Criminal Risk Tools: Behavior Over Time

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Community Justice

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Risk Score Background

Our risk score is the LS/CMI (Level of Service / Case Management Inventory), one of a suite of closely related Level of Service tools that has been repeatedly validated as predictive of criminal recidivism (including by us).

- The LS/CMI is comprised of 43 questions (each worth 1 point) across eight domains (such as criminal history, companions, and pro-criminal attitude), and is administered in a 30-60 minute interview.

The Level of Service tools are used in 28 American states, 10 Canadian provinces or territories, and 17 other countries.

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Overview of Presentation

This talk focuses on two questions:

- Are there consistent trends in criminal risk level over offenders' criminal life times? If so, we can use them to anticipate future risk and improve targeted services.

- Does a risk score alone act as an accurate and unbiased predictor of criminal risk for every offender? If so, staffing and service levels could be set automatically by policy without taking time to examine each offenders' behavior and history.

Question 1: Are there consistent trajectories in LS/CMI scores?

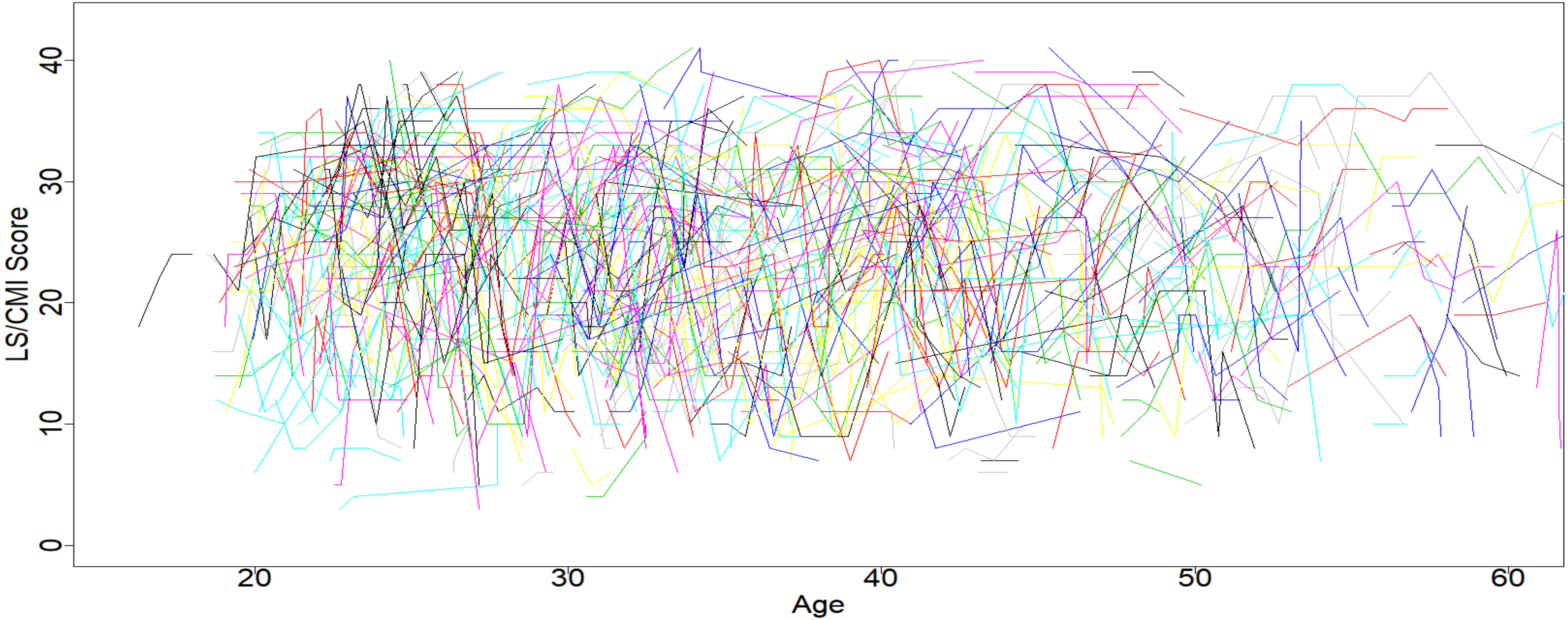
It is widely known that criminal behavior is most frequent among young adults in their twenties and decreases as age increases. However, this is a finding on population averages, not individuals.

Is this – or any other – trend visible in the LS/CMI scores of individual people?

