NBER WORKING PAPER SERIES

RATIONING BY RACE

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Working Paper 30380
http://www.nber.org/papers/w30380

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
August 2022, Revised May 2024

We gratefully acknowledge feedback from seminar participants at the NBER Summer Institute, NBER Conference on Racial and Ethnic Health Disparities, the Health Economics Workshop at NYU Stern School of Business, AEA Annual Meeting, Becker Friedman Institute at the University of Chicago, University of Pennsylvania, Stanford University, Duke University, Carnegie Mellon University, and the University of Virginia, as well as thank David Asch, Bocar Ba, Joseph Benitez, Bernard Black, Jacob Bor, Kate Bundorf, Kitt Carpenter, Ben Castleman, David Chan, Amitabh Chandra, Paula Chatterjee, David Cutler, Janet Currie, Michael Darden, Kit Delgado, Matthew Eisenberg, Jeremy Goldhaber-Fiebert, Jose Fernandes, Ezra Golberstein, Jevay Grooms, Scott Halpern, Noah Hammarlund, Kandice Kapinos, Mireille Jacobson, Hedwig Lee, Judith Long, Dan Ly, Amol Navathe, Ziad Obermeyer, Maya Rossin-Slater, Rosalie Pacula, Carol Propper, Seth Richards-Shubik, Christopher Ruhm, Hannes Schwandt, Peter Schwardmann, Zirui Song, Sebastian Tello-Trillo, Rachel Werner, Morgan Williams, Jr., Michelle White, Derek Wu, and Jacob Zureich for helpful comments and suggestions. We thank Ashvin Gandhi for the title of this paper. This paper substantially updates a previous version, titled "Capacity strain and racial disparities in mortality." The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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JEL No. I10,I14,J15

ABSTRACT

We hypothesize that deepening resource scarcity results in rationing on the basis of group identity in settings with underlying discrimination. We provide evidence of such race-based rationing in a high-stakes setting: health care. Using detailed, time-stamped data on 107,000 patient admissions to a large health system, we find that in-hospital mortality increases for Black, but not White, patients as hospitals reach capacity (a state of resource scarcity likely to trigger or exacerbate biases in decision-making). As a mechanism, we identify rationing by wait time, documenting that sick Black patients wait longer for care than healthy White patients at every capacity level, likely because of systematic misevaluation of medical need. Text analysis of unstructured provider notes reveals differential rationing of provider effort by race as another potential mechanism. Together, these findings demonstrate important linkages between three key economic concepts: scarcity, discrimination, and rationing.

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1 Introduction

Decision-makers seek to ration scarce resources by demonstrated need, willingness to pay (WTP), 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 socially suboptimal ways. For instance, laboratory experiments suggest that 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 or gender, particularly in settings where discrimination is prevalent.[1] In this paper, we provide causal evidence that resource scarcity increases rationing of resources on the basis of race within a highly consequential, real-world setting: health care.

There is a long history of discrimination on the basis of race in health care, at the levels of both 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., 2019a; Schulman et al., 1999a).[2] We hypothesize that when providers and systems face resource, personnel, or time constraints, underlying discrimination may lead to rationing of health care on the basis of race rather than medical need in ways that adversely affect health outcomes.

We delve into this question using uniquely detailed, time-stamped electronic health record data. Our data include over 107,000 patient admissions over 2015–2018 across two hospitals within a large urban academic hospital system in the southeast United States (what we call the "inpatient sample"). Informed by a simple conceptual framework, we leverage plausibly exogenous variation in hourly hospital capacity as our measure of resource scarcity and examine how it affects rationing of hospital resources and outcomes for Black vs. White patients. Our conceptual framework highlights that as hospitals approach maximum capacity—here indicated by a higher share of inpatient beds occupied—patients' escalating demands can strain providers' cognitive bandwidth and overburden the hospital's material resources, such as number of inpatient beds, personnel, diagnostic tools, and treatments (Anesi et al., 2018; Evans & Kim, 2006; Hoe, 2022; Marks & Choi, 2019; Song et al., 2020).

[1] Discrimination—whether taste-based, statistical, or systemic—in the allocation of public goods is common in the United States (Alesina, Baqir, & Easterly, 1999; Darity Jr, 2022). A large body of lab-based research in social psychology 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: for example, Krosch and Amodio (2019) use brain imaging techniques to show that under conditions of scarcity, the neural processing time for images of Black individuals lengthens, a result that might explain the smaller resource allocations to Black than to White participants found in laboratory games.

[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., 2019a), differences in opportunities for patient self-advocacy (Wiltshire et al., 2006), differences in the extent to which relevant comorbid conditions are diagnosed and included in health records (Lyles, Wachter, & Sarkar, 2021), 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 they 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).

Under these conditions of deep resource scarcity—referred to as "capacity strain" (Arogyaswamy et al., 2021)—providers and hospitals may be less able to assess a patient's medical need and may increasingly rely on efficient, but racially 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., 2019a).

Our identifying assumption is one of conditional independence: we assume that any differences between Black and White patients (which are inevitable and not a threat to our identification) that may affect outcomes *remain constant with strain.* For example, our estimates would be biased if admitted Black, but not White, patients were to become increasingly sicker with strain. We provide evidence in support of our identifying assumption by demonstrating that there are no differences between the Black and White patients in our sample in the distribution of (i) time of hospital arrival and (ii) capacity strain at arrival. Further, we adjust 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 seasonality or time (though identification does not require that capacity strain be entirely random—only that it not be differentially correlated with characteristics that predict death in Black vs. White patients). We also put over a dozen observed and estimated patient covariates—such as patient demographic characteristics, validated comorbidity indices, vital signs at hospital arrival (such as temperature, heart rate, blood pressure, respiratory rate, and oxygen saturation), patient socioeconomic status (proxied by insurance status), and "topic" themes (identified by a machine learning algorithm) within the hand-written note that documents a patient's reason for admission—on the left-hand side of our estimating model to show that the differences between Black and White patients on these dimensions do not change as hospitals reach capacity. Moreover, our identifying 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]

To assess the effect of increasing hospital resource scarcity—as captured by capacity strain—on providers' rationing decisions, we begin with the starkest possible outcome of biased allocation of clinical resources: death. We find that in-hospital mortality rises for Black but not White patients as capacity strain increases. Specifically, we document an approximately 15% greater increase in mortality for Black than for White patients as capacity strain increases to its highest decile (in our

[3] Arogyaswamy et al. (2021) conduct a qualitative study of hospital administrators at major academic medical centers similar to the setting we consider in this study; all of the interviewed administrators noted the difficulty in predicting hospital strain and marshaling 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, conditional on the inclusion of time fixed effects in the estimation, hospital strain is an exogenous regressor (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 are generally not available to researchers (Neprash et al., 2021; Song et al., 2020), thus represents a meaningful advance on its own.

sample, an average bed occupancy rate of 90–95%). These findings are highly robust across models that range from sparse (i.e., including only patient age and gender) to saturated (i.e., including a wide variety of patient covariates both individually and in interaction with either patient race or strain at arrival). Together, these results demonstrate that deepening resource constraints disproportionately harm Black individuals.

Before providing direct evidence of race-based rationing of care as a mechanism for these racial differences in mortality, we first rule out a range of alternate explanations—such as differential changes in patient composition with increasing strain—by presenting evidence against selective admission or discharge from the hospital at high strain. We also leverage an innovation of our study: we can observe information on all patients arriving through the emergency department (ED) during our study period (we refer to these data as the "ED sample"), including patients discharged home and those admitted to the hospital from the ED. The ED sample includes information on provider-entered triage scores, which capture how sick the provider *perceives* a patient to be (and are used in EDs to indicate how long a patient can safely wait for treatment and admission to an inpatient bed, if needed). Our access to the ED sample allows us to overcome a data missingness problem in our study and gives us an extra layer of confidence in ruling out the most obvious alternate explanation for our findings: that providers are, observably to them but unobservably to the researcher, turning away the least sick Black patients (or equivalently, prioritizing admitting the sickest Black patients) at high strain in ways they do not at low strain.

Within this ED sample, we show that the relative differences in triage scores between Black and White patients do not change with strain—either for patients admitted to the hospital or for those discharged home. In fact, we find that Black patients are perceived to be less sick (i.e., have lower triage scores) than White patients on average. We are also able to assess the mismatch between perceived need as indicated by the triage score and *actual* medical need within this ED sample. To assess actual medical need, we use a validated measure called the Elixhauser mortality index (Elixhauser et al., 1998a), which is based on 30 different chronic conditions and is constructed by us for the purposes of data analysis but is not directly available to providers. The Elixhauser index is designed to predict mortality and has been shown to do so successfully in a number of contexts, including ours. We find that the mismatch between perceived and actual medical need grows larger for Black than for White patients as strain increases.

This result is consistent with our theory: though a provider could estimate a patient's medical need in the same manner as the mortality index does (i.e., using the entire history of diagnosis codes in the electronic medical record), doing so takes time and effort, both of which are challenged as hospitals reach capacity. The effort required to accurately assess medical need may be larger for Black patients given the increased barriers to care that they face in obtaining diagnoses of comorbid conditions (Institute of Medicine, 2003), their less complete medical records upon which to draw information on existing comorbidities (Lyles, Wachter, & Sarkar, 2021), and challenges in establishing productive provider–patient relationships (Alsan, Garrick, & Graziani, 2019; Schwab & Singh, 2023). Providers may consciously or unconsciously decline to exert the required effort at times of deep resource scarcity and high cognitive load. As a result, the quality of assessment of medical need for Black patients deteriorates with strain, and instead of medical need guiding clinical decisions, providers' reliance on race-based heuristics increases. We find further evidence of this in our data: the Black patients who are more likely to die at high strain are those who would benefit most from careful clinical assessment (e.g., high-need patients), while those for whom there is little uncertainty about clinical need or course of action (e.g., patients admitted with complaints of chest pain and/or shortness of breath) face no strain-related mortality penalty.

We then provide direct evidence for race-based (rather than need-based) rationing of hospital resources as the reason why Black patients' health fares worse at high capacity strain. While there are multiple margins on which resources may be rationed, we focus on two: (i) wait times for an inpatient bed, and (ii) provider effort.

First, we examine wait times because we can observe them in the data with precision and because time is a critical margin of rationing that affects outcomes in health care and other public service settings (Barzel, 1974; Chen et al., 2022; Holt & Vinopal, 2023; Lu, Hanchate, & Paasche-Orlow, 2021; Martin & Smith, 1999). We first show that, in a pattern similar to what we see in our mortality results and consistent with our conceptual model in which increasingly scarce hospital resources are rationed more by race and less by medical need, Black patients experience greater increases in wait times for beds than do White patients as capacity strain increases.[4] We then also show that providers appear to rely more on race than on medical need to assign beds as hospital strain increases: At high strain, the wait times of high-need and low-need patients become indistinguishable, while differences remain between those of Black and White patients. We also document a striking fact: At all levels of capacity strain, sick Black patients wait longer for an inpatient hospital bed than healthy White patients. These rationing results accord well with our earlier finding that triage scores—used in ED settings as a measure of how long a patient can wait for care safely—are generally lower for Black than for White patients. It may well be that this strain-based mistriage of Black patients, which likely translates into longer wait times, has adverse downstream consequences, including higher

[4]While we do not find this pattern for other measures of care intensity, such as likelihood and length of intensive care unit (ICU) care, total charges, and 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 less of these resources than White patients.

mortality.

Second, in a more suggestive set of analyses, we investigate strain-driven disparities in the rationing of provider effort. Effort is a scarce resource that is critical for making a range of important decisions: accurately assessing patient medical need, obtaining a correct diagnosis, implementing a timely and appropriate treatment plan, and responding quickly to changes in the patient's hospital course. Moreover, provider effort is thought to be an important driver 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 medical record (EMR) data, and so, following other authors (Chan, 2016, 2018), we infer it from the patterns it leaves in the data. Specifically, we examine unstructured, free-text entries in the electronic health record documenting the *reason for admission*, a field filled out by a triage provider around the time of initial hospital arrival that plays an important role in setting the course of care (Ly, Shekelle, & Song, 2023; Schrader & Lewis, 2013).

We deploy several machine learning and text analysis methods on the text data from this field to quantify provider effort. We first analyze descriptive features such as time to completion, character counts, and average word length—text features shown to be associated with effort in a wide range of contexts (Galesic & Bosnjak, 2009; Tausczik & Pennebaker, 2010; Yadav, Prabhu, & Chandy, 2007). We also analyze sentiment, focusing on subjectivity and polarity scores. We focus on these two dimensions because greater subjectivity introduces the potential for greater bias (Bloche, 2001; Schrader & Lewis, 2013) and Black patients are often described more negatively than White patients in EMRs (Sun et al., 2022a), which can also result in bias and reduced effort in provision of care to Black patients (Goddu et al., 2018). Finally, to account for the possibility that medical notes may be less well suited than other text corpuses to standard natural language processing techniques (Weissman et al., 2019), we also manually identify adjectives, which are used to provide detail, context, and nuance and 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 exhibits features consistent with lower effort and that, as strain rises, so does the disparity between Black and White patients on several of these measures, most notably the subjectivity of documentation and the number of adjectives used. Simply put, as hospital strain increases, healthcare providers may allocate less effort toward filling in Black patients' medical records than they do those of White patients, which may in turn harm the quality of care provided to them and their health outcomes.

Our findings inform the literature in three topics foundational to economic study—*scarcity*, *rationing*, and *discrimination*—by demonstrating new and consequential linkages among them.

First, our findings reveal a relationship between *scarcity* and *discrimination*: when resource scarcity deepens, underlying discrimination comes to the fore in the form of racially biased allocation practices. This insight suggests a unifying explanation for why discrimination is a defining feature of some settings but not others. For example, our findings reconcile a range of labor market patterns: why migrant workers were three times more likely than nonmigrant workers to be laid off in the industries most profoundly disrupted by the COVID-19 pandemic (Auer, 2022), and why applicants with foreign-sounding names are as likely as those with native-sounding names to be called back for job interviews in tight labor markets (where there are more vacancies than applicants) but face a significant disadvantage in loose labor markets (Baert et al., 2015). More generally, the findings of this paper also help us understand the disparate impacts of policies or shocks that increase scarcity. For example, racial disparities in a range of economic and health outcomes have been shown to manifest in the face of large-scale stressors such as economic shocks, natural disasters, pandemics, and labor shortages (Anderson, Crost, & Rees, 2020; Beck & Tolnay, 1990; Klein et al., 2023; Stoye & Warner, 2023). Similarly, policy-driven cuts to funding in sectors such as education have disproportionately affected racial and ethnic minority students (Jackson, Wigger, & Xiong, 2021). In unifying these observations, our study also makes a critical methodological point: Resource shocks can be a useful way to identify discrimination, particularly in real-world settings where direct measures are difficult to obtain.

