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RATIONING BY RACE

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ABSTRACT

Discrimination may lead to rationing on the basis of group identity when resources become more scarce. We provide evidence of consequential rationing on the basis of an individual's race in a high-stakes setting: health care. Using detailed, time-stamped data on over 107,000 patient admissions from a large health system in the U.S., we find that in-hospital mortality increased for Black, but not White, patients as hospitals reached capacity, a state where biases in care provision are likely to emerge or be exacerbated. We identify rationing by wait times as a mechanism, also documenting that sick Black patients wait longer for care than healthy White patients, regardless of capacity levels. Applying text analysis techniques to clinical documentation, we provide suggestive evidence of disparities in provider effort as another mechanism.

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1 Introduction

Decision-makers often seek to ration resources by demonstrated need, willingness-to-pay, or other dimensions consistent with social values (Akbarpour et al., 2024; Sen, 1982; Weitzman, 1977). However, when resource scarcity deepens, decision-makers may instead ration resources in ways that may be deemed socially suboptimal. In particular, increasing scarcity can exacerbate human biases and reliance on heuristics, which may lead to rationing on the basis of markers of group identity such as race, particularly in societies where discrimination is pervasive.[1] In this paper, we examine whether increasing scarcity causes increases in discriminatory rationing of resources within a highly consequential, high-stakes setting: health care.

There is a long history of discrimination on the basis of individual race in health care, both at the level of the individual provider and the health system (Alsan & Wanamaker, 2018; Balsa & McGuire, 2003; Eli, Logan, & Miloucheva, 2023; Lavizzo-Mourey, Besser, & Williams, 2021; Obermeyer et al., 2019; Schulman et al., 1999).[2] When providers and systems face resource, personnel, or time constraints, underlying discrimination may lead to rationing of necessary care on the basis of race rather than medical need in ways that adversely affect health outcomes (Stepanikova, 2012; Yearby, 2011).

We delve into this question using unique, time-stamped electronic health record data, notable for its exceptional detail rarely available for research. Our data includes over 107,000 patient admissions over the period 2015 to 2018 across two hospitals within a large urban academic hospital system in the Southeast United States. Informed by a simple conceptual framework, we leverage quasi-exogenous variation in hourly hospital capacity (controlling for a range of seasonal and time-based influences) as our measure of resource scarcity, and examine how it affects rationing of hospital resources for Black vs. White patients. As hospitals approach maximum capacity – here, indicated by a higher share of inpatient beds occupied – the escalating demands of patients can strain the cognitive bandwidth of providers and overburden the hospital's material resources such as space or medical

[1] Discrimination in the allocation of public goods is common in the United States (Alesina, Baqir, & Easterly, 1999; Bohren, Hull, & Imas, 2022; Darity Jr, 2022). There is also a large body of lab-based research in social psychology that shows that resource scarcity and competition for finite resources increases discriminatory behaviors and beliefs (Antunes et al., 2023; Berkebile-Weinberg, Krosch, & Amodio, 2022; Brewer & Silver, 1978; Krosch & Amodio, 2014; Krosch, Tyler, & Amodio, 2017; LeVine, 1972; Riek, Mania, & Gaertner, 2006; Skitka & Tetlock, 1992). This research suggests that the link between resource scarcity and discrimination may even manifest at the neural level: e.g., Krosch and Amodio (2019) use brain imaging techniques to show that under conditions of scarcity, neural processing time of images of Black individuals lengthened, potentially explaining a lower allocation of resources to Black vs. White participants in laboratory games. Despite this body of literature, causal evidence on the effect of resource scarcity on consequential discriminatory rationing in a real-world setting remains scarce.

[2] Potential sources of racial discrimination – and racial disparities – in health care include implicit or explicit bias among providers (Balsa & McGuire, 2003; Centola et al., 2021; Stepanikova, 2012); built-in biases in clinical decision algorithms (Obermeyer et al., 2019); differences in opportunities for patient self-advocacy (Wiltshire et al., 2006); differential staffing ratios (Brooks Carthon et al., 2021; Stoye & Warner, 2023); and social distance between providers and patients of different backgrounds (Alsan, Garrick, & Graziani, 2019; Frakes & Gruber, 2022; Schwab & Singh, 2023; Ye & Yi, 2022) At a broader-level, Black patients may receive poorer care because tend to live in geographic areas where health care quality is poor (Chandra & Skinner, 2003) and because of *de facto* rationing on the basis of ability to pay (Yearby, 2011).

treatments (Anesi et al., 2018; Evans & Kim, 2006; Hoe, 2022; Marks & Choi, 2019; Song et al., 2020). Under these conditions – referred to as "capacity strain" (Arogyaswamy et al., 2021) – providers and hospitals may increasingly rely on bandwidth-saving, but potentially biased, individual-level heuristics (Brown et al., 2023; Johnson et al., 2016; Stepanikova, 2012) or systems-level algorithms that may allocate resources in biased ways (Obermeyer et al., 2019). Increased strain may also elevate the importance of patient or family self-advocacy in accessing needed care, which is more likely to result in worse outcomes for Black patients, who face disproportionate constraints to advocate for themselves (Wiltshire et al., 2006).

To assess the impact of escalating resource scarcity – proxied by capacity strain – on care rationing decisions, we begin with the starkest possible outcome of biased treatment allocation decisions: patient death. We document stark racial disparities in health outcomes under conditions where resources become acutely scarce: in-hospital mortality rises for Black patients, but not White patients, as hospitals approach capacity at the hour of patient arrival to the hospital. We find an approximately 15% greater increase in mortality for Black (vs White) patients as hospital strain increases to its highest decile. This increase is driven by patients with the greatest *ex ante* medical need (as measured by the widely validated Elixhauser et al. (1998) mortality index scores as well as vital signs).

We show that these findings cannot be explained by differential selection of patients (on the basis of medical need and race) at different levels of capacity strain – our key identification assumption. This assumption is supported by the literature, which demonstrates how day-to-day variation in hospital strain – let alone the hour-to-hour variation that we leverage in this study – is difficult to predict (Arogyaswamy et al., 2021; Hoe, 2022; Song et al., 2020).[3] The validity of our identification assumption is bolstered by our research design, which controls for hospital-specific hour of day, day of week, month of year, and year fixed effects, accounting for any capacity strain that can be predicted on the basis of by seasonality or time. We provide further support for our identification assumption by empirically documenting: i) no differences in the distribution of capacity strain at the time of arrival for Black and White patients, ii) no capacity strain-related racial differences in observable patient demographic characteristics, comorbidity index scores (a marker of chronic medical need, proxied by Elixhauser mortality index scores), vital signs at hospital arrival (a marker of acute medical need), and themes (identified by a machine learning algorithm) within the hand-written note that documents a patient's reason for hospital admission; and iii) no selective discharge by strain or patient race (e.g.,

[3] Arogyaswamy et al. (2021) conducted a qualitative study of hospital administrators at major academic medical centers similar to the setting of this study, all of whom noted the difficulty in predicting hospital strain and marshalling resources to manage it. This general insight is what supports a common identification strategy in the literature on hospital strain, which is to assume that it is exogenous conditional on time fixed effects (Hoe, 2022; Song et al., 2020). Importantly, the literature to date has typically focused on day-to-day variation in strain. Our use of time-stamped data, which is generally not available to researchers (Neprash et al., 2021; Song et al., 2020), thus represents a meaningful advance on its own.

to hospice care). Moreover, our patient mortality findings are robust to specification, and hold in models that range from sparse (i.e., only account for hospital fixed effects and patient age and gender) to saturated (i.e., include patient insurance status, comorbidity risk scores, physician of record fixed effects, diagnosis related group fixed effects, vitals signs at presentation, and interactions between all of these variables and patient race or level of capacity strain).

We next provide evidence for discriminatory rationing processes as the reason why Black patients' health fares worse at high capacity strain. We focus primarily on wait times for an inpatient bed, following a long literature illustrating time as a critical margin of rationing of health care and a range of public services (Barzel, 1974; Holt & Vinopal, 2023; Lu, Hanchate, & Paasche-Orlow, 2021; Martin & Smith, 1999). We document a striking fact: at all levels of capacity strain, Black patients with *ex ante* greater medical need (whether proxied for by Elixhauser mortality index scores or by vital signs) wait longer for an inpatient hospital bed than healthier White patients. We then present evidence evidence of rationing of wait times by patient race: Black patients experience greater increases in wait times as capacity strain increases compared to White patients. Concordant with the patterns we find for mortality, this pattern is most apparent for patients admitted at the highest decile of strain.[4]

In a more suggestive set of analyses, we also investigate disparities in provider effort, which are thought to be important drivers of racial disparities in health care (Burgess et al., 2006; King et al., 2023) and may also be rationed as capacity strain increases. Effort is not directly measured in electronic health record data. However, following other work (Chan, 2016, 2018; Schut, 2021), we infer it from patterns in the data. Specifically, we examine free-text entries in the electronic health record documenting the reason for admission, a field that is filled out by a triage provider around the time of initial arrival to the hospital that plays an important role in setting the course of care (Ly, Shekelle, & Song, 2023; Schrader & Lewis, 2013). We deploy a constellation of text analysis methods to this text field to measure provider effort.

We first analyze descriptive features such as time to completion, character counts, and average word length, features of text shown to be associated with effort in a wide range of contexts (Galesic & Bosnjak, 2009; Tausczik & Pennebaker, 2010; Yadav, Prabhu, & Chandy, 2007) and which, we argue, are appropriate in the health care context as well. We also analyze sentiment, focusing on subjectivity and polarity scores, given that greater subjectivity introduces the potential for greater bias (Bloche, 2001; Schrader & Lewis, 2013) and emerging evidence that Black patients are often described more negatively than White patients in EMRs (Sun et al., 2022), which can also result in

[4]While we do not find this pattern for other measures of care intensity, such as likelihood and length of ICU care, total charges, or length of stay, we document that on average (i.e., across all levels of capacity strain), and conditional on demographic characteristics and comorbidities, Black patients generally receive fewer of these resources than White patients.

bias and reduced effort in providing care to Black patients (Goddu et al., 2018). Finally, to account for the possibility that medical notes may be less well suited to standard natural language processing techniques (Weissman et al., 2019), we also manually identify adjectives, which are used to provide detail, context, and nuance, as well as to describe change (e.g., in a patient's illness state) (Kennedy & Levin, 2008). We find that, at all levels of capacity strain, documentation for Black patients exhibit features consistent with lower effort, and that this disparity between Black and White patients grows with strain for several of these measures, most notably the subjectivity of documentation and the number of adjectives used.

Our findings contribute to literatures on resource scarcity, rationing, and discrimination, demonstrating important and consequential linkages between these often separately-studied concepts. Specifically, we demonstrate how resource scarcity might lead to inequitable distribution of resources by group identities that are discriminated against. These findings are of course germane to the literature on health care rationing (Brot-Goldberg et al., 2023; Fuchs, 1984; Martin & Smith, 1999; Mechanic, 1995). However, they are equally relevant to the broader literature on economic rationing which typically examines how limited resources are allocated across agents under conditions of excess demand, often relying on price mechanisms or non-price mechanisms (such as queuing, lottery systems, etc) to resolve imbalances (Breza, Kaur, & Shamdasani, 2021; Jacob & Ludwig, 2012; Leshno, 2022; Stiglitz & Weiss, 1981). Our research contributes by highlighting the overlooked impact of group identity on rationing decisions, thereby urging a broader consideration of social factors in rationing models. Our paper also informs the study of discrimination, contributing to a growing literature on how racial disparities in a range of outcomes may manifest or widen in the face of large-scale stressors such as economic shocks, natural disasters, and pandemics (Anderson, Crost, & Rees, 2020; Beck & Tolnay, 1990; Klein et al., 2023). Along these lines, our study provides insights into why Black patients tend to fare worse when hospitals face various large scale shocks, such as personnel strikes (Stoye & Warner, 2023) or ransomware attacks (McGlave, Neprash, & Nikpay, 2023).

In addition to these contributions, our results also help reconcile the mixed findings in the literature on the consequences of hospital or care facility capacity strain on patient outcomes, which collectively examines a range of clinical contexts and patient populations (Andrew & Vera-Hernández, 2024; Anesi et al., 2018; Avdic, Lundborg, & Vikström, 2024; Eriksson et al., 2017; Evans & Kim, 2006; Hoe, 2022; Hoot & Aronsky, 2008; Marks & Choi, 2019; Song et al., 2020; Wilcox et al., 2020), by underscoring the need to focus on heterogeneity in the impacts of strain across patient population. We wrap up by noting that our findings were observed in a sample of admissions that occurred prior to the COVID-19 pandemic. Thus, race-based rationing may in fact have been far more consequential during the COVID-19 pandemic, which was a time of record capacity strain (especially in hospitals serving Black patients (Vohra et al., 2023)), extreme provider burnout (Kadri et al., 2021), and staggering racial disparities in health access and outcomes (Price-Haywood et al., 2020). The COVID-19 pandemic also saw vociferous discussions on whether race-based rationing, as a means to target resources to patients in need, was ethical or legal (Jost, 2022). Our results highlight that regardless of the range of opinions around *de jure* rationing of health care, *de facto* rationing by race appears to occur in typical care settings under regular, typical stressors faced by hospitals.

2 Conceptual Framework

In this section, we formalize the intuition that as resources become more scarce, allocation decisions become more susceptible to heuristics premised around group identity, which may be implicitly or explicitly biased. Focusing on the health care context, our framework illustrates how decisions to allocate care resources – which can range from personnel allocated to care; hospital material resources such as beds, monitoring technologies, or medical and surgical treatments; and provider-specific resources such as cognitive bandwidth – can increasingly reflect group identity rather than medical need.

A team of healthcare providers are indexed by j. Patients are indexed by i, and characterized by medical need (e.g., illness severity) N_i and racial identity R_i. For simplicity, the patient's health outcome Y_{it} can be said to be a function of the healthcare resource allocation decision $A_{ij}(t)$ made at time t and the patient's true medical need N_i: $Y_{it} = f(A_{ij}(t), N_i)$.[5]

We denote $S_j(t) \in [0, 1]$ to signify continuous resource constraints (e.g., capacity "strain") faced by provider team j at time t, with higher values signifying greater resource constraints (or equivalently, availability of fewer resources). The provider assesses medical need, based on which they allocate care resources, $A_{ijt} = f(N^*_{ijt}(t), R^*_{ijt})$. $N_{ij}(t)^*$ is *perceived need,* i.e., the need perceived by provider j for patient i's and $R^*_{ij}(t)$ reflects the *racial weight*, i.e., the weight assigned to the patient's racial identity by provider j at time t when deciding on allocation A_{ijt}:

$$N^*_{ij}(t) = N_i \cdot e^{-\gamma_j \cdot S_j(t)} \tag{1}$$

$$R^*_{ij}(t) = R_i \cdot \phi_j(S_j(t)) \tag{2}$$

Perceived need $N^*_{ij}(t)$ deviates from true patient need N_i (which is unobserved) as strain increases. Specifically the term $\gamma_j \in [0, 1]$ captures the provider team's rapidly diminishing ability

[5]Following, Balsa and McGuire (2003), we model health outcomes as a function of contemporaneous resource allocation and treatment decisions for simplicity. The logic of our framework holds even if we assume that health outcomes are also a function of health outcomes in the previous period (which are functions of past resource allocation decisions).

or willingness to assess true medical need as cognitive bandwidth, personnel, and/or diagnostic and treatment resources decrease with capacity strain. (We have used an exponential function to illustrate non-linearities in this process, but that need not be the case.) The racial weight $R^*_{ij}(t)$, conversely, captures greater reliance by the providers on the patient's racial identity in allocation decisions as resources get more constrained. The racial weight is increasing in capacity strain, captured through the parameter $\phi(S(t)) \in [0, 1]$. This weight reflects the potential for discrimination arising from various factors. These include implicit or explicit biases among healthcare providers (Stepanikova, 2012), biases inherent in treatment algorithms (Obermeyer et al., 2019), inaccuracies in assessing medical needs due to incomplete electronic medical records (Lyles, Wachter, & Sarkar, 2021), mistrust between providers and patients (Alsan, Garrick, & Graziani, 2019), or limited patient advocacy (Wiltshire et al., 2006). These issues, potentially always present, become even more critical under stressful conditions.[6]

Differentiating N^*_{ijt} and R^*_{ijt} with respect to $S_j(t)$, we arrive at two key relationships:

$$\frac{dN^*_{ij}(t)}{dS_j(t)} = -\, N_i \cdot \gamma_j \cdot e^{-\gamma_j \cdot S_j(t)} \tag{3}$$

$$\frac{dR^*_{ij}(t)}{dS_j(t)} = R_i \cdot \frac{d\phi_j(S_j(t))}{dS_j(t)} \tag{4}$$

We formulate two hypotheses from this framework: First, as capacity strain increases, the provider team's ability or willingness to assess the patient's true medical need decreases. However, if this ability is unaffected by strain, or in other words, $\gamma = 0$, then perceived need N^*_i reduces to be the same as the patient's true medical need N_i). Second, as strain increases, the weight assigned to the patient's racial identity – discrimination –increases. This is consistent with studies showing increases in physician implicit biases under stress (Johnson et al., 2016). However, if discrimination does not increase with strain, then there may be two alternative states of the world: (i) there is no discrimination, and racial identity does not get any weighting in the allocation decision outside of patient need, and if so the function can be assumed to be $\phi(.) = 0$ such that the weight assigned to racial identity in the allocation decision collapses to be 0; or (ii) there is a fixed level of discrimination that is unrelated to strain at time t, and if so the function can be assumed to be $\phi(.) = 1$ such that the weight assigned to racial identity in the allocation decision collapses to be 1.

Each of these hypotheses can be modelled as being unrelated to the other OR as compounding the effect of the other. If unrelated, there may be either increasing discrimination with strain but not at the expense of appropriate assessment of patient need (second prediction true but not the first), or

[6] The potential for pervasive discrimination in care parallels the model proposed by Balsa and McGuire (2003), where treatment decisions are based on clinical need but may be influenced by patient race, either by altering the threshold of clinical need for treatment (prejudice) or by impacting the clarity of providers' assessments of medical need (statistical discrimination). Our framework builds on this insight by allowing the discrimination term to become stronger under stressful conditions.

providers may get worse at differentiating between high and low need patients with strain, but in a way that is unrelated to race (first prediction true but not the second). If compounding, there may be an interaction between the two predictions; that is, provider teams may get worse at assessing the need for Black patients, but their assessments for White patients are unaffected.

Consistent with this conceptual framework, we first provide evidence of the fact that the patient's health outcome Y_{it} – here, measured using in-hospital mortality – does indeed vary jointly by the level of hospital strain ($S(t)$) at time of patient's arrival to the hospital and patient race (R_i). We then show that as strain increases: (i) patient race both increasingly determines resource allocation A_{ijt} in the hospital (using wait times as our primary measure, but also using features of the *Reason for Admission* text field as a measure of provider effort), and that (ii) medical need (measured using comorbidities and vitals) becomes less predictive of resource allocation as strain increases.

