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# HOSPITAL ALLOCATION AND RACIAL DISPARITIES IN HEALTH CARE

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## ABSTRACT

We develop a simple framework to measure the role of hospital allocation in racial disparities in health care and use it to study Black and white Medicare patients who are treated for heart attacks – a condition where virtually everyone receives care, hospital care is highly effective, and hospital quality has been validated. We report four facts. (1) Black patients receive care at lower-performing hospitals than white patients, even when they live in the same hospital market or ZIP code within a hospital market.(2) Over the past two decades, the gap in performance between hospitals treating Black and white patients shrank by over two-thirds. (3) This progress is due to more rapid performance improvement at hospitals that tended to treat Black patients, rather than faster reallocation of Black patients to better hospitals. (4) Hospital performance improvement is correlated with adoption of a high-return low-cost input, beta-blockers. Closing remaining disparities in allocation and harnessing the forces of performance improvement, including technology diffusion, may be novel levers to further reduce disparities.



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A data appendix is available at http://www.nber.org/data-appendix/w28018

# 1 Introduction

Black 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 non-Hispanic Black Americans than their non-Hispanic white peers (Murphy et al., 2015). The causes behind this gap are multifactorial and interrelated (Williams and Jackson, 2005). They include inequities existing prior to health care delivery related to living conditions, like income and education (Cutler, Deaton and Lleras-Muney, 2006; Braveman, Egerter and Williams, 2011); differences in the quality of care from a given health care provider due to communication and biases (Institutes of Medicine, 2003; Chandra and Staiger, 2010; Alsan, Garrick and Graziani, 2019); and differences in the health care providers patients use.

This last source of racial disparities derives from *allocation*: Black and white patients are often treated by different health care providers, some of which may have much higher (or lower) performance. Health care providers that serve Black patients tend to have poorer patient outcomes and report lacking the resources to deliver high-quality care (Bach and Schrag, 2004; Barnato et al., 2005; Skinner et al., 2005; Jha et al., 2007). The allocative forces that generate these disparities reflect historical and current inequities, including the long shadow of *de jure* hospital segregation, trust, and neighborhood segregation (Smith, 2005; Sarrazin, Campbell and Rosenthal, 2009; Chandra, Frakes and Malani, 2017; Alsan and Wanamaker, 2018). Differences in allocation may derive from decisions made by patients and by agents acting on their behalf, including physicians, ambulance drivers, and family members.

Over time, patients tend to reallocate towards higher-performing hospitals (Chandra et al., 2016). Whether these allocative forces exacerbate or reduce racial disparities over time is ambiguous. Reallocation could be easier for better-resourced groups or it may be more feasible for groups receiving care from low-performing hospitals because there is more room to improve. The role of allocation in racial disparities is of central importance because it is a powerful driver of improving outcomes: Chandra et al. (2016) found that reallocation to higher-performing hospitals accounted for 1 percentage point of the increase in heart attack survival rates from 1996 to 2008, a similar magnitude to that of breakthrough medical technologies.

This study focuses on Black and white patients in Medicare experiencing an acute myocardial

infarction (AMI), or heart attack, between 1995 and 2014. Taking an allocation perspective derived from the literature on firm productivity growth (Baily et al., 1992; Olley and Pakes, 1996; Foster, Haltiwanger and Krizan, 2001, 2006; Bartelsman, Haltiwanger and Scarpetta, 2013), we first show that during the 1990s, Black patients' were treated at lower-performing hospitals relative to white patients (Figure 1). Next, by reweighting white patients to have the same distribution of geography as Black patients, we show that in the 1990s differences in the hospital markets patients live in explain 44% of the Black-white gap (we use 306 hospital referral regions to describe hospital markets). Much of the 1990s disparity therefore derives from Black patients living in markets with low-performing hospitals, a feature that would also hamper reallocation as a tool for disparity reduction because it would require patients to travel long distances in search of better treatment. Differences in the ZIP codes patients live in (within hospital markets) explain a further 25% of the gap. This component of the disparity may reflect differences in where patients live in markets relative to high-performing facilities and may be more amenable to reallocation. The remaining 32% reflects differences in the performance of hospitals that white and Black patients are treated at despite living in the same ZIP code. This component could encompass differences by race in where patients live within small areas areas as well as differing beliefs about hospital performance on the part of patients or agents acting on their behalf.

By the 2010s we find that the gap in the performance of hospitals used by Black and white AMI patients had shrunk by 70% (Figure 2). By this point in time, it was no longer the case that differences in the hospital markets that Black and white patients lived in contributed to the gap. These findings suggest that Black-white disparities in heart attack care no longer emanate from large-region differences in where patients live (e.g. the North versus the South, or even Nashville versus Memphis). Rather, more local differences in where patients live and in the hospitals that use now drive the observed but much smaller racial gap. The remaining gap is also potentially actionable through allocation policies because it would not depend on emergency patients traveling long distances to access better hospitals. Still, it is important not to view a change in the disparity as automatically reflecting the force of reallocation to higher-performing hospitals. For example, there may have been no change in where patients were treated, but greater improvement at the hospitals where Black patients tended to receive care. Further investigation is required to demonstrate whether reallocation or performance improvement is responsible for the narrowing disparity

uncovered by the static analyses.

We next develop a dynamic decomposition framework to elucidate the economic forces behind these trends. We find larger performance gains at hospitals used by Black patients than those used by white patients at baseline. In fact, the entire closing of the gap results from *differential performance improvement* (Figure 3) – meaning that hospitals which tended to treat Black patients raised their performance more than other hospitals. Under one-third of the convergence can be attributed to *differential reallocation*, where Black patients increased their use of higher performing facilities at a faster rate than white patients. These findings show that in the AMI context, performance improvement has acted as a force to improve outcomes and reduce disparities, highlighting the potential importance of this channel in analyses of disparities in the health care system. The framework we develop also represents a methodological contribution that can be applied to study the role of allocation in disparities in many contexts such as education, employment, and criminal justice.

Finally, we investigate the role of technology in performance improvement by analyzing the adoption of low- and high-cost AMI treatment technologies. Beta-blockers are inexpensive medications that were known to substantially improve outcomes at the onset of our analysis period, and we find that the use of these drugs grew more rapidly at hospitals that tended to treat Black patients at baseline. Thus, the adoption of beta-blockers and other technologies for which they are a surrogate, including better management, may have contributed to differential performance improvements (Bloom et al., 2012; McConnell et al., 2013; Skinner and Staiger, 2015; Bloom, Sadun and Van Reenen, 2016). At the same time, we find that the adoption patterns of capital-intensive technologies like cardiac catheterization are disparity-expanding. These findings allow us to connect the literature on racial disparities to literatures on allocative forces as well as the productivity of medical treatments.

Our results are robust to a host of alternative approaches to measuring hospital performance. They hold under richer or coarser controls for patient observables, suggesting that endogenous selection of hospitals does not drive the results. Moreover, they are insensitive to whether we measure hospital performance for Black patients or white patients, ruling out alternative explanations for our findings like hospitals addressing within-facility racial disparities in treatment rather than improving performance for all patients.

The remainder of the paper proceeds as follows. Section 2 covers our data and performance measurement approach, Section 3 explains our static and dynamic decomposition frameworks, Section 4 presents results, Section 5 provides evidence on the role of technology adoption, and Section 6 concludes.

