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EHR-Based Surveillance of Diabetes Care Disruption During a Public Health

Emergency: Neighborhood Patterns Across Chicago Census Tracts

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ABSTRACT

Public health emergencies can disrupt efforts to prevent chronic disease complications that begin silently. We studied the COVID-19 pandemic as a prolonged emergency and diabetes as a model of care that depends on repeated testing, vital sign checks, and preventive medication review. We assessed whether EHR-derived quality indicators could serve as surveillance signals for neighborhood-level gaps in documented testing, blood pressure checks, and preventive care during emergencies. We analyzed annual census tract estimates for adults with diabetes in Chicago during 2017-2022. Clinical data came from seven health systems in the Chicago Area Patient Centered Outcomes Research Network. Outcomes were undocumented HbA1c measurement, documented poor HbA1c control, undocumented blood pressure measurement, controlled blood pressure, and statin prescribing. Analyses compared 2017–2019 with 2020–2022 across 782 tracts. We mapped tract percentages, tested spatial clustering, estimated period changes, and fitted Bayesian spatial models for documented poor HbA1c control, controlled blood pressure, and statin prescribing. Undocumented HbA1c measurement increased from 42.7% to 60.7%. Documented poor HbA1c control improved from 11.8% to 8.6%, but this finding should be interpreted alongside reduced HbA1c measurement. Undocumented blood pressure measurement remained widespread, decreasing from 78.7% to 74.8%. Controlled blood pressure improved from 12.2% to 16.0%. Statin prescribing declined from 65.7% to 59.6%. All indicators showed annual spatial grouping. These findings suggest that EHR-based quality indicators can identify documented neighborhood gaps in monitoring and preventive care. They should be interpreted as surveillance signals from participating EHR data, not as complete measures of all care received.

INTRODUCTION

Chronic conditions account for most health care spending in the United States.¹ Diabetes is a common chronic condition of increasing global prevalence. The Centers for Disease Control and Prevention estimated that 40.1 million people in the United States were living with diagnosed or undiagnosed diabetes in 2023, representing 12.0% of the U.S. population.² High quality diabetes care requires hemoglobin A1c (HbA1c) monitoring, blood pressure management, medication review, and follow up. These activities can prevent complications when results are acted on. Electronic clinical quality measures (eCQMs)³⁻⁵ and related electronic health records (EHR) indicators can summarize these care processes across populations.^{6,7}

Public health emergencies can draw attention away from chronic disease care. For example, the COVID-19 pandemic created a prolonged “stress test” for health systems, across broad areas of both acute and chronic care.⁸ It also provides an example of a public health emergency that was not fully anticipated. Routine care continued. However, many supports for chronic disease care were disrupted. In many areas, these disruptions persisted for an extended period. In the United States, 21.7% of adults reported delayed or missed medical care in 2022 because of nonfinancial access barriers.⁹ A PCORnet® study reported persistent gaps in preventive service use and chronic disease diagnoses across 2020–2022.¹⁰ Diabetes care was particularly vulnerable because monitoring and management need to occur repeatedly within a year to be effective. U.S. studies reported declines in HbA1c testing and delayed diabetes monitoring during the pandemic.^{11,12} These disruptions have special importance for urban health. Citywide averages can hide neighborhood differences in care access and recovery, and Chicago data provides an effective example of this. During the early COVID-19 period, mortality varied markedly across

neighborhoods,^{13,14} suggesting that citywide averages may not reflect local differences in disruption and recovery.

Another challenge is measurement. Standard quality indicators can look better or worse for reasons that do not reflect true clinical change.¹⁵ For example, a lower rate of poor HbA1c control may look favorable if many patients have no documented HbA1c result. A higher rate of controlled blood pressure may also be misleading if blood pressure measurement is less complete. In this study, we use the term “clinical visibility” to describe the presence of structured information in participating EHR systems that can support chronic disease monitoring and follow-up. No documented HbA1c measurement and no documented blood pressure measurement represent gaps in EHR documented clinical visibility. A patient without a recent HbA1c result may not be identified for medication intensification, kidney risk review, or complication prevention. A patient without a structured blood pressure value may not be identified for treatment adjustment. Statin prescribing is different. It is a documented preventive pharmacotherapy signal. A high-risk patient without current statin therapy may remain exposed to preventable cardiovascular risk.¹⁶

When documented gaps are clustered in neighborhoods, they identify places where routine systems of care may need review. These signals can help public health agencies and health systems decide where outreach, laboratory access, pharmacy support, and community partnerships may be useful.¹⁷ In this study, we examined diabetes care indicators across Chicago census tracts from 2017 through 2022. We compared 2017–2019 (pre-pandemic/pre-emergency) with 2020–2022 (pandemic/emergency) for five indicators: No documented HbA1c measurement, documented poor HbA1c control, no documented blood pressure measurement, controlled blood pressure, and statin prescribing. We asked whether routinely available EHR

indicators aligned with eQMs could identify neighborhood differences in documented diabetes measurement and preventive care during a prolonged public health emergency. The goal was descriptive and practical. We did not estimate the causal effect of infection, policy, telehealth, or any single intervention. Although this study focused on Chicago, the problem is relevant to other cities with fragmented outpatient care, multiple health systems, and neighborhood differences in access to care.

METHODS

Study design and data sources. We conducted an observational ecological study using the Chicago census tract year as the analytic unit. The study period was 2017–2022. We defined 2017–2019 as the period before COVID-19 and 2020–2022 as the COVID-19 period. With eligible EHR-derived data, the analysis included 782 of 801 Chicago census tracts and up to six annual observations per tract, yielding 4,692 possible tract-years for each outcome.

Data sources and linkages. Clinical data came from EHR data contributed through the Chicago Area Patient Centered Outcomes Research Network (CAPriCORN). Participating health systems were Cook County Health, Northwestern Medicine, Rush University, Endeavor Health, University of Illinois Health, University of Chicago Medicine, and AllianceChicago. Sites used the PCORnet® common data model version 6.0 to standardize data format.¹⁸ CAPriCORN provided patient-level data that was deduplicated across participating institutions before analysis. Each health system assigned patient home addresses to Chicago census tracts. The spatial scaffold used 2020 United States Census Bureau TIGER/Line tract and place files.¹⁹ We identified the Chicago place polygon and included tracts whose representative interior point fell within the Chicago polygon. The analysis was restricted to records assignable to these 2020 Chicago census tracts. The study therefore estimates documented care quality and documented

measurement patterns among patients connected to CAPriCORN. The denominators do not represent all Chicago residents with diabetes.

Study population

Adults with diabetes were identified using the SUPREME-DM framework,²⁰ which was developed to create multisite diabetes surveillance cohorts from EHR and administrative data. The original algorithm uses evidence from inpatient and outpatient diabetes diagnosis codes, diabetes-range laboratory values, and diabetes medication records. It also includes safeguards to reduce misclassification, such as excluding isolated use of selected medications when no other diabetes evidence is present and not counting diabetes indicators during pregnancy windows. For this study, the framework was adapted to CAPriCORN data value sets.²¹ We describe the cohort as adults with diabetes rather than type 2 diabetes because diabetes subtype was not adjudicated in the SUPREME-DM.

To enter the analytic population for a measurement period, patients required evidence of diabetes, at least one encounter in CAPriCORN network of health systems during that year, and a residential address assignable to a Chicago census tract. Patients could contribute to more than one year and more than one outcome. For each outcome, patients were counted once within their residential census tract and measurement period (year). Patient-level analytic-scaffold exclusions are detailed in Supplementary Materials Section B.

Outcomes

We examined five annual tract-level indicators derived from the Centers for Medicare and Medicare Services (CMS) health system quality indicators: No documented HbA1c measurement, documented poor HbA1c control⁴ (eCQM CMS122v9), no documented blood pressure measurement, controlled blood pressure⁵ (eCQM CMS165v10), and statin prescribing³

(eCQM CMS347v8). For each outcome and tract-year, we constructed a numerator count and denominator count from EHR data. No documented HbA1c measurement was defined as the percentage of eligible adults with diabetes who did not have a structured EHR-documented HbA1c value during the measurement year. Documented poor HbA1c control was defined as the percentage of eligible adults with diabetes whose most recent structured HbA1c value during the measurement period was greater than 9.0%. Unlike the CMS HbA1c poor-control eCQM,⁴ which treats missing HbA1c as numerator noncompliance, we analyzed no documented HbA1c measurement separately from documented poor control. This separation allowed us to distinguish poor documented glycemic control from loss of EHR-documented clinical visibility. No documented blood pressure measurement was defined as the percentage of adults with diabetes and hypertension who did not have a structured EHR-documented blood pressure value during the measurement year. Controlled blood pressure⁵ was defined as the percentage of adults with diabetes and hypertension whose most recent documented blood pressure during the measurement year was systolic blood pressure <140 mmHg and diastolic blood pressure <90 mmHg.⁵ Patients without a structured blood pressure value remained important for interpretation because estimates of blood pressure control may vary depending on which patients had measurement recorded. Statin prescribing was defined as the percentage of adults in the study's high-risk diabetes statin denominator who had statin therapy prescribed or documented during the measurement period.³ This measure was interpreted as documented preventive pharmacotherapy. It does not establish that medication was filled or taken.

Overall, no documented measurement means absence of a structured value in participating EHR data. Therefore, it may reflect no measurement, care outside participating systems, documentation outside structured fields, or home readings not entered into structured EHR fields.

A harmonized telehealth indicator and encounter-density summary were not available, so the study could not distinguish telehealth-only care from in-person care without recorded measurements.

Patient-year characteristics and tract-level covariates

Patient characteristics were summarized at the patient-year level, separately for each outcome denominator and numerator. Denominator summaries include all eligible patient-years for that outcome, whereas numerator summaries include patient-years meeting the outcome definition. Because patients could contribute multiple years, patient-year percentages do not represent unique-patient prevalence. Categorical variables were summarized as counts and percentages, and age was summarized as reported in the tables.

Tract-level covariates came from 2018–2022 American Community Survey estimates and were linked to the 2020 Chicago tract scaffold. Selected covariates were percent uninsured, percent below poverty, unemployment, percent non-Hispanic Black, percent Hispanic, and percent non-Hispanic Asian. These variables represented stable tract-level social context relevant to diabetes care access and were not treated as time-varying exposures. Numeric ACS covariates were standardized before modeling, so odds ratios represent associations with a one-standard-deviation higher tract-level value.

Tract-year panel and observed summaries

For each outcome, analytic inputs included year, census tract identifier, numerator, and denominator. Data was audited for missing numerators or denominators, and zero-denominator tract-years. Observed tract-year rates were calculated as numerator divided by denominator when the denominator was positive and the numerator was observed. Rates were multiplied by 100 and

reported as percentages. Tract-years with zero denominators, or missing denominators were treated as missing in observed-rate summaries and maps.

Annual citywide rates were denominator-weighted. Numerators were summed across observed tract-years with positive denominators and divided by the corresponding summed denominators. Pre-COVID and COVID-period rates used the same approach after pooling counts across 2017–2019 and 2020–2022. Weighted change, in percentage points, was the COVID-period denominator-weighted rate minus the pre-period denominator-weighted rate. This measure gives more influence to tract-years with larger eligible denominators.

Tract-level period change was calculated separately. For each tract, mean observed rates were calculated for 2017-2019 and 2020-2022 using years with finite rates. Tract-level change was the COVID-period mean minus the pre-period mean. Median tract change, in percentage points, was the median of these tract-level changes among tracts with finite values in both periods. This measure gives each tract equal weight and describes the typical tract-level change. Positive change was unfavorable for no documented HbA1c measurement, documented poor HbA1c control, and no documented blood pressure measurement, but favorable for controlled blood pressure and statin prescribing. Precision for Table 1 was estimated with a nonparametric tract bootstrap using 10,000 resamples of census tracts. Intervals are the 2.5th and 97.5th percentiles.

Observed spatial analyses. Observed spatial analyses were conducted for all five outcomes. They included annual tract-level rate maps, annual global Moran I,²² annual Local Moran analysis,²³ and pre-COVID versus COVID-period change analysis. Global Moran I assessed whether nearby tracts had similar observed rates, neighboring tracts were defined by queen contiguity. Local Moran analysis identified local spatial patterns. High-high clusters were tracts with high outcome values surrounded by nearby tracts that also had high values. Low-low

clusters followed the same pattern, but for low values. The analysis also identified spatial outliers, where a tract differed from its neighbors. For pre-COVID versus COVID-period maps, high-high means clustered high during-minus-pre change. It does not mean that the tract was high in both periods. The clinical meaning depends on outcome direction.

Adjusted spatial modeling

The adjusted modeling pipeline was applied to documented poor HbA1c control, controlled blood pressure, and statin prescribing. No documented HbA1c and no blood pressure measurement were analyzed only with observed spatial methods and were not included in missingness, imputation, Bayesian modeling, residual diagnostic, or sensitivity analyses.

For modeled outcomes, missing numerator and denominator values were assessed as compatible with Missing Completely at Random (MCAR), Missing at Random (MAR), or potential Missing not at Random (MNAR). When missingness was associated with observed temporal, spatial, prior-year, or tract-level covariate information, analyses proceeded under an MAR-compatible assumption, with sensitivity analyses for plausible MNAR departures. For each of the three modeled outcomes, 20 completed datasets were generated. Denominators were imputed with a negative-binomial mixed model with a tract random intercept. Numerators were imputed with a binomial mixed model conditional on the completed denominator. For each imputed dataset, tract-year numerators were modeled as binomial counts. The model included categorical year effects; standardized tract-level ACS covariates for uninsured status, poverty, unemployment, and racial and ethnic composition; a BYM2 tract-level spatial effect; and independent tract-year heterogeneity. Bayesian estimation used integrated nested Laplace approximation.²⁴⁻²⁶

ACS- and spatially adjusted contrasts were calculated from denominator-weighted posterior fitted probabilities. Prespecified contrasts compared 2020–2022 with 2019 and with the 2017–2019 mean. Contrasts were reported in percentage points and pooled across imputations using Rubin’s rules. ACS covariate effects were reported as odds ratios with 95% intervals.

Model evaluation and sensitivity analyses

Model diagnostics included summaries of model fit and residual spatial autocorrelation. We compared global Moran I for observed rates with Moran I for response and Pearson residuals after model fitting. Persistent residual Moran I was interpreted as remaining tract-level spatial structure after adjustment.