3 Setting and Data

3.1 Setting

We used comprehensive electronic health record data from 107,221 patient admissions between 2015 and 2018 at two hospitals in a well-respected academic hospital system. This system is located in a Southeastern U.S. city known for its sizable Black population. Both hospitals within the health system are large, busy teaching hospitals with over 500 beds. They offer medical, surgical, intensive care, and obstetric services, and serve as level I trauma centers. One of the hospitals is highly-ranked nationally in multiple specialty services. This setting is typical for where Black patients receive health care, as large teaching hospitals are disproportionately represented among hospitals that care for Black patients (Burke et al., 2017; Himmelstein, Ceasar, & Himmelstein, 2023).

A key advantage of our data is that it provides a rich set of information at a level of detail generally not available to researchers. For example, the data contain time-stamps (up to the second) documenting the patient's entire journey through each hospital wing from arrival to discharge, a comprehensive list of patient diagnoses and procedures, vital signs on admission, discharge disposition, patient sociodemographics characteristics, physician of record identifiers, and text from a provider-inputted field documenting the reason for admission.

3.2 Measures

A description of key variables used in our analysis (with reference to how they relate to our conceptual framework) is as follows:

Patient race (R_i): We focus our analysis on non-Hispanic Black (hereafter, "Black") and non-Hispanic White ("White") patients; our sample includes all admissions of patients in these racial categories.[7] Like in most medical settings, race is either self-reported by the patient or recorded by staff; our data, like most electronic health record data, do not distinguish between these different types of reporting. While errors in race attribution are possible, they are relatively infrequent (Agawu et al., 2023; Cook, 2006).

Hospital capacity strain (S_{ht}): We measure hospital based on the total number of patients occupying an inpatient bed in hospital (h) during the hour of the patient's arrival at the hospital (t). We explicitly chose this capacity-based measure given evidence from the clinical literature of its strength in predicting health outcomes (Kohn et al., 2019). We first calculated strain at every hour of every day in our sample separately for each hospital, based on which we then generated hospital-specific deciles of capacity strain (which allows the effect of strain on outcomes to be nonlinear). We calculated capacity strain deciles separately for each hospital to create equivalent levels of strain; i.e., even though number of filled beds may vary at each decile, the top deciles of strain in each of the two hospitals equivalently identify hospitals that are close to capacity. The mean proportion of inpatient beds filled in the first decile of strain in both hospitals ranged from 69-78%; at the tenth decile the mean range of filled beds was 91-95% (Table A.1). Importantly, we calculate hospital strain at time of patient *arrival* – not *admission* – to the hospital, as time of admission to the ward is endogenous (as we show in our analysis), but the time of patient arrival to the hospital is plausibly less so (as we discuss in Section 4.2).

Patient medical need (N_i): A patient's medical need is measured in two ways: using chronic, and acute factors. The chronic measure of need is based on the patients' comorbid medical conditions while the acute measure is captured by vital signs on arrival to the hospital. Both measures identify medical need on average (instead of with certainty for any given patient), leaving room for physician discretion in allocating care resources. For example, patients with multiple medical comorbidities and patients with abnormal vitals both have higher likelihood of dying in the hospital, but whether they do so is a complex function of many different factors that are generally unobservable to researchers and healthcare providers.

(i) *Chronic measure*: The Elixhauser mortality index is one of the most widely used and heavily validated scores for predicting in-hospital mortality in public health and medical research (Elixhauser

[7] Sample sizes for admissions of patients in other race and ethnicity groups were at least two orders of magnitude smaller.

et al., 1998; Fortin et al., 2017; Moore et al., 2017).[8]. The Elixhauser Mortality Index holds a predictive ability (area under the curve or AUC) of 0.92 (Gundtoft et al., 2021) and has been used to refine neural networks for predicting in-hospital mortality in Medicare data (Liu et al., 2023).[9]

These Elixhauser index values for individual patients were not necessarily available to members of the care team, though they may have been aware of at least some patient comorbidities. We use information from a given patient's current and past medical records to calculate them. While the provider can observe the diagnoses codes for these comorbidities for each patient (though not all of them are immediately salient in the medical record and may be easily missed), the physician cannot predict how they individually and jointly may predict a patient's likelihood of in-hospital mortality. For our measure of *chronic* medical need, we split Elixhauser Index scores at the median, such that above median values signify (relatively) sick patients, and below median signify (relatively) healthy patients.[10]

(ii) *Acute measure*: We use the patient's first recorded vital signs in the hospital encounter – specifically, temperature, diastolic and systolic blood pressure, respiratory rate, heart rate, and oxygen saturation – to capture *acute* medical need. We construct a binary measure to indicate "abnormal vitals" equal to 1 if a patient has any one of the following : (i) body temperature above 37.8 C (100 F) or below 35 C (95 F) ; (ii) diastolic blood pressure less than 60 or systolic blood pressure less than 90; (iii) respiratory rate less than 12 or above 20; (iv) heart rate less than 60 or above 100; and (v) oxygen saturation less than 90. The thresholds denoting abnormal vitals reflect common criteria used by clinicians.[11]

It is important to note that patients' clinical need at the time of their hospital arrival is often assessed noisily. Patient mortality is difficult to predict even with state-of-the-art machine learning models (Einav et al., 2018), so it is easy to imagine that, as hospital capacity gets overwhelmed, that a patient's true clinical need becomes even harder to assess. While the measures we use in this paper capture fewer dimensions of medical need than are usually available to providers (e.g., we do not have results of lab or imaging tests), we can still assess whether our measures are predictive of mortality in

[8]In our data, it is a discrete variable ranging in our data from -7 to 87 (mean= 12.58; SD= 13.3; median= 11), which is a weighted combination of 30 different chronic conditions, i.e., acquired immune deficiency syndrome, alcohol abuse, deficiency anemia, rheumatoid arthritis/collagen vascular diseases, chronic blood loss anemia, congestive heart failure, chronic pulmonary disease, coagulopathy, depression, diabetes (uncomplicated), diabetes with chronic complications, drug abuse, hypertension (combined uncomplicated and complicated), hypothyroidism, liver disease, lymphoma, fluid and electrolyte disorders, metastatic cancer, other neurological disorders, obesity, paralysis, peripheral vascular disorders, psychoses, pulmonary circulation disorders, renal failure, solid tumor without metastasis, peptic ulcer disease excluding bleeding, valvular disease, and weight loss.

[9]The predictive accuracy of the Elixhauser is higher than that of the the Charleson Score, another weighted index of comorbid conditions that is widely used in health economics research (Sharma et al., 2021)

[10]Importantly, we show that higher Elixhauser scores predict higher mortality risk for both Black and White patients, countering concerns of racial disparities in the accuracy of such measures (Table A.2).

[11]Similar to Elixhauser scores, we show that our measure of vital sign abnormalities predict mortality risk for both Black and White patients, countering concerns that some methods to measure vitals may be inaccurate in Black patients (Bhavani et al., 2022; Fawzy et al., 2022).

the hospital (we find that they are), and whether racial differences in likelihood of death by patient medical need emerge as strain increases (we find that they do).

Patient health outcome (Y_i): We focus on in-hospital mortality – defined as death occurring anytime after arrival to the hospital but prior to hospital discharge – as our health outcome,given that it is an extreme potential consequence of health care resource misallocation decisions as well as due to its wide use as a quality measure (Jha et al., 2007). (Moreover, it has a high correlation with alternate quality measures, such as 30-day mortality)[12] (Borzecki et al., 2010).

Allocation of care resources - rationing (A_{ijt}): We present the rationale for which resource allocation decisions we focus on and their measurement in greater detail in Section 5. To briefly summarize here, our primary measure of care rationing is the time a patient waits to receive an inpatient bed, which is motivated by large literature documenting wait times as a key margin of rationing care and periods of capacity strain as a driver of wait times. In analyses we consider more suggestive, we also examine measures of provider effort. Effort is not directly measured in electronic health record data, and so we analyze features of the provider-inputted free-text entry field documenting the reason for admission that have been shown to reflect effort in a range of settings.

3.3 Descriptive Statistics

Patient characteristics, stratified by patient race, are provided in Table 1. Black patients accounted for 60% of admissions to the two study hospitals, consistent with the city's predominantly Black population. Compared to Whites, Black patients were on average younger (52 vs 59 years) and more likely to be female (65% vs. 50%).

Despite these demographic differences, Black patients had similar comorbidity burdens, as denoted by the number of recorded comorbidities and Elixhauser mortality and readmission scores (which we describe below in this section), and similar in-hospital death rates (about 2% of patient admissions in both cases). We also note that Black patients receive fewer resources on average: they wait over 2 hours longer on average for an inpatient hospital bed, they have slightly lower length of inpatient stays, and 27% less likely to be admitted to the ICU.

4 In-Hospital Mortality

In this section, we examine whether patient health – here, in-hospital mortality – worsens under capacity strain in a race-dependent manner. We discuss our research design, clarify our identifying

[12]While 30-day mortality would also have been a useful outcome to examine, we did not have access to this measure in our data.

assumptions, and provide evidence that these assumptions are likely to hold. We then show that health outcomes worsen for Black – but not White – patients as hospitals reach capacity and resources become increasingly scarce, consistent with our hypothesis of race-based rationing of resources under such conditions. The subsequent Section 5 examines race-based care allocation more directly.

4.1 Research Design

Our core specification, which estimates the differences in the likelihoods of in-hospital mortality between Black and White patients at each decile of hospital strain, is as follows:

$$\begin{aligned} Y_{iht} = \zeta \cdot R_i + \sum_{p=2}^{10} \alpha_p \cdot 1\big[S_{ht} = p\big] + \sum_{p=2}^{10} \beta_p \cdot \Big(R_i \times 1\big[S_{ht} = p\big]\Big) \\ + X_i + \delta_j + \pi_{ht} + \varepsilon_{iht} \end{aligned} \tag{5}$$

Specifically, we regress in-hospital mortality for each admission i on patient race ($R_i = 1$ if patient is Black), decile of hospital strain (S_{ht}) at the hour of arrival to the hospital, and the full series of interactions between patient race and deciles of hospital strain. The coefficients on the interactions between patient race and hospital strain (β_p) are of specific interest, as they recover how the likelihood of in-hospital mortality varies by race across different levels of capacity strain.

We include in our models a vector of patient-level characteristics (X_i) including age and second order polynomial for age; sex; whether or not the patient was insured; and fixed effects for the number of Elixhauser comorbidities; the Elixhauser mortality index scores; and the Elixhauser readmission index scores. In a robustness check, we also include each of the five abnormal vitals as covariates in a secondary specification.[13]

We also include hospital-year, hospital-month of year, hospital day-of-week, and hospital hour-of-day fixed effects (π_{ht}), and physician of record fixed effects (δ_j). The inclusion of hospital day of week and hour of day fixed effects account for typical patient flows over these dimensions, ensuring that our measure of capacity strain is net of these potentially expected averages and therefore less likely to be anticipated (an assumption we will further discuss below). In robustness checks, we demonstrate that incorporating these fixed effects does not alter our estimates. This indicates that, even if some anticipation of strain is possible, it does not necessarily mean effective management of the strain nor the mitigation of its adverse impacts on care processes and patient outcomes. We also use physician of record fixed effects to adjust for specific service lines represented in our sample of admissions (e.g., surgery, internal medicine, labor and delivery) and, to the extent that the physician of

[13]We do not use them for our main specification as for about 6,000 patients from our sample, none of the five vitals are recorded.

record participated in the entire care episode, fixed physician-specific differences in practice patterns.

We thereafter examine how mortality varies not just by patient race and hospital strain, but also by patient need (N_i). As described in the previous section, we use two binary measures, one capturing chronic needs (median-split Elixhauser mortality index scores) and another capturing acute needs (any abnormal vitals using six different measures of vitals). We re-run Equation 5 now with a fully-saturated triple interaction (the "×" term signifies the estimation of all direct effects, as well as double and triple interaction interaction terms):

$$\begin{aligned} Y_{iht} = R_i \times \sum_{p=2}^{10} \cdot \big[S_{ht} = p\big] \times N_i \\ + X_i + \delta_j + \pi_{ht} + \varepsilon_{iht} \end{aligned} \tag{6}$$

4.2 Identifying Assumptions and Balance Tests

Our core identifying assumption is that hospital-wide strain at the hour of patient arrival is as-if random, i.e., strain is conditionally independent of factors correlated with patient need and patient race. This assumption may be violated in the direction of our hypothesis if, for example, Black patients who arrive at times of high hospital strain have greater likelihood of death than White patients who arrive at high strain.

This assumption (and the identification strategy based on this assumption) is commonly invoked in the literature that studies the causal effect of hospital or ward capacity strain on a variety of clinical and operational outcomes (Freedman, 2016; Hoe, 2022; KC & Terwiesch, 2012; Kim et al., 2014; Song et al., 2020). Its validity is supported by the clinical literature, which shows that periods of capacity strain are difficult to anticipate ex ante even at the day to day level, let alone by the hour. For example, a recent qualitative analysis of hospital leaders at 13 U.S. academic medical centers – a setting that is similar to ours – concluded that "hospital capacity strain is complex and difficult to predict" (Arogyaswamy et al., 2021). In our case, this contention is further bolstered by the fact that our empirical models account for month of day, day of week, and hour of day, such that residual variation in strain is by definition of the type that cannot be predicted by typical hospital operational patterns.

Even if capacity strain is difficult to predict, once it materializes hospitals may selectively divert or admit patients on the basis of key medical characteristics. Alternatively, patients and ambulances may choose to obtain care at less strained hospitals. For these processes to bias our findings, any strain-related selection on the basis of patient characteristics would have to differ by race. At the provider level, such coordinated processes to divert specific types of patients are less likely to occur on an hour to hour basis, given known difficulties in responding to capacity strain in real time (Arogyaswamy et al., 2021). In addition, studies examining racial differences in patient arrival to hospitals find that Black patients with acute, life threatening health conditions may be more likely to be diverted to other hospitals during periods of high strain (Hsia, Sarkar, & Shen, 2017), which would imply that Black patients who show up to the hospitals in our data at high strain are less sick than White patients, which in turn would bias estimates of strain-related racial disparities in hospital mortality against our hypothesis. It is also important to note that we compute hospital strain at time of patient's arrival to the hospital, not time of hospital admission, which further bolsters our identification assumption. While time of patient admission to an inpatient hospital bed may be sensitive to hospital capacity at that time (and would thus make our measure of hospital capacity at time of admission endogenous), the time at which the patient walks through the doors and is registered into the hospital system is plausibly random.

Even with theoretical support of our causal identification assumption in the literature, we empirically assess for violations of this assumption in our sample, and show in several ways that hospital capacity strain is not associated with changes in the composition of admitted patients in ways that vary by patient race. First, we show that distribution of Black and White patients is nearly identical in terms of hour of arrival to the hospital as well as average hospital strain at the time of arrival (Figure A.1). Thus, the racial distribution of patients upon hospital arrival does not vary either by time of arrival, nor by capacity strain at time of arrival.

Second, while our data does not include information on patients who were not admitted to the hospital (e.g., patients diverted to other hospitals by ambulances, or patients who arrived to the emergency room but were not admitted to the hospital), we are able to perform several checks to test for differential patient selection by race across varying levels of strain by regressing the characteristics of patients who were admitted on the main treatment terms, (race, strain deciles, and interactions between the two, adjusting for all other covariates). We do this in two ways. We run regressions using *observed* patient characteristics as outcomes, such as exogenously observed covariate such as age, sex, and insurance status, as well as the entire range of chronic measures of clinical need (Elixhauser comorbidities, mortality index scores, and readmission index score) and acute measures of clinical need (five abnormal vitals). Results in Tables A.3 Cols 2 - 7 and A.4 Cols 1 - 5 show that Black patients admitted to the hospital with increasing strain are not systematically and significantly different from White patients on these observed patient characteristics. We also run regressions using *estimated* patient characteristics as outcomes, such as the five primary themes identified from the *Reason for Admission* variable using a machine learning technique called Latent Direchlet Allocation (Blei, Ng,

& Jordan, 2003) (LDA) (See Appendix A for details). The *Reason for Admission* field is typically recorded manually by healthcare providers as soon as a patient arrives at the hospital as part of the triage process. Word clouds (Figures A.4 and A.5) and formal analyses on the five topics identified by the LDA (Figure A.6, Table A.5) demonstrate that the composition of admitted Black and White patients changes similarly with increasing strain.

Third, we examine an alternate form of selection, which is selective discharge of patients to hospice care as hospitals reach capacity. We do so given the known higher rates of hospice referral for White compared to Black patients (Asch et al., 2021; Cohen et al., 1994), which may lead to estimates of racial disparities in in-hospital mortality to be overstated. We find no evidence of selective discharge, with point estimates biasing in the opposite direction of our hypothesis (Table A.6 Col 8).

Collectively, these analyses support our literature-based contention and qualitative reports of hospital administrators (Arogyaswamy et al., 2021) that suggest that differential patient selection is unlikely confounding our main empirical model.

4.3 Results

Estimates from Equation 1 are plotted in Figure I, and also presented in tabular form in Table 2 Col 1. Figure I (a) presents the interaction coefficient – i.e., the joint effect of race and strain on mortality relative to the first decile – for each decile of strain. Figure I (b) presents the predictive margins of in-hospital mortality (or, in other words, the fitted values at the means of all other variables) by race and strain decile.

The results show that at higher levels of capacity strain, mortality for Black patients not only rises, but also diverges sharply from that of White patients. While the difference is sharpest at decile 10, the differences start emerging around decile 7. At decile 10, mortality for Black patients is 0.7 pp higher than White mortality (47.6% higher than the 1.47% mortality rate for White patients at the same decile). However, the difference-in-difference estimate is more informative about the relative change in mortality between the races across strain. 15% of Black patients who died at "high strain" (i.e., decile 10) would not have died if Black patients had the same strain-mortality relationship as White patients[14] (coefficient on the difference-in-difference estimate after pooling all observations across deciles 1 - 9 into "low strain": 0.0052, p = 0.025). In contrast, we see no changes in likelihood of death at the highest strain level for White patients. For deciles 7-9, we find increases in the relative likelihood of death between Black and White patients, which appear to be driven in part by a small decrease in mortality for White patients.[15] We speculate on why these decreases, which persist in sign

[14] This estimate is 17% if we consider deciles 7 through 10 as high strain.

[15] Mortality for White patients decreases by 0.2 pp from lower strain levels (decile 1 - 5) to higher strain levels (deciles 6-10).

but not statistical significance across specifications, may occur in Section 5.3.2.

We next present results from Equation 6 – which disaggregates mortality by patient medical need – in both figure and tabular form using the chronic measure of patient need (Figure II and Table A.7 Col 1), as well as the acute measure of patient need (Figure A.2 and Table A.8 Col 1). The chronic measure of patient need appears to be more predictive of patient mortality than the acute measure (i.e., the difference in mortality between high-need and low-need patients is greater when need is measured using Elixhauser scores than vitals), suggesting that the chronic measures allows a stronger and more precise test of heterogeneities by patient need. This is likely because abnormal vitals identify a patient population at only moderate risk of death (e.g., a temperate of 100F at time of hospital arrival is a suggestive but not a strong signal of severity) while the Elixhauser mortality index has been created and validated specifically for predicting mortality while also capturing the patient's prior medical history in a way that vitals cannot. Thus, we focus on explaining results using the chronic measure of need in this section, but note that both sets of patient need measures reveal similar results.

