Left-Digit Bias in the Emergency Room

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Abstract

In high-stakes medical care, physicians' decisions are informed by many types of clinical data. Vital signs like temperature are particularly salient because they measure the body's essential physiologic function. But data interpretation may be influenced by common heuristics unrelated to established clinical decision rules. Using a regression discontinuity design to analyze electronic health record data on 405,690 visits to 102 VA emergency departments across the United States, we find that a difference of 0.1 degree in patient temperature (101.0 versus 100.9) leads to a 2.5 percent relative increase in the probability of being admitted into the hospital, with similar relative increases in laboratory testing and medication administration; services that diagnose or treat infection show larger increases at this threshold, suggesting that a temperature of 101.0 increase the salience of the risk of infection. The additional care induced by left-digit bias does not improve patients' health.

JEL codes: I10

Introduction

Medical care in an emergency department (ED) epitomizes high-stakes decision-making under uncertainty and occurs at enormous scale. There is roughly one ED visit for every two U.S. residents annually (Cairns et al. 2024). Ten percent of US deaths occur in an ED, and 38% occur within one month of an ED visit (Elmer et al. 2022). The task of ED providers is to evaluate, treat, and make disposition decisions (e.g., hospital admission or discharge), resulting in ED providers playing a large role in allocating intensive medical resources. Key decisions regarding diagnostic testing, treatment, and disposition can have immediate and serious consequences for patients (Newman-Toker et al. 2022).

Interpreting clinical data is central to ED care. ED providers synthesize large amounts of clinical information, measured both subjectively and objectively. Particularly salient are vital signs (e.g., temperature and heart rate), which reflect core physiologic function. Important for our purposes, a patient's vital signs are obtained at triage, prior to a physician evaluating a patient. Other clinical data tend to be actively generated by physicians; that is, providers determine which tests to conduct and what diagnoses to document. This downstream clinical data complicate efforts to use this data to study provider decision-making, because the very data used to infer clinical reasoning are often themselves the product of earlier decisions.

In this complex information environment, providers may be influenced by heuristics, or rules of thumbs that can simplify decision-making (Tversky and Kahneman 1974). Such simplification is adaptive if it allows physicians to act quickly and consistently, while preserving decision quality. However, simplification can yield bias when data interpretation hinges on data features that are salient to the provider but otherwise arbitrary (Singh 2021). In this study, we examine how provider decision-making may be shaped by a patient's triage temperature at EDs within the US Veterans Health Administration (VA). We focus on discontinuities in decision-making around a temperature of 101.0˚F, which we interpret as providers being influenced by the heuristic of left-digit bias, which refers to the tendency to focus on the left digits and partially ignore other digits when processing numbers.

Several features of our study are well-suited for examining this heuristic. First, the VA is the largest integrated health care system in the United States, and its electronic health record (EHR) data are large and clinically-rich enough not only for detecting heuristic-induced behavior, but also for investigating its mechanisms and outcomes. Second, the vital sign we use to study left-digit bias, temperature, is measured ubiquitously and relevant to many clinical decisions. It is also measured automatically by calibrated instruments, and this automatic measurement makes it difficult to manipulate. This means that patients just below 101.0˚F are otherwise similar to those at or above 101.0˚F, but due to left digit bias, these two groups of patients may receive different levels and types of care. Third, the threshold we examine is not only arbitrary but also unrelated to established clinical decision rules. We do not study fever, which was originally defined in Celsius as 38.0˚C, such that its U.S. equivalent—100.4˚F—is not an integer threshold. Fever (and the temperature of 100.4˚F) underly some clinical protocols such as for sepsis. We instead study the threshold of 101.0˚F, which distinguishes our study from prior research on clinical thresholds that are both salient and codified in clinical protocols (Goulden et al. 2021; Douglas Almond et al. 2010), such as blood pressure (Boone 2025). Thus, any changes in decision-making we observe at 101.0˚F are more likely to reflect cognitive processing of the clinical data itself rather than institutional or professional standards of care. In addition, the lack of connection of our examined threshold to an institutional or professional standard of care also guards against the type of patient or provider manipulation of a variable (or recording of a variable) to induce or reduce care provision that is found in other clinical scenarios (Boone 2025).

We use nationwide time-stamped VA EHR data to examine the impact on patients in the ED of crossing the 101.0˚F threshold on intensity of care, including laboratory tests, radiology tests, medications, and admission into the hospital. Because we suspect that left digit bias in our clinical scenario discontinuously raises the salience of the risk of severe infection, we additionally examine changes in particular tests and medications associated with infection. Finally, we examine important patient outcomes resulting from changes in

care at our threshold, such as mortality. We use a regression discontinuity design with a patient's first temperature reading after arrival to the ED.

We find that the intensity of care increases at the 101.0˚F threshold. The number of laboratory tests increases by 0.47 (a relative increase of 5.8%), the number of radiology tests increases by 0.03 (a relative increase of 2.4%), the number of medications increases by 0.14 (a relative increase of 4.2%), and the admission rate increases by 2.5 pp (a relative increase of 4.9%). Laboratory tests for infection also increase (e.g., rates of blood culture increase by 6.3 pp [a relative increase of 12.3%]). While rates of any antibiotic do not increase at the threshold, the types of antibiotics do; the use of powerful, broad-spectrum antibiotics increases by 1.8 pp (a relative increase of 12.6%). This increase in the amount and type of care does not appear to result in better outcomes for patients, as overall mortality rates do not decrease at the threshold. Taken together, our results suggest that left-digit bias influences provider processing of clinical data, inducing additional and higher-intensity care that does not appear to benefit marginal patients.

We build on prior literature in economics that examines the effects of left digit bias, predominantly outside of health. An earlier study found that left digit bias in the used-car market leads to discontinuous drops in sales prices at 10,000-mile odometer thresholds (Lacetera et al. 2012). Recent work finds that demand for rideshares discontinuously drops as prices cross dollar thresholds (List et al. 2023). Prior medical literature studying left digit bias has largely focused on provider behavioral responses to decadal age thresholds. For example, patients with a heart attack admitted 2 weeks after their 80th birthday were significantly less likely to undergo coronary-artery bypass grafting surgery than those admitted 2 weeks prior (although this pattern was not found for other age thresholds) (Olenski et al. 2020). Similar patterns were found for the utilization of kidneys from deceased donors aged 70 years versus aged 69 years (but again, this pattern was not found for other donor age thresholds) (Husain et al. 2021).

Relative to the prior economics literature on left-digit bias primarily focused on consumer settings (List et al. 2023; Stiving and Winer 1997; Lacetera et al. 2012), evidence

of its presence among experts in high-stakes decision-making is more limited (Cai et al. 2024). The prior medical literature on left-digit bias has focused almost exclusively on patient age, which may influence both physician and patient beliefs regarding the appropriateness of a treatment. While age is one piece of clinical data correlated with patient health, our use of clinically-rich VA EHR data allows us to study a type of clinical data that is variable over time, indicative of short-term health status at the time of evaluation, and less likely to influence care by affecting patients' beliefs.

