Outcome Evaluation of the Trade Institute of Pittsburgh's Programs on Recidivism

FINAL REPORT

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Executive Summary

Project Overview

The objective of our project was to evaluate the effectiveness of the Trade Institute of Pittsburgh (TIP) program in reducing recidivism among program graduates. Due to data restrictions, we could only evaluate criminal justice outcomes for TIP classes up to September 2018.

We conducted two main analyses. The first compared TIP program graduates to nongraduates, defined as those individuals who started but did not finish the TIP program. We evaluated offense rates over time to identify signaling effects and regression analysis to determine causality. We found no statistically significant evidence that TIP's programs produced signaling effects or causally reduced recidivism in its graduates, relative to its nongraduates.

Our second analysis looked at TIP program graduates who had at least one prior offense. We compared the offense rates of these graduates with a matched group made up of individuals in the general Allegheny County population. We tried to identify signaling effects by analyzing offense rates over time, and we conducted linear regression robustness checks. We again saw no statistically significant evidence that TIP acts as a signaling mechanism or that it causes reductions in recidivism risk.

We acknowledge the limitations of our analysis that stem from our restricted dataset and small sample sizes. We also recognize the complexity of criminal behavior, which extends beyond employment (as is TIP's focus) and which is influenced by various personal, social, and economic factors.

Recommendations

From our literature review and conversations with TIP and our advisory board, we posit the following recommendations for TIP:

1. Conduct analyses that include more recent versions of the program to assess if recent programming changes have had an impact.
2. Qualitatively investigate why graduates recidivate after completing the TIP program.
3. Continue checking in on graduates post-graduation to provide support.
4. Incorporate services into programming that focus on risk factors for recidivism outside employment.
5. Target services for reducing recidivism to those with the highest risk of recidivism.

Introduction

About the Trade Institute of Pittsburgh (TIP)

The **Trade Institute of Pittsburgh** (*TIP*) is a nonprofit organization and vocational training provider located in the Homewood neighborhood of Pittsburgh. TIP serves individuals who face significant barriers to employment, including individuals who are formerly incarcerated. It offers tuition-free courses in **masonry** (11-week program) **and carpentry** (7-week program). These vocational courses are supplemented by **additional life skills training and social service support**, including financial literacy education, interview coaching, and driver's license assistance (Trade Institute of Pittsburgh). From our team's conversations with TIP, we know that they strive to prepare their students not only for the trades but also for successful lives after the program.

Project Objective

As TIP centers on individuals with barriers to employment, they have a sizable number of students who are formerly incarcerated. Because of this, and because of its overall mission, TIP was interested in the effect of its programs on **recidivism**. Recidivism is "a person's relapse into criminal behavior, often after the person receives sanctions or undergoes intervention for a previous crime" (*Recidivism*). The goal of our project, then, was to **evaluate the effect TIP's program has on reducing recidivism** for their program graduates. Because some graduates entered the program without a criminal history, however, we also conducted analyses measuring the impact of the program on future offense rates more broadly.

TIP Project from 2023

This project is building off analyses done in a previous Heinz Capstone Project with TIP focused on labor market outcomes. According to this previous project, on average, graduates had a slight increase in earnings that dissipated over time. The analysis shows a **bimodal distribution of graduates' outcomes**, dividing them into "Top Half" and "Bottom Half" based on their post-graduation earnings trajectories. After dividing TIP graduates into these groups, it was found that labor market outcomes varied drastically between the groups. Quarterly earnings for graduates in the "Top Half" increased significantly, 140.45% more than they earned before joining TIP. In contrast, the earnings of the "Bottom Half" of graduates initially increase slightly but gradually decrease over time, eventually going below pre-graduation earnings levels.

Another notable finding is the **role of a driver's license** in boosting earnings potential; on average, having a license increased earnings by around $600.

Finally, in looking at broader employment and economic outcomes, the analysis found that a large number of TIP graduates found **jobs outside construction**. Their **reliance on social assistance programs** was also reduced after TIP program completion.

Relevant Findings in Literature

To provide more context for our project, we reviewed relevant literature on recidivism and its relationship to workforce training programs. Looking at recidivism in general, research suggests **the most reliable predictors** for recidivism are age, time since last conviction, and number of prior convictions. The risk of recidivism decreases as age or time since the last conviction increases (Bushway, 2024). At the same time, the risk increases as the number of past convictions increases (Stolzenberg et al., 2020).

Risk factors for recidivism are classified on a scale from major (e.g., history of antisocial behavior) to moderate (e.g., substance abuse) to minor (e.g., social class). Employment–or, more specifically, unemployment–is a **moderate risk factor** for recidivism (Duwe & Henry-Nickie, 2021). This is especially challenging because the path back to the labor market for formerly convicted individuals is **fraught with obstacles**, including not only widespread hiring discrimination but also educational and skill deficits relative to their peers (Bushway & Apel, 2012; Bushway & Kalra, 2021; Duwe & Henry-Nickie, 2021).

When it comes to workforce training programs and their effects on recidivism, the literature presents **mixed results**. When a positive effect is found, it is usually mild (Bushway & Apel, 2012; Holliday et al., 2023). The lack of significant effects is complex. Criminal behavior stems from a **variety of personal and environmental factors** that are difficult to alter (Bushway & Apel, 2012; Duwe & Henry-Nickie, 2021). Additionally, even if a workforce training program does reduce recidivism, it does so very **indirectly**. It relies on the individual to first become employed and then additionally have that employment decrease the individual's risk of recidivism (Bushway & Apel, 2012).

Imagine, for instance, a workforce training program increases employment by 20%, and employment decreases recidivism by 20%. These are both sizable impacts independently, but, because we want to see them together, their probabilities are multiplied (0.2 X 0.2). We are thus looking for a 4% overall decrease in recidivism, which is hard to find in research, especially with small samples. This illustrates that **although a workforce training program makes an impact, the impact is often indiscernible** (Bushway & Apel, 2012).

Despite this, workforce training programs can still be highly useful for individuals because of their **signaling effects**. Formerly incarcerated individuals who self-select into workforce training programs may be more likely to **desist**, desistance being "a permanent state of nonoffending" (Bushway & Apel, 2012; *Recidivism*). Normally, this motivation is internal and hidden. However, graduating from a workforce training program allows individuals to demonstrate to employers **their commitment to desist** (Bushway & Apel, 2012; Bushway, 2024). This benefits everyone involved; desisters are more likely to be employed, and employers know which individuals to hire (Bushway & Apel, 2012).

There is some evidence that completion of a training program really is a **strong signal to employers** (Bushway, 2024; Bushway & Apel, 2012). As a 2024 RAND brief states, completion of a training program is a "more-predictive factor[...] of a low risk of reoffending than some other factors that employers could consider" (Bushway, 2024, p. 5).

