Supplemental Appendix

Manuscript Title: Rationing by Race

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A Identifying themes in the text data with latent Dirichlet allocation

We first provide exploratory evidence of what the *reason for admission* text field contains, and whether – at first glance – it appears starkly different between Black and White patients. We first create word clouds for Black and White patients (Figure A.7), visualizing 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 among Black patients.

Black and White patients may be described differently in their reason for admission for many reasons: differences in the actual reason, 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 being admitted to the hospital, this may represent a threat to our identification strategy. We try to test this formally using a commonly used machine learning technique for text analysis, 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 preprocess the data to make inference easier. Free-text notes in EMRs such as the *reason for admission* have many features that make them 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 over type I error rate. In other words, we preprocess the data such 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 be the case if we had a stricter preprocessing protocol. To this end, we remove all punctuation, nonalphabetic characters, and stopwords (*and*, *or*, *if*, etc.) from the text field. We also lemmatize each word, i.e., converte it to its root form (e.g., *painful* and *paining* 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) and 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 shown in the top panel in Figure A.8: For example, Topic 3 is associated with the words *right*, *left*, *back*, *hip*, and *surgery*. The visual distribution of the topics is also shown in 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 among Black patients. Regardless, the formal analysis in Table A.5 (which reestimates Equation 1a 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 differential patient selection with strain is not a concern or 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 are the following:

- “Patient expresses pain as a 3 out of 10” = 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. 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. Examples of hypothetical physician notes to illustrate variation in polarity scores are as follows:

- “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 notes have two different subjects and relay different information.

Adjectives: Finally, to measure the level of detail provided in the text data, we perform a rudimentary analysis where we simply count the number of adjectives in a given provider note. However, using ML techniques (such as the NLP toolkit) on physician notes is difficult because these algorithms are trained to identify adjectives based on the context in which they appear – such as the words before and after. As already discussed, physician notes largely do not follow 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*].

C Assessment of medical need by providers under strain

We examine strain-related racial disparities in mortality by triage score, motivated by the finding that Black patients in the ED are consistently perceived to be less sick, as indicated by lower triage scores, than White patients (Figure III). This lower perception of need contrasts with Black patients' higher mortality rates, which suggests there may be a "mismatch" between perceived and actual medical need.

We test the hypothesis that the increased mortality of Black relative to White patients at high strain stems from increasingly inaccurate clinical assessments. For the subsample of inpatients admitted through the ED, we reestimate Equation 1b, first with triage scores as the outcome (Figure A.6 Panel (a) and Table A.7 Column 1) and then with mortality (Figure A.6 Panel (b) and Table A.7 Column 2), adding a triple interaction between race, high strain, and patient medical need (using the Elixhauser mortality index median split from the entire inpatient sample).

Figure A.6 Panel (a) shows that the average triage scores are higher for high- than for low-need patients, both Black and White, and lower for Black patients than for White patients. Moreover, while high strain widens the racial mortality gap for high-need patients (Figure A.6 Panel (b)), no corresponding pattern in triage scores explains this pattern: For example, strain does not reduce the triage scores for high-need Black patients relative to those of high-need White patients. Consistent with this, the triple interaction in Table A.7 is not statistically significant. Therefore, we are unable to detect systematic strain-induced differences in provider assessments of medical need by race.

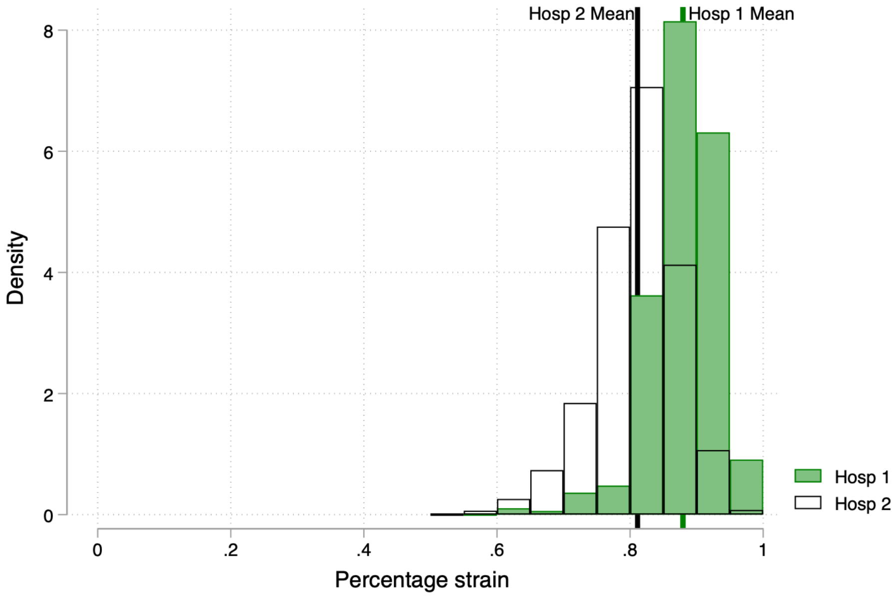
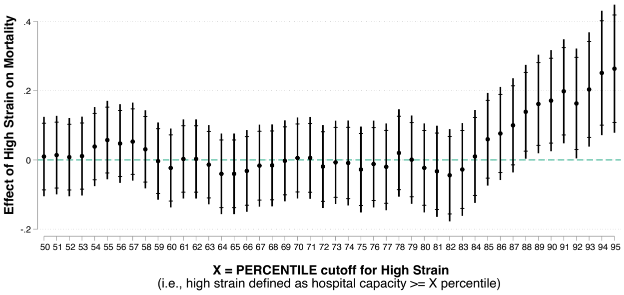
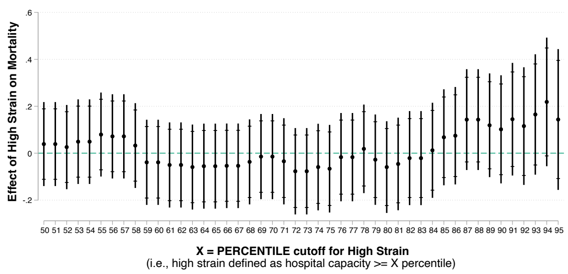