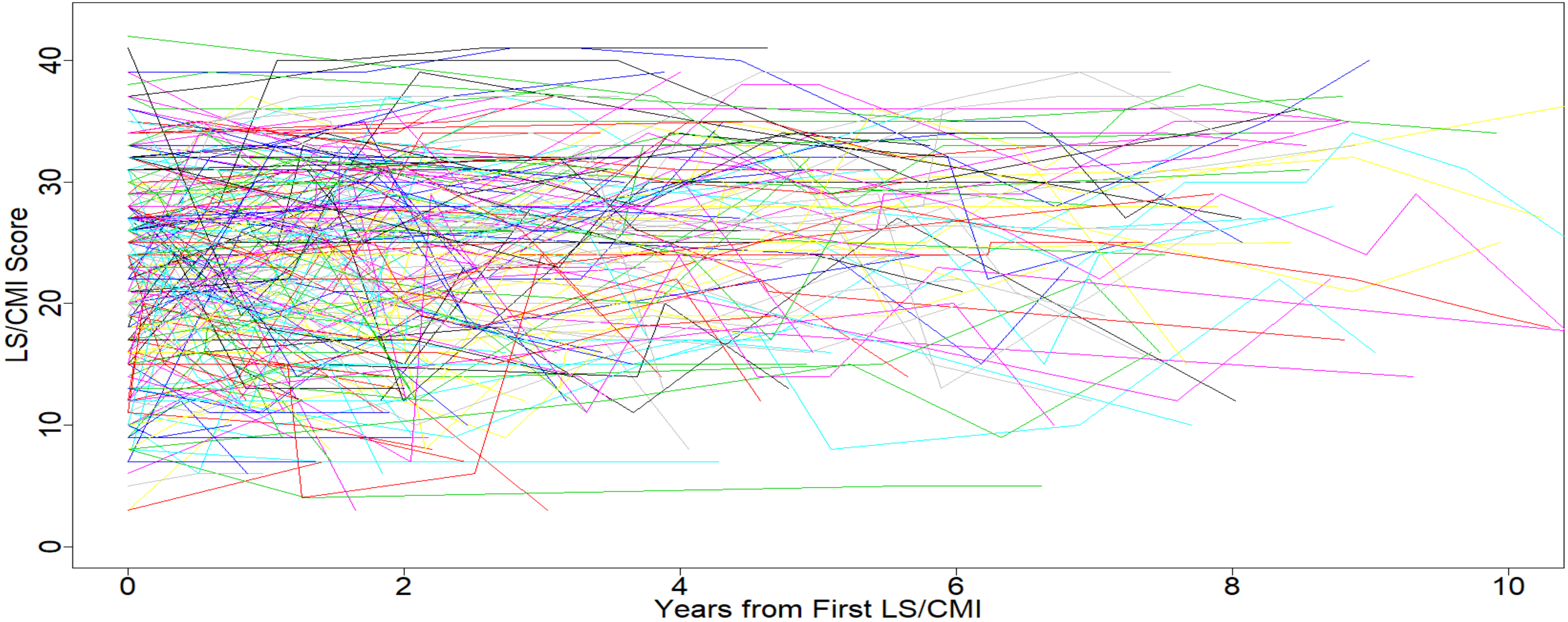
For this analysis, we examined all LS/CMIs collected between 2006 and 2017. We removed all people with fewer than three LS/CMIs, leaving us with 60,750 LS/CMIs across 13,276 people.

The next few slides show graphics containing 250 to 500 randomly selected people; their LS/CMI trend lines are plotted in different ways, looking for a pattern.