Further, this relationship between scarcity and discrimination suggests that policies aimed at alleviating resource scarcity can be viable for reducing discriminatory practices. For instance, consider current and historical discrimination against Black homebuyers—a key factor in persistent racial wealth gaps (Bayer, Ferreira, & Ross, 2018; Charles & Hurst, 2002; Rugh & Massey, 2010). Our study suggests that increasing housing supply would not only accomplish the primary goals favored by proponents of this policy (e.g., alleviating homelessness, helping younger individuals build assets (Glaeser & Gyourko, 2018; Green & White, 1997)) but could also reduce discriminatory rationing of resources in housing markets, mitigating racial disparities in homeownership and wealth accumulation to some extent. This reasoning could even apply to a range of other settings: Increasing available resources for schools, for example, may mitigate racial disparities in student outcomes (Card & Krueger, 1996), interventions to increase cognitive bandwidth among police officers may mitigate racial disparities in arrests and the use of force (Dube, MacArthur, & Shah, 2023), and interventions to improve available capacity in hospitals may help reduce disparities in health care outcomes (Vohra et al., 2023a; White, Villarroel, & Hick, 2021).

Second, we contribute to the economic literature on *rationing* and *discrimination*, which has largely focused on how limited resources are allocated across agents under conditions of excess demand, often relying on price or nonprice mechanisms (such as queuing and lottery systems) to resolve imbalances (Breza, Kaur, & Shamdasani, 2021; Jacob & Ludwig, 2012; Leshno, 2022; Stiglitz & Weiss, 1981). We propose—and our findings support—that a generally unexplored *social* factor—group identity—should be integrated into positive theories of rationing to explain skewed outcomes in sectors where the stakes for equitable distribution are high.

Third, we identify a link between *scarcity* and *rationing*. The literature on the distribution of scarce resources has most commonly concerned itself with matters of macroeconomic importance, for example, how some rationing mechanisms (e.g., those relying on consumer WTP) may result in poverty and inequality (Piketty, 2014; Stiglitz, 2012) and in political violence and conflict (André & Platteau, 1998; Kahl, 2006). In contrast, this study delves into the micro-level dynamics of scarcity: we highlight how underlying discriminatory preferences influence the rationing of scarce resources at the point of service delivery and individual decision-making in an important setting.

Finally, our paper contributes to the literature on cognitive biases by highlighting a connection between two well-documented theories. It is widely recognized that cognitive strain often causes individuals to resort to heuristic-based, or "type I," thought processes (Kahneman, 2011). Similarly, scarcity—of any kind—is known to induce a specific decision-making mindset that causes a hyperfocus on some problems while inducing a neglect of others (Mullainathan & Shafir, 2013; Shah, Mullainathan, & Shafir, 2012). We propose that the type of resource scarcity documented in our study (i.e., hospital strain) can cause cognitive strain on individuals in ways that exacerbate racial bias, which is both a type of heuristic decision-making and a psychological process that favors one problem at the expense of another (i.e., how to provide care to White patients instead of all patients). Our findings demonstrate the existence and tangible harms of this mental process, aligning with research indicating that physicians, often working under resource constraints, are prone to adopting decision-making heuristics that significantly affect patient outcomes (Schwab & Singh, 2023; Singh, 2021).

We wrap up by noting that our findings are derived from 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—a time of record capacity strain (especially in hospitals serving Black patients (Vohra et al., 2023b)), 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 of targeting 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 typical stressors faced by hospitals.

2 Conceptual Framework

In this section, we formalize the intuition that as resource scarcity deepens, allocation decision-making becomes more susceptible to heuristics premised on 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 care personnel or hospital material resources such as beds, monitoring technologies, or medical and surgical treatments to provider-specific resources such as cognitive bandwidth and effort—can increasingly reflect group identity rather than the intended margin of medical need when resources become scarce.

A team of healthcare providers is 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 the 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 team assesses medical need, based on which it allocates 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, 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 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 nonlinearities in this process, but the nonlinearities need not be exponential.) The racial weight $R^*_{ij}(t)$, conversely, captures greater reliance by the providers on the patient's racial identity in allocation decisions as resources grow 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—which could be taste-based, statistical, or systemic—arising from various factors. These factors include im-

[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).

plicit or explicit biases among healthcare providers (Hoffman et al., 2016; Stepanikova, 2012), biases inherent in treatment algorithms (Obermeyer et al., 2019a), inaccuracies in assessment of medical need due to incompleteness in EMRs (Lyles, Wachter, & Sarkar, 2021) or unfamiliarity with the distribution of disease risk among Black patients (Balsa & McGuire, 2001), mistrust between providers and patients (Alsan, Garrick, & Graziani, 2019), and limited patient advocacy (Wiltshire et al., 2006). These issues, which are potentially always present, become even more critical in stressful conditions.[6]

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

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

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

Two hypotheses emerge 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, in other words, if $\gamma = 0$, 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 hypothesis is consistent with the findings of increases in physicians' implicit biases under stress (Johnson et al., 2016; Stepanikova, 2012). 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 receive any weighting in the allocation decision outside of patient need, in which case 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. Alternatively, (ii) there is a fixed level of discrimination that is unrelated to strain at time t, in which case 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.

The effects specified by the two hypotheses can be modeled as being unrelated to each other *or* as each compounding the effect of the other. If they are unrelated, it could be the case either that discrimination increases with strain but not at the expense of appropriate assessment of patient need (that is, that the second hypothesis is true but not the first) or that, with strain, providers become worse at differentiating between high- and low-need patients but in a manner unrelated to race (that is, that the first hypothesis is true but not the second). If the effects are compounding, there may be an interaction between the two hypothesized effects: Provider teams may become worse at assessing

[6] Our conceptualization of the potential for pervasive discrimination in care parallels the logic of the model proposed by Balsa and McGuire (2003) in which treatment decisions are based on clinical need but may be influenced by patient race, which could either alter the threshold of clinical need for treatment (reflecting racial prejudice) or impact the clarity of providers' assessment of medical need (reflecting statistical discrimination). Our framework builds on this insight by allowing the discrimination term to become stronger under stressful conditions, such as those that materialize under deepening resource scarcity.

need for Black patients, while their assessments for White patients are unaffected.

Consistent with this conceptual framework, we first provide evidence that the patient's health outcome Y_{it}—here measured by in-hospital mortality—does indeed vary jointly by the level of hospital strain ($S(t)$) at the time of the patient's hospital arrival and patient race (R_i). We then show that as strain increases, patient race both increasingly determines resource allocation A_{ijt} in the hospital (we use wait times as our primary measure but also measures of provider effort inferred from clinical documentation). Regarding what undergirds these patterns, we next show that actual medical need (as measured by the comorbidities index) is systematically underestimated for Black patients as strain increases and that need becomes less predictive of resource allocation as strain increases.

3 Setting and Data

3.1 Setting

We use comprehensive electronic health record data from 107,221 patient admissions between 2015 and 2018 at two hospitals in a well-respected academic hospital system. We refer to this sample as the "inpatient sample," which we use for our primary analyses. The two study hospitals are located in a southeastern U.S. city known for its sizable Black population. Both 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 of those where Black patients receive health care, as large teaching hospitals are disproportionately represented among the hospitals that care for Black patients (Burke et al., 2017; Himmelstein, Ceasar, & Himmelstein, 2023).

Our sample includes patients admitted to the hospital both through the ED ($\sim$ 50% of admissions) and directly from outpatient or specialty clinics or transfers from other facilities. We consider these groups together because patients admitted through both ED and non-ED pathways can be high acuity on arrival or have the potential to become very ill during the course of the hospitalization. For example, patients admitted to the hospital through non-ED pathways often have acute care needs (e.g., cardiac conditions, sepsis) and may have worse outcomes such as higher mortality.[7] Importantly, the share of patients arriving from the ED relative to direct admits does not change with capacity strain (see Figure A.1).

Our data have several advantages. First, they provide 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

[7]For example, studies have shown that directly admitted patients have higher mortality risks than patients coming in through the emergency room from specific conditions such as sepsis (Powell et al., 2012) and from all causes (Kocher, Dimick, & Nallamothu, 2013).

second) documenting the patient's entire journey through each hospital wing from initial arrival to discharge, vital signs on admission, mode of arrival to the hospital, patient sociodemographic characteristics, insurance status, physician of record identifiers, a comprehensive list of patient diagnoses and procedures, discharge disposition, and text from a provider-inputted field documenting the *reason for admission.*

Second, we also have access to a (less detailed) dataset on all ED visits in these hospitals during the study period (a sample we refer to as the "ED sample"). Importantly, these data include ED triage scores (valued from 1, denoting least severe, to 5, denoting most severe), which are entered by triage providers and reflect their assessments of patient acuity. We also have data on the arrival mode for all ED visits (e.g., walk-in, brought in by ambulance). We use this dataset to test alternative explanations for our main results, e.g., whether Black and White patients admitted from the ED or discharged home from the ED change differentially with increasing hospital strain.

Third, and finally, to investigate our research question, we need *complete* data. In other words, we need to be able to observe 100% of *all* the patients seen in an inpatient (or ED) setting during our time frame to correctly construct our measure of capacity strain. While EMR data of this nature are already exceptionally rare in research, even when they are available, usually only a subset of the data is provided to the researchers (such subsets are either sampled randomly or based on insurance status). Thus, even though our data cover only two hospitals, they reflect *all* encounters within them. Using data from a larger number of hospitals would have necessitated our forgoing variables and data features essential to answering our research question.

3.2 Measures

Here, we describe the key variables used in our analysis, with reference to how they relate to our conceptual framework.

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.[8] As is typical in medical settings, race is either self-reported by the patient or recorded by staff. Our data, similarly to most EMR data, do not distinguish between these different types of reporting. Regardless of the reporter, measurement error in patient racial classification is unlikely to affect our analysis, as errors in race attribution are possible but tend to be infrequent (Agawu et al., 2023; Cook, 2006).

Hospital capacity strain (S_{ht}): We measure hospital capacity strain based on the total number of

[8]We did not have sufficient power to analyze patients of other races or ethnicities given that the sample sizes for these groups were at least two orders of magnitude smaller than those of the non-Hispanic Black and White patients.

patients occupying an inpatient bed in the hospital (h) during the hour of the patient's hospital arrival (t). We explicitly choose this capacity-based measure given the evidence from the clinical literature of its strength in predicting health outcomes (Kohn et al., 2019). We first calculate strain at every hour of every day in our sample separately for each hospital, based on which we then generate hospital-specific deciles of capacity strain (an approach that allows the effect of strain on outcomes to be nonlinear). Given that the hospitals have different distributions of capacity, we then calculate the 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 the hospitals as being close to capacity. The mean proportion of inpatient beds filled in the first decile of strain for both hospitals ranges from 69% to 78%; at the tenth decile, the mean range of filled beds is 91% to 95% (Table A.1). Importantly, we calculate hospital strain at time of patient *arrival*—not *admission*—to the hospital, as the time of ward admission is endogenous but the time of patient arrival is plausibly less so.

Actual vs. perceived medical need (N_i vs. N_i^*): We use the Elixhauser mortality index as our measure of *actual* medical need. This index—which predicts a patient's mortality risk on the basis of a weighted combination of the presence of 30 different chronic conditions—is one of the most widely used and heavily validated scores for predicting in-hospital mortality in medical research (Elixhauser et al., 1998b; Fortin et al., 2017; Moore et al., 2017).[9] The Elixhauser 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).[10]

The Elixhauser indices for individual patients in our sample were not directly available to the provider teams caring for them; that is, they are known to the econometrician, but not the clinician. To compute these indices, we use information from a given patient's current and past medical records. While providers 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 electronic medical record does not summarize them in the form of an index. Providers are thus left to predict how these diagnoses individually and jointly may affect a patient's likelihood of in-hospital mortality; this is a difficult and cognitively demanding task.

Figure I provides context relevant for our analyses about the Elixhauser index, illustrating

[9] In our data, the Elixhauser index is a discrete variable ranging from -7 to 87 (mean=12.58; SD=13.3; median=11). The chronic conditions used to construct the index are 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.

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

the challenges providers face when they assess medical need. The top panel plots the distribution of Elixhauser mortality scores and relationship with the probability of in-hospital death by patient race. The proportion of patients dying in the hospital rises nonlinearly with the index scores and does so similarly for both Black and White patients (see also Table A.2).

We can observe only *perceived* medical need for the ED sample (i.e., all patients who visited the ED during our time frame, regardless of whether they were admitted into the inpatient sample). We do so using triage scores, which range from 1 (lowest medical need) to 5 (highest medical need). Triage scores are assessed for patients as they walk through the ED by triage providers (either a physician or nurse) and reflect the patient's medical need as perceived by the provider; i.e., the scores are supposed to identify how long a patient can wait safely for treatment or admission.

The bottom panel in Figure I assesses how providers *perceive* medical need among patients admitted to the hospital from the ED. This graph relates patients' triage scores with their Elixhauser index scores. The triage scores appropriately increase with the Elixhauser scores up to a point, but this relationship flattens at higher values of the latter—where mortality risk begins to increase exponentially, consistent with work showing that providers may inaccurately assess patient need (Mullainathan & Obermeyer, 2022). This also illustrates how providers assess Black patients as having lower medical need than than White patients for any given Elixhauser score, consistent with systematic racial biases affecting assessments of patient clinical need (Balsa & McGuire, 2003; Hoffman et al., 2016; Sax et al., 2023; Schulman et al., 1999a). (This panel is consistent with Figure A.2, which plots the distribution of triage scores for Black and White ED patients admitted to the hospital and those discharged home from the ED. These histograms show that Black patients are always assessed to be of lower medical need than White patients—note the leftward shift in the distribution of their triage scores). Later in Section 4.5, we present suggestive evidence that the mismatch between actual medical need (Elixhauser scores) and perceived medical need (triage scores) grows larger for Black patients than for White patients with increasing strain.

Collectively, the patterns in Figure I demonstrate that (1) Elixhauser scores are a useful proxy for actual medical need for both Black and White patients, (2) providers underestimate actual medical need among patients with higher Elixhauser mortality scores, and (3) providers systematically underestimate medical need for Black patients. These data make it easy to imagine that, as hospital capacity becomes overwhelmed, actual clinical need becomes even harder to assess than it is on average, particularly for Black patients.

<u>Allocation of care resources – rationing</u> (A_{ijt}): We present the rationale for which resource allocation decisions we focus on and their measurement in greater detail in Section 5. To summarize here, our

primary measure of care rationing is the time a patient waits to receive an inpatient bed; our choice of this measure is motivated by the large literature documenting that wait times are a key margin along which care is rationed and that periods of capacity strain drive wait times. In further analyses that we consider more suggestive in nature, we also examine allocation of provider effort. Effort is not directly measured in EMR 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 account for 60% of the admissions to the two study hospitals, consistent with the city's population being predominantly Black. Compared to White patients, Black patients are on average younger (52 vs. 59 years) and more likely to be female (65% vs. 50%).

