**Supplementary Digital Content**

**Substance use treatment completion and criminal justice system contact in Chile: A retrospective, linked data, cohort study**

### Section 1. Specifics on the data wrangling

We started with a cohort of SENDA patients used in other publications (1, 2). Then, we managed to link these patients with Prosecutor’s Office data regarding offences where patients were involved (as victims or offenders).

However, we focused on cases in which patients were found as offenders. We did not require any minimum duration of first SUT enrolment for study inclusion to reduce the risk of selection bias and strengthen the generalizability of results. Readers must know that dropouts occur due to voluntary or involuntary causes. Voluntary causes include when the patient explicitly states their will to discontinue treatment or non-attendance and/or lose contact with the patient for a period equal to or greater than 45 days. And involuntary causes include interruptions due to serious misconduct against treatment norms. Also, we excluded external referrals.

The time to event was defined after treatment outcome (completion or dropout). Thus, we avoided survival bias due to a dropout explained by the event (reverse causation).

The process is summarised in Supplementary Table 1.

Supplementary Table 1 Sample flow chart of main methodological decision per each database

|  |  |  |  |
| --- | --- | --- | --- |
| **Order** | **Description** | **Total patients** | **% Changed from the previous step** |
| **Database 1: Patients in substance use treatment** | | | |
| 1 | Individuals with ongoing SUT between 2010 and 2019 | 85,048 | 100% |
| **Database 2: Prosecutor's Office information** | | | |
| 1 | Patients of Database 1 that had records in the Prosecutor’s Office | 74,833 | 100% |
| 2 | Excluded records with dates of commission after November 13th, 2019 (n= 47) | 74,786 | 99.90% |
| 3 | Erased records with missing information, discrepancies in ages between SENDA, and aberrant ages of commission (n= 41) | 74,745 | 99.90% |
| 4 | Excluded records with at least one of the conditions: administrative annulment, grouped to another criminal case, commission dates earlier than January 01, 2010, and duplicated records (n=210) | 74,535 | 99.70% |
| 5 | Excluded records of patients with at least one of the following conditions: found as a victim (n=20,624), if the patient did not receive a sentence (n=23,667) | 49,970 | 67.04% |
| **Database 3: Joined database (Database 1 + Database 2)** | | | |
| 1 | Individuals with ongoing SUT between 2010 and 2019 | 85,048 | 100.00% |
| 2 | Excluded individuals referred by other prior SUT (n=8,657) | 76,391 | 89.82% |
| 3 | Excluded individuals with ongoing treatments at the date of information retrieval (November 13th, 2019) (n=5,521) | 70,870 | 92.77% |
| 4 | Excluded individuals with missing dates of birth (n=7) | 70,863 | 99.99% |
| 5 | Excluded patients without treatment outcomes (n=9) | 70,854 | 99.99% |

### Section 2. Statistical analysis: Proportional hazards test, model specification and model selection criteria

We divided this section into proportional hazards, model specification, and model selection criteria and added a summary of the survival models.

1. **Proportional hazards test**

First, we used Schoenfeld’s global goodness of fit test of proportional hazards. The test indicated a significant deviation from expected proportionality in the modelling of time to any contact with the criminal justice system (X²(d.f.=51) = 233.36, p<0.001), and time to contact leading to imprisonment (X²(d.f.=51)= 160.56, p<0.001). Thus, evidence do not support the proportional hazards assumption.

1. **Model specification**

We tested different model specifications, from 1 to 10 degrees of freedom to model time-dependent baseline distribution functions (i.e., restricted cubic spline on log cumulative hazard scale), and from 1 to 7 degrees of freedom (d.f.) to model time-dependent effects of treatment outcomes (both early and late dropout, vs. treatment completion). Then, we selected the models that showed the best trade-off between lower complexity and better fit. This is why we considered both the Bayesian Information Criteria (BIC) and the Akaike Information Criteria (AIC). If a model with fewer parameters had greater or equal AIC (or differences lower than 4) but also had better BIC (<=3), we favoured the model with fewer parameters. All models incorporated a transformation of Age into a restricted cubic spline variable with 4 knots due to nonlinearity, sacrificing interpretability for improvement in deviance (X²(d.f.=51) = 9.12, p=0.003).