Data

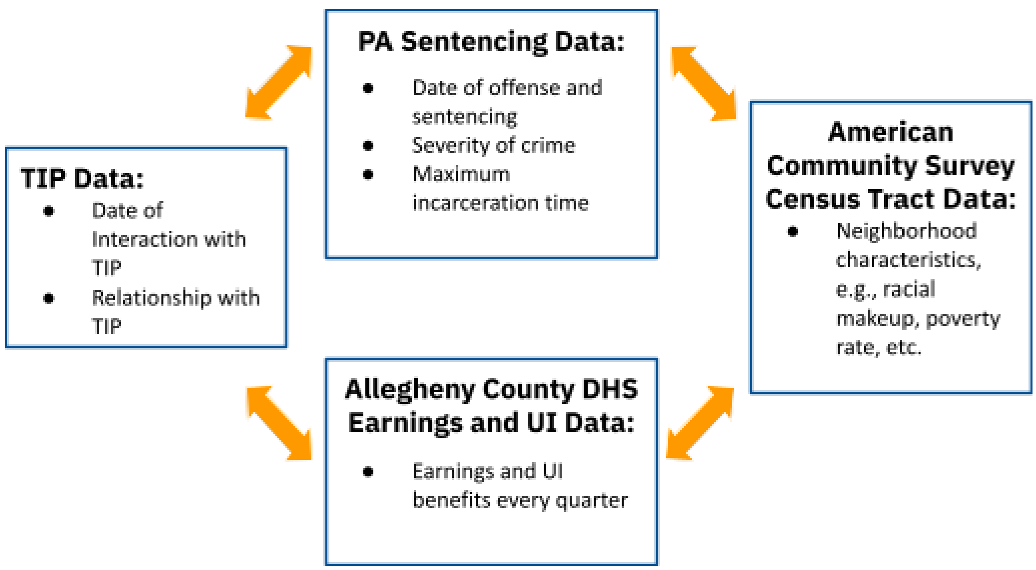
Overview of Datasets and Variables

To capture a wide range of variables in our analyses, we used four different data sets: Pennsylvania Commission on Sentencing (PCS) Data, TIP Data, Allegheny County Department of Human Services (DHS) Demographics, Income and Unemployment Insurance (UI) Data, and American Community Survey data on the Census Tract level.

We used the PCS dataset to gauge offense records for TIP participants and other individuals in Allegheny County. The PCS dataset provides information about **convictions in the state of Pennsylvania**, including: date of offense, date of sentencing, maximum incarceration time for the type of crime, and severity of crime. When considering crime severity, note that we **did not have access to the specific offenses** for which individuals were convicted, due to privacy concerns. However, we did have access to each offense's **Offense Gravity Score** (OGS). The OGS ranges from 1 to 15, with 15 being the most severe type of crime, first- or second-degree murder (Law Offices of Marni Jo Snyder, 2023). Our PCS dataset included **offenses from 1998 through September of 2019**.

TIP's internal dataset provided us with information on **enrolled students and interviewees**, including their demographic characteristics (such as age, race, and sex) and participant completion status. Though the dataset ranged from 2009 through the present, we focused on those who interacted with TIP from **2009 through 2018**. These data sets form the core of our recidivism analysis, as we connected TIP participant records to PCS and Allegheny County DHS data.

The Allegheny County DHS datasets helped us determine the **economic and social welfare dimensions of those individuals in our analyses**. The Earnings and UI Data provides information on reported earnings and UI benefits individuals in Allegheny County receive every quarter. We had access to data from **2018 to 2022**, so we focused largely on these measures in individuals' post-TIP periods. The American Community Survey Census Tract Data allowed us to see neighborhood characteristics such as racial makeup or poverty rate. We used the 5-year American Community Survey estimates based on data from 2014-2018 to best align with the time periods we analyzed for recidivism.



Graphic 1: Datasets Used in Our Analyses

Note: Convictions vs. Background Checks

Because we are discussing the variables and datasets we used, we want to touch briefly on a point of confusion from the beginning stages of the project. During early conversations with TIP, we found that our count of people in the TIP dataset with a criminal background **differed substantially** from TIP's count. According to our discussions with criminologists, the likely reason behind this is that while TIP had used background checks to determine criminal background, we used **convictions**. We chose to look at convictions because background checks include arrests, and arrests are not necessarily indicative of criminal behavior. This is a common method in recidivism research, and we undertook it under the advice of our advisory board.

Important Limitations

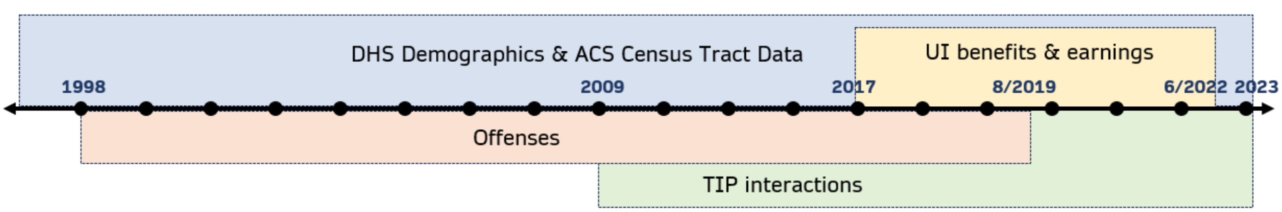
As with any project, our datasets are not perfect. Before continuing onto our analyses, we want to note and address the **following limitations**:

Incomplete Data Coverage

Our datasets span different time periods, with a few select overlaps. This is visualized in **Graphic 2** below. The most important data limitation to mention is our limited coverage in our offenses dataset. As previously mentioned, this data formed the crux of our recidivism analysis. However, the coverage of this dataset **only extends to September 2019**.

The reason behind this is that criminologists are **confused by trends in crime data starting in 2020**; as a result, the Pennsylvania Commission on Sentencing (PCS) and criminologists on our advisory board did not have that data readily available to us when we undertook our project. Because procuring additional offense data from the PCS is a lengthy process, we were unable to extend the duration of our analysis beyond 2019.

The consequences of our limited dataset is that we **could not examine 3-year recidivism** rates for any TIP graduating class **after September 2016**. We also could not assess **any form of recidivism rates** at all for TIP graduating classes **after September 2018**. This is an important caveat to keep in mind as we review our analyses; the most recent graduating class in our data completed the program over five years ago.



Graphic 2: Incomplete Data Coverage

Another noteworthy limitation of our data coverage that we want to highlight is regarding our DHS UI benefits and earnings data. Statistics regarding UI benefits and earnings only refer to the TIP participants who **interacted with TIP in 2017 and 2018**. This is because DHS only started tracking UI benefits and earnings a few years before the pandemic, and as a result, the only full years of data overlap that we have with TIP graduates are 2017 and 2018.

Small Sample Size

We also want to acknowledge the small sample size we utilized for this evaluation. After the TIP dataset was cleaned and we incorporated additional variables, we kept only the individuals in the dataset who could be **accurately identified as a TIP graduate or non-graduate**. This shrank the dataset down from 2052 individuals to 1262 individuals. When we further only included those for whom recidivism rates could be reliably calculated (those people interacting with TIP from 2009 through 2018), we had just **547 individuals for 1-year recidivism data** and **297 individuals for 3-year recidivism data**. These numbers are even smaller for our second Outcome Analysis, where we only consider **TIP graduates with prior convictions** (186 individuals for 1-year recidivism data, 74 individuals for 3-year recidivism).