Question 1: Trajectories by age



Question 1: Trajectories from first LS/CMI



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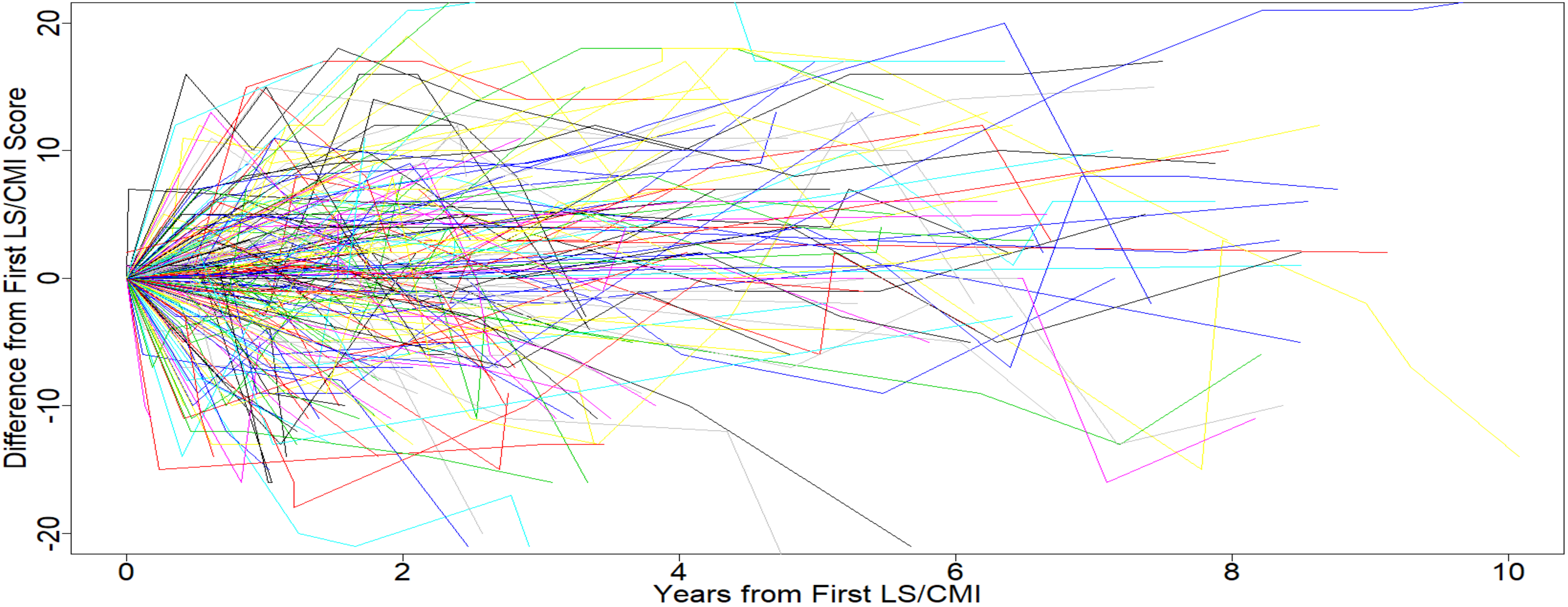
Question 1: Trajectories from first LS/CMI, with first LS/CMI set as a baseline



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Question 1: Confirming Trends with Modeling

We want to validate our visual inspection with actual statistics. For this, we fit a mixed model regression with random slope and intercept, and time (either age or years from first LS/CMI) as a quadratic. We show results both overall and stratified by age.