# 2 Setting, Data, and Measurement

## 2.1 Setting

We examine Medicare beneficiaries with Fee-for-Service (FFS) coverage hospitalized for an AMI between 1995-2014. This setting has a number of advantages for this study. One is that it essentially removes insurance coverage as a determinant of patient allocation to hospitals. FFS Medicare patients 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. Selection into the hospitalization data is also less of an issue because AMI is an emergent condition requiring immediate treatment at a hospital – there is little scope for patients to go untreated or undiagnosed. AMI also has validated hospital quality measures: hospital measures of quality using risk-adjusted survival and calculated using observational data correlate extremely well with quality measured from patients who are quasi-randomly assigned to facilities (Hull, 2020; Doyle, Graves and Gruber, 2019). This research suggests that the rich patient data in Medicare claims accounts for endogenous hospital selection well, yielding quality measures with a strong signal of true performance. The rich data on AMI treatment also provides observable measures of technology use like beta-blockers and cardiac catheterization that allow us to probe the mechanisms underlying changes in hospital performance. Finally, allocative forces have been shown to operate at a point in time and over time for heart attacks (Chandra et al., 2016), and there has been technological progress that is tracked in data, allowing us to understand why hospitals are improving (e.g. McClellan, McNeil and Newhouse, 1994; Cutler et al., 1998; Chandra and Staiger, 2007, 2020). Given the aforementioned reasons, we do not study allocation to physicians rather than hospitals or allocation for common chronic diseases. While these sources of health care would be important to study, analyses would suffer from a lack of validated outcomes measures and the potential selection into an office visit or hospital stay.

We conduct point-in-time analyses during a baseline period (1995-1999) and an endline period

(2010-2014). Our over-time analyses consider changes from the baseline to endline period. Thus, for each hospital, we measure allocation and performance in those two periods. In addition, we estimate allocation and performance for intermediate periods (2000-2004 and 2005-2009) when visualizing their evolution in figures. To conduct inference, we use a hospital-level bootstrap approach with 1000 replicates (Appendix Section D).

### 2.2 Data

Our primary data source is Medicare hospitalization records for 100% of beneficiaries between 1995-2014 linked to enrollment records with demographic information about these individuals. Together these data provide rich information about patients, including their race, location of residence, the hospital at which they receive treatment, and their diagnoses.[1] To define hospital markets, we use Hospital Referral Regions (HRRs) from the Dartmouth Atlas. This market definition uses the empirical patterns of where Medicare patients go for major surgeries to create 306 hospital markets for the U.S. Lastly, to observe use of beta-blockers, which is not tracked in the claims, we link to 1994-1995 patient records abstracted for the Cooperative Cardiovascular Project (CCP), a large-scale effort to measure hospital quality, and publicly reported process of care measures from CMS for 2010-2014 (see Appendix Section C.1).

The initial sample consists of patients who were hospitalized for AMI during the study period, omitting hospital stays within one year of a prior AMI admission to exclude return visits. Following the literature, we call these hospitalizations index events. We limit our sample to patients age 66 and above with full FFS Medicare coverage during the year prior to admission and the year subsequent to it (or until death if the patient dies during that year). Patients with Medicare Advantage coverage and those with a lapse in full (Part A+B) coverage are omitted because they are poorly observed in the data. We further restrict to events at short-term acute care or critical access hospitals, because these are the hospitals that treat heart attack patients. Because we use index events to estimate hospital performance, we require that the hospital have at least 25 events during the relevant 5-year measurement period (1995-1999, 2000-2004, 2005-2009, or 2010-2014).

[1] Because hospital identifiers in Medicare data may change over time, we use a longitudinal crosswalk provided by Jonathan Skinner and the Dartmouth Institute for Health Policy and Clinical Practice to merge together all identifiers that ever refer to the same facility. Hospitals that change identifiers are tracked as one facility; hospitals that merge or de-merge are treated as one facility for the entire analysis period.

After imposing these restrictions, the result is the main analysis sample, which we use to estimate hospital performance. To analyze allocation, we focus on hospitals that met this patient volume threshold in the baseline period (1995-1999) and the endline period (2010-2014), yielding a balanced panel; we later show that our findings are robust to adding hospitals that only meet this restriction in one of the two periods.

### 2.3 Performance measurement

To measure hospital performance, we estimate adjusted survival rates for hospitals in each of the 5-year baseline and endline periods. Specifically, we calculate the 30-day survival rate of AMI patients at the hospital after adjusting for patient comorbidities and demographic factors. We describe our approach here and in more detail in Appendix Section A. Starting with the analysis sample, we calculate hospital performance by estimating the following equation:

$$s_{iht} = \alpha_t + \beta_t X_{iht} + \gamma_{ht} + \epsilon_{iht}, \tag{1}$$

where $i$ indexes patients, $h$ indexes hospitals, $t$ indexes time period, $s_{iht}$ is an indicator for whether the patient survived 30 days from their hospital admission date, $X_{iht}$ is a vector of comorbidity and demographic indicators, $\gamma_{ht}$ are hospital fixed effects, and $\epsilon_{iht}$ is a disturbance term. The comorbidities consist of indicators for whether a patient had diagnoses for any of 23 conditions during a hospital stay in the year prior to the admission and the demographic indicators are age-race-sex interactions. This regression is estimated separately in each period.

We then develop performance measures reflecting the expected 30-day survival for the average Black and white patient at the given hospital and time period:

$$\hat{q}^B_{ht} = \hat{\alpha}_t + \hat{\gamma}_{ht} + \bar{X}^B_t \hat{\beta}_t \tag{2}$$

$$\hat{q}^W_{ht} = \hat{\alpha}_t + \hat{\gamma}_{ht} + \bar{X}^W_t \hat{\beta}_t, \tag{3}$$

where $\bar{X}^B_t$ and $\bar{X}^W_t$ are the average comorbidity and demographic indicators for Black and white patients in period $t$, respectively. Within a period, the measures from equations 2 and 3 are perfectly correlated because each is a level-shift of the other. This model pools patients of all races when

estimating hospital performance. It allows Black and white patients to have different outcomes on average, but does not allow for race-specific hospital effects—such a model would be hampered by the fact that 20% of hospitals do not treat a single Black patient and many others treat too few Black patients to estimate a precise race-specific hospital effect (Barnato et al., 2005; Chandra, Frakes and Malani, 2017). Robustness analyses reported in Section 4.3 describe this assumption in more detail and show that our results are robust to an alternative approach to performance measurement that relaxes it. This approach highlights another key point about the forces we analyze: they are are distinct from those which reduce racial disparities in outcomes *within* a given hospital. This source of disparities is a crucial object of study but is not the focus of this work.[2]

### 2.4 Allocation measurement

Using these data, we measure the allocation of Black and white patients to hospitals during the baseline and endline periods. We define allocation as the national market share of the hospital among patients in the given race group in the given time period:

$$\theta_{ht}^B = N_{ht}^B / N_t^B, \quad \theta_{ht}^W = N_{ht}^W / N_t^W. \tag{4}$$

### 2.5 Summary statistics

Table 1 presents summary statistics on the patients and hospitals included in our main analyses. Panel A describes Black and white patients in the baseline and endline periods. Overall, in both periods, Black patients were more likely to be female, had a greater burden of illness as measured by the comorbidities, and were younger. The number of heart attack patients decreased from baseline to endline. This decline reflects reductions in AMI incidence during this period as well as the rise of private insurance coverage in the Medicare program (Medicare Advantage), since these patients are poorly observed in our data and are thus excluded (Jacobson, Damico and 2018, 2018; Yeh and Selby, 2010). Black patients had higher survival rates in both periods than their white counterparts. This pattern is well-documented in AMI and other emergent conditions in the above-65 population, and may be due to unobserved health status differences by race among people

[2] A recent analysis at the frontier of research on how disparities could arise from differences in the quality of care within providers comes from Alsan, Garrick and Graziani (2019), who consider the role of physician race in the quality of health care for Black men.

who survive to older age as well as differences in the use of medical procedures with short-term risks of mortality (Barnato et al., 2005; Polsky et al., 2007, 2008; Thomas et al., 2011; Downing et al., 2018; Huckfeldt et al., 2019).