FIGURE A.1
Distribution of Capacity Strain by Hospital

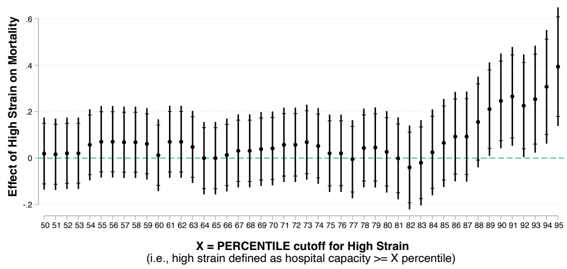
Note: This figure displays the distribution of hospital strain, defined as the percentage of inpatient beds occupied, separately for Hospital 1 (green) and Hospital 2 (white). Vertical lines indicate the mean strain levels for each hospital.



Panel (a): Full Sample



Panel (b): Hospital 1 (N= 43,834)



Panel (c): Hospital 2 (N= 63,390)

FIGURE A.2

Relationship Between Strain and Mortality

Note: Each estimate in a panel plots the coefficient from regressing in-hospital mortality on the [High strain] term from a separate regression. High strain equals 1 if hospital capacity at the patient's arrival hour is at or above percentile X, and 0 otherwise, where $X \in (50, 51, 52, \ldots, 95)$. Panel (a) reports results for the pooled sample; Panels (b) and (c) repeat the analysis for Hospital 1 and Hospital 2, respectively. Covariates include year, month, day-of-week, and hour-of-day, and major holiday fixed effect. Heteroskedasticity-robust 90% and 95% confidence intervals are shown.

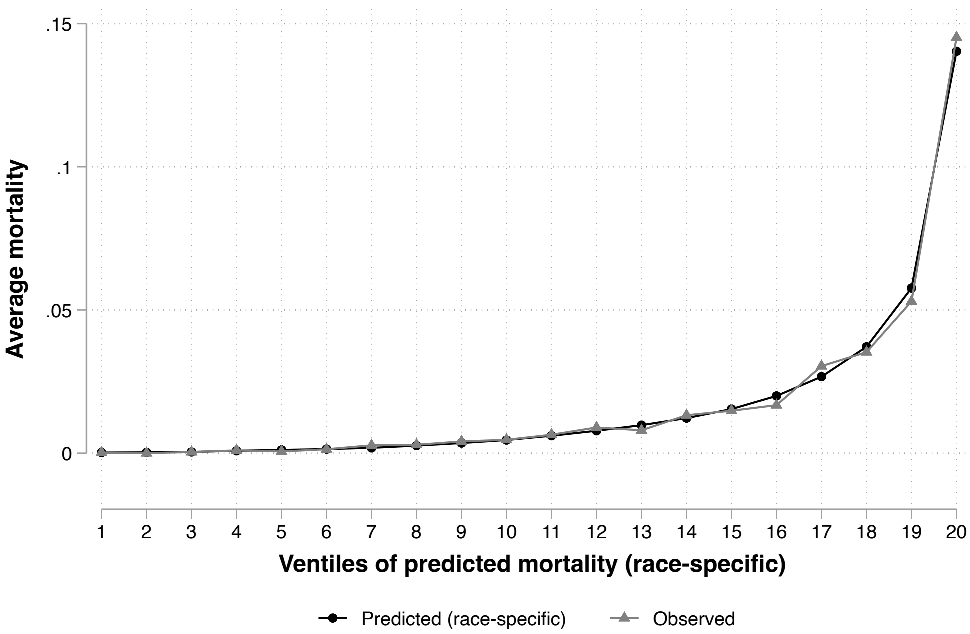
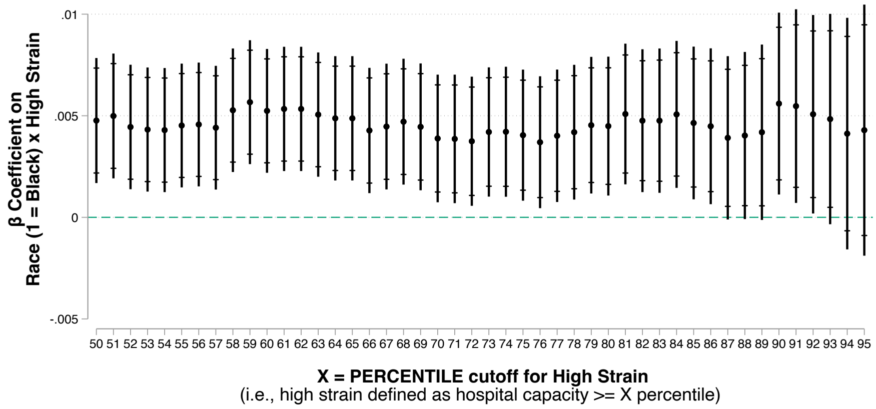


