and $\hat{q}_{h,t}$ differ by only a constant term. For ease of expression we will use $\hat{q}_{h,t}$ for our estimation.

We then further decompose the racial disparity in hospital allocation into three sub-components: (1) "macro-geography", or differences in where black and white patients live across markets, (2) "micro-geography", differences in where black and white patients live within markets

but across zip codes, and (3) "residual" differences, or differences in the hospitals black and white patients use within a zip code.

We quantify the contribution of each component using inverse probability weighting (Barsky et al., 2002; DiNardo, Fortin and Lemieux, 1996). Specifically, we re-weight white patients to match the contemporaneous geographic distribution of black patients at the zip-code and market level. This allows us to control for differences in the geographic distribution of both populations and assess how allocation for black and white patients compares within market or within zip-code. We do this by weighting each white patient by the function $\omega_{zip}(\cdot)$ or $\omega_{mkt}(\cdot)$ per equation 7. Re-weighting by $\omega_{zip}(\cdot)$ matches racial distributions at the zip-code level, and re-weighting by $\omega_{mkt}(\cdot)$ matches racial distributions at the market level. The covariates Z^{zip} and Z^{mkt} are indicators for different zip codes or markets respectively, z_i^{zip} and z_i^{mkt} are the zip code and market in which patient i resides, and B_t and W_t is the set of black and white patients in period t. The set B_t excludes fewer than 2% of black patients who live in zip codes with no white patients, in order to maintain common support.

$$\omega_a(z_i) = \frac{\hat{\Pr}(black|Z^a = z_i^a)}{\hat{\Pr}(white|Z^a = z_i^a)} = \frac{\sum_{j\in B_t} I\left(z_j^a = z_i^a\right)}{\sum_{j\in W_t} I\left(z_j^a = z_i^a\right)}, a \in (zip, mkt) \tag{7}$$

Using the inverse probability weights, we construct counterfactual black and white patient market shares that assume black and white patients have the same geographic distribution across markets and zip codes as follows:

$$\theta_{h,t}^{W_a'} = \frac{\sum_{i\in W_t}(C_i = h)\,\omega_a(z_i)}{\sum_{i\in W_t}\omega_a(z_i)},\ a \in \{zip, mkt\} \tag{8}$$

Here, W_t is the set of white people in our sample in period t, C_i is the hospital chosen by patient i, and $\omega_a(z_i)$ is as defined in equation 7. Thus, $\theta_{h,t}^{W_{mkt}'}$ and $\theta_{h,t}^{W_{zip}'}$ are the national share of white patients in period t that use hospital h, where white patients are reweighted to match the contemporaneous distribution of black patients at the market and zip-code level.

We then decompose the racial disparity in hospital quality into four components per equation 9.

$$\underbrace{\sum_{h \in H_t} \left(\theta^B_{h,t} - \theta^W_{h,t}\right) \hat{q}_{h,t}}_{\text{Racial disparity in hospital allocation}} = \underbrace{\sum_{h \in H_t} \left(\theta^{W'_{zip}}_{h,t} - \theta^{W'_{mkt}}_{h,t}\right) \hat{q}_{h,t}}_{\text{micro-geography (within markets)}} + \underbrace{\sum_{h \in H_t} \left(\theta^{W'_{mkt}}_{h,t} - \theta^{W}_{h,t}\right) \hat{q}_{h,t}}_{\text{macro-geography (across markets)}} + \underbrace{\sum_{h \in H_t} \left(\theta^{B}_{h,t} - \theta^{W'_{zip}}_{h,t}\right) \hat{q}_{h,t}}_{\text{within zip codes}} \tag{9}$$

The macro-geography term captures the racial disparity in hospital quality due to differences in where patients live across regions of the U.S. (e.g., gaps due to many black patients living in the South). The micro-geography term captures the racial disparity in hospital quality due to where patients live within regions (e.g., gaps due to black patients living in the poorer parts of most cities). The within zip code term captures the racial disparity in hospital quality that persists within zip-codes. This may include different preferences of black and white patients within zip code. Finally, the residual arises due to a lack of common support across zip codes, and specifically captures the disparity explained by black patients living in zip codes where there are no white patients. Empirically the contribution of this component is negligible. Standard errors were calculated using 1000 bootstrap replicates at the hospital-level.

3.2 Dynamic decomposition

We then analyzed the factors contributing to the evolution of racial disparities in hospital performance over time. We identify two main forces that could contract or expand disparities over time: (1) stronger re-allocation of black patients than white patients to better performing hospitals from 1995-2014 and (2) stronger performance improvement at hospitals that historically served disproportionately black patients. To assess the relative contribution of these two forces to a reduction of disparities in hospital performance, we applied a dynamic decomposition of the total change in the racial disparity in hospital allocation from 1995-1999 to 2010-2014 by estimating the components of equation 10. This can also be characterized more generally as a decomposition of a difference-in-differences.

$$
\begin{aligned}
\underbrace{(\hat{S}_{b,t} - \hat{S}_{w,t}) - (\hat{S}_{b,t-1} - \hat{S}_{w,t-1})}_{\text{Change in Racial Disparity in Hospital Allocation}} &= \sum_{h \in B} (\theta^B_{h,t} - \theta^W_{h,t}) \hat{q}_{h,t} - \sum_{h \in B} (\theta^B_{h,t-1} - \theta^W_{h,t-1}) \hat{q}_{h,t-1} \\
&= \underbrace{\sum_{h \in B} \hat{q}_{h,t-1} [(\theta^B_{h,t} - \theta^B_{h,t-1}) - (\theta^W_{h,t} - \theta^W_{h,t-1})]}_{\text{Reallocation}} \\
&+ \underbrace{\sum_{h \in B} (\theta^B_{h,t-1} - \theta^W_{h,t-1})(\hat{q}_{h,t} - \hat{q}_{h,t-1})}_{\text{Differential Performance Improvement}} \\
&+ \underbrace{\sum_{h \in B} (\hat{q}_{h,t} - \hat{q}_{h,t-1}) [(\theta^B_{h,t} - \theta^B_{h,t-1}) - (\theta^W_{h,t} - \theta^W_{h,t-1})]}_{\text{Cross}}
\end{aligned} \tag{10}
$$

Here, B represents the set of hospitals h in the balanced panel, periods t and $t-1$ refer to 2010-2014 and 1995-1999 respectively, $\theta^B_{h,t}$ and $\theta^W_{h,t}$ refers to the market share of hospital h among black and white patients in period t respectively, and $q_{h,t}$ refers to 30-day risk adjusted survival at hospital h in period t for a patient with no comorbidities.

The reallocation term captures the change in the racial disparity in hospital allocation explained by stronger reallocation by black patients towards better performing hospitals. A positive reallocation term would imply that black patients shifted towards better performing hospitals at a faster rate than white patients from 1995-2014. The differential performance improvement term captures the change in the racial disparity in hospital allocation explained by stronger performance improvement at hospitals with higher relative black patient shares. Finally, the cross-term captures change in the racial disparity in hospital allocation explained by stronger performance improvement at hospitals that had stronger relative gains in black patient market share over time. Standard errors were calculated using 1000 bootstrap replicates at the hospital-level.

4 Decomposition Results

4.1 Static Decomposition

Table 2 depicts the static decomposition results from 1995-1999 and 2010-2014. Our results show that in 1995-1999 black patients used hospitals with significantly lower performance than white patients; black patients used hospitals with 1pp lower 30-day risk-adjusted survival than white patients on average. However, by 2010-2014, this disparity had shrunk by nearly 70% with

black patients using hospitals with only 0.3pp lower 30-day risk adjusted survival.

Using a re-weighting approach to equalize the geographic distribution of black and white patients at the market and zip code level, we find that geography appears to play an important role in explaining the disparity in both periods, though its contribution of macro-geography has decreased significantly over time. In 1995-1999 both macro-geography and micro-geography appeared to play an important role in explaining the disparity. In 1995-1999, nearly half (44%) of the disparity is explained by macro-geographic differences in where black and white patients. In other words, (56%) of the racial disparity in hospital allocation persists within HRR. An additional 25% is explained by differences in where micro-geography, or where patients live across zip codes within HRR. In 2010-2014, only 5% of the remaining disparity was explained by macro-geographic differences in where black and white patients live. Meanwhile 46% of the remaining disparity was explained by micro-geographic differences in where patients live within HRRs but across zip codes. These results imply that 61% of the reduction in racial disparities in hospital performance is explained by reductions in disparities due to differences macro-geography. Meanwhile, we find that the relative importance of racial disparities in hospital performance within zip codes has increased. In 1995-1999, disparities within zip-code only accounted for 31% of the national disparity in hospital performance by race. However, by 2010-2014, 50% of the national disparity persisted within zip codes.