Panel B shows baseline and endline characteristics of the 2,712 hospitals in our main analyses. We note large variations in performance across hospitals as operationalized by 30-day survival adjusting for patient observables and measurement error (see Appendix Section A). In both periods the standard deviation of survival rates across hospitals is 4 percentage points. To benchmark this magnitude, we note that survival rates rose 5 percentage points for both groups of patients between the baseline and endline periods. Thus going to a hospital with 1 standard deviation greater AMI performance at a point in time yields a similar benefit to the average rise in performance nationally over two decades.

The remainder of Panel B shows statistics about the allocation of patients to hospitals. The average hospital has hundreds of AMI patients during each 5 year period. Nearly every hospital treats at least one white patient, but due to the smaller numbers of Black patients as well as geographic segregation, 531 hospitals treat no Black patients at baseline and 592 treat no Black patients at endline.

## 3 Analytical Approach: Static and Dynamic Decompositions

Our main empirical analyses document and decompose disparities in the performance of hospitals that Black and white patients use. We first study these disparities at a point-in-time, yielding a static decomposition. Our approach draws on methods previously employed to study the firm-level drivers of sector-wide productivity growth (Foster, Haltiwanger and Krizan, 2001; Foster, Haltiwanger and Syverson, 2008; Baily et al., 1992). Our core insight is that just as one can decompose productivity growth in a sector into changes in allocation across firms and productivity growth within firms, so too can one decompose differences in AMI outcomes between Black and white patients into differences in allocation across hospitals and performance differences within hospitals. This method also uses re-weighting to document the role of geography in the gap, building on research that has decomposed the Black-white wealth gap as well as work studying the contributors to wage inequality over time (Barsky et al., 2002; DiNardo, Fortin and Lemieux, 1996). Finally, we

further extend the static approach to study how Black-white disparities evolve over time, leading to a dynamic decomposition. We now review these decompositions in more detail.

### 3.1 Static decomposition

In the static decomposition, we quantify the degree to which Black patients' use of lower (or higher) performing hospitals reduces (or raises) their average 30-day survival relative to white patients in a given time period (baseline or endline). We can express the difference in survival rates between Black and white patients as:

$$\bar{q}_t^B - \bar{q}_t^W = \sum_{h \in H} \theta_{ht}^B \hat{q}_{ht}^B - \sum_{h \in H} \theta_{ht}^W \hat{q}_{ht}^W \tag{5}$$

$$= \sum_{h \in H} \theta_{ht}^W (\hat{q}_{ht}^B - \hat{q}_{ht}^W) \qquad \leftarrow \text{Within}_t \tag{6}$$

$$+ \sum_{h \in H} (\theta_{ht}^B - \theta_{ht}^W) \hat{q}_{ht}^B, \qquad \leftarrow \text{Between}_t \tag{7}$$

where $\bar{q}_t^B$ and $\bar{q}_t^W$ are the 30-day survival rates of Black and white patients in period $t$, $q_{ht}^B$ and $q_{ht}^W$ are the performance measures for hospital $h$ in period $t$ for Black and white patients (i.e. expected 30-day survival rates at the hospital for the average Black and white patient), $\theta_{ht}^B$ and $\theta_{ht}^W$ are the national market share of hospital $h$ in period $t$ among Black and white patients, and $H$ is the set of hospitals.

Equation 5 illustrates that the difference in survival rates can be divided into two conceptually distinct components. The *within* ($\text{Within}_t$) refers to the difference in survival between Black and white patients resulting from disparities in the performance of a given provider for Black versus white patients. These race-specific performance differences could arise for a variety of reasons including biases or racism by providers and differences in the prevalence of underlying unobserved risk factors.

The *between* term ($\text{Between}_t$), or between-race gap, refers to the difference in survival resulting from hospital allocation, specifically, Black patients' use of lower or higher performing hospitals than white patients. In our analyses, this term is insensitive to the reference population we use for performance because $\hat{q}_{ht}^B$ and $\hat{q}_{ht}^W$ differ by a constant that drops from the summation. For ease of expression we omit the superscript in the remainder of the text.

In the empirical section we will decompose the between-race gap into three sub-components: (1) *between hospital market differences* that reflect differences in the hospital markets where Black and white patients live (defined as Dartmouth Hospital Referral Regions, or HRRs), (2) *between ZIP code differences* that measure differences in the small areas, or more colloquially neighborhoods, that Black and white patients live in within markets, and (3) *within ZIP code differences* in the hospitals Black and white patients use, even when they live in the same ZIP code. For ease of exposition, we detail this method later alongside the results.

### 3.2 Dynamic decomposition

We also develop a decomposition of the evolution of the between-race gap in hospital allocation over time, or the change in $\text{Between}_t$. This dynamic decomposition complements the static decomposition by showing the role of performance and allocation in driving changes in the gap that occur over time. Two forces could contract disparities over time: (1) stronger performance improvement at hospitals that historically tended to serve Black patients, and (2) stronger reallocation of Black patients than white patients to historically better performing hospitals. To assess the relative contribution of these two forces to a reduction of disparities in hospital performance, we note that the first difference of $\text{Between}_t$ can be expressed as:

$$\Delta\text{Between}_t = \sum_{h\in H} \left(\theta^B_{h,t-1} - \theta^W_{h,t-1}\right)\left(\Delta\hat{q}_{h,t}\right) \quad \leftarrow\text{Differential Performance Improvement} \tag{8}$$

$$+ \sum_{h\in H} \left(\Delta\theta^B_{h,t} - \Delta\theta^W_{h,t}\right)\hat{q}_{h,t-1} \quad \leftarrow\text{Differential Hospital Reallocation} \tag{9}$$

$$+ \sum_{h\in H} \left(\Delta\theta^B_{h,t} - \Delta\theta^W_{h,t}\right)\left(\Delta\hat{q}_{h,t}\right), \quad \leftarrow\text{Cross} \tag{10}$$

where $\Delta$ is the first difference operator. In practice, $t$ is the endline period (2010-2014) and $t-1$ is the baseline period (1995-1999).

The first term, *differential performance improvement*, measures the relationship between the Black-white market share difference at baseline and the growth in hospital performance over time. Specifically, its left side shows whether the hospital was relatively popular among Black or white patients at baseline, while its right side captures the change in performance. Thus, the term captures the change in the between-race gap explained by hospital performance growth, fixing

allocation at baseline values. A positive contribution from this term would imply that performance grew more rapidly at hospitals that were historically relatively popular among Black patients.