Supplementary Table 2 AIC and BIC for survival models of the time to any contact with the justice system with different survival probability distributions

|  |  |  |
| --- | --- | --- |
| **Model Specification** | **AIC** | **BIC** |
| rp (df=9) tvc (df=1) | 135187.0 | 135691.7 |
| rp (df=10) tvc (df=1) | 135187.6 | 135700.4 |
| rp (df=9) tvc (df=3) | 135189.7 | 135726.5 |
| rp (df=9) tvc (df=2) | 135189.8 | 135710.6 |
| rp (df=10) tvc (df=3) | 135190.3 | 135735.1 |
| rp (df=8) tvc (df=1) | 135190.3 | 135687.1 |
| rp (df=10) tvc (df=2) | 135190.4 | 135719.2 |
| rp (df=9) tvc (df=4) | 135193.2 | 135746.0 |
| rp (df=8) tvc (df=3) | 135193.2 | 135722.0 |
| rp (df=8) tvc (df=2) | 135193.2 | 135705.9 |
| rp (df=7) tvc (df=1) | 135193.2 | 135681.9 |
| rp (df=10) tvc (df=4) | 135193.7 | 135754.6 |
| rp (df=9) tvc (df=5) | 135195.2 | 135764.1 |
| rp (df=9) tvc (df=6) | 135195.9 | 135780.7 |
| rp (df=10) tvc (df=5) | 135195.9 | 135772.7 |
| rp (df=7) tvc (df=2) | 135196.0 | 135700.8 |
| rp (df=7) tvc (df=3) | 135196.1 | 135716.8 |
| rp (df=10) tvc (df=6) | 135196.5 | 135789.4 |
| rp (df=8) tvc (df=4) | 135196.5 | 135741.3 |
| rp (df=6) tvc (df=1) | 135197.9 | 135678.6 |
| rp (df=8) tvc (df=6) | 135198.2 | 135775.0 |
| rp (df=8) tvc (df=5) | 135198.5 | 135759.3 |
| rp (df=7) tvc (df=4) | 135199.3 | 135736.0 |
| rp (df=9) tvc (df=7) | 135199.5 | 135800.4 |
| rp (df=7) tvc (df=5) | 135200.4 | 135753.2 |
| rp (df=10) tvc (df=7) | 135200.4 | 135809.3 |
| rp (df=7) tvc (df=6) | 135200.4 | 135769.3 |
| rp (df=6) tvc (df=3) | 135200.6 | 135713.4 |
| rp (df=6) tvc (df=2) | 135200.7 | 135697.5 |
| rp (df=8) tvc (df=7) | 135200.9 | 135793.8 |
| rp (df=6) tvc (df=4) | 135203.7 | 135732.5 |
| rp (df=5) tvc (df=1) | 135204.3 | 135677.0 |
| rp (df=6) tvc (df=5) | 135205.3 | 135750.1 |
| rp (df=7) tvc (df=7) | 135205.9 | 135790.7 |
| rp (df=6) tvc (df=6) | 135206.8 | 135767.6 |
| rp (df=5) tvc (df=3) | 135206.9 | 135711.6 |
| rp (df=5) tvc (df=2) | 135207.2 | 135696.0 |
| rp (df=5) tvc (df=4) | 135209.8 | 135730.6 |
| rp (df=6) tvc (df=7) | 135210.4 | 135787.3 |
| rp (df=5) tvc (df=7) | 135210.9 | 135779.8 |
| rp (df=5) tvc (df=6) | 135211.4 | 135764.2 |
| rp (df=5) tvc (df=5) | 135212.6 | 135749.4 |
| rp (df=4) tvc (df=7) | 135213.4 | 135774.3 |
| rp (df=4) tvc (df=6) | 135214.3 | 135759.1 |
| rp (df=3) tvc (df=7) | 135216.6 | 135769.4 |
| rp (df=3) tvc (df=6) | 135216.7 | 135753.5 |
| rp (df=4) tvc (df=5) | 135221.2 | 135750.0 |
| rp (df=3) tvc (df=5) | 135223.1 | 135743.9 |
| rp (df=4) tvc (df=3) | 135225.0 | 135721.8 |
| rp (df=4) tvc (df=1) | 135225.7 | 135690.4 |
| rp (df=4) tvc (df=2) | 135228.6 | 135709.3 |
| rp (df=4) tvc (df=4) | 135231.7 | 135744.5 |
| rp (df=3) tvc (df=4) | 135247.2 | 135751.9 |
| rp (df=3) tvc (df=1) | 135257.3 | 135714.0 |
| rp (df=3) tvc (df=3) | 135259.3 | 135748.0 |
| rp (df=3) tvc (df=2) | 135259.9 | 135732.6 |
| rp (df=2) tvc (df=6) | 135266.7 | 135795.5 |
| rp (df=2) tvc (df=7) | 135267.0 | 135811.8 |
| rp (df=2) tvc (df=5) | 135271.6 | 135784.4 |
| rp (df=2) tvc (df=4) | 135285.9 | 135782.6 |
| rp (df=2) tvc (df=3) | 135313.8 | 135794.5 |
| rp (df=1) tvc (df=6) | 135425.7 | 135946.4 |
| rp (df=1) tvc (df=7) | 135426.1 | 135962.9 |
| rp (df=1) tvc (df=5) | 135430.7 | 135935.4 |
| rp (df=2) tvc (df=2) | 135439.3 | 135904.0 |
| rp (df=2) tvc (df=1) | 135439.5 | 135888.1 |
| rp (df=1) tvc (df=4) | 135444.4 | 135933.1 |
| rp (df=1) tvc (df=3) | 135466.7 | 135939.4 |
| rp (df=1) tvc (df=2) | 135593.9 | 136050.6 |
| rp (df=1) tvc (df=1) | 136344.2 | 136784.9 |