We also visualize these results in Exhibit 3 graphically by plotting the distribution of hospital 30-day risk-adjusted survival with and without geographic reweighting. In sequentially reweighting white patients to match the geographic distribution of black patients at finer levels of granularity (i.e., moving from market to zip code), we can visualize disparity in hospital performance explained by macro-geography, micro-geography, and within zip code differences.

These results suggest either that hospitals in markets with historically large African American populations experienced greater average quality improvement than hospitals in other areas, or that black patients re-allocated to better performing hospitals at a rate faster than white patients. This re-allocation would occur either by patients moving to markets with better performing hospitals or patients utilizing higher performing hospitals in their own markets. We investigate these two possibilities in our dynamic decomposition analysis.

4.2 Dynamic Decomposition

Exhibit 4 illustrates the dynamic decomposition results, in which we decompose the total disparity reduction of 0.66pp to understand the relative contribution of re-allocation and differential performance improvement to this change. We find that differential performance improvement alone fully explains the disparity reduction over time. This implies that hospitals disproportionately treating black patients in 1995-1999 experienced stronger performance gains. We also find a non-significant role for greater re-allocation of black patients to hospitals with better performance in 1995-1999, which contributed 0.19pp to the aggregate disparity reduction. Finally, a negative cross term implies that hospitals improving performance over this time period increased their relative share of white patients. This contributed negatively to the aggregate disparity by 0.21pp, but was also non-significant.

We can also visualize these results in Exhibit 5 graphically by comparing the trend in average hospital 30-day risk adjusted survival for black and white patients (Panel A), to counterfactuals in which we assume hospitals' market share (Panel B) or performance (Panel C) remains constant at 1995-1999 levels. The closure of the disparity fully explained by the counterfactual under which we hold hospital market share constant at 1995-1999 levels is the component attributable to differential performance improvement. Similarly, the closure of the disparity fully explained by the counterfactual under which we hold hospital performance constant at 1995-1999 levels is the component attributable to reallocation.

4.3 Robustness

We probed the robustness of both our static and dynamic decomposition results using several approaches. In general, our results are little changed under these alternative approaches.

One concern we sought to address is that our claims-based risk-adjusters may not adequately control for factors that impact 30-day survival. In this case, patients may well select to certain hospitals on unobservable qualities that in turn bias our estimated quality. To assess whether this source of bias is likely to be meaningfully influencing our results, we repeated our analyses with alternative specifications including no risk-adjusters, fewer risk-adjusters (age/race/sex interactions only), and more detailed risk-adjusters (race-comorbidity interactions). This approach to testing for selection on unobservables has been commonly used in the literature (Altonji, Elder and Taber, 2005, 2019). A description of the model specifications used in these sensitivities can be

found in Appendix Section 1, and the results can be found in in Appendix Tables A1 and A2. We find that our results using these alternative specifications are very similar to our main specification. These results suggest that the availability of even more detailed risk-adjusters would likely not influence our estimates of risk-adjusted quality. Furthermore, regression-adjusted quality estimates have been shown to approximate quasi-experimental estimates in other work (Hull, 2018; Doyle, Graves and Gruber, 2018).

Another potential concern is that because we estimate a single measure of 30-day risk adjusted survival for each hospital, our analysis does not account for race-specific aspects of hospital performance. If hospitals differ substantially in their race-specific performance, then our estimated disparity in hospital performance at a point-in-time and over time may be incorrect. To illustrate this point, consider the possibility that at a point in time, black patients disproportionately use hospitals that are high performing for black patients and low performing for the majority of patients. In this case, using a single measure of hospital performance would likely imply a larger disparity in hospital performance than is actually experienced by patients. Similarly, consider the possibility that hospitals historically serving disproportionately black patients improved performance but only for their white patients. In this case, using a single measure of hospital performance would likely imply a large effect of differential performance improvement in reducing disparities in hospital performance than is actually experienced by black patients. Unfortunately, we have limited capacity to test this hypothesis given that many hospitals have very few black patients; only 521 hospitals in our balanced sample have more than 24 black and 24 white patients in both periods. This prevents us from estimating a race-specific hospital quality measure precisely for the majority of our sample. However, we do show in sensitivity analyses that our results are robust to specifications that allow quality to vary by race in Appendix Table A1 (static analysis) and A2 (dynamic analysis). We also show a high correlation between hospitals' estimated black and white race-specific quality in Appendix Table A3, suggesting that the presence of race-specific quality is unlikely to meaningfully impact our results.

An additional concern for our analysis is that Medicare Advantage penetration is increasing during our study period. Medicare Advantage enrollees are disproportionately white and prior work shows that they tend to be healthier than Fee-for-Service enrollees on both observable and unobservable characteristics (Brown et al., 2014). Thus it may be that the reduction in disparity is due to selection of white patients with strong allocation towards high quality providers into Medicare Advantage. To address this concern, we repeat our analysis limiting to markets with below

median penetration of Medicare Advantage as of 2014 where any selection-mediated effects would likely be attenuated. We find these results are very similar to our main analysis findings, suggesting that selection of patients into Medicare Advantage within markets is not driving our findings. The results from this analysis can be found in Appendix Table A1 (static decomposition) and Appendix Table A2 (dynamic decomposition).

Finally, we modified and repeated our analysis using an unbalanced panel. Accounting for entry and exit in an analysis of an unbalanced panel requires a more complex decomposition approach, which we discuss in Appendix Section 2. Here, again, we find results very similar to our main analysis findings. The results from this analysis can be found in Appendix Table A1 (static decomposition) and Appendix Table A2 (dynamic decomposition).

5 Mechanisms underlying differential performance improvement

While our dynamic decomposition results show that differential quality improvement reduced disparities in hospital allocation, these results do not explain why. Thus, we probed two potential mechanisms that may have caused differential performance improvement at hospitals disproportionately treating black patients. First, we probe whether there was a relative increase in technological inputs (e.g., greater increases in rates of technology use or adoption) among hospitals disproportionately treating black patients. Second, we probe whether there was a relative increase in skill of technology use among hospitals disproportionately treating black patients.

Overall, we find no evidence that hospitals disproportionately treating black patients had a relative increase in technological inputs. However, we find signs that hospitals treating disproportionately black patients may have improved their relative skill of technology use. Specifically we find that differential performance improvement is over twice as strong among patients receiving cardiac catheterization than those who do not. This suggests that increasing skill in using cardiac catheterization may have driven differential performance improvement. This could plausibly include using cardiac catheterization on patients who are more likely to benefit, treating patients in a more timely fashion, or improving technique or follow-up in patients receiving cardiac catheterization.

5.1 Technological inputs

In the years prior to our study period, the frontier for AMI treatment moved forward dramatically leading to variations in the use of clinical standards of care. These included variations

in the use of life-saving medications (e.g., beta blockers, aspirin, fibrinolytics) and in the use of more capital and labor-intensive techniques such as percutaneous coronary intervention using cardiac catheterization (Jencks et al., 2000; Jencks et al., 2009; Cutler et al., 1998). If hospitals with disproportionately black patients were late adopters but were catching up to the frontier during our study period, this could reduce disparities.

To probe this hypothesis, we repeat our dynamic decomposition analysis using measures of cardiac technology adoption in lieu of 30-day risk-adjusted survival. If the results followed a pattern similar to our main results, namely that hospitals disproportionately serving black patients saw the greatest increases in technology adoption, this would provide evidence for a role for technology adoption in driving differential performance improvement.