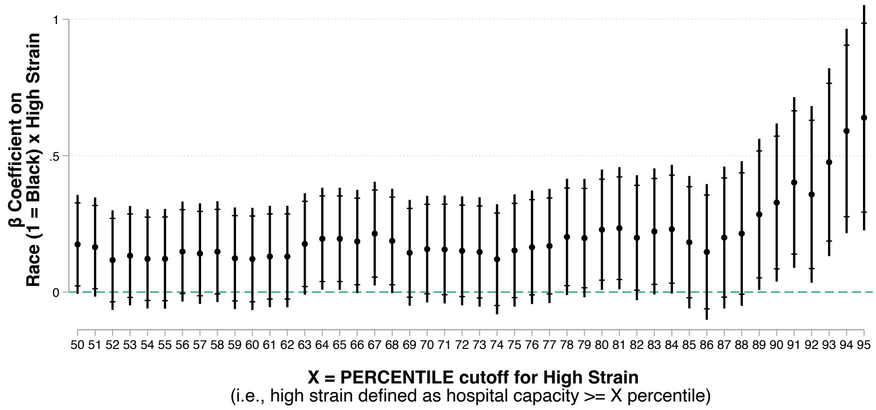
FIGURE A.3

Predictive Ability of (Race-Specific) Predicted Mortality Measure for Observed Mortality

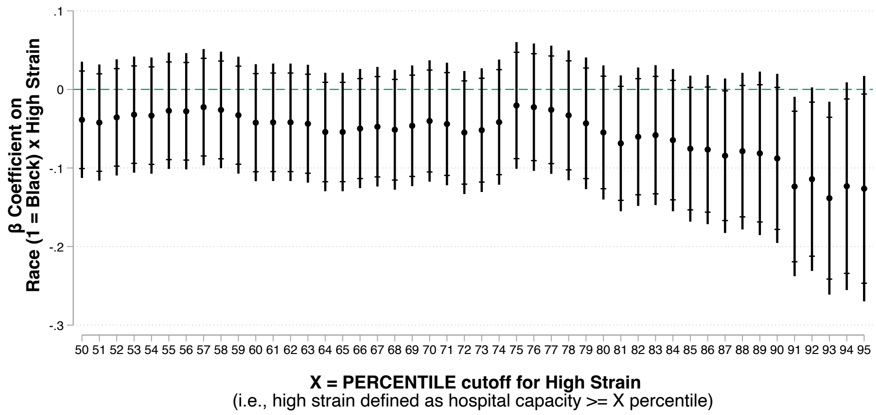
Note: Figure plots the average (race-specific) predicted mortality and the average observed mortality at each ventile of predicted mortality. The predicted (race-specific) mortality measure is estimated by logistic regressions of observed mortality on patient age, sex, insurance status, number of comorbidities, and Elixhauser mortality and readmission indices separately for Black and White patients.



Panel (a): In-hospital mortality



Panel (b): Wait times

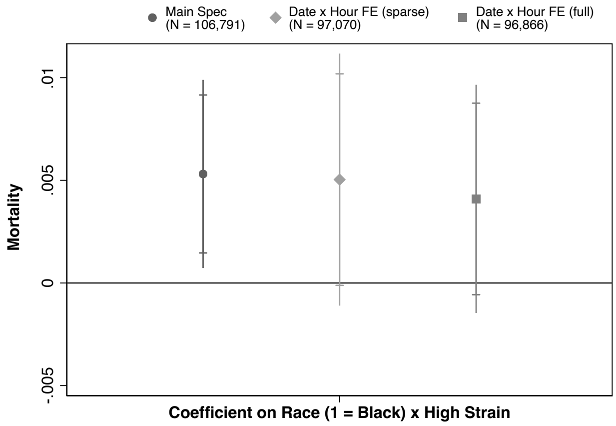


Panel (c): Provider effort index

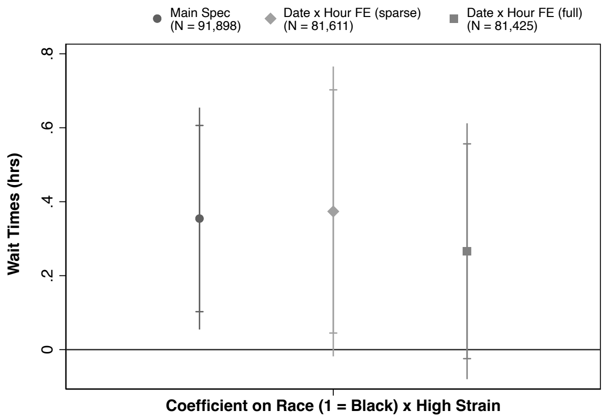
FIGURE A.4

Robustness to Definitions of High Strain at Alternative Percentile Cutoffs

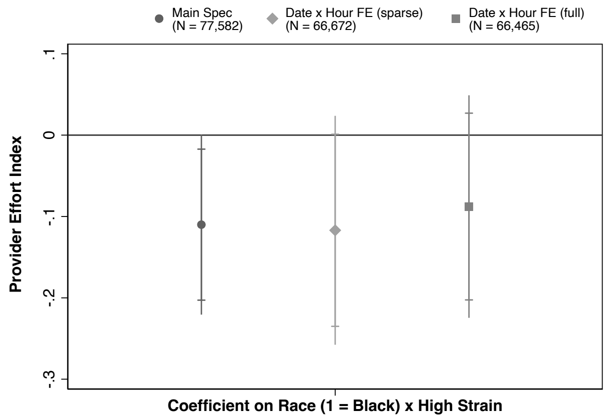
Note: Outcomes are: in-hospital mortality in Panel (a), wait times in Panel (b), and provider effort index in Panel (c). Each estimate in a panel plots the interaction coefficient on $\left[\text{Race (Black} = 1) \times \text{High strain}\right]$ from a separate regression of Equation 1b . High Strain equals 1 if hospital capacity at the patient's arrival hour is at or above percentile X, and 0 otherwise, where $X \in (50, 51, 52, \ldots, 95)$. Heteroskedasticity-robust 90% and 95% confidence intervals are shown.