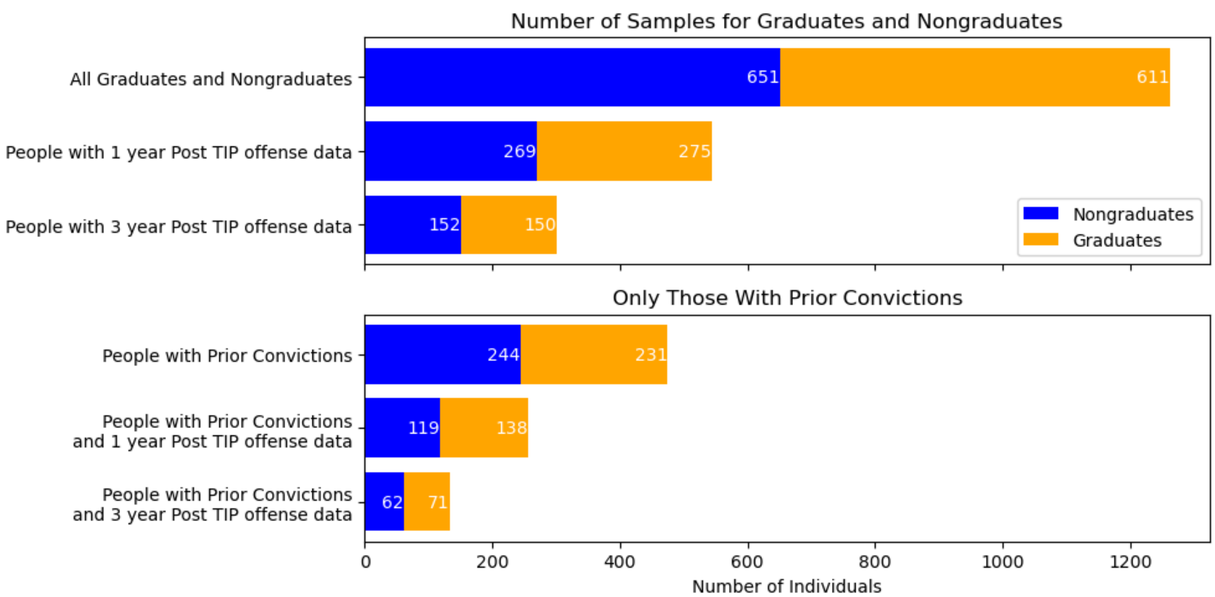


Figure 1: Sample Sizes across Graduate/Nongraduate Groups and Offense Statuses

Demographic Statistics

Across the TIP Dataset

Who interacts with TIP? Our demographic analysis of the TIP dataset–in connection with our other datasets–gives us a glimpse. Importantly, we want to note that this analysis considers the **TIP dataset in its entirety**, which means it looks at TIP since its inception. As such, current or incoming TIP classes may have different demographic makeups than what we show here.

Race, Gender, and Age

The **majority of the people who connect with TIP are Black**. The following table provides a more complete racial breakdown of the dataset:

Black	White	Other Race
89.93%	9.03%	1.04%

Table 1: Racial Breakdown of the TIP Dataset

People who interact with TIP are also largely **male**, with men making up 90.89% of the dataset. Only about 9.11% are female. Looking at age, we see that **50% of people in the dataset are between 22 and 31 years old** at the time of interacting with TIP. The youngest person is 18 years old, the oldest is 48 years old, and the average is 27 years old.

Age and gender are two demographic characteristics that we know are **changing in the last few years**. As we have learned in discussions with TIP, more and more women are joining the program. Recent classes have also had a higher proportion of individuals in their late teens and early twenties than in previous years.

Income and Employment

On average, people who interact with TIP make an **average annual salary of $14,093** before they connect with the organization. This is well below the per-capita average income of Allegheny County (U.S. Census Bureau).

More than half– about 56.87% – report employment for at least 3 months of the year before they interact with TIP. For context, Allegheny County's unemployment rate in 2024 is about 3.0%

(Pennsylvania Department of Labor & Industry, 2024). Note that because of our limited employment data, this statistic is only representative of those who interacted with TIP from 2017 - 2023.

Those with 1 or More Convictions

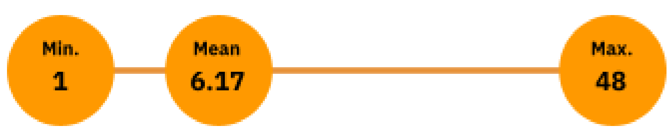
As our project centers around recidivism and offense rates, we also looked at how the TIP dataset breaks down for those who have interacted with TIP ***and*** have had 1 or more convictions.

General

Less than half of people in the TIP dataset (about **38.67%, or 488 individuals**) have 1 or more convictions in the PA Sentencing database. 473 people of these individuals, or **37.48% of the dataset**, have a conviction *before* they interact with TIP. This indicates that **around 40% of the people who connect with TIP are formerly convicted at the time of interaction.** We note that 40% may be a slight underestimate of the true rate of prior offenses due to our methodology of linking TIP individuals to offenses records via name and birthdate matching, an inherently imperfect process despite our careful analysis to catch errors**.**

The median time between these individuals' most recent conviction and their interaction with the TIP is **32.09 months**. This is about 2.6 years.

Across the TIP dataset, the number of offenses varies. The minimum number of offenses for a single individual is 1, and the maximum is 48. For people with at least one offense in the TIP dataset, the mean number of offenses for an individual is **6.17 offenses**.



Graphic 3: Offenses per Person in the TIP Dataset

Offense Gravity Scores

Figure 2 below shows the distribution of severity scores for individuals in the TIP dataset with 1 or more convictions. As the graph demonstrates, generally, individuals in the TIP dataset are convicted of **low-severity offenses**. The **most common OGS is 3.0**. Crimes with an OGS of 3.0 include simple assault and drug possession (Ratcliffe, 2014).

The minimum OGS we see in the data is **1.0**, which is the same level of severity as possession of drug paraphernalia. The maximum OGS is **14.0**, equivalent to the crime of attempting to commit homicide (Ratcliffe, 2014).

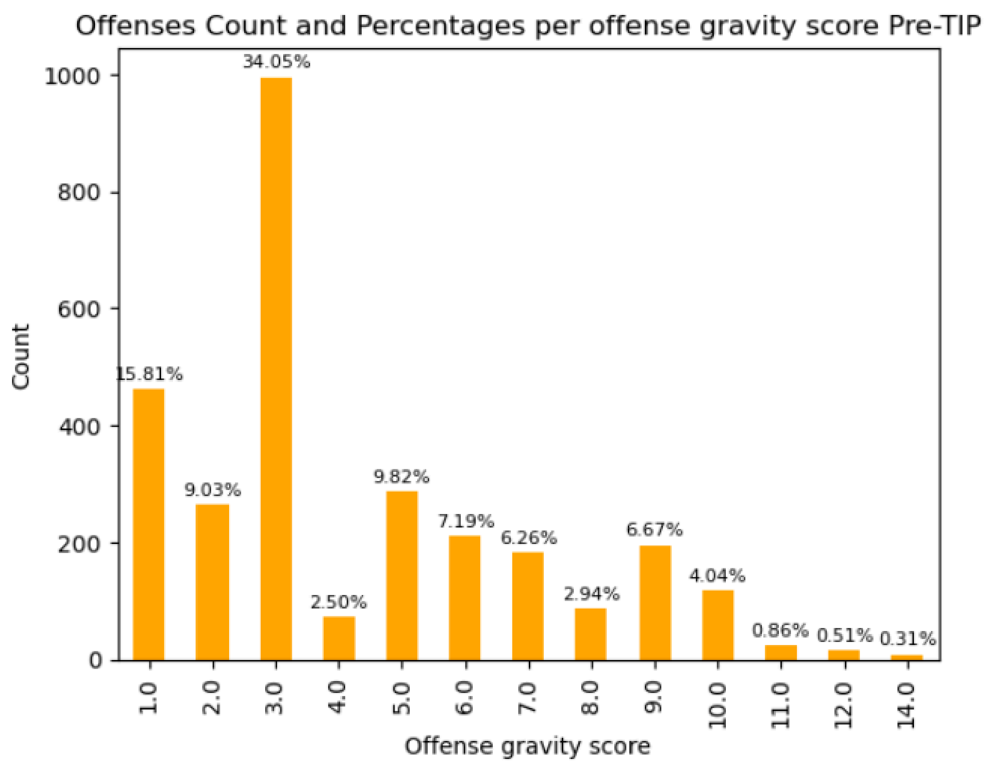


Figure 2: Distribution of OGS for People with 1 or More Convictions

Outcome Analysis 1: Graduates & Non-Graduates

Our first outcome analysis sought to find the impact of completing the TIP program on recidivism by comparing **TIP graduates** and **non-graduates**.