We used four main measures of technology adoption. First, for each hospital, we estimate a risk-adjusted rate of same-day cardiac catheterization. We focus on same-day cardiac catheterization, as medical evidence suggests only same-day catheterization, also known as percutaneous transluminal coronary angioplasty or percutaneous coronary intervention, has a meaningful impact on survival (Hartwell et al., 2005; Hochman et al., 2006). We estimate risk-adjusted same-day catheterization for each hospital in each period using the same approach used to calculate risk-adjusted 30-day survival described in Section 2. Notably, the ICD-9 procedure codes for catheterization are unable to distinguish between diagnostic and interventional catheterization.

Second, we build an aggregate measure of cardiac technology adoption using data from the American Hospital Association (AHA) Survey. The specific cardiac technology variables available vary from year-to-year due to changes in the AHA survey over time. From 1995-1999, the AHA survey has data on whether a hospital has a cardiac intensive care unit, performs open heart surgery, and / or has either diagnostic or interventional catheterization. From 2010-2014, the AHA data indicate whether a hospital has either diagnostic or interventional catheterization, cardiac intensive care, adult cardiology services, adult cardiac surgery, adult cardiac electrophysiology, or heart transplant services. To compare across periods, we add all the indicators available in a period and ranking each hospital relative to other hospitals within period. A hospital's percentile rank relative to other hospitals within period is its aggregate cardiac technology index.

Finally, we use the share of elderly patients receiving beta blockers and aspirin at discharge. These measures are obtained from the CCP for 1995-1999 and from CMS for 2010-2014. Details of the exclusion criteria applied to estimate these measures are available in Appendix Section 3.1.

Our results from our analysis are presented alongside our main results in Table 3. The results suggest that hospitals treating disproportionately black patients increased adoption of capital-intensive technology and aspirin at discharge at a slower rate than other hospitals. This is reflected in the negative term associated with differential quality improvement. In robustness analyses, depicted in Appendix Table A5, we also show similar results for risk-adjusted rates catheterization including non-same day catheterization, risk-adjusted rates of of cardiac bypass surgery (CABG), and individual AHA measures that are available in both periods (presence of a catheterization lab, presence of a cardiac intensive care unit). However, as with risk-adjusted survival, the gap between black and white patients in hospitals' average use of beta blockers at discharge decreased by 1.45 percentage points over time. Furthermore, of the 1.45 percentage point change, 1.34 percentage points are explained by faster adoption of beta blockers at discharge among hospitals disproportionately serving black patients.

In aggregate, these results suggest that differential quality improvement are likely not be due to faster adoption of capital intensive technologies. However, the faster adoption of low-cost technologies, namely beta blockers, at hospitals serving disproportionately black patients may partially explain differential performance improvement at these hospitals.

5.2 Skill in technology use

The second hypothesis we probe is whether hospitals with high market shares among black patients improved their relative skill in technology use. We specifically focus on returns to use of catheterization, a key procedure used to manage AMI. We probe this hypothesis by estimating equation 11.

$$s_{iht} = \beta_{0t} + \beta_{1t}X_{iht} + \beta_{2t}A_{iht} + \beta_{3t}c_{iht} + \beta_{4t}b_{ih} + \beta_{5t}c_{iht}b_{ih} + \epsilon_{iht} \tag{11}$$

Here, as previously, s_{iht} is an indicator of 30-day survival of patient i treated at hospital h in period t, X_{iht} is a set of 25 comorbidities, A_{iht} is a vector of age/race/sex interactions, c_{iht} is an indicator for whether patient received same-day cardiac catheterization, b_{ih} is share of black patients in 1995-1999 visiting hospital h, and ϵ_{iht} is an i.i.d. error term. We estimate this regression separately in each period using ordinary least squares. Standard errors are estimated analytically and are robust to heteroskedasticity.

Observing the changes in β_{4t} and β_{5t} over time allow us to make several important in-

ferences. First, the expression $\beta_{5,2010-2014} - \beta_{5,1995-1999}$ represents the relative increase in returns to catheterization at hospitals serving 100% black patients versus hospitals serving 100% white patients. Thus $\beta_{5,2010-2014} > \beta_{5,1995-1999}$ would imply that differential performance improvement was stronger among patients receiving catheterization than those who did not receive catheterization.

Second, we can use our estimation approach to understand the degree to which differential quality improvement was stronger among patients receiving catheterization than those who did not receive catheterization. Specifically, we can do this by comparing $(\beta_{4,2010-2014} + \beta_{5,2010-2014}) - (\beta_{4,1995-1999} + \beta_{5,1995-1999})$ and $(\beta_{4,2010-2014} - \beta_{4,1995-1999})$, which represent the risk-adjusted survival gains for catheterization and non-catheterization patients at hospitals serving 100% black patients versus those serving 100% white patients. Thus comparing $(\beta_{4,2010-2014} + \beta_{5,2010-2014}) - (\beta_{4,1995-1999} + \beta_{5,1995-1999})$ to $(\beta_{4,2010-2014} + \beta_{5,2010-2014})$ represents the degree to which differential performance improvement was larger for catheterization versus non-catheterization patients.

Our results suggest that increasing skill in use of catheterization technology may have contributed to differential performance improvement at hospitals serving disproportionately black patients. As seen in Exhibit 5, hospitals treating disproportionately black patients experienced greater returns to catheterization (i.e., $\hat{\beta}_{5,2010-2014}\,(0.0125) > \hat{\beta}_{5,1995-1999}\,(-0.0275)$). In Appendix Table A6, we show that this result is not simply driven by increasing returns to catheterization for black patients within hospitals. Furthermore, the relative growth in returns to treatment at a hospital treating 100% black patients vs. no black patients for catheterization patients ($\hat{\beta}_{4,2010-2014} + \hat{\beta}_{5,2010-2014}) - (\hat{\beta}_{4,1995-1999} + \hat{\beta}_{5,1995-1999}) = (-.0275 + .0125) - (-.0597 + -.0275) = .0722$) is more than double the relative growth in returns to treatment at a hospital treating 100% black patients vs. 100% white patients for non-catheterization patients ($\hat{\beta}_{4,2010-2014} - \hat{\beta}_{4,1995-1999} = .0319$). This implies that hospitals treating disproportionately large shares of black patients improved their relative performance in treating catheterization patients over twice as strongly as their performance treating non-catheterization patients.

6 Conclusion

In this paper, we investigate the determinants of black-white disparities in hospital performance from 1995 to 2014, focusing on AMI in Medicare patients. We find that in the 1995-1999, differences in the performance of hospitals used by black and white patients subtracted as much as 1pp off survival rates, explained primarily by differences in where black and white patients live

both across and within markets. We view this to be a clinically significant disparity considering that certain breakthrough medical innovations in AMI treatment, such as reperfusion therapy and primary angioplasty were associated with 2pp greater survival than predecessor therapies. However, by 2010-2014, this disparity had attenuated by nearly 70%. We find that this reduction is fully explained by differential performance improvements at hospitals with historically high black patient shares as opposed to stronger re-allocation of black patients to better performing hospitals. Finally, we find evidence that stronger performance improvements at hospitals with historically high black patient shares may be mediated by greater adoption of beta blockers and stronger improvements in catheterization skill.

There are, however, notable limitations to our work that create opportunities for future research. First, our analysis focuses specifically on black-white disparities in hospital performance for AMI in Traditional Medicare. While racial disparities in AMI are an important public health priority, these results may not generalize to a broader set of diseases, populations, and provider types. Second, our analysis focuses on disparities in medical outcomes arising from black and white patients use of different providers. Thus we are unable to compare how other determinants of racial disparities in medical outcomes have evolved over our study period. Finally, it remains unclear why hospitals with disproportionately high black patient shares saw relative improvements in catheterization skill and beta blocker use over this time period.

Taken together, our results offer important lessons for addressing racial disparities in health. Our work illustrates that quality improvements at hospitals serving disproportionately underprivileged patients can be an important mechanism for reducing overall disparities in medical outcomes. This is an important consideration for government programs designed to support such hospitals such as the Medicaid Disproportionate Share Payments (DSH) program. Nonetheless, our work shows that the disparities in AMI outcomes arising from black and white patients' use of different hospitals have attenuated significantly in the last 20 years. Thus efforts to address disparities in AMI outcomes may be more prudent to focus on other sources of disparities including social determinants of health and / or institutional biases within hospitals.