*Differential hospital reallocation*, which appears next, has two parts. Its left side is a difference-in-difference of Black vs. white market share at endline vs. baseline, and it shows whether Black patients re-allocated at a faster rate to the given hospital than white patients. The right expression is the hospital's performance during the baseline period. A positive reallocation term would imply that Black patients shifted towards historically better performing hospitals at a faster rate than white patients.

The first two terms associate a change over time with a baseline value. They thus fail to capture the fact that reallocation over time and performance improvement over time could co-occur. The cross term accounts for this final component of the change in the between-race gap. It captures the change explained by stronger performance improvement at hospitals that had stronger relative gains in Black patient market share over time.

# 4 Results

## 4.1 Static Decomposition

Table 2 displays the static decomposition results. Our first key finding, shown in column 1 of the table, is that Black patients used hospitals with significantly lower performance than white patients during the baseline period — that is, $\text{Between}_t$ is negative. Specifically, Black patients used hospitals with 1 percentage point lower expected survival rates than white patients on average. Panel A of Figure 1 visualizes this result, plotting the distribution of hospital performance among Black patients and white patients at baseline. The vertical bars indicate the means of the distributions and are 1 percentage point apart, matching Table 2. To put the magnitude of this result into context, reperfusion therapy for AMI – developed in the late 1980s, still used today, and widely acknowledged to be a transformational treatment – increases survival by 2 percentage points (Fibrinolytic Therapy Trialists' Collaborative Group, 1994).

We next quantify the contribution of geography using an inverse probability weighting approach, where we re-weight white patients to match the contemporaneous geographic distribution of Black patients at the hospital market (as given by HRRs) and ZIP code level. This method allows us to

account for differences in the geographic distribution of the populations and assess how allocation for Black and white patients compares among patients in the same market or neighborhood. We so by developing the weighting function (c.f. Barsky et al., 2002):

$$\omega(z) = \frac{\Pr(black|Z=z)}{\Pr(white|Z=z)} \cdot \frac{\Pr(white)}{\Pr(black)}, \tag{11}$$

where $z$ is a vector of covariates. $\omega(\cdot)$ serves to reweight white patients such that their distribution of $z$ is equalized with that of Black patients. Thus, letting $z$ be a vector of indicators for HRRs or a vector of indicators for ZIP codes, we can define the reweighting functions $\omega_t^{HRR}(\cdot)$ and $\omega_t^{ZIP}(\cdot)$ which match distributions at the market and neighborhood level, respectively, in time $t$.

Using the weights given by the $\omega(\cdot)$ functions, we construct counterfactual hospital market shares for white patients. The resulting objects are $\theta_{ht}^{W,HRR}$, which is the national market share for hospital $h$ in time $t$ for white patients after reweighting them to have the same market-level distribution as Black patients, and $\theta_{ht}^{W,ZIP}$ which has the same interpretation except that the reweighting occurs at the more finely-grained neighborhood level.[3]

We can decompose the between-race gap into three components:

$$\text{Between}_t = \sum_{h\in H}\left(\theta_{ht}^{W,HRR} - \theta_{ht}^{W}\right)\hat{q}_{ht} \qquad \leftarrow\text{Between Markets} \tag{12}$$

$$+ \sum_{h\in H}\left(\theta_{h,t}^{W,ZIP} - \theta_{ht}^{W,HRR}\right)\hat{q}_{ht} \quad \leftarrow\text{Between ZIP Codes} \tag{13}$$

$$+ \sum_{h\in H}\left(\theta_{ht}^{B} - \theta_{ht}^{W,ZIP}\right)\hat{q}_{ht}. \qquad \leftarrow\text{Within ZIP Codes} \tag{14}$$

The remainder of Table 2 presents this decomposition. Nearly half (44%) of this disparity is explained by differences in the hospital markets that Black and white patients live in, which means that just more than half (56%) of the disparity exists even when comparing patients in the same market. 25% of the total gap is explained by neighborhood differences in residence within a market. The remainder, reflecting differences in hospital choice among Black and white patients in the same neighborhoods, is 32% of the total. Panels B-D of Figure 1 visualize these findings by sequentially

[3]Because the weighting function is only defined in the support of the white patient geographic distribution, the ZIP code weights for white patients are developed from the over 98% of Black patients who live in ZIP codes in which there was at least one white patient.

reweighting white patients to match the geographic distribution of Black patients at finer levels of geography and showing how the means, displayed as vertical bars, evolve. This approach visualizes the disparity explained at the market level, depicting between-market differences (Panel B); at the neighborhood level, showing between-neighborhood differences within the same market (Panel C); and the remainder, depicting the within neighborhood differences (Panel D).

By the mid 2010s, we find that these disparities have shrunk substantially – the racial disparity is less than one-third its level at baseline. Column 3 of Table 2 shows that at endline, black patients use hospitals with 0.3 percentage points lower expected survival rates than white patients (Figure 2 visualizes this closure of the gap). The subsequent rows of the table show that the role of geography also changes: only 5% of the disparity is now explained by market differences in where Black and white patients live, and the contribution is not statistically significant. ZIP code differences play a much larger relative role at this time period, explaining 46% of the disparity; the contribution is about half its absolute value in percentage points at baseline and is significant at the 10% level. The remaining half of the gap persists within market and ZIP code.

Column 5 of Table 2 confirms that we reject the null hypothesis of no closing of the gap: the change in $\text{Between}_t$ from baseline to endline of 0.7 percentage points is highly statistically significant. Moreover, it is mostly accounted by the declining contribution of market-level differences. Given the difficulty patients would experience attempting to cross markets to access higher-performing facilities during an emergency like AMI, it is hard to explain the totality of these findings by patients re-allocating because they have become more elastic to hospital performance. In the next section, we formally investigate the role of reallocation in this result and contrast it with another mechanism we have identified: differential performance improvement.

### 4.2 Dynamic Decomposition

Table 3 displays the dynamic decomposition results. Here, we divide the total disparity reduction of 0.7 percentage points into the contributions of differential performance improvement and differential hospital reallocation. We find that the former channel fully accounts for the disparity reduction over time and its contribution is highly statistically significant. This result implies that hospitals that tended to treat Black patients at baseline experienced stronger performance gains than hospitals that tended to treat white patients. While we also find a role for the reallocation

channel – Black patients reallocating to hospitals with better performance at baseline at a faster rate than white patients – it is quantitatively smaller than the role of differential performance improvement. Reallocation contributes 0.2 percentage points to the aggregate disparity reduction. Finally, the negative cross term implies that hospitals improving performance over this time period increased their relative share of white patients. This term contributes -0.2 percentage points to the disparity.

We visualize these results in Figure 3. Panel A graphs the between-race gap at baseline, endline, and two intermediate periods. The change in the gap from baseline to endline is the quantity that we decompose. The subsequent panels display counterfactuals in which we assume hospital market shares (Panel B) or performance levels (Panel C) remain constant at baseline levels. The changes in the gaps from baseline to endline visualized in these two panels are algebraically identical to the differential performance improvement and reallocation terms, respectively. Specifically, in Panel B we fix market share but allow performance to evolve, isolating the component of the disparity reduction due to performance changes alone. Panels A and B look strikingly similar, reflecting that differential performance improvement can account for the entire reduction. Similarly, in Panel C we fix performance but allow market share to evolve, depicting the role of reallocation in disparity reduction. Here, the gap attenuates only slightly, indicating that reallocation plays a much smaller role than changes in performance.