We compared these groups through two perspectives: a **descriptive analysis**, where we looked for observational differences in the groups' outcomes, and regression analysis, where we looked for a causal link between graduating the TIP program and recidivism.

Our analyses focused on the **following questions**:

- At what rate do TIP graduates reoffend relative to nongraduates?
- How does this vary with the severity of the offense?

- *For the regression analysis only:* How does recidivism depend on the individual characteristics of the graduate?

Groups of Interest

Our two groups of interest are TIP graduates and nongraduates. With our data restrictions, and after reducing the TIP dataset to those with one or more convictions, we had **231** individuals in our graduate group and **244** in our non-graduate group.

TIP graduates are defined as those who have completed the TIP program. In the TIP dataset, these individuals had an associated program start date and graduation date. As they experienced the whole program, they acted as our treatment group.

Non-graduates, on the other hand, are defined as those who have started the TIP program but did not complete the program. In the dataset, they have a program start date but no graduation date. The median non-graduate only spends 2 weeks in the program.

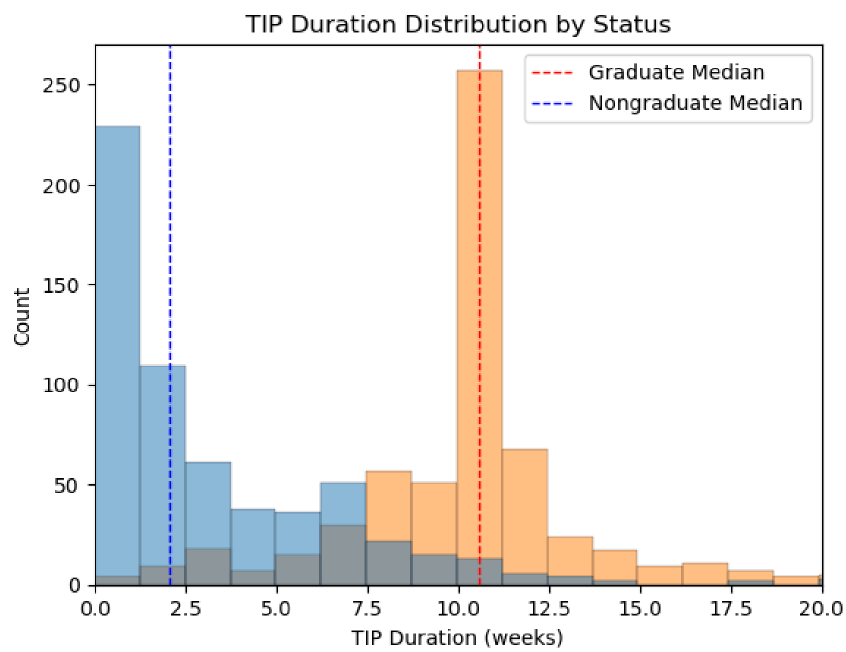


Figure 3: Distribution of TIP Duration by Graduation Status

Non-graduates are our comparison group. They are similar to graduates in terms of observable characteristics, as seen in Table 2, but for whatever reason they did not complete the full program. They are thus used as a measure of what the graduates' offense and recidivism rates would have been if they had not completed the TIP program.

Graduates	Non-graduates
37.81% have 1 or more convictions pre-TIP	37.17% have 1 or more convictions pre-TIP
88.60% Black	91.18% Black
91.90% male	89.94% male
Median age: 27; average age: 28	Median age: 25; average age: 26
Average annual salary of $16570.80 pre-TIP	Average annual salary of $11784.37 pre-TIP

Table 2: Observable Characteristics of Graduates vs. Non-graduates

While the two groups are similar on these characteristics, we have to note that we are making an **assumption** that they are similar on unobservable characteristics as well. An important limitation, then, is that this assumption may not hold. Non-graduates could leave the program for a variety of reasons: repeatedly violating TIP rules, tending to extenuating circumstances, pursuing other opportunities, or losing motivation, to name a few. The presence of certain characteristics–lack of motivation or access to other opportunities, for example–may make them a weaker comparison group than we would otherwise see.

Signaling Analysis

Offense Rates over Time

The first part of our signaling analysis focused on **offense rates** pre- and post-TIP interaction for graduates and non-graduates. A group's offense rate for a specific time period is equal to the percentage of the group that was convicted of an offense in that time period. In plainer terms, and using **Figure 4** as an example, the offense rate for graduates "3 years before TIP interaction" (at -2.5) is the percentage of graduates who were convicted of an offense in the window of time between 2 and 3 years before they started TIP.

Looking at **Figure 4** as a whole, we can compare the offense rates of the two groups over time, from 10 years before an individual begins TIP to 4 years after they finish, or leave, the program. The wide bands around the lines are **95% confidence intervals**; they provide us margins of error for determining what the true offense rates might be for the larger TIP population, given our smaller sample sizes. If we added more enrollees into our analysis, the statistical estimates displayed may go up or down slightly, but we expect them to most likely remain within these bands.

What **Figure 4** shows us is that the groups' offense rates **look fairly similar** over time. Both are gradually increasing before TIP and then decreasing after TIP. They also both see a big dip before and during TIP, at the -1.5 mark. Though we do not know why for certain, we hypothesize that this might be because of two reasons: (1) the period before and during TIP is associated with maximum support and motivation to desist; (2) a sizable amount of TIP individuals are incarcerated during this pre-period and enter the program directly upon release.

After interacting with TIP, the graduate line is below the non-graduate line, indicating lower offense rates. However, the confidence bands have large overlap, meaning the groups' rates are statistically indistinguishable from each other.

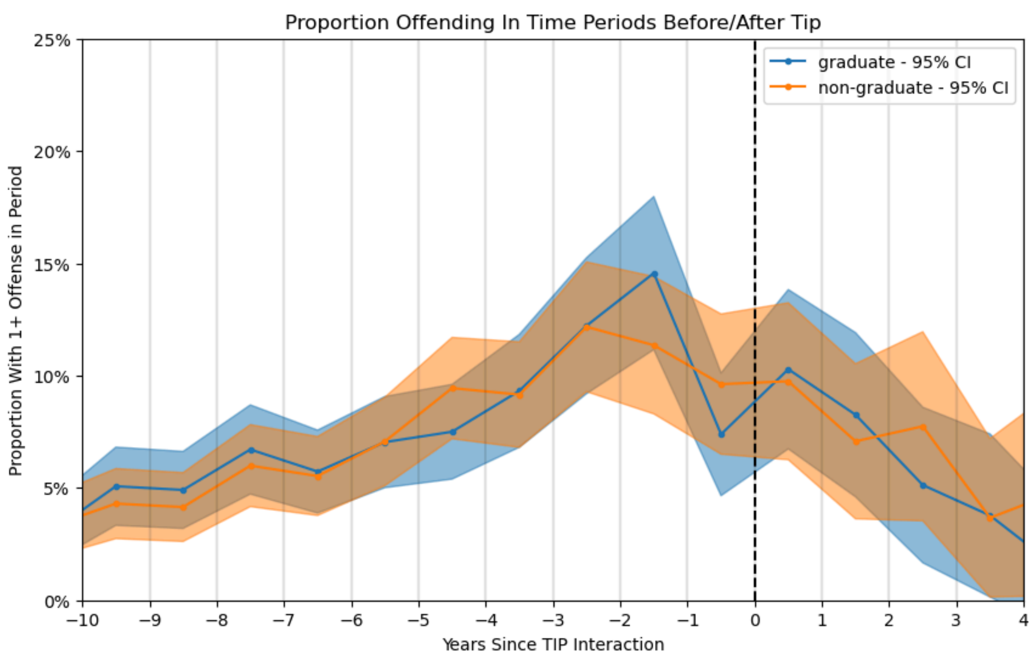


Figure 4: Offense Rates of Graduates vs. Non-graduates Over Time

Figure 5 presents a similar graph but only for **severe offense rates**. We consider **severe offenses** to be those with OGS of 6 or above, as that is when crimes get notably more serious (e.g., vehicular homicide, arson, burglary) (Jerry H. Ratcliffe, 2014).