Main Exhibits

Table 1: Summary statistics on individuals and hospital risk-adjusted survival

Time period	1995-1999		2010-2014	
Race	Black	White	Black	White
Panel A: Individual characteristics				
Average unadjusted 30-day survival	81.7%	81.2%	86.7%	85.8%
Age	76.8	77.6	77.7	79.3
SD	7.5	7.3	8.2	8.2
Female	59.8%	49.5%	58.7%	48.2%
History of heart failure	18.2%	12.5%	24.2%	15.0%
History of stroke	2.1%	1.2%	1.2%	0.6%
History of COPD	7.6%	7.5%	10.4%	8.9%
Total No. of Comorbidities	1.3	0.9	1.9	1.3
SD	2.0	1.7	2.6	2.2
Patients	66,092	1,018,234	60,204	710,068
Panel B: Hospital measures				
Economy-wide 30-day survival	81.2%		85.9%	
(SD of risk-adjusted measure)	(3.8%)		(4.3%)	
Total patients per hospital	411.2		297.4	
SD	369.5		310.1	
Group-specific patient counts per hospital	24.4	375.5	22.2	261.8
SD	47.2	347.6	45.8	283.0
Hospitals per market	8.9			
SD	(8.1)			
No. of hospitals	2712			
No. of hospitals with >=1 patient in race group	2181	2711	2120	2706

Note: Analysis restricted to balanced sample of hospitals that have 25 or more patients in each period. SD of risk-adjusted survival is calculated using an empirical-bayes shrinkage approach.

Table 2: Static decomposition of racial disparity in hospital allocation between black and white AMI patients

	Percentage points					
Time period	1995-1999		2010-2014		Difference	
	Value (SE)	Share	Value (SE)	Share	Value (SE)	Share
Racial disparity in	-0.95		-0.29		0.66	
hospital performance	(0.11)		(0.11)		(0.13)	
Geography (within market)	-0.24	25%	-0.13	46%	0.10	16%
	(0.07)		(0.07)		(0.10)	
Geography (across market)	-0.42	44%	-0.01	5%	0.40	61%
	(0.07)		(0.07)		(0.09)	
Within zip code	-0.30	31%	-0.14	50%	0.15	23%
	(0.05)		(0.05)		(0.06)	
N	2712					

Note: This table decomposes the difference in risk-adjusted survival between black and white patients during the 1995-1999 and 2010-2014 periods. The decomposition is performed nationally. Risk-adjusted 30-day survival is calculated from a regression of survival is calculated from a regression of survival on hospital fixed effects and patient risk-adjusters (age/race/sex interactions and comorbidities) on the full population. The analysis is restricted to balanced sample of hospitals that have 25 or more patients in each period. Standard errors were calculated using 1000 boostrap replicates clustered at the hospital level.

Table 3: Difference-in-difference decomposition of risk-adjusted survival and potential explanatory variables

	Percentage points				
	30-day risk-adjusted survival	Risk-adjusted same-day catheterization	AHA technology index	Hospital average beta blocker use at discharge	Hospital average aspirin use at discharge
Average across patients in 1995-1999	89.6	16.4	69.2	37.3	58.4
Reduction of racial disparity in hospital allocation	0.66	-1.58	-2.17	1.45	-1.88
SE	(0.13)	(0.39)	(0.53)	(0.56)	(0.57)
Re-allocation	0.19	-0.16	-1.07	0.58	-1.03
SE	(0.08)	(0.25)	(0.43)	(0.34)	(0.38)
Differential performance improvement	0.68	-0.64	-0.88	1.34	-1.81
SE	(0.15)	(0.32)	(0.45)	(0.58)	(0.56)
Cross	-0.21	-0.78	-0.22	-0.47	0.97
SE	(0.09)	(0.21)	(0.31)	(0.36)	(0.37)
N	2712	2712	2500	2600	2532

Note: Analysis restricted to balanced sample of hospitals that have 25 or more patients in each period. All risk-adjusted measures based on fixed effect regression including patient characteristics (age-race-sex interactions and comorbidities); technology index calculated summing indicators for all technologies with data available in the AHA and then calculating hospitals' within period percentile over the summed measure - the percentile constitutes the final index to facilitate comparison across periods in which different variables are available. Catheterization limited to same day catheterization. Standard errors were calculated using 1000 boostrap replicates clustered at the hospital level.

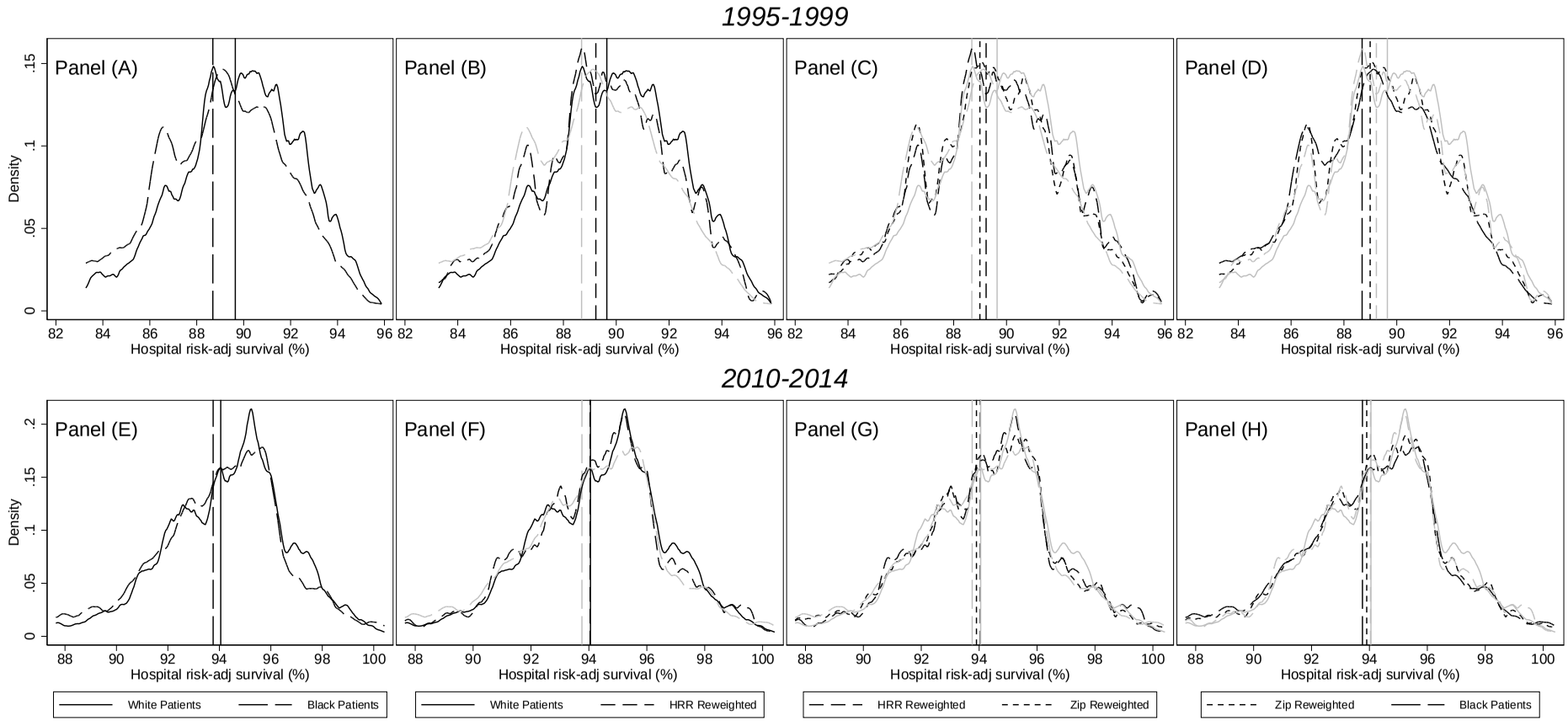
Table 4: Association between same-day catheterization and 30-day survival at hospitals with higher black patient shares