Panel (a): Mortality



Panel (b): Wait times



Panel (c): Provider effort index

FIGURE A.5

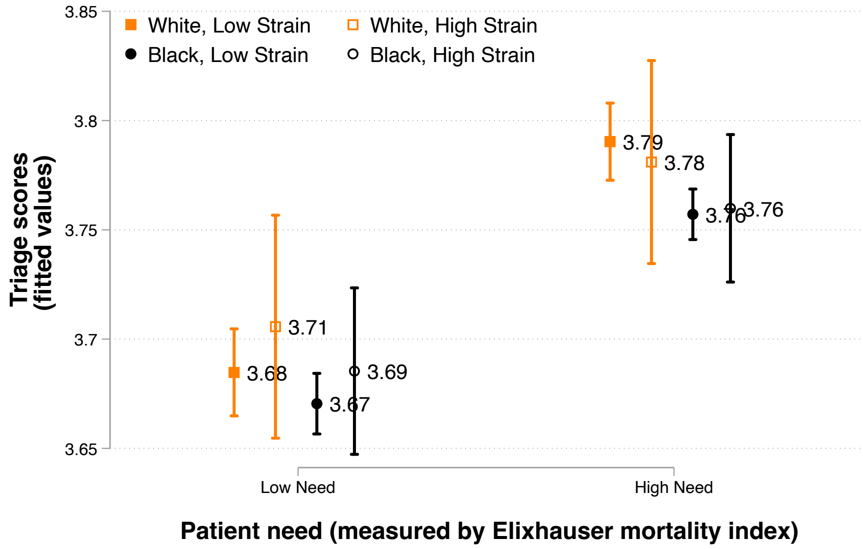
Robustness: Hospital × Date × Hour Fixed Effects

Note: Outcomes are: in-hospital mortality in Panel (a), wait times in Panel (b), and provider effort index in Panel (c). Heteroskedasticity-robust 90% and 95% confidence intervals are shown. Each estimate in a panel plots the interaction coefficient on [Race (Black = 1) × High strain] from one of the following 3 models:

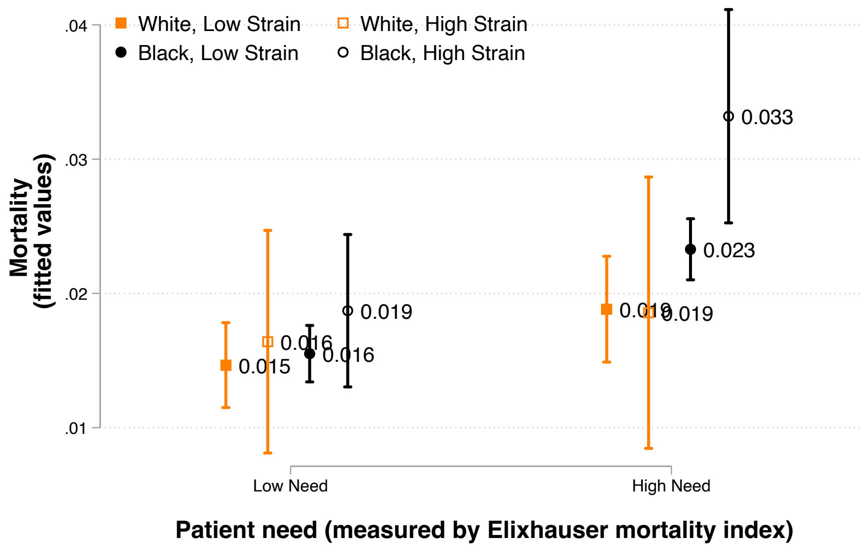
(1) *Main Spec:* Baseline model (Eq 1b)

(2) *Date × Hour FE (sparse)*: Baseline model (Eq 1b) with only race, high strain, and race x high strain on the RHS, as well as [hospital x year x month x day of week x hour of day] FEs replaced with 20,298 to 26,629 [hospital x arrival date x hour of day] FEs

(3) *Date × Hour FE (full)*: Baseline model (Eq 1b) with *all* variables on the RHS, as well as [hospital x year x month x day of week x hour of day] FEs replaced with 20,298 to 26,629 [hospital x arrival date x hour of day] FEs



Panel (a): Fitted values of triage scores
1 (lowest severity) - 5 (highest severity)

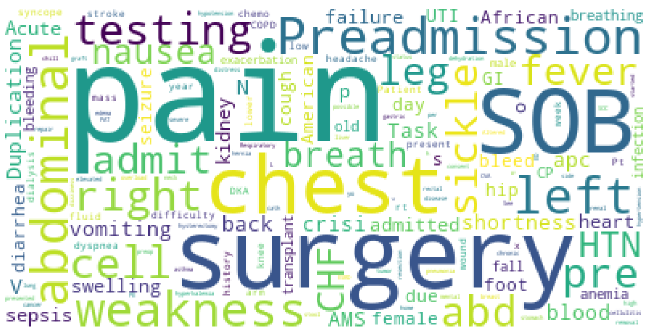


Panel (b): Fitted values of in-hospital mortality

FIGURE A.6
Test of Mismatch Between Patient Medical Need and Need as Assessed by Providers

Note: Outcomes are triage scores (discrete values of 1–5, reverse coded so higher values imply greater severity) in Panel (a) and in-hospital mortality in Panel (b) from estimating Equation 1b with all interactions between race (=1 for Black) × high strain (defined by the tenth decile) × high medical need (defined as above the inpatient sample median for Elixhauser mortality index). Estimated only on the sample of inpatients admitted through the ED. Estimates evaluated at the means of other covariates, with 95% confidence intervals based on robust standard errors. Regression coefficients are presented in Table A.7.