In addition to the research on left-digit bias, we also build on a broader literature on heuristics in health care decision-making. For example, physicians appear to be influenced by the availability heuristic, under which the assessment of an event's likelihood is influenced by how easily the event can be recalled, particularly recent events, such as poor outcomes and recent diagnoses (Ly 2021; Singh 2021). Physicians also appear to be influenced by anchoring, or the focus on a single—often initial—piece of information when making decisions (Ly et al. 2023). Our study advances the literature by examining how heuristics influence provider interpretation of fluid and fundamental clinical data. Related literature focuses on what happens around cutoffs specifically used in clinical guidelines, such as very low birth weight, advanced maternal age, diabetes, and hypertension (D. Almond et al. 2005; Geiger et al. 2021; Alalouf et al. 2024; Boone 2025). While these studies ask what care is induced or reduced by cutoffs specified by clinical guidelines, we instead ask how care is affected by more arbitrary thresholds.

Finally, we also contribute to the literature on the value of additional care for marginal patients. While marginal patients differ across studies and correspondingly, results for the value of additional care are mixed, we focus on a particularly sick population; those who come to the ED with a particularly high temperature around 101.0˚F, for which the mean 30-day mortality rate is 3.2%. Whether additional care benefits these very sick patients is important to understand.

Background

We focus on provider interpretation of temperature measured in the emergency department. Temperature (and other vital signs) are measured at triage, before a physician sees the patient. This temperature is then recorded in the VA EHR, and the provider can read this temperature right before, during, or right after seeing the patient. We focus on temperature rather than other vital signs like blood pressure and heart rate because temperature is measured more precisely by calibrated instruments and less prone to manipulation (Boone 2025). Previously, blood pressures were taken manually via sphygmomanometer; as air pressure was released from a cuff, clinicians would note the position of a moving needle on a dial at the moment a heartbeat was heard (systolic blood pressure) and then not heard (diastolic blood pressure). Similarly, heart rates were often taken by measuring the pulse for 10, 15, or 30 seconds and multiplying by the relevant number to get heart rate per minute. Such measurement methods, which may have been relevant particularly in earlier years of our examined time period, are prone to imprecision and manipulation, making use of a regression discontinuity design more challenging.

Data

We used VA EHR data from the VA Corporate Data Warehouse (CDW), which includes patient demographics, time-stamped vital signs, time-stamped test orders, and patient locations within a VA hospital. It also includes VA ED visit data in EDIS (Emergency Department Integration Software), which the VA fully implemented in 2011. We identified patients aged 20-99 years who visited a VA ED from January 2011 through December 2024. Our sample includes 405,690 patient visits with a temperature between 100.0˚F and 100.2˚F, cared for by 10,801 providers across 102 VA EDs (and their associated hospitals).

We first focus on four categories of health care provision: 1) number of laboratory tests, 2) number of radiology tests, 3) number of medications, and 4) admission to the hospital. We then focus on specific laboratory tests and treatments associated with infection to examine whether left-digit bias may increase the perceived probability of

infection or serious infection. These specific laboratory tests are: 1) complete blood count, 2) lactate (elevated in severe infection), 3) blood culture, and 4) urinalysis/urine culture. These specific treatments are: 1) any antibiotic, 2) broad-spectrum antibiotics used for more severe infections (vancomycin, cefepime, piperacillin/tazobactam), 3) acetaminophen (i.e. Tylenol, which reduces temperature), 4) intravenous normal saline infusion (i.e., fluids used in suspected severe infections), and 5) prednisone (a steroid which is recommended not to be used during infections because it suppresses the immune response). We examine two health outcomes: 1) 30-day mortality rate and 2) intensive care unit (ICU) stay within 30 days.

We include the following four patient covariates: 1) patient age at time of ED arrival, 2) patient sex, 3) patient race and ethnicity, and 4) Elixhauser comorbidity score, defined using diagnosis codes from the prior two years.

Table 1 shows our sample characteristics, both overall and within optimally selected bandwidth. Overall, the average age is 61.4, and reflecting our VA patient population, 9.8% are women. Within our bandwidth, the average age is 61.7, and 9.2% are women. The average Elixhauser comorbidity score within our bandwidth is 3.44.

Empirical Strategy

We use regression discontinuity (RD) to examine changes in health care provision and health outcomes at the 101.0˚F threshold. For our analyses, we use a local linear regression with a uniform kernel and optimal bandwidth selection, although we test the sensitivity of our results to alternative bandwidths. Our full models adjust for baseline patient covariates, time fixed effects (hour of day, day of week, month, year), and facility fixed effects.

As is important in RD designs, we examine whether there is evidence of manipulation in our running variable. As noted above in Background, we suspect the scope for manipulation of temperature is minimal. There is little evidence of manipulation based

on the distribution of ED visits by temperature (Figure 1). We also formally test for discontinuities in patient baseline covariates across the threshold, and we also, as a falsification test, examine whether there is a discontinuity in number of days hospitalized in the 365 days prior to ED arrival.

Results

We first examine changes in our baseline patient covariates (age, sex, race/ethnicity, and Elixhauser comorbidity score) at our 101.0˚F threshold, as well as changes in our falsification test of number of days hospitalized in the prior year (Figure 2). We find no evidence of discontinuities in these variables.

We then examine changes in health care provision at our 101.0˚F threshold. The first two panels of Figure 3 show patterns in diagnostic tests (laboratory and radiology tests). The first panel of Figure 3 shows number of laboratory tests. At the threshold, the number of laboratory tests increases by 0.47, which is an increase of 5.8% relative to the mean (within the bandwidth). Similarly, the second panel of Figure 3 shows that the number of radiology tests increases by 0.03 at the threshold (relative increase of 2.4%). The third panel of Figure 3 focuses on treatment; the number of medications at the threshold increases by 0.14 (relative increase of 4.2%). Finally, admission to the hospital is a consequential decision both for the patient (disruption, exposure to health care-associated infections) and the hospital (filling limited inpatient beds, stressing inpatient providers and nurses), and the fourth panel of Figure 3 shows that the admission rate increases by 2.5 pp at the threshold (relative increase of 4.9%).

To examine whether left-digit bias may act to increase the perceived probability of infection or severe infection at 101.0˚F, we first examine select laboratory tests. In Figure 4, we find that orders for complete blood count, lactate, blood culture, and urinalysis/urine culture all discontinuously increase at the threshold. We then examine in Figure 5 the use of any antibiotic and specific, broad-spectrum antibiotics often used when there is a suspicion for sepsis, a life-threatening condition in which there is a dysregulated response

to infection. While there is no discontinuous increase in the use of any antibiotic, it appears that the composition of the type of antibiotic changes, with a shift to the use of broad-spectrum antibiotics for sepsis. In Figure 6, we also find changes in select treatments. The use of acetaminophen discontinuously increases at the threshold, and so does the use of intravenous normal saline, which is also an integral part of the treatment for suspected sepsis (first and second panel, respectively). In the third panel, we find that use of prednisone, which is recommended **not** to be given when there's a suspicion for infection because it suppresses the immune response, discontinuously **drops** at the threshold.