As we can see, severe offense rates follow the **same pattern** as overall offense rates: a gradual increase in the pre-TIP period, a stark decline before TIP, and then a general decrease after. Again, here, graduates have a consistently lower severe offense rate post-TIP–even more so than regarding overall offense rates. However, according to the confidence intervals, the two groups are still **statistically indistinguishable**.

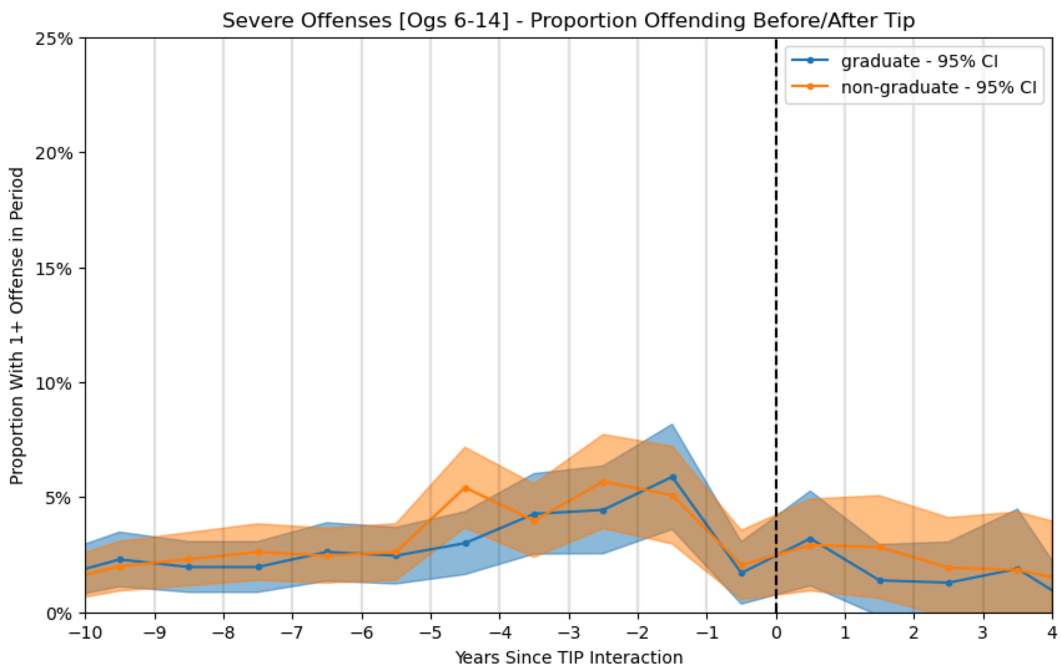


Figure 5: Severe Offense Rates of Graduates vs. Non-graduates Over Time

Time Period Analyses

We also conducted signaling analyses looking at **general pre- and post-TIP interaction periods**. Our conversations with criminologists noted the industry practice of looking at 3-year offense rates for recidivism studies. Thus, we considered the offense rates of TIP graduates and non-graduates 3 years before they began the TIP program and 3 years after they graduated or left.

Note that if an offense was committed at all during either 3-year period, it was included in the offense rate. For example, if a TIP graduate committed an offense 1 year after graduation, it was reflected in the 3-year post-TIP offense rate.

Table 3 demonstrates our findings. Regarding the overall offense rate, we find that the two groups see a **decline after interacting with TIP**. They are not statistically different from each other, with both graduates and non-graduates seeing about a 9 percentage-point decrease in the post-TIP period.

The severe offense rates follow a similar path. Both groups have **lower severe offense rates in the post-TIP period**. They are statistically very similar. We find it notable, though, that TIP graduates have a much starker decline than non-graduates. The **3-year severe offense rate is 2 times smaller** after graduation.

	Offense Rates			
	Graduates		Non-Graduates	
	3 Years Pre-TIP	3 Years Post-TIP	3 Years Pre-TIP	3 Years Post-TIP
All	25.5% *+/- 5.1%*	18.6% *+/- 6.1%*	23.8% *+/- 5.0%*	15.5% *+/- 5.7%*
Severe Only (OGS 6+)	12.1% *+/- 3.8%*	5.8% *+/- 3.7%*	12.3% *+/- 3.9%*	7.7% *+/- 4.2%*

Table 3: +/- 3-Year Time Period Analyses

Statistical Regression Analysis

For the next branch of our first outcome analysis, we created **two logistic regression models**. Logistic regression is a statistical method that calculates the likelihood (as log odds) of seeing a certain outcome (*IBM*).

The value in using regression analysis in addition to simply calculating the offense rates between groups is that we are theoretically able to **control for other factors** that affect offense rates besides being a program graduate, such as age and prior criminal history. When performed correctly, regression analysis can help us answer the question of "All else being equal between two individuals, what is the impact of graduation on the probability of offending ?" We used a 95% confidence level to establish whether a relationship had statistical significance.

Our dependent variables, or the outcomes for which we wanted to know the associated probability, for our first regression model were **offending 1 year after TIP and 3 years after TIP**. Our dependent variables for the second model were similar but focused only on **severely offending**.

The dependent variables are binary (0 if an offense is not committed, 1 if an offense is committed). We coded the information as we did for our time-period analyses. For example, if a TIP graduate commits an offense 18 months after TIP, we coded it as a 0 for offending 1-year post-TIP but as a 1 for offending 3-years post-TIP.

In each regression, we had the following independent variables:

- **TIP graduation**: This is our independent variable of interest. We want to know whether there is a causal relationship between graduating from TIP and the probability of offending. This is a binary variable: coded as a 1 if an individual graduated from TIP and 0 if they started but did not finish the program.
- **Age at TIP**: This is a control variable. It is continuous, meaning we input their age at the time of interacting with TIP. This is an important control variable, as age is highly correlated with offending (Bushway, 2024).
- **Prior offense**: This is also a control variable. It is binary: 1 if a person had committed an offense before beginning TIP and 0 if not. Prior offenses are also strongly correlated with probability of offending (Stolzenberg et al., 2020).

Model 1: All Offenses

The results of our first logistic regression model are displayed in Table 4. Results that are significant at a 95% confidence level are bolded and signified with a *. For context, an odds of less than 1 indicates that the independent variable (e.g., TIP graduation) decreases the likelihood that the dependent variable (e.g., an offense within 1 year of TIP interaction) occurs. An odds of greater than 1 indicates the opposite.

From the table, we see that TIP graduation **does not have a statistically significant relationship** with the probability of offending 1 or 3 years post-TIP. There is also no significant association between probability of offending post-TIP and age. Prior offense, however, does have a significant relationship with the likelihood of offending after TIP interaction. It appears that an individual with a prior offense is 6 times more likely to offend 1 year post-TIP and 5 times more likely to offend 3 years post-TIP than someone without a prior offense.

Outcome Variable	Graduation (odds ratio)	Age (odds ratio)	Pre-TIP Offense (odds ratio)
Offense 1 year post-TIP	0.92	0.96	**5.89***
Offense 3 years post-TIP	1.16	0.98	**4.79***

*Table 4: Logistic Regression Model 1 Results. Bolded results with a * denote statistical significance at a 95% confidence level.*

Model 2: Severe Offenses

Table 5 presents the results of our second logistic regression model, which had the same independent variables but instead focused on likelihood to commit severe offenses 1 and 3 years after TIP interaction. Here we also find **no significant relationship** between TIP graduation and the likelihood to commit a severe offense 1- and 3-years post-TIP.