Black patients, despite being younger, have similar comorbidity burdens, as denoted by the number of recorded comorbidities and Elixhauser scores (the distributions of the latter are provided in Figure I), 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, have slightly shorter inpatient stays, and are 27% less likely to be admitted to the ICU.[11]

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 and clarify and defend the validity of our core identifying assumption. We then show that mortality increases for Black—but not White—patients as hospitals reach capacity and resources become increasingly scarce, consistent with our hypothesis of race-based resource rationing under such conditions. We assess and rule out a range of alternate explanations. For example, we rule out the primary alternative explanation for our mortality results: that sicker Black, but not White, patients are being admitted to the hospital at high strain. In fact, we find that (i) Black patients both admitted to the hospital, and discharged home, from the ED are assessed as being of lower medical need than Whites on average and that (ii) the mismatch between perceived and actual medical need widens for Black patients relative to

[11] Note that these differences in characteristics between Black and White patients are not a threat to our identification. Rather, our concern, addressed in the next section, is whether the differences *change* with strain.

the mismatch for White patients with increasing strain. We provide direct evidence of race-based rationing of specific care inputs in Section 5 below.

4.1 Research Design

Our core specification estimates the difference in the likelihood of in-hospital mortality between Black and White patients at each decile of hospital strain:

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

Specifically, we regress in-hospital mortality for each admission i on patient race ($R_i = 1$ if the 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. The β_ps can be interpreted as a series of difference-in-differences terms.

We include in our models a vector of patient-level covariates and fixed effects, including:

- continuous variables for first- and second-order polynomials for patient age
- patient sex
- whether the patient was insured, to account for differences in care patterns for uninsured and low-socioeconomic-status patients (Doyle Jr, 2005; Stepanikova & Cook, 2008)
- fixed effects for (i) the total number of Elixhauser comorbidities (up to 30), (ii) the Elixhauser mortality index scores, and (iii) the Elixhauser readmission index scores (validated to be highly predictive of 30-day hospital readmission); we use fixed effects because of the nonlinear relationship between these measures and mortality (see Figure I)
- fixed effects for the attending physician (δ_j) 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 attending physician (typically, the one attending at the time of discharge) provided care during periods critical to the patient's hospital outcome, for fixed physician-specific differences in practice patterns
- hospital–time fixed effects (π_{ht}), i.e., hospital–year, hospital–month of year, hospital–day of week, and hospital–hour of day fixed effects, to account for typical patient flows over these dimensions, which ensures that our measure of capacity strain is net of these potentially expected averages

and therefore less likely to reflect anticipated strain (an assumption that we further discuss below)

In a robustness check, we additionally include covariates capturing abnormalities in 5 vital signs (heart rate, temperature, blood pressure, respiratory rate, oxygen saturation) recorded at the time of hospital arrival. (We do not use these in our main specification, as the sample for which all these variables are available is much smaller.) In another robustness check, we demonstrate that our estimates are robust across both parsimonious specifications (e.g., including only age and sex as covariates) and saturated ones (including many other covariates individually and in interaction with race or strain).

4.2 Identification

Our identifying assumption is one of conditional independence: We assume that any differences between Black and White patients (which are inevitable and not a threat to our identification) that may affect outcomes *remain constant with strain*. For example, our estimates would be biased if admitted Black, but not White, patients were to become increasingly sicker with strain. Note that identification does not require that the variation in hospital strain be completely random—that is, we do not need the strain as measured at any hour to be completely random. This assumption is much stronger and may not always hold (as seasonality and hospital operational schedules may cause predictable patterns in strain, though we do include hospital–time fixed effects and, as we discuss below, the literature suggests that the fact that strain can be anticipated does not mean its adverse consequences can be prevented). Our assumption is thus narrower in scope.

We support this identifying assumption with four arguments. First, we show in several ways that hospital capacity strain is not associated with changes in admitted patients' composition in a manner that varies by patient race. We start by demonstrating that the distributions for Black and White patients are nearly identical in terms of hour of hospital arrival and average hospital strain at arrival time (Figure A.3). Thus, the racial distribution of patients upon hospital arrival does not vary either by arrival time or by capacity strain at arrival time. We then use patient covariates in our main estimating model—age, sex, insurance status, number of comorbidities, mortality index, readmission index—on the left-hand side in a series of balancing tests (Pei, Pischke, & Schwandt, 2019), demonstrating that the relative values of these covariates do not change by race with increasing strain (Table A.3).

Second, in Section 4.5, we address alternate explanations for our core findings, providing further evidence suggesting there was no selective admission or discharge on the basis of patient race or clinical need with increasing strain, further supporting our identifying assumption. Selective admission to, or discharge from, the hospital is a concern because though capacity strain is difficult to predict (as we discuss next), 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. However, at the provider level, such coordinated processes to divert specific types of patients are less likely to occur on an hour-to-hour basis (which is the dimension of strain that we leverage in this study) given the known difficulties in responding to capacity strain in real time (Arogyaswamy et al., 2021). Even so, we support this contention with tests examining a range of variables on the left-hand side, including mentions of themes in clinical documentation that we identify with machine learning algorithms, triage scores for patients admitted and discharged from the ED sample, the likelihood of being brought to the hospital via an ambulance, discharge to hospice, out-transfers to other hospitals, etc. We find no strain-related changes in differences in any of these variables between Black and White patients.

Third, we support our identification assumption by reviewing the literature. An even stronger version of this assumption—i.e., complete randomness of day-to-day capacity strain—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 similar to the one we examine here—concludes that "hospital capacity strain is complex and difficult to predict

Fourth, we compute hospital strain at the time of patient *arrival* to the hospital, not the time of hospital *admission*, which further bolsters the case that our identification assumption holds. While the 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 admission time endogenous), the time at which the patient walks through the doors and is registered into the hospital system can be considered plausibly random (a contention supported by the evidence noted above).

4.3 Results

Our estimates from Equation 5 are plotted in Figure II and presented in tabular form in Table 2 Col 1. Figure II (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 II (b) presents the predictive margins of in-hospital mortality (in other words, the fitted values at the means of all covariates) 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 percentage points (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-differences estimates (β_p in Equation 5) are more informative about the relative change in mortality between the races across different levels of capacity strain. They imply that 15% of the 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[12] (coefficient on the difference-in-difference estimate after all observations across deciles 1–9 are pooled as "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.[13] We speculate on what drives these impacts, whose sign but not necessarily statistical significance persists across our specifications, in Section 5.3.2.

To summarize, we find that Black patients suffer higher risks of death as hospital capacity strain increases. After conducting specification checks and ruling out alternate explanations in the next two subsections, we offer one potential explanation, which follows from our conceptual model, for why this is the case: deepening resource scarcity induced by capacity strain makes assessing patient need more difficult. As a result, to simplify this decision complexity, care providers allocate resources not by patient need but by patient race, a heuristic that is biased against Black patients given the prevalence of underlying discrimination in health care. We offer evidence in support of this explanation by examining heterogeneity in the treatment effects (Section 4.6) and evaluating potential mechanisms by which care is rationed by race rather than need (Section 5).

4.4 Specification Checks

Our core findings are robust across specifications. 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 first present estimates from more parsimonious versions of the model where we use no covariates or

[12]This estimate is 17% if we consider deciles 7 through 10 to be high strain.

[13]Mortality for White patients decreases by 0.2 pp from lower strain levels (decile 1–5) to higher strain levels (deciles 6–10), with a p-value of 0.14.

fixed effects at all (Col 2), from both linear and logistic probability models that include only patient age, gender, and hospital– year fixed effects (in Cols 3 and 4), and from more saturated models that additionally include, for example, diagnosis-related group (DRG) fixed effects to ensure that we are making comparisons within a specific health condition (Col 5), that interact hospital strain with all the control variables in X_i to account for their potentially differential effects on mortality by hospital strain (e.g., older patients may have greater mortality at high strain than younger patients; Col 6), and that interact patient race with all the control variables in X_i for similar reasons (e.g., older Black patients may have higher mortality than White patients; Col 7). Our use of the parsimonious models helps us address the potential biases to which ordinary least squares models are subject when treatment effects are heterogeneous across groups (Słoczyński, 2022), while our consideration of the saturated models helps us address the potential omitted variable bias affecting models where the primary object of interest is an interaction term (Feigenberg, Ost, & Qureshi, 2023). We find that the results are substantively unchanged across the different specifications (Cols 2–7): No matter the specification, Black patients die more than White patients with increasing strain in a fashion nearly identical to the pattern in our main figure (note the significant interactions at strain deciles 7 and 10 across specifications).

Additionally, to address concerns that our making adjustments 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 30 comborbidities that comprise the Elixhauser indices separately as covariates (instead of using fixed effects for the summed mortality and readmission indices). In this case, as well, we find no substantive differences in our estimates (Col 8).

We also estimate Equation 5 where, instead of using heteroskedasticity-robust standard errors, we cluster the standard errors by date of hospital admission to allow for within-date correlation of the residuals. Our results are unchanged (Col 9).

Finally, we include covariates for 5 different measures of abnormal vital signs at admission (Table A.4 Col 6). We include 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 at the time of arrival.[14] We find that our main results are entirely unchanged.

[14] "Abnormal" measures on each vital sign are designated as follows: (i) body temperature above 37.8 C (100 F) or below 35 C (95 F), (ii) diastolic blood pressure below 60 or systolic blood pressure below 90, (iii) respiratory rate below 12 or above 20, (iv) heart rate below 60 or above 100, and (v) oxygen saturation below 90. The thresholds denoting abnormal vitals reflect common criteria used by clinicians.

4.5 Alternate Explanations

A competing explanation for the findings in Figure II is that there are strain-related differences in the selection of patients in our inpatient sample on the basis of patient race and clinical acuity. Such selection is possible if the marginal admission with increasing strain is a sicker Black patient or the marginal discharge is a less sick White patient. In this section, we provide evidence suggesting that neither selective patient admission nor discharge can explain our core findings.

We reiterate: Any alternative explanation must show that the variable X *changes differentially* between Black and White patients with increasing strain (where X is correlated with mortality). It cannot simply be the case that Black and White patients have different levels of X on average; Black and White patients are clearly different on many dimensions, but these level differences do not jeopardize our main findings. Thus, for all of the tests described below, we plot the interaction terms (i.e., the interaction coefficients between the race and strain deciles from Equation 5) as evidence that the differences in any variable X remain constant across strain and thus cannot explain differential changes in mortality between Black and White patients.

Are patients being *selectively admitted* to the hospital at high strain?

First, we test for selective admission by race across varying levels of strain by using the following *observed* patient characteristics in our inpatient sample on the left-hand side of our main estimating model (Equation 5): age, sex, and insurance status, as well as the entire range of measures of clinical need (Elixhauser comorbidities, mortality index scores, and readmission index scores) and the five abnormal vitals described in the previous subsection. The 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.

Second, we estimate regressions using *estimated* patient characteristics as outcomes, specifically, the five primary "topic" themes identified from the *reason for admission* free-text field by means of a machine learning technique called latent Dirichlet allocation or LDA (Blei, Ng, & Jordan, 2003). (See Appendix A for details.)

The *reason for admission* field is typically filled in manually by health care providers as soon as a patient arrives at the hospital as part of the triage process. We first provide exploratory evidence of what this field contains. We create word clouds for Black and White patients (Figure A.4), which provide a visual representation of the most common words and phrases appearing in this text field. We find that similar words—*surgery*, *preadmission*, *pain*—occur most frequently for patients of both races, though there are some differences. *Pain*, *chest*, and *sob* (which stands for shortness of breath) are more frequently reported for Black patients. We then create word clouds for Black and White patients seen at low capacity strain (deciles 1, 2, 3) and high capacity strain (deciles 8, 9, 10) (Figure A.5). There are no obvious changes in the frequency of the most common words, but, of course, visual inspection is a highly informal method of assessing changes.

Thus, we use LDA to conduct a more formal test of differences in the themes captured by this text field between White and Black patients as strain increases. LDA cannot identify what these themes are, but the five most common words from each theme are shown in the top panel in Figure A.6. We also show a visual distribution of the topic distributions using the heatmap in the bottom panel. For example, Topic 4 is equally represented on average among Black and White patients, but Topics 1 and 2 are represented more among White patients, and Topics 3 and 5 appear more for Black patients. Regardless, the formal analysis in Table A.5 (which reestimates Equation 5 using each of the five topics on the left-hand side) finds that the distribution of topics does not change differentially with strain for Black vs. White patients, which once again confirms that patient selection with strain is not a concern or a threat to our identification.

Third, we examine the possibility of selective admission of patients arriving through the ED (recall that admissions from the ED make up 50% of our inpatient sample). To do so, we obtain data on all 251,280 patients who entered the emergency room during our study period (i.e., the ED sample). We examine these data even though the characteristics of *admitted* Black and White patients in our inpatient sample remain similarly stable with increasing strain because admission to the hospital is a choice made by the providers and thus is itself endogenous. Without being able to observe the larger and more complete sample on which this choice is made (at least for the 50% of the patients in our inpatient sample for which such data are available), we may be failing to perceive relevant selection into the sample. The ED sample thus allows us to overcome a data missingness problem and shores up our confidence that we can rule out the most obvious alternate explanation for our research findings: that providers are, observably to them but unobservably to us (the researchers), turning away the least sick Black patients (or equivalently, prioritizing admission of the sickest Black patients) at high strain in ways they do not at low strain. Critically, this ED sample has a variable that allows us to observe the medical need of the patient as perceived by the provider: the patient's triage score, which ranges from 1 (lowest medical need) to 5 (highest medical need).

We rule out this alternative explanation with two pieces of evidence: (i) Black patients are no more likely to be admitted to the hospital from the ED than White patients with increasing strain, suggesting that selective admission of Black patients from the ED does not drive our results (Figure A.7 top panel); and (ii) conditional on their being admitted from the ED, Black patients' triage scores do not change relative to White patients' with increasing strain (Figure A.7 middle panel), suggesting that selective admission of sicker Black patients from the ED with increasing hospital strain does not drive our main results.

It is important to note here that Black patients both admitted to the hospital, and discharged home, from the ED are triaged as having lower medical need than White patients on average (i.e., notice in Figure A.2 that Black patients' triage score distributions are shifted to the left compared to those of White patients in both graphs). Moreover, at each discrete score of the Elixhauser mortality index (a more objective measure of actual medical need than triage scores that is based on current and prior medical diagnoses), Black patients receive lower triage scores on average (Figure I bottom panel). This mismatch is possibly the clearest evidence that it is likely discrimination that drives the racial disparity in mortality because the triage score allows us to assess what providers *believe* about Black patients' medical need while the Elixhauser index allows us to measure Black patients' *actual* need (with some degree of noise; see the correlation between mortality and the Elixhauser index in Figure I top panel). That is, regardless of Black patients' *actual* medical need, we see that providers consistently perceive Black patients as having lower medical need than White patients on average. However, that Black patients are more likely to die at high strain conflicts sharply with providers' assessment, so it may be that Black ED patients are incorrectly triaged and coded as having lower medical need than they actually do (which diverts important resources needed by Black patients). The effort required to assess medical need may be greater for Black patients, given the increased barriers they face to having comorbidities diagnosed and managed, less complete documentation of these medical risk factors, and well-documented challenges in provider–patient relationships—effort that providers may consciously or unconsciously choose to forgo at times of high strain and cognitive load, resulting in inaccurate triaging of Black patients. There is some evidence of this phenomenon in the data as well: Figure A.8 shows that as hospital strain increases, the mismatch between the Elixhauser and physician triage scores (for those admitted from the ED) increases more for Black patients than for White patients.[15] That this mismatch increases more for Black patients than for White patients with increasing strain is highly suggestive of increasing difficulties in assessing patient need, as posited by our conceptual framework; however, given that we have triage scores for only half our main sample (i.e., those who enter through the ED), we do not include this variable in our mechanism section.