*rp = Restricted cubic splines in the baseline cumulative hazards; tvc= Restricted cubic splines in time-varying coefficients.*

The best model had 8 degrees of freedom in the baseline hazard function (with potentially 7 nodes, possibly located at 12.5th, 25th, 37.5th, 50th, 62.5th, 75th, and 87.5th percentiles of the log-time distribution) and an effect that represents a monotonic increase or decrease (1 d.f.) of treatment outcomes (shape) over follow-up time.

Supplementary Table 3 Adjusted coefficients, time to any contact with the justice system

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Term (exp)** | **Estimate** | **95%CI lo** | **95%CI up** | **Sig.** |
| Early dropout | 1.74 | 1.66 | 1.83 | <0.001 |
| Late dropout | 1.58 | 1.52 | 1.65 | <0.001 |
| time-independent: knot 1 | 2.66 | 2.59 | 2.73 | <0.001 |
| time-independent: knot 2 | 1.11 | 1.10 | 1.12 | <0.001 |
| time-independent: knot 3 | 1.05 | 1.04 | 1.06 | <0.001 |
| time-independent: knot 4 | 1.02 | 1.02 | 1.03 | <0.001 |
| time-independent: knot 5 | 1.01 | 1.01 | 1.02 | <0.001 |
| time-independent: knot 6 | 1.01 | 1.01 | 1.01 | <0.001 |
| time-independent: knot 7 | 1.01 | 1.01 | 1.01 | <0.001 |
| time-independent: knot 8 | 1.00 | 1.00 | 1.01 | <0.001 |
| time-independent: Early discharge | 0.91 | 0.88 | 0.94 | <0.001 |
| time-independent: Late discharge | 0.94 | 0.92 | 0.97 | <0.001 |
| time-dependent: knot 1 | 0.98 | 0.95 | 1.00 | <0.001 |
| time-dependent: knot 2 | 0.11 | 0.10 | 0.12 | <0.001 |
| time-dependent: knot 3 | 0.05 | 0.04 | 0.05 | <0.001 |
| time-dependent: knot 4 | 0.02 | 0.02 | 0.03 | <0.001 |
| time-dependent: knot 5 | 0.01 | 0.01 | 0.02 | <0.001 |
| time-dependent: knot 6 | 0.01 | 0.01 | 0.01 | <0.001 |
| time-dependent: knot 7 | 0.01 | 0.01 | 0.01 | <0.001 |
| time-dependent: knot 8 | 0.00 | 0.00 | 0.01 | <0.001 |
| time-dependent: Early discharge (log) | -0.10 | -0.13 | -0.07 | <0.001 |
| time-dependent: Late discharge (log) | -0.06 | -0.09 | -0.03 | <0.001 |

Note: knots represent knot areas (knots+1).