Figure II (a) plots the coefficient on the triple interaction from Equation 6; Panel (b) plots the double interaction coefficient terms (Race × Strain) for the below- and above- median mortality index scores; and Panel (c) plots the predictive margins (i.e., fitted values) of in-hospital mortality by race, strain, and patient need (at the means of all other covariates).

We note three patterns of interest: (i) Panel (c) shows that high-need patients have significantly higher mortality than low-need patients at all levels of hospital strain (which reassuringly validates our measure of patient need); (ii) Panel (b) confirms that high-need patients are driving the racial difference in mortality described in the previous section, mirroring the pattern observed in Figure I (a); and (iii) Panel (c) shows that high-need Black patients experience a sharp increase in mortality at decile 10, again mirroring the mortality results shown in the Figure I (b). Overall, these findings clarify that the overall relationship between in-hospital mortality and capacity strain for Black patients is driven by the *ex ante* sick (or high-need) Black patients. The results are qualitatively similar when using acute measures of patient need (with the only difference being that the coefficient on the triple interaction is not statistically significant as it is with the chronic measure of patient need, but it is similarly signed; compare Figures II and A.2). This is consistent with point-in-time acute measures such as vitals being noisier measures of acute patient need than the Elixhauser indices are of chronic medical need.

4.4 Additional Robustness Checks

Our core findings are robust to specification. In Table 2, we present coefficient estimates from a range of different specifications. To make sure our results are not driven by the choice of covariates, we present estimates from more parsimonious versions of this model using both logistic and linear probability models (including only patient age, gender, and hospital and year fixed effects) (Col 2 and 3), as well as more saturated models (e.g., additionally including diagnosis related-group (DRG) fixed-effects to ensure comparisons within a specific health condition (Col 4). and interacting patient race with all the control variables in X_i, Col 6). The more parsimonious models help address potential biases in ordinary least squares models when treatment effects are heterogeneous across groups (Słoczyński, 2022), while the more saturated models help address potential omitted variable bias in interacted models (Feigenberg, Ost, & Qureshi, 2023). We find that the results are substantively unchanged across different specifications (Cols 2 - 6).

Additionally, to address concerns that adjustment using weighted, summative indices of comorbidities may be more prone to bias than adjusting for the individual components that make up these indices (Möller, Bliddal, & Rubin, 2021), we estimate models in which we included each of the 31 comborbidities that comprise the Elixhauser indices as covariates. In this case, as well, we find no substantive differences in our estimates (Col 7).

Finally, we include each of the five abnormal vitals as covariates (Table A.4 Col 6) and find that our main results are entirely unchanged.

5 Rationing by Race as a Mechanism

In the previous section, we showed that Black patients – but not White patients – experienced higher likelihoods of in-hospital mortality with increasing capacity strain. In this section, we provide evidence for discriminatory rationing of scarce resources as the key mechanism behind the observed mortality patterns. We first discuss the two margins for rationing we will focus on in this section (and how we measure these constructs in our data): (i) wait times for inpatient beds, and more speculatively, (ii) provider effort. We then provide evidence for racial disparities in the allocation of these two resources, noting that these disparities exist at all levels of hospital strain, but worsen markedly as strain increases. Finally, we link these findings back to our conceptual framework by providing evidence that, as hospital capacity strain increases, not only does racial identity play an increasingly greater role in allocation mechanisms, but patient medical need plays an increasingly smaller role as well. This finding underscores how, under increasing strain, providers may be unable to accurately assess patient medical needs, and may (implicitly or explicitly) resort to salient, yet inaccurate and bias-prone, heuristics for decision-making based on patient race.

5.1 Potential Margins of Rationing

Health care resources can be rationed on multiple margins. Our primary margin of interest is wait times. Barzel (1974) and Lindsay and Feigenbaum (1984) represent early theoretical contributions identifying wait times as a means to allocate scarce resources. Wait times (or wait lists) are widely used to allocate resources such as patient visits and surgeries in health care worldwide, with the idea being that patients with more acute needs receive care more promptly than those with less acute needs (Martin & Smith, 1999). In practice, however, wait times may not reflect patient acuity. Chan and Gruber (2020) demonstrate high rates of "inversions", where sicker patients wait longer than less-sick patients for emergency care. In addition, Black patients may wait longer for care than White patients (Lu, Hanchate, & Paasche-Orlow, 2021), a finding that holds for other non-healthcare public services as well (Chen et al., 2022; Holt & Vinopal, 2023). Further motivating our analysis of wait times is the fact that hospital capacity strain has been linked to longer wait times in a range of clinical settings (Janke, Melnick, & Venkatesh, 2022a, 2022b; Kohn et al., 2019).

We also examine potential rationing of provider effort, though – given that this construct cannot be directly measured – we view these analyses as more suggestive. Under personnel or resource constraints, providers (e.g., physicians, nurses) may ration effort towards sicker, higher risk patients. However, as with wait times, there may be sub-optimal rationing of effort by need. For example, physicians may systematically misjudge need (Mullainathan & Obermeyer, 2022) or shift their effort in response to incentives that are uncorrelated with patient need (Chan, 2016, 2018). Providers may also hold pre-existing systematic biases, which, under stressors, may manifest into lower intensities of effort for Black patients (Burgess et al., 2007; Burgess et al., 2006). The potential for this bias is highlighted by audit studies of treatment decisions (Schulman et al., 1999), patient perspectives (Brown et al., 2023), and analysis of physician implicit attitudes, which become more biased against Black patients under capacity strain (Johnson et al., 2016). Biased provider effort may also be driven by systemic factors, such as algorithms that underpredict patient needs for racial and ethnic minority groups (Obermeyer et al., 2019).

In addition to these margins, we also investigate rationing by other dimensions of care quality/intensity: (i) ICU admission; (ii) ICU length of stay; (iii) Length of inpatient stay; and (iv) Inpatient charges. For these additional measures, because lower or higher values may both reflect inappropriate care (resulting from poor triage, longer wait times, or inadequate attention or effort

(Mullainathan & Obermeyer, 2022)) and lead to harm (Brownlee et al., 2017), estimates on these measures will be harder to interpret. We thus view them as less informative to our study question.

5.2 Measures

Wait times: For our primary rationing decision of interest, our measure of wait times follows from our unique time stamped data: the exact time (with precision in seconds) elapsed between patient arrival to hospital (either through the ED or Main Registration) and placement in an inpatient (ward) bed.[16]

Provider effort: Unlike wait times, provider effort is not directly measured in standard clinical data. While proxies can be found for specific types of clinical encounters (Chan, 2018), effort is difficult to capture when looking at the entire course of a hospitalization and in contexts like ours where patients come in with many different health conditions and care needs.

To get around these challenges, we turn to analysis of medical documentation. Specifically, we focus on *Reason for Admission*, a text field that is filled out at the time of hospital arrival (typically as a triage step) by a physician or nurse. Documentation in this field is consequential, as elicited reason for admission helps set the initial course of health services and care provided, including in ways that match care patterns by patient race (Ly, Shekelle, & Song, 2023; Schrader & Lewis, 2013).

We infer effort (at least from the provider who documents the reason for admission) by analyzing features of the documented text.[17] We begin by examining several descriptive features of this text field: (i) time to completion: the time elapsed from patient arrival to the hospital to the time when the note was completed and finalized in the EMR[18], (ii) character count: a binary measure split at the median of number of characters used in the field[19]; and (iii) average word length: total character count divided by number of words. These measures have been shown to be strongly correlated with effort outside of health care (Galesic & Bosnjak, 2009; Tausczik & Pennebaker, 2010; Yadav, Prabhu, & Chandy, 2007), and have the attractive feature of requiring making minimal assumptions (Quinn et al., 2010), which is relevant in our context given the vast number of decisions that could be made across the diverse range of patients in our data. In general, shorter time to document completion,

[16] We note that we can only compute arrival time for 86% of our main sample (though re-running Equation 5 on this sub-sample with mortality as the outcome does not change our main result (Table A.6 Col 2); if anything, the joint effect of race and strain on mortality is slightly larger, suggesting that wait times are an appropriate allocation decisions to be focusing on).

[17] Similar to wait times, a minority (28%) our main sample has an empty *Reason for Admission* field. Re-running Equation 5 on this subsample with mortality as the outcome does not change our main result either (Table A.9 Col 1).

[18] Ideally, we would like to measure the actual time the provider spent documenting this note but we cannot see when the note was started. However, using the time of completion of the note, we can document the *maximum* time the provider could have possibly spent documenting the note. For example, imagine that the hospital is at strain decile 10 and the value of this variable for a patient is 30 hours. It is unlikely that the physician spent 30 hours documenting the note. Instead, the provider may have started the note when the patient came in, but because they were busy, filled the note partially over multiple sessions until they finally completed it after 30 hours. Alternatively, the provider could have begun filling it at 29.5 hours after the patient's arrival, and finished it in a single session of 0.5 hrs. We are interested in both types of documentation, and whether they vary by patient race and hospital strain.

[19] We use a median split of the character count because the variable is so skewed: amongst non-missing text data, the skew is 4.5. The skew of the average word length for comparison is 1.6.

lower character counts, and shorter word lengths are associated with lower levels of effort. We would expect this to also hold in health care, with additional nuances that reflects the nature of hospital care work flows. Specifically, providers face competing demands, especially under capacity strain. When faced with a large number of patients – as would occur when hospitals become strained – providers will defer documentation tasks to prioritize clinical tasks such as obtaining a history from patients, conducting physical exams, ordering tests and interpreting the result data, and coordinating tasks with other members of the care team (Rotenstein et al., 2021). In this environment, we would expect providers to take longer to complete their documentation (i.e., complete them after immediate care tasks are finished), which we would interpret as greater attention and effort to patient care (Apathy et al., 2023; Tai-Seale et al., 2017). Deferral of documentation to after-hour periods or when care task burden has waned would also allow for lengthier, more complete notes, which inform the care patterns of subsequent providers.

In addition to these descriptive features of notes, we also perform sentiment analysis using the TextBlob library (a Python-based natural language processing tool grounded in the lexicon of commonly occurring words) to calculate the (i) subjectivity and (ii) polarity of text. Details of methods are provided in Appendix B. Subjectivity refers to the degree of personal opinion vs factual information encoded in text. Fully objective (factual) documentation would receive a score of zero whereas fully personal views or subjective information would receive a score of 1.[20] More subjective notes allow room for implicit bias or negative descriptors in documentation, and may lack the precision and clarity necessary to make an accurate diagnosis, in ways that may lead to less care for Black patients (Bloche, 2001; Schrader & Lewis, 2013). Polarity refers to the emotional leaning of the text, i.e., whether there is an opinion expressed in the text or not and whether the opinion is negative or positive. Polarity scores range from -1 to 1 (with -1, 0, and 1 representing negative, neutral, and positive text).[21] The potential importance of polarity comes from evidence of providers being more likely to use negative descriptors with Black patients (Sun et al., 2022) and that doing so may lead to reduced effort (Goddu et al., 2018).[22]

While sentiment analysis is increasingly being used in clinical applications, there are some concerns that standard tools to do so may not always be appropriate in clinical settings (Weissman et al., 2019). To this point, we make no strong inferences about what these scores mean by themselves. Rather, we are interested in how these scores *vary* by capacity strain and patient race, hypothesizing

[20] A statement such "Patient's X-ray shows inflammation" could receive a subjectivity score of zero. In contrast, a statement such as "I am deeply optimistic that this patient may survive" or "Patient describing unimaginable levels of pain" could receive a subjectivity score of 0.9.

[21] A statement such as "Patient received 5 mg of medication" could receive a polarity score of 0. A statement such as "concerning lack of progress in patient's recovery" could receive a polarity score of -0.5.

[22] Other work has shown that subjectivity and polarity in clinical notes can predict mortality (Waudby-Smith et al., 2018).

that under stress providers may be more likely to use more subjective and polarized terms for Black vs. White patients, consistent with an increased reliance on biased heuristics (Johnson et al., 2016). We also address this concern by analyzing a less "black box" measure, the number of adjectives as a measure of the descriptiveness and detail in notes. Here adjectives are identified using common suffixes.[23] We focus on adjectives in this analysis because adjectives provide nuance, context, and depth about the object of description (in this case, the patient), and more importantly, can express changes (for example, in the condition of a patient's illness) along a scalar dimension (Kennedy & Levin, 2008). That is, greater use of adjectives would be consistent with greater effort.

5.3 Results

5.3.1 Wait times

Results for wait times are shown in Figure III (a) (with coefficients provided in Table A.6 Col 3). Our estimates show that Black patients wait longer for an inpatient bed than White patients as strain increases. We see a clear bump in wait times at the top decile of hospital strain, matching exactly our findings in Figure I for in-hospital mortality.[24]

Disaggregating these patterns by measures of clinical need, we find that strain increases wait times for Black patients relative to White patients similarly amongst both high- and low-need patients, with non-significant but larger effects for high-need patients. We see this pattern whether we measure patient need using either the chronic measure of need (Elixhauser indices, Figure III (b) and Table A.7 Col 2) or the acute measure (abnormal vital signs, Figure A.3 (a) and Table A.8 Col 2). Given how much data is needed to precisely estimate triple interactions, this pattern – though not statistically significant – is suggestive of a potential mechanism for explaining the patterns observed in Figure II (i.e., the racial disparity that exacerbates with strain is larger for high-need vs. low-need patients).

Finally, it is worth considering in greater depths three patterns seen in Figure III (c). First, as one would expect, low-need patients wait longer for care than high-need patients at lower capacity levels, regardless of patient race. However, at higher capacity levels (deciles 8 - 10), this gap almost fully vanishes, suggesting that at higher levels of capacity strain , resources are allocated less based on patient need than they are at lower capacity levels. This evidence is consistent with our conceptual framework which argues that, with increasing capacity strain, the provider's ability to accurately

[23] We use this method as opposed to relying on a part-of-speech tagger in TextBlob, which would perform poorly on medical text because it uses both definition and context in a sentence to identify adjectives and the *Reason for Admission* field does not always follow regular English grammatical and syntactical structure.

[24] Table A.6 Col 4 -7 shows how various other measures of care resources and intensity (ICU admission, ICU length of stay, inpatient length of stay, and inpatient charges) are allocated to Black v White patients across various capacity strain levels. It is clear that only the analysis of wait times (Cols 3) matches our mortality result (Cols 1 using the whole sample, and Col 2 using the sample for which wait times can be computed).

assess patient need when allocating care resources, decreases.

Second, the figure shows that Black patients wait longer for a bed than White patients at all capacity levels. In fact, the difference in wait times between Black and White patients is larger than the difference observed between high- and low- need patients, even though one could argue that medical need should (normatively) be more predictive of wait times than race (especially given that our measure of medical need is indeed predictive of mortality, as shown in Figure II (c)). Moreover, as strain increases, though the difference in wait times between high- and low-need patient disappears, it is this large difference in wait times between Black and White patients that persists. This finding, too, is concordant with our conceptual framework: with increasing strain, the patient's racial identity plays a larger role in allocation decisions of healthcare resources (while reliance on patient need as a guiding factor diminishes). This result should further quash lingering concerns about whether the observed differences in mortality at high strain are driven by unobserved (to the researcher) differences in medical need between Black and White patients: if Black patients are unobservably sicker than White patients, they should not wait longer for care as well.

The third – and perhaps most startling – pattern is that high-need Black patients (blue line) wait longer than low-need White patients (grey line) at all capacity levels, with this difference being the largest at higher strain levels. Given that this disparity exists even at decile 1, when resources are most abundant, it implies that wait time differences are not just due to logistical constraints, scarcity of resources, or poor management of patient flow. Instead, they likely reflect ingrained factors in healthcare protocols and decision-making, such as implicit or explicit biases, and/or racial disparities in the quality of available clinical information. These factors that are both independent of *and* exacerbated by capacity strain.

5.3.2 Provider effort

We first estimate how descriptive features of the *Reason for Admission* text field vary by patient race and hospital strain, adjusting for patient characteristics, hospital, and year. Results are presented in Figure IV and in tabular form in Table A.9. Consistent with providers deferring documentation for more pressing tasks, we find that the average time taken to complete and file documentation increases with strain for both Black and White patients. For example, the time for completion of this field for a Black patient increases from 0.18 days (4.3 hrs) at decile 1 to 0.93 days (22.3 hrs) at decile 10. As a result of these strain-related delays in documentations, they are able to complete longer, more detailed notes (as measured by character counts and average word length).[25]

[25] We also examined the likelihood of the *Reason for Admission* note being empty and find that this decreases with strain for all patients though it decreases to a significantly greater extent for White patients. Moreover, consistent with all other patterns

Importantly, these objective text characteristics vary by race. On every objective measure and across almost every decile of strain, Black patients are more likely to have shorter times to completing documentation, and documentation with fewer characters and shorter words. For some measures we see differential outcomes for Black patients relative to White patients with increasing strain, though these are only precisely estimated for time to documentation. Overall, the fact that notes for Black patients have some features that are correlated with less effort – namely, providers are less prone to deferring documentation tasks at times of strain (potentially at the expense of more important patient care tasks) and less likely to write detailed notes – is consistent with the wait times result presented in the prior section. These findings underscore that while strain may exacerbate racial disparities in care on many margins, there are – consistent with discrimination – baseline disparities that exist regardless of strain.

We now present results from our analyses of text sentiment, shown in Figure V Panels a - d and presented in tabular form in Table A.10 Cols 1 -2. Similar to our mortality and wait time findings, we find evidence of a bump in the subjectivity scores at the highest decile of strain (Panel a), implying at the notes describing Black patients' *Reason for Admission* become relatively more subjective as strain increases. This divergence of subjectivity scores is both driven by an increase in Black patients' note subjectivity and a decrease in White patient's note subjectivity with strain (Panel b), though Black patients' notes are always more subjective than White patients'. Again, we caution against over-interpreting these results, given that medical documentation may challenge standard tools for sentiment analyses. However, given how subjectivity may be detrimental to patient care, the fact that strain exacerbates subjectivity in notes in ways that mirror our mortality and wait time results, suggests that documentation of Black and White patients is changing with strain in a manner that may have prognostic value (and should motivate further research). Polarity scores, on the other hand, remain remarkably stable by race and strain (Panel c - d).

Finally, we find that adjective use – a proxy for effort given to capture detail and clinical context – also diverges by race and strain (ibid, Panel e - f). We find that as strain increases, Black patients receive fewer adjectives than Whites (Panel e), though this is largely driven by an increase in adjectives for White patients (Panel f). We can tie this result back to our analysis of the descriptive features of the text note: as strain increases, it appears that providers use more adjectives for White patients – while writing longer notes over longer documentation filing times – than they did at lower levels of strain. Conversely, Black patients; notes have fewer descriptors at all levels of strain.