Sensitivity analyses assessed robustness in three ways. First, the primary model was refit using a beta-binomial likelihood to assess overdispersion. Second, imputed numerator probabilities for 2020 and later years were shifted on the logit scale to evaluate plausible departures from the missing-at-random assumption. Third, zero-denominator tract-years were recoded as missing and the missingness assessment, imputation, model fitting, and pooling steps were repeated.

Analyses were performed in R using packages for spatial data processing, spatial autocorrelation testing, mixed-effects modeling, missingness assessment, and Bayesian spatial modeling. Detailed implementation procedures for the analytic workflow (Fig. 1) are provided in Section A in the Supplementary Materials.

RESULTS

Analytic coverage and patient-year characteristics

Most outcomes had observed rates for 779 of 781 tracts each year. Statin prescribing had fewer observed tracts, ranging from 758 to 776. The clinical denominators were large. The

HbA1c measures included 244855 patient-years. The blood pressure measures included 226990 patient-years. The statin measure included 41903 high-risk patient-years. Table 1 summarizes denominator-weighted citywide rates and median tract changes before and during the COVID-19 period. Annual observed rates are provided in Supplementary Table S1, and annual citywide trajectories are shown in Supplementary Fig. S1. Supplementary Tables S9 and S10 provide patient-year characteristics for numerator and denominator groups. Overall denominator sizes (i.e. patient-years) for each indicator (Table S1) did not vary dramatically by study year, suggesting that patients continued to complete encounters, though modality (office versus telehealth) could be changing. However, examining the numerator and denominator characteristics (Tables S9; S10), patient-years with self-pay insurance declined by about half in the COVID-19 period, offset by an increase in patient-years contributed by patients with commercial insurance. The patient sample denominator for the HbA1c indicators was very broad, with similar age and sex across comparison groups. Patient-years identified with non-measurement of HbA1c (numerator) rose precipitously in 2021 and 2022 (Table S1), and those with no measured A1c were less likely to identify as Hispanic or to have self-pay insurance (Tables S9; S10). Those with documented poor HbA1c control (numerator), which requires HbA1c measurement, were younger (median age 54 versus 58 overall) and more likely to identify as Hispanic (35% versus 26% overall) or to have Medicaid or self-pay insurance. The blood pressure denominator was also broad. Patient-years identified with non-measurement of blood pressure declined in 2021 but then returned to prior year levels in 2022, and those with no measured blood pressure were less likely to identify as Hispanic or to have Medicaid or self-pay insurance (Tables S9; S10). Those with controlled blood pressure, which requires blood pressure measurement, were more likely to identify as Hispanic (34% versus 25% overall) and less likely

to identify as non-Hispanic Black (48.8% versus 55.8% overall). The statin prescribing denominator reflected an older and higher-risk population. The mean age was 62.9 years. Cardiovascular comorbidity burden was higher than in the other denominator groups.

Citywide changes in diabetes care indicators

Rates of no documented HbA1c measurement increased during the pre-COVID years and became substantially higher during the COVID-19 period. It rose from 42.7% to 60.7%, a denominator-weighted increase of 18.0 percentage points (Table 1). The median tract increase was 17.8 percentage points. Over the same period, documented poor HbA1c control improved from 11.8% to 8.6%. Rates of no documented Blood pressure measurement remained widespread and showed the least stable annual pattern. It improved from 78.7% to 74.8% in the two-period summary, but it fell to 57.9% in 2021 and rose to 85.7% in 2022 (Supplementary Fig. S1). Controlled blood pressure showed the inverse pattern, with a peak of 27.5% in 2021 and a decrease to 9.0% in 2022. Statin prescribing declined during the COVID-19 period, from 65.7% to 59.6%. Annual statin rates declined from 67.1% in 2017 to 57.4% in 2022.

Spatial clustering and tract-level change

Pre-to-during Local Moran maps identified tract clusters where changes were concentrated (Fig. 2A). A multi-outcome priority map then counted how many clinically unfavorable clusters overlapped in each tract (Fig. 3). Annual tract-level maps, global Moran I statistics, LISA cluster counts, and annual LISA maps are shown in Supplementary Fig. S2, Supplementary Table S2, Supplementary Table S3, and Supplementary Fig. S3. Pre-to-during change summaries and continuous change maps are shown in Supplementary Table S4 and Supplementary Fig. S4. No tract was flagged for more than three outcomes. Tracts prioritized with three unfavorable outcomes occurred in Brighton Park, East Garfield Park, and West Englewood. Tracts with two

priority outcomes occurred in Ashburn, Chicago Lawn, Englewood, Gage Park, New City, North Lawndale, Roseland, South Lawndale, and West Garfield Park. Communities with a maximum tract-level value of one priority outcome are displayed in Fig. 3 and summarized in Supplementary Table S14.

The adjusted Bayesian spatial models supported the observed patterns for the three modeled outcomes (Fig. 3). Because pre-period trends were present, contrasts used both 2019 and the 2017–2019 average as references. Documented poor HbA1c control had adjusted differences of -2.56 percentage points (95% interval, -2.89 to -2.22) versus 2019 and -3.18 percentage points (-3.42 to -2.94) versus the pre-period average. Controlled blood pressure had adjusted differences of 4.65 percentage points (4.28 to 5.02) and 3.26 percentage points (2.98 to 3.54), respectively. Statin prescribing had adjusted differences of -4.68 percentage points (-5.94 to -3.41) and -6.10 percentage points (-6.99 to -5.21), respectively. Supplementary Table S11 gives detailed period estimates. Posterior BYM2 spatial effect maps and residual spatial diagnostics are provided in Supplementary Figs. S5 and S6 and Supplementary Tables S5 and S13.

Tract neighborhood context was associated with modeled outcomes, as shown in Supplementary Table S12. Documented poor HbA1c control was higher in tracts with higher percentages of Hispanic residents, non-Hispanic Black residents, non-Hispanic Asian residents, poverty, and uninsured residents. Controlled blood pressure was lower in tracts with higher unemployment and higher percentages of Hispanic residents. Statin prescribing was lower in tracts with higher unemployment. These are tract-level associations. They are not individual patient effects.

Sensitivity analyses are shown in Supplementary Tables S6 and S7. Beta-binomial models produced estimates that were similar to the primary models. This suggests that overdispersion

did not drive the findings. The MNAR analyses asked whether results changed when missing 2020–2022 numerator values were assumed to be systematically higher or lower than predicted by the primary imputation model. These shifts did not materially change the estimated contrasts. They do not prove that missingness was ignorable. They also do not rule out selection related to loss of clinical visibility.

DISCUSSION

This study found that EHR-documented diabetes care indicators changed during the COVID-19 period within the participating CAPriCORN network. The strongest signal was loss of clinical visibility. No documented HbA1c measurement increased sharply, and no documented blood pressure measurement remained widespread. Documented poor HbA1c control declined, but this apparent improvement must be interpreted with the concurrent loss of HbA1c information, which appears to impact some population subgroups (self-pay; Medicaid) differentially. Controlled blood pressure increased in adjusted models, but this finding is difficult to interpret without considering incomplete blood pressure measurement, which also impacted population subgroups differentially. Statin prescribing declined among high-risk patient-years.

Clinical visibility is important because it can function as an early warning signal. Diabetes complications may take years to appear, but missing HbA1c values, missing blood pressure values, and gaps in preventive prescribing can be detected much sooner. A city that monitors only hospitalizations, emergency visits, amputations, or mortality may identify harm after opportunities for prevention have already been missed. For clinicians, loss of visibility means that patients who need treatment intensification, blood pressure follow-up, or cardiovascular risk reduction may not be identified in time.

Our findings are consistent with U.S. reports of reduced HbA1c testing and delayed diabetes monitoring during the pandemic.^{11,12} They are also consistent with PCORnet® evidence of persistent gaps in preventive care and chronic disease diagnosis during 2020–2022.¹⁰ The contribution of this study is its neighborhood perspective. Citywide averages showed broad changes, while the tract analyses showed that these changes were spatially organized. This suggests that COVID-period disruption occurred on top of preexisting neighborhood differences.

The apparent improvement in documented poor HbA1c control and controlled blood pressure should therefore be read cautiously. Adjustment for tract-level ACS covariates, spatial structure, and missing data improves comparability, but it cannot fully remove selection related to who was measured. The sensitivity analyses did not materially change the adjusted contrasts, but they do not prove that missingness was ignorable. A clinically plausible interpretation is that standard quality outcomes and measurement-gap indicators must be reviewed together during disruptions.

The spatial findings give the results practical value. The highest multi-outcome overlap occurred in Brighton Park, East Garfield Park, and West Englewood, where tracts were flagged for three clinically unfavorable outcomes. Tracts in nine additional community areas were flagged for two outcomes: Ashburn, Chicago Lawn, Englewood, Gage Park, New City, North Lawndale, Roseland, South Lawndale, and West Garfield Park. These locations are not definitive rankings of need. They are planning signals for reviewing testing access, structured blood pressure capture, medication review, and outreach workflows. The maps also show that priority signals overlapped only partly across outcomes, since no tract was flagged for four or five outcomes.

Several limitations should guide interpretation. First, the census tract-year was the unit of analysis, so results cannot be interpreted as individual patient associations. Second, the data

came from participating health systems, not every source of care in Chicago. Third, the study was descriptive and was not designed to estimate the causal effect of COVID-19 infection, public health mandates, telehealth, or local initiatives. Fourth, measurement changes may reflect access barriers, care delivery changes, documentation practices, patient preferences, or site mix. Fifth, ACS covariates were contextual measures and were not time-varying exposures. Some residual spatial clustering remained, especially for controlled blood pressure, suggesting that unmeasured local factors still mattered.

URBAN HEALTH IMPLICATIONS

When care gaps cluster, public investment in strategies to address those gaps must be directed disproportionately to where need is greatest. Our study highlights the feasibility of health systems and public health agencies to monitor a small set of EHR-derived continuity indicators continuously, including during prolonged disruptions and recovery.^{27 28,29} A simplified workflow could use EHR registries to identify patients without recent HbA1c results, structured blood pressure values, or current statin therapy. Patient-level lists could support outreach by clinical personnel, while tract and community-area summaries could show where recovery is lagging. Local responses could span sectors and include activities such as ‘catch-up’ HbA1c testing, structured clinic or community blood pressure capture, home blood pressure monitoring support, medication review, access and appointment navigation, pharmacy support, and additional partnered community approaches.^{30-33 34-37} A monitoring and response architecture of this form would of course require additional inputs, such as governance, agreed denominators, privacy protections, reporting intervals, and accountability chains, but a scalable platform of EHR-derived continuity indicators, as we have demonstrated here, could serve as a valuable foundation.

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Competing interests. Dr. TLW received funding from Gilead Sciences, Inc for work unrelated to this project. Dr. ANK serves on the advisory board of Datavant. AF, BN, JKM, RCS, ESH, SW, FR, TLW, RA, ANK, AW have no conflicts of interest

Ethics approval. The study was approved by the Chicago Area Institutional Review Board, which serves as the central IRB for CAPriCORN supported research.

Data availability. Individual level EHR data cannot be shared because they contain confidential patient information. Aggregate analytic outputs, code, and nonidentifying derived files may be available subject to institutional approvals and data use agreements.

Author contributions.

All coauthors gave the final approval of the version to be published. AF and BN had full access to all the data in the study and take responsibility for the integrity of the data and the accuracy of the data analysis.

Concept and design: AF, AW, TLW, ANK, RA.

Contribution of data: RCS, LKS, ESH, SW, FR, AS.

Acquisition, analysis, or interpretation of data: AF, BN, TLW, AW, ANK, RA.

Drafting of the manuscript: AF, DN.

Critical revision of the manuscript for important intellectual content: JKM, RCS, LKS, ESH, SW, FR, TLW, RA, ANK, AW, AS.

Statistical analysis: AF, BN.

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Tables

Table 1. Diabetes care indicators before and during the COVID-19 period, Chicago, 2017 to 2022. The table uses denominator-weighted citywide percentages and median tract changes. Values in parentheses are 95% tract-bootstrap intervals from 10,000 census tract resamples. No documented HbA1c and no documented blood pressure measurement are interpreted as loss of clinical visibility.

Outcome	Interpretation of higher rate	2017-2019 denominator	2017-2019 rate, % (95% interval)	2020-2022 denominator	2020-2022 rate, % (95% interval)	Weighted change, pp (95% interval)	Median tract change, pp (95% interval)
No documented HbA1c measurement	Larger measurement gap	120,517	42.7 (42.1 to 43.2)	124,338	60.7 (60.0 to 61.3)	18.0 (17.2 to 18.8)	17.8 (16.9 to 18.6)
Documented poor HbA1c control	Worse documented glycemic control	120,517	11.8 (11.5 to 12.1)	124,338	8.6 (8.2 to 8.9)	-3.2 (-3.5 to -3.0)	-3.0 (-3.4 to -2.7)
No documented blood pressure measurement	Larger measurement gap	110,896	78.7 (77.9 to 79.6)	116,094	74.8 (74.3 to 75.3)	-3.9 (-4.7 to -3.1)	-3.6 (-4.3 to -2.6)
Controlled blood pressure	Better documented blood pressure control	110,896	12.2 (11.7 to 12.8)	116,094	16.0 (15.6 to 16.4)	3.7 (3.2 to 4.3)	3.1 (2.6 to 3.7)
Statin prescribing	Better preventive pharmacotherapy	19,158	65.7 (64.3 to 67.0)	22,745	59.6 (58.0 to 61.1)	-6.1 (-7.1 to -5.2)	-6.0 (-7.5 to -4.6)

Figures

Fig. 1. Study workflow for tract level diabetes care continuity analysis that shows how EHR counts, census tract geography, observed spatial analyses, Bayesian adjustment, and study outputs were connected. It also shows which analyses applied to all five outcomes and which applied only to the three modeled outcomes.