The model identified an association of 1.74 (95% CI 1.66, 1.83) for early vs. completion, and 1.58 (95% CI 1.52, 1.65) for late vs. completion. In this case, however, the shape seems to show a monotonic decrease in the association of Early and Late dropout vs. treatment completion, in which the hazard ratio will likely decrease over time (See Supplementary Table 3).

Supplementary Table 4 Akaike and Bayesian Information Criteria for survival models of the time to contact with the justice system leading to imprisonment with different survival probability distributions.

|  |  |  |
| --- | --- | --- |
| **Model Specification** | **AIC** | **BIC** |
| rp (df=9) tvc (df=1) | 43635.0 | 44034.3 |
| rp (df=8) tvc (df=1) | 43635.1 | 44027.9 |
| rp (df=7) tvc (df=1) | 43635.4 | 44021.6 |
| rp (df=6) tvc (df=1) | 43635.7 | 44015.4 |
| rp (df=10) tvc (df=1) | 43637.0 | 44042.8 |
| rp (df=9) tvc (df=2) | 43638.5 | 44050.8 |
| rp (df=8) tvc (df=2) | 43638.6 | 44044.4 |
| rp (df=7) tvc (df=2) | 43638.8 | 44038.1 |
| rp (df=6) tvc (df=2) | 43639.2 | 44031.9 |
| rp (df=10) tvc (df=2) | 43640.4 | 44059.4 |
| rp (df=5) tvc (df=1) | 43641.3 | 44014.4 |
| rp (df=9) tvc (df=3) | 43641.5 | 44066.9 |
| rp (df=8) tvc (df=3) | 43641.6 | 44060.5 |
| rp (df=7) tvc (df=3) | 43642.0 | 44054.3 |
| rp (df=9) tvc (df=4) | 43642.1 | 44080.7 |
| rp (df=6) tvc (df=3) | 43642.2 | 44048.0 |
| rp (df=7) tvc (df=4) | 43642.3 | 44067.8 |
| rp (df=8) tvc (df=4) | 43642.5 | 44074.5 |
| rp (df=6) tvc (df=4) | 43642.6 | 44061.6 |
| rp (df=10) tvc (df=3) | 43643.4 | 44075.4 |
| rp (df=10) tvc (df=4) | 43644.2 | 44089.3 |
| rp (df=5) tvc (df=4) | 43644.6 | 44057.0 |
| rp (df=5) tvc (df=2) | 43644.7 | 44030.9 |
| rp (df=7) tvc (df=5) | 43645.0 | 44083.6 |
| rp (df=6) tvc (df=5) | 43646.1 | 44078.1 |
| rp (df=9) tvc (df=5) | 43646.2 | 44097.8 |
| rp (df=8) tvc (df=5) | 43646.3 | 44091.4 |
| rp (df=7) tvc (df=6) | 43646.8 | 44098.4 |
| rp (df=9) tvc (df=6) | 43647.5 | 44112.3 |
| rp (df=5) tvc (df=3) | 43647.8 | 44047.1 |
| rp (df=8) tvc (df=6) | 43648.0 | 44106.2 |
| rp (df=10) tvc (df=5) | 43648.0 | 44106.2 |
| rp (df=6) tvc (df=6) | 43648.9 | 44094.0 |
| rp (df=4) tvc (df=1) | 43649.6 | 44016.1 |
| rp (df=5) tvc (df=6) | 43650.2 | 44088.7 |
| rp (df=10) tvc (df=6) | 43650.4 | 44121.7 |
| rp (df=4) tvc (df=6) | 43650.4 | 44082.4 |
| rp (df=8) tvc (df=7) | 43650.5 | 44121.8 |
| rp (df=5) tvc (df=5) | 43652.1 | 44077.6 |
| rp (df=7) tvc (df=7) | 43652.6 | 44117.4 |
| rp (df=9) tvc (df=7) | 43652.9 | 44130.7 |
| rp (df=4) tvc (df=2) | 43653.0 | 44032.6 |
| rp (df=3) tvc (df=6) | 43653.0 | 44078.5 |
| rp (df=5) tvc (df=7) | 43653.8 | 44105.4 |
| rp (df=4) tvc (df=7) | 43654.1 | 44099.2 |
| rp (df=10) tvc (df=7) | 43654.2 | 44138.6 |
| rp (df=6) tvc (df=7) | 43654.6 | 44112.8 |
| rp (df=4) tvc (df=3) | 43654.9 | 44047.6 |
| rp (df=3) tvc (df=7) | 43656.0 | 44094.5 |
| rp (df=3) tvc (df=5) | 43656.6 | 44069.0 |
| rp (df=4) tvc (df=4) | 43656.7 | 44062.5 |
| rp (df=3) tvc (df=1) | 43657.0 | 44017.0 |
| rp (df=4) tvc (df=5) | 43657.8 | 44076.7 |
| rp (df=2) tvc (df=6) | 43659.1 | 44078.0 |
| rp (df=3) tvc (df=2) | 43660.4 | 44033.5 |
| rp (df=2) tvc (df=7) | 43662.3 | 44094.3 |
| rp (df=2) tvc (df=5) | 43662.4 | 44068.2 |
| rp (df=3) tvc (df=4) | 43662.9 | 44062.1 |
| rp (df=3) tvc (df=3) | 43663.4 | 44049.6 |
| rp (df=2) tvc (df=4) | 43665.9 | 44058.7 |
| rp (df=1) tvc (df=6) | 43669.3 | 44081.7 |
| rp (df=2) tvc (df=3) | 43670.0 | 44049.6 |
| rp (df=1) tvc (df=7) | 43672.6 | 44098.0 |
| rp (df=1) tvc (df=5) | 43672.8 | 44072.1 |
| rp (df=1) tvc (df=4) | 43676.1 | 44062.3 |
| rp (df=1) tvc (df=3) | 43679.4 | 44052.5 |
| rp (df=2) tvc (df=1) | 43690.1 | 44043.5 |
| rp (df=2) tvc (df=2) | 43693.2 | 44059.7 |
| rp (df=1) tvc (df=2) | 43702.8 | 44062.8 |
| rp (df=1) tvc (df=1) | 43818.5 | 44165.4 |