Finally, we examine health outcomes across the threshold. We find no statistically significant changes in 30-day mortality, suggesting that all this additional care induced by left-digit bias does not improve the important outcome of mortality. The 95% CI of our mortality estimate ranges from -0.1 to 0.5. Thus, we can rule out absolute mortality improvements of 0.1 percentage points, or 4.0 percent of the bandwidth mean. We also examine ICU stay within 30 days of ED arrival across the threshold. We find that the rate of 30-day ICU stay increase by 0.7 pp, a relative increase of 7.1%. Importantly, the additional ICU stays may result partly from hospital admission itself, rather than from iatrogenesis. For example, hospitalization involves increased surveillance of worsening health states (e.g. concerning vital signs that would not be noticed if a patient were at home), as well as a low marginal cost of escalating care to an ICU. However, even if these factors were the primary drivers of increased ICU stays, this finding, in combination with the null mortality finding, suggests that the high-intensity monitoring and care in the ICU does not improve mortality for these sick patients.

Numerical estimates for our figures can be found in Table 2 and Table 3. Appendix Figure 1 shows that left-digit bias appears to be a broad-based phenomenon influencing care of all examined subgroups of patients (by age, sex, race/ethnicity, and Elixhauser co-morbidity score). Appendix Figure 2 shows that this heuristic also occurs broadly across VA-defined regions in the United States. Finally, Appendix Table 1 shows that our results are robust to the use of different bandwidths.

Conclusion

Health care providers, particularly those in the ED, must interpret large amounts of clinical data when making high-stakes medical decisions. The paper examines whether a particular heuristic—left-digit bias—shapes how such data are interpreted. We find that when a patient's temperature crosses the 101.0˚F threshold (a threshold unrelated to clinical guidelines), there are substantive changes in the amount and type of care provided in the ED. There are discontinuous increases at this temperature threshold in diagnostic testing, administration of treatments, and hospital admission. It appears that crossing the 101.0˚F threshold heightens concerns about infection, as the increases in testing for infection and treatments for infection are even larger in magnitude than the increases in overall testing and overall treatments.

Among these patients who come to the ED with a temperature around this threshold, this additional care does not appear to improve health, at least as measured by mortality. This lack of improvement in mortality suggests that this additional care is of low marginal benefit for these patients.

Our results suggest that heuristics meaningfully influence health care provider interpretation of clinical data when making high-stakes medical decisions. In our setting, heuristics lead to the provision of care that is of low marginal benefit. Given that health care providers are largely influential in the amount and type of care patients receive, it is important to understand the drivers to their delivery of lower marginal benefit care and higher marginal benefit care.

Acknowledgments and conflicts of interest

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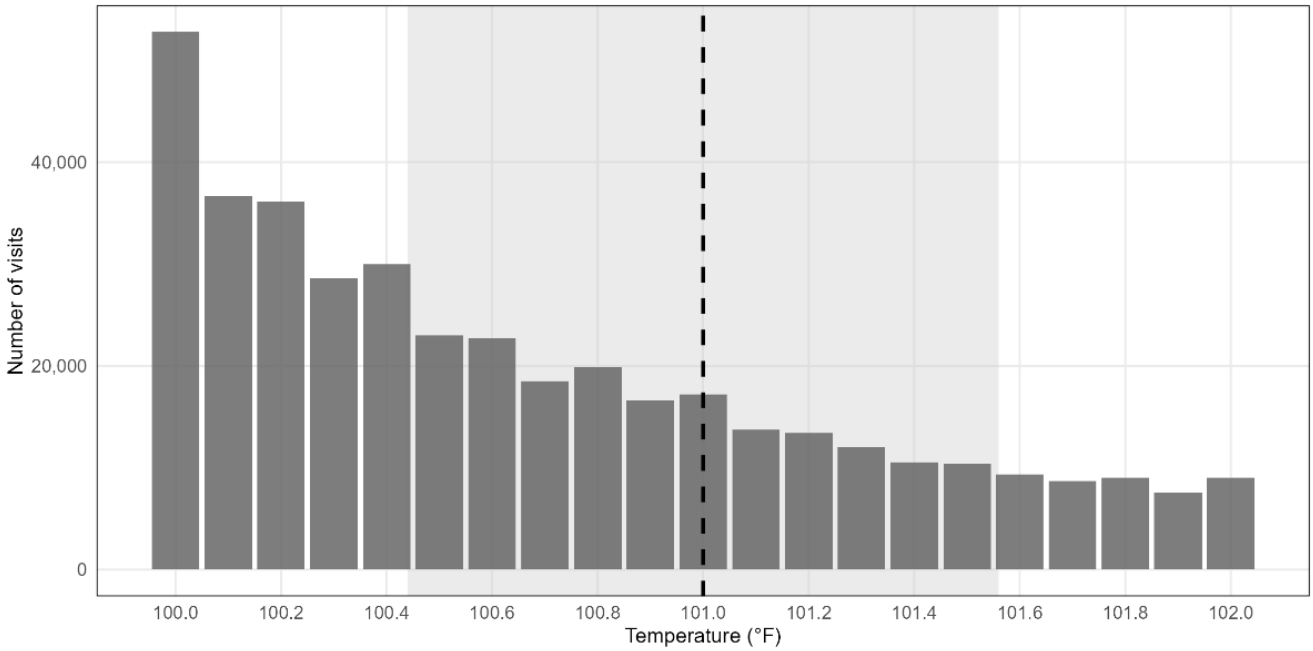
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Table 1: Sample characteristics

Characteristic	Total (n = 405,690)	Within bandwidth (n = 167,513)	Below threshold (n = 100,666)	Above threshold (n = 66,847)	Estimate (95% CI)	% Change Relative to Mean
Age	61.4	61.7	61.6	61.9	-0.17 (-0.48, 0.15)	-0.3
Female, %	9.8	9.2	9.3	9.0	-0.00 (-0.01, 0.00)	-1.0
Male, %	90.2	90.8	90.7	91.0	0.00 (-0.00, 0.01)	0.1
Non-White, %	41.8	41.8	41.6	41.9	0.00 (-0.01, 0.01)	1.0
White, %	58.2	58.2	58.4	58.1	-0.00 (-0.01, 0.01)	-0.7
Elixhauser Score	3.41	3.44	3.42	3.46	-0.01 (-0.06, 0.04)	-0.4
Number of inpatient care days, prior year	12.1	12.2	12.3	12.2	0.1 (-0.5, 0.7)	0.5