For: $i = Person1, \ldots, PersonN,\ t = \text{time},\ L = \text{LS/CMI score}$

$$L_{it} = (\mu + Intercept_i) + (\beta + Slope_i)t + \gamma t^2 + e_{it}$$

$$Intercept_i, Slope_i \sim N(0, \sigma)$$

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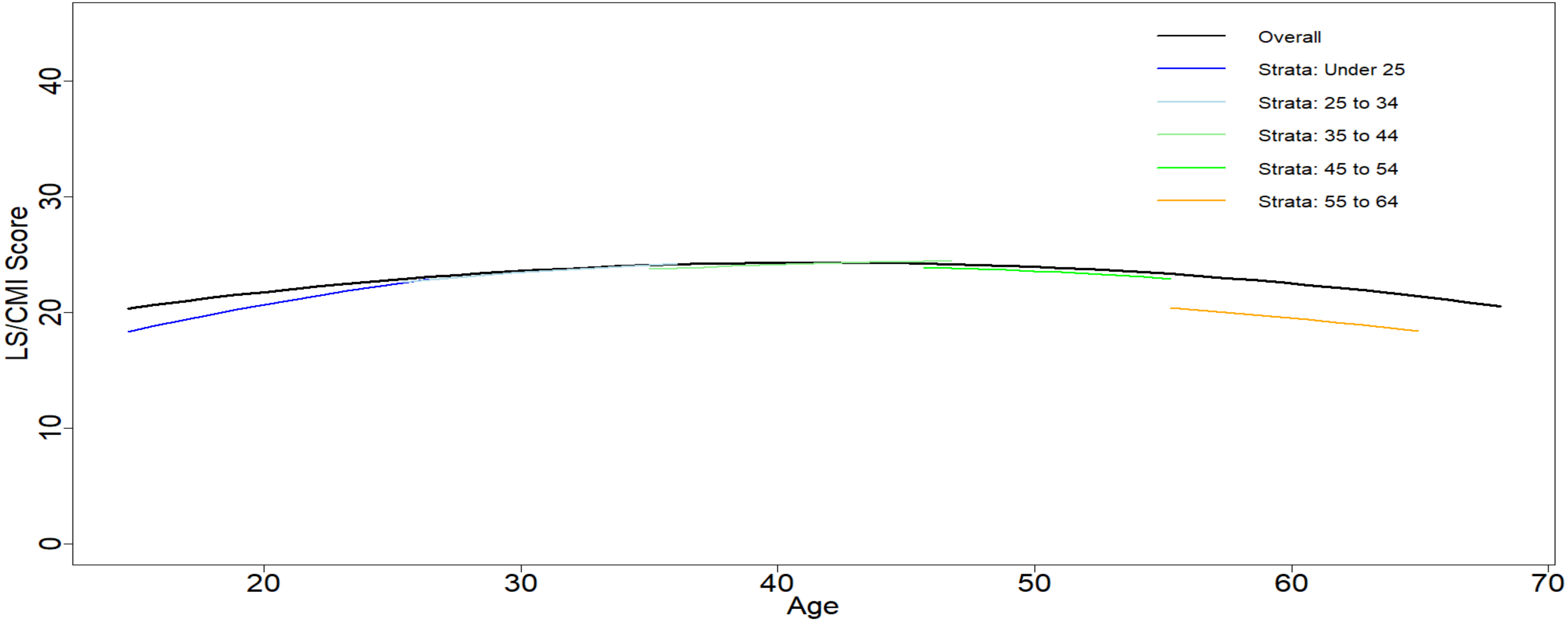
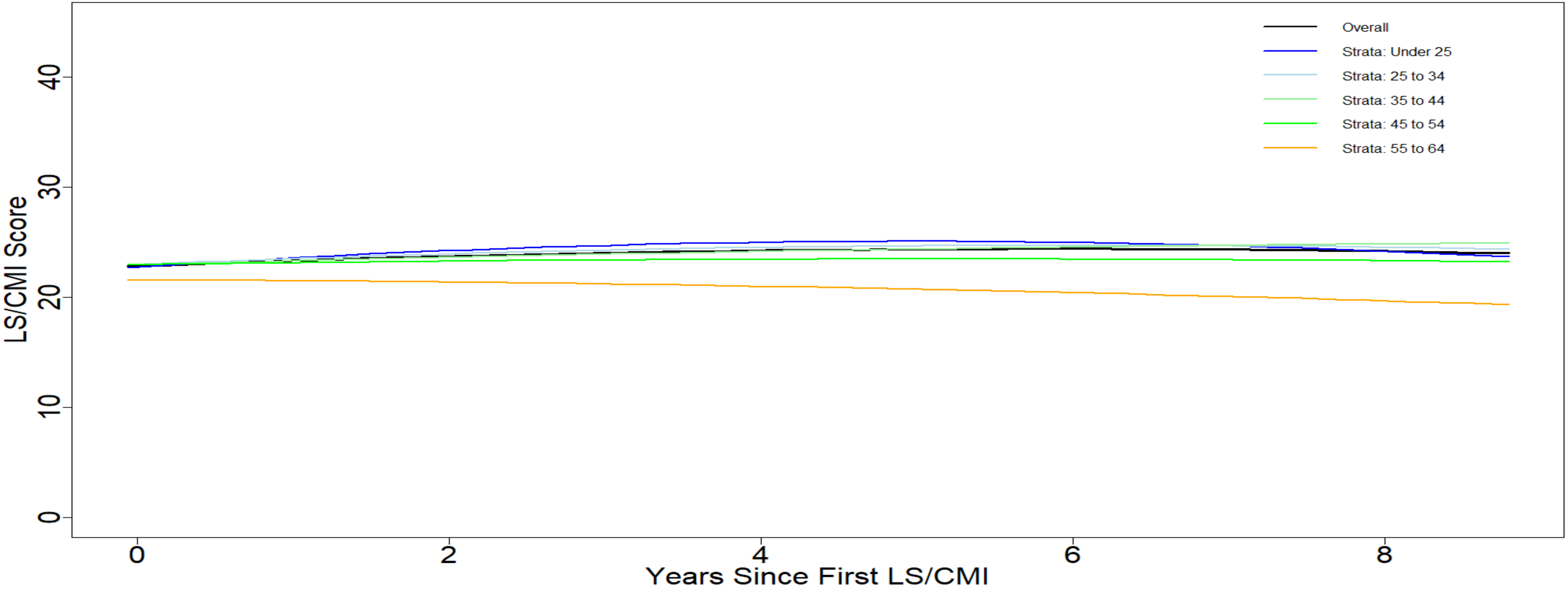
Question 1: Fitted Trajectories by Age