### 4.3 Robustness

We report the robustness of both our static and dynamic decomposition results to several alternative specifications and measures to address concerns about selection, race-specific hospital performance, MA penetration, and the role of hospital entry and exit. Our findings are highly robust to these alternative approaches.

**Selection** Our measures of hospital performance could be biased if patients select hospitals on the basis of unobserved health status. If this selection is correlated with hospital volume, one could observe a spurious relationship between performance and allocation leading to biased estimates of the between-race gap. Though prior work has validated our approach (e.g. Hull, 2020; Doyle, Graves and Gruber, 2019), as an additional falsification test of the selection on observables assumption we consider the sensitivity of our findings to the richness of controls in the performance model

(Altonji, Elder and Taber, 2005; Oster, 2019). We try two alternative specifications with coarser controls: no patient-level controls and demographic controls only (age/race/sex interactions); we also test two additions to the main specification: adding interactions between the race and comorbidity variables, and a control for the type of AMI (see Appendix Section A). Our findings using these alternative specifications are qualitatively unchanged from the main specification (Appendix Tables A1 and A3), though the role of performance improvement is slightly larger when all patient controls are omitted.

**Race-Specific Performance** Our model of hospital performance allows for differences in patient outcomes by race but assumes that the difference does not vary by hospital. This assumption will not bias our estimates if hospitals have idiosyncratic race gaps in their treatment quality or outcomes due to, for example, provider prejudice. However, if Black patients disproportionately choose hospitals that are (or become) relatively high-performing for Black patients, the decompositions would overstate the race gap in performance and potentially misstate how it has evolved over time. For example, if hospitals that were popular among Black patients were more likely to address within-hospital disparities, raising performance more for Black patients than white patients, our analyses might show a declining between-race gap that actually represents a declining within-hospital gap.

We investigate this concern with an alternative model in which hospital performance is allowed to differ by race. Augmenting the fixed effects model to permit hospital-race effects raises measurement issues because only a handful of hospitals treat large numbers of Black *and* white patients in both periods – under one-fifth treat at least 25 Black and 25 white patients at baseline and endline – and many hospitals treat no Black patients at all. We estimate a random effects model in which hospital performance is drawn from a trivariate normal distribution: one hospital random effect and two hospital random slopes (for Black patients and non-Black non-white patients). This model emits an estimate of the underlying variance-covariance matrix of the distribution which is robust to measurement error from small samples of Black or white patients at the hospital level. It also emits best linear unbiased predictions (BLUPs) of hospital performance for Black and white patients. Appendix Section 2.3 describes the approach in more detail.

The findings support our main approach and results. In Appendix Table A5, we show that hospital performance for Black and white patients is highly correlated: 90% and 83% during the baseline and endline periods, respectively. Such a high correlation limits the potential scope for

selection on race-specific performance. We use the BLUPs to re-estimate the decompositions with the performance measure $\hat{q}_{ht}$ replaced with predicted performance for Black or white patients. The results, presented in Appendix Tables A2 and A4, are similar to those of our main approach regardless of whether we use performance for Black or white patients. While the disparity at baseline is somewhat smaller, it continues to attenuate substantially over time and this decline is due to differential performance improvement.[4] These findings are inconsistent with declining within-hospital gaps driving the over-time changes, since they are so similar for Black patient performance and white patient performance.

**Attrition to Medicare Advantage** Patients who enter Medicare Advantage (MA), the private insurance system in Medicare, are not observed in our data. MA penetration was increasing during our study period and MA enrollees are disproportionately white and more likely to be healthy (Brown et al., 2014); if marginal MA enrollees make different hospital choices than those in fee-for-service Medicare, particularly if they tend to allocate toward high-performing hospitals, their attrition from the sample could generate the declining race gaps we observe. To address this concern, we repeat our analyses in markets with below median MA penetration in 2014 to limit the potential for attrition to MA. The results are reported in Appendix Tables A2 and A4 and are very similar to our main findings, suggesting that selection into MA is not driving the patterns we report.

**Entry and Exit** To this point, all results have analyzed a balanced panel of hospitals, omitting any role for hospital entry and exit. The productivity decomposition literature has emphasized the importance of this channel (Foster, Haltiwanger and Syverson, 2008; Melitz and Polanec, 2015), and the entry of higher-performing facilities and the exit of lower-performing ones drives some of the improvement in aggregate hospital performance over time (Chandra et al., 2016). To test whether net entry expands or contracts disparities, we relax the requirement that hospitals treat at least 25 patients at baseline and endline and return those that only meet the threshold in one of the periods to the sample. Accounting for entry and exit requires a more complex decomposition approach, which we discuss in Appendix Section B. To summarize, an entry term reduces the Black-white gap

[4] A similar pattern obtains from a random effects model without race-specific random slopes and is presented in the same tables. Unlike the main model of performance, BLUPs from random effects models are shrunk toward the mean. These results suggest that shrinkage drives the smaller disparity at baseline in the race-specific performance model, rather than the race-specific slopes.

when entering hospitals are relatively popular among Black patients and have higher than average performance; an exit term reduces the gap when, for example, exiting hospitals were relatively popular among Black patients but have lower than average performance.

We find results similar to those of our main analyses. The static decomposition in Appendix Table A2 shows that at each point in time, the between-race gap is slightly larger with the unbalanced panel; the reduction in the gap over time is also slightly larger. Decomposing this change, Appendix Table A4 shows that net entry plays a role in reducing disparities where, by design, it previously could not (entry exacerbates the disparity but is is more than offset by exit). Differential performance improvement continues to make the largest contribution to disparity reduction, though the magnitude is somewhat less than in the main specification.

## 5 Technology Adoption as a Mechanism

Earlier, we noted that differential performance improvement can explain the totality of the narrowing between-race gap in hospital performance. To understand this finding we explore the adoption of new treatment technologies as a mechanism for improvement. The adoption patterns of these technologies could play a key role in determining hospital performance, and through this channel, racial disparities in care outcomes. Our framing draws on work showing that a disproportionate share of survival gains come from the diffusion of low-cost technologies that benefit virtually all patients rather than high-cost interventions which exhibit diminishing returns (Chandra and Skinner, 2012; Skinner and Staiger, 2015). In the years prior to the study period, the technology frontier of AMI treatments moved forward dramatically as both types of interventions diffused through hospitals. Beta-blocker drugs provide an example of low-cost, high-benefit, TFP raising AMI technology. Their value was established in a series of trials in the 1980s, and by the beginning of the study period, guidelines recommended their use in nearly all AMI patients (Yusuf et al., 1985; Lee, 2007). Cardiac catheterization, in contrast, is an example of a capital-intensive intervention that requires costly and specialized labor inputs (Jencks et al., 2000; Jencks, Williams and Coleman, 2009; Cutler et al., 1998). It enabled improved imaging of the heart as well as a procedure called percutaneous coronary intervention (PCI) to open blocked blood vessels.

Rapid adoption of these technologies by hospitals with that were relatively popular among

Black patients could reduce the between-race gap. To test this hypothesis, we repeat the dynamic decomposition replacing the hospital performance outcome with the use of beta-blockers, and separately, cardiac catheterization. We consider whether the results follow a pattern similar to our main results: that Black patients tend to use hospitals with lower levels of technology adoption at baseline compared to white patients; that this gap attenuates from baseline to endline; and that the attenuation is explained by faster technology adoption at hospitals with relatively high Black patient shares *ex ante*. Such patterns would support technology adoption as a mechanism for the findings of the previous section.