	1995-1999	2000-2004	2005-2009	2010-2014	Endline - Baseline	P-value
Catheterization	0.0184	0.0335	0.0310	0.0160	-0.0024	0.125
SE	(0.0013)	(0.0009)	(0.0009)	(0.0009)	(0.0016)	
Share Black at Baseline	-0.0594	-0.0461	-0.0245	-0.0275	0.0319	<0.001
SE	(0.0046)	(0.0045)	(0.0049)	(0.0052)	(0.0969)	
Catheterization X Share Black at Baseline	-0.0275	-0.0336	-0.0247	0.0125	0.0400	0.013
SE	(0.0134)	(0.0097)	(0.0090)	(0.0090)	(0.0161)	
Constant	0.894	0.908	0.922	0.935	0.040	<0.001
	(0.0014)	(0.0013)	(0.0014)	(0.0014)	(0.0020)	
N	1,115,228	1,186,468	959,615	806,472		

Note: The model includes age-race-sex interaction terms and comorbidities as risk-adjusters (output suppressed). The model is estimated on balanced panel of hospitals with a performance measures. Standard errors are heteroskedasticity robust and estimated analytically. P-value reflects a two-sided test for equality between baseline and endline coefficients

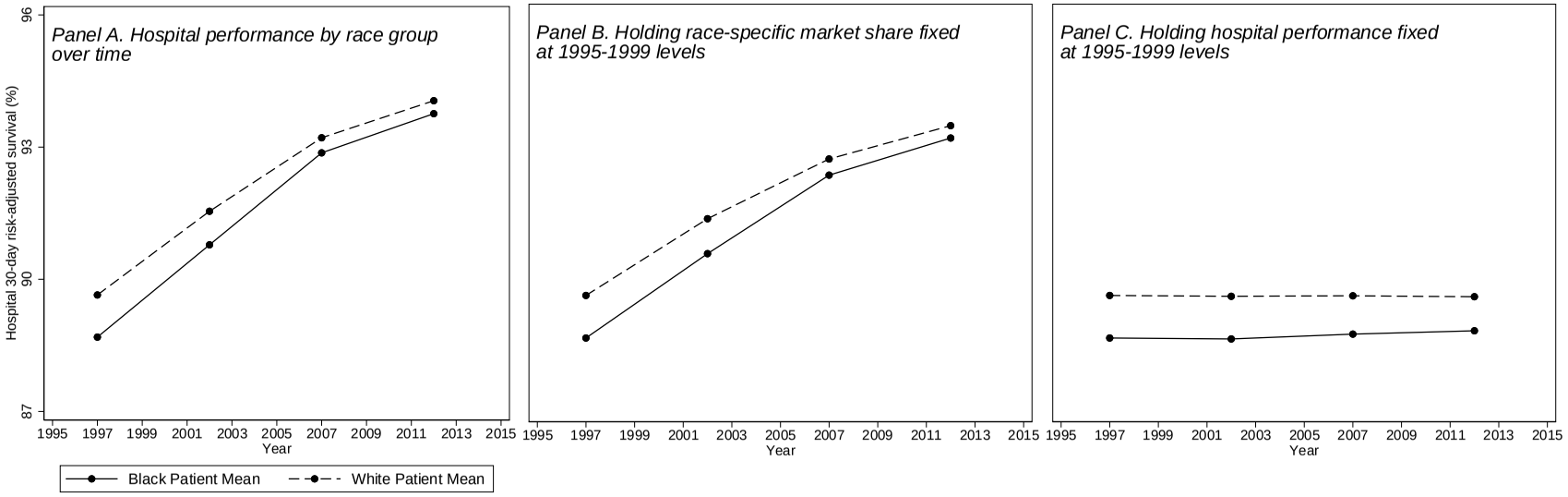
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Figure 1: Distribution of hospital performance across black and white patients



Note: Panels A and E reflect the distribution of hospital risk-adjusted survival for white and black patients. The gap between these two distributions reflects the total racial disparity in hospital performance. Panels B and F reflect the distribution of hospital risk-adjusted survival for white patients and white patients reweighted to match the distribution of black patients at the market level. The gap between these two distributions reflects the component of the racial disparity in hospital performance explained fully by macro-geography (i.e., differences in where patients live across markets). Panels C and G reflect the distribution of hospital risk-adjusted survival for white patients reweighted at the market level and at the zip code level. The gap between these two distributions reflects the component of the racial disparity in hospital performance explained fully by micro-geography (i.e., differences in where patients live within markets). Panels D and H reflect the distribution of hospital risk-adjusted survival for black patients and white patients reweighted at the zip code level. The gap between these two distributions reflects the component of the racial disparity in hospital performance that persists within markets. Across all panels the vertical lines represent the mean hospital risk-adjusted survival for the group. Hospital risk-adjusted survival refers to the expected survival for a patient with no comorbidities. Figures reflect all white and black patients seen at hospitals in our main sample.

Figure 2: Average hospital performance for black and white patients (1995-2014)



Note: Panel A shows unadjusted average hospital 30-day risk-adjusted survival for black and white patients .The change in the gap between black and white patients from 1995-1999 to 2010-2014 is equivalent to the quantity decomposed in Exhibit 4 and is the total disparity reduction from 1995 to 2014. Panel B shows average 30-day risk-adjusted survival for black and white patients under a counterfactual in which race-specific market share remains fixed at 1995-1999 levels. The change in the gap between black and white patients from 1995-1999 to 2010-2014 is equivalent to the component of disparity reduction explained by differential performance improvement in Exhibit 4. Panel C shows average 30-day risk-adjusted survival for black and white patients under a counterfactual in which hospital performance remains fixed at 1995-1999 levels. The change in the gap between black and white patients from 1995-1999 to 2010-2014 is equivalent to the component of disparity reduction explained by reallocation in Exhibit 4. Hospital 30-day risk adjusted survival is the expected survival of a patient with no comorbidities.

Appendix

1 Quality measurement

1.1 Main analysis

Our main dataset uses the 100% Medicare Fee-for-Service (FFS) inpatient claims (MEDPAR) linked to the Master Beneficiary Summary File from 1995-2001. We identify patients who have suffered an AMI by identifying claims with the following primary ICD-9 diagnosis codes: 410, 410.X, 410.X0 - 410.X1, 410.X3-410.X9.

As described in Section 2, we estimate risk-adjusted survival for each hospital separately in each period by estimating the following equation:

$$s_{iht} = \beta_{0t} + \beta_{1t} X_{iht} + \beta_{2t} A_{iht} + \gamma_{ht} + \epsilon_{iht} \tag{12}$$

where s_{ih} is 30-day survival following hospital admission for patient i at hospital h in each period t, X_{iht} refers to indicators for comorbidities, and A_{iht} refers to age/race/sex interactions. This regression is estimated separately in each period. Comorbidities consider all diagnosis codes listed in a medpar claims in the year prior to the index event including non-primary diagnosis codes. The comorbidities captured are: unstable angina, chronic atherosclerosis, respiratory failure, hypertensive heart disease or heart failure, valvular heart disease, arrhythmia, hypertension, stroke, cerebrovascular disease, renal failure disease, dialysis, COPD, pneumonia, diabetes, protein calorie malnutrition, dementia, paralysis and disability, peripheral vascular disease, metastatic cancer, trauma, substance abuse, major psychiatric disorder, and chronic liver disease. The age groups are 66-69, 70-74, 75-79, 80-84, 85-89, 90-94, and 95+. The race groups are black, white, and other. The model is estimated using a fixed-effects linear regression approach.

As described in Section 2, we then develop a quality measure for each hospital h in each period t ($\hat{q}_{h,t}$) per equation 13, which correspond to the expected 30-day survival for an AMI patient with no comorbidities recorded in the prior year at hospital h in period t. Specifically, this measure can be interpreted as the expected survival a white female, age 66-70, with no comorbidities.

$$\hat{q}_{h,t} = \hat{\beta}_{0t} + \hat{\gamma}_{ht} \tag{13}$$

1.2 Alternative quality measures used for robustness tests

In sensitivity analyses, we also use risk-adjusted survival calculated using several alternative specifications. The results of the sensitivity analyses using alternative quality measures can be found in Appendix Table A1 (static decomposition) and Appendix Table A2 (dynamic decomposition). Below we describe each of the alternative specifications used.