Question 1: Fitted Trajectories from first LS/CMI



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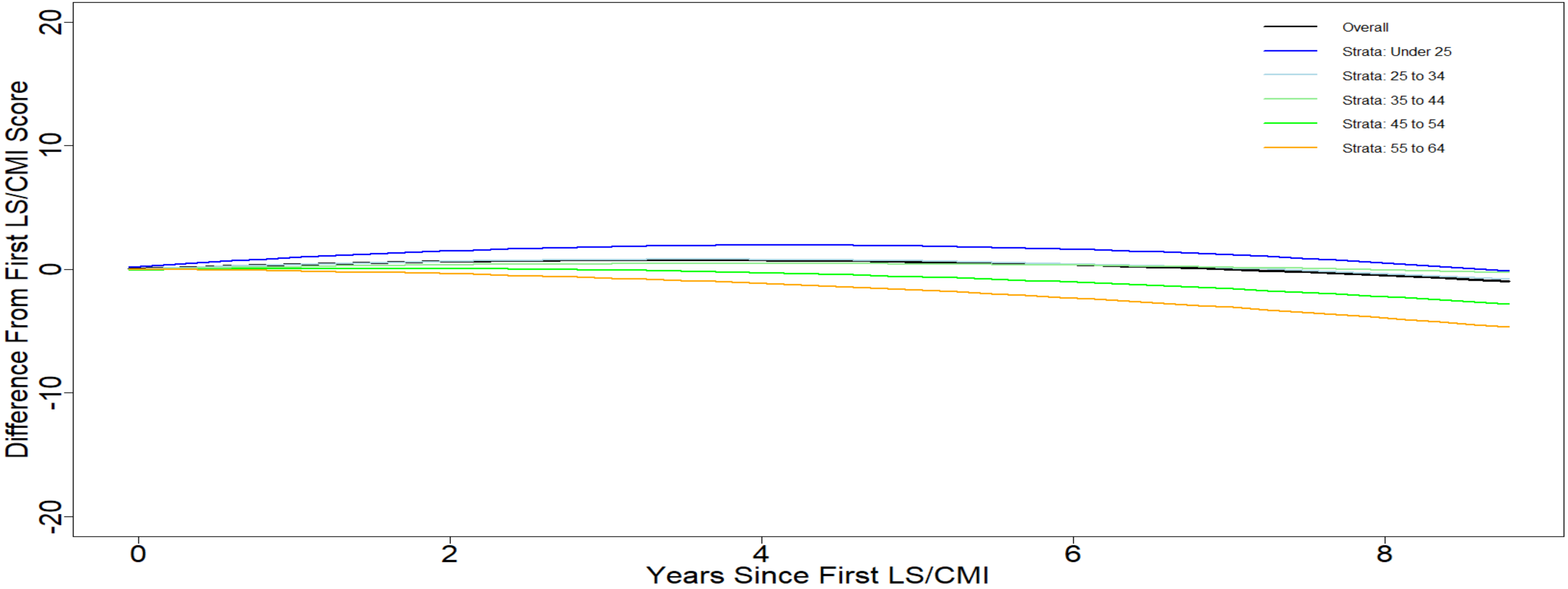
Question 1: Fitted Trajectories from first LS/CMI, with first LS/CMI set as a baseline



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Question 1: Conclusion

The average LS/CMI change over 4 to 8 years is small, even when our population is broken into similarly aged cohorts.

The average non-linear component of change (the quadratic "bend") is also small.

This indicates we cannot generalize the entire population of offenders as behaving in similar ways; even similarly aged cohorts do not show strong, consistent patterns we can generalize from.

Question 2 Sample: Testing Predictive Accuracy

Each year from 2009 to 2016, we took a snapshot of all adults actively supervised by Multco DCJ on January 1st. Each snapshot included the most recent LS/CMI risk score on or before that date. We then tracked those adults for an entire year (until December 31st), counting all arrests during that year regardless of whether that adult remained on supervision or moved elsewhere.

- This method was chosen to provide a representative sample of what DCJs population looks like, to ensure non-overlapping outcome windows, and to continue tracking outcomes even after negative events correlated with arrests (such as probation revocations or absconding) might remove an adult from a more rapidly updated measure of active supervision.

Question 2 Sample: Testing Predictive Accuracy

Our outcome variable is re-arrest recidivism, measured using arrests from LEDS (the Law Enforcement Data System), which collects all fingerprinted arrests in Oregon.

- We filtered out arrests for non-new-crime events such as probation violations.
- We coded recidivism as binary: 1 = at least one new arrest
  0 = no new arrests.

Total over this time period: 65,313 records across 29,457 unique people.
Removing records without valid LS/CMI scores:
34,905 records across 16,866 unique people.
Our analyses require multiple years of data, so we removed any person with fewer than 3 different years: 17,692 records across 4,936 unique people.

Question 2: Do all people with the same risk score have the same recidivism rate?