*rp = Restricted cubic splines in the baseline cumulative hazards; tvc= Restricted cubic splines in time-varying coefficients.*

The best model had 6 degrees of freedom in the baseline hazard function (with 5 nodes potentially located at the 17th, 33rd, 50th, 67th, and 83rd percentiles of the log-time distribution), and an effect that represents a constant increase or decrease (1 d.f.) of treatment outcomes (shape) over follow-up time.

Supplementary Table 5 Adjusted coefficients, time to contact with the justice system leading to imprisonment.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Term (exp)** | **Estimate** | **95%CI lo** | **95%CI up** | **Sig.** |
| Early dropout | 1.99 | 1.79 | 2.22 | <0.001 |
| Late dropout | 1.65 | 1.51 | 1.81 | <0.001 |
| time-independent: knot 1 | 2.18 | 2.07 | 2.30 | <0.001 |
| time-independent: knot 2 | 1.07 | 1.06 | 1.09 | <0.001 |
| time-independent: knot 3 | 1.03 | 1.02 | 1.05 | <0.001 |
| time-independent: knot 4 | 1.02 | 1.01 | 1.03 | <0.001 |
| time-independent: knot 5 | 1.01 | 1.01 | 1.02 | <0.001 |
| time-independent: knot 6 | 1.01 | 1.01 | 1.01 | <0.001 |
| time-independent: Early discharge | 0.90 | 0.85 | 0.95 | <0.001 |
| time-independent: Late discharge | 0.92 | 0.87 | 0.97 | 0.004 |
| time-dependent: knot 1 | 0.78 | 0.73 | 0.83 | <0.001 |
| time-dependent: knot 2 | 0.07 | 0.06 | 0.08 | <0.001 |
| time-dependent: knot 3 | 0.03 | 0.02 | 0.04 | <0.001 |
| time-dependent: knot 4 | 0.02 | 0.01 | 0.03 | <0.001 |
| time-dependent: knot 5 | 0.01 | 0.01 | 0.02 | <0.001 |
| time-dependent: knot 6 | 0.01 | 0.01 | 0.01 | <0.001 |
| time-dependent: Early discharge | -0.11 | -0.17 | -0.05 | <0.001 |
| time-dependent: Late discharge | -0.08 | -0.14 | -0.03 | 0.004 |

Note: knots represent time frames covered until reaching each knot (knot# +1).