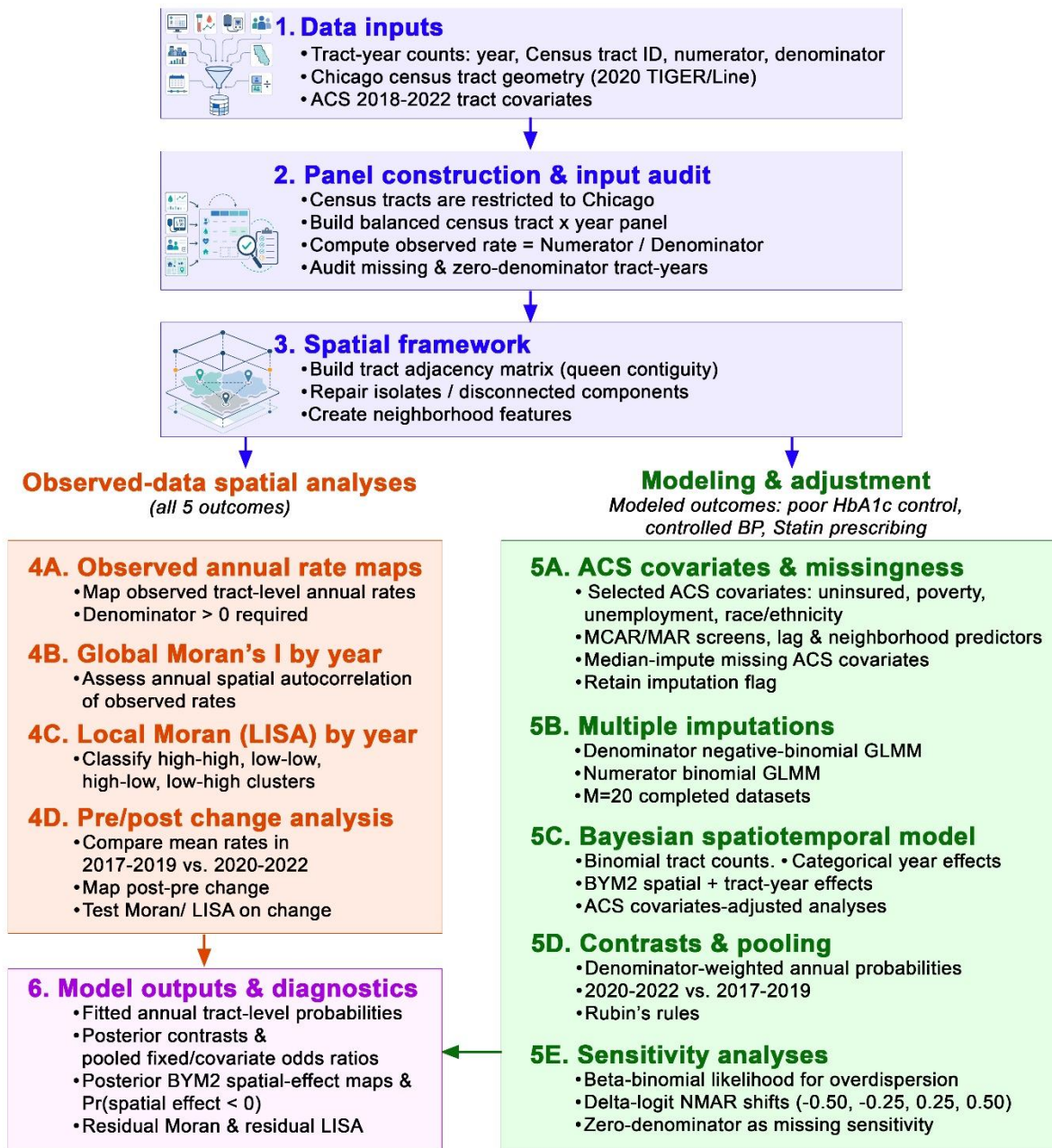


Fig. 2. Pre-to-during change and priority-area summary. Panel A shows Local Moran cluster categories for tract-level change from 2017 to 2019 to 2020 to 2022. Red indicates a priority or clinically unfavorable cluster. Blue indicates an improvement or clinically favorable cluster. Orange indicates a spatial outlier. Gray indicates no significant local cluster. Panel B summarizes the number of clinically unfavorable outcomes in each tract, using different color shading to highlight tracts with higher levels of clustering. Community names are shown when at least one tract in that community had a value above zero. Community boundaries are shown in black.

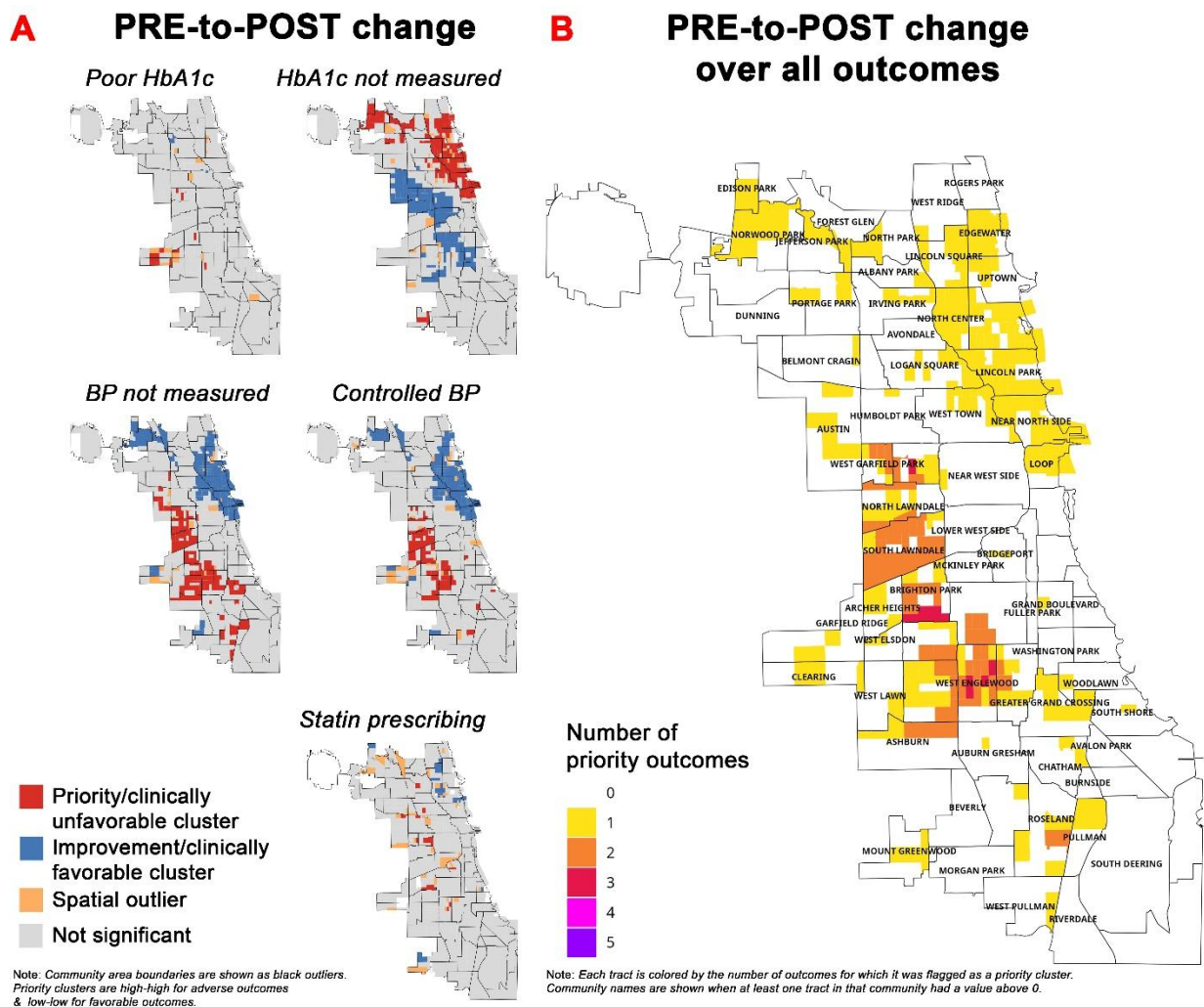
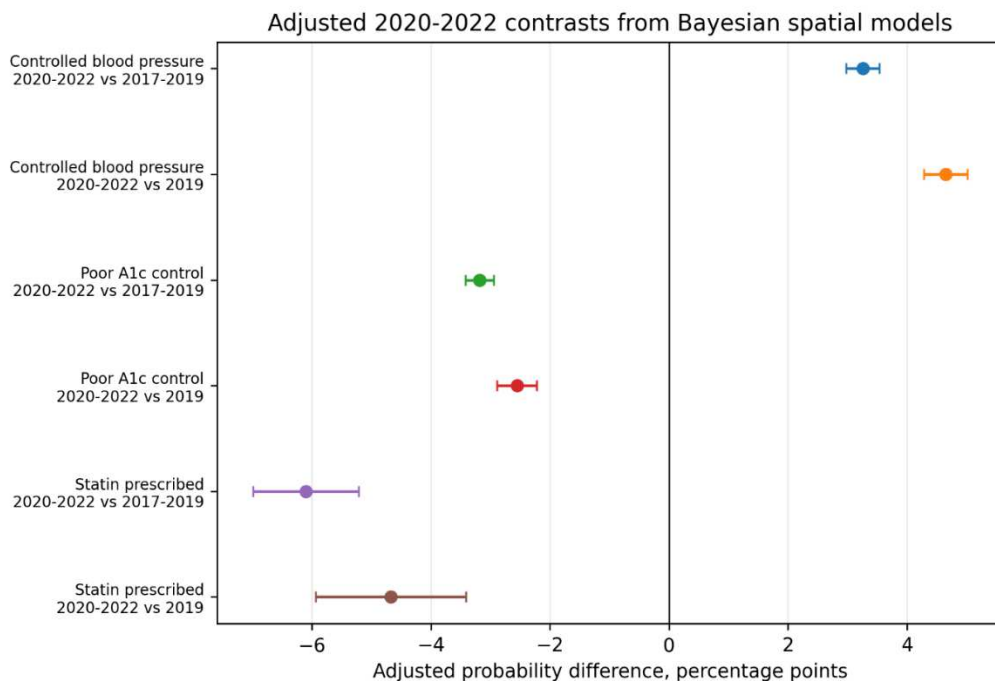


Fig. 3. Adjusted period contrasts from Bayesian spatial models. Dots show adjusted mean probability differences in percentage points. Bars show 95% intervals. Estimates are shown only for the three outcomes included in adjusted modeling: documented poor HbA1c control, controlled blood pressure, and statin prescribing. Two pre-COVID references are shown because the annual observed data suggested pre-period trends. The 2019 contrast compares 2020 to 2022 with the immediate pre-COVID year. The 2017 to 2019 contrast compares 2020 to 2022 with the average pre-COVID baseline. These model-based estimates complement Fig. 2. Fig. 2 shows where observed tract-level changes were concentrated across neighborhoods. Fig. 3 shows whether the main period differences remained after adjustment for tract-level ACS covariates, spatial structure, and missing-data handling. Colors distinguish plotted contrasts only and do not indicate clinical direction.



Supplementary Materials

Section	Element
Analytic cohort flow	Section A. Extra methods details Section B. Planned patient-level geocoding and analytic scaffold exclusions.
Observed annual rates	Table S1. Annual observed rates by outcome and year. Rates are denominator-weighted citywide rates and unweighted mean tract rates among tract years with positive denominators. Fig. S1. Annual denominator-weighted citywide rates by outcome. Fig. S2. Annual observed tract level rate maps. Grey areas indicate tract years without a positive denominator or without observed rate information.
Observed spatial autocorrelation and local clusters	Table S2. Annual global Moran I for observed tract level rates. Table S3. Annual LISA cluster counts for observed tract level rates. Fig. S3. Annual Local Moran cluster maps for observed rates.
Pre-to-during change analyses	Table S4. Tract level during minus pre change summaries and spatial clustering. Fig. S4. Original tract-level continuous during -minus- pre change maps.
BYM2 spatial effects and residual diagnostics	Fig. S5. Posterior mean BYM2 spatial effect maps for the three modeled outcomes. Table S5. Global Moran I for observed rates and during model residuals. Fig. S6. Local Moran cluster maps for pooled response residuals
Sensitivity and missingness analyses	Table S6. Sensitivity analysis summary for adjusted period contrasts. Table S7. Missingness decision summaries for modeled outcomes.
Initiative geographies and timing	Fig. S7. Maps the Chicago initiative geographies used to contextualize the difference hotspot findings. Table S8. Timing and interpretation of Chicago initiatives used for contextual hotspot discussion.
Detailed patient year characteristics moved from the main manuscript	Table S9. Characteristics of numerator and denominator samples for no documented blood pressure and HbA1c measurement, and statin prescribing Table S10. Characteristics of numerator and denominator samples for controlled blood pressure and poor A1c control

Adjusted model and covariate details moved from the main manuscript	Table S11. Adjusted period contrasts from Bayesian spatial models with categorical year effects. Table S12. Adjusted associations between tract level ACS covariates and modeled outcomes. Table S13. Global Moran I ranges for observed rates and during model residuals.
Community-area priority summary	Table S14. Community-area summary of unfavorable outcome overlap supporting Fig. 3.

Section A. EXTRA METHODS DETAILS

Patient-year characteristics

Patient characteristics were summarized at the eligible patient-year level. Characteristics were summarized separately for each outcome denominator and each outcome numerator. Numerator summaries therefore describe the subset of eligible patient-years that met the outcome definition. Denominator summaries describe all eligible patient-years for that outcome.

The descriptive summaries included unique patients, patient-years, age, sex, Hispanic ethnicity, race, insurance category, and selected comorbidities. Because patients could contribute to more than one year, patient-year percentages should not be interpreted as unique-patient prevalence. Categorical variables were summarized as counts and percentages. Age was summarized with mean and standard deviation, median and interquartile range, or both, depending on the table.

American Community Survey covariates

Tract-level contextual covariates were derived from 2018 - 2022 American Community Survey 5-year estimates. These covariates were selected to represent tract-level social and structural context relevant to diabetes care access. They were treated as relatively stable tract-level context across the study period. They were not interpreted as time-varying exposures. Missing values in selected ACS covariates were median imputed across non-missing Chicago target tracts. The model-ready ACS file included an indicator for tracts with imputed ACS covariates. This avoided treating undefined ACS values as true zeros and preserved information that a contextual covariate required imputation. Numeric ACS covariates were standardized to one-standard-deviation units before modeling. Odds ratios for ACS covariates therefore represent the association with a one-standard-deviation higher tract-level covariate value. The ACS imputation flag was included for adjustment but was not interpreted as a substantive tract characteristic.