We know that higher risk scores indicate higher recidivism rates. We can measure recidivism rates at each score, but this is a population average. If the population of adults with a score of 25 have a 30% recidivism rate, does this mean that all adults with a score of 25 have exactly a 30% recidivism rate? Or does it mean that some have a 10% recidivism rate, some have a 30% recidivism rate, and some have a 50% recidivism rate?

In statistical terms:

Each person i has some unknown true recidivism rate p_i.

Each person i has a known LS/CMI score s_i and recidivism outcome o_i.

Each LS/CMI score s has some unknown true recidivism rate r_s.

Does $r_s = p_i$ for all i where $s_i = s$?

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Question 2: Methodology

To answer this question, I turned to a simulation. If we assume that every person with LS/CMI score s has the same recidivism rate r_s, then we can estimate that recidivism rate as $\widehat{r_s} = \overline{o_{\forall\, i \text{ where } s_i = s}}$.

- In practice, we averaged together every four points of the LS/CMI's 44 point scale, which gave us about 2000 observations per strata.
- Since people can change LS/CMI score, we calculated over person-years ij rather than simply persons i.

We simulated results for every o_{ij} as if every person-year had $p_{ij} = \widehat{r_{s_{ij}}}$. We can then find the simulated recidivism rate for every person, $\overline{p_i} = \frac{1}{n}\sum_{j=1}^{n} o_{ij}$.

After 1500 simulations, we compared the range of simulated $\overline{p_i}$s with observed $\overline{p_i}$s.

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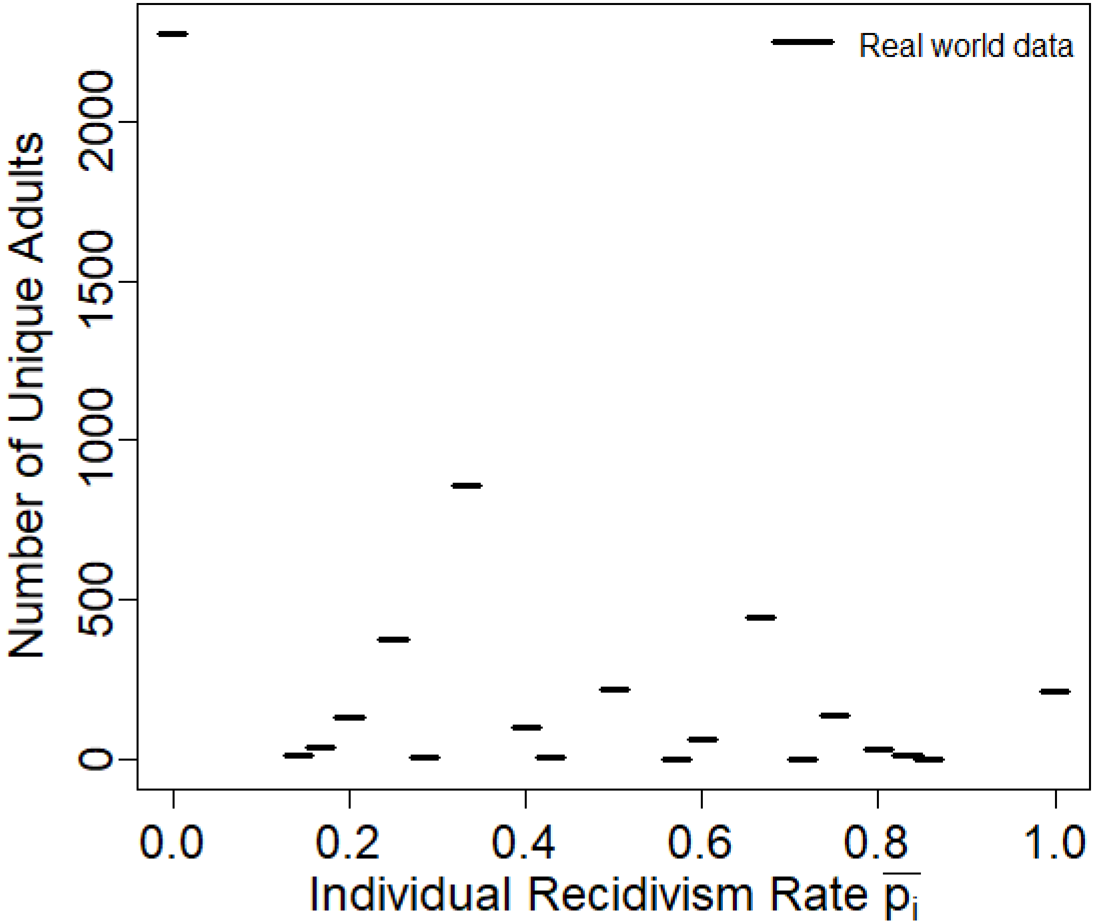
Question 2: Results Displayed

To display the results of our simulations, we first plot the number of adults by individual recidivism rate from our actual observed data.