1.2.1 No risk adjustment

Here we set $\hat{q}_{h,t} = \bar{s}_{h,t}$.

1.2.2 Age-race-sex adjustment

Here we estimate equation the below separately in each period using a linear fixed-effects regression.

$$s_{iht} = \beta_{0t} + \beta_{1t} A_{iht} + \gamma_{ht} + \epsilon_{iht} \tag{14}$$

Thus we define $\hat{q}_{h,t}$ as follows:

$$\hat{q}_{h,t} = \hat{\beta}_{0t} + \hat{\gamma}_{ht} \tag{15}$$

1.2.3 Race-comorbidity interactions

Here we estimate equation 16 using a linear fixed-effects regression. The variables $black_{iht} * X_{iht}$ and $other_{iht} * X_{iht}$ are a set of interaction terms between comorbidities and an indicator for whether patient i as hospital h in period t is "black" or "other" (i.e., non-black and non-white) respectively.

$$s_{iht} = \beta_{0t} + \beta_{1t} X_{iht} + \beta_{2t} black_{iht} * X_{iht} + \beta_{3t} other_{iht} * X_{iht} + \beta_{4t} A_{iht} + \gamma_{ht} + \epsilon_{iht} \tag{16}$$

Thus we define $\hat{q}_{h,t}$ as follows:

$$\hat{q}_{h,t} = \beta_{0t} + \gamma_{ht} \tag{17}$$

1.2.4 Random effects

We estimate our main specification using a random effects approach to estimate hospital effects rather than a fixed effects approach.

1.2.5 Race-specific quality and random effects

We estimate a race specific quality using equation 18 where γ_{ht}, δ_{iht}, and τ_{iht} are estimated using random effects and random slopes.

$$s_{iht} = \beta_{0t} + \beta_{1t}X_{iht} + \beta_{2t}A_{iht} + \gamma_{ht} + black_{iht} * \delta_{iht} + other_{iht} * \tau_{iht} + \epsilon_{iht} \tag{18}$$

This allows us to define for each hospital h in each period t two quality measures, $q^B_{h,t}$ and $q^W_{h,t}$. These quality measures reflect the expected 30-day survival at the hospital for a black and white patient respectively, where both are assumed to be female, age 66-69 and have no comorbidites. Specifically we estimate the following:

$$\hat{q}^B_{h,t} = \beta_{0t} + \gamma_{ht} + \delta_{iht} + \beta_{2t}A^B_{iht} \tag{19}$$

$$\hat{q}^W_{h,t} = \beta_{0t} + \gamma_{ht} \tag{20}$$

where A^B_{iht} refers to the age-race-sex vector for a black female age 66-69.

2 Dynamic decomposition sensitivities

We assess the robustness of the dynamic decomposition to several alternative specifications. As described in Appendix Section 1, We repeat the dynamic decomposition analysis using the various versions of hospital quality measured including: average survival without risk-adjustment, age-race-sex adjustment only (fixed effect model), race-comorbidity interactions (fixed effect model), random effects model, and race-specific quality. We also repeat the dynamic decomposition limiting to the set of markets with MA penetration below the median MA penetration in 2014 to assure that effects are not driven by selection into MA. MA penetration by health referral region is available publicly via the Centers for Medicare and Medicaid Services (CMS).

Finally, we repeat the dynamic decomposition without the restriction that hospitals appear in both periods (i.e., unbalanced panel) to assure that effects are not sensitive to inclusion of hospitals that enter or exit throughout the study period. We do this by estimating the following equation:

$$
\begin{aligned}
&\underbrace{\left(\sum_{h\in A}(\theta^B_{h,t}-\theta^W_{h,t})q_{h,t}\right)-\left(\sum_{h\in A}(\theta^B_{h,t-1}-\theta^W_{h,t-1})q_{h,t-1}\right)}_{\text{Difference-in-Difference}}= \\
&\underbrace{\sum_{h\in B}(q_{h,t-1}-\bar{q}_{t-1})[(\theta^B_{h,t}-\theta^B_{h,t-1})-(\theta^W_{h,t}-\theta^W_{h,t-1})]+}_{\text{Pure Reallocation}} \\
&\underbrace{\sum_{h\in B}(\theta^B_{h,t-1}-\theta^W_{h,t-1})(q_{h,t}-q_{h,t-1})+}_{\text{Pure Quality Improvement}} \\
&\underbrace{\sum_{h\in B}(q_{h,t}-q_{h,t-1})[(\theta^B_{h,t}-\theta^B_{h,t-1})-(\theta^W_{h,t}-\theta^W_{h,t-1})]+}_{\text{Cross}} \\
&\underbrace{\sum_{h\in N}(\theta^B_{h,t}-\theta^W_{h,t})(q_{h,t}-\bar{q}_{t-1})-}_{\text{Entry}} \\
&\underbrace{\sum_{h\in X}(\theta^B_{h,t-1}-\theta^W_{h,t-1})(q_{h,t-1}-\bar{q}_{t-1})}_{\text{Exit}}
\end{aligned}
\tag{21}
$$

where N is the set of hospitals open in 2010-2014 but not 1995-1999, let X be the set of hospitals open in 1995-1999 but not 2010-2014, let B be the set of hospitals in both 1995-1999 and 2010-2014, and let A be the set of all hospitals open in either 1995-1999 or 2010-2010. Let $\theta^B_{h,t}$ and $\theta^W_{h,t}$ represent the share of black and white patients at hospital h in period t. Let $\bar{q}_{h,t}$ represent hospital performance for hospital h in period t, and let $\bar{q}_t$ represent the market-share weighted average hospital performance across all patients in period t. We require hospitals to have ¿24 patients in our data in a period to be considered open, in order to assure sufficient sample to measure hospital performance.

Per Equation 21, the total difference-in-difference effect can be decomposed into the following terms: pure reallocation, pure quality improvement, cross (between), entry (between), and exit (between). As in the main analysis, the pure reallocation term captures the difference-in-difference effect explained by stronger reallocation by black patients, relative to white patients,

towards hospitals with high quality as baseline. The pure quality improvement term captures the difference-in-difference effect explained by stronger quality improvement at hospitals with higher relative black patient shares at baseline. The cross term captures the difference-in-difference effect explained by stronger quality improvement at hospitals that had stronger relative gains in black patient market share over time. The entry term captures the difference-in-difference effect explained by black patients using higher quality hospitals than white patients, among newly entering hospitals. Finally, the exit term enters negatively and captures the difference-in-difference effect explained by black patients using higher quality hospitals than white patients, among exiting hospitals.

The results of these alternative specifications can be found in Appendix Table A2.

3 Measures of technology adoption

3.1 Main analysis

As discussed in section 5, we probe the role of technology in explaining racial disparities using multiple measures of technology adoption at the hospital level. One measure we use is same-day catheterization, which is observable in Medicare claims. Specifically, we identify a patient as having received cardiac catheterization if one of the following ICD-9 procedure codes appeared on their claims: 37.21, 37.22, 37.23, 88.5, 88.5X, 00.66, 36.0, 36.00-36.02, 36.05-36.07, 36.09.

We also use binary measures of hospital technology captured at the hospital-level by the American Hospital Association Annual Survey. In cases where the medicare provider ID was missing from the American Hospital Association Annual Survey for a specific year, but was available for the same hospital in an adjacent year, we used the medicare provider ID from the adjacent years. The specific variables used vary period to period due to differences in the variables collected in the American Hospital Association survey in the baseline and endline period. In the baseline period (1995-1999), the American Hospital Association variables used indicate whether the hospital has a cardiac intensive care unit, whether the hospital performs open heart surgery, and whether the hospital offers diagnostic or interventional catheterization. In the baseline period, the technology index is calculated by first summing each of these 3 indicators and then imputing a percentile rank of this sum for each hospital within the period. In the endline period, the AHA variables used indicate that a hospital has either diagnostic or interventional catheterization (i.e., hospital either has an indicator for adult diagnostic catheterization or adult internventional cardiac cath), cardiac intensive care, adult cardiology services, adult cardiac surgery, adult cardiac electrophysiology, or

heart transplant services. In the endline period, the technology index is calculated by first summing each of these 6 indicators and then imputing a percentile rank of this sum for each hospital within the period.