Fourth, we assess whether there are strain-related racial differences in the likelihood of a patient

[15] We assess mismatch as follows. First, we create quintiles of the Elixhauser score, where 1 and 5 represent the lowest and highest levels (quintiles) of medical need, respectively. The mortality index is considered to be mismatched to the patient's triage score (which also ranges from 1 to 5, with higher numbers indicating increasing acuity) if the two scores are more than 2 points apart. Thus, a patient with a mortality index of 4 and a triage score of 1 has a mismatch in assessment, while a patient with a mortality index of 4 and a triage score of 3 does not. Our approach is similar to others in the nascent medical literature on accuracy of triage decisions (Sax et al., 2023).

admitted through the ED arriving via ambulance (another marker of medical need). The results of these analyses are presented in the lowermost panel of Figure A.7: we find Black patients are not more likely to arrive by ambulance than White patients under increasing strain.

Overall, we find, across multiple tests and measures, no evidence of selective admission of sicker Black patients to the hospital when the hospital is under higher strain.

Are patients being *selectively discharged* from the hospital at high strain?

We next assess whether there is selective discharge of patients as hospitals reach capacity. We focus primarily on selective discharge to hospice given the known higher rates of hospice referral for White than for Black patients (Asch et al., 2021; Cohen et al., 1994). Given that, by definition, mortality is imminent for patients placed into hospice, selective discharge of White patients to hospice during times of high capacity strain may mean that our estimates of racial disparities in in-hospital mortality are overstated. We find no evidence of selective discharge to hospice (Figure A.9).

We also examine whether there is selective transfer out of the hospital (to another hospital) on the basis of patient race, finding no evidence for this, either (Figure A.9).

Overall, we once again find no evidence of selective discharge of White patient (over Black patients) out of the hospital with increasing hospital strain.

4.6 Treatment Effect Heterogeneity

To more concretely link our main findings to our conceptual model—and to lay the groundwork for our examination of specific mechanisms in Section 5—we analyze heterogeneity in the treatment effects by patient clinical need (N_i). In the last subsection, we provided evidence suggesting that as capacity strain increases and resources grow scarcer, the mismatch between a patient's perceived clinical need (measured by triage score) and true clinical need (measured by the Elixhauser index) widens more for Black patients than for White patients, suggesting poorer quality of clinical assessment (possibly because of less effort, either conscious or subconscious, on the part of physicians). Thus, we here examine whether the racial differences in in-hospital mortality that we observe are higher for the patients who would benefit most from higher-quality clinical assessment (or greater effort more generally). This hypothesis follows from our conceptual model, in which, as strain rises, identifying high-need patients becomes more challenging for providers while recurrence to potentially biased, race-based heuristics increases, both of which may differentially compromise care for Black patients.[16]

We conduct these analyses by first splitting our sample at the median Elixhauser index value, which facilitates interpretation (above- and below-median observations correspond to high- and low-

[16]In addition, we may expect to see a more prominent strain-related mortality pattern among high-need patients given their higher baseline mortality risk.

need patients, respectively) and preserves statistical power while accounting for the nonlinear relationship between the mortality index and likelihood of death (as depicted in Figure I). We then reestimate Equation 5, but now with a fully saturated triple interaction (the "×" term signifies the estimation of all main effects, as well as double and triple interaction terms):

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

Figure III (a) 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), and Panel (b) plots the double interaction coefficient terms (Race × Strain) for the high- and low-need patients.

We note three patterns of interest: (i) High-need patients have significantly higher mortality than low-need patients at all levels of hospital strain (consistent with Figure I), (ii) Panel (a) shows that high-need Black patients experience a sharp increase in mortality at decile 10, and (iii) Panel (b) confirms that high-need patients drive the racial differences in strain-related mortality, mirroring the pattern observed in Figure II (a).

Overall, these results support the mechanism delineated in our conceptual model: inaccurate assessments of patient need and reliance on potentially biased heuristics can drive worse health outcomes for Black patients during periods of deep resource scarcity, ostensibly because of inappropriate rationing of care resources. As a result, racial disparities in mortality are higher among patients who would benefit most from accurate assessment of true patient need, i.e., those whom the Elixhauser index identifies as having high medical need.

We strengthen our conceptual model's credibility by presenting evidence for an inverse scenario: Though patients with higher medical need experience more significant differences in mortality rates with increasing strain (because of deteriorating quality of medical assessment), those with easily assessable medical needs should show *lower* mortality disparities. To explore this conjecture, we focus on patients arriving at the hospital with complaints of chest pain and/or shortness of breath. These complaints are common, are well known by all medical practitioners to be high risk given they may reflect high-mortality conditions such as heart attacks, pulmonary embolisms, and asthma, and are addressed with a highly protocolized suite of diagnostic tests, including chest x-rays, electrocardiograms, and cardiac enzyme testing (Kasper et al., 2015). Thus, medical need can more easily inferred from these complaints, and they can be more quickly acted on as well. In other words, decision-makers lean on heuristics when there is uncertainty, and there is far less uncertainty about the course of action that a provider should take when a patient comes to the hospital complaining of chest pain or shortness of breath. In these cases, a patient's race is less likely to displace the role of medical need in resource allocation for these conditions, which is also consistent with recent work demonstrating convergence in quality of care received by Black and White patients for heart attacks (Chandra, Kakani, & Sacarny, 2022).

We search the *reason for admission* free-text field for phrases that capture these two complaints (and variants, as well, e.g., "sob" and "shortness of breath"). Consistent with our hypothesis, we find no evidence of strain-related racial disparities in mortality among patients admitted for these easily observed, high-need complaints (Figure A.10). In fact, our main mortality results appear to be driven by other complaints that are not as highly protocolized, suggesting once again that it is for the patients who would benefit most from higher-quality need assessment (or greater physician effort, more broadly) that we see the most adverse consequences of resource scarcity.

5 Rationing by Race as a Mechanism

In the previous section, we showed that Black patients—but not White patients—experience higher likelihoods of in-hospital mortality with increasing capacity strain. We rule out a range of possible mechanisms, establishing a critical fact: Admitted Black patients do not become sicker than White patients with increasing strain. If anything, they are perceived as less sick by their providers (as observed by the consistently lower triage scores and greater strain-related mismatch between these and their Elixhauser index scores).

In this section, we provide direct evidence for race-based rationing of scarce resources as the key mechanism behind the observed mortality patterns. In doing so, we will be able provide evidence for each of the relationships described in our conceptual model: namely, strain-related resource constraints leading to inaccurate assessments of patient need and increased reliance on race-based heuristics, all of which may lead to misallocation of specific care resources and, consequently, poor health outcomes for Black patients.

We first discuss the two margins for rationing we 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 as strain increases. 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, once again, how, under increasing capacity strain, providers may be unable to accurately assess patient medical needs and may (implicitly or explicitly) resort to salient, yet inaccurate and bias-prone, race-based heuristics for decision-making.

5.1 Potential Margins of Rationing

Health care resources can be rationed on multiple margins, many of which are not observable in EMR data. We focus on two margins that are observable, noting that evidence of race-based rationing for these measures may speak to the possibility of race-based rationing on other (unmeasured or unobservable) margins of care, as well.

Our primary margin of interest is wait time, given its importance in both the health care literature and the broader literature on the economics of rationing (Barzel, 1974; Lindsay & Feigenbaum, 1984). 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. For example, 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 public services other than health care, 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 assessed—we view these analyses as more suggestive. However, we embark on this analysis because of the centrality of effort in our conceptual model. Greater effort is needed to accurately assess clinical need and diagnose and treat patients, but effort is also a scarce resource: Under personnel or resource constraints, providers (e.g., physicians, nurses) may ration effort in favor of sicker, higher-risk patients, but as with wait times, there may be suboptimal rationing of effort by need.

The possibility of race-based rationing of effort is supported by both our own findings—e.g., of greater bias in assessments of clinical need among Black patients (Figure I bottom panel), potentially exacerbated by higher capacity strain (Figure A.8)—and findings from the literature. For example, providers have been shown to shift their effort in response to incentives uncorrelated with patient need (Chan, 2016, 2018). Providers have also been shown to hold systematic biases, which, under stressors, may manifest into lower intensities of effort exerted for Black patients (Burgess et al., 2007;

Burgess et al., 2006; Stepanikova, 2012). The potential for this bias is highlighted by audit studies of treatment decisions (Schulman et al., 1999a), patient perspectives (Brown et al., 2023), and analyses of physicians' 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 need for racial and ethnic minority groups (Obermeyer et al., 2019a).

In addition to these margins, we investigate rationing along other dimensions of care quality/intensity: (i) ICU admission, (ii) ICU stay length, (iii) inpatient stay length, and (iv) inpatient charges. For these additional measures, because both lower and higher values may 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), the estimates on these measures will be harder to interpret. We thus view them as less informative with respect to our study question but present them for sake of completeness.

5.2 Measures

Wait times: Our measure of wait times follows from our unique time-stamped data. We calculate the exact time (with precision in seconds) elapsed between patient arrival to the hospital (either through the ED or main registration) and placement in any inpatient (ward) bed.[17]

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

To circumvent these challenges, we turn to analysis of unstructured medical notes. Specifically, we focus on the *reason for admission*, a text field 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 the 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 that of the provider who documents the reason for admission) by analyzing features of the documented text.[18] We begin by examining several descriptive features of

[17] We note that we can compute arrival time for only 86% of our main sample (though reestimating Equation 5 on this subsample 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 for us to focus on).

[18] As in the case of wait times, a minority (28%) of our main sample has an empty *reason for admission* field. Reestimating Equation 5 on this subsample with mortality as the outcome does not change our main result, either (Table A.8 Col 1).

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),[19] (ii) character count (a binary measure split at the median number of characters used in the field),[20] 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 minimal assumptions on the part of the researcher for their interpretation (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, a shorter time to document completion, lower character count, and shorter word length are associated with lower levels of effort. We would expect these interpretations to hold in health care, conditional on consideration of some additional nuances that reflect 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 their results, 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 it after immediate care tasks are finished), which we would interpret as indicative of greater attention paid to and effort exerted on patient care (Apathy et al., 2023; Tai-Seale et al., 2017). Deferral of documentation to after-hour periods or when the care task burden has waned would also allow the provide to write lengthier, more complete notes, which inform the care patterns of subsequent providers.

In addition to these descriptive features of notes, we 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) text subjectivity and (ii) text polarity. Details on the methods are provided in Appendix B. Subjectivity refers to the degree of personal opinion vs. factual information encoded in a text. Fully objective (factual) documentation would receive a score of zero, whereas fully personal views or subjective information would receive a score of 1.[21] More subjective

[19] 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 filling out 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 completing the note. Instead, the provider may have started the note when the patient came in, but because she was busy, filled out the note partially over multiple sessions until she finally completed it 30 hours later. Alternatively, the provider could have begun filling it in 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.

[20] We use a median split of the character count because the variable is so skewed: among the nonmissing text data, the skew is 4.5. The skew of the average word length, for comparison, is 1.6.

[21] 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.

notes allow room for implicit bias in documentation and may lack the precision and clarity necessary for a provider to make an accurate diagnosis, in ways that may lead to poorer 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 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).[22] The potential importance of polarity arises from the evidence that providers are more likely to use negative descriptors with Black patients (Sun et al., 2022a) and that doing so may lead to reduced effort (Goddu et al., 2018).[23]

While sentiment analysis is increasingly being used in clinical applications, there are some concerns that the standard tools for doing so may not always be appropriate in clinical settings (Weissman et al., 2019). To this point, we make no strong inferences about what our calculated sentiment scores mean by themselves. Rather, we are interested in how the scores *vary* by capacity strain and patient race, hypothesizing that under stress, providers may be more likely to use more subjective and polarized terms for Black than for White patients, consistent with an increased reliance on biased heuristics (Johnson et al., 2016). We also address this concern by analyzing a measure that is less of a "black box," the number of adjectives, as a measure of the descriptiveness and detail in notes. Here, adjectives are identified by means of the presence of common suffixes.[24] 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

The results for wait times for an inpatient hospital bed are shown in Figure IV (a) (with coefficients provided in Table A.6 Col 3). Our estimates show that Black patients' wait times increase more than White patients' as strain increases. We see a clear bump in wait times at the top decile of hospital strain, matching our findings in Figure II Panel (a) for in-hospital mortality.[25] While this telltale

[22] 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.

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

[24] 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.

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

bump at the tenth decile is not strictly necessary for us to to infer that wait time is a mechanism, it is a certainly highly suggestive that this is the case.

We next try to connect these results to our conceptual framework by asking the following: As strain increases, are beds being rationed by medical need, or by race? Disaggregating these patterns by medical need (where above- and below-median Elixhauser index values capture high- and low-need patients, respectively) reveals three patterns of relevance to our conceptual framework (Figure IV Panel (b)). 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 resources are allocated less based on patient need at higher than at lower capacity levels of capacity strain. This evidence is consistent with our conceptual framework, which argues that, with increasing capacity strain, the provider's ability to accurately 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 time than race (especially given that our measure of medical need is indeed predictive of mortality, as shown in Figure I Panel (a) and Figure III Panel (b)). 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. In other words, at high strain, if we could only observe patient wait times, we would not be able to distinguish between high- and low-need patients but we would be able to tell apart Black and White patients. This finding is concordant with our conceptual framework: With increasing strain, the patient's racial identity plays a larger role in allocation decisions of health care resources (while reliance on patient need as a guiding factor diminishes).[26]

The third—and most striking—pattern is that high-need Black patients (blue line) wait longer than low-need White patients (gray line) at all capacity levels, with this difference being the largest at higher strain levels. That this disparity exists even at decile 1, when resources are most abundant, implies that wait time differences are not due solely 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 are both independent of *and* exacerbated by capacity strain.

[26] This result should further address any 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 results for wait times accord well with our earlier finding that Black patients generally receive lower triage scores than White patients (even for each discrete Elixhauser mortality score), given that triage scores are used in ED settings as a measure of how long a patient can wait for care safely. It may well be that this strain-based mistriage of Black patients, which likely translates into longer wait times for an inpatient bed (Section 5) has adverse downstream consequences such as higher mortality.

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). The results are presented in Figure V and in tabular form in Table A.8. Consistent with providers deferring completion of documentation to attend to 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 to 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 completing documentation, providers are able to complete longer, more detailed notes (as measured by character count and average word length).[27]

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 documentation completion and documentation with fewer characters and shorter words. For some measures, we see differential outcomes for Black patients relative to those of White patients with increasing strain, though these results are precisely estimated only for the time to documentation. Overall, the fact that notes for Black patients have some features correlated with less effort—namely, providers are less prone to deferring documentation tasks at times of strain (potentially at the expense of attending to 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 the presence of discrimination—baseline disparities that exist regardless of strain.