Most adults have 3 years of data, many have 4, some have 5, and a few have 6 or 7. This effects the frequency of recidivism rates: most observations are a multiple of $^1/_3$ rd, many are a multiple of $^1/_4$ th, some are a multiple of $^1/_5$ th, and very few are multiples of $^1/_6$ th or $^1/_7$ th.

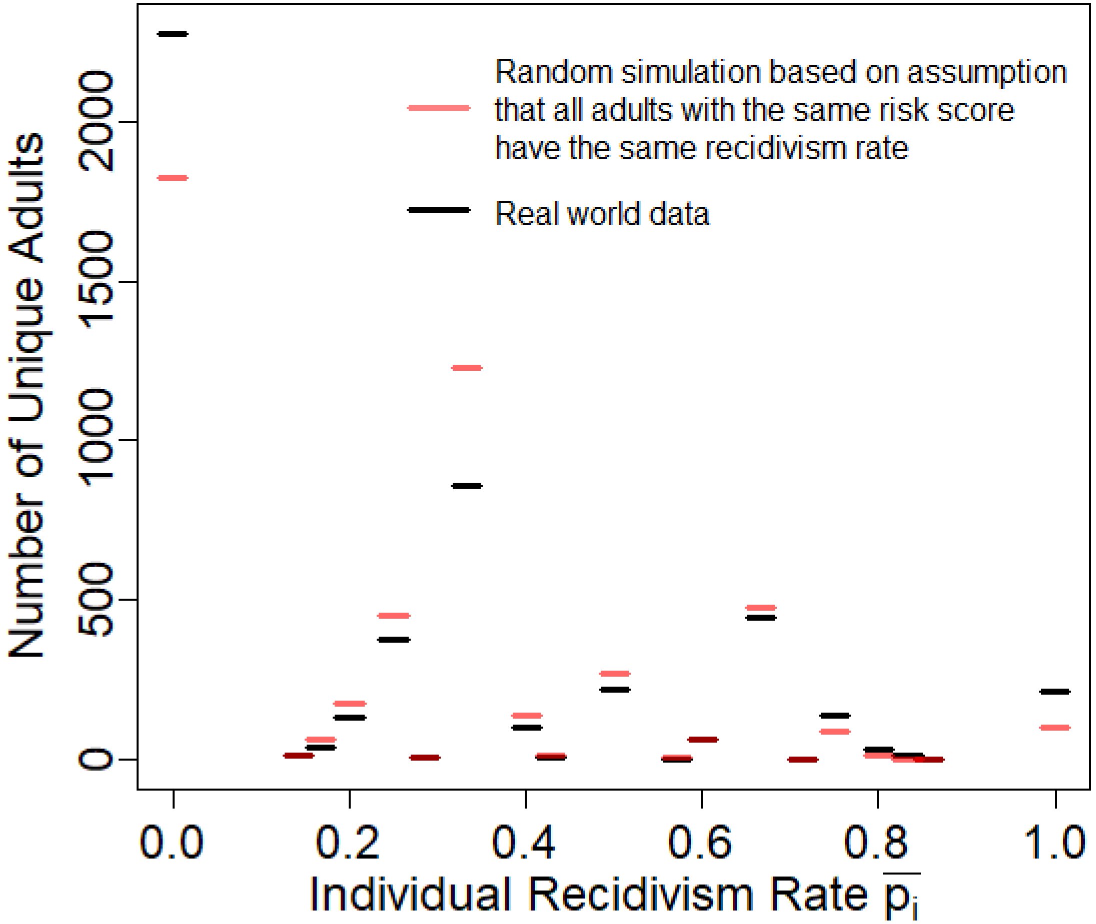


Question 2: Results Displayed

We can now add the same frequency plot, but using data from one of our randomly generated simulations.

We can see this simulation has fewer adults with low (0) or high (1) observed recidivism rates, but more adults with medium (.33) recidivism rates.

Is this the case for all simulations?