Finally, we use the share of AMI patients receiving beta blockers and aspirin, among those for whom it is appropriate. In 2010-2014, this measure was publicly reported by CMS and in 1995-1999, this measure was obtained from the CCP. The CMS estimates of share of patients receiving beta blockers (and asiprin) at discharge excludes the following patients: patients who are <18 years of age, with length of stay >120 days, enrolled in clinical trials, discharged to another hospital, dying in hospital, leave against medical advice, discharged for hospice care, for whom only comfort measures are documented, and with a documented reason for not providing a beta blocker (or aspirin) at discharge. The CCP data includes only Medicare Fee-for-Service patients and does not contain all the data elements necessary to perfectly replicate CMS exclusion criteria in order to fully replicate the CMS measure. However, we apply a series of exclusions to our estimates of rates of beta blocker (and aspirin) use at discharge to approximately replicate the CMS exclusions. Specifically, we exclude the following patients for our 1995-1999 estimates of rates of beta blocker (and aspirin) use at discharge from the CCP: patients with lengths of stay >120 days, patients with a terminal illness, patients dying during the hospital stay, patients discharged to another facility, or patients with a documented reason for not receiving beta blockers (or aspirin). Details of the acceptable reasons for which a patient may be exempt from receiving beta blockers and aspirin can be found in Marciniak et al. (1998)

3.2 Additional measures used in robustness

In sensitivity analyses, we estimate the robustness of our results regarding the role of technology adoption in explaining racial disparities in hospital allocation to alternative measures of technology adoption. First, we develop a measure of risk-adjusted catheterization on any day of the admission, and risk-adjusted same-day CABG. We do this using a linear fixed effects model as described in Section 5. We identify CABG using the following ICD-9 procedure codes: 36.03, 36.10-36.19,36.2, 36.3, 36.31-36.39. We also use other measures of technology adoption from the American Hospital Association Annual Survey. For example, we test robustness to an alternative technology index using a simple sum of all technology indicators in a period rather than a percentile rank. We also repeat the dynamic decomposition analysis for two variables that appear in both the baseline and endline periods, namely an indicator for the presence of a cardiac catheterization

lab and cardiac intensive care. The results of these sensitivity analyses are in Appendix Table A5.

Table A1: Sensitivity Analyses of Difference in Survival between Black and White AMI Patients

Sensitivity	Main analysis			No risk adjustment			Age/Race/Sex adjustment			Race-comorbidity interactions		
Time period	**95-99**	**10-14**	Δ	**95-99**	**10-14**	Δ	**95-99**	**10-14**	Δ	**95-99**	**10-14**	Δ
Racial disparity in hospital allocation	-0.95	-0.29	0.66	-0.62	-0.10	0.52	-1.04	-0.47	0.57	-0.95	-0.31	0.64
SE	(0.11)	(0.11)	(0.13)	(0.11)	(0.12)	(0.13)	(0.11)	(0.10)	(0.12)	(0.11)	(0.10)	(0.13)
Geography (within HRR)	-0.24	-0.13	0.10	-0.05	0.04	0.09	-0.23	-0.16	0.07	-0.24	-0.14	0.09
SE	(0.07)	(0.07)	(0.10)	(0.07)	(0.08)	(0.09)	(0.07)	(0.07)	(0.09)	(0.07)	(0.07)	(0.09)
Geography (across HRR)	-0.42	-0.01	0.40	-0.32	-0.02	0.30	-0.48	-0.12	0.36	-0.41	-0.01	0.40
SE	(0.07)	(0.07)	(0.09)	(0.08)	(0.08)	(0.10)	(0.07)	(0.07)	(0.09)	(0.07)	(0.07)	(0.09)
Within zip code	-0.30	-0.14	0.15	-0.26	-0.12	0.13	-0.33	-0.19	0.14	-0.30	-0.15	0.14
SE	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.07)
N		2712			2712			2712			2712	

Sensitivity	Performance for white patients			Performance for black patients			Below median MA penetration			Unbalanced panel		
Time period	**95-99**	**10-14**	Δ	**95-99**	**10-14**	Δ	**95-99**	**10-14**	Δ	**95-99**	**10-14**	Δ
Racial disparity in hospital allocation	-0.60	-0.25	0.34	-0.56	-0.16	0.41	-1.15	-0.38	0.77	-1.06	-0.32	0.74
SE	(0.08)	(0.07)	(0.09)	(0.08)	(0.07)	(0.09)	(0.16)	(0.13)	(0.18)	(0.10)	(0.10)	(0.12)
Geography (within HRR)	-0.14	-0.12	0.02	-0.14	-0.07	0.07	-0.30	-0.11	0.19	-0.27	-0.13	0.13
SE	(0.05)	(0.05)	(0.07)	(0.05)	(0.05)	(0.07)	(0.11)	(0.09)	(0.13)	(0.07)	(0.07)	(0.09)
Geography (across HRR)	-0.28	-0.02	0.25	-0.27	-0.02	0.25	-0.64	-0.16	0.48	-0.46	-0.03	0.43
SE	(0.06)	(0.05)	(0.07)	(0.06)	(0.05)	(0.07)	(0.12)	(0.09)	(0.13)	(0.07)	(0.07)	(0.09)
Within zip code	-0.18	-0.11	0.07	-0.16	-0.07	0.09	-0.21	-0.11	0.10	-0.33	-0.15	0.18
SE	(0.04)	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)	(0.07)	(0.05)	(0.09)	(0.05)	(0.05)	(0.07)
N		2712			2712			1199		3986	2876	

Note: This table decomposes the difference in risk-adjusted survival between black and white patients during the 1995-1999 and 2010-2014 periods using multiple alternative measures. Analysis restricted to balanced sample of hospitals that have 25 or more patients in each period. The no risk adjustment panel does not adjust for race, sex, age or comorbidities. The age/race/sex adjustment panel adjusts for age/race/sex interaction terms. The race-comorbidity interactions panel includes interactions between race indicators (white, black or other) and comorbidities. The performance for white and black patients panels use race-specific quality measure for each hospital that is specific to white and black patients respectively. The below median MA penetration panel includes only markets below the median MA penetration by 2014. The unbalanced panel includes hospitals entering and exiting between 1995 and 2014. Standard errors were calculated using 1000 boostrap replicates clustered at the hospital level.

Table A2: Sensitivity Analyses of Dynamic Decomposition of 30-day Risk-Adjusted Survival (1995-2014)

	Contribution in percentage points							
	Main analysis	**No risk adjustment**	**Age/race/sex adjustment only**	**Race-comorbidity interactions**	**Performance for white patients**	**Performance for black patients**	**Below median MA penetration**	**Unbalanced panel**
Average across patients in 1995-1999	89.6	81.2	88.5	89.6	89.5	89.4	89.6	89.4
Reduction in racial disparity in hospital performance	0.66	0.53	0.57	0.64	0.35	0.41	0.77	0.75
SE	(0.13)	(0.13)	(0.12)	(0.13)	(0.09)	(0.09)	(0.15)	(0.13)
Pure reallocation	0.19	0.03	0.17	0.19	0.14	0.14	0.11	0.10
SE	(0.08)	(0.09)	(0.08)	(0.08)	(0.05)	(0.05)	(0.15)	(0.08)
Pure differential performance improvement	0.68	0.92	0.67	0.66	0.38	0.38	0.64	0.46
SE	(0.15)	(0.15)	(0.14)	(0.14)	(0.09)	(0.09)	(0.27)	(0.14)
First cross	-0.21	-0.42	-0.27	-0.21	-0.17	-0.11	0.02	0.08
SE	(0.09)	(0.10)	(0.09)	(0.08)	(0.05)	(0.05)	(0.17)	(0.09)
Entry								-0.12
SE								(0.03)
Exit								-0.22
SE								(0.04)
N	2712	2712	2712	2712			1199	4163

Note: This table decomposes the reduction in the racial disparity in hospital allocation from 1995-2014 using multiple alternative specifications. The decomposition is performed for nationally. Analysis are restricted to hospitals that have 25 or more patients in each period. The no risk adjustment panel does not adjust for race, sex, age or comorbidities. The age/race/sex adjustment panel adjusts for age/race/sex interaction terms only. The race-comorbidity interactions panel includes interactions between race indicators (white, black or other) and comorbidities. The performance for black and white patient panels use race-specific quality measure for each hospital that is specific to white and black patients respectively. The below median MA penetration panel includes only markets below the median MA penetration by 2014. The unbalanced panel includes hospitals entering and exiting between 1995 and 2014. Standard errors were calculated using 1000 boostrap replicates clustered at the hospital level.