Panel (a): White patients

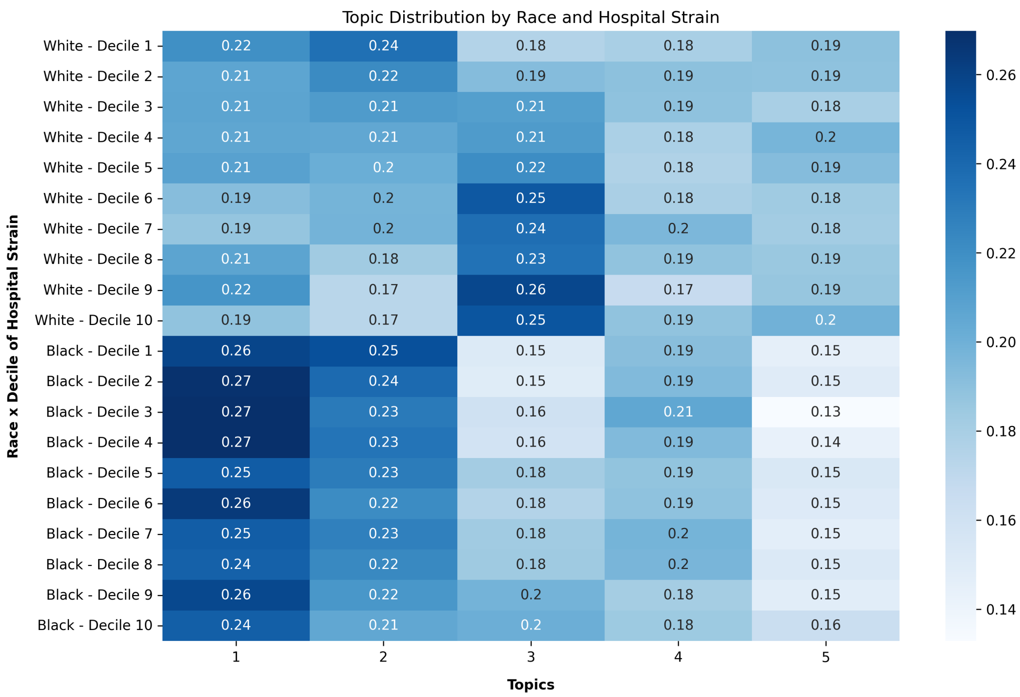


Panel (b): Black patients

FIGURE A.7
Word Clouds of *Reason for Admission* Note by Race

	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
Word 1	cell	duplication	right	am	breath
Word 2	preadmission	task	left	patient	right
Word 3	weakness	abdominal	back	yo	left
Word 4	testing	chest	hip	admitted	knee
Word 5	sob	pain	surgery	htn	fever

Panel (a): Themes identified by LDA

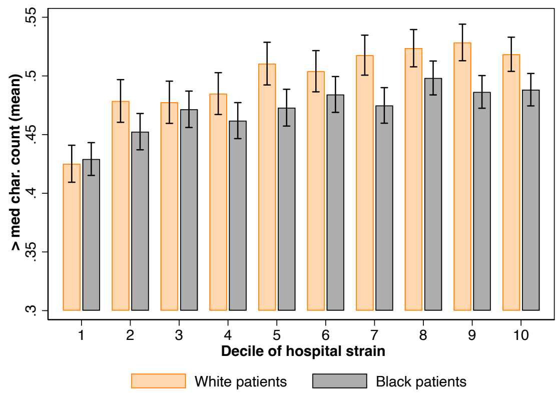


Panel (b): Heatmap of topic distribution

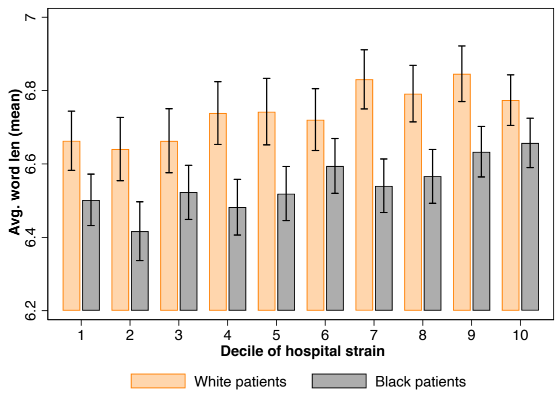
FIGURE A.8

Topic Identification and Distribution from Latent Dirichlet Allocation Analysis

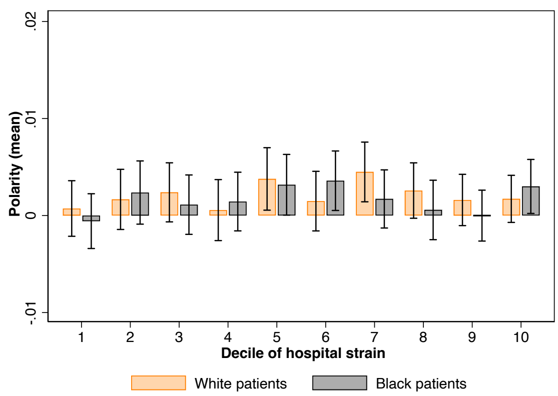
Note: Details about LDA are provided in Appendix A. Panel (a) identifies the five themes identified by LDA in the *reason for admission* note and the five most common words associated with each theme. Panel (b) provides a heatmap of the topic distribution by race and decile of hospital strain.