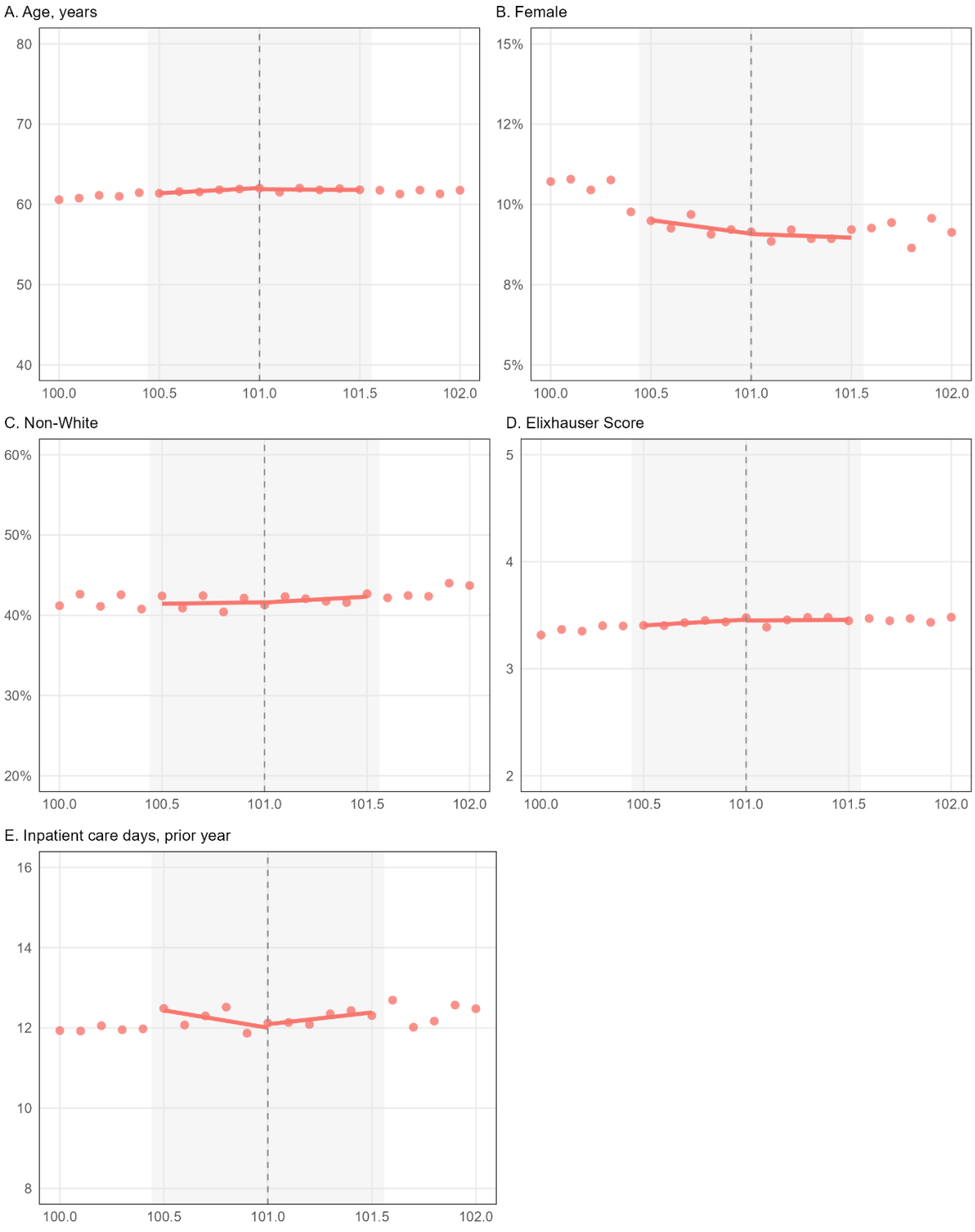
Note: Authors' calculation using Veterans Affairs electronic health record data from 2011-2024. Total sample refers to patients with initial temperature upon emergency department arrival between 100˚F -102˚F.

Figure 1: Distribution of patient visits by temperature



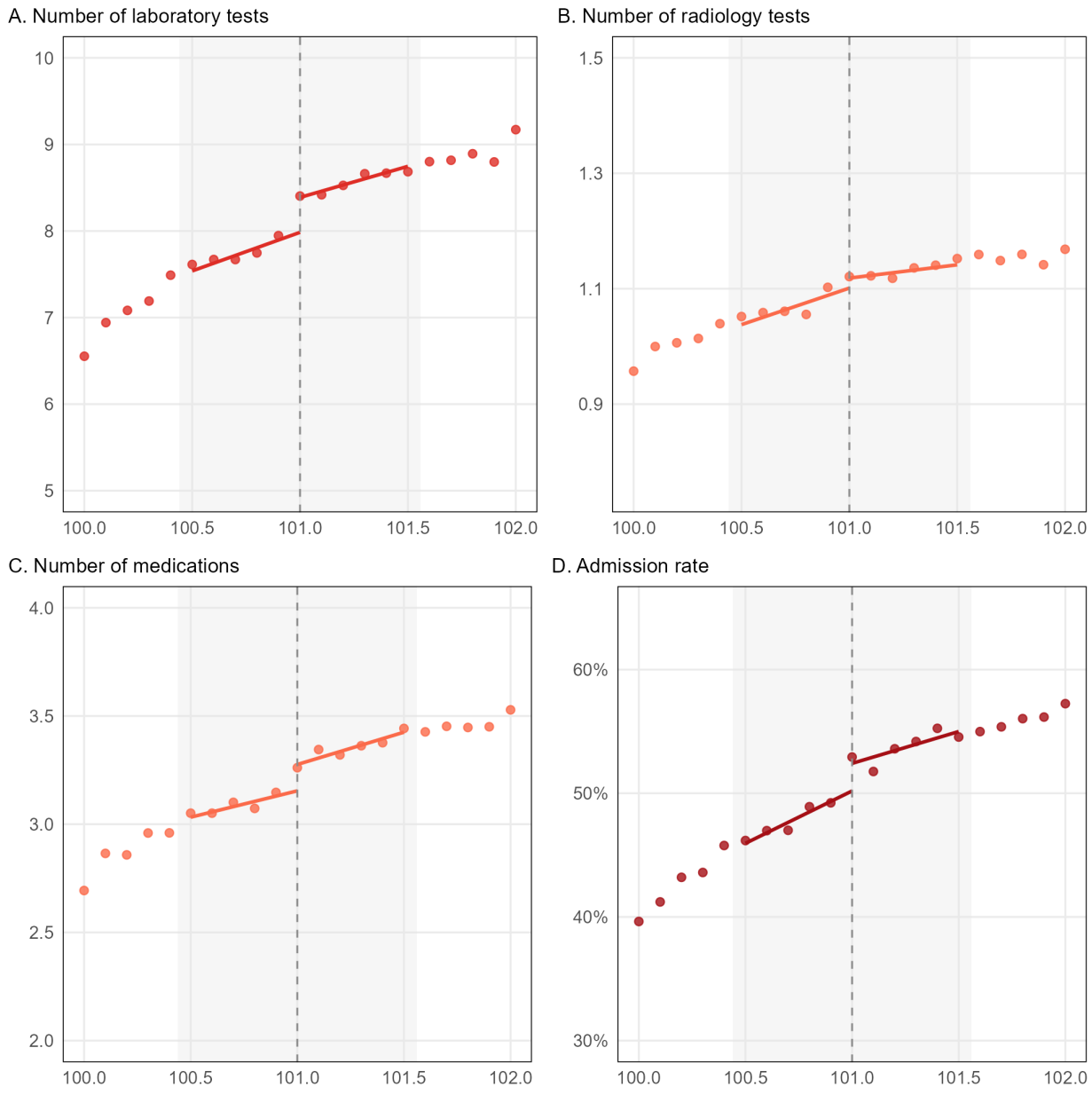
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Figure 2: Baseline patient characteristics and falsification test across the threshold