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Table A3: Variation in and correlation between race-specific performance measures

	1995-1999	2000-2004	2005-2009	2010-2014
SD(hospital-intercept)	2.94	2.86	3.20	2.63
SD(black patient slope)	1.31	1.61	1.86	1.50
Corr(intercept, black patient slope)	-0.21	-0.27	-0.28	-0.32
Corr(white-patient performance, black-patient performance)	0.901	0.843	0.832	0.834

Note: The white performance measure is an estimate of 30-day survival for a white, female patient, age 66-69 at hospital h in the respective period. Similarly, the black performance measure is an estimate of 30-day survival for a black, female patient, age 66-69 at hospital h in the respective period. The standard deviation and correlation terms are measured at hospital-level within period. Units for standard deviation are percentage points.

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Table A4: Static Analysis of Outcomes Related to Hospital Technology Adoption Between Black and White AMI Patients

	Contribution in percentage points														
	Main analysis			**Risk-adjusted same-day catheter -ization**			**AHA technology index**			**Hospital average beta blocker use at discharge**			**Hospital average average aspirin use at discharge**		
Time period	95-99	10-14	Δ	95-99	10-14	Δ	95-99	10-14	Δ	95-99	10-14	Δ	95-99	10-14	Δ
Racial disparity in hospital allocation	-0.95	-0.29	0.66	0.65	-0.94	-1.59	4.17	1.98	-2.20	-1.68	-0.23	1.45	1.73	-0.15	-1.88
SE	(0.11)	(0.11)	(0.13)	(0.36)	(0.46)	(0.39)	(0.66)	(0.57)	(0.53)	(0.57)	(0.08)	(0.56)	(0.58)	(0.06)	(0.57)
Geography (within HRR)	-0.24	-0.13	0.10	1.42	0.65	-0.78	2.60	1.21	-1.39	0.45	-0.03	-0.48	1.63	-0.05	-1.68
SE	(0.07)	(0.07)	(0.10)	(0.23)	(0.25)	(0.38)	(0.39)	(0.35)	(0.37)	(0.36)	(0.05)	(0.36)	(0.40)	(0.03)	(0.40)
Geography (across HRR)	-0.42	-0.01	0.40	-0.35	-0.77	-0.42	2.01	1.24	-0.77	-1.98	-0.003	1.98	-0.23	0.04	0.27
SE	(0.07)	(0.07)	(0.09)	(0.31)	(0.27)	(0.31)	(0.52)	(0.36)	(0.43)	(0.38)	(0.04)	(0.38)	(0.44)	(0.03)	(0.44)
Within zip code	-0.30	-0.14	0.15	-0.43	-0.81	-0.38	-0.44	-0.47	-0.04	-0.16	-0.20	-0.05	0.32	-0.14	-0.46
SE	(0.05)	(0.05)	(0.06)	(0.17)	(0.17)	(0.18)	(0.26)	(0.21)	(0.24)	(0.23)	(0.05)	(0.23)	(0.26)	(0.03)	(0.25)
N		2712			2712			2500			2600			2532	

Note: This table decomposes the difference in risk-adjusted catheterization and AHA technology index between the black and white subpopulation during the 1995-1999 and 2010-2014 periods. The decomposition is performed for nationally. Risk-adjusted catheterization is calculated from a regression of survival on hospital fixed effects and patient risk-adjusters (age/race/sex interactions and comorbidities). The AHA technology index calculated summing indicators for all technologies with data available in the AHA and then calculating hospitals' within period percentile over the summed measure. The percentile constitutes the final index to facilitate comparison across periods in which different variables are available. All analyses include a balanced sample of hospitals with 25 or more patients in each period. The technology index, beta blocker, and aspirin analyses have a smaller sample as hospitals with missing entries in the AHA data, CCP data, or CMS data were excluded. Standard errors were calculated using 1000 boostrap replicates clustered at the hospital level.

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Table A5: Dynamic Analysis of Hospital Technology Adoption Between Black and White AMI Patients, Alternative Measures

	Main analysis				
	30-day risk-adjusted survival	**Risk-adjusted same-day catheterization**	**AHA technology index**	**Hospital average beta blocker use at discharge**	**Hospital average aspirin use at discharge**
Average across patients in 1995-1999	89.6	16.4	69.2	37.3	58.4
Reduction in racial disparity in hospital allocation	0.66	-1.58	-2.17	1.45	-1.88
SE	(0.13)	(0.39)	(0.53)	(0.56)	(0.57)
Reallocation	0.19	-0.16	-1.07	0.58	-1.03
SE	(0.08)	(0.25)	(0.43)	(0.34)	(0.38)
Differential performance improvement	0.68	-0.64	-0.88	1.34	-1.81
SE	(0.15)	(0.32)	(0.45)	(0.58)	(0.56)
Cross	-0.21	-0.78	-0.22	-0.47	0.97
SE	(0.09)	(0.21)	(0.31)	(0.36)	(0.37)
N	2712	2712	2500	2600	2532
	Alternative technology adoption measures				
	Risk-adjusted any-day catheterization rate	**Risk-adjusted any-day catheterization or CABG rates**	**Risk-adjusted CABG rate**	**Catheterization lab (AHA survey)**	**Cardiac intensive care (AHA survey)**
Average across patients in 1995-1999	53.8	54.4	9.9	77.0	69.0
Reduction in racial disparity in hospital allocation	-3.33	-3.33	-0.81	-0.05	-0.02
SE	(0.57)	(0.61)	(0.23)	(0.01)	(0.01)
Reallocation	-1.01	-0.96	-0.13	-0.02	0.002
SE	(0.45)	(0.47)	(0.18)	(0.01)	(0.01)
Differential performance improvement	-1.56	-1.63	-0.60	-0.02	-0.01
SE	(0.50)	(0.52)	(0.21)	(0.01)	(0.01)
Cross	-0.76	-0.75	-0.08	-0.01	-0.01
SE	(0.32)	(0.32)	(0.13)	(0.01)	(0.01)
N	2712	2712	2712	2500	2500

Note: This table decomposes the racial differences in hospital technology adoption from 1995-2014 using multiple alternative measures of technology adoption. The decomposition is performed for nationally. Analysis are restricted to hospitals that have 25 or more patients in each period and hospitals in the sample in both the baseline and endline period. The technology index analysis has a smaller sample as hospitals with missing entries for the AHA data were excluded. Standard errors were calculated using 1000 boostrap replicates clustered at the hospital level.

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Table A6: Association between same-day catheterization and 30-day survival at hospitals with higher black patient shares

	1995-1999	2000-2004	2005-2009	2010-2014	Endline - Baseline	P-value
Catheterization	0.0149	0.0284	0.0251	0.0123	-0.0026	0.225
SE	(0.0018)	(0.0014)	(0.0013)	(0.0012)	(0.0021)	
Catheterization X Black	-0.0081	-0.0073	-0.0244	-0.0224	0.0143	0.024
SE	(0.0052)	(0.0037)	(0.0035)	(0.0035)	(0.0063)	
Catheterization X Share Black at Baseline	-0.0281	-0.0254	-0.0124	0.0468	0.0749	<0.001
SE	(0.0164)	(0.0131)	(0.0120)	(0.0137)	(0.0214)	
Constant	0.893	0.907	0.923	0.934	0.041	<0.001
	(0.0013)	(0.0013)	(0.0014)	(0.0014)	(0.0019)	
N	1,115,228	1,186,468	959,615	806,472		

Note: The model includes age-race-sex interaction terms and comorbidities as risk-adjusters (output suppressed) and hospital fixed-effects. The model is estimated on balanced panel of hospitals with a performance measures. Standard errors are heteroskedasticity robust and estimated analytically. P-value reflects a two-sided test for equality between baseline and endline coefficients

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