Descriptive observed rates and period changes

For each outcome and tract-year, the observed tract rate was calculated as numerator divided by denominator among tract-years with a positive denominator and observed numerator. Observed percentages were reported after multiplying this rate by 100. Tract-years with a zero denominator, or missing denominator were left as missing for observed-rate maps and summaries.

Annual citywide rates were calculated as denominator-weighted percentages. For each year, numerator counts were summed across observed tract-years with positive denominators and divided by the corresponding summed denominators. Annual observed citywide rates are shown in Fig. S1.

For Table 1, pre-COVID and COVID-period rates were also denominator-weighted. The pre-period rate was calculated as the sum of numerators from 2017 to 2019 divided by the sum of denominators from 2017 to 2019. The COVID-period rate was calculated similarly for 2020 to 2022. Weighted change, in percentage points, was calculated as:

$$100 \times \left[\frac{\sum \text{numerators}_{2020-2022}}{\sum \text{denominators}_{2020-2022}} - \frac{\sum \text{numerators}_{2017-2019}}{\sum \text{denominators}_{2017-2019}} \right]$$

This statistic gives more weight to tracts and years with larger eligible denominators.

We also summarized tract-level period changes. For each tract, we calculated the mean observed rate during 2017 to 2019 and the mean observed rate during 2020 to 2022. Annual tract rates were averaged only across years with finite observed rates. Tract-level change was calculated as the COVID-period mean minus the pre-period mean. Median tract change, in

percentage points, was the median of these tract-level changes across tracts with finite pre-period and COVID-period means. This statistic gives each tract equal weight and describes the typical tract-level change.

The clinical interpretation of positive change differed by outcome. Higher values were unfavorable for no documented HbA1c measurement, documented poor HbA1c control, and no documented blood pressure measurement. Higher values were favorable for controlled blood pressure and statin prescribing.

Spatial framework

The spatial adjacency graph used queen contiguity among the 2020 Chicago census tracts. The snap tolerance was 0.0000001. Isolated tracts were attached to their nearest tract centroid. Disconnected graph components were bridged using minimum-distance edges. The repaired adjacency graph contained no isolated tracts. The binary adjacency was exported as an INLA graph file.

Binary weights assigned weight 1 to each neighboring tract and 0 to non-neighbors. Row-standardized weights divided each tract's neighbor weights by its number of neighbors, so the weights for each tract summed to 1. Row-standardized weights were used when neighborhood averages or observed Local Moran classifications were needed. Binary weights were used for selected global and residual Moran diagnostics. Neighborhood support variables were calculated as the mean value among adjacent tracts.

For each tract-year, the prior-year values of the denominator, numerator, and observed rate were created. We also created prior missingness indicators and neighbor means of denominator, observed rate, and missingness. Remaining predictor missingness was filled with the median of the available values. Indicator variables flagged where selected support predictors had required filling.

Observed spatial analyses

Observed spatial analyses were applied to all five outcomes. These included annual tract-level observed-rate maps, annual global Moran I, annual Local Moran analysis, and pre-COVID versus COVID-period change analysis.

Annual observed-rate maps showed tract-level percentages for each outcome and year. Grey areas indicated tract-years without a positive denominator or without observed-rate information. Global Moran I tested whether nearby tracts had similar observed rates. For each year, the test was performed among tracts with finite observed rates. Both analytic Moran test statistics and Monte Carlo permutation tests were computed. The permutation tests used 499 permutations and a significance threshold of 0.05.

Local Moran analysis was used to identify local clusters and spatial outliers. Local Moran statistics were calculated with permutation-based inference. Tracts were classified by their outcome values as high-high, low-low, high-low, low-high, or not significant. High-high indicated a tract with a high value surrounded by neighboring tracts with high values. Low-low indicated a tract with a low value surrounded by neighboring tracts with low values. High-low and low-high indicated spatial outliers. The Local Moran classifications used an unadjusted local significance threshold of 0.05.

Pre-COVID versus COVID-period change spatial analysis

For each outcome, we calculated each tract's mean observed rate during 2017 to 2019 and during 2020 to 2022. Tract-level change was calculated as the COVID-period mean minus the pre-period mean. These during-minus-pre-change changes are summarized in Fig. 2A and

Supplementary Table S4, with continuous tract-level change maps shown in Supplementary Fig. S4.

Global spatial autocorrelation of tract-level change was tested with Moran I using 499 permutations. Local clustering of tract-level change was evaluated with Local Moran statistics. The same high-high, low-low, high-low, and low-high definitions were used for change maps. For change maps, high-high means neighboring tracts had similarly high during -minus-pre change values. Low-low means neighboring tracts had similarly low during-minus-pre change values. The clinical meaning of high or low change depends on whether higher values are favorable or unfavorable for the outcome.

Outcomes included in adjusted modeling

The full missingness, multiple-imputation, Bayesian spatial modeling, residual evaluation, and sensitivity-analysis pipeline was applied to three outcomes: documented poor HbA1c control, controlled blood pressure, and statin prescribing. These outcomes represented the main adjusted clinical quality and preventive pharmacotherapy analyses.

No documented HbA1c and blood pressure measurement were analyzed with observed spatial methods only. These two outcomes were treated as substantive care-process and clinical-visibility outcomes. They were not passed through the missingness, imputation, Bayesian spatial model, residual diagnostic, or sensitivity-analysis pipelines.

Missingness assessment for modeled outcomes

For each modeled outcome, we assessed whether missing numerator or denominator values were compatible with missing completely at random, missing at random, or potentially missing not at random. MCAR indicates missingness unrelated to observed or unobserved data. MAR indicates missingness explainable by observed data. MNAR indicates that missingness may depend on unobserved values.

The missingness assessment used three checks. First, we applied a global multivariable MCAR screen using `MissMech::TestMCARNormality`. The screen used year, denominator, numerator, prior-year values, neighbor features, and missingness support variables. Second, we fitted logistic regression models for three missingness indicators: missing denominator, missing numerator, and either value missing. Predictors included calendar year, log prior-year denominator, prior-year rate, prior missingness, neighborhood missingness, and standardized tract-level covariates. Third, we tested whether missingness showed spatial clustering by estimating annual global Moran I for the missingness indicator.

Missingness was classified as approximately MCAR only when all three checks supported that interpretation. The global MCAR screen had to be non-significant. The missingness regressions had to show no significant non-intercept predictors. The annual missingness Moran I tests also had to be non-significant. When any check suggested association with observed time, prior values, neighborhood missingness, spatial context, or tract-level covariates, the primary analysis proceeded under an MAR-compatible assumption. MNAR cannot be proven from observed data alone, so plausible departures from MAR were evaluated through sensitivity analyses.

Multiple imputation

For each modeled outcome, we generated 20 complete datasets when missing numerator or denominator values were present. The primary pipeline used multiple imputations even for outcomes whose missingness screen was approximately MCAR, unless no missing values were present.

The denominator was imputed first. The denominator imputation model was a negative-binomial generalized linear mixed model with a tract random intercept. Predictors were calendar year, log prior-year denominator, prior-year rate, neighbor mean denominator, neighbor mean rate, and prior missingness. The denominator model was refit on a bootstrap sample of complete cases. Missing denominators were drawn from a negative-binomial distribution using the predicted mean and fitted dispersion.

The numerator was imputed conditional on the complete denominator. The numerator imputation model was a binomial generalized linear mixed model with a tract random intercept. Predictors were calendar year, log completed denominator, log prior-year denominator, prior-year rate, neighbor mean rate, and prior missingness. Missing numerators were drawn from a binomial distribution using the completed denominator as the number of trials and the predicted probability as the event probability.

Bayesian spatial hierarchical model

For each imputed dataset, we modeled the tract-year numerator as a binomial count among eligible patients in that tract-year. Let Y_{it} be the numerator for census tract i in year t . Let n_{it} be the denominator. Let p_{it} be the tract-year outcome probability. The model was $Y_{it} \sim \text{Binomial}(n_{it}, p_{it})$, with $\text{logit}(p_{it}) = \alpha + \gamma_{it} + X_i \beta + u_i + \epsilon_{it}$. The model included categorical year effects, standardized ACS covariates, a BYM2 tract spatial effect, and independent tract-year heterogeneity.³²⁻³⁴

The categorical year term allowed each study year to have its own mean level, with 2019 as the reference year. The vector X_i contained standardized tract-level ACS covariates and the ACS imputation indicator. The term u_i represented residual spatial variation shared by neighboring tracts. The BYM2 parameterization combines spatially structured and unstructured tract-level variation. The term ϵ_{it} represented independent tract-year heterogeneity. Tract-years with a final denominator of zero were retained in the audit but excluded from the binomial likelihood because zero-trial observations do not inform the outcome probability.

Bayesian estimation used integrated nested Laplace approximation. Model adequacy was summarized using the deviance information criterion, the Watanabe-Akaike information criterion, and the conditional predictive ordinate. These measures summarize model fit, predictive performance, and observation-level predictive support.

Posterior contrasts and covariate effects

For each fitted model, we drew 1,000 posterior samples and transformed the linear predictor to the response scale. For each posterior draw and year, we calculated the denominator-weighted mean fitted probability across tracts:

$$\bar{p}_t = \frac{\sum_i n_{it} p_{it}}{\sum_i n_{it}}$$

The prespecified adjusted contrasts were the mean fitted probability during 2020 to 2022 minus the fitted probability in 2019, and the mean fitted probability during 2020 to 2022 minus the mean fitted probability during 2017 to 2019. These contrasts were reported in percentage points.

Within each imputed dataset, point estimates and variances were calculated from posterior draws. Estimates were then pooled across imputed datasets using Rubin's rules. The reported intervals combine within-imputation posterior variance with between-imputation variance. The P values reported in the adjusted contrast tables are two-sided Rubin-rule P values based on the pooled estimate and standard error. They should not be interpreted as posterior probabilities.

Fixed effects were extracted from each imputed model and pooled across imputations. Covariate effects were reported as odds ratios and 95% intervals after exponentiating pooled log-

odds coefficients. Because ACS covariates were standardized, odds ratios correspond to one-standard-deviation higher tract-level covariate values.

BYM2 spatial effects

For each modeled outcome, we summarized the BYM2 tract-level spatial random effect. The posterior mean BYM2 spatial effect was extracted for each tract and pooled across imputed datasets. We also summarized the posterior probability that the spatial effect was below zero. These maps were used to identify residual spatial context after adjustment for calendar year and ACS tract-level covariates.

During-model residual diagnostics

During-model residual diagnostics were performed for the three modeled outcomes. For each imputed dataset, we refit the primary binomial BYM2 model and extracted fitted probabilities. The observed rate was calculated as the completed numerator divided by the completed denominator. Count residuals were calculated as observed numerator minus expected numerator. Pearson residuals divided the count residual by the binomial standard deviation. Response residuals were calculated as observed rate minus fitted probability.

Residuals were pooled across the 20 imputed datasets by averaging within each tract-year. For each year, global Moran I was calculated for observed rates, pooled response residuals, and pooled Pearson residuals. Local Moran analysis was also applied to pooled response residuals to identify residual spatial clusters. Persistent residual Moran I was interpreted as evidence of remaining tract-level spatial structure after model adjustment.

Sensitivity analyses

We assessed robustness in three ways. First, we refit the primary model using a beta-binomial likelihood. This tested whether the data showed more variability than expected under the standard binomial model.

Second, we evaluated plausible departures from the MAR imputation assumption. We repeated imputation after shifting imputed numerator probabilities for 2020 and later years on the logit scale. The shifts were -0.50 , -0.25 , $+0.25$, and $+0.50$. We then refit the primary Bayesian spatial model and pooled the period contrasts again. The resulting range of contrasts was compared with the primary contrast.

Third, we tested how results changed when zero-denominator tract-years were handled differently. In the primary analysis, zero-denominator tract-years were treated as structural-zero observations and did not contribute to the binomial likelihood. In the sensitivity analysis, zero-denominator tract-years were recoded as missing. The pipeline then repeated missingness assessment, multiple imputation, model fitting, and pooling. Pooled contrasts from this analysis were compared with the main results.

Software and reproducibility

Analyses were performed in R. Core packages included `sf`, `spdep`, `spatialreg`, `igraph`, `lme4`, `MissMech`, `INLA`, `data.table`, `dplyr`, `tidyr`, `readr`, `broom`, `broom.mixed`, and `jsonlite`.

Section B. ANALYTIC COHORT FLOW

Definition of diabetes

We identified “detected” diabetes in adult patients using a modified version of the SUPREME-DM³⁸ criterion. A patient was classified as having diabetes if the EHR contained (i) prescription of diabetes-specific medications at least once, or (ii) on two different visits one observed (a) a diabetes diagnosis code, or (b) HbA1c $\geq 6.5\%$, or (c) random glucose ≥ 200 mg/dL, or (d) fasting glucose ≥ 126 mg/dL, or (iii) prescription of a diabetes-relevant but not a diabetes-specific medication (for example, metformin) plus a single occurrence of one of the events in category. Newly detected diabetes was assigned to the earliest date among these events. We refer to diabetes detection rather than incidence because the true incidence is not known. Diabetes diagnosis codes were used exactly as specified in table 1 of the SUPREME-DM³⁸ while adopted to CAPriCORN value sets diabetes mellitus laboratory measurements are listed in table D1.

Table A1. Specifying diabetes mellitus laboratory measurements.

Lab name	LOINC
HbA1c	'17855-8', '4548-4', '4549-2', '17856-6', '41995-2', '59261-8', '62388-4', '71875-9', '54039-3'
Random glucose	'2345-7', '2339-0', '10450-5', '17865-7', '1554-5', '6777-7', '54246-4', '2344-0', '41652-9'
Fasting glucose	'1558-6', '10450-5', '1554-5', '17865-7', '35184-1'

As was reported earlier,²¹ we defined diabetes-related medications to include both diabetes-specific medications (sulfonylurea, insulin, biguanide, thiazolidinedione, α -glucosidase inhibitor, incretin mimetic, meglitinide, amylin analog, or dipeptidyl peptidase inhibitor) and non-specific medications that can also be prescribed for other conditions (metformin, any thiazolidinedione, or exenatide). We used information on both prescription and dispensing, using both medication name and medication code fields (Appendix, Table S1 published elsewhere²¹).