We develop and describe our two measures of adoption in more detail in Appendix Section C.1. Briefly, we measure beta-blocker take-up as the share of AMI patients at the hospital who were prescribed beta-blockers at discharge. CMS and accreditation agencies have used this metric as an indicator of hospital quality. Like CMS, we do not risk-adjust this metric because the drugs are thought to be appropriate for the vast majority of patients. We take it as a surrogate for hospital use of low-cost technologies that generate large benefits including but not limited to beta-blockers themselves. To measure high-cost technology adoption, we examine the use of cardiac catheterization on the day of admission, adjusted for patient risk-factors – the clinical literature suggests that only these catheterizations have a meaningful impact on survival (Hartwell et al., 2005; Hochman et al., 2006; Likosky et al., 2018). We re-run the model specified in equations 1-3 with catheterization as the outcome, yielding hospital-level estimates of adoption at baseline and endline.

Table 4 presents decompositions of the measures. Takeup of both technologies rose substantially from the baseline to endline periods. In column 1, we focus on beta-blockers, where the Black-white gap was substantial at baseline. Compared to white patients, Black patients receive treatment at hospitals with 1.7 percentage point lower rates of beta-blocker use at baseline but 0.2 percentage points lower use at endline. The dynamic decomposition shows that over 90% of the closure of the gap is due to differential performance improvement: hospitals relatively popular among Black patients were also faster to adopt the drug. Reallocation also contributes about 40% of the closure; the excess over unity is offset by a negative cross term: there was some reallocation away from hospitals that grew their use of beta-blockers.

In contrast, the findings for catheterization in column 2 are the reverse: at baseline, Black

patients received treatment at hospitals with slightly higher cardiac catheterization rates than white patients. This gap attenuates and flips over time – at endline white patients use hospitals with higher cardiac catheterization rates. We found similar results when we measured high-cost intervention in other ways: counting catheterizations on any day, counting catheterization or bypass surgery, or counting bypass surgery alone. Results for aspirin, a low-cost technology with a racial disparity at baseline that matched the high-cost measures in that it favored white patients, are also similar to the findings for high-cost technologies (Appendix Table A6).[5]

These results suggest that diffusion of beta-blockers and technologies for which they serve as surrogates attenuated disparities in the performance of hospitals used by Black and white patients. On the other hand, the patterns of diffusion for capital-intensive technologies like catheterization expanded disparities. Our findings highlight the potential role of technology adoption in the evolution of performance gaps between hospitals used by Black and white patients.

## 6 Conclusion

We quantified the role of patient allocation in Black-white disparities in AMI treatment and outcomes by analyzing nearly two decades of Medicare patients. We first showed that in the 1990s, Black patients tended to use hospitals with substantially worse patient outcomes during the 1990s – the survival rate of a typical patient was a percentage point lower at hospitals used by Black patients than at hospitals used by white patients. Our work next highlighted the role of geography in accounting for the racial gap. While this point has been recognized in the literature (Baicker, Chandra and Skinner, 2005; Skinner et al., 2005), we add to it by developing a novel reweighting approach to decompose the contributions of markets and neighborhoods. Differences in where Black and white patients live between markets drive a nontrivial share, nearly one-half, of the gap in the 1990s. Yet by the same token, just over half of the disparity persists even within markets. Of this gap, about half reflects patients living in different ZIP codes and the other half reflects different hospital choices among patients in the same ZIP code. These findings reinforce

[5] We also investigated if hospitals that tended to treat more Black patients experienced greater gains in the returns to catheterization. Gains could occur if hospitals improved their skill at using the procedure or if they came to better target it at patients who were likely to benefit. Hospitals with larger Black patient shares experienced lower returns to catheterization at baseline. However, this gap persisted through endline, suggesting that differential gains in returns do not drive the findings we observe.

the research on place-based and person-based policies by highlighting the performance of hospitals as important component of place and thus a potential focus of intervention (Bartik, 1991; Glaeser and Gottlieb, 2009). Our work complements 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).

Next, we found that between the 1990s and 2010s, the Black-white gap shrank by two-thirds. We developed a dynamic decomposition framework to determine whether this trend was driven by stronger reallocation of Black patients to better performing hospitals or stronger performance improvement among hospitals treating disproportionately Black patients. Our framework can be generalized to study the evolution of allocation-related disparities in other health care settings, like physicians or nursing facilities, as well as non-health contexts like schools, employers, and judges.

Given Chandra et al. (2016)'s findings that reallocation played an important role in improving overall patient outcomes over time, one might have suspected that reallocation to better hospitals acted to shrink the disparity, too. However, we did not find first-order evidence for that view, finding instead that differential performance improvement among hospitals that disproportionately treated Black patients led to the narrowing between-race gap in hospital performance. Lastly, we demonstrated that diffusion of a low-cost technology, beta-blockers, followed a similar, disparity-reducing path. This result suggests that take-up of beta-blockers and performance-improving strategies correlated with them may have been responsible for this progress. We note that our results do not establish that the diffusion of beta-blockers per se was responsible for improving outcomes at these hospitals; instead, we follow Chandra and Skinner (2012), Skinner and Staiger (2015), and other work in viewing beta-blockers as a surrogate for a variety of TFP-improving changes that can include superior management and leadership in the hospital (Bloom et al., 2012; Tsai et al., 2015; Bloom, Sadun and Van Reenen, 2016).

More generally, our research connects a large literature on racial disparities in health care with the economics of productivity (Baily et al., 1992; Foster, Haltiwanger and Krizan, 2006; Melitz and Polanec, 2015) and the economics of medical innovation and diffusion (Chandra and Skinner, 2012; Chandra and Staiger, 2007; Skinner and Staiger, 2015). These connections raise the question of whether performance improvement and reallocation could be harnessed to address the disparities highlighted for AMI as well as disparities in other parts of the health care system with

similar features. The power of the differential performance improvement channel over the past two decades suggests that direct efforts to increase the performance of hospitals in markets that serve a large share of Black patients can close the gap. These efforts would not change where patients receive treatment but could directly resource the hospitals they use. This approach aligns with Baicker, Chandra and Skinner (2005), who argued that place-based quality improvement efforts could address racial disparities.

While we showed that reallocation was a smaller force for stemming racial disparities in AMI, there is still scope to use this channel going forward. In AMI, for example, about half of remaining racial disparities originate from patients who live in the same ZIP code receiving treatment at different hospitals. This finding points to the potential for reallocative policies like efforts to change referral patterns or provider networks to close ongoing gaps. Hospital closure and entry, which are powerful forces for improvement in other sectors, could also play a role here – though the emergency nature of AMI necessitates more study of this channel.

Our approach focused on hospital performance for the typical patient, abstracting away from racial disparities in outcomes within the facility. By taking this approach, we are able to uncover a surprising decline in the gap in the performance of hospitals used by Black and white patients. While encouraging, this approach measures only one of the multitude of structural forces deteriorating health outcomes for Black patients at the point of care. Another key force comes from biases and discrimination on the part of practitioners. Regardless of whether they originate inside or outside the hospital, these forces can persist even as "between" hospital disparities close. The dynamics of disparities, whether arising within hospitals or from patient allocation between them, are a crucial area for future research.