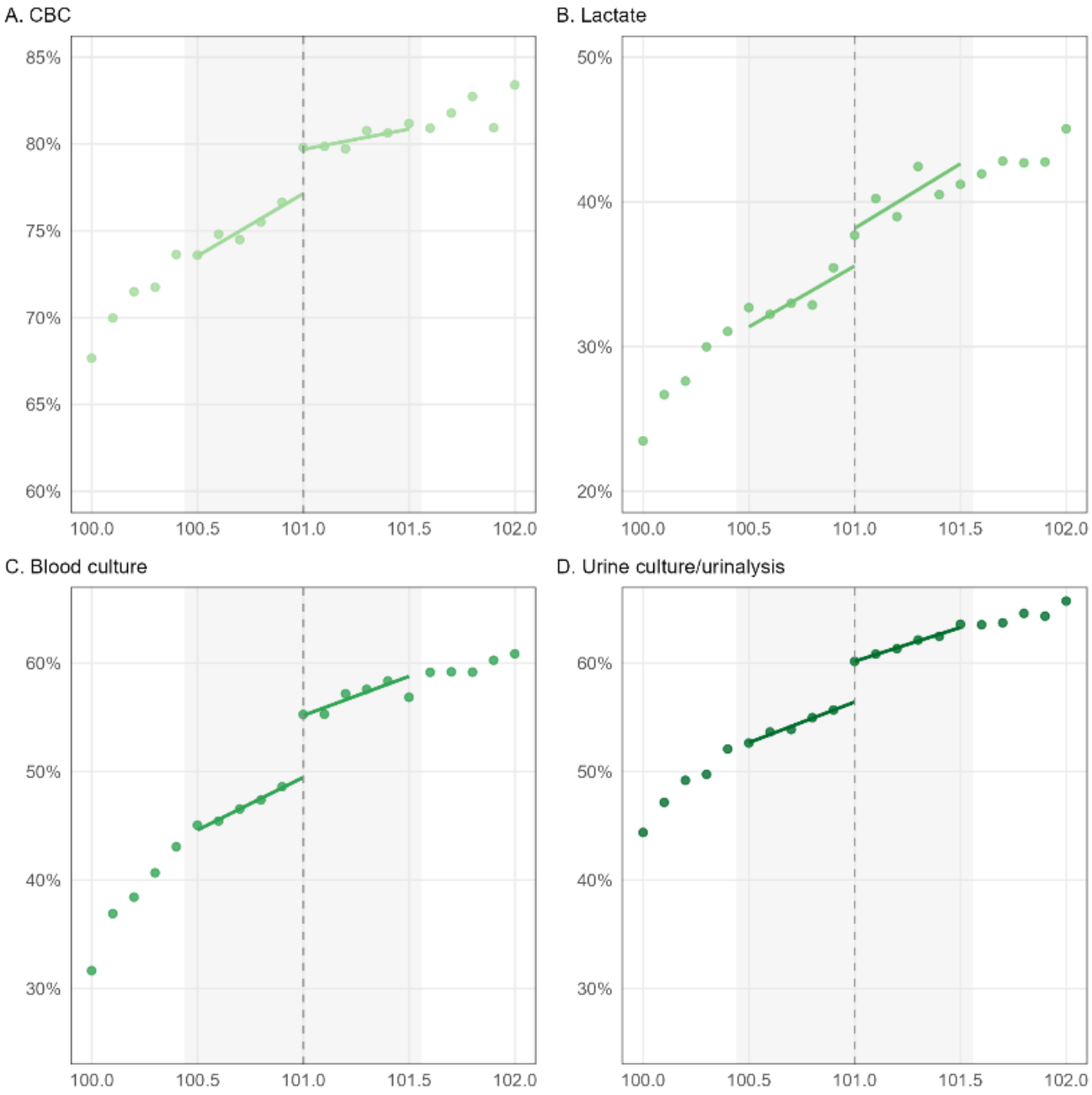
Note: Authors' calculation using Veterans Affairs electronic health record data from 2011-2024. Vertical dashed line is the 101.0˚F threshold. The bandwidth is shaded.