We do see a significant association between age and probability of committing a severe offense. Older individuals are less likely to be convicted of a severe offense. A 1-year increase in age is associated with a 9 percentage point decrease in the probability of committing a severe offense 1 or 3 years post-TIP. On a more meaningful scale, a 10-year increase in age is associated with an almost 60% lower likelihood of severe offense.

We also see a significant relationship between having been convicted of a severe offense pre-TIP and the probability of committing a severe offense 1 year post-TIP. An individual who has a prior severe offense at the time of interacting with TIP is 3 times more likely to commit a severe offense 1 year post-TIP.

Outcome Variable	Graduation (odds)	Age (odds)	Pre-TIP Severe Offense (odds)
Severe Offense 1 year Post-TIP	0.87	**0.91***	**3.43***
Severe Offense 3 years Post-TIP	0.82	**0.91***	2

*Table 5: Logistic Regression Model 2 Results. Bolded results with a * denote statistical significance at a 95% confidence level.*

Summary of Findings from Outcome Analysis 1

Regarding the statistical regression analysis, we saw **no significant relationship** between graduating from TIP and offending. This is, to some extent, expected. As relayed by Bushway and Appel (2012), it is very difficult to capture a causal effect on recidivism when it comes to workforce development programs. This is exacerbated by the small sample size we have, due to our data restrictions.

In the signaling effect analysis, we see the offense rates for graduates and non-graduates are **not statistically different** from each other. Both groups demonstrate lower overall offense rates in the post-TIP period, compared with the pre-TIP period.

When we think about why we may not have found statistically different post-TIP offense rates for graduates and non-graduates, we pinpoint two possible explanations. One, we have a **small sample and a limited dataset**, one that ends with TIP graduating classes of 2017. If the TIP program has become more involved in combating recidivism since then, it would not be reflected in the results. Two, there may be a substantial number of non-graduates that are **similar to graduates in their motivation to desist**. We do not know why certain people leave the program; they may find alternative employment opportunities. This may encourage them to desist in a parallel way as TIP would have.

Outcome Analysis 2: General Comparison Group

Following our first outcome analysis, we determined **two possible paths** for further research: (1) find a more general comparison group to identify signaling effects; (2) undergo a more complete causal analysis of TIP program completion on (re)conviction. TIP expressed interest in the first approach, particularly because–as we learned from the relevant literature–identifying causal effects for workforce development programs is difficult.

As in Outcome Analysis 1, our treatment group for this outcome analysis is **TIP graduates with at least one conviction before TIP**.

This restriction is important because it allows us to build a refined comparison group from the general Allegheny County population using a statistical technique called **matching**. Matching allowed us to pair each TIP graduate with 10 reference people in Allegheny County who share similar demographics, socio-economic statuses, and criminal backgrounds but have one distinct difference: The people in the comparison group never enrolled in TIP. More information about how we crafted our comparison group is described in the following Matching section.

Using this comparison group, we compared the **offense rates** of the TIP participants at 1 and 3 years post-TIP with their paired comparison individuals. We looked for evidence of **signaling effects** using observational techniques.

Matching

Technique

Like we had described earlier, we used a **matching technique** to build our comparison group. We merged DHS data on Allegheny County residents with relevant PCS offense data and took out anyone who had interacted with TIP. This became our pool of possible references.

We then matched each TIP graduate with 10 people in this pool based on characteristics such as **age, race, gender, neighborhood characteristics, and "pre-TIP" offense at a specific time of life**. A chart of the characteristics we matched on, as well as the weights given to each characteristic (the higher the weight, the more important it was to have an exact match) can be found in **Appendix I**. In general, we placed a higher weight on criminal histories as they are the most predictive of future criminal behavior. We also tried multiple combinations of weights for robustness and observed only minor changes to our results.

We used the characteristics and their associated weights to create **similarity scores** between TIP graduates and every individual with one or more convictions in Allegheny County. We then matched each TIP graduate to 10 distinct individuals that scored the highest in similarity to them.

Key Assumption

When we are considering characteristics related to "pre-TIP" offenses at a specific time of life for individuals who never did TIP, we are making an underlying assumption. We assume that the "post-TIP" offense record of the reference people for a TIP graduate are what the post-TIP offense record for that TIP graduate would have been had they not done the TIP program at all.

To contextualize that assumption, imagine there is a 25 year-old Black male in Allegheny County who is in a low-income census tract and who has been convicted of two offenses. He sees information about TIP and thus is confronted with a **fork-in-the-road decision**: He can either join the TIP program or ignore and continue on his way. A TIP graduate in our sample is the person who joins and finishes the TIP program. We see his post-TIP period, but we cannot see what his trajectory would have been if he had chosen not to do the program.

When we are matching, then, we find one or more reference people who are Black males, in their mid-twenties, in Allegheny County, who reside within a similar low-income census tract, and who had two convictions at around the same time that our TIP graduate did. We then assume their fork-in-the-road moment was around the same time of our TIP graduate, and their offenses after that period is their "post-TIP" offense record. We assume this "post-TIP" offense record is **representative** of what our graduate's offense record would have been if they had chosen not to do the TIP program.

Matching Results

We successfully matched every TIP graduate with 10 individuals in the Allegheny County dataset. The matches look **incredibly similar** to their corresponding TIP graduates in terms of demographic characteristics, neighborhood characteristics, and criminal histories. **Table 6** below demonstrates that over 90% of matches were the same as, or very similar to, their TIP graduate on characteristics such as race, sex, age, and offense record. **Figure 6**'s map shows that matches were also often from the same census tracts as TIP graduates.

Characteristic	Percent Matching
Race	94%
Sex	93%
Any Offense before TIP	
0-1 years	91%
1-2 years	100%
2-5 years	99%
5-10 years	100%
Severe Offense before TIP	
0-1 years	92%
1-2 years	100%
2-5 years	100%
Birth Year (within +/- 2 years)	99%

Table 6: Demographic and Criminal History Similarities between Matched Group and TIP Graduates