Electronic Quality measurements.

This section contains the list of modifications authors performed to adjust eQCMs of interest³⁻⁵ to CAPriCORN's value sets.

Note on no documented-measurement and encounter modality: *No documented measurement outcomes were defined from structured EHR fields available in CAPriCORN. The analytic file did not include a harmonized telehealth indicator or encounter-density summary by year. Therefore, the study cannot distinguish lack of measurement during an in-person visit from telehealth-only care, measurement outside participating systems, or a value documented outside the structured fields available for analysis. Future work should add encounter modality, encounter frequency, and site-specific capture checks when these variables are available.*

HbA1c poor control:

- Hospice services provided to patients were poorly populated. Therefore, to identify this condition the following codes were used

'Q5007', 'Q5006', 'Q5005', 'G0180', 'G0179', 'G0299', 'G0300', 'G0166', 'Q5001', 'Q5002', 'Q5003', 'Q5004', 'Q5005', 'Q5006', 'Q5007', 'Q5008', 'Q5009', 'Q5010', 'T2042', 'T2043', 'T2044', 'T2045', 'T2046', 'I1013823', '99377', '99378', 'G0182', 'G9473', 'G9474', 'G9475', 'G9476', 'G9477', 'G9478', 'G9479', 'G9687', 'G9688', 'G9690', 'G9691', 'G9692', 'G9693', 'G9694', 'G9700', 'G9702', 'G9709', 'G9710', 'G9713', 'G9714', 'G9720', 'G9723', 'G9740', 'G9741', 'G9758', 'G9761', 'G9768', 'G9805', 'G9819', 'G9858', 'G9860', 'G9861', 'M1067'

As well as [ADMITTING_SOURCE]='HS' or DISCHARGE_STATUS='HS' fields present in PCORI CDM to describe encounter information.

Blood pressure control:

- Hospice services provided to patients were poorly populated. See **HbA1c poor control** for details on alteration performed to identify this condition

Statin prescription:

- [illegible]

- Hypertension treatment was expanded toward CAPriCORN value sets on specified in the eCQM medications using the following list of RxNORM codes:

1013932, 1013934, 1013935, 1013936, 1013937, 1013938, 1013940, 102317, 102318, 102338, 1033889, 1036821, 1036822, 103932, 103933, 103934, 104216, 104218, 104227, 104228, 104229, 104231, 104232, 104238, 104267, 104270, 104271, 104276, 104277, 104300, 104306, 104308, 104311, 104324, 104332, 104337, 104338, 104340, 104348, 104349, 104357, 104363, 104368, 104369, 104370, 104375, 104378, 104382, 104388, 104389, 104412, 1007711, 1007929, 1050333, 1050339, 1050796, 1050805, 1050806, 1050807, 1007942,

[illegible]

OBSERVED ANNUAL RATES

Table S1. Annual observed rates by outcome and year. Rates are denominator-weighted citywide rates and unweighted mean tract rates among tract years with positive denominators.

Year	Observed tracts	Denominator, eligible patient-years	Numerator, eligible patient- years	Weighted rate, %	Mean tract rate, %
<i>Outcome: Poor HbA1c control</i>					
2017	781	40,095	4,985	12.4	12
2018	781	39,168	4,624	11.8	11.2
2019	781	41,254	4,611	11.2	10.8
2020	779	38,263	4,094	10.7	10.4
2021	780	44,706	3,525	7.9	7.2
2022	781	41,369	3,019	7.3	6.7
<i>Outcome: Controlled blood pressure</i>					
2017	781	36,536	5,376	14.7	13.7
2018	781	36,069	4,028	11.2	10.6
2019	781	38,291	4,158	10.9	10.2
2020	779	35,360	3,574	10.1	9.7
2021	779	41,802	11,479	27.5	29.9
2022	781	38,932	3,496	9	8.4
<i>Outcome: Statin prescribed</i>					
2017	758	6,522	4,374	67.1	66.4

2018	758	6,077	3,999	65.8	65.2
2019	765	6,559	4,217	64.3	63.4
2020	767	6,286	3,787	60.2	58.9
2021	773	8,190	5,017	61.3	61.5
2022	776	8,269	4,749	57.4	57.5

Outcome: no documented HbA1c measurement

2017	781	40,095	15,439	38.5	37.3
2018	781	39,168	16,998	43.4	42.6
2019	781	41,254	18,981	46	45.7
2020	779	38,263	19,399	50.7	49.7
2021	780	44,706	29,550	66.1	68
2022	781	41,369	26,506	64.1	66

Outcome: no documented blood pressure measurement

2017	781	36,536	27,494	75.3	77.2
2018	781	36,069	28,764	79.7	81.3
2019	781	38,291	31,052	81.1	82.5
2020	779	35,360	29,279	82.8	83.6
2021	779	41,802	24,219	57.9	55
2022	781	38,932	33,361	85.7	86.6

Note: Denominator and numerator are counts of eligible patient-years aggregated across observed Chicago tract-years with positive denominators. Denominator indicates the number of eligible patient-years for the outcome in that year. Numerator indicates the number of those eligible patient-years meeting the outcome definition. Weighted rate was calculated as $100 \times$

numerator divided by denominator. Mean tract rate is the unweighted mean of tract-level observed percentages among tract-years with positive denominators. Denominator changes across years reflect changes in the EHR-observed eligible population and should not be interpreted as changes in the total number of Chicago residents with diabetes. Annual blood pressure patterns should be interpreted cautiously because they may reflect changes in structured EHR capture, site mix, documentation, or care delivery.

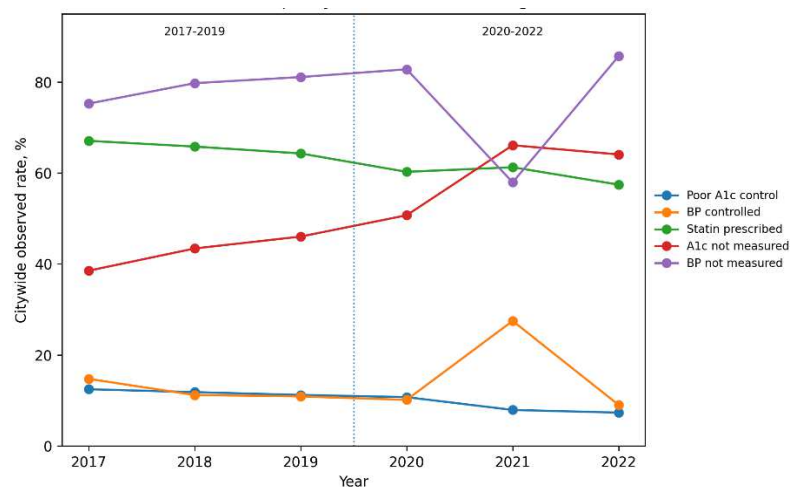
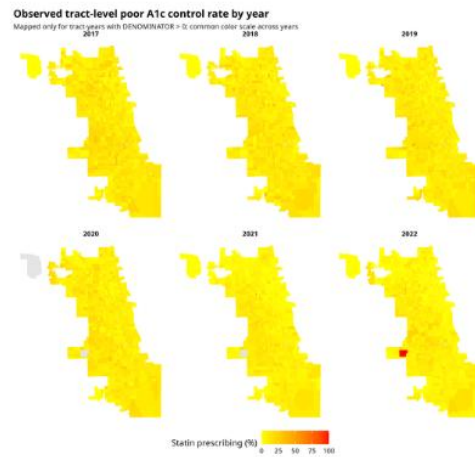
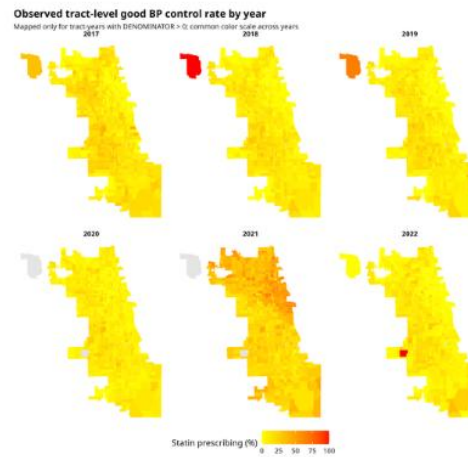


Fig. S1. Annual denominator-weighted citywide percentages by outcome. The vertical dotted line separates 2017 - 2019 from 2020 - 2022. No documented HbA1c measurement is the dominant disruption signal. Statin prescribing declined during the COVID-19 period.

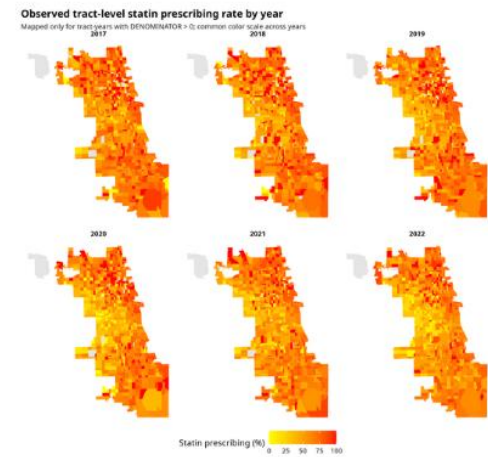
A. Poor A1c control



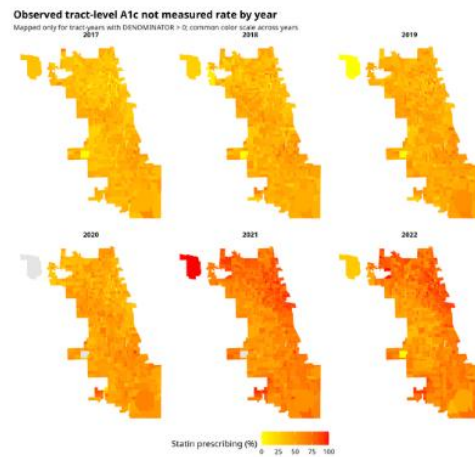
B. Controlled blood pressure



C. Statin prescribed



D. A1c not measured



E. Blood pressure not measured

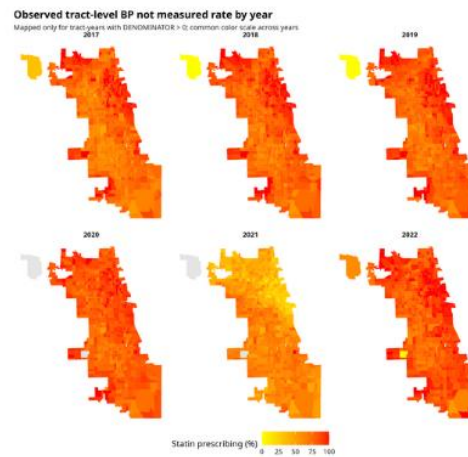


Fig. S2. Annual observed tract level rate maps. Grey areas indicate tract years without a positive denominator or without observed rate information.

OBSERVED SPATIAL AUTOCORRELATION AND LOCAL CLUSTERS

Annual Moran I results (Table S2) support the conclusion that diabetes care indicators were geographically structured throughout the study period. The spatial pattern was strongest for measurement gap outcomes and controlled blood pressure. This suggests that neighborhood differences in ascertainment and care delivery were important study findings, not only data quality issues.

Table S2. Annual global Moran I for observed tract level rates.

Year	Observed tracts	Moran I	Permutation p-value*
<i>Outcome: Poor HbA1c control</i>			
2017	781	0.165	<.01
2018	781	0.138	<.01
2019	781	0.159	<.01
2020	779	0.154	<.01
2021	780	0.355	<.01
2022	781	0.245	<.01
<i>Outcome: Controlled blood pressure</i>			
2017	781	0.431	<.01
2018	781	0.399	<.01
2019	781	0.406	<.01
2020	779	0.226	<.01
2021	779	0.643	<.01
2022	781	0.292	<.01
<i>Outcome: Statin prescribed</i>			
2017	758	0.14	<.01
2018	758	0.191	<.01
2019	765	0.192	<.01
2020	767	0.32	<.01
2021	773	0.234	<.01
2022	776	0.294	<.01
<i>Outcome: HbA1c not measured</i>			
2017	781	0.303	<.01
2018	781	0.213	<.01
2019	781	0.165	<.01
2020	779	0.291	<.01
2021	780	0.577	<.01
2022	781	0.543	<.01
<i>Outcome: Blood pressure not measured</i>			
2017	781	0.536	<.01
2018	781	0.514	<.01
2019	781	0.512	<.01
2020	779	0.343	<.01
2021	779	0.717	<.01
2022	781	0.417	<.01

*Value <0.01 means significant.

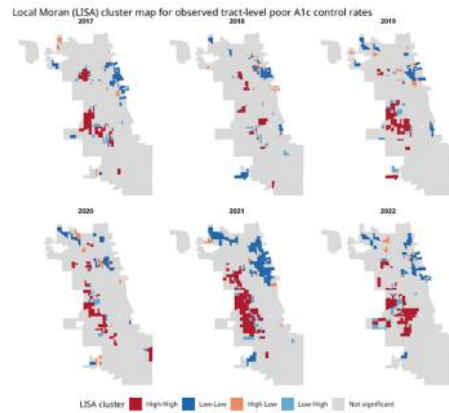
Table S3. Annual LISA cluster counts for observed tract level rates.

Year	High-High*	Low-Low*	High-Low**	Low-High**	Not significant
<i>Outcome: Poor HbA1c control</i>					
2017	45	39	13	20	664
2018	24	43	17	14	683
2019	41	40	14	13	673
2020	48	26	14	14	677
2021	81	99	11	21	568
2022	61	54	7	20	639
<i>Outcome: Controlled blood pressure</i>					
2017	105	102	15	11	548
2018	86	105	8	11	571
2019	97	105	13	14	552
2020	69	33	7	20	650
2021	139	133	5	11	491
2022	71	85	3	27	595
<i>Outcome: Statin prescribed</i>					
2017	21	42	10	11	674
2018	34	53	16	8	647
2019	31	60	12	10	652
2020	51	109	12	11	584
2021	36	68	17	15	637
2022	45	98	16	17	600
<i>Outcome: no documented HbA1c measurement</i>					
2017	81	75	17	8	600
2018	60	51	24	5	641
2019	50	35	10	9	677
2020	72	73	25	12	597
2021	138	132	9	11	490
2022	124	156	11	12	478
<i>Outcome: no documented blood pressure measurement</i>					
2017	137	124	8	8	504
2018	135	115	13	6	512
2019	134	113	13	10	511
2020	68	85	19	16	591
2021	138	154	4	5	478
2022	109	106	25	5	536

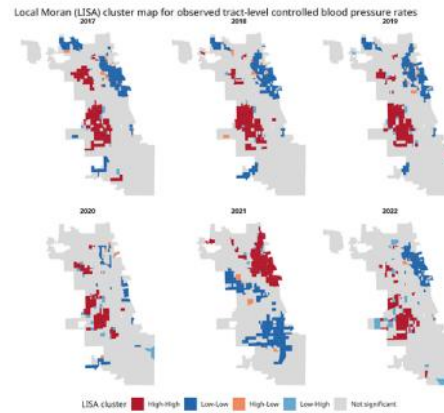
*High-high and low-low indicate statistically significant local clusters of high or low tract rates.