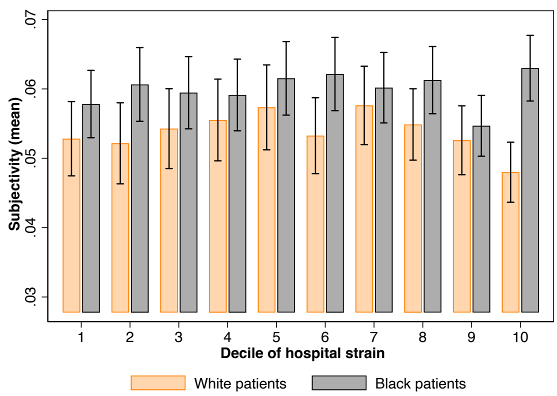
Panel (a): Character count



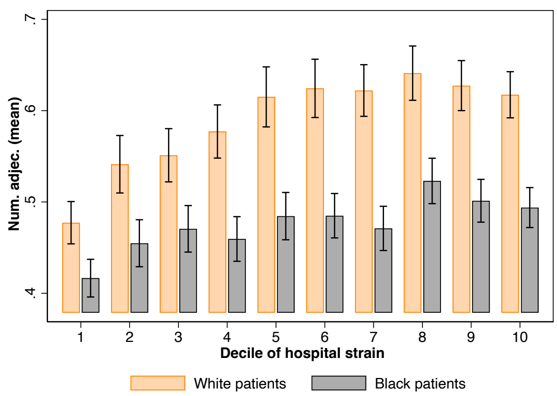
Panel (b): Word length



Panel (c): Polarity



Panel (d): Subjectivity

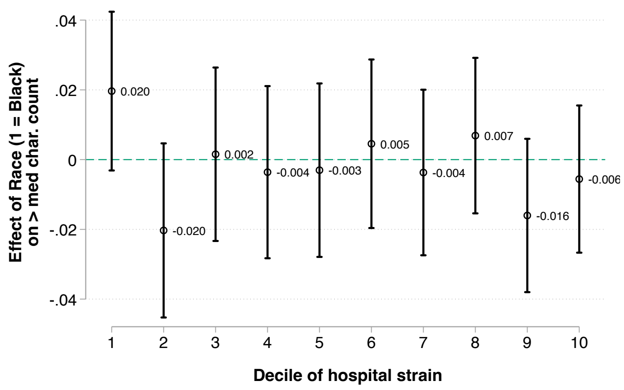


Panel (e): Adjectives

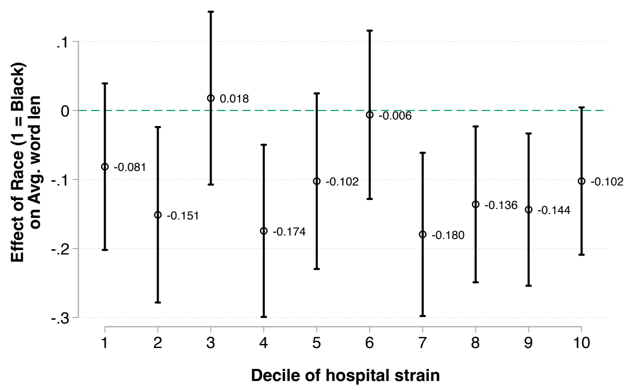
FIGURE A.9

Five (Text-Based) Measures of Provider Effort

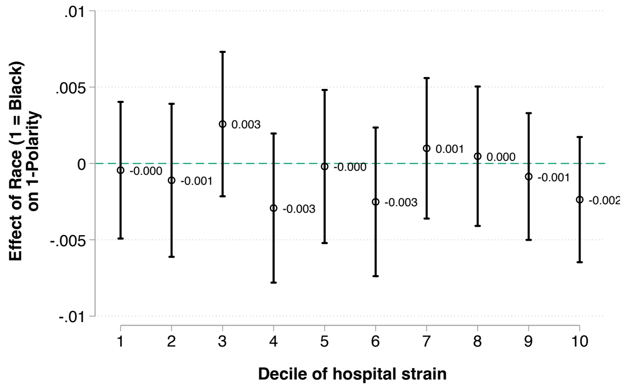
Note: Figure plots the raw means of the five different text-based features of the reason for admission note used to generate the summed provider effort index, by patient race and decile of strain. These include the (a) proportion above the sample median of character count, (b) average word length (in characters), (c) polarity (measured on a scale ranging from -1 to 1), (d) subjectivity (measured on a scale of 0 to 1), and (e) number of adjectives.



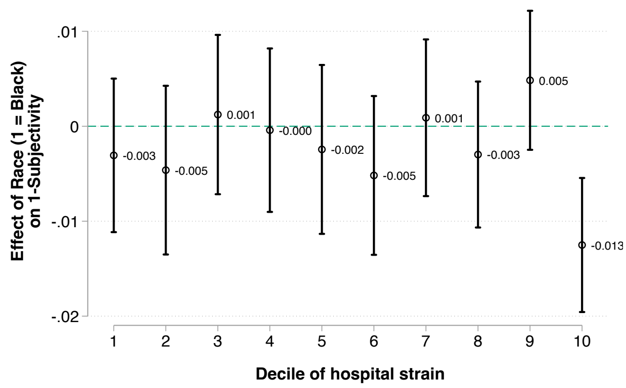
Panel (a): Marginal effect of race on character count



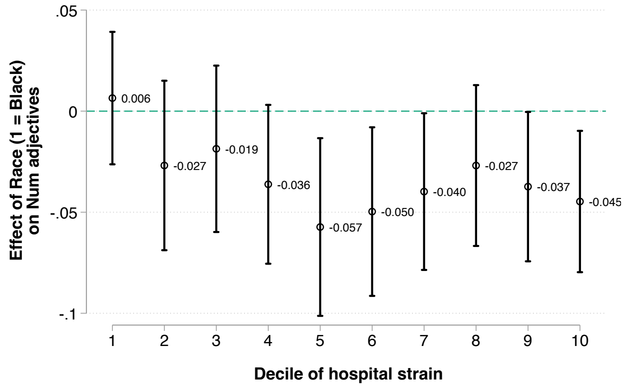
Panel (b): Marginal effect of race on word length



Panel (c): Marginal effect of race on polarity (reverse coded)



Panel (d): Marginal effect of race on subjectivity (reverse coded)



Panel (e): Marginal effect of race on number of adjectives

FIGURE A.10

Analysis of Each Component of the Provider Effort Index

Estimates from Equation 1a with each of the five effort measures derived from the *reason for admission* note (used to construct the summed provider effort index) as the outcome. Outcomes are: above-median character count (Panel (a)), average word length (Panel (b)), 1 - polarity (Panel (c); 1 - subjectivity (Panel (d)); number of adjectives (Panel (e)). All effects are evaluated at the means of other covariates. Heteroskedasticity-robust 95% confidence intervals are shown.