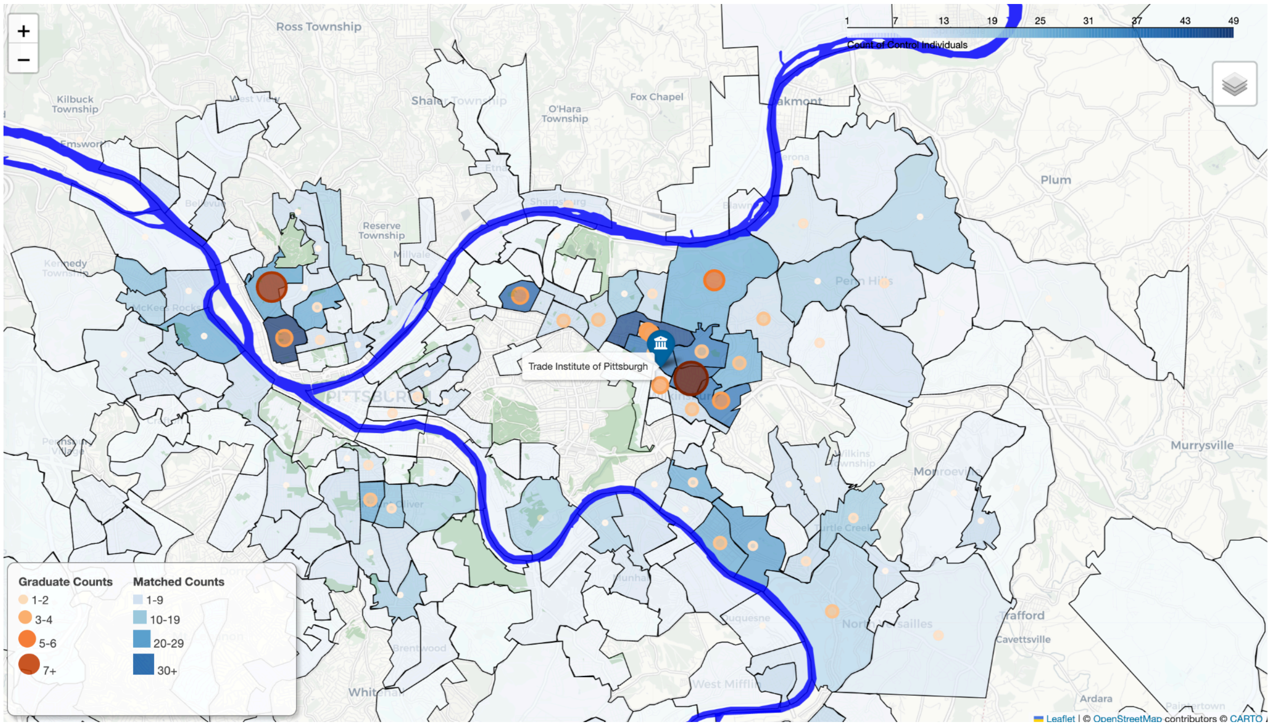


Figure 6: Map of Census Tracts for TIP Graduates and Matched Group

For a more detailed table on the likeness between the matched group and TIP graduates, see **Appendix II**.

Signaling Analysis

Like we did in Outcome Analysis 1, we graphed offense rates for TIP graduates (here, just those graduates with 1 or more offenses pre-TIP) and our matched comparison group over time. We hoped to identify any statistically significant differences. As mentioned in the Matching section, we assume the time of TIP interaction for matches is when **they are at the age** that their corresponding TIP graduate entered the TIP program.

The graph comparing overall offense rates between the two groups is shown in **Figure 7**. As we can see, the offense trends are quite similar in both groups prior to TIP, indicating that the matching process was done well. Both groups see an increase in their pre-TIP period and a general decrease in their post-TIP period. The confidence intervals overlap at nearly every time in the graph. This indicates that the groups are **statistically indistinguishable from each other**.

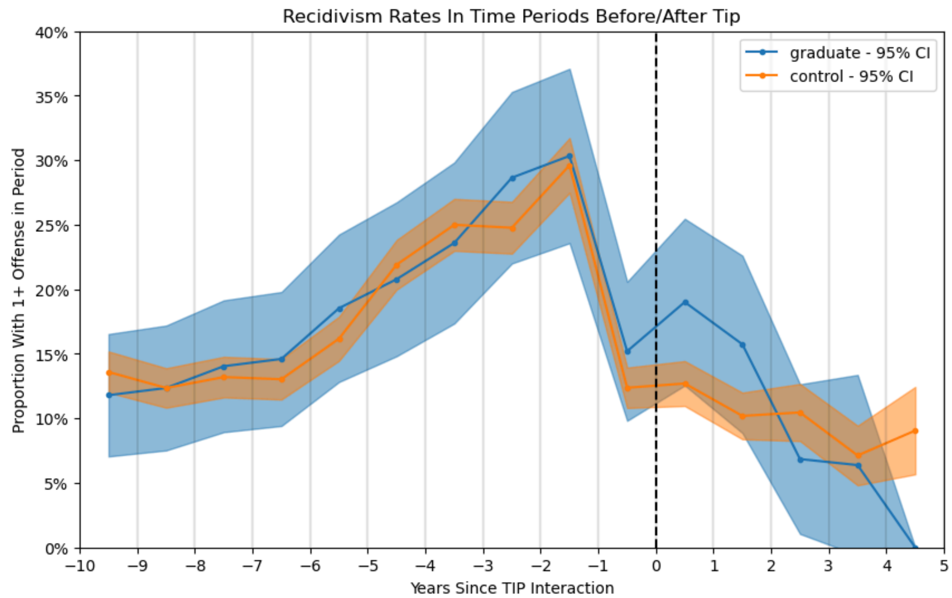


Figure 7: Offense Rates of Graduates vs. Matched Group Over Time

We also considered only severe offense rates over time for the two groups. **Figure 8** displays the results. Here, too, the close pre-TIP trend between the groups indicates a strong matching process. Both groups see a similar pattern as in Figure 5, with rates increasing pre-TIP and a decreasing trend post-TIP. Again, the confidence bands overlap at almost every point; we see **no statistically significant difference** between the TIP graduates and the matched group for severe offense rates.

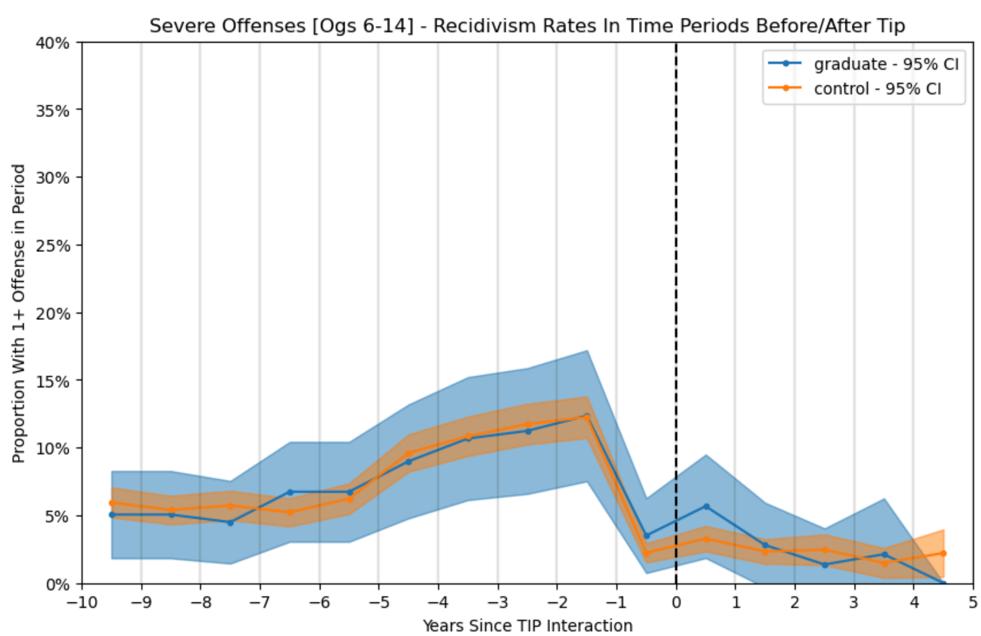


Figure 8: Severe Offense Rates (OGS 6+) of Graduates vs. Matched Group Over Time

Robustness Check: Statistical Regression Analysis

To provide a **robustness check** for our signaling analyses and ensure we were not missing significant differences, we conducted four regression analyses. TIP graduates with 1 or more prior convictions were our treatment group, and their matches were our comparison group. Following the advice of our advisory board, we utilized linear regression predominately in our second outcome analysis instead of logistic regression models. We were also advised to focus our study on offenses with an OGS of 3 or higher to exclude minor offenses and better target the most impactful outcomes.

Both linear regression and logistic regression (used in Outcome Analysis 1) accomplish the **same goal**–assessing the impact of graduation on recidivism rates while controlling for other factors–but linear regression models are easier to interpret and have some nuanced statistical properties that make them preferable in our context. Our results obtained from linear regression models did not change when we checked them using logistic regression models.