Figure 3: Health care provision



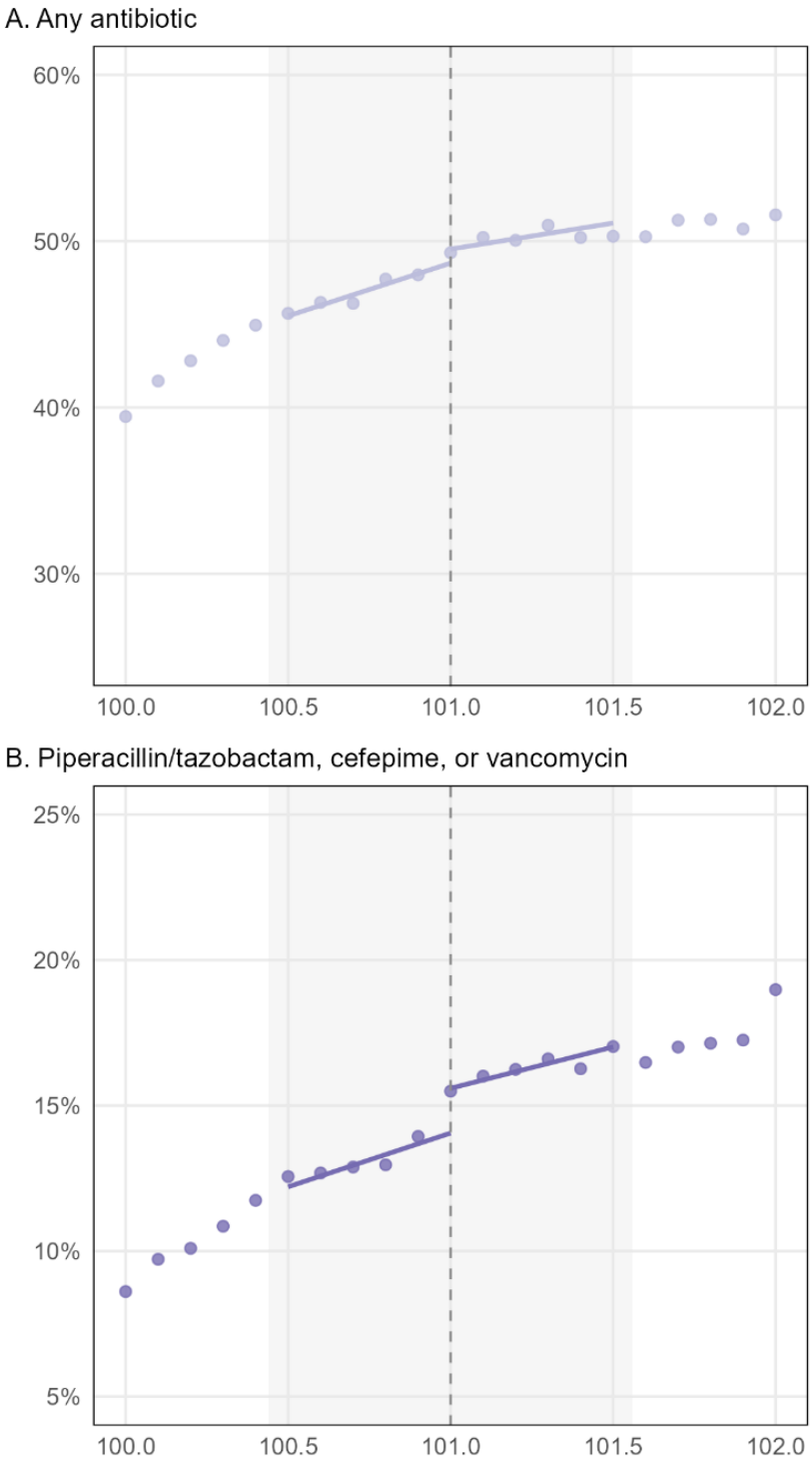
Note: Authors' calculation using Veterans Affairs electronic health record data from 2011-2024. Vertical dashed line is the 101.0˚F threshold. The bandwidth is shaded.

Figure 4: Select laboratory tests



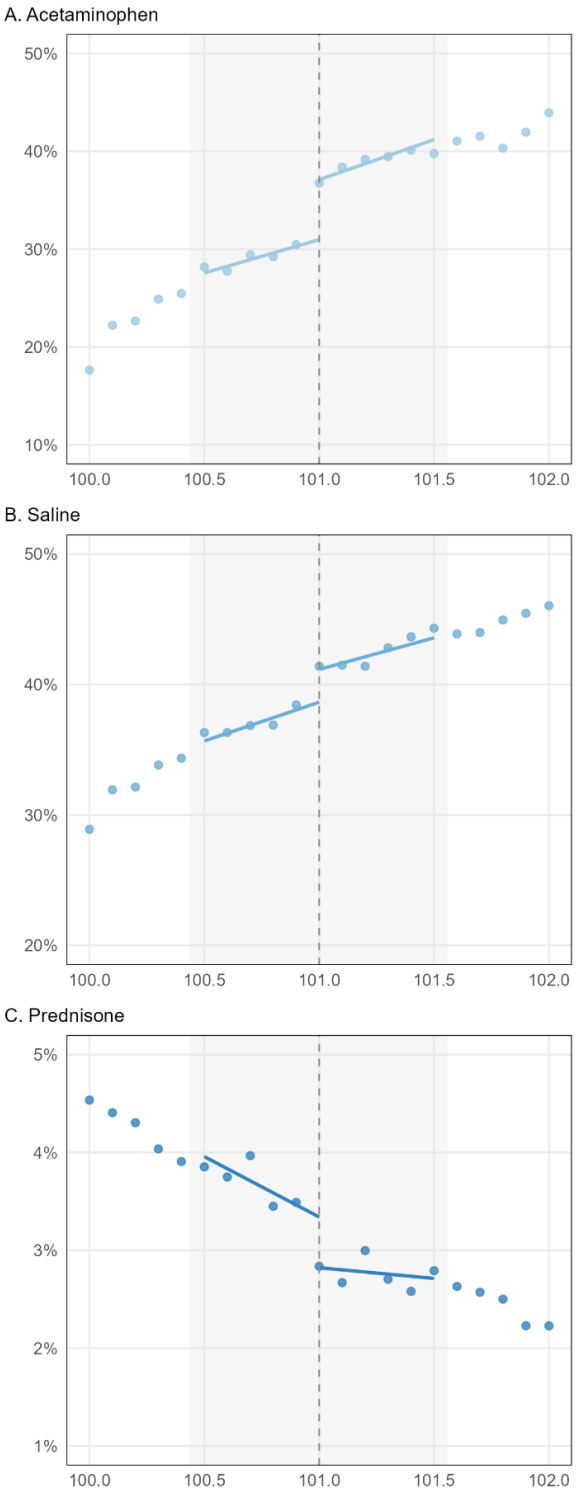
Note: Authors' calculation using Veterans Affairs electronic health record data from 2011-2024. Vertical dashed line is the 101.0˚F threshold. The bandwidth is shaded.