We now present the results from our analyses of text sentiment, as shown in Figure VI Panels (a)–(d) and in tabular form in Table A.9 Cols 1–2. As in the case of our mortality and wait time findings, we find evidence of a bump in the subjectivity scores at the highest decile of strain (Panel

[27] We also examine the likelihood of the *reason for admission* note's being empty and find that this decreases with strain for all patients though it decreases to a significantly greater extent for White patients, likely because deferral of documentation to times of lower strain allows for higher rates of documentation completion. Moreover, consistent with all the other patterns of service documented within this paper, Black patients always (regardless of strain level) have a higher likelihood of having missing documentation than do White ones (Figure A.11).

(a)), implying that the notes describing Black patients' *reason for admission* become relatively more subjective as strain increases. This divergence in subjectivity scores is driven by both 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'. Recall that we interpret the *divergence* in trends for Black vs. White patients with strain, not the *level* differences in subjectivity (given that interpretation of sentiment analysis of medical documentation conducted with standard tools may pose challenges). Thus, given that 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 practices for Black and White patients change 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 (Panels (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 (Figure VI Panels (e)–(f)). We find that as strain increases, Black patients' documentation has fewer adjectives than White patients' (Panel (e)), though this is driven largely by an increase in adjective use for the latter (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 do at lower levels of strain. Conversely, Black patients' notes have fewer descriptors at all levels of strain.

Our findings from this mechanism section suggest that not only do providers ration material resources such as beds as resources grow scarcer but they may ration cognitive resources—such as effort—as well. While rationing by wait time has been previously shown in a range of contexts (though never on the basis of race), this evidence of rationing of *cognitive* resources is a potential contribution to the literature by itself.

Collectively, these patterns are consistent with a set of provider behavioral responses to capacity strain that may differ by patient race. Speculatively, these changes in effort may reflect behaviors that go beyond simply deferring nonessential tasks such as documentation to attend to more essential tasks during periods of strain. Recall in Figure II that we observe a small (though imprecisely estimated and statistically non-significant) decrease in White patients' mortality at higher levels of strain. In light of the results from our analysis of the *reason for admission* note—which suggest that providers may exert greater effort in attending 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 because of resource limitations. 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 of strain more for White than for Black patients, which in itself can be considered a type of strain-induced rationing of resources. This interpretation of this result is, however, purely speculative and warrants further investigation in future research.

6 Conclusion

Our study documents important connections between resource scarcity, discrimination, and rationing. Focusing on the high-stakes setting of hospital care, we find that as resources becomes scarcer during periods of high capacity strain, underlying discrimination manifests as race-based rationing of care, leading to worse health outcomes for Black patients. We first show that Black–White disparities in patient death—an extreme consequence of rationing on the basis of race rather than need—markedly increase at the highest levels of hospital capacity strain. This pattern cannot be explained by racial differences in the types of patients admitted or discharged at high levels of strain. In fact, we find suggestive evidence that the quality of assessment of clinical need declines for Black relative to that for White patients with increasing strain, and it is among the patients who could benefit most from better clinical need assessment (i.e., high-need patients, patients *without* highly protocolized clinical conditions) that we observe higher mortality. We then provide direct evidence of race-based rationing by waiting time and more speculative evidence of rationing of a *cognitive* resource— provider effort— (based on unstructured clinical notes) as potential mechanisms. We show that racial 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 study was conducted with data from two hospitals, and so external validity is an important concern. However, we believe the study is likely to replicate in other samples and setting, as the growing literature on racial biases in the provision of health care draws from reports of patient experiences and administrative records from hospitals and clinics across the United States (Agarwal et al., 2024; Ashana et al., 2021; Johnson & Rehavi, 2016; Obermeyer et al., 2019b; Sax et al., 2023; Schulman et al., 1999b; Silva, Durden, & Hirsch, 2023; Sun et al., 2022b). That is, conditions ripe for race-based rationing of care are widespread in the care settings where Black patients are typically seen.

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 temporary ones (lasting hours or days)—can throw into sharper relief discrimination that otherwise is difficult to discern without external manipulation (such as in audit studies). In this sense, our research echoes the work 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) and how improved economic prospects (due to either labor demand shocks or policy-led increases in access to new markets) helped reduce intergroup 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).

Our approach also illustrates how analysis of documentation and text holds the potential to help uncover subtle but consequential forms discrimination that otherwise may not be apparent in typically analyzed statistics. Our findings connect to a growing literature that has begun to utilize documentation for this purpose in health care (Goddu et al., 2018; Sun et al., 2022a) and a nascent literature in economics (Adukia et al., 2023; Capraro, Halpern, & Perc, 2024; Moreno-Medina et al., 2022).

Our research highlights the importance of addressing biases in how critical health care services are distributed. Doing so could involve several strategies: increasing awareness among health care providers (Vela et al., 2022); creating and using new algorithms to improve decision-making 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); developing 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 likely more acute. 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 taking 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).

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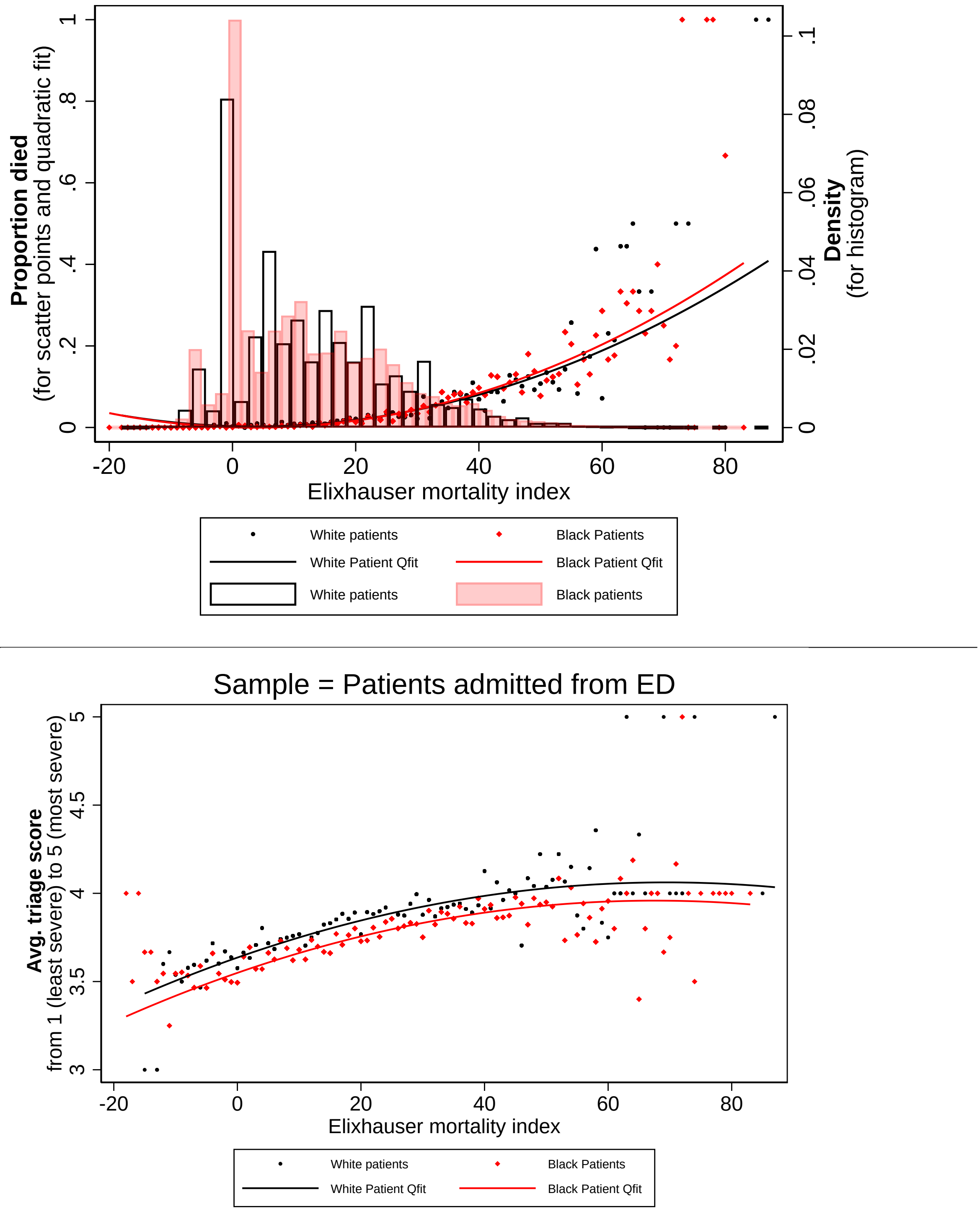
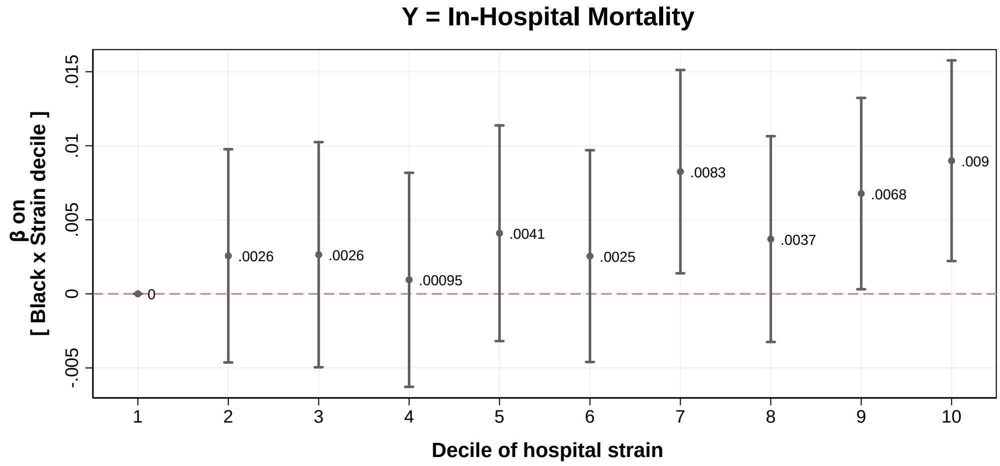


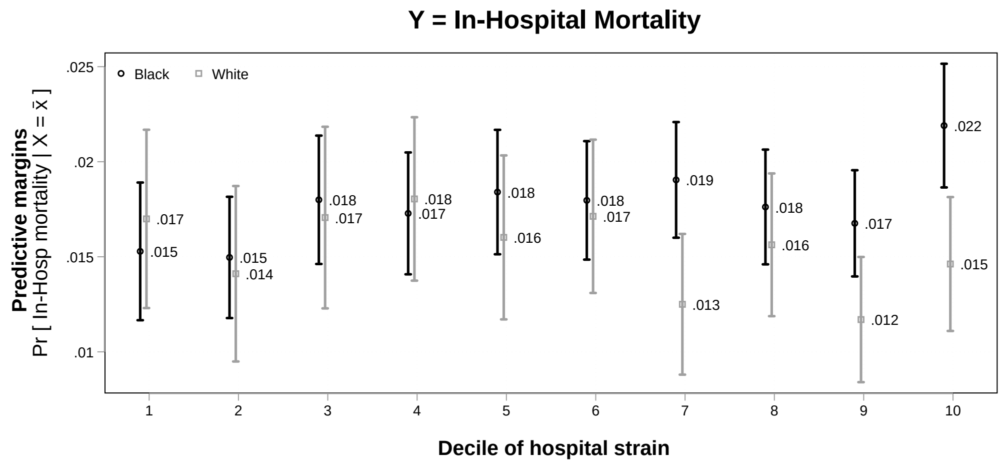
FIGURE I

Using the Elixhauser Mortality Index to Measure Patient Medical Need

The top panel plots the distribution of Elixhauser mortality index scores and their (unadjusted) relationship with in-hospital mortality using scatter plots and a quadratic best fit line for Black and White patients in the inpatient sample. The bottom panel plots the (unadjusted) relationship between Elixhauser mortality index scores and triage scores for Black and White patients in the ED sample.



(a)



(b)

FIGURE II

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). We present 95% robust standard errors. Estimates are also presented in tabular form in Table A.6 Col 1.

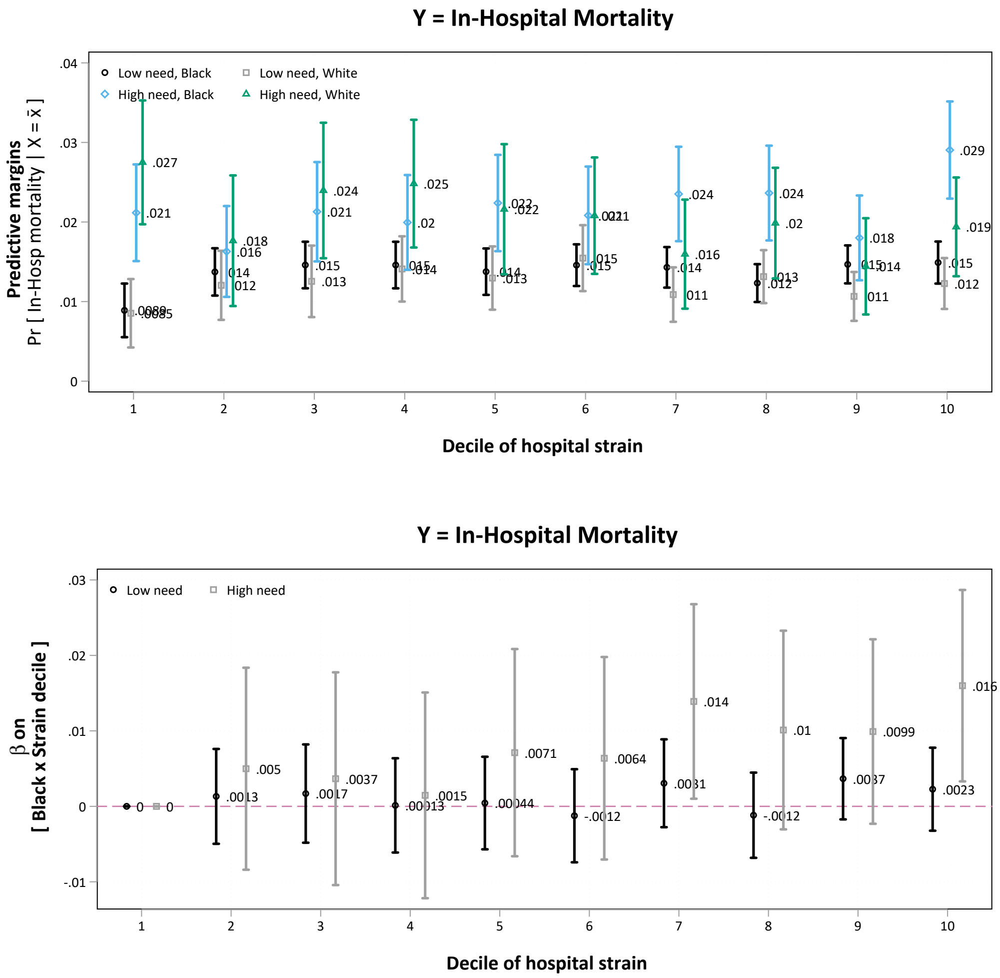


FIGURE III

Racial Disparities in Hospital Mortality by Strain and Medical Need

Estimates from Equation 6 with in-hospital mortality as the outcome by race and patient need (i.e., below- and above-median Elixhauser index scores signifying low- and high-need patients, respectively). Panel (a) 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). Panel (b) plots the coefficient on the interaction between patient race and decile of hospital strain, separately for high- and low-need patients. We present 95% robust standard errors. Estimates also presented in tabular form in Table A.7 Col 1.