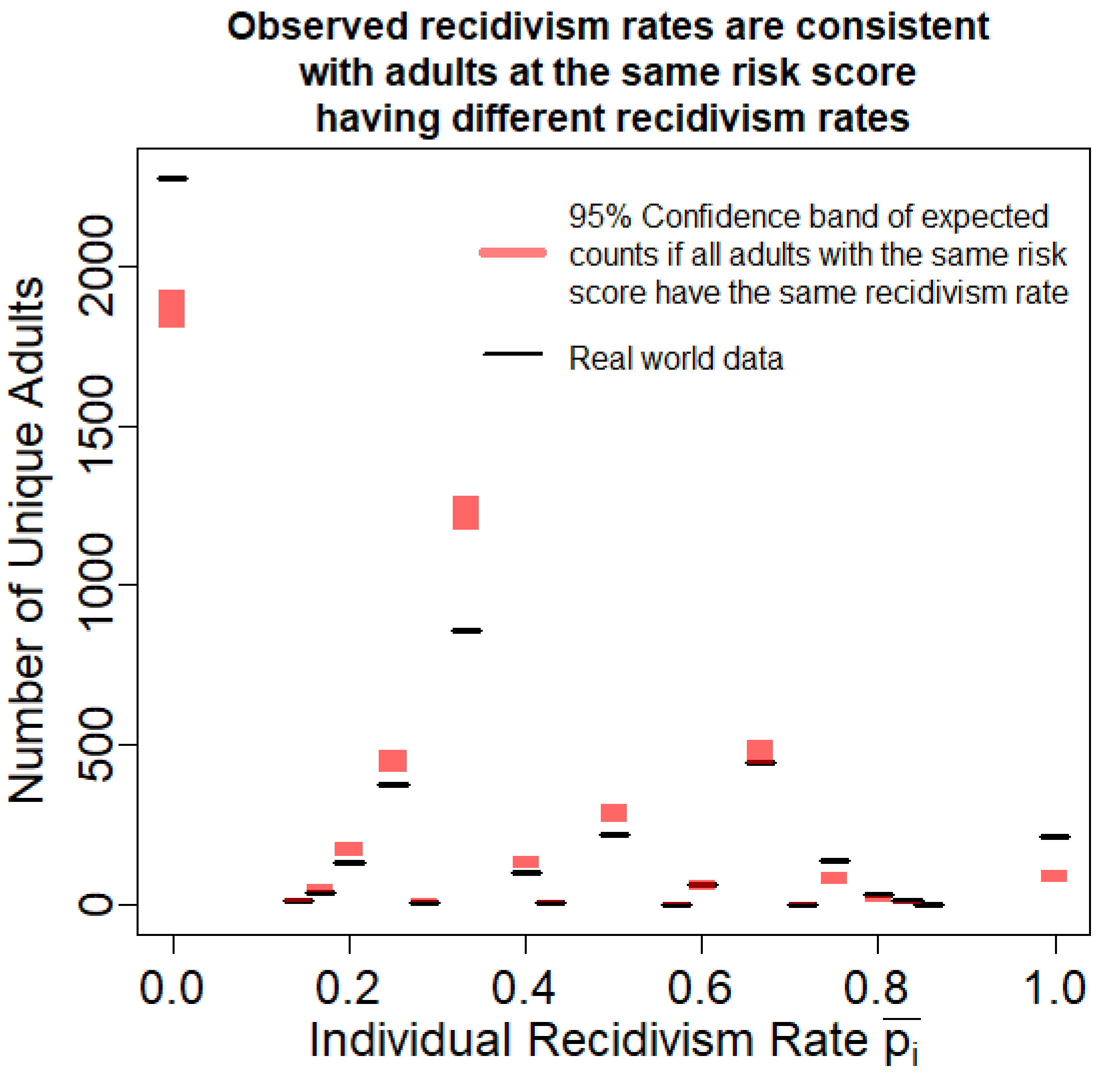


Question 2: Answered

By plotting the middle 95% of all simulations, we can create a 95% confidence band.

It can be clearly seen that our real data has far more people with recidivism rates of 0 and 1, and far fewer with recidivism rates near .33, than we would expect if the assumptions of the simulation matched reality.

Thus, we have evidence that the simulation *doesn't* match reality: people with the same risk score *don't* all have the same risk of recidivism. Rather, even with the same LS/CMI score, different people have a greater or lesser likelihood of recidivating.



Further Research: Are changes in risk score over time predictive?

DCJ takes risk scores on the same person over many years, but we should remember that these risk scores are created by looking at only a single time measurement. It is convenient to believe that changes in an adults risk score indicate changes in their criminal risk, but there is no guarantee this is the case. Some competing hypothesis:

- The chance of an adult recidivating given their most recent risk score is independent of previous risk scores.
- The chance of an adult recidivating is somewhere in between where their most recent risk score and previous risk scores indicate, whether simply from reversion to the mean or a more complicated covariance effect.
- The chance of an adult recidivating is fixed, and changes in risk score represent only noise and measurement error.

Thank you for attending!

Questions?