Figure 5: Antibiotics



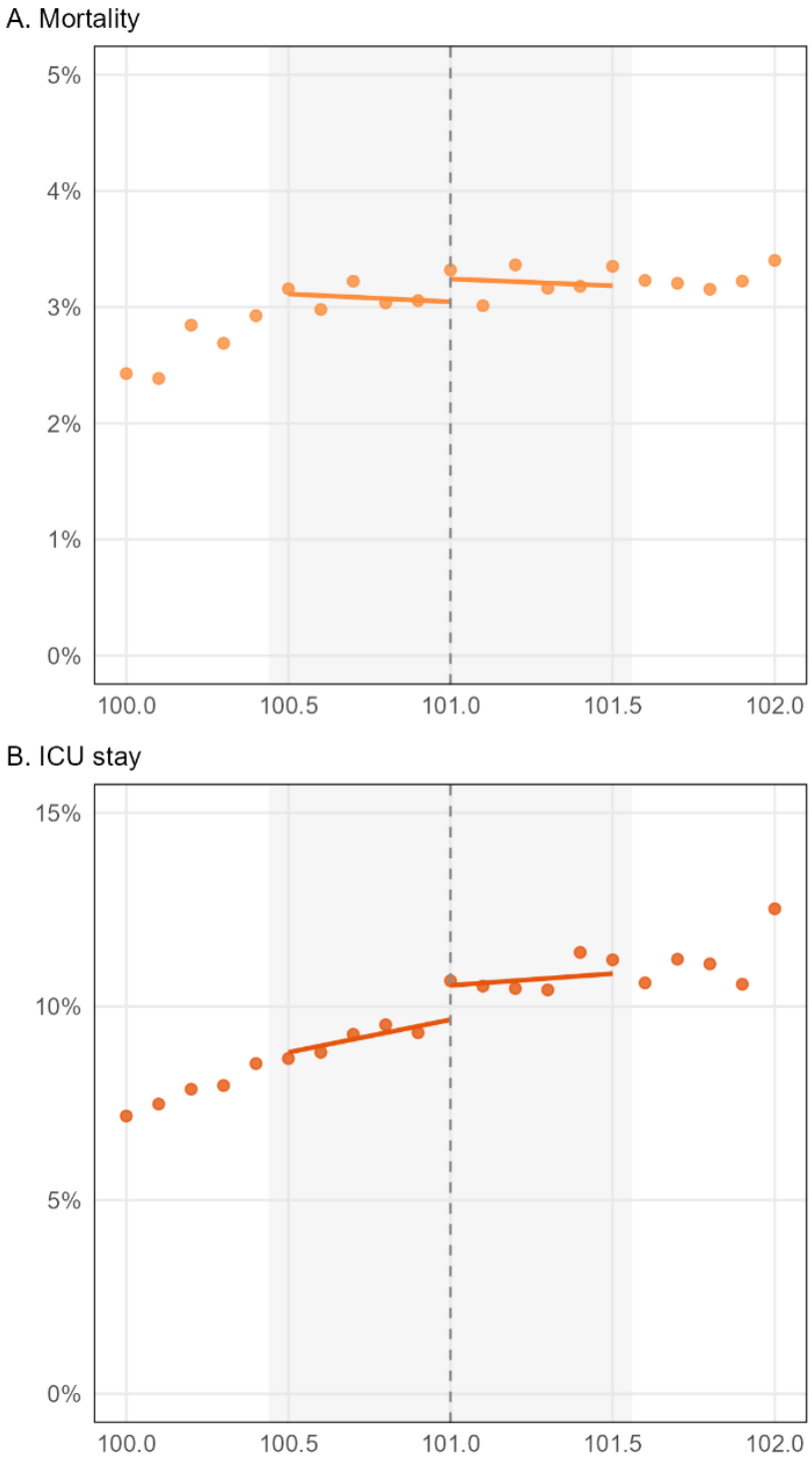
Note: Authors' calculation using Veterans Affairs electronic health record data from 2011-2024. Vertical dashed line is the 101.0˚F threshold. The bandwidth is shaded.

Figure 6: Other select treatments



Note: Authors' calculation using Veterans Affairs electronic health record data from 2011-2024. Vertical dashed line is the 101.0˚F threshold. The bandwidth is shaded.

Figure 7: Health outcomes



Note: Authors' calculation using Veterans Affairs electronic health record data from 2011-2024. Vertical dashed line is the 101.0˚F threshold. The bandwidth is shaded.

Table 2: RD estimates of effects on health care provision

Outcome	Mean within bandwidth (n = 167,513)	Mean below threshold (n = 100,666)	Mean above threshold (n = 66,847)	Estimate (95% CI)	% Change relative to mean
Number of laboratory tests	8.08	7.72	8.54	0.47 (0.37, 0.57)	5.8
CBC, %	77.2	74.9	80.2	2.8 (2.0, 3.5)	3.6
Lactate, %	36.1	33.1	40.0	3.7 (2.8, 4.5)	10.2
Blood culture, %	50.9	46.5	56.6	6.3 (5.4, 7.2)	12.3
Urine test/urinalysis, %	57.3	54.1	61.6	3.9 (3.0, 4.8)	6.7
Number of radiology tests	1.09	1.06	1.13	0.03 (0.01, 0.04)	2.4
Number of medications	3.19	3.08	3.34	0.14 (0.09, 0.19)	4.2
Any antibiotic, %	48.2	46.7	50.1	1.1 (0.2, 2.1)	2.3
Piperacillin/tazobactam, cefepime, or vancomycin, %	14.4	13.0	16.2	1.8 (1.2, 2.5)	12.6
Acetaminophen, %	33.2	28.9	38.7	6.6 (5.8, 7.5)	19.9
Saline, %	39.3	36.9	42.3	2.7 (1.8, 3.6)	6.9
Prednisone, %	3.3	3.7	2.8	-0.6 (-0.9, -0.2)	-17.5
Admission rate, %	50.2	47.6	53.6	2.5 (1.6, 3.3)	4.9

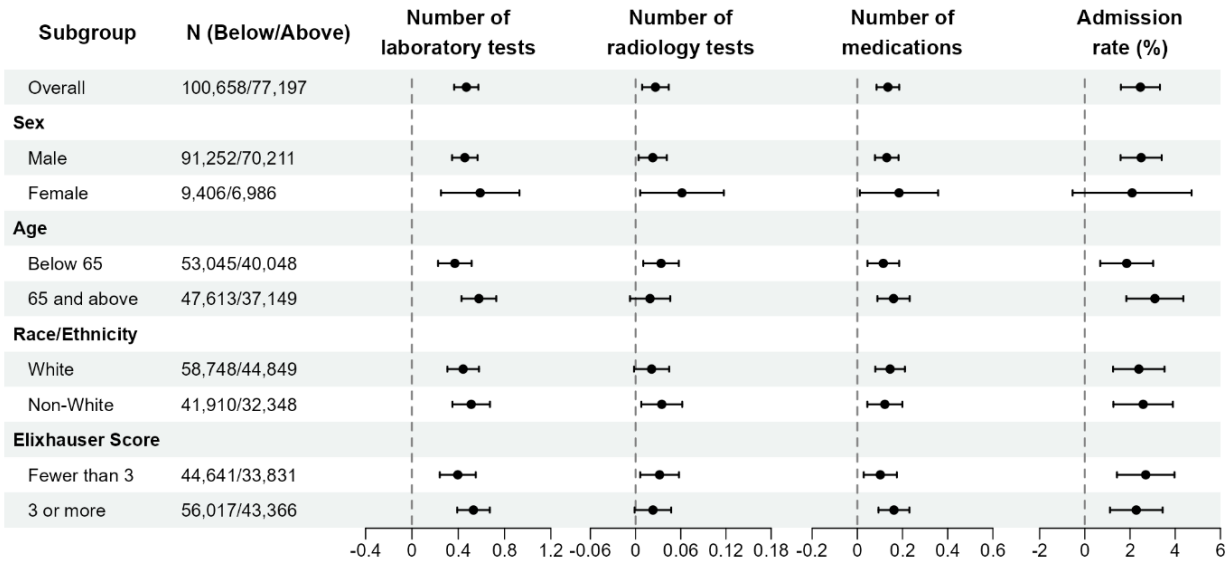
Note: Authors' calculation using Veterans Affairs electronic health record data from 2011-2024. Estimates are from a local linear regression with a uniform kernel and optimal bandwidth selection, adjusting for baseline patient covariates (age, sex, race/ethnicity, Elixhauser comorbidity score), time fixed effects (hour of day, day of week, month, year), and facility fixed effects.