Collectively, these patterns are consistent with a set of provider behavioral responses to capacity

of service documented within this paper, Black patients always (regardless of strain level) have higher likelihoods of missing documentation than Whites. (Figure A.7).

strain that may differ by patient race. Speculatively, these responses may reflect behaviors that go beyond simply deferring non-essential tasks such as documentation for more essential tasks during periods of strain. Recall in Figure I that we observe a small (though imprecise) decrease in White patient's mortality at higher levels of strain. In light of the results from analyzing the *Reason for Admission* note – which suggest that providers may exert greater effort to White patients (at least as revealed in documentation) as strain increases – it may be that providers anticipate a decrease in care quality at high strain, due to fewer resources. As a result, they may change their behavior to be more careful when hospitals are at greater capacity (than they are at low strain), by becoming more conscientious with note documentation (as can be observed by lower rates of missing documentation, higher character count, average word length, use of adjectives etc) and perhaps other care processes correlated with these measures. However, they engage in these protective compensatory behaviors at high strain far more for White patients than for Black patients, the effects of which may translate into better health outcomes for White patients. In short, providers may adjust their care patterns in anticipation for strain more for White than Black patients, which in itself can be considered to be a type of strain-induced rationing of resources. This interpretation of this result is however purely speculative, and thus warrants further investigation in future research.

6 Conclusion

Focusing on a high-stakes health care setting, our study provides evidence that, as resources becomes more scarce, discriminatory rationing results in worse health outcomes for Black patients compared to White patients. We first show that Black-White disparities in patient death – an extreme consequence of discriminatory rationing – markedly increase at the highest levels of hospital capacity strain. This pattern is driven by patients with the highest ex-ante medical need and cannot be explained by racial differences in the types of patients admitted or discharged at high levels of strain. We then provide evidence that they arise due to race-based rationing by waiting times and, more speculatively, provider effort (based on clinical documentation). Disparities in wait times and our measures of provider effort exist at all levels of strain, but become particularly large at the highest levels of strain.

Our research highlights the importance of tackling biases in how critical healthcare services are distributed. This could involve several strategies: increasing awareness among healthcare providers (Vela et al., 2022); creating and using new algorithms to help make better decisions about who receives care, especially for patients at high risk of death who might otherwise be overlooked (Chan & Gruber, 2020; Mullainathan & Obermeyer, 2022); correcting existing care algorithms that are biased (Obermeyer et al., 2021); development of provider peer networks to help reduce biased treatment decisions (Centola et al., 2021),; and supporting patients in advocating for themselves. These efforts are particularly crucial when hospitals are under strain and biases in providing care are more likely to increase. Our findings also illustrate the importance of developing and testing new interventions to ensuring high quality patient care during periods of capacity strain. The COVID-19 pandemic has spurred new approaches to predicting periods of high capacity (Weissman et al., 2020), which may help hospitals respond to strain in advance by increasing staffing or other measures. Creating *ex ante* networks and decision rules to promote load-shifting to other hospitals during periods of elevated strain can also help ensure that hospital resources for existing patients are not stretched beyond capacity (Boudourakis et al., 2020).

Our findings inform future work seeking to identify discrimination in health care and a variety of real world settings. Specifically, they demonstrate how systemic shocks – even those that are temporary (over hours or days) – can help uncover discrimination that otherwise is difficult to ascertain without external manipulation (such as in audit studies). In this sense, our research echoes the work by in health care by Gandhi (2020), who shows that dynamic changes in bed availability can help identify whether nursing homes cherry pick patients on the basis of their health insurance. Our approach and findings echo work from other contexts, documenting how adverse economic shocks led to increases in lynchings of Black individuals in the U.S. (Beck & Tolnay, 1990) and in civil conflict globally (Miguel, Satyanath, & Sergenti, 2004), as well as how improved economic prospects (either due to shocks to labor demand or policy-led increases in access to new markets) helped reduce inter-group inequality (Aizer et al., 2020; Black & Strahan, 2001). By leveraging such unexpected shocks, we can gain insights into the mechanisms of discrimination that are otherwise hidden by the routine operations of markets and institutions. This approach can complement newly-developed techniques in economics to identify hidden systemic discrimination (Bohren, Hull, & Imas, 2022).

Finally our approach illustrates how analysis of documentation and text holds the potential to help uncover subtle but consequential forms discrimination that may not be otherwise by apparent in typically analyzed statistics. Our findings connect to a growing literature has begun to utilize documentation for this purpose in health care (Goddu et al., 2018; Sun et al., 2022), as well as a nascent literature in economics (Adukia et al., 2023; Moreno-Medina et al., 2022).

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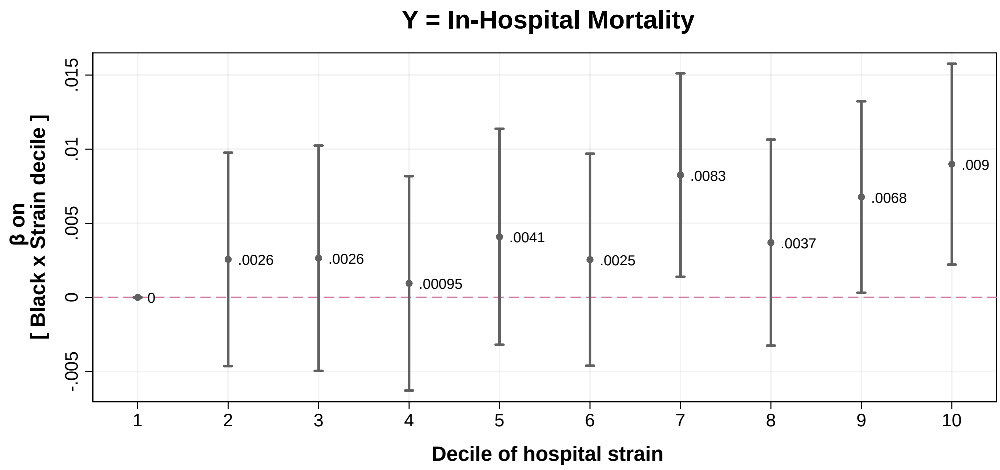
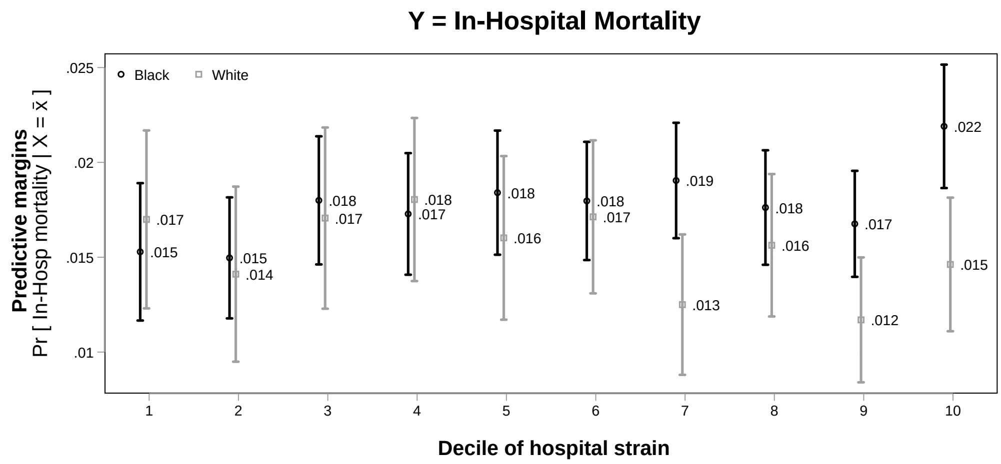


(a)



(b)

FIGURE I

Racial disparities in in-hospital mortality by hospital strain

Estimates from Equation 5 with in-hospital mortality as the outcome. Panel (a) plots the interaction coefficients (β) on patient race (=1 if Black) and decile of hospital strain at time of patient arrival. Panel (b) plots the predictive margins of in-hospital mortality for Black and White patients at each decile of hospital strain (at the means of all other covariates). 95% robust standard errors are presented. Estimates are also presented in tabular form in Table A.6 Col 1.

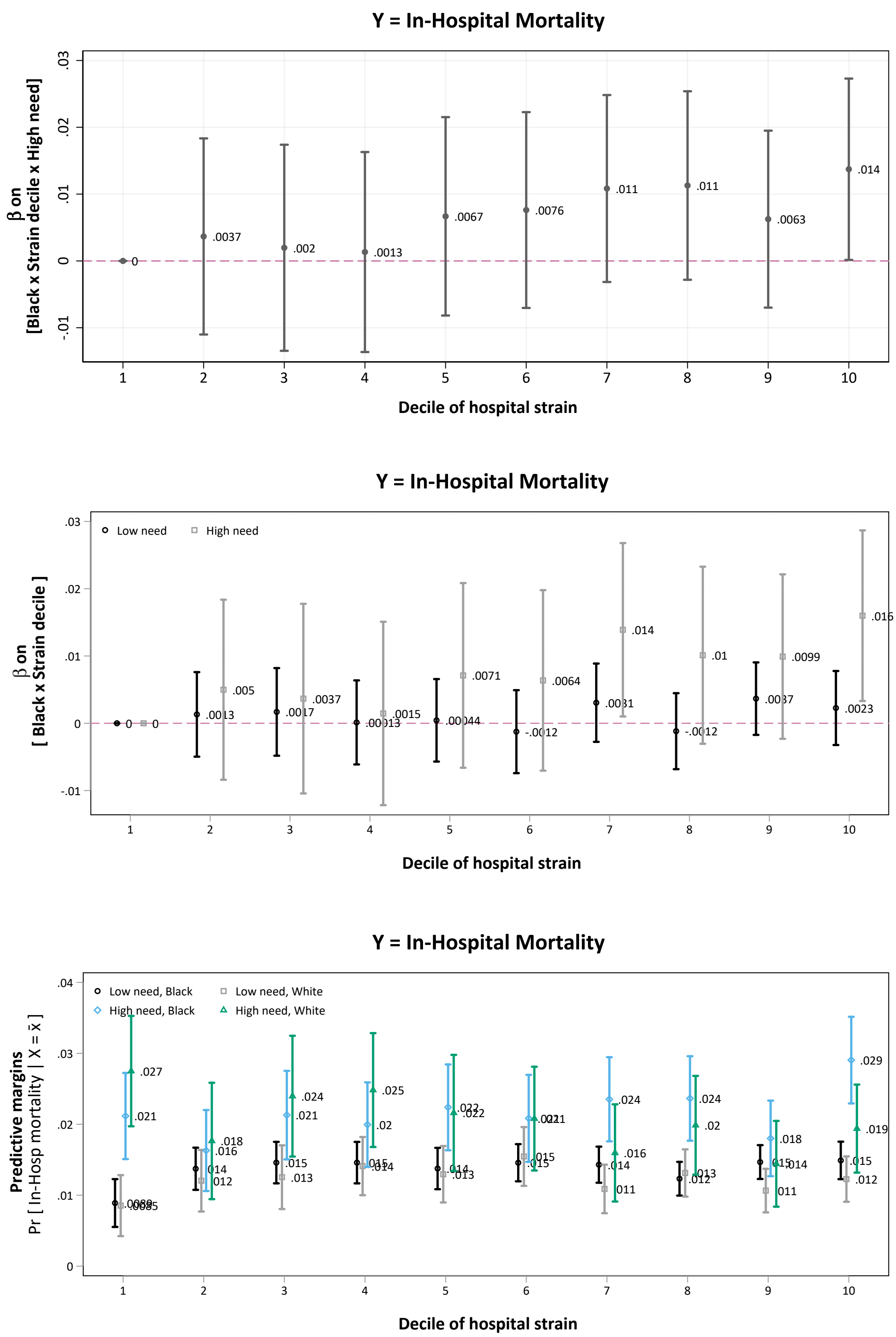


FIGURE II

Racial Disparities in Hospital Mortality by Strain and Medical Need (Chronic measure)

Estimates from Equation 6 with in-hospital mortality as the outcome and patient need (using the chronic measure, i.e., below- and above- median Elixhauser index scores signifying low- and high- need patients respectively). (a) plots the coefficient on the triple interaction (β) between patient race (=1 if Black), patient need, and decile of hospital strain at time of patient arrival. (b) plots the coefficient on the interaction between patient race and decile of hospital strain, separately for high- and low- need patients. (c) plots the predictive margins of in-hospital mortality by race and patient need at each decile of hospital strain (at the means of all other covariates). 95% robust standard errors are presented. Estimates also presented in tabular form in Table A.7 Col 1.

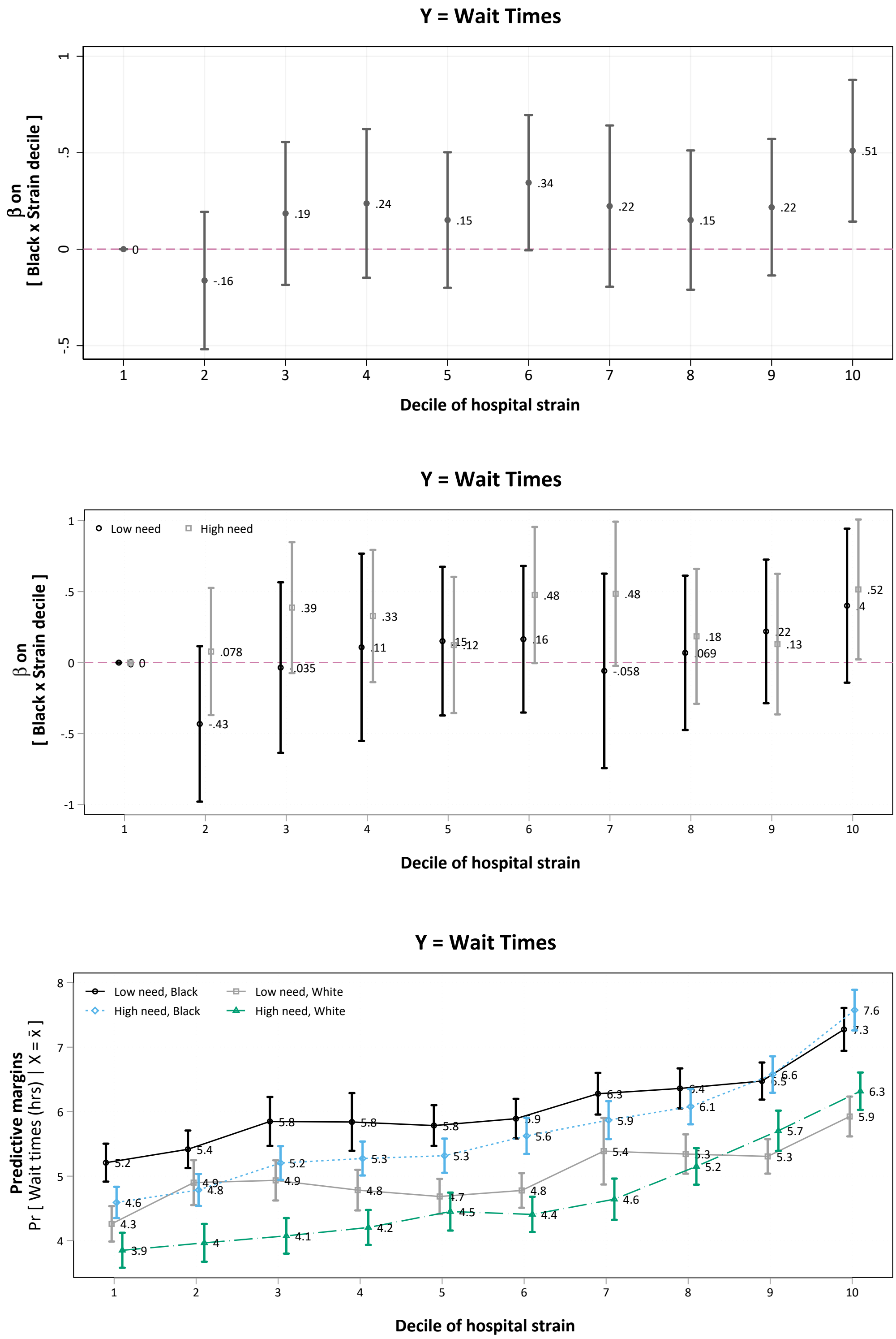
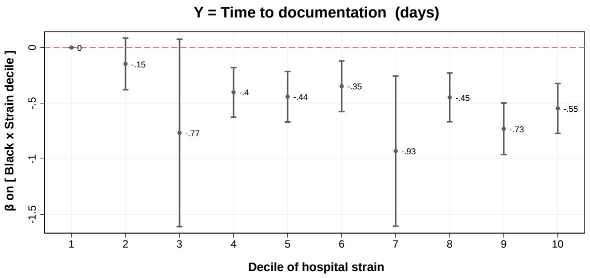


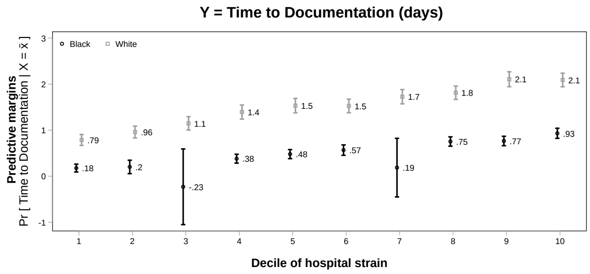
FIGURE III

Wait Times: Rationing by Race and Medical Need (chronic measure)

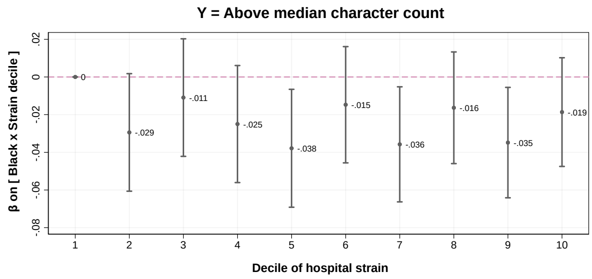
Estimates from Equation 5 in Panel (a) and from Equation 6 in Panels (b) - (c), with wait times as the outcome, and patient need measured using the chronic measure (i.e., below- and above- median Elixhauser index scores signifying low- and high- need patients respectively). Panel (a) plots the coefficients on the interaction (β) between patient race (=1 if Black) and decile of hospital strain at time of patient arrival. Panel (b) plots the coefficient on the interaction between patient race and decile of hospital strain, for high- and low- need patients. Panel (c) plots the predictive margins of wait times by race and patient need at each decile of hospital strain (at the means of all other covariates). 95% robust standard errors are presented. Estimates also presented in tabular form in Table A.7 Col 2.