**High-low and low-high indicate spatial outliers.

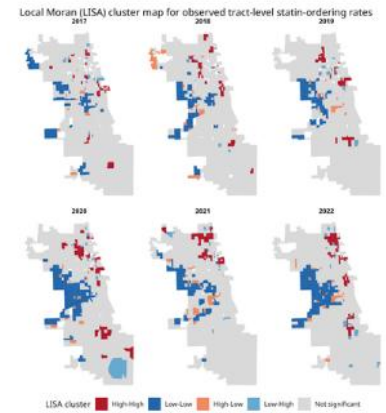
A. Poor A1c control



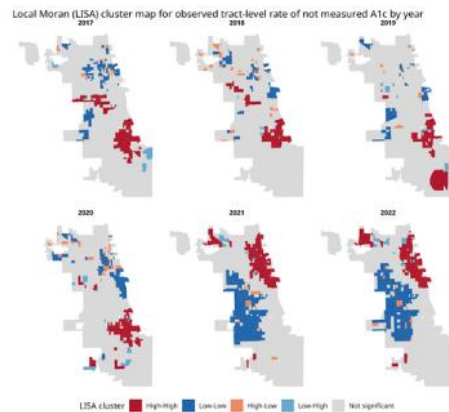
B. Controlled blood pressure



C. Statin prescribed



D. A1c not measured



E. Blood pressure not measured

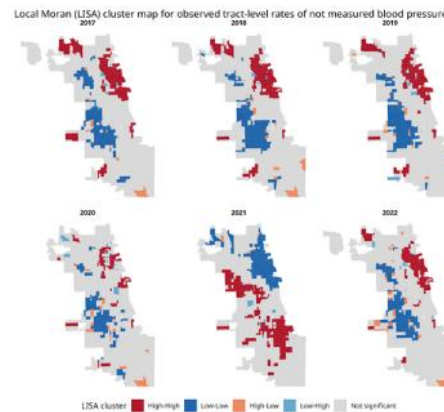


Fig. S3. Annual Local Moran cluster maps for observed rates. High-high clusters are clinically unfavorable for no documented HbA1c measurement, documented poor HbA1c control, and no documented blood pressure measurement, but favorable for controlled blood pressure and statin prescribing.

PRE-TO-DURING CHANGE ANALYSES

The pre-to-during change analyses identify where the COVID-19 period was associated with clustered worsening or improvement. Because figure colors show direction of change, the meaning of worsening differs by outcome. Higher values are adverse for no documented HbA1c measurement, documented poor HbA1c control, and no documented blood pressure measurement. Lower values are adverse for controlled blood pressure and statin prescribing. Fig. S4 shows the original continuous during-minus-pre-change maps.

Table S4. Tract level during-to-pre change summaries and spatial clustering. Change is the mean 2020-2022 tract rate minus the mean 2017 - 2019 tract rate.

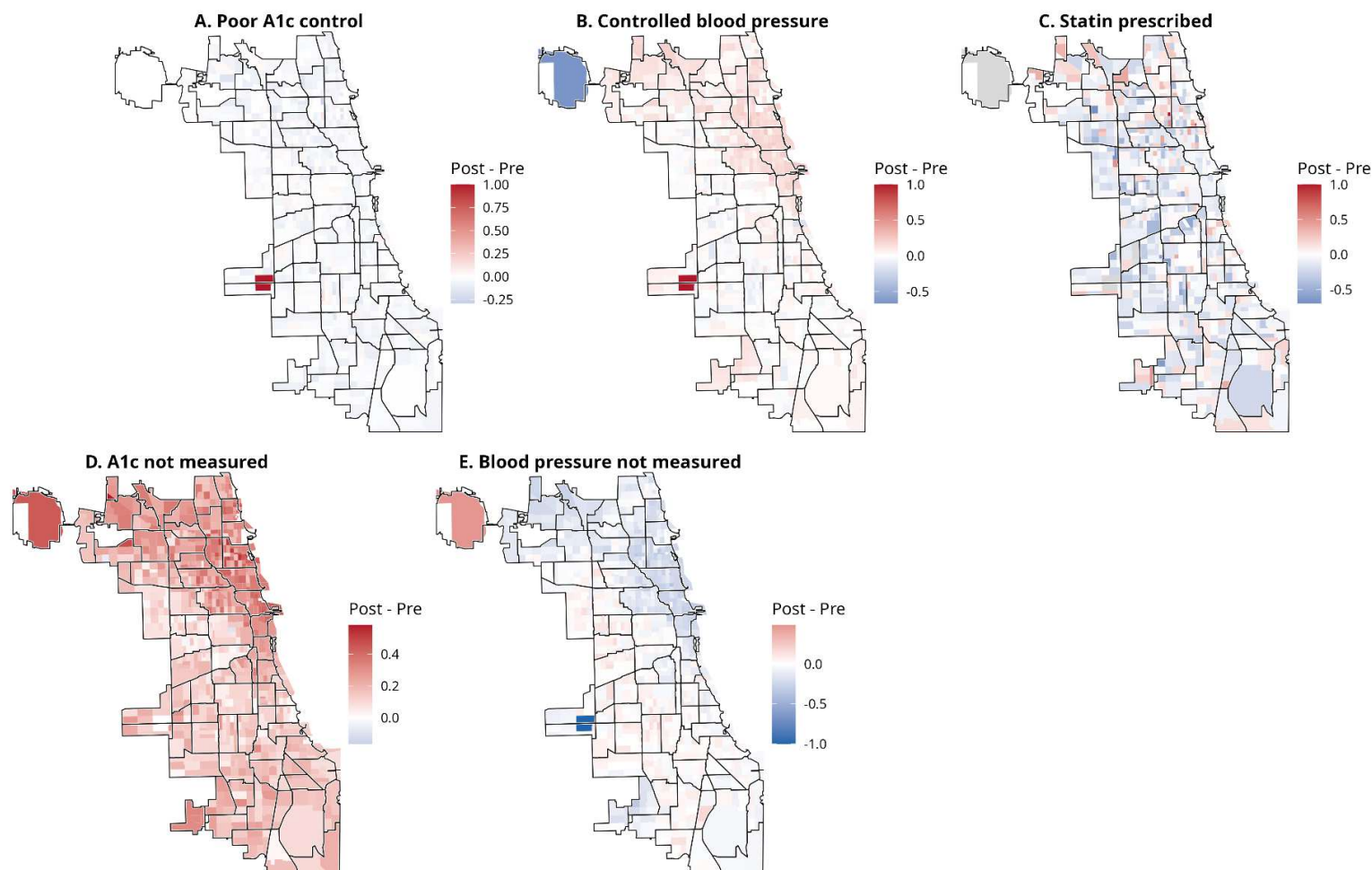
Characteristic	Outcome				
	Poor HbA1c control	Controlled blood pressure	Statin prescribed	no documented HbA1c measurement	no documented blood pressure measurement
Mean tract change, pp*	-3.14	4.58	-5.77	19.31	-5.31
Median tract change [IQR], pp*	-3.03 [-5.79, -0.80]	3.06 [-0.96, 9.91]	-6.01 [-16.28, 3.70]	17.77 [11.26, 26.26]	-3.58 [-12.04, 2.65]
Tracts increased, %	19.2	69.2	32.9	98.1	36.8
Change	0.01	0.437	0.07	0.535	0.572
Moran I					
Permutation p-value	0.266	<.01	<.01	<.01	<.01
High-High	11	134	20	131	101
Low-Low	2	58	13	115	145
Not significant	755	563	710	511	515

* pp indicates percentage points

Fig. S4. Tract-level during-minus-pre change maps for the five outcomes. These maps show direction of change, not whether care improved. Red indicates higher percentages during 2020 to 2022. Blue indicates lower percentages during 2020 to 2022. Higher percentages are unfavorable for no documented HbA1c measurement, documented poor HbA1c control, and no documented blood pressure measurement. Higher percentages are favorable for controlled blood pressure and statin prescribing.

Observed tract-level change in diabetes care indicators after COVID-19 onset

Mean observed rate in 2020–2022 minus mean observed rate in 2017–2019. Community-area boundaries are shown in black.



BYM2 SPATIAL EFFECTS AND RESIDUAL DIAGNOSTICS

For each imputed dataset, we modeled the tract-year numerator as a binomial count among eligible patients in that tract-year. Let Y_{it} be the numerator for census tract i in year t . Let n_{it} be the denominator. Let p_{it} be the tract-year outcome probability. The model was $Y_{it} \sim \text{Binomial}(n_{it}, p_{it})$, with $\text{logit}(p_{it}) = \alpha + \gamma_t + X_i \beta + u_i + \epsilon_{it}$. The model included categorical year effects, standardized ACS covariates, a BYM2 tract spatial effect, and independent tract-year heterogeneity.³²⁻³⁴

The categorical year term allowed each study year to have its own mean level, with 2019 as the reference year. The vector X_i contained standardized tract-level ACS covariates and the ACS imputation indicator. The term u_i represented residual spatial variation shared by neighboring tracts. The BYM2 parameterization combines spatially structured and unstructured tract-level variation. The term ϵ_{it} represented independent tract-year heterogeneity. Tract-years with a final denominator of zero were retained in the audit but excluded from the binomial likelihood because zero-trial observations do not inform the outcome probability.

The residual diagnostics (Fig. S6) show whether the modeled calendar year and tract level contextual terms sufficiently captured spatial patterning. Persistent residual clustering, especially for controlled blood pressure, suggests unmeasured geographic or health system delivery factors.

Fig. S5. Posterior mean BYM2 spatial effect maps for the three modeled outcomes.

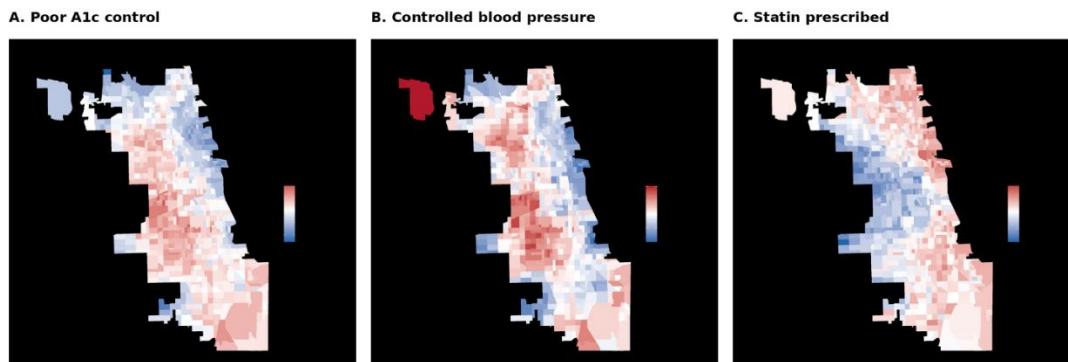


Table S5. Global Moran I for observed rates and during model residuals. Persistent residual Moran I indicates remaining spatial structure after model adjustment

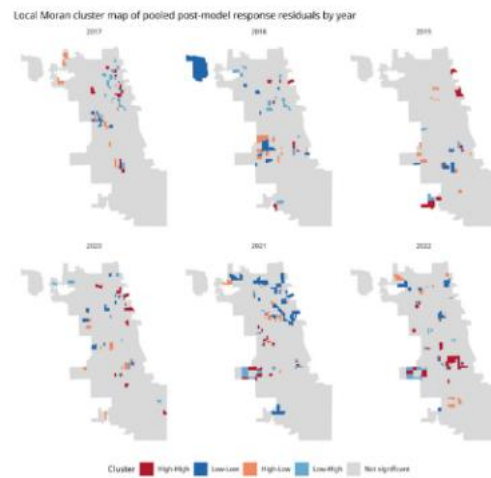
Year	Moran I, p-value		
	Observed rate	Response residual	Pearson residual
<i>Output: Poor HbA1c control</i>			
2017	0.171 (<.01*)	0.011 (0.256)	0.019 (0.15)
2018	0.121 (<.01*)	-0.003 (0.556)	0.023 (0.118)
2019	0.161 (<.01*)	-0.003 (0.536)	0.002 (0.37)
2020	0.133 (<.01*)	0.03 (0.056)	0.073 (<.01*)
2021	0.298 (<.01*)	0.071 (<.01*)	0.159 (<.01*)
2022	0.238 (<.01*)	0.052 (0.01)	0.133 (<.01*)
<i>Output: Controlled blood pressure</i>			
2017	0.431 (<.01*)	0.212 (<.01*)	0.258 (<.01*)
2018	0.368 (<.01*)	0.155 (<.01*)	0.234 (<.01*)
2019	0.391 (<.01*)	0.172 (<.01*)	0.252 (<.01*)
2020	0.213 (<.01*)	0.001 (0.5)	0.008 (0.306)
2021	0.628 (<.01*)	0.646 (<.01*)	0.682 (<.01*)
2022	0.281 (<.01*)	0.073 (<.01*)	0.214 (<.01*)
<i>Output: Statin prescribed</i>			
2017	0.128 (<.01*)	0.033 (0.054)	0.027 (0.082)
2018	0.18 (<.01*)	0.01 (0.164)	0.016 (0.222)
2019	0.181 (<.01*)	-0.014 (0.728)	0.001 (0.44)
2020	0.299 (<.01*)	0.059 (<.01*)	0.055 (<.01*)
2021	0.208 (<.01*)	-0.031 (0.914)	-0.045 (0.99)
2022	0.289 (<.01*)	0.038 (0.026)	0.076 (<.01*)

*Statistically significant

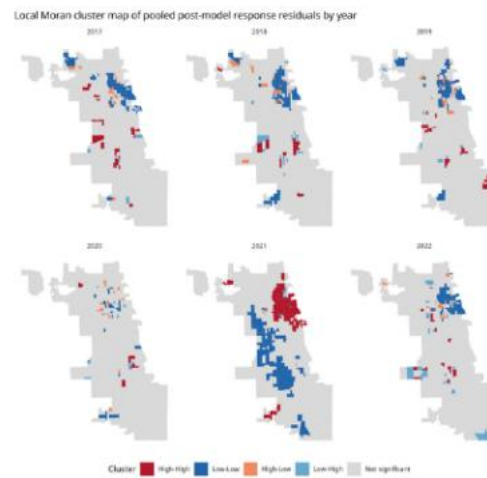
Controlled blood pressure had persistent residual clustering in several years, especially in 2021. This suggests that the model did not fully capture the neighborhood pattern for that outcome.