Table 3: RD estimates of effects on health outcomes

Outcome	Mean within bandwidth (n = 167,513)	Mean below threshold (n = 100,666)	Mean above threshold (n = 66,847)	Estimate (95% CI)	% Change relative to mean
Mortality, %	3.2	3.1	3.2	0.2 (-0.1, 0.5)	6.1
ICU stay, %	9.8	9.1	10.7	0.7 (0.2, 1.3)	7.1

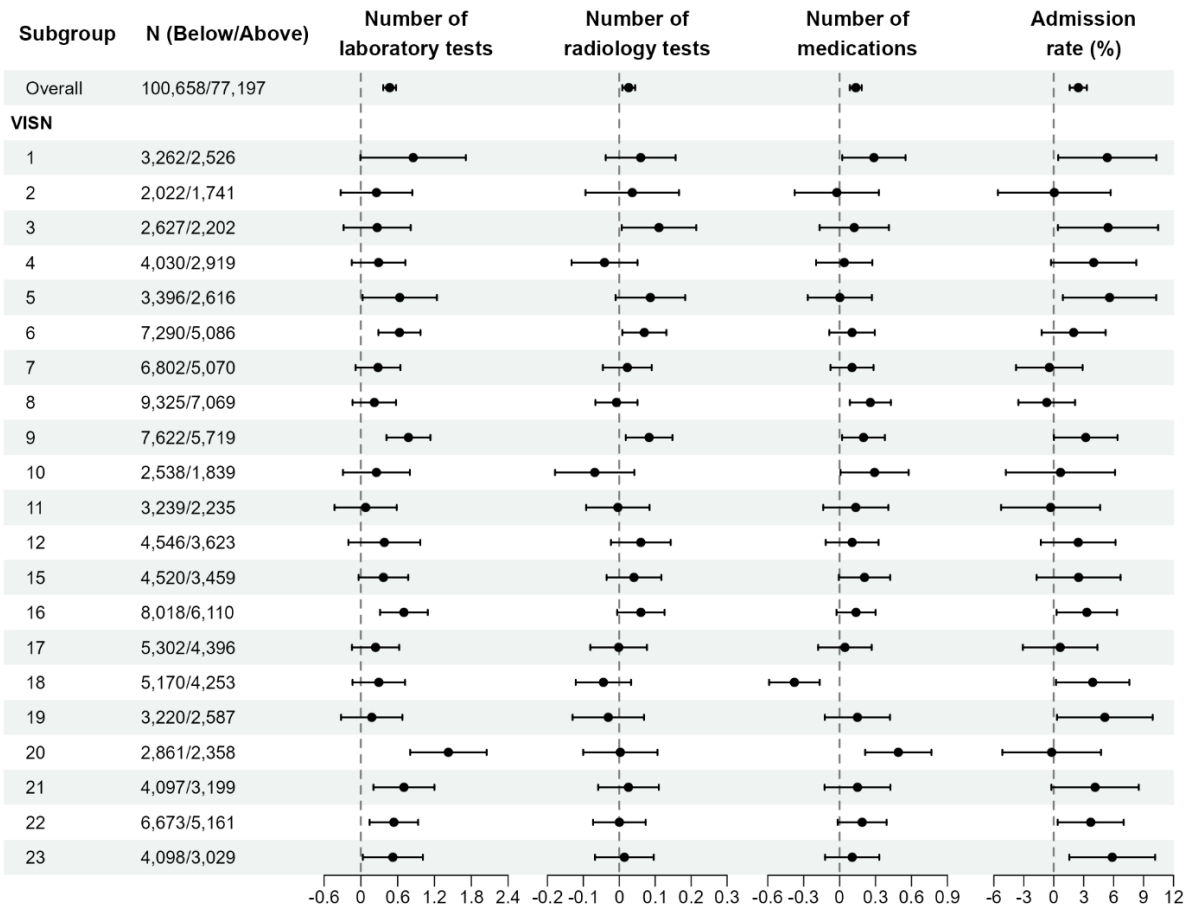
Note: Authors' calculation using Veterans Affairs electronic health record data from 2011-2024. Estimates are from a local linear regression with a uniform kernel and optimal bandwidth selection, adjusting for baseline patient covariates (age, sex, race/ethnicity, Elixhauser comorbidity score), time fixed effects (hour of day, day of week, month, year), and facility fixed effects.

Appendix Figure 1: Analysis across subgroups of patients



Note: Authors' calculation using Veterans Affairs electronic health record data from 2011-2024.

Appendix Figure 2: Analysis across VA regions



Note: Authors' calculation using Veterans Affairs electronic health record data from 2011-2024. VISN is Veterans Integrated Service Network; the United States is divided into 23 VISNs.

Appendix Table 1: Alternative bandwidths

Outcome	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
Number of laboratory tests	0.35 (0.20, 0.49)	0.44 (0.33, 0.56)	0.47 (0.37, 0.57)	0.46 (0.36, 0.55)	0.38 (0.29, 0.47)	0.35 (0.27, 0.43)	0.34 (0.26, 0.41)	0.23 (0.16, 0.30)
Number of radiology tests	0.01 (-0.01, 0.04)	0.02 (0.00, 0.04)	0.03 (0.01, 0.04)	0.03 (0.01, 0.04)	0.02 (0.01, 0.04)	0.02 (0.01, 0.04)	0.02 (0.01, 0.04)	0.02 (0.00, 0.03)
Number of medications	0.14 (0.07, 0.21)	0.15 (0.09, 0.20)	0.14 (0.09, 0.19)	0.12 (0.08, 0.17)	0.12 (0.08, 0.16)	0.11 (0.07, 0.15)	0.11 (0.08, 0.15)	0.08 (0.04, 0.11)
Admission rate, %	1.9 (0.7, 3.1)	2.1 (1.1, 3.1)	2.5 (1.6, 3.3)	2.6 (1.8, 3.4)	2.3 (1.6, 3.0)	2.2 (1.6, 2.9)	1.9 (1.3, 2.5)	1.5 (0.9, 2.1)
Mortality, %	0.3 (-0.1, 0.8)	0.2 (-0.2, 0.5)	0.2 (-0.1, 0.5)	0.1 (-0.2, 0.4)	0.0 (-0.3, 0.3)	0.0 (-0.2, 0.3)	-0.1 (-0.3, 0.2)	-0.1 (-0.4, 0.1)
ICU stay, %	1.2 (0.5, 2.0)	0.8 (0.12, 1.4)	0.7 (0.2, 1.3)	0.8 (0.3, 1.3)	0.6 (0.2, 1.1)	0.7 (0.2, 1.1)	0.7 (0.3, 1.1)	0.5 (0.1, 0.9)

Note: Authors' calculation using Veterans Affairs electronic health record data from 2011-2024. Estimates are from a local linear regression with a uniform kernel and alternative bandwidths, adjusting for baseline patient covariates (age, sex, race/ethnicity, Elixhauser comorbidity score), time fixed effects (hour of day, day of week, month, year), and facility fixed effects.