	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	6006	5803	3836	5641	3895	5902	3989	5768	3672	6462	3542	6508	3766	6556	4747	7464	4506	7281	5424

TABLE A.1

Hospital Capacity at Each Decile of Strain

Note: For hospitals H1 and H2, this table presents the mean proportion of beds filled at each of the ten deciles of strain, with SD rounded to 2 decimals points in parentheses.

	Dep Var: In-Hospital Mortality		
	(1) Pooled	(2) Hospital 1	(3) Hospital 2
Black	0.0019*	-0.0001	0.0043***
	(0.0010)	(0.0014)	(0.0013)
High strain (=dec 10)	-0.0005	-0.0020	0.0019
	(0.0019)	(0.0026)	(0.0026)
Black × High strain	0.0053**	0.0072*	0.0026
	(0.0023)	(0.0038)	(0.0031)
N	106,791	43,534	63,170
R^2	0.292	0.298	0.303
Sample mean	0.017	0.020	0.014

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.001$

TABLE A.2

Mortality Results by Hospital

Note: Coefficients from regressions of in-hospital mortality on race (=1 if Black) and the top decile of hospital strain (Eq. 1b). Column 1 reports estimates from the pooled sample. Columns 2 and 3 restrict to admissions at Hospital 1 and Hospital 2, respectively. Heteroskedasticity-robust standard errors in parentheses. The p-value for equality of the interaction coefficients across Columns 2 and 3 is equal to 0.35, and obtained from a fully interacted triple-difference model (Race × Strain × Hospital), in which all covariates are also interacted with hospital

	Dep Var: In-Hospital Mortality		
	(1)	(2)	(3)
Black	0.0012	-0.7931***	0.0009
	0.0008	0.1796	0.0010
High strain (dec=10)	0.0004	-0.0565	-0.0010
	0.0016	0.3219	0.0019
High medical need	0.0084***	1.0000***	
	0.0016	0.1489	
Black × High strain (dec=10)	0.0013	0.5688	0.0054**
	0.0018	0.4704	0.0024
Black × High medical need	-0.0009	0.7001***	
	0.0018	0.1861	
High strain (dec=10) × High medical need	-0.0014	0.0857	
	0.0035	0.3440	
Black × High strain (dec=10) × High medical need	0.0081*	-0.2884	
	0.0048	0.4952	
Objective symptoms			-0.0066*
			0.0036
Black × Objective symptoms			-0.0028
			0.0040
High strain (dec=10) × Objective symptoms			0.0169
			0.0115
Black × High strain (dec=10) × Objective symptoms			-0.0135
			0.0131
N	106800	107177	106800
R^2	0.284		0.284
Spec	Elix (LPM)	Elix (Poisson)	Symptom subjectivity (LPM)

TABLE A.3

Heterogeneity in Mortality by Patient Need/Subjectivity of Symptoms

Note: Estimates from Equation 1b with all main and interaction terms for Race x High strain x $[Var_i]$. Var_i is patient need (as measured by Elixhauser mortality index) for Columns 1 and 2, and objective symptoms (as measured by mentions of "chest pain" or "shortness of breath" in the *reason for admission* note) in Column 3. $p < .001^{***}$ $p < .05^{**}$ $p < 0.1^{*}$.

	(1)	(2)	(3)	(4)	(5)	(6)
	Age (yrs.)	Female	Uninsured	# comorb	Mort index	Readm index
Black	-3.34***	0.10***	0.01***	-0.06***	-0.88***	1.66***
	(0.12)	(0.00)	(0.00)	(0.01)	(0.05)	(0.06)
High strain (=dec 10)	0.19	-0.00	0.00	0.01	-0.01	-0.14
	(0.25)	(0.01)	(0.00)	(0.02)	(0.11)	(0.12)
Black × High strain (=dec 10)	-0.07	0.01	-0.00	0.00	-0.04	0.22
	(0.29)	(0.01)	(0.01)	(0.02)	(0.13)	(0.14)
N	106791	106791	106791	106792	106800	106800
R^2	0.506	0.253	0.213	0.856	0.779	0.900
Mean of outcome	54.78	0.59	0.13	4.09	12.58	24.50

TABLE A.4

Tests for Patient Selection Using Individual Patient Covariates as Outcomes

Note: Estimates of Equation 1b with the following outcomes assessed in the full sample of inpatients: patient age (Col 1), patient sex (Col 2), insurance status (Col 3), total number of Elixhauser comorbidities (Col 4), Elixhauser mortality index (Col 5), and Elixhauser readmission index (Col 6). Covariates are the same as in Eq. 1b (except for the exclusion of the dependent variable in each column). $p < .001^{***}$ $p < .05^{**}$ $p < 0.1^{*}$

	(1) Topic 1	(2) Topic 2	(3) Topic 3	(4) Topic 4	(5) Topic 5
Black	0.018***	0.008**	-0.006*	-0.004	-0.016***
	(0.004)	(0.004)	(0.003)	(0.004)	(0.003)
High strain (=dec 10)	-0.015*	-0.007	0.004	0.017**	0.001
	(0.008)	(0.007)	(0.008)	(0.007)	(0.007)
Black × High strain (=dec 10)	-0.002	0.001	0.000	-0.012	0.014
	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)
N	76156	76156	76156	76156	76156
R^2	0.199	0.247	0.264	0.199	0.214
Mean of outcome	0.23	0.21	0.20	0.19	0.17