Fig. S6. Local Moran cluster maps for pooled response residuals.

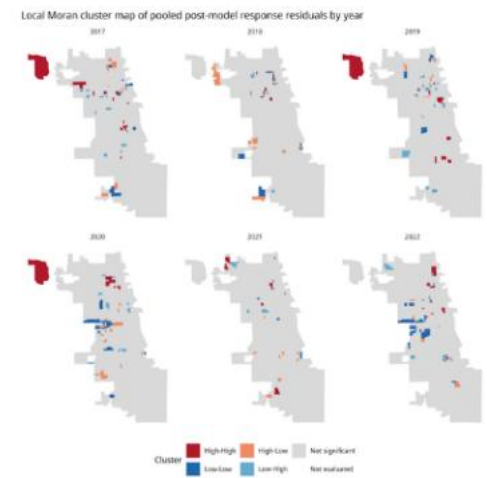
A. Poor A1c control



B. Controlled blood pressure



C. Statin prescribed



SENSITIVITY AND MISSINGNESS ANALYSES

The sensitivity analyses support the main direction of inference for all three modeled outcomes. The controlled blood pressure zero denominator as missing sensitivity analysis was outcome specific and aligned with the primary model. This supports the conclusion that zero denominator handling did not drive the controlled blood pressure finding.

Table S6. Sensitivity analysis summary for adjusted period contrasts. Values are probability differences in percentage points

Contrast	Primary pp	MNAR shift range pp	Zero denominator as missing pp
<i>Outcome: Poor HbA1c control</i>			
2020-2022 vs 2019	-2.56	-2.56 to -2.56	-2.56
2020-2022 vs 2017-2019	-3.18	-3.19 to -3.18	-3.18
<i>Outcome: Controlled blood pressure</i>			
2020-2022 vs 2019	4.65	4.64 to 4.65	4.65
2020-2022 vs 2017-2019	3.26	3.25 to 3.26	3.26
<i>Outcome: Statin prescribed</i>			
2020-2022 vs 2019	-4.68	-4.72 to -4.65	-4.68
2020-2022 vs 2017-2019	-6.1	-6.14 to -6.07	-6.10

Table S7. Missingness decision summaries for modeled outcomes. MCAR indicates missing completely at random. MAR indicates missing at random compatible. MNAR indicates missing not at random.

Outcome	Missingness decision	MCAR p-value	Observed-data GLM signal	Spatial missingness signal
Poor HbA1c control	MAR compatible primary MNAR requires sensitivity	0.023	No	No
Controlled blood pressure	Approximately MCAR	0.172	No	No
Statin prescribed	MAR compatible primary MNAR requires sensitivity	<.01	Yes	Yes

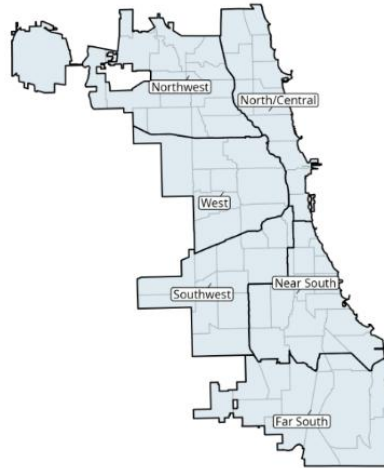
INITIATIVE GEOGRAPHIES AND TIMING

The contextual map, not a causal analysis, helps readers compare study hot spots with real world implementation geographies. Initiatives depicted bellow (Fig. S7) that began before or during the study period may have overlapped with areas of relative protection or worsening. Initiatives created late in the study period are better interpreted as potential recovery platforms.

Fig. S7. Maps the Chicago initiative geographies used to contextualize the difference hotspot findings. These overlays are intended for interpretation and implementation planning.

Healthy Chicago Equity Zones

Transparent zone polygons over Chicago community areas



Base layer: Chicago community areas

West Side United

Derived ZIP-based West Side service area



Base layer: Chicago community areas

Wellness West / WSHEC

Derived ZIP-based West Side Health Equity Collaborative area



Base layer: Chicago community areas

South Side Healthy Community Organization

Derived ZIP-based South Side service area



Base layer: Chicago community areas

Table S8. Timing and interpretation of Chicago initiatives used for contextual hotspot discussion. Hot spots refer to high-high worsening clusters in the pre-to- during change analysis. Cold spots refer to low-low change clusters with relatively less worsening or greater protection. Initiative overlays support planning and hypothesis generation only.

Initiative	Geography shown in Fig. S7	Timing relative to 2017-2022 study period	Relevance to hotspot interpretation
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Healthy Chicago Equity Zones[ref 1-3]	Six zones covering the city and its 77 community areas: Far South, Near South, North/Central, Northwest, Southwest, and West.	Created by CDPH in June 2021 and active during the later COVID-period. The program was created after the 2020 disruption had already begun.	Best interpreted as a citywide recovery and targeting platform. It could use high-high worsening clusters to prioritize A1c catch-up testing, blood pressure checks, preventive medication review, and community health worker outreach. It is unlikely to explain pre-2021 trends.
West Side United[ref 4,5]	West Side collaborative and service geography.	Launched before the pandemic period, with public descriptions identifying launch in 2017 and later documentation describing establishment in 2018.	Most plausibly positioned to have prevented or blunted adverse trends during the study period if its geography overlaps low-low worsening clusters. If it overlaps high-high worsening clusters, maps can guide recovery investments. This ecological study cannot test causal protection.
Wellness West/West Side Health Equity Collaborative[ref 6,7]	West Side service area derived from ZIP-based collaborative geography.	Healthcare Transformation Collaborative application and funding activity began during the later part of the study period. Wellness West describes itself as funded by the Illinois Department of Healthcare and Family Services Healthcare Transformation Collaborative.	Best interpreted as a late-period or during-study recovery platform. The hotspot maps can help align West Side continuity-of-care, social-service linkage, medication access, and community health worker resources with tracts showing worsening measurement gaps or statin-prescribing decline.

South Side Healthy Community Organization[ref 8,9]	Fifteen South Side ZIP codes and related service area.	Awarded healthcare transformation funding on July 2, 2021 and began receiving funding in January 2022.	Best interpreted as a late-period or during -study recovery platform for South Side hot spots. Its care coordination, chronic disease management, transportation, and social-resource linkage model is directly relevant to A1c measurement, blood pressure monitoring, and preventive medication continuity.
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References:

1. Chicago Department of Public Health. Healthy Chicago Zones. Chicago, IL: City of Chicago. Accessed May 27, 2026.
2. Public Health Institute of Metropolitan Chicago. Healthy Chicago Equity Zones. Published May 24, 2022. Accessed May 27, 2026. <https://phimc.org/2022/05/24/healthy-chicago-equity-zones/>
3. City of Chicago. Mayor Lightfoot and Chicago Department of Public Health declare racism a public health crisis and establish Healthy Chicago Equity Zones. Published June 17, 2021. Accessed May 27, 2026.
4. Civic Consulting Alliance. 2020 Impact: West Side United. Accessed May 27, 2026. <https://www.ccachicago.org/news-projects/west-side-united>
5. West Side United. Transforming Chicago's West Side Through Collaboration and Investment. Accessed May 27, 2026. <https://www.westsideunited.org/>
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7. Illinois Department of Healthcare and Family Services. Healthcare Transformation Collaboratives. Accessed May 27, 2026. <https://hfs.illinois.gov/healthcaretransformation.html>
8. South Side Healthy Community Organization. Transforming healthcare on South Side Chicago. Accessed May 27, 2026. <https://southsidehealthycommunity.com/>
9. University of Chicago Medicine. Coalition that includes UChicago Medicine is awarded state funds for South Side Healthy Community Organization model. Published July 8, 2021. Accessed May 27, 2026. <https://www.uchicagomedicine.org/forefront/community-articles/2021/july/south-side-health-transformation-award>

DETAILED PATIENT YEAR CHARACTERISTICS MOVED FROM THE MAIN MANUSCRIPT

Table S9. Characteristics of numerator and denominator samples for no documented blood pressure and HbA1c measurement, and statin prescribing

Characteristics calculated at eligible patient-year	BP not measured				A1c not measured				Statin prescribed			
	2017–2019		2020–2022		2017–2019		2020–2022		2017–2019		2020–2022	
Sample name	DENOM	NUMER	DENOM	NUMER	DENOM	NUMER	DENOM	NUMER	DENOM	NUMER	DENOM	NUMER
Unique patients	59561	69650	61859	50233	66966	35541	68281	48131	12124	8276	14207	8853
Patient-years	110896	87310	116094	86859	120517	51418	124338	75455	19158	12590	22745	13553
Mean age, years	56.5	56.6	56.6	56.6	56.2	55.3	56.4	56.1	62.7	62.7	63.1	63.3
	(11.9)	(12.2)	(12.3)	(12.5)	(12.2)	(12.8)	(12.4)	(12.7)	(8.9)	(8.6)	(8.9)	(8.6)
Sex = Female	60066	48043	62874	47922	65343	28456	67057	40999	9638	6192	11284	6513
	(54.2%)	(55.0%)	(54.2%)	(55.2%)	(54.2%)	(55.3%)	(53.9%)	(54.3%)	(50.3%)	(49.2%)	(49.6%)	(48.1%)
Ethnicity = Hispanic	27700	19554	29226	20485	31210	12614	32359	17443	3349	2022	4156	2140
	(25.0%)	(22.4%)	(25.2%)	(23.6%)	(25.9%)	(24.5%)	(26.0%)	(23.1%)	(17.5%)	(16.1%)	(18.3%)	(15.8%)
Race:												
Black or African American	62986	49462	63643	49074	67800	31481	67579	41568	11646	7705	13276	7905
	(56.8%)	(56.7%)	(54.8%)	(56.5%)	(56.3%)	(61.2%)	(54.4%)	(55.1%)	(60.8%)	(61.2%)	(58.4%)	(58.3%)
White	28751	22707	30332	21135	31364	11729	32505	19511	4930	3339	5858	3717
	(25.9%)	(26.0%)	(26.1%)	(24.3%)	(26.0%)	(22.8%)	(26.1%)	(25.9%)	(25.7%)	(26.5%)	(25.8%)	(27.4%)
Other	19159	15141	22119	16650	21353	8208	24254	14376	2582	1546	3611	1931
	(17.3%)	(17.3%)	(19.1%)	(19.2%)	(17.7%)	(16.0%)	(19.5%)	(19.1%)	(13.5%)	(12.3%)	(15.9%)	(14.2%)
Insurance:												
Commercial/private or BCBS	30450	29343	39011	32626	33017	14790	41559	26629	3946	2025	5782	2873
	(28.72 %)	(35.07 %)	(35.05 %)	(39.05 %)	(27.4 %)	(28.76 %)	(33.42 %)	(35.29 %)	(20.6 %)	(16.08 %)	(25.42 %)	(21.2 %)
Medicaid	24619	16896	26810	17702	28398	12276	30636	17351	3536	2772	4147	2914
	(23.22 %)	(20.19 %)	(24.09 %)	(21.19 %)	(23.56 %)	(23.87 %)	(24.64 %)	(23 %)	(18.46 %)	(22.02 %)	(18.23 %)	(21.5 %)
Medicare	25500	21495	26496	20999	29744	12105	30369	18452	7696	4529	9083	4993
	(24.05 %)	(25.69 %)	(23.8 %)	(25.13 %)	(24.68 %)	(23.54 %)	(24.42 %)	(24.45 %)	(40.17 %)	(35.97 %)	(39.93 %)	(36.84 %)
Medicare-Medicaid dual evidence	8488	7392	7999	6300	11040	5508	10279	7193	2867	2315	3038	2269
	(8.01 %)	(8.83 %)	(7.19 %)	(7.54 %)	(9.16 %)	(10.71 %)	(8.27 %)	(9.53 %)	(14.97 %)	(18.39 %)	(13.36 %)	(16.74 %)
Self-pay/no payment only	12022	5120	7367	3315	13028	3703	7708	3353	849	752	448	357
	(11.34 %)	(6.12 %)	(6.62 %)	(3.97 %)	(10.81 %)	(7.2 %)	(6.2 %)	(4.44 %)	(4.43 %)	(5.97 %)	(1.97 %)	(2.63 %)
Other	4930	3425	3622	2616	5290	3036	3787	2477	264	197	247	147
	(4.66 %)	(4.1 %)	(3.26 %)	(3.13 %)	(4.38 %)	(5.91 %)	(3.04 %)	(3.28 %)	(1.37 %)	(1.57 %)	(1.09 %)	(1.08 %)
Comorbidities:												
Chronic kidney disease / renal failure	8368	6811	12266	9141	17831	7112	21520	11913	4574	2967	5982	3697
	(7.89 %)	(8.14 %)	(11.02 %)	(10.94 %)	(14.8 %)	(13.83 %)	(17.31 %)	(15.79 %)	(23.88 %)	(23.57 %)	(26.3 %)	(27.28 %)
Coronary artery disease / ischemic heart disease	13811	11556	16446	12488	17980	6970	21105	12002	12379	8078	14236	8230
	(13.03 %)	(13.81 %)	(14.78 %)	(14.95 %)	(14.92 %)	(13.56 %)	(16.97 %)	(15.91 %)	(64.62 %)	(64.16 %)	(62.59 %)	(60.72 %)