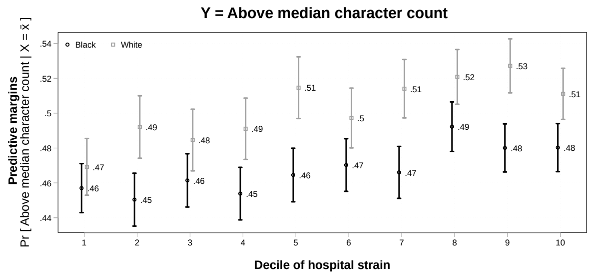
(a) Regression coefficients



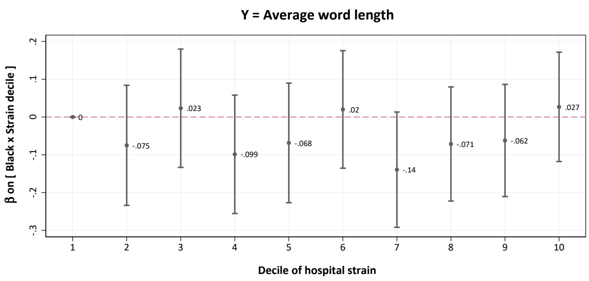
(b) Predictive margins



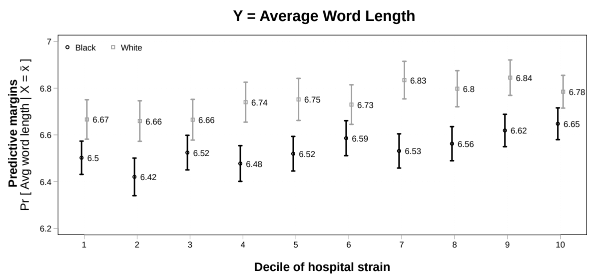
(c) Regression coefficients



(d) Predictive margins



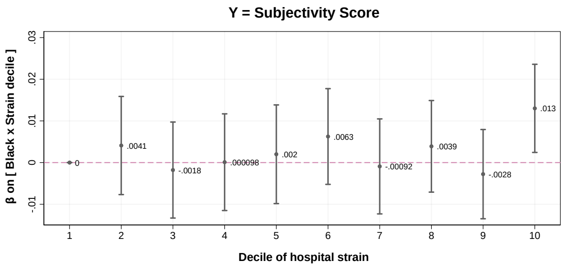
(e) Regression coefficients



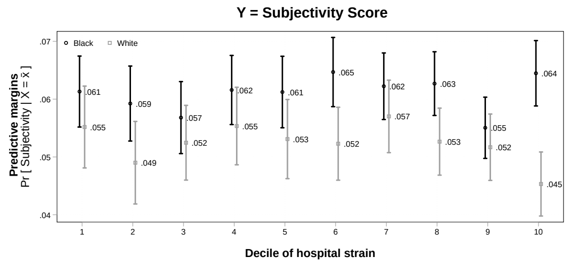
(f) Predictive margins

FIGURE IV
Rationing of Provider Effort:
Analysis of Descriptive Features of *Reason for Admission* Note

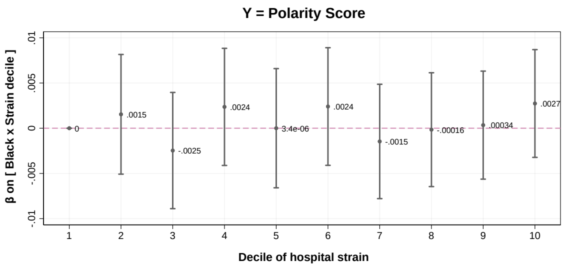
Estimates from regressing descriptive features of the *Reason for Admission* note (time to documentation completion, above median character count, and average word length, described in Section 5.2) on race, deciles of hospital strain, an interaction between the two, patient covariates (age, sex, insurance status, Elixhauser comorbidities, mortality index, readmission index), and fixed effects (hospital-year). Panels in the left column plot the interaction coefficients (β) on patient race (=1 if Black) and decile of hospital strain at time of patient arrival. Panels in the right column plot the predictive margins of the outcome separately for Black and White patients at each decile of hospital strain (at the means of all other covariates). Estimates also presented in tabular form in Table A.9.



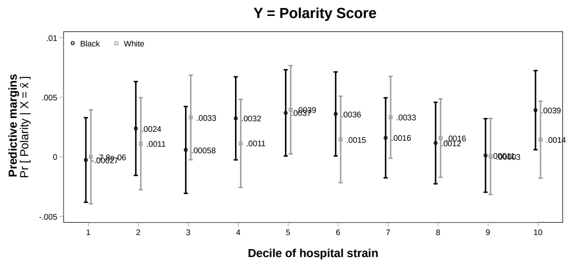
(a) Regression coefficients



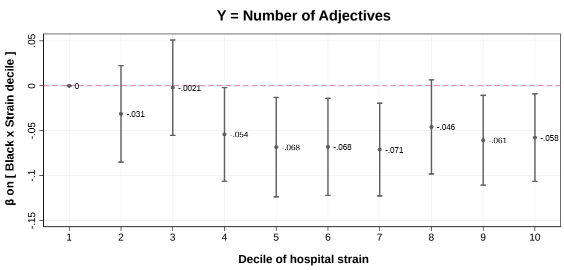
(b) Predictive margins



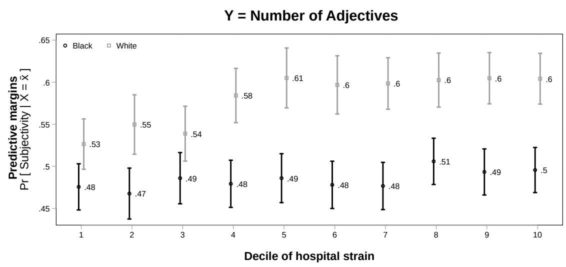
(c) Regression coefficients



(d) Predictive margins



(e) Regression coefficients



(f) Predictive margins

FIGURE V

Rationing of Provider Effort:
Sentiment and Adjective Analysis

Estimates from Equation 5 with subjectivity score, polarity score, and number of adjectives (described in Appendix B) as the outcome. Panels in the left column plots the interaction coefficient (β) on patient race (=1 if Black) and decile of hospital strain at time of patient arrival. Panels in the right column plot the predictive margins of the outcome separately for Black and White patients at each decile of hospital strain (at the means of all other covariates). 95% robust standard errors are presented. Estimates are also presented in tabular form in Table A.10.

TABLE 1
Summary Statistics

	White Patients mean/sd	Black Patients mean/sd
Age (yrs.)	59.03	51.95
	(18.06)	(19.51)
Uninsured	0.10	0.14
	(0.30)	(0.35)
Female	0.50	0.65
	(0.50)	(0.48)
Elixhauser mortality index score	12.97	12.32
	(13.12)	(13.44)
Elixhauser 30-day readmission index score	23.32	25.30
	(19.72)	(22.13)
# of comorbidities	4.08	4.10
	(2.73)	(3.05)
ICU admission	0.28	0.22
	(0.45)	(0.42)
Wait time (hrs)	4.22	6.40
	(6.70)	(7.61)
Length of stay (days)	6.72	6.48
	(9.40)	(10.23)
30-day readmission	0.16	0.16
	(0.36)	(0.37)
Strain decile at hospital arrival	5.74	5.61
	(2.99)	(2.95)
In-hospital mortality	0.02	0.02
	(0.13)	(0.13)
Observations	42946	64275

TABLE 2

Sensitivity of estimates to alternative specifications

	(1) In-Hosp Mort b/se	(2) In-Hosp Mort b/se	(3) In-Hosp Mort b/se	(4) In-Hosp Mort b/se	(5) In-Hosp Mort b/se	(6) In-Hosp Mort b/se	(7) In-Hosp Mort b/se
Black	-0.0010 (0.003)	0.0085 (0.130)	0.0000 (0.003)	-0.0009 (0.003)	-0.0012 (0.003)	-0.0063 (0.006)	-0.0003 (0.003)
Strain Decile=1	0.0000 (.)	0.0000 (.)	0.0000 (.)	0.0000 (.)	0.0000 (.)	0.0000 (.)	0.0000 (.)
Strain Decile=2	-0.0029 (0.003)	-0.1332 (0.148)	-0.0035 (0.003)	-0.0040 (0.003)	0.0038 (0.012)	-0.0029 (0.003)	-0.0028 (0.003)
Strain Decile=3	-0.0014 (0.003)	-0.0540 (0.147)	-0.0020 (0.003)	-0.0006 (0.003)	-0.0017 (0.012)	0.0001 (0.003)	0.0005 (0.003)
Strain Decile=4	-0.0052 (0.003)	-0.2319 (0.153)	-0.0005 (0.003)	-0.0001 (0.003)	0.0100 (0.012)	0.0011 (0.003)	0.0020 (0.003)
Strain Decile=5	-0.0075** (0.003)	-0.3666** (0.161)	-0.0031 (0.003)	-0.0019 (0.003)	0.0028 (0.012)	-0.0010 (0.003)	-0.0007 (0.003)
Strain Decile=6	-0.0078** (0.003)	-0.3720** (0.159)	-0.0038 (0.003)	-0.0005 (0.003)	0.0190 (0.012)	0.0002 (0.003)	0.0006 (0.003)
Strain Decile=7	-0.0107*** (0.003)	-0.5625*** (0.166)	-0.0077** (0.003)	-0.0045 (0.003)	0.0080 (0.011)	-0.0045 (0.003)	-0.0043 (0.003)
Strain Decile=8	-0.0081** (0.003)	-0.3950** (0.153)	-0.0040 (0.003)	-0.0022 (0.003)	0.0030 (0.011)	-0.0014 (0.003)	-0.0006 (0.003)
Strain Decile=9	-0.0148*** (0.003)	-0.9029*** (0.176)	-0.0088*** (0.003)	-0.0057* (0.003)	0.0047 (0.011)	-0.0053* (0.003)	-0.0049 (0.003)
Strain Decile=10	-0.0111*** (0.003)	-0.5788*** (0.153)	-0.0056** (0.003)	-0.0025 (0.003)	0.0012 (0.012)	-0.0024 (0.003)	-0.0014 (0.003)
Strain Decile=1 × Black	0.0000 (.)	0.0000 (.)	0.0000 (.)	0.0000 (.)	0.0000 (.)	0.0000 (.)	0.0000 (.)
Strain Decile=2 × Black	-0.0032 (0.004)	-0.2415 (0.204)	0.0004 (0.004)	0.0031 (0.004)	0.0018 (0.004)	0.0026 (0.004)	0.0027 (0.004)
Strain Decile=3 × Black	-0.0011 (0.004)	-0.0822 (0.196)	0.0009 (0.004)	0.0018 (0.004)	0.0019 (0.004)	0.0026 (0.004)	0.0024 (0.004)
Strain Decile=4 × Black	0.0005 (0.004)	-0.0398 (0.203)	-0.0012 (0.004)	0.0005 (0.004)	0.0005 (0.004)	0.0009 (0.004)	0.0002 (0.004)
Strain Decile=5 × Black	0.0036 (0.004)	0.1445 (0.208)	0.0021 (0.004)	0.0037 (0.004)	0.0043 (0.004)	0.0041 (0.004)	0.0035 (0.004)
Strain Decile=6 × Black	0.0037 (0.004)	0.1350 (0.206)	0.0026 (0.004)	0.0016 (0.004)	0.0023 (0.004)	0.0025 (0.004)	0.0024 (0.004)
Strain Decile=7 × Black	0.0071* (0.004)	0.3567* (0.210)	0.0072** (0.003)	0.0065* (0.003)	0.0078** (0.004)	0.0082** (0.004)	0.0083** (0.004)
Strain Decile=8 × Black	0.0038 (0.004)	0.1465 (0.198)	0.0038 (0.003)	0.0032 (0.003)	0.0035 (0.004)	0.0037 (0.004)	0.0029 (0.004)
Strain Decile=9 × Black	0.0080** (0.003)	0.4744** (0.218)	0.0057* (0.003)	0.0053 (0.003)	0.0052 (0.003)	0.0068** (0.003)	0.0064* (0.003)
Strain Decile=10 × Black	0.0096** (0.004)	0.4950** (0.191)	0.0078** (0.003)	0.0073** (0.003)	0.0084** (0.004)	0.0090** (0.003)	0.0075** (0.003)
N	106518	106518	106362	106042	106082	106082	106101
r2	0.005		0.181	0.333	0.293	0.293	0.288
controls	Age	Logistic	Age, sex	+ DRG	x Strain	x Black	Elix comps

Coefficients from regressions of in-hospital mortality on race (=1 if Black) and deciles of hospital strain, using varying models and combinations of controls. Col 1 documents the main specification from Equation 5. Details provided in Section 4.4.

Online Appendix

A Identifying themes in the text data using Latent Direchlet Allocation

We first provide exploratory evidence of what the *Reason for Admission* text field contains, and whether – at first glance – it appears to be starkly different between Black and White patients. We first create wordclouds for Black and White patients (Figure A.4), which provide a visual representation of the most common words and phrases in this text field. We find that similar words – *surgery*, *preadmission*, *pain* – occur the most frequently for both races, though there are some differences. *Pain*, *chest*, and *sob*, which stands for shortness of breath, are more frequent amongst Black patients. We also create wordclouds for Black and White patients seen at Low Strain (deciles 1, 2, 3) and High Strain (deciles 8, 9, 10) (Figure A.5).

Black and White patients may be described differently in their reason for admit for many reasons: differences in their actual reason for admit, differences in how they describe their symptoms to the providers, and/or differences how providers interpret those symptoms. If differences in words with increasing strain represent differences in the types of patients that are being admitted to the hospital, that may represent a threat to our identification strategy. We try to test this formally using a commonly used machine learning technique for text analysis, called Latent Dirichlet Allocation (LDA).

LDA is a generative probabilistic model for collections of discrete data such as text corpora. Introduced by Blei, Ng, and Jordan (2003), it is a three-level hierarchical Bayesian model where each item of a collection is modeled as a finite mixture over an underlying set of topics. Each topic is, in turn, modeled as an infinite mixture over an underlying set of topic probabilities.

LDA posits that documents (in this case, a patient entry for *Reason for Admission*) are composed of multiple topics, and a topic is a distribution over words in the lexicon. The fundamental assumption of LDA is that documents are mixtures of topics and that the topics are mixtures of words. We use LDA for its ability to uncover the underlying thematic structure of a document collection.

Before applying LDA, we first pre-process the data to make inference easier. Free-text notes in electronic medical records such the one for *Reason for Admission* has many features that make it resistant to standard text analysis methods. For example, they are filled with medical jargon and medical abbreviations, do not follow standard sentence structure, often deviate from grammatical syntax, and have a very high rate of typographical errors. Keeping this in mind, we set our preprocessing parameters to be quite lax, in essence favoring a higher Type II error rate over a Type I. In other words, we preprocess the data in such a way that there is a high likelihood of retaining actual medical terminology with real information but also allows more "filler" words to influence analysis that would if had a stricter pre-processing protocol. To do so, we remove all punctuation, non-alphabetic characters, and stopwords ("and", "or", "if" etc) from the text field. We also lemmatized each word, i.e., converted it to its root form (e.g., "painful" and "paining" would become "pain"). When creating our bag of words for the LDA analysis, we drop any words that occur in more than 95% of admissions (common words such as "yo", signifying "year old" are unlikely to be meaningful) as well as any words that occur only once in the entire dataset (with the goal of excluding typos). Other than that, we make no restrictions.

We use LDA analysis to identify five primary themes. LDA does not identify what these themes are, but the five most common words from each theme are shows in the top panel in Figure A.6. The visual distribution of the topic distributions is also shown using the heatmap in the bottom panel. For example, Topic 4 is equally represented on average amongst Black and White patients, but Topics 1 and 2 are represented more amongst White patients and Topics 3 and 5 are moreso found in Black patients. Regardless, the formal analysis in Table A.5 (which re-estimates Equation 5 using each of the five topics as an outcome) finds that the distribution of topics does not change differentially with strain for Black vs White patients, which once again serves as confirmation that patient selection with strain is not a concern nor a threat to our identification assumption.

B Analysis of sentiment and detail

In this analysis, we use the TextBlob library, a Python-based natural language processing (NLP) tool, to perform sentiment analysis on a corpus of text data. TextBlob simplifies text processing in Python, providing an accessible interface for a range of NLP tasks including part-of-speech tagging, noun phrase extraction, and sentiment analysis. Of particular interest to this study is its application to evaluating the sentiment polarity and subjectivity of text data.

TextBlob's sentiment analysis function is grounded in a lexicon of words, where each word is associated with sentiment scores. When analyzing a given text, TextBlob calculates the overall sentiment by aggregating the sentiment scores of the words contained within the text. This process involves two primary components:

Subjectivity Analysis: This quantifies the degree of personal opinion and factual information contained in the text. The subjectivity score is a reflection of the presence of personal views and subjective evaluations as opposed to factual, objective information, ranging from 0 to 1, where 0 is entirely objective and 1 is entirely subjective. Examples of hypothetical physician notes to illustrate variation in subjectivity scores would be:

- "Patient's X-ray shows inflammation" = Subjectivity Score of 0
- "The patient's symptoms suggest possible risk of stroke" = Subjectivity Score of 0.6
- "I am deeply optimistic that this patient may survive" or "Patient describing unimaginable levels of pain" = Subjectivity Score of 0.9.

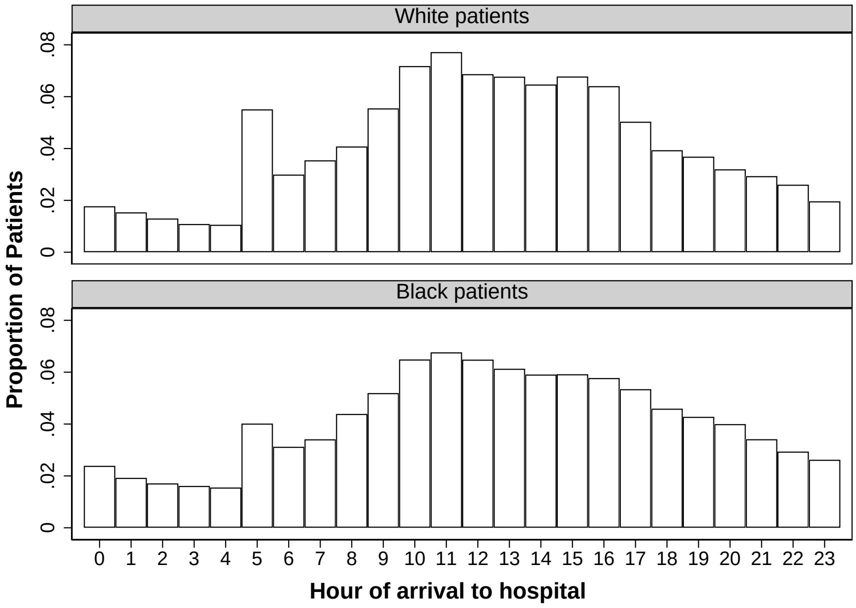
Subjectivity is assessed independently from polarity (described below, which identifies emotional tone), though there can be a correlation between the two scores. The third example above attempts to highlight the difference: a physician can write a subjective note that either conveys positive information or negative information. Thus, in our sample, the correlation between subjectivity and polarity is 0.15.