The model found an association of 1.99 (95% CI 1.79, 2.22) in early dropout vs. completion, and 1.65 (95% CI 1.50, 1.81) in late dropout vs. completion. Nevertheless, the shape seems to show a monotonic association of early and late discharge vs. treatment completion, in which the hazard ratio will likely decrease over time (See Supplementary Table 5).

### Section 3. Sensitivity analysis

We divided this section into the analysis of missing data and the original and extended Cox model.

1. **Analysis of missing data: Alternative analysis with complete cases & imputing comorbidities in study**

We tested the sensitivity of our results to missing data bias, so we compared two models with the main analysis: (i) using complete cases (no imputation) and (ii) imputing missing data with unknown (under study) severe physical and psychiatric comorbidity given that we suspected informative missingness. The informative missingness presumption relies on the fact that we observed that in the case of the variable "Psychiatric Comorbidity (ICD-10)", the people with early dropout had much more unknown diagnoses (reaching 60.2%) than the groups that dropped out late (9.5%) and those who completed (1.8%). Something similar was observed for “Severe physical comorbidity”, despite the differences between groups were much narrower, but it was plausible that the same mechanisms could exists (i.e., subject to the availability of a professional capable of diagnosing).

Thus, the imputation was carried out using chained random forests through the missRanger package. We used 200 trees, 3 candidate values of predictive matching (thus, avoiding unlikely numbers), with a maximum of 50 iterations per chaining steps. (3-5)

After 5 iterations, we obtained fairly low standardized mean squared errors reductions (Mdn= 5e-04 Q1= 0, Q3= 0.0024).

We compared the probabilities and restricted mean survival times to those obtained by imputing missing data only.

Regarding the first outcome variable (any contact with the criminal justice system), differences were similar in terms of direction and significance, with less survival and average survival at different time points for those who drop out when compared to those who complete, while more survival and average survival at different years for those who had a late dropout vs. those who drop out early (See Supplementary Table 6).

Supplementary Table 6 Differences in survival probabilities, time to any contact with the justice system for complete case analysis (a) and with imputed values replacing comorbidities in study (b)

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | **a)** |  |  | **b)** |  |  |
| **Time** | **Comp. vs Late** | **Comp. vs Early** | **Early vs Late** | **Comp. vs Late** | **Comp. vs Early** | **Early vs Late** |
| Probs. |  |  |  |  |  |  |
| 1\_yr | -5.3 (-5.9,-4.8) | -6.8 (-7.6,-6.1) | 1.5 (0.9,2.2) | -5.6 (-6.1,-5.1) | -7.6 (-8.3,-7.0) | 2.0 (1.5,2.6) |
| 3\_yrs | -8.2 (-9.0,-7.4) | -9.9 (-10.9,-8.8) | 1.7 (0.7,2.6) | -8.6 (-9.3,-7.9) | -11.1 (-11.9,-10.2) | 2.4 (1.7,3.2) |
| 5\_yrs | -9.1 (-10.0,-8.2) | -10.5 (-11.8,-9.3) | 1.5 (0.4,2.5) | -9.6 (-10.4,-8.8) | -11.9 (-12.9,-11.0) | 2.4 (1.5,3.2) |
| RMST |  |  |  |  |  |  |
| 1\_yr | -0.034 (-0.037,-0.030) | -0.045 (-0.050,-0.040) | 0.011 (0.006,0.016) | -0.035 (-0.039,-0.032) | -0.050 (-0.054,-0.045) | 0.014 (0.010,0.019) |
| 3\_yrs | -0.171 (-0.187,-0.154) | -0.214 (-0.236,-0.192) | 0.044 (0.023,0.064) | -0.180 (-0.195,-0.165) | -0.239 (-0.258,-0.221) | 0.060 (0.043,0.076) |
| 5\_yrs | -0.340 (-0.372,-0.309) | -0.414 (-0.457,-0.371) | 0.074 (0.036,0.112) | -0.359 (-0.387,-0.330) | -0.465 (-0.500,-0.430) | 0.107 (0.076,0.137) |

Regarding the second outcome variable (contact leading to imprisonment), differences were similar in terms of direction and significance, with less survival and average survival at different time points for those who dropout when compared to those who complete, while more survival and average survival at different years for those who had a late dropout vs. those who dropout early (See Supplementary Table 7).