Heart failure	9086 (8.57 %)	7311 (8.74 %)	10924 (9.81 %)	8300 (9.93 %)	13193 (10.95 %)	5216 (10.14 %)	15276 (12.29 %)	8501 (11.27 %)	5562 (29.03 %)	3772 (29.96 %)	6766 (29.75 %)	4234 (31.24 %)
Cerebrovascular disease	5815 (5.49 %)	4749 (5.68 %)	6744 (6.06 %)	5070 (6.07 %)	7277 (6.04 %)	2670 (5.19 %)	8392 (6.75 %)	4547 (6.03 %)	4729 (24.68 %)	3225 (25.62 %)	5373 (23.62 %)	3280 (24.2 %)
Peripheral vascular disease	6663 (6.29 %)	5636 (6.74 %)	9049 (8.13 %)	6723 (8.05 %)	9424 (7.82 %)	3583 (6.97 %)	12449 (10.01 %)	7103 (9.41 %)	4156 (21.69 %)	2854 (22.67 %)	5668 (24.92 %)	3441 (25.39 %)
Obesity	30819 (29.07 %)	25953 (31.02 %)	37526 (33.71 %)	29737 (35.59 %)	35918 (29.8 %)	14304 (27.82 %)	42998 (34.58 %)	24138 (31.99 %)	7175 (37.45 %)	4282 (34.01 %)	9381 (41.24 %)	5272 (38.9 %)
Depression or serious mental illness	15388 (14.52 %)	12383 (14.8 %)	16274 (14.62 %)	11883 (14.22 %)	17868 (14.83 %)	6994 (13.6 %)	18691 (15.03 %)	10496 (13.91 %)	3805 (19.86 %)	2539 (20.17 %)	4264 (18.75 %)	2722 (20.08 %)
Chronic pulmonary disease	16967 (16.01 %)	13401 (16.02 %)	17409 (15.64 %)	12983 (15.54 %)	19675 (16.33 %)	8298 (16.14 %)	20015 (16.1 %)	11519 (15.27 %)	4745 (24.77 %)	3108 (24.69 %)	5427 (23.86 %)	3215 (23.72 %)
Cancer (active solid/metastatic/hematologic; in situ excluded)	9479 (8.94 %)	7766 (9.28 %)	11011 (9.89 %)	7869 (9.42 %)	11137 (9.24 %)	4138 (8.05 %)	12602 (10.14 %)	7139 (9.46 %)	2871 (14.99 %)	1881 (14.94 %)	3711 (16.32 %)	2208 (16.29 %)

Table S10. Characteristics of numerator and denominator samples for controlled blood pressure and poor A1c control

Characteristics calculated at eligible patient-year	good BP control				Poor A1c control			
	2017–2019		2020–2022		2017–2019		2020–2022	
Sample name	DENOM	NUMER	DENOM	NUMER	DENOM	NUMER	DENOM	NUMER
Unique patients	59561	9213	61859	14731	66966	10993	68281	8727
Patient-years	110896	13562	116094	18549	120517	14220	124338	10638
Mean age (SD), years	56.5 (11.9)	54.8 (11.2)	56.6 (12.3)	55.7 (12.0)	56.2 (12.2)	52.6 (12.0)	56.4 (12.4)	52.6 (12.4)
Sex = Female	60066 (54.2%)	6855 (50.5%)	62874 (54.2%)	9472 (51.1%)	65343 (54.2%)	7138 (50.2%)	67057 (53.9%)	5284 (49.7%)
Ethnicity = Hispanic	27700 (25.0%)	5215 (38.5%)	29226 (25.2%)	5812 (31.3%)	31210 (25.9%)	4721 (33.2%)	32359 (26.0%)	3976 (37.4%)
Race:								
Black or African American	62986 (56.8%)	7131 (52.6%)	63643 (54.8%)	8533 (46.0%)	67800 (56.3%)	7856 (55.2%)	67579 (54.4%)	5711 (53.7%)
White	28751 (25.9%)	3806 (28.1%)	30332 (26.1%)	6310 (34.0%)	31364 (26.0%)	3691 (26.0%)	32505 (26.1%)	2758 (25.9%)
Other	19159 (17.3%)	2625 (19.4%)	22119 (19.1%)	3706 (20.0%)	21353 (17.7%)	2673 (18.8%)	24254 (19.5%)	2169 (20.4%)
Insurance:								
Commercial/private or BCBS	30450 (28.72 %)	595 (4.63 %)	39011 (35.05 %)	4511 (25.59 %)	33017 (27.4 %)	3562 (25.05 %)	41559 (33.42 %)	2838 (26.68 %)
Medicaid	24619 (23.22 %)	4372 (34.03 %)	26810 (24.09 %)	5583 (31.67 %)	28398 (23.56 %)	4157 (29.23 %)	30636 (24.64 %)	3744 (35.19 %)
Medicare	25500 (24.05 %)	2052 (15.97 %)	26496 (23.8 %)	3370 (19.12 %)	29744 (24.68 %)	2205 (15.51 %)	30369 (24.42 %)	1586 (14.91 %)
Medicare-Medicaid dual evidence	8488 (8.01 %)	612 (4.76 %)	7999 (7.19 %)	1004 (5.7 %)	11040 (9.16 %)	942 (6.62 %)	10279 (8.27 %)	537 (5.05 %)
Self-pay/no payment only	12022 (11.34 %)	4267 (33.21 %)	7367 (6.62 %)	2531 (14.36 %)	13028 (10.81 %)	2728 (19.18 %)	7708 (6.2 %)	1572 (14.78 %)
Other	4930 (4.66 %)	951 (7.4 %)	3622 (3.26 %)	629 (3.56 %)	5290 (4.38 %)	626 (4.4 %)	3787 (3.04 %)	361 (3.4 %)
Comorbidities:								
Chronic kidney disease / renal failure	8368 (7.89 %)	768 (5.98 %)	12266 (11.02 %)	1806 (10.25 %)	17831 (14.8 %)	1854 (13.04 %)	21520 (17.31 %)	1781 (16.74 %)
Coronary artery disease / ischemic heart disease	13811 (13.03 %)	1327 (10.33 %)	16446 (14.78 %)	2540 (14.41 %)	17980 (14.92 %)	2044 (14.37 %)	21105 (16.97 %)	1729 (16.25 %)
Heart failure	9086 (8.57 %)	1002 (7.8 %)	10924 (9.81 %)	1660 (9.42 %)	13193 (10.95 %)	1544 (10.86 %)	15276 (12.29 %)	1298 (12.2 %)
Cerebrovascular disease	5815 (5.49 %)	562 (4.37 %)	6744 (6.06 %)	989 (5.61 %)	7277 (6.04 %)	889 (6.25 %)	8392 (6.75 %)	774 (7.28 %)
Peripheral vascular disease	6663 (6.29 %)	553 (4.3 %)	9049 (8.13 %)	1508 (8.55 %)	9424 (7.82 %)	976 (6.86 %)	12449 (10.01 %)	933 (8.77 %)
Obesity	30819 (29.07 %)	2680 (20.86 %)	37526 (33.71 %)	4894 (27.76 %)	35918 (29.8 %)	4145 (29.15 %)	42998 (34.58 %)	3740 (35.16 %)
Depression or serious mental illness	15388 (14.52 %)	1807 (14.06 %)	16274 (14.62 %)	2920 (16.56 %)	17868 (14.83 %)	2224 (15.64 %)	18691 (15.03 %)	1777 (16.7 %)

ADJUSTED MODEL AND COVARIATE DETAILS

Table S11 gives the adjusted estimates behind Fig. 3. Values below zero indicate lower modeled outcome probability in the COVID-19 period. Values above zero indicate higher modeled outcome probability. The statin decline is the most direct adverse modeled clinical care signal.

Table S11. Adjusted period contrasts from Bayesian spatial models with categorical year effects.

Contrast	Primary binomial, pp (95% CI)	Beta-binomial, pp (95% CrI)	p value
<i>Outcome: Poor A1c control</i>			
2020-2022 vs 2019	-2.56 (-2.89, -2.22)	-2.59 (-2.95, -2.23)	<.001
2020-2022 vs 2017-2019	-3.18 (-3.42, -2.94)	-3.22 (-3.47, -2.97)	<.001
<i>Outcome: Controlled blood pressure</i>			
2020-2022 vs 2019	4.65 (4.28, 5.02)	4.67 (4.28, 5.05)	<.001
2020-2022 vs 2017-2019	3.26 (2.98, 3.54)	3.27 (2.99, 3.56)	<.001
<i>Outcome: Statin prescribed</i>			
2020-2022 vs 2019	-4.68 (-5.94, -3.41)	-4.69 (-5.95, -3.43)	<.001
2020-2022 vs 2017-2019	-6.10 (-6.99, -5.21)	-6.11 (-7.00, -5.23)	<.001

Table S12 shows associations between neighborhood context and modeled outcomes. The odds ratios describe tract level context, not individual patient race, ethnicity, or socioeconomic status. They are best used to identify where structural context may shape care quality and clinical visibility.

Table S12. Adjusted associations between tract level ACS covariates and modeled outcomes.

Covariate, 1 SD higher	Poor HbA1c control	Controlled blood pressure	Statin prescribed
Uninsured	1.03 (1.00, 1.06)	1.07 (1.03, 1.11)	1.02 (0.97, 1.07)
Poverty	1.04 (1.01, 1.07)	1.05 (1.01, 1.09)	0.99 (0.94, 1.04)
Unemployment	1.01 (0.98, 1.04)	1.03 (0.99, 1.07)	1.04 (0.98, 1.10)
Non-Hispanic Black	1.34 (1.25, 1.43)	1.32 (1.21, 1.44)	1.02 (0.90, 1.16)
Hispanic	1.36 (1.29, 1.44)	1.41 (1.31, 1.51)	1.01 (0.90, 1.12)
Non-Hispanic Asian	1.06 (1.02, 1.09)	1.04 (1.00, 1.09)	0.98 (0.93, 1.04)

Table S13 condenses the residual diagnostic findings. Smaller residual Moran I values mean the model explained more of the original spatial clustering. Persistent residual clustering suggests that important local factors were not captured by the available covariates.

Table S13. Global Moran I ranges for observed rates and during model residuals.

Outcome	Observed Moran I range	Response residual Moran I range	Pearson residual Moran I range	Response residual significant years	Pearson residual significant years
Poor A1c control	0.121-0.298	-0.003-0.071	0.002-0.159	2/6	3/6
Controlled blood pressure	0.213-0.628	0.001-0.646	0.008-0.682	5/6	5/6
Statin prescribed	0.128-0.299	-0.031-0.059	-0.045-0.076	2/6	2/6

Community-area priority summary supporting Fig. 3

Table S14. Community-area summary of unfavorable outcome overlap supporting Fig. 3. Community area labels were assigned by largest spatial overlap between 2020 census tracts and Chicago community area boundaries. The maximum priority outcomes column reports the largest number of clinically unfavorable outcomes found in any single tract within the community area.

Maximum priority outcomes in any tract	Community area	Outcomes represented
3	West Englewood	no documented blood pressure measurement; Controlled blood pressure; Documented poor HbA1c control; Statin prescribing
3	East Garfield Park	no documented blood pressure measurement; Controlled blood pressure; Documented poor HbA1c control; Statin prescribing
3	Brighton Park	no documented blood pressure measurement; Controlled blood pressure; Documented poor HbA1c control; Statin prescribing
2	South Lawndale	no documented blood pressure measurement; Controlled blood pressure
2	Chicago Lawn	no documented blood pressure measurement; Controlled blood pressure
2	North Lawndale	no documented blood pressure measurement; Controlled blood pressure
2	West Garfield Park	no documented blood pressure measurement; Controlled blood pressure; Documented poor HbA1c control; Statin prescribing
2	Englewood	no documented blood pressure measurement; Controlled blood pressure
2	New City	no documented blood pressure measurement; Controlled blood pressure
2	Roseland	no documented blood pressure measurement; Controlled blood pressure
2	Gage Park	no documented blood pressure measurement; Controlled blood pressure
2	Ashburn	no documented blood pressure measurement; Controlled blood pressure
1	Lake View	no documented HbA1c measurement
1	Lincoln Park	no documented HbA1c measurement
1	Near North Side	no documented HbA1c measurement
1	Edgewater	no documented HbA1c measurement

Maximum priority outcomes in any tract	Community area	Outcomes represented
1	North Center	no documented HbA1c measurement
1	Austin	no documented Blood pressure non-measurement; Statin prescribing
1	Logan Square	no documented HbA1c measurement; Statin prescribing
1	West Town	no documented HbA1c measurement
1	Greater Grand Crossing	no documented blood pressure measurement
1	Lincoln Square	no documented HbA1c measurement
1	Clearing	Documented poor HbA1c control
1	Loop	no documented HbA1c measurement
1	Norwood Park	no documented HbA1c measurement
1	Uptown	no documented HbA1c measurement
1	Irving Park	no documented HbA1c measurement; Statin prescribing
1	Portage Park	no documented HbA1c measurement
1	Archer Heights	Controlled blood pressure
1	Belmont Cragin	no documented blood pressure measurement
1	Chatham	no documented blood pressure measurement; Controlled blood pressure
1	Edison Park	no documented HbA1c measurement
1	Garfield Ridge	Documented poor HbA1c control
1	Mount Greenwood	no documented HbA1c measurement
1	Albany Park	no documented HbA1c measurement
1	Auburn Gresham	no documented blood pressure measurement
1	Bridgeport	Statin prescribing
1	Forest Glen	no documented HbA1c measurement
1	Grand Boulevard	Controlled blood pressure
1	Humboldt Park	Statin prescribing
1	Jefferson Park	no documented HbA1c measurement
1	Near West Side	no documented Blood pressure measurement
1	North Park	no documented HbA1c measurement
1	Pullman	no documented blood pressure measurement

Maximum priority outcomes in any tract	Community area	Outcomes represented
1	South Shore	Controlled blood pressure
1	Washington Heights	no documented blood pressure measurement
1	West Elsdon	Documented poor HbA1c control
1	West Lawn	no documented blood pressure measurement
1	West Pullman	no documented blood pressure measurement
1	West Ridge	no documented HbA1c measurement
1	Woodlawn	no documented blood pressure measurement

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [SM.docx](#)