Polarity Analysis: This is a measure of the emotional leaning of the text, indicating whether the expressed opinion in the text is positive, negative, or neutral. The polarity score provided by TextBlob is used to determine the sentiment orientation of each text entry in the dataset, ranging from -1 to 1, representing negative to positive sentiment, respectively. Examples of hypothetical physician notes to illustrate variation in polarity scores would be:

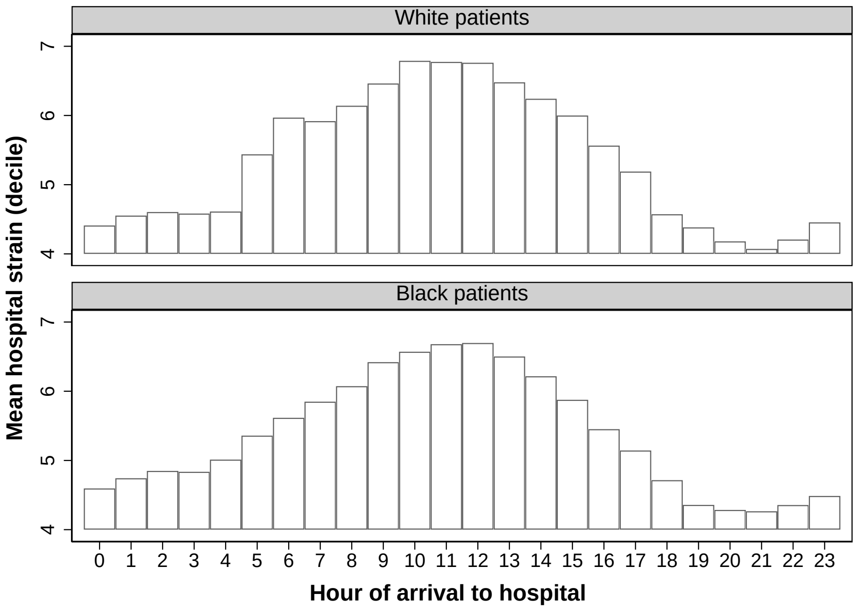
- "Patient responding exceptionally well to new treatment" = Polarity Score of +0.7
- "Concerning lack of progress in patient's recovery" = Polarity Score of -0.5
- "Patient received 5mg of medication" = Polarity Score of 0.

It is important to note that like most basic sentiment analysis tools, TextBlob primarily analyzes the sentiment of individual words rather than sentiment based on syntactical structure or the context beyond immediate word combinations. For example, a physician note that stated "Concerned about lack of patient progress" would be assigned a similar polarity score to a note that stated "Patient is concerned about lack of progress", even though the note has two different subjects and is relaying different information.

Adjectives: Finally, to measure the level of detail provides in the text data, we perform a rudimentary analysis where we simply count the number of adjectives in a given provider note. However, using machine learning techniques (such as the natural language processing toolkit) on physician notes is difficult because these algorithms are trained to identify adjectives based on the context – such as the words before and after it – in which they appear. However, as already discussed, physician notes largely do not follow usual syntax and grammar rules and so such ML techniques may not be reliable. Thus, instead, we rely on a very basic rule: we identify adjectives as words that end in ['able', 'al', 'ant', 'ary', 'ful', 'ic', 'ish', 'ive', 'less', 'ous', 'y', 'er'].



(a)



(b)

FIGURE A.1

Distribution by race of (a) hour of hospital arrival and
(b) mean decile of hospital strain at hour of hospital arrival

Panel (a) presents the distribution of White and Black patients by the hour of their arrival to the hospital. Panel (b) presents the mean decile of hospital strain for White and Black patients by the hour of their arrival to the hospital.

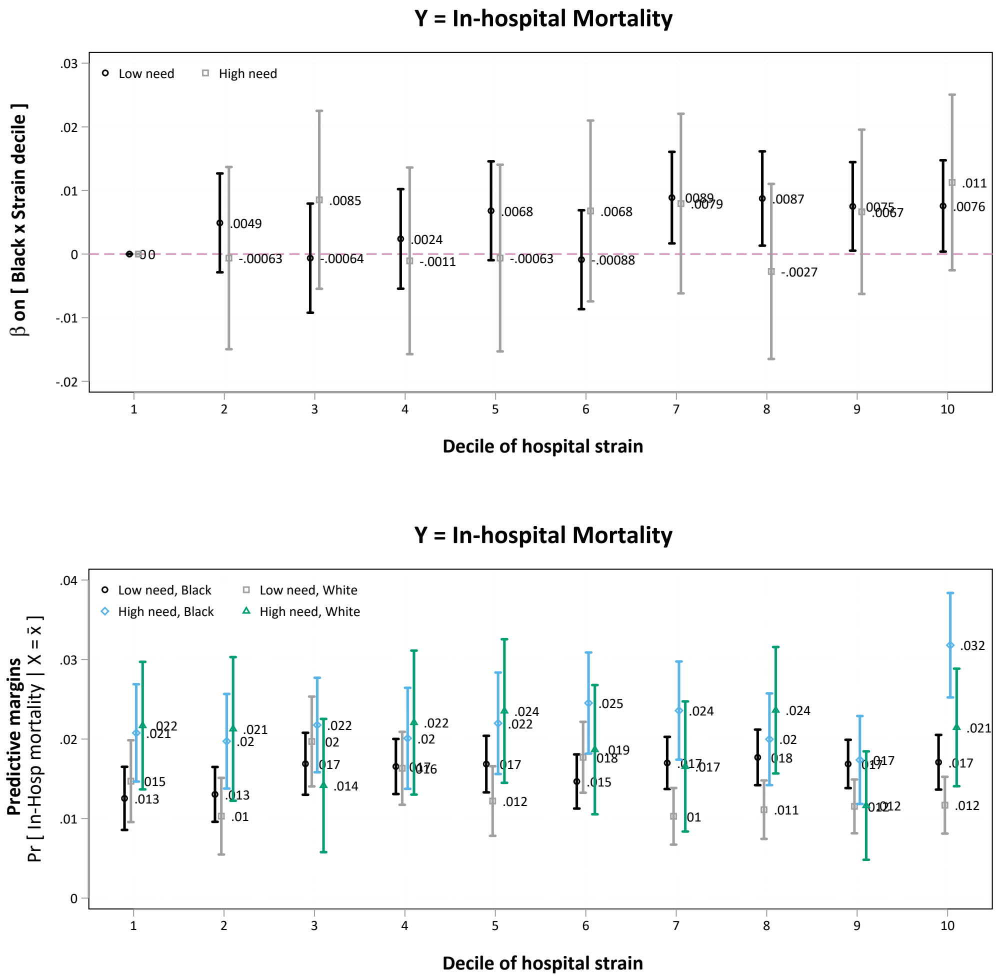


FIGURE A.2

Racial Disparities in Hospital Mortality by Strain and Medical Need (Acute measure)

Estimates from Equation 6 with in-hospital mortality as the outcome and patient need (using the acute measure, i.e., normal and abnormal signifying low- and high- need patients respectively). Panel (a) plots the coefficient on the triple interaction (β) between patient race (=1 if Black), patient need, and decile of hospital strain at time of patient arrival. Panel (b) plots the coefficient on the interaction between patient race and decile of hospital strain, separately for high- and low- need patients. Panel (c) plots the predictive margins of in-hospital mortality by race and patient need at each decile of hospital strain (at the means of all other covariates). 95% robust standard errors are presented. Estimates also presented in tabular form in Table A.8 Col 1.

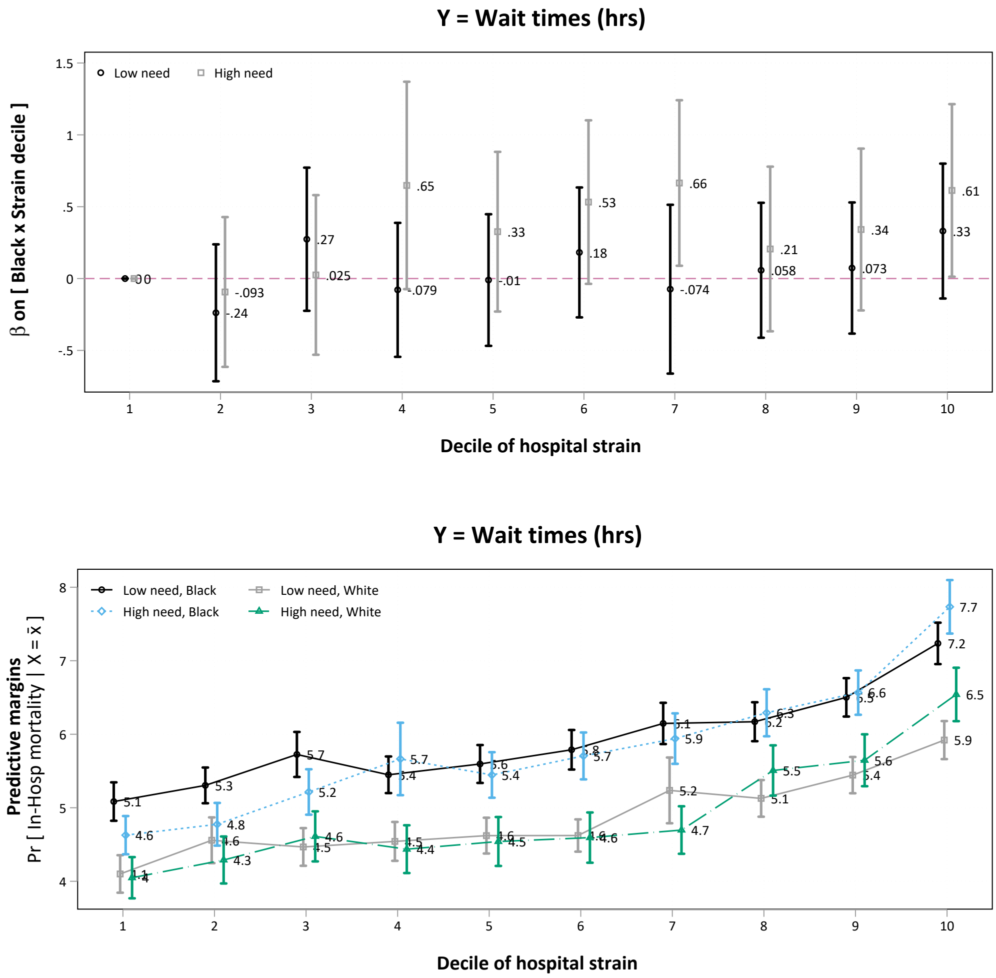
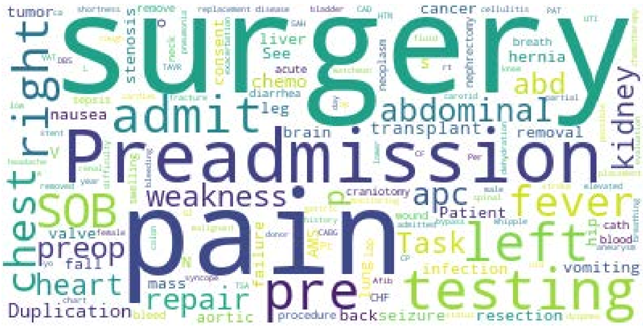


FIGURE A.3
Wait Times: Rationing by Race and Medical Need (Acute measure)

Estimates from Equation 6, with wait times as the outcome, and patient need measured using the acute measure (i.e., normal and abnormal vitals signifying low- and high- need patients respectively). Panel (a) plots the coefficient on the interaction between patient race and decile of hospital strain, for high- and low- need patients. Panel (b) plots the predictive margins of wait times by race and patient need at each decile of hospital strain (at the means of all other covariates). 95% robust standard errors are presented. Estimates are also presented in tabular form in Table A.8 Col 2.

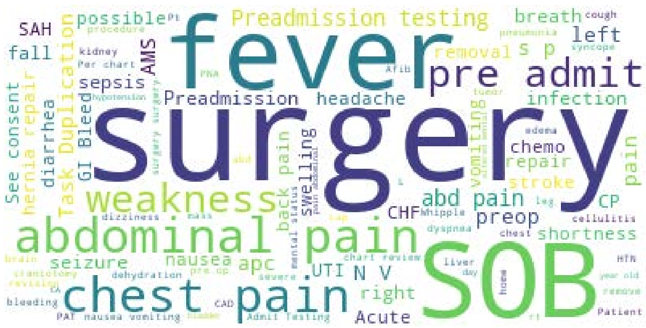


(a) White

(b) Black

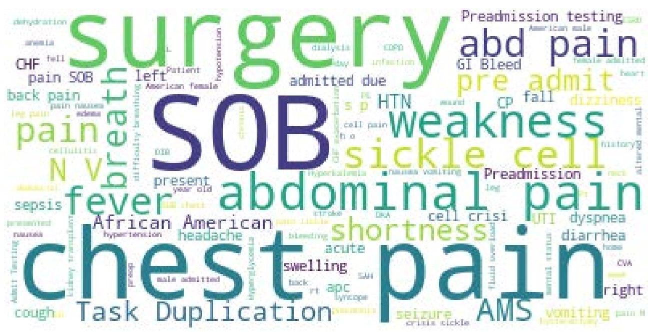
FIGURE A.4

Word Clouds of *Reason for Admission* Note by Race

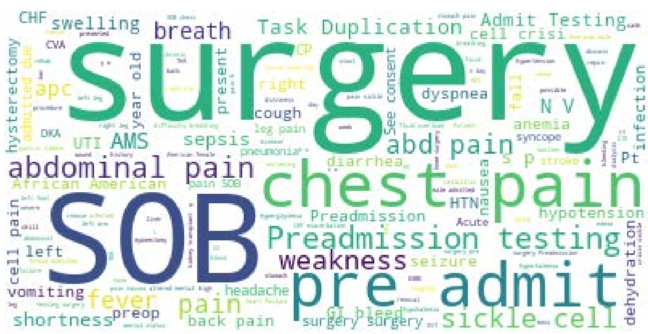


(a) White, Low Strain

(b) White, High Strain



(c) Black, Low Strain



(d) Black, High Strain

FIGURE A.5
Word Clouds of *Reason for Admission* Note
by Race and Strain

High strain identifies deciles 8 - 10. Low strain identifies deciles 1 - 3.

	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
Word 1	aortic	hernia	left	abdominal	pt
Word 2	mass	left	task	preadmission	nausea
Word 3	blood	pat	weakness	chest	htn
Word 4	failure	repair	fever	pain	seizure
Word 5	heart	right	sob	surgery	cell

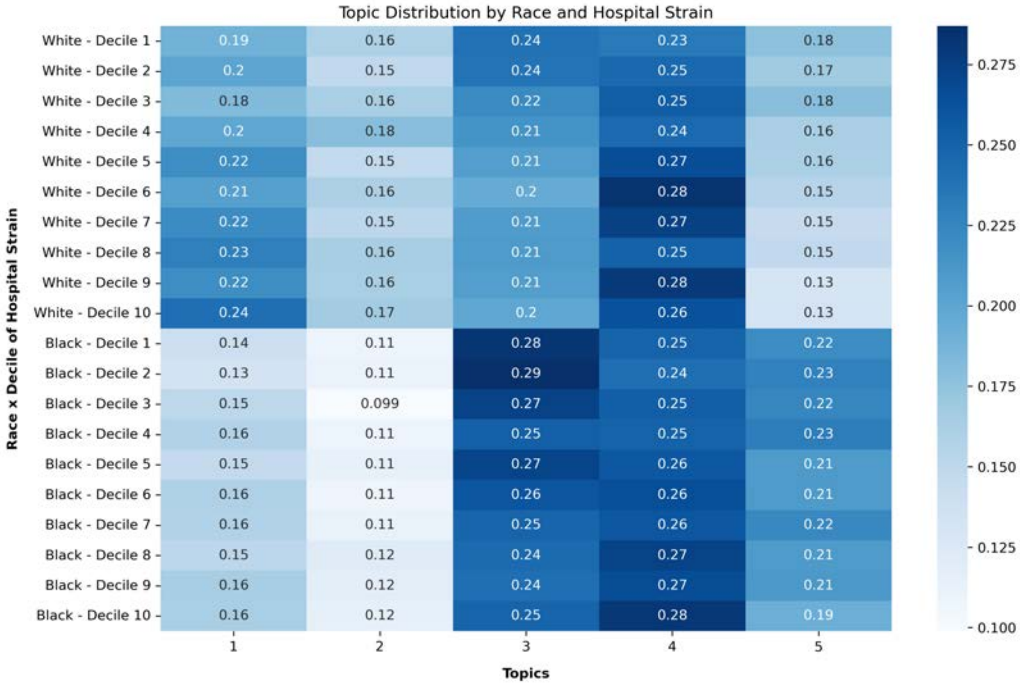
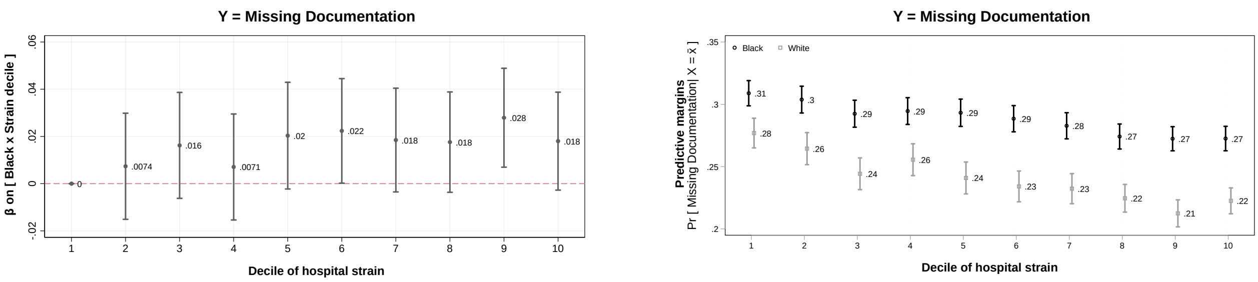


FIGURE A.6

Topic identification and distribution by Latent Derichlet Allocation (LDA) analysis

Details about LDA are provided in Appendix A. The top panel identifies the five themes identified by LDA in the *Reason for Admission* note, and the five most common words associated with each theme. The bottom panel provides a heatmap of the topic distribution by race and deciles of hospital strain.



(a) Regression coefficients

(b) Predictive margins

FIGURE A.7

Analysis of Missingness of *Reason for Admission* Note

Estimates from regressing missingness of the *Reason for Admission* note on race, deciles of hospital strain, an interaction between the two, patient covariates (age, sex, insurance status, Elixhauser comorbidities, mortality index, readmission index), and fixed effects (hospital-year). Panels in the left column plot the interaction coefficients (β_3) on patient race (=1 if Black) and decile of hospital strain at time of patient arrival. Panels in the right column plot the predictive margins of missingness separately for Black and White patients at each decile of hospital strain (at the means of all other covariates). Estimates also presented in tabular form in Table A.9.

TABLE A.1

Proportion Full at Each Decile of Hospital Strain

	Decile 1		Decile 2		Decile 3		Decile 4		Decile 5		Decile 6		Decile 7		Decile 8		Decile 9		Decile 10	
	H1	H2	H1	H2	H1	H2	H1	H2	H1	H2	H1	H2	H1	H2	H1	H2	H1	H2	H1	H2
Proportion full	0.69	0.78	0.75	0.84	0.78	0.85	0.80	0.87	0.81	0.88	0.82	0.89	0.84	0.90	0.85	0.91	0.87	0.93	0.91	0.95
	(0.04)	(0.05)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.02)	(0.01)
Observations	5758	6019	5803	3838	5641	3896	5902	3988	5768	3693	6462	3529	6508	3765	6556	4765	7464	4522	7281	5365

For hospitals H1 and H2, this table presents the mean proportion of beds filled at each of the ten deciles of strain, with SD in parentheses.