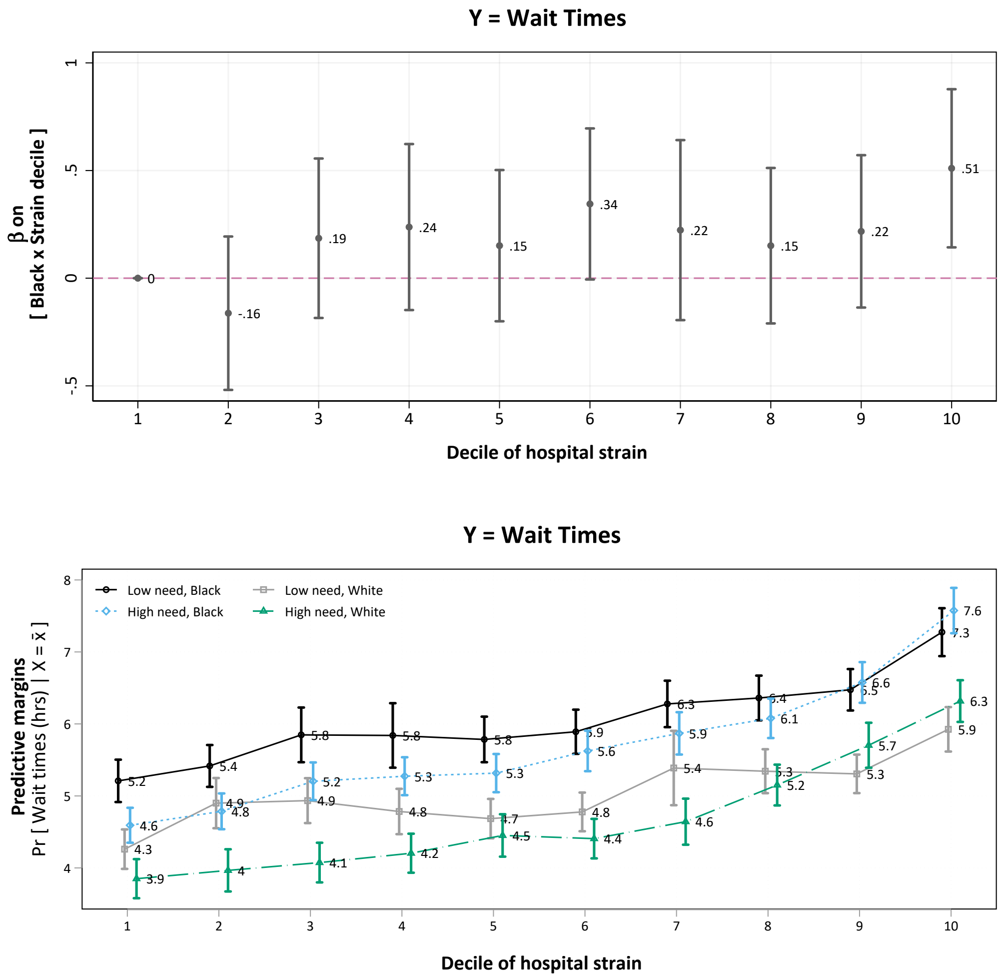
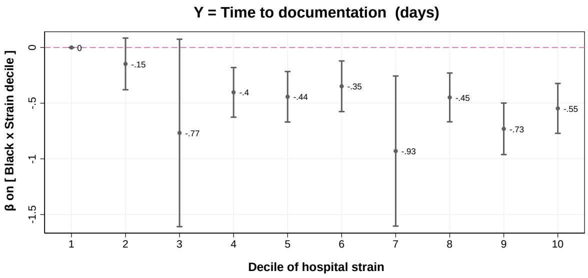
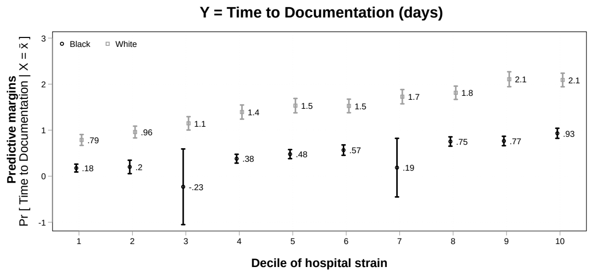


FIGURE IV
Wait Times: Rationing by Race and Medical Need

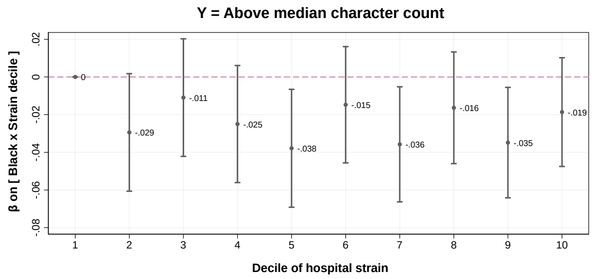
Estimates from Equation 5 in Panel (a) and from Equation 6 in Panel (b), with wait times as the outcome by patient need (with below- and above-median Elixhauser index scores signifying low- and high-need patients, respectively). Panel (a) plots the coefficients on the interaction (β) between patient race (=1 if Black) and decile of hospital strain at time of patient arrival. Panel (b) plots the predictive margins of wait times by race and patient need at each decile of hospital strain (at the means of all other covariates). We present 95% robust standard errors. Estimates presented in tabular form in Table A.6 Col 3 for Panel (a), and Table A.7 Col 2 for Panel (b).



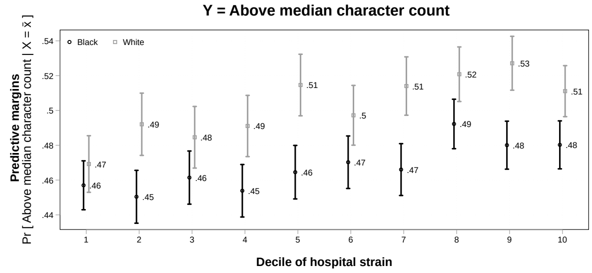
(a) Regression coefficients



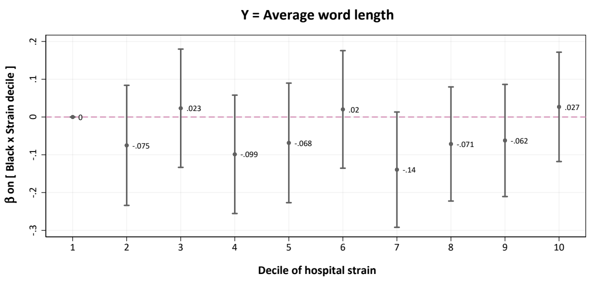
(b) Predictive margins



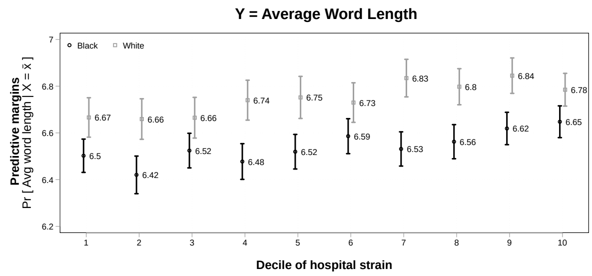
(c) Regression coefficients



(d) Predictive margins



(e) Regression coefficients

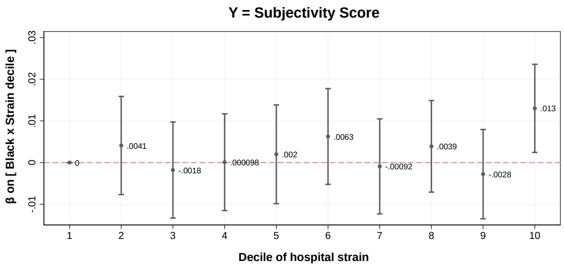


(f) Predictive margins

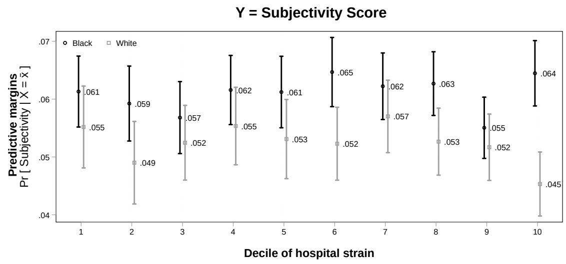
FIGURE V

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

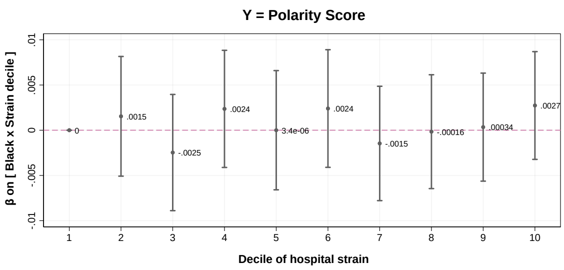
Estimates from regressing descriptive features of the *reason for admission* note (time to documentation completion, above-median character count, and average word length, described in Section 5.2) on race, deciles of hospital strain, an interaction between the two, patient covariates (age, sex, insurance 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 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.8.



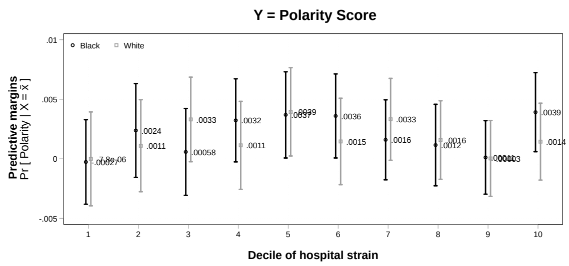
(a) Regression coefficients



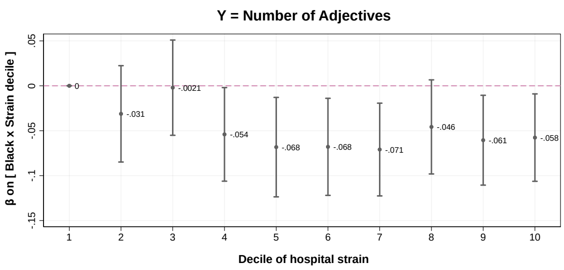
(b) Predictive margins



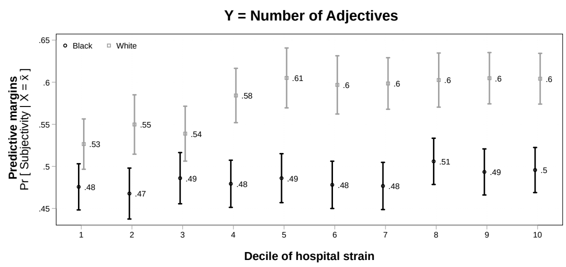
(c) Regression coefficients



(d) Predictive margins



(e) Regression coefficients



(f) Predictive margins

FIGURE VI

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 plot 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). We present 95% robust standard errors. Estimates are also presented in tabular form in Table A.9.

TABLE 1
Summary Statistics

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

TABLE 2

Sensitivity of Estimates to Alternative Specifications

	Dep Var: In-Hospital Mortality								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Black	-0.0017	-0.0049*	-0.0010	0.0085	-0.0009	-0.0012	-0.0063	-0.0003	-0.0020
	(0.003)	(0.003)	(0.003)	(0.130)	(0.003)	(0.003)	(0.006)	(0.003)	(0.003)
Strain Decile=1	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Strain Decile=2	-0.0029	-0.0029	-0.0029	-0.1332	-0.0040	0.0038	-0.0029	-0.0028	-0.0029
	(0.003)	(0.003)	(0.003)	(0.148)	(0.003)	(0.012)	(0.003)	(0.003)	(0.003)
Strain Decile=3	0.0001	-0.0017	-0.0014	-0.0540	-0.0006	-0.0017	0.0001	0.0005	0.0001
	(0.003)	(0.003)	(0.003)	(0.147)	(0.003)	(0.012)	(0.003)	(0.003)	(0.003)
Strain Decile=4	0.0010	-0.0051	-0.0052	-0.2319	-0.0001	0.0100	0.0011	0.0020	0.0011
	(0.003)	(0.003)	(0.003)	(0.153)	(0.003)	(0.012)	(0.003)	(0.003)	(0.003)
Strain Decile=5	-0.0010	-0.0072**	-0.0075**	-0.3666**	-0.0019	0.0028	-0.0010	-0.0007	-0.0009
	(0.003)	(0.003)	(0.003)	(0.161)	(0.003)	(0.012)	(0.003)	(0.003)	(0.003)
Strain Decile=6	0.0001	-0.0076**	-0.0078**	-0.3720**	-0.0005	0.0190	0.0002	0.0006	0.0003
	(0.003)	(0.003)	(0.003)	(0.159)	(0.003)	(0.012)	(0.003)	(0.003)	(0.003)
Strain Decile=7	-0.0045	-0.0105***	-0.0107***	-0.5625***	-0.0045	0.0080	-0.0045	-0.0043	-0.0047
	(0.003)	(0.003)	(0.003)	(0.166)	(0.003)	(0.011)	(0.003)	(0.003)	(0.003)
Strain Decile=8	-0.0014	-0.0078**	-0.0081**	-0.3950**	-0.0022	0.0030	-0.0014	-0.0006	-0.0013
	(0.003)	(0.003)	(0.003)	(0.153)	(0.003)	(0.011)	(0.003)	(0.003)	(0.003)
Strain Decile=9	-0.0053*	-0.0145***	-0.0148***	-0.9029***	-0.0057*	0.0047	-0.0053*	-0.0049	-0.0055*
	(0.003)	(0.003)	(0.003)	(0.176)	(0.003)	(0.011)	(0.003)	(0.003)	(0.003)
Strain Decile=10	-0.0024	-0.0101***	-0.0111***	-0.5788***	-0.0025	0.0012	-0.0024	-0.0014	-0.0023
	(0.003)	(0.003)	(0.003)	(0.153)	(0.003)	(0.012)	(0.003)	(0.003)	(0.003)
Strain Decile=1 × Black	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Strain Decile=2 × Black	0.0026	-0.0035	-0.0032	-0.2415	0.0031	0.0018	0.0026	0.0027	0.0024
	(0.004)	(0.004)	(0.004)	(0.204)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Strain Decile=3 × Black	0.0026	-0.0009	-0.0011	-0.0822	0.0018	0.0019	0.0026	0.0024	0.0026
	(0.004)	(0.004)	(0.004)	(0.196)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Strain Decile=4 × Black	0.0009	0.0003	0.0005	-0.0398	0.0005	0.0005	0.0009	0.0002	0.0007
	(0.004)	(0.004)	(0.004)	(0.203)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Strain Decile=5 × Black	0.0041	0.0032	0.0036	0.1445	0.0037	0.0043	0.0041	0.0035	0.0040
	(0.004)	(0.004)	(0.004)	(0.208)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Strain Decile=6 × Black	0.0025	0.0032	0.0037	0.1350	0.0016	0.0023	0.0025	0.0024	0.0023
	(0.004)	(0.004)	(0.004)	(0.206)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Strain Decile=7 × Black	0.0083**	0.0065*	0.0071*	0.3567*	0.0065*	0.0078**	0.0082**	0.0083**	0.0084**
	(0.004)	(0.004)	(0.004)	(0.210)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Strain Decile=8 × Black	0.0037	0.0035	0.0038	0.1465	0.0032	0.0035	0.0037	0.0029	0.0035
	(0.004)	(0.004)	(0.004)	(0.198)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Strain Decile=9 × Black	0.0068**	0.0076**	0.0080**	0.4744**	0.0053	0.0052	0.0068**	0.0064*	0.0069**
	(0.003)	(0.003)	(0.003)	(0.218)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Strain Decile=10 × Black	0.0090**	0.0092**	0.0096**	0.4950**	0.0073**	0.0084**	0.0090**	0.0075**	0.0090**
	(0.003)	(0.004)	(0.004)	(0.191)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
N	106082	106518	106518	106518	106042	106082	106082	106101	106083
r2	0.293	0.001	0.005		0.333	0.293	0.293	0.288	0.289
controls	Main Spec	No Controls	Age, H-Y	Logistic	+ DRG	x Strain	x Black	Elix comorbs	Cluster SEs

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 results from the main specification from Equation 5. The specification corresponding to Col 2 has no control variables. The Col 3 specification adds age and hospital–year FEs. The Col 4 specification reestimates the results from Col 3 with a logistic regression. The Col 5 specification adds DRG FEs to the main model from Col 1. The Col 6 specification interacts age, sex, and insurance status with race. The Col 7 specification interacts age, sex, and insurance status with hospital strain decile. The Col 8 specification includes each of the Elixhauser comorbidities separately instead of the summed indices. The Col 9 specification uses standard errors clustered by admission date.