Supplementary Table 7 Differences in survival probabilities, time to contact with the justice system leading to imprisonment for complete case analysis (a) and with imputed values replacing comorbidities in study (b)

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | **a)** |  |  | **b)** |  |  |
| **Time** | **Comp. vs Late** | **Comp. vs Early** | **Early vs Late** | **Comp. vs Late** | **Comp. vs Early** | **Early vs Late** |
| Probs. |  |  |  |  |  |  |
| 1\_yr | -1.2 (-1.4,-1.0) | -1.8 (-2.1,-1.4) | 0.5 (0.2,0.9) | -1.2 (-1.5,-1.0) | -2.0 (-2.3,-1.7) | 0.8 (0.5,1.0) |
| 3\_yrs | -2.1 (-2.5,-1.7) | -3.1 (-3.6,-2.5) | 0.9 (0.4,1.4) | -2.2 (-2.5,-1.8) | -3.5 (-3.9,-3.0) | 1.3 (0.9,1.7) |
| 5\_yrs | -2.6 (-3.1,-2.1) | -3.7 (-4.3,-3.0) | 1.1 (0.5,1.7) | -2.6 (-3.1,-2.2) | -4.3 (-4.8,-3.7) | 1.6 (1.1,2.1) |
| RMST |  |  |  |  |  |  |
| 1\_yr | -0.007 (-0.009,-0.006) | -0.011 (-0.013,-0.009) | 0.004 (0.001,0.006) | -0.008 (-0.009,-0.006) | -0.012 (-0.014,-0.010) | 0.005 (0.003,0.007) |
| 3\_yrs | -0.041 (-0.049,-0.033) | -0.059 (-0.070,-0.049) | 0.018 (0.009,0.028) | -0.042 (-0.049,-0.034) | -0.068 (-0.077,-0.059) | 0.026 (0.018,0.034) |
| 5\_yrs | -0.087 (-0.103,-0.071) | -0.125 (-0.147,-0.104) | 0.038 (0.018,0.058) | -0.089 (-0.103,-0.074) | -0.144 (-0.162,-0.126) | 0.055 (0.039,0.071) |

### **Original and extended Cox model**

As a sensitivity analysis, we obtained the hazard ratios from the original Cox model under the proportional hazards assumption and adjusting for covariates. Additionally, the R package "coxphw" was used to conduct a weighted Cox analysis while accounting for non-proportional hazards and adjusting for covariates. This method uses inverse probability weighting to adjust for censoring and to estimate robust standard errors, ruling out outlying survival times that may affects the value of parameter estimates. The method has been shown to be effective in both parametric and non-parametric survival models, and It has been used in a variety of applications, including studies of cancer, COVID-19, heart disease, and HIV/AIDS (6-9).

Using the Cox model under the proportional hazard assumption, patients with late and early dropouts had a 53% (HR= 1.53 95% CI 1.47, 1.59) and 66% (HR= 1.66 95% CI 1.58, 1.74) greater likelihood of any contact with the criminal justice system vs. those who completed treatment, respectively, while 58% (HR= 1.58 95% CI 1.45, 1.72) and 88% (HR= 1.88 95% CI 1.70, 2.09) greater likelihood of contact with the criminal justice system leading to imprisonment vs. those who completed treatment.(6)

However, these hazards dropped in terms of magnitude but not in direction. Also, none of them overlaps the null association (See Supplementary Table 8).

Supplementary Table 8 Averaged adjusted HRs from weighted Cox model.

| **Term** | **Time to…** | **Estimation** | **95% CI** |
| --- | --- | --- | --- |
| Early dropout vs. tr. completion | Condemnatory Sentence | 1.70 | 1.59, 1.81 |
| Late dropout vs. tr. completion | Condemnatory Sentence | 1.54 | 1.46, 1.62 |
| Early dropout vs. tr. completion | Imprisonment | 1.82 | 1.57, 2.11 |
| Late dropout vs. tr. completion | Imprisonment | 1.48 | 1.31, 1.66 |

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