TABLE A.2

Predictive Power of Elixhauser measures for Black and White Patients

	(1) White Pr(in-hosp mort) b/se	(2) Black Pr(in-hosp mort) b/se
# Comorbidities	0.007***	0.006***
	(0.001)	(0.001)
Elixhauser mortality index	0.002***	0.002***
	(0.000)	(0.000)
Elixhauser readmission index	-0.001***	-0.001***
	(0.000)	(0.000)
N	42944	64272
r2	0.036	0.046
FE	H-Y	H-Y

This table presents estimates from regressing in-hospital mortality on the three Elixhauser measures: number of comorbidities, mortality index, and readmission index separately for Black and White patients. All patient covariates used in the primary specification are used, along with hospital-year fixed effects.

TABLE A.3

Test of Selection: Regressors as Outcomes

	(1) In-hospital mortality b/se	(2) Age (yrs.) b/se	(3) Female b/se	(4) # comorbs b/se	(5) Elix mort score b/se	(6) Elix readm score b/se	(7) Uninsured b/se
Black	-0.0017	-3.8740***	0.0964***	-0.0436*	-0.9251***	1.6243***	0.0010
	(0.003)	(0.310)	(0.010)	(0.025)	(0.134)	(0.144)	(0.006)
Strain decile at hospital arrival=1	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Strain decile at hospital arrival=2	-0.0029	-0.0745	0.0009	-0.0101	-0.0834	0.0060	-0.0128*
	(0.003)	(0.382)	(0.012)	(0.031)	(0.163)	(0.176)	(0.007)
Strain decile at hospital arrival=3	0.0001	-1.2436**	0.0128	-0.0062	0.0318	0.0216	-0.0193**
	(0.003)	(0.386)	(0.012)	(0.032)	(0.168)	(0.183)	(0.008)
Strain decile at hospital arrival=4	0.0010	-0.3159	0.0014	-0.0002	-0.0683	0.0416	-0.0094
	(0.003)	(0.380)	(0.012)	(0.031)	(0.165)	(0.179)	(0.008)
Strain decile at hospital arrival=5	-0.0010	-0.3194	0.0039	-0.0155	-0.1084	0.1381	-0.0148*
	(0.003)	(0.391)	(0.012)	(0.032)	(0.169)	(0.185)	(0.008)
Strain decile at hospital arrival=6	0.0001	-0.2683	-0.0044	-0.0053	0.0150	-0.0137	-0.0179**
	(0.003)	(0.386)	(0.012)	(0.032)	(0.170)	(0.184)	(0.008)
Strain decile at hospital arrival=7	-0.0045	-0.4276	-0.0106	-0.0378	-0.0481	0.1597	-0.0080
	(0.003)	(0.385)	(0.012)	(0.032)	(0.169)	(0.183)	(0.008)
Strain decile at hospital arrival=8	-0.0014	-0.5645	0.0072	-0.0448	-0.1381	0.2411	-0.0088
	(0.003)	(0.382)	(0.012)	(0.031)	(0.166)	(0.180)	(0.008)
Strain decile at hospital arrival=9	-0.0053*	-0.6707*	-0.0202*	-0.0081	-0.0614	-0.0099	-0.0080
	(0.003)	(0.385)	(0.012)	(0.032)	(0.168)	(0.181)	(0.008)
Strain decile at hospital arrival=10	-0.0024	-0.2096	-0.0100	-0.0128	-0.0827	-0.0382	-0.0077
	(0.003)	(0.382)	(0.012)	(0.031)	(0.167)	(0.180)	(0.008)
Strain decile at hospital arrival=1 × Black	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Strain decile at hospital arrival=2 × Black	0.0026	0.4031	0.0074	-0.0375	0.2698	-0.1024	0.0143
	(0.004)	(0.445)	(0.014)	(0.036)	(0.198)	(0.212)	(0.009)
Strain decile at hospital arrival=3 × Black	0.0026	1.2322**	-0.0011	0.0056	0.0513	-0.0646	0.0255**
	(0.004)	(0.448)	(0.014)	(0.036)	(0.200)	(0.216)	(0.009)
Strain decile at hospital arrival=4 × Black	0.0009	0.2244	0.0019	-0.0427	0.1003	0.1551	0.0139
	(0.004)	(0.436)	(0.014)	(0.036)	(0.194)	(0.209)	(0.009)
Strain decile at hospital arrival=5 × Black	0.0041	0.4603	0.0005	-0.0081	-0.0649	0.0728	0.0178*
	(0.004)	(0.445)	(0.014)	(0.036)	(0.198)	(0.215)	(0.009)
Strain decile at hospital arrival=6 × Black	0.0025	0.5186	0.0087	-0.0436	-0.0268	0.2381	0.0200**
	(0.004)	(0.436)	(0.014)	(0.035)	(0.195)	(0.210)	(0.009)
Strain decile at hospital arrival=7 × Black	0.0083**	0.4425	0.0198	-0.0057	-0.0005	0.0854	0.0044
	(0.004)	(0.431)	(0.014)	(0.035)	(0.194)	(0.209)	(0.009)
Strain decile at hospital arrival=8 × Black	0.0037	0.5621	-0.0091	0.0185	0.1446	-0.1717	0.0097
	(0.004)	(0.425)	(0.013)	(0.034)	(0.188)	(0.203)	(0.009)
Strain decile at hospital arrival=9 × Black	0.0068**	1.0438**	0.0198	-0.0196	-0.0523	0.1427	0.0137
	(0.003)	(0.420)	(0.013)	(0.034)	(0.186)	(0.200)	(0.009)
Strain decile at hospital arrival=10 × Black	0.0090**	0.4390	0.0204	-0.0090	0.0164	0.2476	0.0119
	(0.003)	(0.413)	(0.013)	(0.034)	(0.183)	(0.197)	(0.009)
N	106082	106082	106082	106083	106091	106091	106082
r2	0.293	0.507	0.254	0.856	0.779	0.900	0.213

Regression coefficients presented from Equation 5 with the following outcomes: in-hospital mortality (Col 1); Age (Col 2); Female (Col 3); Number of Elixhauser comorbidities (Col 4); Elixhauser mortality index score (Col 5); Elixhauser readmission index score (Col 6); Uninsured (Col 7). When covariates used an outcome, all other covariates included on the RHS. $p < .001^{***}$ $p < .05^{**}$ $p < 0.1^{*}$

TABLE A.4

Test of Selection: Using the Acute Measure of Need

	(1) Abn. temp (C) b/se	(2) Low BP b/se	(3) Abn. heart rate b/se	(4) Abn. resp rate b/se	(5) Abn. O2 rate b/se	(6) In-Hosp Mort b/se	(7) Wait Times (hrs) b/se
Black	0.0052	0.0003	0.0069	-0.0068	-0.0079**	-0.0015	0.7867***
	(0.005)	(0.003)	(0.009)	(0.007)	(0.003)	(0.003)	(0.119)
Strain Decile=1	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Strain Decile=2	0.0046	0.0022	-0.0110	-0.0063	-0.0004	-0.0030	0.3751**
	(0.006)	(0.004)	(0.011)	(0.008)	(0.004)	(0.003)	(0.150)
Strain Decile=3	-0.0041	-0.0040	-0.0058	-0.0072	-0.0017	0.0004	0.4376**
	(0.005)	(0.004)	(0.011)	(0.008)	(0.004)	(0.003)	(0.147)
Strain Decile=4	-0.0067	0.0026	-0.0180	-0.0098	0.0013	0.0010	0.4267**
	(0.005)	(0.004)	(0.011)	(0.008)	(0.004)	(0.003)	(0.148)
Strain Decile=5	-0.0022	-0.0022	-0.0111	-0.0120	0.0003	-0.0010	0.5055***
	(0.006)	(0.004)	(0.012)	(0.008)	(0.004)	(0.003)	(0.153)
Strain Decile=6	-0.0045	-0.0034	-0.0134	-0.0073	-0.0015	0.0010	0.5278***
	(0.006)	(0.004)	(0.012)	(0.008)	(0.004)	(0.003)	(0.151)
Strain Decile=7	-0.0030	-0.0007	-0.0111	-0.0146*	0.0022	-0.0046	0.9556***
	(0.005)	(0.004)	(0.011)	(0.008)	(0.004)	(0.003)	(0.193)
Strain Decile=8	-0.0066	-0.0041	-0.0123	-0.0302***	0.0010	-0.0015	1.1542***
	(0.005)	(0.004)	(0.011)	(0.008)	(0.004)	(0.003)	(0.160)
Strain Decile=9	-0.0080	-0.0050	-0.0111	-0.0233**	-0.0044	-0.0052*	1.4069***
	(0.005)	(0.004)	(0.011)	(0.008)	(0.004)	(0.003)	(0.161)
Strain Decile=10	-0.0059	-0.0025	-0.0076	-0.0261**	-0.0046	-0.0020	2.0192***
	(0.005)	(0.004)	(0.011)	(0.008)	(0.004)	(0.003)	(0.168)
Strain Decile=1 × Black	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Strain Decile=2 × Black	-0.0164**	-0.0082*	-0.0127	0.0031	0.0009	0.0030	-0.1681
	(0.007)	(0.004)	(0.013)	(0.010)	(0.005)	(0.004)	(0.182)
Strain Decile=3 × Black	-0.0013	-0.0001	-0.0029	0.0127	0.0009	0.0026	0.1950
	(0.007)	(0.004)	(0.013)	(0.010)	(0.005)	(0.004)	(0.189)
Strain Decile=4 × Black	0.0031	-0.0062	-0.0018	0.0052	-0.0028	0.0011	0.2376
	(0.006)	(0.005)	(0.013)	(0.010)	(0.005)	(0.004)	(0.197)
Strain Decile=5 × Black	-0.0011	-0.0006	-0.0049	0.0039	0.0036	0.0040	0.1494
	(0.007)	(0.004)	(0.013)	(0.010)	(0.005)	(0.004)	(0.180)
Strain Decile=6 × Black	-0.0027	-0.0005	-0.0015	-0.0007	-0.0025	0.0019	0.3410*
	(0.006)	(0.004)	(0.013)	(0.010)	(0.005)	(0.004)	(0.179)
Strain Decile=7 × Black	-0.0012	-0.0009	-0.0083	0.0029	0.0010	0.0084**	0.2203
	(0.006)	(0.004)	(0.013)	(0.009)	(0.005)	(0.004)	(0.214)
Strain Decile=8 × Black	0.0021	0.0001	-0.0088	0.0169*	-0.0045	0.0044	0.1735
	(0.006)	(0.004)	(0.013)	(0.009)	(0.005)	(0.004)	(0.184)
Strain Decile=9 × Black	0.0090	0.0003	-0.0159	0.0145	0.0061	0.0066*	0.2388
	(0.006)	(0.004)	(0.013)	(0.009)	(0.005)	(0.003)	(0.181)
Strain Decile=10 × Black	0.0011	0.0044	-0.0062	0.0110	0.0045	0.0088**	0.5275**
	(0.006)	(0.004)	(0.012)	(0.009)	(0.004)	(0.004)	(0.188)
N	105661	105530	106082	105723	101653	101426	91026
r2	0.141	0.135	0.151	0.184	0.132	0.298	0.296

Regression coefficients presented from Equation 5 with the following outcomes (described in Section 3.2: abnormal temperature (Col 1); Low blood pressure (Col 2); Abnormal heart rate (Col 3); Abnormal respiratory rate (Col 4); Abnormal oxygen saturation (Col 5); In-hospital morality (Col 6); Wait Times (Col 7). Col 6 and 7 include all five abnormal vitals as covariates on the RHS. $p < .001^{***}$ $p < .05^{**}$ $p < 0.1^{*}$

TABLE A.5

Topic Analysis

	(1) Topic 1 b/se	(2) Topic 2 b/se	(3) Topic 3 b/se	(4) Topic 4 b/se	(5) Topic 5 b/se
Black	-0.0200**	-0.0107	0.0007	0.0211**	0.0089
	(0.009)	(0.008)	(0.010)	(0.010)	(0.009)
Strain Decile=1	0.0000	0.0000	0.0000	0.0000	0.0000
	(.)	(.)	(.)	(.)	(.)
Strain Decile=2	0.0031	0.0111	0.0082	-0.0183	-0.0040
	(0.011)	(0.010)	(0.012)	(0.012)	(0.011)
Strain Decile=3	-0.0068	0.0132	0.0014	-0.0185	0.0106
	(0.011)	(0.010)	(0.012)	(0.012)	(0.011)
Strain Decile=4	0.0003	0.0223**	-0.0092	-0.0221*	0.0088
	(0.011)	(0.010)	(0.012)	(0.012)	(0.011)
Strain Decile=5	0.0128	-0.0093	-0.0084	-0.0080	0.0130
	(0.012)	(0.010)	(0.013)	(0.012)	(0.011)
Strain Decile=6	0.0036	0.0128	-0.0130	-0.0151	0.0115
	(0.012)	(0.011)	(0.012)	(0.012)	(0.011)
Strain Decile=7	0.0195*	-0.0034	-0.0059	-0.0190	0.0088
	(0.012)	(0.010)	(0.012)	(0.012)	(0.011)
Strain Decile=8	0.0188	-0.0012	-0.0060	-0.0186	0.0069
	(0.011)	(0.010)	(0.012)	(0.012)	(0.011)
Strain Decile=9	0.0068	0.0066	-0.0032	-0.0137	0.0035
	(0.011)	(0.010)	(0.012)	(0.012)	(0.011)
Strain Decile=10	0.0231**	0.0020	-0.0160	-0.0193	0.0101
	(0.012)	(0.010)	(0.012)	(0.012)	(0.011)
Strain Decile=1 × Black	0.0000	0.0000	0.0000	0.0000	0.0000
	(.)	(.)	(.)	(.)	(.)
Strain Decile=2 × Black	-0.0075	-0.0065	0.0148	-0.0091	0.0083
	(0.013)	(0.012)	(0.015)	(0.015)	(0.014)
Strain Decile=3 × Black	0.0173	-0.0243**	0.0011	0.0069	-0.0010
	(0.013)	(0.012)	(0.015)	(0.015)	(0.014)
Strain Decile=4 × Black	0.0137	-0.0213*	-0.0005	-0.0006	0.0088
	(0.013)	(0.012)	(0.015)	(0.014)	(0.013)
Strain Decile=5 × Black	-0.0095	0.0133	0.0202	-0.0093	-0.0148
	(0.013)	(0.012)	(0.015)	(0.015)	(0.013)
Strain Decile=6 × Black	0.0160	-0.0204*	0.0170	-0.0017	-0.0110
	(0.013)	(0.012)	(0.014)	(0.014)	(0.013)
Strain Decile=7 × Black	-0.0090	0.0010	0.0070	-0.0095	0.0105
	(0.013)	(0.012)	(0.014)	(0.014)	(0.013)
Strain Decile=8 × Black	-0.0166	0.0050	0.0025	0.0058	0.0033
	(0.013)	(0.011)	(0.014)	(0.014)	(0.013)
Strain Decile=9 × Black	0.0083	-0.0014	-0.0022	-0.0177	0.0130
	(0.013)	(0.011)	(0.014)	(0.014)	(0.012)
Strain Decile=10 × Black	-0.0131	-0.0045	0.0120	0.0060	-0.0004
	(0.012)	(0.011)	(0.014)	(0.013)	(0.012)
N	75597	75597	75597	75597	75597
r2	0.206	0.217	0.220	0.284	0.240

Regression coefficients from Equation 5 with the five topics (identified by the Latent Direchlet Allocation) as outcomes. Details on LDA provided in Appendix A. $p < .001^{***}$ $p < .05^{**}$ $p < 0.1^{*}$

TABLE A.6

	(1) In-Hosp Mort b/se	(2) In-Hosp Mort b/se	(3) Wait times (hrs) b/se	(4) ICU adm b/se	(5) ICU LOS (hrs) b/se	(6) LOS (days) b/se	(7) Charges b/se	(8) Hospice b/se
Black	-0.0017	-0.0025	0.7993***	-0.0069	-10.9926	0.0645	-3363.3733**	-0.0065*
	(0.003)	(0.003)	(0.119)	(0.008)	(8.766)	(0.237)	(1493.056)	(0.004)
Strain Decile=1	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Strain Decile=2	-0.0029	-0.0042	0.3761**	0.0094	7.0365	0.2704	1384.2363	0.0023
	(0.003)	(0.004)	(0.149)	(0.009)	(11.330)	(0.234)	(2014.363)	(0.005)
Strain Decile=3	0.0001	0.0001	0.4391**	0.0120	-3.2671	0.2813	1918.2239	-0.0055
	(0.003)	(0.004)	(0.147)	(0.010)	(10.105)	(0.240)	(1930.317)	(0.004)
Strain Decile=4	0.0010	-0.0004	0.4294**	0.0046	8.1410	0.3516	1758.2652	-0.0030
	(0.003)	(0.004)	(0.148)	(0.009)	(12.879)	(0.244)	(2056.411)	(0.004)
Strain Decile=5	-0.0010	-0.0017	0.5051***	-0.0011	-0.9079	0.1009	327.0336	-0.0050
	(0.003)	(0.004)	(0.153)	(0.010)	(12.640)	(0.236)	(2143.913)	(0.004)
Strain Decile=6	0.0001	-0.0003	0.5299***	0.0018	-1.9960	0.1029	-167.2749	-0.0075*
	(0.003)	(0.003)	(0.151)	(0.010)	(10.285)	(0.236)	(1955.253)	(0.004)
Strain Decile=7	-0.0045	-0.0053	0.9584***	0.0006	5.7100	0.3202	2494.2081	-0.0001
	(0.003)	(0.003)	(0.193)	(0.009)	(11.009)	(0.248)	(1980.166)	(0.004)
Strain Decile=8	-0.0014	-0.0030	1.1811***	-0.0038	-10.7576	-0.2605	-1023.8033	-0.0016
	(0.003)	(0.003)	(0.160)	(0.009)	(10.304)	(0.232)	(1931.168)	(0.004)
Strain Decile=9	-0.0053*	-0.0061*	1.4273***	-0.0074	-5.9212	-0.0301	2066.5006	-0.0035
	(0.003)	(0.003)	(0.161)	(0.009)	(9.950)	(0.229)	(1991.403)	(0.004)
Strain Decile=10	-0.0024	-0.0036	2.0419***	-0.0197**	-9.3500	0.0140	806.6618	-0.0051
	(0.003)	(0.003)	(0.168)	(0.009)	(11.464)	(0.245)	(1922.878)	(0.004)
Strain Decile=1 × Black	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Strain Decile=2 × Black	0.0026	0.0032	-0.1626	-0.0087	-12.0426	-0.1775	-1134.1985	-0.0017
	(0.004)	(0.004)	(0.182)	(0.011)	(14.619)	(0.286)	(2222.477)	(0.005)
Strain Decile=3 × Black	0.0026	0.0023	0.1856	-0.0063	0.1068	-0.1418	-1627.4162	0.0037
	(0.004)	(0.004)	(0.189)	(0.011)	(12.609)	(0.307)	(2064.994)	(0.005)
Strain Decile=4 × Black	0.0009	0.0019	0.2375	-0.0041	-8.0044	-0.2043	-651.6233	0.0019
	(0.004)	(0.004)	(0.197)	(0.011)	(13.973)	(0.292)	(2089.800)	(0.005)
Strain Decile=5 × Black	0.0041	0.0053	0.1512	0.0021	0.6360	-0.2184	1934.2427	0.0056
	(0.004)	(0.004)	(0.179)	(0.011)	(14.513)	(0.292)	(2414.337)	(0.005)
Strain Decile=6 × Black	0.0025	0.0022	0.3449*	-0.0095	-11.0483	0.0300	-28.8512	0.0070
	(0.004)	(0.004)	(0.179)	(0.011)	(12.416)	(0.318)	(2058.115)	(0.005)
Strain Decile=7 × Black	0.0083**	0.0096**	0.2233	-0.0071	2.6319	-0.2414	-696.1315	-0.0001
	(0.004)	(0.004)	(0.213)	(0.011)	(12.710)	(0.295)	(2008.958)	(0.005)
Strain Decile=8 × Black	0.0037	0.0057	0.1510	0.0014	4.8053	0.2986	2258.2344	0.0023
	(0.004)	(0.004)	(0.184)	(0.010)	(11.765)	(0.279)	(1896.183)	(0.005)
Strain Decile=9 × Black	0.0068**	0.0074**	0.2175	-0.0023	-2.3983	0.2167	-490.3380	0.0035
	(0.003)	(0.004)	(0.181)	(0.010)	(11.560)	(0.269)	(1946.316)	(0.005)
Strain Decile=10 × Black	0.0090**	0.0109**	0.5105**	0.0126	10.7057	0.1958	1879.2016	0.0040
	(0.003)	(0.004)	(0.187)	(0.010)	(12.500)	(0.300)	(1898.313)	(0.005)
N	106082	91243	91243	106082	23578	106082	106060	106082
r2	0.293	0.306	0.294	0.412	0.459	0.275	0.423	0.226