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'].

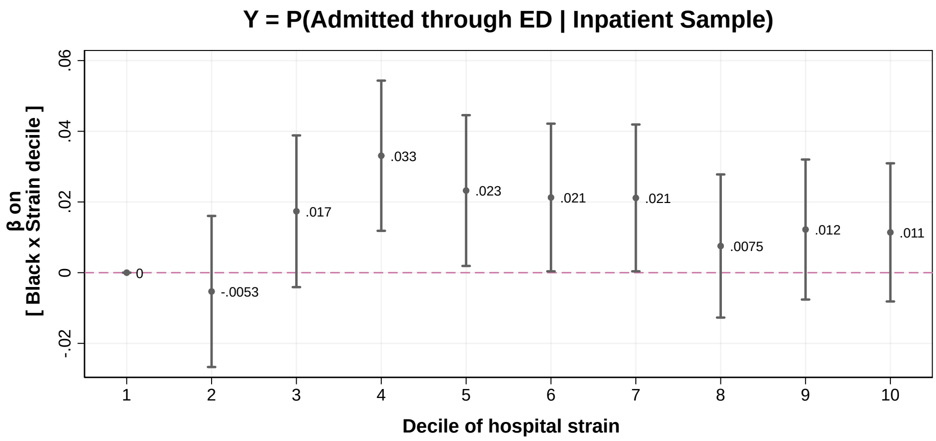
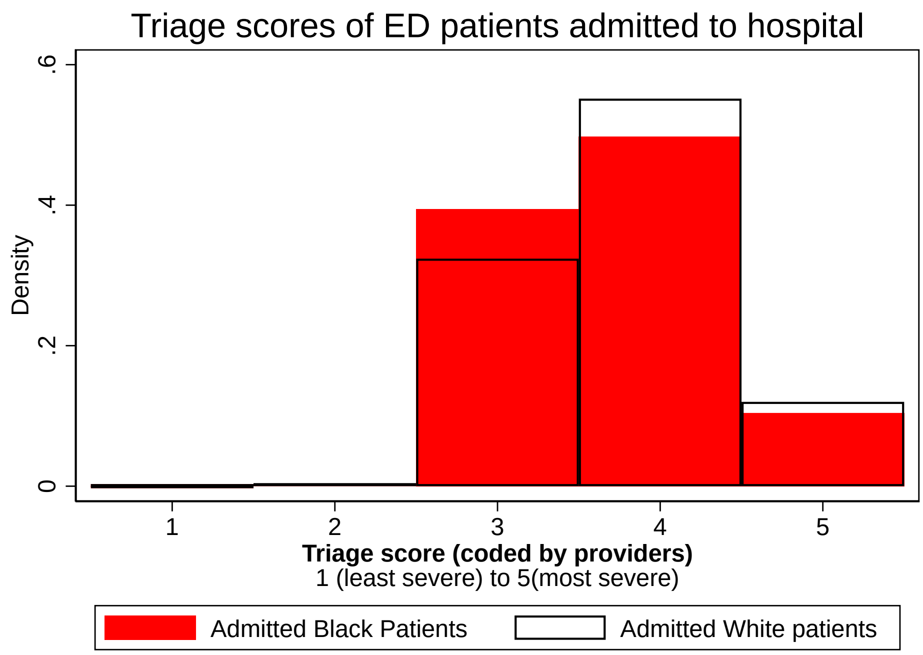


FIGURE A.1

Does the share of patients in the Inpatient sample coming through the ED change with strain?

Estimates from Equation 5 with admission from ED as the outcome. Figure plots the interaction coefficients (β) on patient race (=1 if Black) and decile of hospital strain at time of patient arrival. 95% robust standard errors are presented.



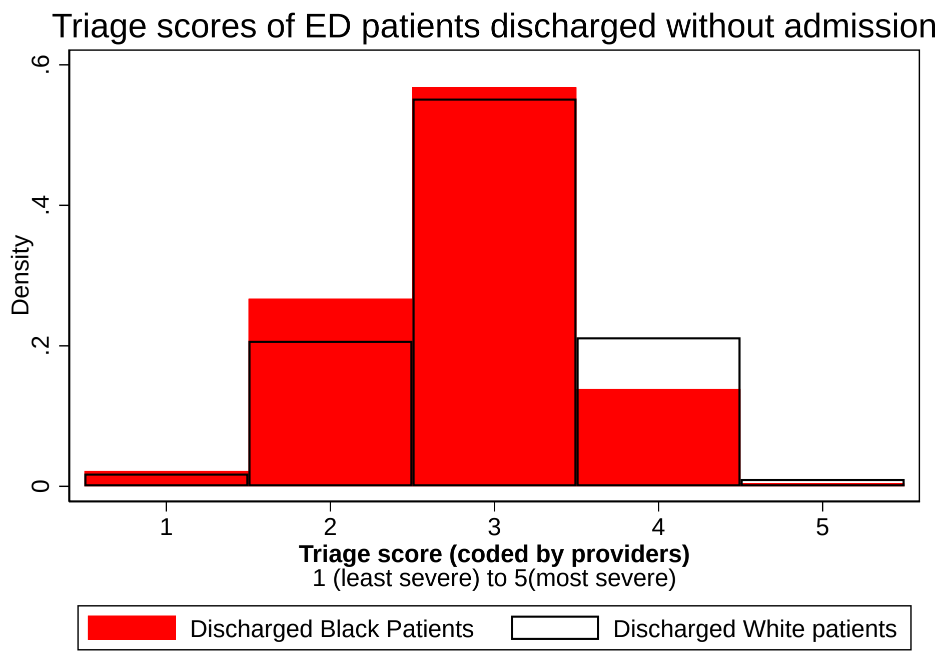
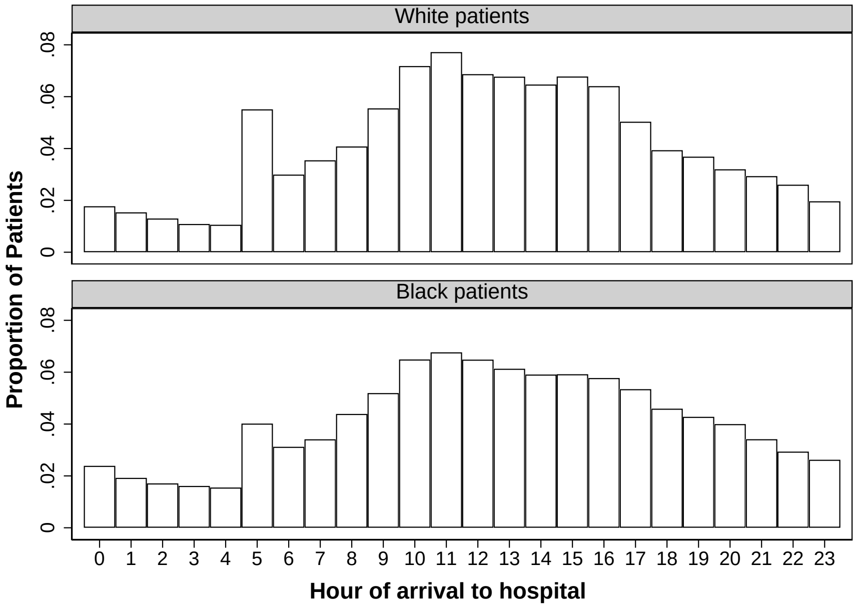
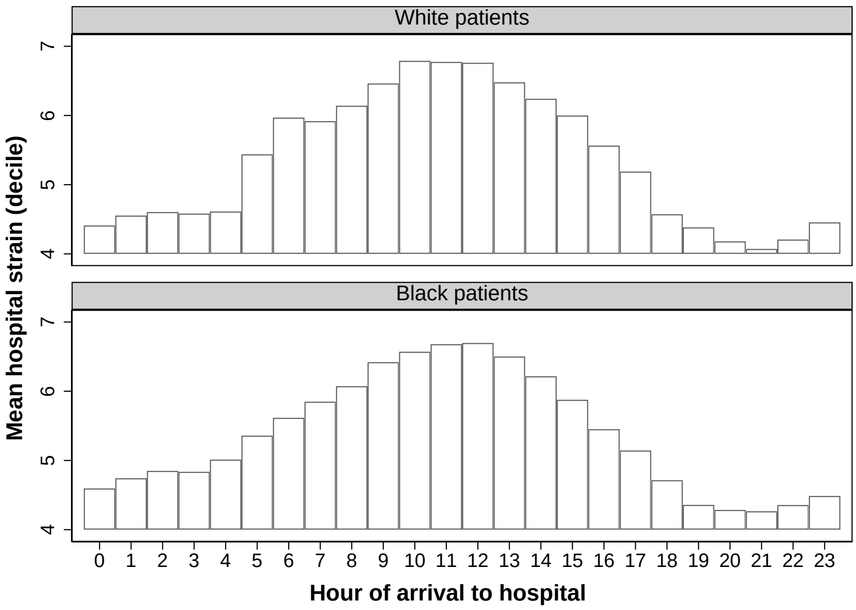


FIGURE A.2

Histogram of Triage Scores for Black and White patients admitted to the hospital, and discharged home, from the ED



(a)

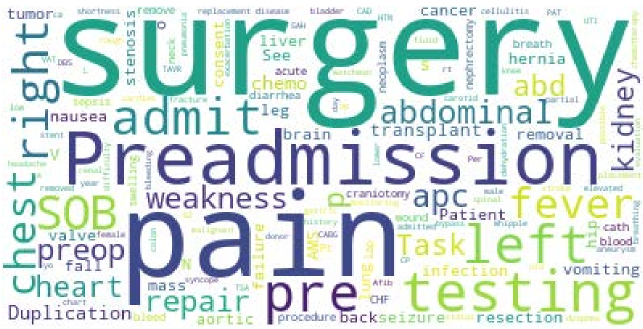


(b)

FIGURE A.3

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

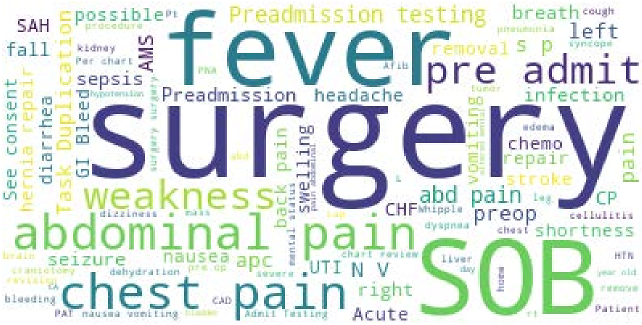
Panel (a) presents the distribution of White and Black patients by the hour of their arrival to the hospital. Panel (b) presents the mean decile of hospital strain for White and Black patients by the hour of their arrival to the hospital.



(a) White

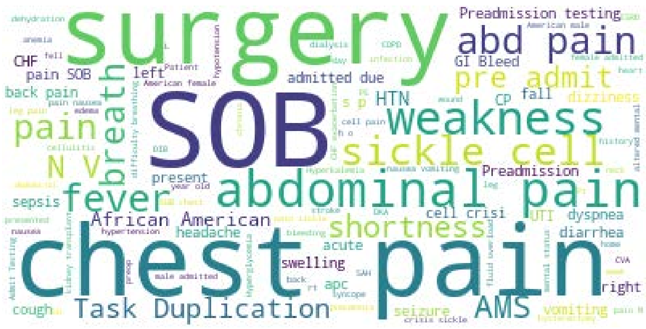
(b) Black

FIGURE A.4
Word Clouds of *Reason for Admission* Note by Race

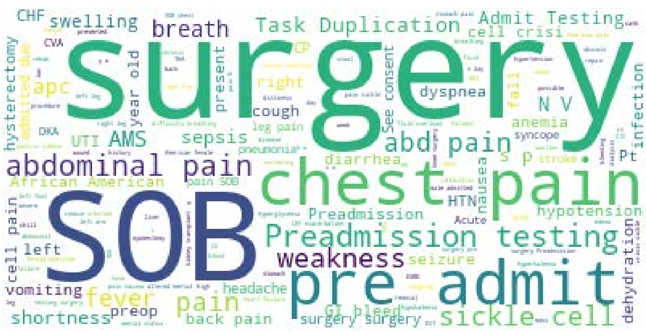


(a) White, Low Strain

(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

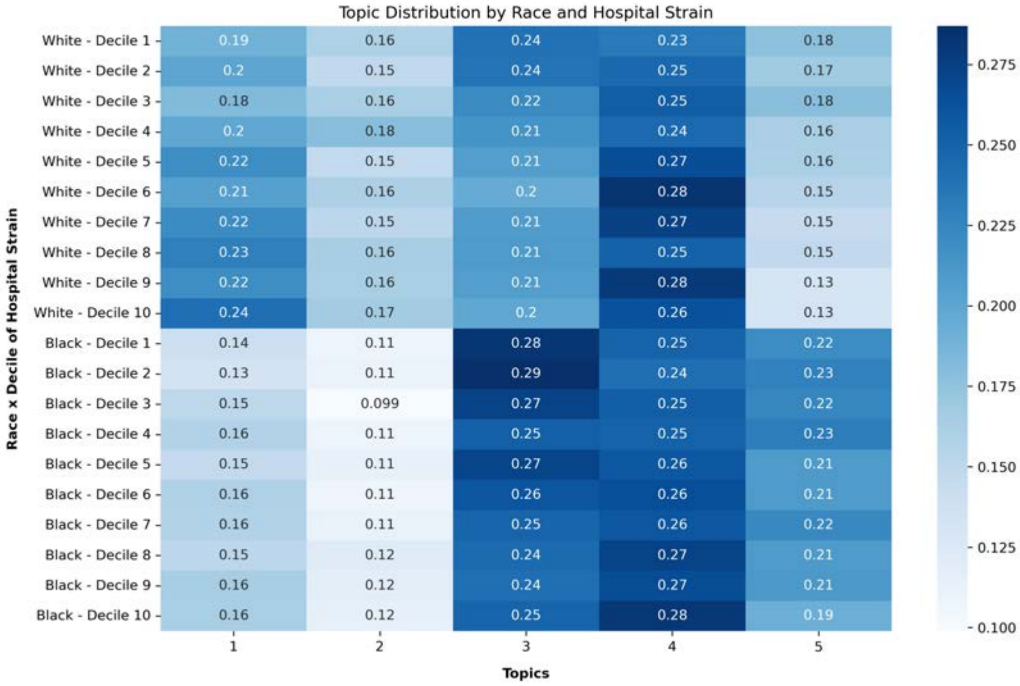


FIGURE A.6

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.