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# Tables

Table 1 - Summary Statisics on Patients and Hospitals

| Time period | Baseline (1995-1999) | | Endline (2010-2014) | |
|---|---|---|---|---|
| Race | Black | White | Black | White |
| Panel A: Patients | | | | |
| Survival, 30 Days | 81.7% | 81.2% | 86.7% | 85.8% |
| Age | 76.8 | 77.6 | 77.7 | 79.3 |
| | (7.5) | (7.3) | (8.2) | (8.2) |
| Female | 59.8% | 49.5% | 58.7% | 48.2% |
| Comorbid Conditions | | | | |
| Heart Failure | 18.2% | 12.5% | 24.2% | 15.0% |
| Stroke | 2.1% | 1.2% | 1.2% | 0.6% |
| COPD | 7.6% | 7.5% | 10.4% | 8.9% |
| Count (out of 23) | 1.3 | 0.9 | 1.9 | 1.3 |
| | (2.0) | (1.7) | (2.6) | (2.2) |
| Patients | 66,092 | 1,018,234 | 60,204 | 710,068 |
| Panel B: Hospitals | | | | |
| Survival, 30 Days, Risk-Adjusted* | 81.1% | 79.6% | 85.3% | 84.2% |
| | (3.8pp) | | (4.3pp) | |
| Patients per Hospital (Total) | 411.2 | | 297.4 | |
| | (369.5) | | (310.1) | |
| Patients per Hospital (by Race) | 24.4 | 375.5 | 22.2 | 261.8 |
| | (47.2) | (347.6) | (45.8) | (283.0) |
| Hospitals (≥1 Patient in Race Group) | 2,181 | 2,711 | 2,120 | 2,706 |
| Hospitals (Total) | 2,712 | | | |

Notes: Panel A displays statistics about the sample of patients used to measure allocation and performance. Panel B shows statistics about the hospitals in our main analyses. All cells report averages or rates except those in parentheses which report standard deviations. See text for more details.

* Reports the expected survival of the average Black or white patient at the average hospital, the measure of hospital performance described in equations 2 and 3. The standard deviation is adjusted for measurement error and in our main specification it is always equal for Black and white patients in the same time period.

Table 2 - Static Decomposition of Hospital Performance

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Time period | Baseline (1995-1999) | | Endline (2010-2014) | | Change | |
| | Value | Share | Value | Share | Value | Share |
| Between-Race Gap (Black-White) | -0.96 | 100% | -0.29 | 100% | 0.66 | 100% |
| | (0.11) | | (0.11) | | (0.13) | |
| Components of Between-Race Gap | | | | | | |
| Between Hospital Markets | -0.42 | 44% | -0.01 | 5% | 0.40 | 61% |
| | (0.07) | | (0.07) | | (0.09) | |
| Between ZIP Codes (Within | -0.24 | 25% | -0.13 | 45% | 0.10 | 15% |
| Hospital Markets) | (0.07) | | (0.07) | | (0.10) | |
| Within ZIP Codes | -0.30 | 32% | -0.15 | 50% | 0.16 | 24% |
| | (0.05) | | (0.05) | | (0.06) | |

N=2,712 hospitals. All values are percentage points (i.e. 1 indicates 1 percentage point) except for shares indicated with a % symbol. Notes: This table displays the between-race gap, or the difference in the average performance of hospitals used by Black and white patients, during the baseline period (columns 1 and 2), endline period (columns 3 and 4), and the change from baseline to endline (columns 5 and 6). Hospital performance is measured by the risk-adjusted survival rate. The decomposition uses reweighting to successively equalize the geographic distribution of Black and white patients at the hospital market (HRR) and ZIP code levels. It separates the between-race gap into a between hospital market component, a between ZIP code component, and a within ZIP code component. See text for more details. Bootstrapped standard errors using 1,000 replicates in parentheses.

Table 3 - Dynamic Decomposition of Hospital Performance

| | (1) Value | (2) Share |
|---|---|---|
| Change in Between-Race Gap | 0.66 | 100% |
| from Baseline to Endline | (0.13) | |
| Components of Change | | |
| Differential Performance | 0.68 | 102% |
| Improvement | (0.15) | |
| Differential Hospital | 0.19 | 29% |
| Reallocation | (0.08) | |
| Cross | -0.21 | -31% |
| | (0.09) | |

N=2,712 hospitals. All values are percentage points (i.e. 1 indicates 1 percentage point) except for shares indicated with a % symbol. Notes: This table displays and decomposes the change in the between-race gap from the baseline period to the endline period. The decomposition separates the change into differential performance improvement, or changes in performance associated with baseline Black-white allocation differences; differential hospital reallocation, or changes in Black and white patient allocation associated with baseline performance differences; and cross, or changes in allocation and performance co-occurring. See text for more details. Bootstrapped standard errors using 1,000 replicates in parentheses.

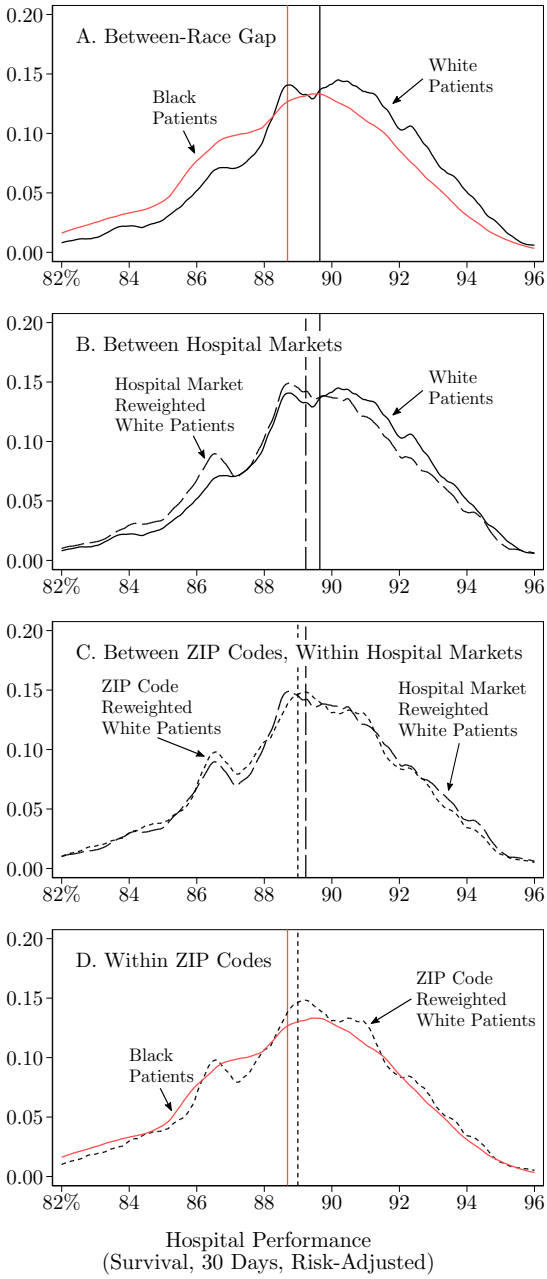
Table 4 - Decomposition of Hospital Technology Adoption

| | (1) Beta-Blockers (Low-Cost) | (2) Cardiac Cath (High-Cost) |
|---|---|---|
| Avg at Baseline (All Patients) | 37.3% | 16.4% |
| Avg at Endline (All Patients) | 98.5% | 41.9% |
| Between-Race Gap (Black-White) | | |
| Baseline | -1.70 | 0.65 |
| | (0.56) | (0.35) |
| Endline | -0.23 | -0.93 |
| | (0.09) | (0.46) |
| Change | 1.46 | -1.58 |
| | (0.56) | (0.39) |
| Components of Change | | |
| Differential Performance Improvement | 1.35 | -0.64 |
| | (0.58) | (0.32) |
| Differential Hospital Reallocation | 0.59 | -0.16 |
| | (0.34) | (0.25) |
| Cross | -0.48 | -0.78 |
| | (0.36) | (0.21) |
| Hospitals | 2,602 | 2,712 |