Regression coefficients from Equation 5 with the following outcomes: in-hospital mortality (Col 1 and 2: Col 1 uses the whole sample, Col 2 uses the sample for which wait times could be computed); Wait times (Col 3); ICU admission (Col 4); ICU length of stay (Col 5); Length of inpatient stay (Col 6); Inpatient charges (Col 7); and Discharge to hospice (Col 8). $p < .001^{***}$ $p < .05^{**}$ $p < 0.1^{*}$

TABLE A.7

Outcomes by Race × Strain × Medical Need (chronic measure)

	(1) In-hosp Mort b/se	(2) Wait time (hrs) b/se
Black	0.0004	0.9485***
	(0.002)	(0.182)
Above median mort. ind.	0.0190***	-0.4100**
	(0.004)	(0.175)
Strain decile=1	0.0000	0.0000
	(.)	(.)
Strain decile=2	0.0035	0.6394**
	(0.003)	(0.213)
Strain decile=3	0.0040	0.6740***
	(0.003)	(0.200)
Strain decile=4	0.0056*	0.5231**
	(0.003)	(0.202)
Strain decile=5	0.0044	0.4243**
	(0.003)	(0.192)
Strain decile=6	0.0069**	0.5176**
	(0.003)	(0.192)
Strain decile=7	0.0023	1.1272***
	(0.003)	(0.300)
Strain decile=8	0.0046	1.0827***
	(0.003)	(0.207)
Strain decile=9	0.0021	1.0458***
	(0.003)	(0.195)
Strain decile=10	0.0037	1.6645***
	(0.003)	(0.212)
Strain decile=1 × Black	0.0000	0.0000
	(.)	(.)
Strain decile=2 × Black	0.0013	-0.4320
	(0.003)	(0.279)
Strain decile=3 × Black	0.0017	-0.0352
	(0.003)	(0.306)
Strain decile=4 × Black	0.0001	0.1079
	(0.003)	(0.337)
Strain decile=5 × Black	0.0004	0.1512
	(0.003)	(0.267)
Strain decile=6 × Black	-0.0012	0.1646
	(0.003)	(0.263)
Strain decile=7 × Black	0.0031	-0.0584
	(0.003)	(0.349)
Strain decile=8 × Black	-0.0012	0.0687
	(0.003)	(0.277)
Strain decile=9 × Black	0.0037	0.2197
	(0.003)	(0.258)
Strain decile=10 × Black	0.0023	0.4010
	(0.003)	(0.277)
Black × Above median mort. ind.	-0.0067	-0.2066
	(0.005)	(0.237)
Strain decile=1 × Above median mort. ind.	0.0000	0.0000
	(.)	(.)
Strain decile=2 × Above median mort. ind.	-0.0134**	-0.5240**
	(0.006)	(0.263)
Strain decile=3 × Above median mort. ind.	-0.0075	-0.4503*
	(0.006)	(0.254)
Strain decile=4 × Above median mort. ind.	-0.0082	-0.1695
	(0.006)	(0.258)
Strain decile=5 × Above median mort. ind.	-0.0103*	0.1761
	(0.006)	(0.250)
Strain decile=6 × Above median mort. ind.	-0.0136**	0.0387
	(0.006)	(0.245)
Strain decile=7 × Above median mort. ind.	-0.0139**	-0.3354
	(0.006)	(0.356)
Strain decile=8 × Above median mort. ind.	-0.0122**	0.2179
	(0.006)	(0.258)
Strain decile=9 × Above median mort. ind.	-0.0152**	0.8074**
	(0.005)	(0.253)
Strain decile=10 × Above median mort. ind.	-0.0118**	0.8024**
	(0.005)	(0.251)
Strain decile=1 × Black × Above median mort. ind.	0.0000	0.0000
	(.)	(.)
Strain decile=2 × Black × Above median mort. ind.	0.0037	0.5101
	(0.007)	(0.355)
Strain decile=3 × Black × Above median mort. ind.	0.0020	0.4227
	(0.008)	(0.389)
Strain decile=4 × Black × Above median mort. ind.	0.0013	0.2197
	(0.008)	(0.422)
Strain decile=5 × Black × Above median mort. ind.	0.0067	-0.0273
	(0.008)	(0.363)
Strain decile=6 × Black × Above median mort. ind.	0.0076	0.3113
	(0.007)	(0.359)
Strain decile=7 × Black × Above median mort. ind.	0.0108	0.5430
	(0.007)	(0.444)
Strain decile=8 × Black × Above median mort. ind.	0.0113	0.1163
	(0.007)	(0.366)
Strain decile=9 × Black × Above median mort. ind.	0.0063	-0.0892
	(0.007)	(0.358)
Strain decile=10 × Black × Above median mort. ind.	0.0137**	0.1142
	(0.007)	(0.371)
N	106091	91252
r2	0.285	0.293

Regression coefficients from Equation 6 using the chronic measure of patient medical need, with the following outcomes: in-hospital mortality (Col 1) and wait times (Col 2). $p < .001^{***}$ $p < .05^{**}$ $p < 0.1^{*}$

TABLE A.8

Outcomes by Race × Strain × Medical Need (acute measure)

	(1) In-hosp Mort b/se	(2) Wait time (hrs) b/se
Black	-0.0029	1.0158***
	(0.003)	(0.160)
Abnormal vitals	0.0089*	-0.0821
	(0.005)	(0.165)
Strain decile=1	0.0000	0.0000
	(.)	(.)
Strain decile=2	-0.0044	0.4541**
	(0.003)	(0.190)
Strain decile=3	0.0053	0.3621**
	(0.004)	(0.177)
Strain decile=4	0.0022	0.4405**
	(0.004)	(0.185)
Strain decile=5	-0.0023	0.5220**
	(0.004)	(0.182)
Strain decile=6	0.0034	0.5189**
	(0.004)	(0.175)
Strain decile=7	-0.0041	1.1356***
	(0.003)	(0.264)
Strain decile=8	-0.0037	1.0243***
	(0.003)	(0.189)
Strain decile=9	-0.0026	1.3427***
	(0.003)	(0.188)
Strain decile=10	-0.0026	1.8211***
	(0.003)	(0.195)
Strain decile=1 × Black	0.0000	0.0000
	(.)	(.)
Strain decile=2 × Black	0.0056	-0.2403
	(0.004)	(0.243)
Strain decile=3 × Black	-0.0009	0.2795
	(0.004)	(0.254)
Strain decile=4 × Black	0.0019	-0.0847
	(0.004)	(0.238)
Strain decile=5 × Black	0.0066*	-0.0197
	(0.004)	(0.234)
Strain decile=6 × Black	-0.0016	0.1864
	(0.004)	(0.231)
Strain decile=7 × Black	0.0082**	-0.0709
	(0.004)	(0.300)
Strain decile=8 × Black	0.0094**	0.0610
	(0.004)	(0.239)
Strain decile=9 × Black	0.0067*	0.0820
	(0.004)	(0.233)
Strain decile=10 × Black	0.0070*	0.3305
	(0.004)	(0.239)
Black × Abnormal vitals	-0.0007	-0.3828
	(0.006)	(0.233)
Strain decile=1 × Abnormal vitals	0.0000	0.0000
	(.)	(.)
Strain decile=2 × Abnormal vitals	0.0037	-0.2072
	(0.007)	(0.263)
Strain decile=3 × Abnormal vitals	-0.0128*	0.2161
	(0.007)	(0.263)
Strain decile=4 × Abnormal vitals	-0.0016	-0.0295
	(0.007)	(0.267)
Strain decile=5 × Abnormal vitals	0.0046	-0.0178
	(0.007)	(0.261)
Strain decile=6 × Abnormal vitals	-0.0068	0.0484
	(0.007)	(0.258)
Strain decile=7 × Abnormal vitals	-0.0013	-0.4787
	(0.006)	(0.329)
Strain decile=8 × Abnormal vitals	0.0057	0.4565*
	(0.006)	(0.264)
Strain decile=9 × Abnormal vitals	-0.0084	0.2713
	(0.006)	(0.265)
Strain decile=10 × Abnormal vitals	0.0023	0.6819**
	(0.006)	(0.267)
Strain decile=1 × Black × Abnormal vitals	0.0000	0.0000
	(.)	(.)
Strain decile=2 × Black × Abnormal vitals	-0.0052	0.1127
	(0.008)	(0.355)
Strain decile=3 × Black × Abnormal vitals	0.0102	-0.2744
	(0.008)	(0.378)
Strain decile=4 × Black × Abnormal vitals	-0.0023	0.6982
	(0.009)	(0.453)
Strain decile=5 × Black × Abnormal vitals	-0.0077	0.3453
	(0.008)	(0.366)
Strain decile=6 × Black × Abnormal vitals	0.0095	0.3124
	(0.008)	(0.370)
Strain decile=7 × Black × Abnormal vitals	0.0008	0.7244*
	(0.008)	(0.430)
Strain decile=8 × Black × Abnormal vitals	-0.0116	0.1103
	(0.008)	(0.376)
Strain decile=9 × Black × Abnormal vitals	0.0016	0.2323
	(0.007)	(0.365)
Strain decile=10 × Black × Abnormal vitals	0.0046	0.2728
	(0.008)	(0.386)
N	101435	91035
r2	0.287	0.293

Regression coefficients from Equation 6 using the acute measure of patient medical need, with the following outcomes: in-hospital mortality (Col 1) and wait times (Col 2). $p < .001^{***}$ $p < .05^{**}$ $p < 0.1^{*}$

TABLE A.9

Analysis of Descriptive Features of *Reason for Admission* Note

	(1) In-Hosp Mort b/se	(2) Missingness b/se	(3) Time to document b/se	(4) > med char count b/se	(5) Avg. Word length b/se
Black	-0.0031	0.0320***	-0.6108***	-0.0122	-0.1639**
	(0.003)	(0.008)	(0.071)	(0.011)	(0.055)
Strain Decile=1	0.0000	0.0000	0.0000	0.0000	0.0000
	(.)	(.)	(.)	(.)	(.)
Strain Decile=2	-0.0038	-0.0125	0.1721**	0.0228*	-0.0068
	(0.004)	(0.009)	(0.085)	(0.012)	(0.061)
Strain Decile=3	0.0007	-0.0327***	0.3608***	0.0154	-0.0012
	(0.004)	(0.009)	(0.093)	(0.012)	(0.061)
Strain Decile=4	0.0010	-0.0214**	0.6065***	0.0219*	0.0740
	(0.004)	(0.009)	(0.097)	(0.012)	(0.061)
Strain Decile=5	-0.0006	-0.0360***	0.7456***	0.0454***	0.0858
	(0.004)	(0.009)	(0.099)	(0.012)	(0.063)
Strain Decile=6	-0.0013	-0.0428***	0.7386***	0.0280**	0.0637
	(0.004)	(0.009)	(0.096)	(0.012)	(0.061)
Strain Decile=7	-0.0034	-0.0446***	0.9399***	0.0448***	0.1685**
	(0.004)	(0.009)	(0.099)	(0.012)	(0.060)
Strain Decile=8	-0.0019	-0.0524***	1.0253***	0.0516***	0.1316**
	(0.004)	(0.008)	(0.095)	(0.012)	(0.059)
Strain Decile=9	-0.0060*	-0.0645***	1.3190***	0.0579***	0.1789**
	(0.003)	(0.008)	(0.103)	(0.012)	(0.058)
Strain Decile=10	-0.0030	-0.0544***	1.3026***	0.0419***	0.1187**
	(0.004)	(0.008)	(0.098)	(0.011)	(0.057)
Strain Decile=1 × Black	0.0000	0.0000	0.0000	0.0000	0.0000
	(.)	(.)	(.)	(.)	(.)
Strain Decile=2 × Black	0.0030	0.0074	-0.1472	-0.0294*	-0.0750
	(0.004)	(0.011)	(0.118)	(0.016)	(0.081)
Strain Decile=3 × Black	0.0038	0.0162	-0.7672*	-0.0109	0.0232
	(0.005)	(0.011)	(0.429)	(0.016)	(0.080)
Strain Decile=4 × Black	0.0006	0.0071	-0.4027***	-0.0250	-0.0988
	(0.004)	(0.011)	(0.114)	(0.016)	(0.080)
Strain Decile=5 × Black	0.0034	0.0203*	-0.4425***	-0.0379**	-0.0685
	(0.004)	(0.012)	(0.116)	(0.016)	(0.081)
Strain Decile=6 × Black	0.0040	0.0224**	-0.3482**	-0.0147	0.0201
	(0.004)	(0.011)	(0.116)	(0.016)	(0.079)
Strain Decile=7 × Black	0.0078**	0.0185*	-0.9301**	-0.0358**	-0.1394*
	(0.004)	(0.011)	(0.344)	(0.016)	(0.078)
Strain Decile=8 × Black	0.0056	0.0176	-0.4481***	-0.0163	-0.0714
	(0.004)	(0.011)	(0.112)	(0.015)	(0.077)
Strain Decile=9 × Black	0.0082**	0.0279**	-0.7304***	-0.0348**	-0.0621
	(0.004)	(0.011)	(0.118)	(0.015)	(0.076)
Strain Decile=10 × Black	0.0114**	0.0180*	-0.5468***	-0.0186	0.0269
	(0.004)	(0.011)	(0.114)	(0.015)	(0.074)
Observations	76998	106518	77907	77907	77907
Mean	0.0172	0.269	0.926	0.484	6.635
r2	0.316	0.150	0.0160	0.0405	0.00869

Coefficients from regressing descriptive features of the *Reason for Admission* note – missingness (Col 2), time to documentation completion (Col 3), above median character count (Col 4), and average word length (Col 5), described in Section 5.2) on race, deciles of hospital strain, an interaction between the two, patient covariates (age, sex, insurance status, Elixhauser comorbidities, mortality index, readmission index), and fixed effects (hospital-year). Col 1 regresses in-hospital mortality on the same RHS variables for the sample of encounters with a non-missing note. $p < .001^{***}$ $p < .05^{**}$ $p < 0.1^{*}$

TABLE A.10

Sentiment and Adjective Analysis of *Reason for Admission* Note

	(1) Subjectivity Score b/se	(2) Polarity Score b/se	(3) Num. Adjectives b/se
Black	0.0061	-0.0003	-0.0508**
	(0.004)	(0.002)	(0.017)
Strain Decile=1	0.0000	0.0000	0.0000
	(.)	(.)	(.)
Strain Decile=2	-0.0062	0.0011	0.0233
	(0.005)	(0.003)	(0.022)
Strain Decile=3	-0.0027	0.0033	0.0124
	(0.005)	(0.003)	(0.022)
Strain Decile=4	0.0002	0.0011	0.0577**
	(0.005)	(0.003)	(0.022)
Strain Decile=5	-0.0021	0.0040	0.0786**
	(0.005)	(0.003)	(0.024)
Strain Decile=6	-0.0029	0.0015	0.0703**
	(0.005)	(0.003)	(0.024)
Strain Decile=7	0.0018	0.0033	0.0720**
	(0.005)	(0.003)	(0.023)
Strain Decile=8	-0.0025	0.0016	0.0761**
	(0.005)	(0.003)	(0.023)
Strain Decile=9	-0.0035	0.0000	0.0783***
	(0.005)	(0.003)	(0.023)
Strain Decile=10	-0.0099**	0.0014	0.0777***
	(0.005)	(0.003)	(0.023)
Strain Decile=1 × Black	0.0000	0.0000	0.0000
	(.)	(.)	(.)
Strain Decile=2 × Black	0.0041	0.0015	-0.0312
	(0.006)	(0.003)	(0.027)
Strain Decile=3 × Black	-0.0018	-0.0025	-0.0021
	(0.006)	(0.003)	(0.027)
Strain Decile=4 × Black	0.0001	0.0024	-0.0541**
	(0.006)	(0.003)	(0.027)
Strain Decile=5 × Black	0.0020	0.0000	-0.0683**
	(0.006)	(0.003)	(0.028)
Strain Decile=6 × Black	0.0063	0.0024	-0.0680**
	(0.006)	(0.003)	(0.028)
Strain Decile=7 × Black	-0.0009	-0.0015	-0.0710**
	(0.006)	(0.003)	(0.026)
Strain Decile=8 × Black	0.0039	-0.0002	-0.0458*
	(0.006)	(0.003)	(0.027)
Strain Decile=9 × Black	-0.0028	0.0003	-0.0606**
	(0.005)	(0.003)	(0.026)
Strain Decile=10 × Black	0.0130**	0.0027	-0.0577**
	(0.005)	(0.003)	(0.025)
Observations	77154	77154	77154
Mean	0.0571	0.00181	0.528
r2	0.134	0.130	0.179

Regression coefficients from Equation 5 with the following as outcomes: Subjectivity score (Col 1); Polarity score (Col 2); Number of adjectives (Col 3). Details on construction of these variables provided in Appendix B. $p < .001^{***}$ $p < .05^{**}$ $p < 0.1^{*}$