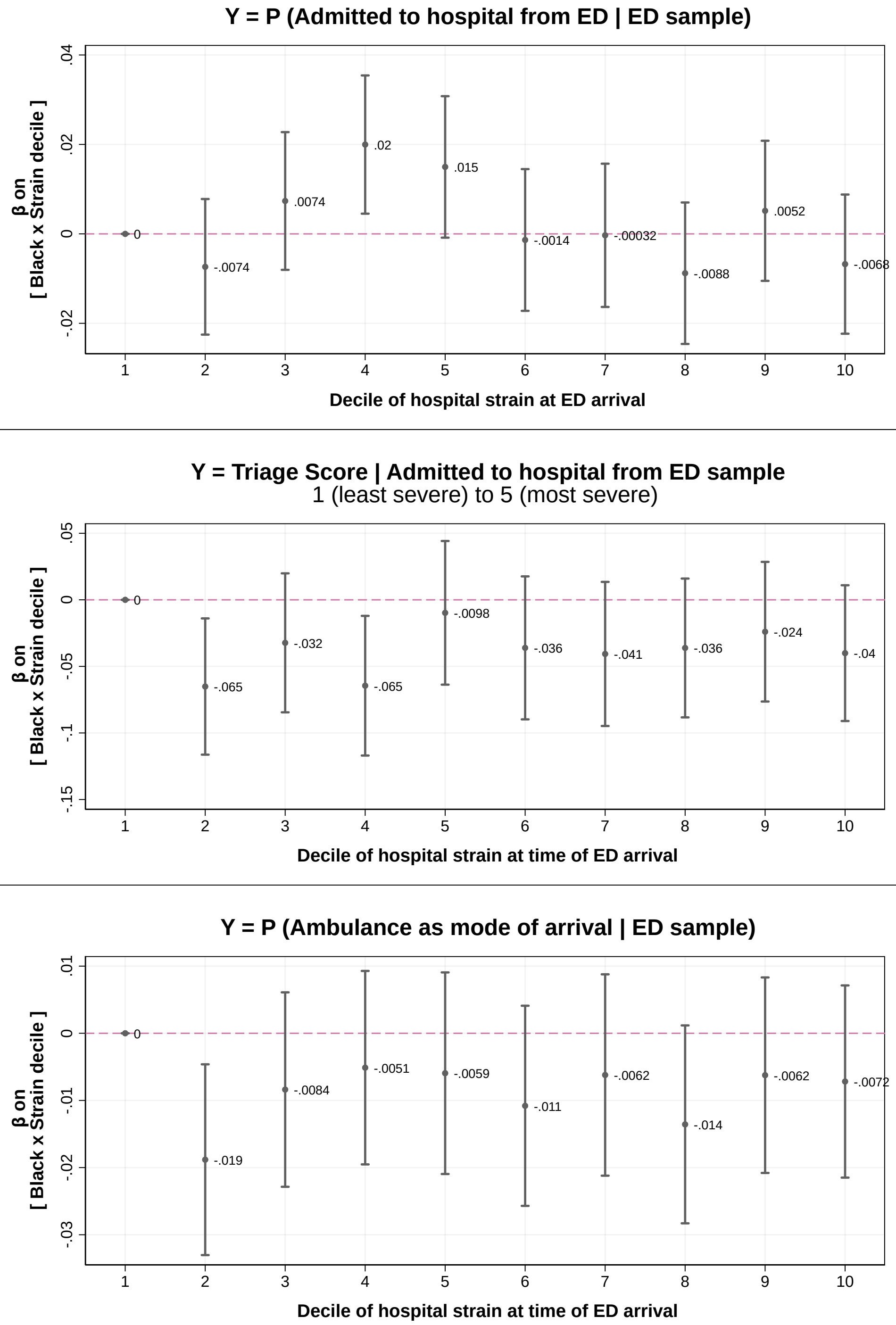


FIGURE A.7
Is there selective admission into the ED?

Estimates from regressing the specified outcome on a saturated interaction between patient race and deciles of hospital strain at time of ED arrival, controlling for age, age-squared, sex, and fixed effects for hospital-specific year, month, day-of-week and hour-of-day on the ED sample. Figure plots the interaction coefficients (β) on patient race (=1 if Black) and decile of hospital strain at time of patient arrival to the ED. 95% robust standard errors are presented.

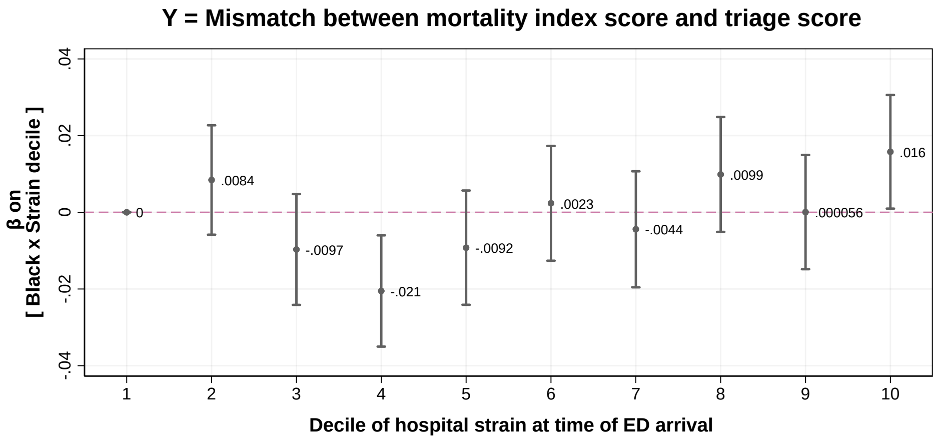


FIGURE A.8

Mismatch between triage scores and Elixhauser mortality index

Estimates from Equation 5 on the ED sample, with mismatch between triage scores (1-5) and Elixhauser mortality index quintiles (1-5) as the outcome. Mismatch =1 if the difference between the two variables is more than 2. Figure plots the interaction coefficients (β) on patient race (=1 if Black) and decile of hospital strain at time of patient arrival to the ED. 95% robust standard errors are presented.

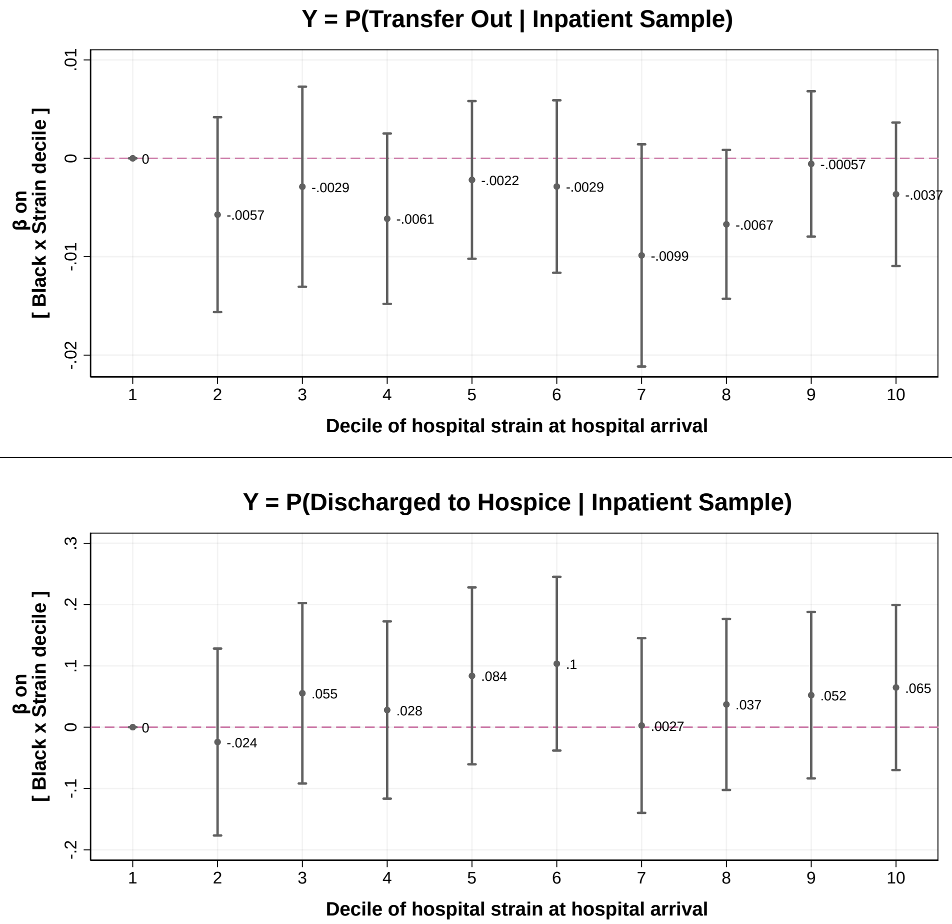
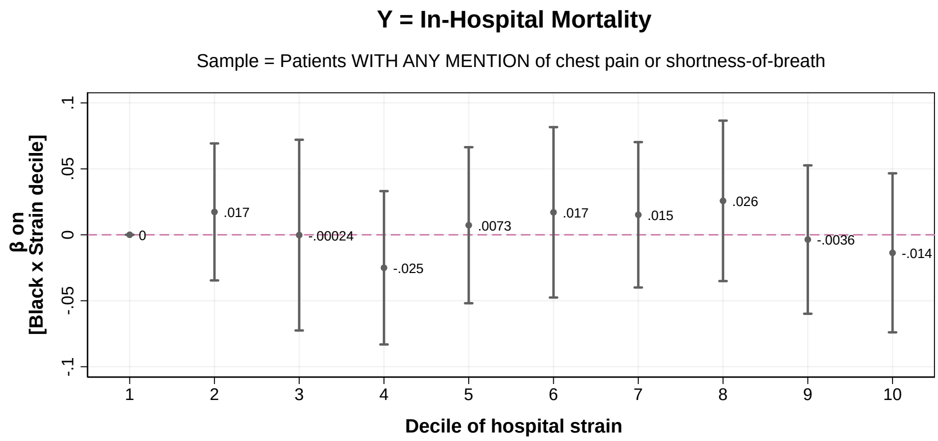


FIGURE A.9

Is there selective discharge from the hospital?

Estimates from Equation 5 with the specified outcome as the regressor, using the Inpatient sample. Panels plot the interaction coefficients (β) on patient race (=1 if Black) and decile of hospital strain at time of patient arrival. 95% robust standard errors are presented.



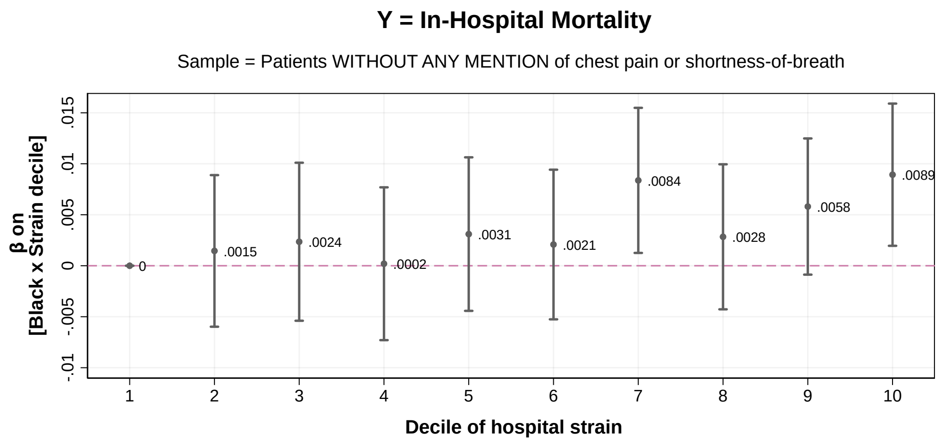
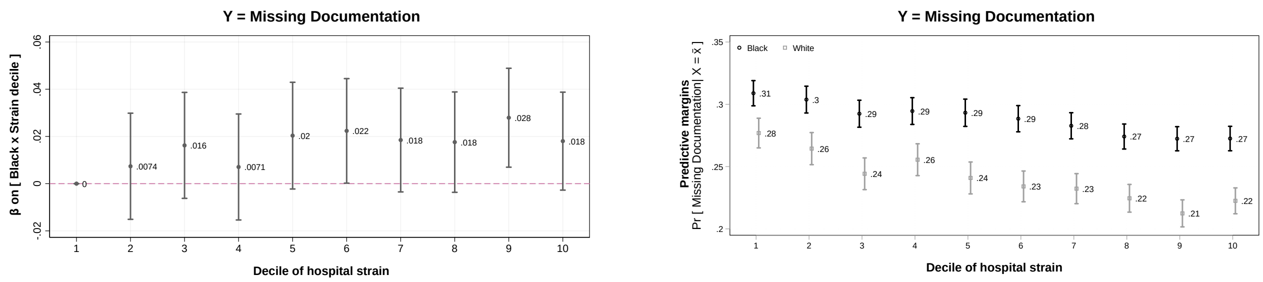


FIGURE A.10
Chest pain

Estimates from Equation 5 with the in-hospital mortality, separately for patients who did not, and did, have mentions of "shortness of breath" or "chest pain" in their *Reason for Admission.* Panels plot the interaction coefficients (β) on patient race (=1 if Black) and decile of hospital strain at time of patient arrival. 95% robust standard errors are presented.



(a) Regression coefficients

(b) Predictive margins

FIGURE A.11

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.8.

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 Abnormal Vital Signs

	(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

Wait Times and Other Input to Care

	(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

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

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

TABLE A.8

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.9

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. $p < .001^{***}$ $p < .05^{**}$ $p < 0.1^{*}$