All values are percentage points (i.e. 1 indicates 1 percentage point) except for shares indicated with a % symbol. Notes: This table displays and decomposes the change in the between-race gap from the baseline period (1995-1999) to the endline period (2010-2014) for hospital technology adoption and use. The between-race gap is the Black - white rate; thus a negative value would indicate that Black patients receive treatment at less technology intensive hospitals than white patients. Column 1 analyzes the use of a low-cost technology, beta-blockers at discharge. Column 2 analyzes the use of a high-cost technology, cardiac catheterization, on the same day as admission. See text for more details. Bootstrapped standard errors using 1,000 replicates in parentheses.

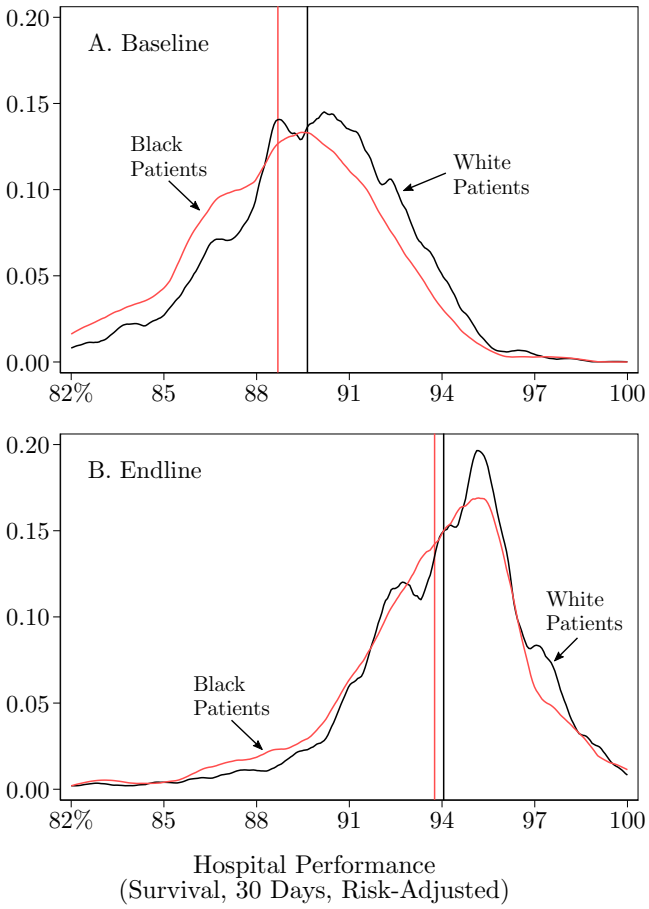
# Figures

**Figure 1: Decomposition of Between-Race Gap in Hospital Performance at Baseline**



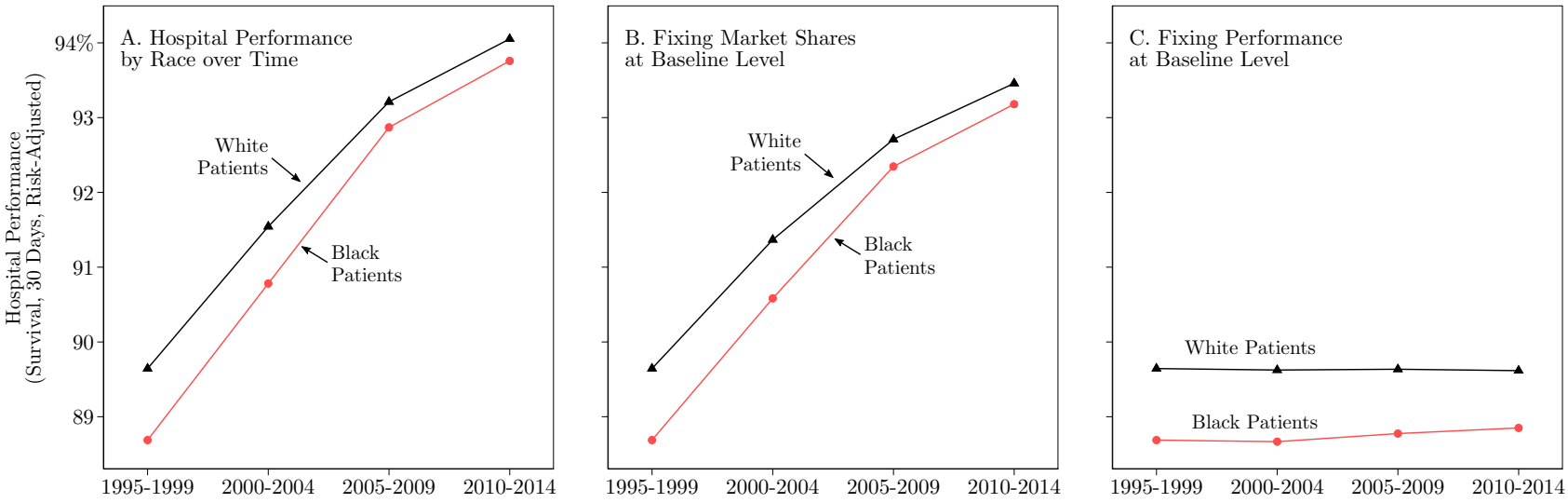

Note: This figure visualizes the static decomposition during the baseline (1995-1999) period. Each panel presents kernel densities of hospital performance for Black and white patients, with the vertical lines representing means. Panel A compares the actual densities for white and Black patients (the between-race gap). Subsequent panels reweight white patients to have the same geographic distribution as Black patients. Panel B compares densities for actual and market-level reweighted white patients (the between hospital markets term). Panel C compares densities for market- and ZIP code-level reweighted white patients (the between ZIP codes, within hospital markets term). Panel D compares the density for ZIP code-level reweighted white patients with the actual density for Black patients (the within ZIP codes term). See text for more details.

**Figure 2: Between-Race Gap in Hospital Performance at Baseline and Endline**




Note: This figure visualizes the between-race gap term of the static decomposition during the baseline (1995-1999) and endline (2010-2014) periods. Each panel presents kernel densities of hospital performance for Black and white patients, with the vertical lines representing means. See text for more details.

**Figure 3: Decomposition of Between-Race Gap in Hospital Performance Over Time**




Note: This figure visualizes the dynamic decomposition. Panel A shows the average hospital performance for Black and white patients in each period. The change in the Black-white gap from baseline (1995-1999) to endline (2010-2014) equals the change in between-race gap decomposed in Table 3. Panel B shows a counterfactual in which market shares remain at baseline levels but hospital performance evolves, depicting the differential performance improvement term. Panel C displays a counterfactual in which hospital performance remains at baseline levels but market shares evolve, depicting the differential reallocation term. See text for more details.