TABLE A.5
Topic Analysis

Note: Regression coefficients from Equation 1b with the five topics (identified by the latent Dirichlet allocation) as outcomes. Details on LDA provided in Appendix A. $p < .001^{***}$ $p < .05^{**}$ $p < 0.1^{*}$

	(1) ICU Admission	(2) Length of stay	(3) Charges ($)
Black	-0.01***	0.03	-3416.52***
	(0.00)	(0.07)	(566.26)
High strain (=dec 10)	-0.02**	-0.05	-127.50
	(0.01)	(0.14)	(1095.53)
Black × High strain (=dec 10)	0.02**	0.22	1798.61
	(0.01)	(0.18)	(1295.75)
N	106791	106791	106768
R^2	0.411	0.276	0.423
Mean of outcome	0.24	6.57	52047.56

TABLE A.6
Wait Times and Other Inputs of Care

Note: Regression coefficients from Equation 1b with the following outcomes: ICU admission (Col 1), total length of inpatient stay in days (Col 2), and total inpatient charges (Col 3). $p < .001^{***}$ $p < .05^{**}$ $p < 0.1^{*}$

	(1) Triage score	(2) In-hospital mortality
Black	-0.014	0.001
	(0.011)	(0.002)
High medical need	0.106***	0.004
	(0.014)	(0.003)
High strain (=dec 10)	0.021	0.002
	(0.027)	(0.004)
Black × High strain (=dec 10)	-0.006	0.001
	(0.032)	(0.005)
Black × High medical need	-0.019	0.004
	(0.015)	(0.003)
High strain (=dec 10) × High medical need	-0.030	-0.002
	(0.035)	(0.007)
Black × High strain (=dec 10) × High medical need	0.018	0.009
	(0.043)	(0.008)
N	49433	49433
R^2	0.272	0.361
Mean of outcome	3.728	0.020

TABLE A.7

Triage Score by Race, Need, and Strain

Note: Regression coefficients from estimating Equation 1b with all interactions between race (=1 for Black) × high strain (defined by the tenth decile) × high medical need (defined as above the sample median for Elixhauser mortality index). Outcomes are (i) Col 1: triage scores (1–5, reverse coded so higher values imply greater severity) and (ii) Col 2: in-hospital mortality. Estimated on the sample of inpatients admitted through the ED. $p < .001^{***}$ $p < .05^{**}$ $p < 0.1^{*}$.

	(1) Wait time (hrs)	(2) Provider effort
Black	0.98***	-0.14***
	(0.08)	(0.03)
High medical need	-0.41***	0.05
	(0.09)	(0.04)
High strain (dec=10)	0.65***	0.09
	(0.16)	(0.06)
Black × High strain (dec=10)	0.37*	-0.08
	(0.22)	(0.08)
Black × High medical need	-0.00	0.07*
	(0.10)	(0.04)
High strain (dec=10) × High medical need	0.82***	-0.06
	(0.20)	(0.08)
Black × High strain (dec=10) × High medical need	-0.10	-0.04
	(0.30)	(0.11)
N	91907	77593
R^2	0.292	0.218
Mean of outcome	5.46	0.00

TABLE A.8

Heterogeneity in Wait Times and Provider Effort by Patient Need

Note: Estimates from Equation 1b with wait times (Column 1) and provider effort index (Column 2) as outcomes and all main and interaction terms for race × high strain × patient medical need. High and low patient need measured by above- and below-median sample values for the Elixhauser mortality index. $p < .001^{***}$ $p < .05^{**}$ $p < 0.1^{*}$.

	Dep Var: In-Hospital Mortality	
	(1)	(2)
Black	0.0018*	0.0011
	(0.0011)	(0.0011)
High strain (dec=10)	-0.0008	-0.0007
	(0.0020)	(0.0021)
Black × High strain (dec=10)	0.0065**	0.0070**
	(0.0026)	(0.0028)
N	91898	77582
R^2	0.306	0.315
Mean of outcome	0.0186	0.0172

TABLE A.9

Mortality: Wait Time and Provider Effort Subsamples

Note: Regression coefficients from Equation 1b for in-hospital mortality using only those observations for which data on wait time (Col 1) or provider effort (Col 2) are available. $p < .001^{***}$ $p < .05^{**}$ $p < 0.1^{*}$.

	(1)	(2)	(3)	(4)	(5)	(6)
	Provider effort	> med chars	Avg. word len	1-Polarity	1-Subjectivity	Num adjectives
Black	-0.096***	-0.001	-0.109***	-0.000	-0.001	-0.030***
	(0.022)	(0.004)	(0.023)	(0.001)	(0.002)	(0.007)
High strain (=dec 10)	0.064	0.005	0.008	-0.000	0.008**	0.006
	(0.045)	(0.009)	(0.046)	(0.002)	(0.003)	(0.016)
Black × High strain (=dec 10)	-0.110*	-0.004	0.009	-0.002	-0.011**	-0.014
	(0.056)	(0.011)	(0.057)	(0.002)	(0.004)	(0.019)
N	77582	77582	77582	77582	77582	77582
R^2	0.220	0.227	0.172	0.142	0.153	0.241
Mean of outcome	0.003	0.483	6.637	0.998	0.943	0.528

TABLE A.10

Provider Effort Index (Summed, and Components)

Note: Regression coefficients from Equation 1b. Col 1 uses the main provider effort index as the outcome. The outcomes for the remaining columns are the five individual components of this index, as follows: above the median character count (Col 2), average word length (Col 3), 1 - polarity (Col 4), 1 - subjectivity (Col 5), and number of adjectives (Col 6). Descriptions for each of these outcomes are provided in Section 5. $p < .001^{***}$ $p < .05^{**}$ $p < 0.1^{*}$.