We conducted linear regressions for **four different outcomes**: 1-year reoffense rates for any offense, 1-year reoffense rates for severe offenses only, 3-year reoffense rates for any offense, and 3-year reoffense rates for severe offenses only. We had the following **independent variables**:

- **Status**: This is our variable of interest. It delineated whether an individual was a TIP graduate (coded as a 1) or a matched reference person (coded as a 0).
- **Age at TIP**: As in our earlier logistic regression, this is the age that a TIP graduate enters the TIP program. For reference individuals, this is the age that person was when their matched TIP graduate completed the program
- **Recent prior offense (OGS 3+)**: This is a binary variable, with 1 indicating that an individual had a prior offense of an OGS of 3 or above committed within 3 years of beginning TIP (or the age that they would have begun TIP) and 0 indicating otherwise.
- **Occurrence of severe prior offense (OGS 6+)**: Another binary variable, this indicates whether an individual committed a severe offense in their pre-TIP/"pre-TIP" period.
- **Number of prior offenses**: This is a continuous variable. It is the number of offenses committed by an individual in their pre-TIP/"pre-TIP" period.

Our linear regression results are in **Appendix III**, but a summary of the variables' coefficients and their significance is in **Table 7 below**. The coefficient estimates represent the change in the likelihood of recidivism corresponding to a one-unit change in the independent variable. For example, the coefficient of -0.004 for age in Regression 1 means that each additional year of age is associated with a 0.4 percentage point decrease in the likelihood of recidivism within one year.

Across the models, we found **no evidence** that being a TIP graduate significantly decreased the risk of recidivism. There is one instance where TIP graduate status is significantly associated with a higher risk of recidivism, but we concluded that, within this small sample of TIP graduates, it is likely that there is an omitted variable influencing our results. We also found that **being younger** and **having more prior offenses** significantly increase recidivism risk in all models, and **having a more recent prior offense** is significantly associated with higher recidivism in Regression 1.

	Regression 1: All offenses, 1-year reoffense rates	Regression 2: Severe offenses, 1-year reoffense rates	Regression 3: All offenses, 3-year reoffense rates	Regression 4: Severe offenses, 3-year reoffense rates
Status	**0.079***	0.024	0.08	0.039
Age at TIP	**-0.004***	**-0.003***	**-0.009***	**-0.006***
Recent prior offense	**0.042***	0.007	0.04	0.012
Prior severe offense	**-0.051***	-0.008	-0.064	-0.012
Number of prior offenses	**0.026***	**0.01***	**0.045***	**0.021***

*Table 7: Linear Regression Model Results. Bolded results with a * denote statistical significance at a 95% confidence level.*

Summary of Findings from Outcome Analysis 2

In our Outcome Analysis 2, we found that the offense rates of TIP graduates and our Allegheny County control group are **not statistically different** from each other. Though the lines may cross in the post-TIP period, both groups see a general decline in offenses and the overlap of the confidence bands demonstrates that they are statistically similar. Our linear regression robustness checks **reinforced this finding**. It is worth noting that other factors, such as the **number of prior offenses, recency of last offense, and age**, do show significant associations with recidivism rates. This is consistent with the literature on recidivism (Bushway, 2024; Stolzenberg et al., 2020).

There are various reasons that may explain why we did not find a signaling effect. As we will note further in the Discussion section, we had substantial limitations in our **sample size** and our **restricted**

timeframe. Our small sample resulted in very large confidence bands, which made it difficult to pinpoint a statistically significant difference between the two groups. Additionally, our data only extends until late 2018, which means that current TIP services are not captured in our analysis.

Beyond these two factors, there is a chance that, for the TIP graduates we are observing, the age at which they enter TIP is **around the same age** that they would have been likely to desist regardless. This could be why they and their counterparts have similar declines in offense rates. We also have **no information** on whether the individuals in our matched comparison group attended other working training or re-entry programs. Their participation in those programs may have influenced their offense rates. Finally, we are only considering **TIP graduates with prior offenses** in this analysis, and on average, these graduates begin TIP **1-3 years after their most recent offense**. This group is therefore riskier than other TIP graduates; there is a chance that, while TIP may not significantly help the riskiest of its graduates from reoffending, it may help those who have no prior offense from beginning to offend.

Discussion

In both outcome analyses, we **fail to find evidence** that TIP either causally reduces recidivism or acts as a signaling mechanism. We created fairly sound research designs around the data we had. However, we want to reacknowledge **key limitations** in our project that certainly influenced results and affected their generalizability.

As we have noted throughout this report, one of the key limitations of our analyses and results is our **small sample size**. Our 1-year recidivism sample does not include anyone who interacted with TIP after **September 2018**, and our 3-year recidivism sample does not include anyone who interacted with TIP after **September 2016**. This is a small sample to begin with; when we add further restrictions–such as only including TIP graduates, only including those who interact with TIP who have one or more offenses, or only including those at the intersection of these two groups–it becomes just a couple hundred individuals. This **limited the statistical power of our analyses**, resulting in wider confidence intervals and less precise estimates. It becomes much harder to detect significant differences between our TIP group and comparison groups.

Relatedly, and importantly, our analyses are also essentially considering only **older versions** of the TIP program. This is notable because, as we have learned in conversations with TIP, their current **Executive Director**, Donta Green, took on his role in 2021 and has put a lot of focus on reducing recidivism. In addition, we know the program has also **changed a lot** in the last 6 years. TIP has added many new social services for their students, including important life skills education, that could more effectively decrease recidivism. These effects would not be available in the dataset we used.

Recommendations

Based on our literature review, discussions with criminologists, and analysis results, we drafted **five recommendations** for TIP, some of which we know are already at the top of TIP's to-do list. The first two recommendations are meant to guide further research on behalf of TIP, and the latter three are suggestions for TIP to implement within their programming.

Recommendations for Further Research

1. **Conduct analyses that include more recent versions of the program.**

We had originally chosen not to include classes after 2018 because the pandemic had affected the criminal justice field in ways that are still **not fully understood**. However, we determined how to conduct our analyses so that they rely on comparing outcomes of similar groups to TIP graduates. These comparison groups would be as affected by the pandemic as TIP graduates. Therefore, using our methods, the **pandemic becomes much less of an issue**. By the time we came to this conclusion, we had run out of time to request more data from the PCS; another research project can and should redo our analyses with more current data.

2. **Qualitatively investigate why graduates recidivate after completing the TIP program.**

The people who best know why TIP graduates have offended are those graduates themselves. We recommend TIP leverage its connections to its alumni and to the broader community to reach out to graduates that they know have **reoffended post-TIP**. Staff (or other researchers) can interview them and ask about their lives post-graduation. These interviews can help determine if there are any services that TIP can improve or provide to graduates while they are students, or after they graduate, to better meet their needs. They may also highlight particular patterns in terms of risk factors within TIP's population; perhaps, there are many alumni who cite social groups or substance abuse as the reason behind their reoffending. Such a finding would not only influence what social services to provide but could also help program officials identify which students might have the greatest risk of reoffending.

Recommendations for TIP Programming

3. **Continue checking in on graduates post-graduation to provide support.**

From our visit to TIP and our conversations with leadership, we know that, while students are enrolled in TIP, they have a great deal of support. It might follow, then, that after program completion, TIP graduates are hit hard by the **steep dropoff in support** they experience. This may increase their likelihood to return to old behaviors. Creating support systems for TIP graduates, though maybe not as robust as for students, could help them continue on the path to recovery that they experienced in the TIP program.

4. **Incorporate services into programming that focus on risk factors for recidivism outside employment.**

TIP serves people with criminal backgrounds and people without. As such, much of TIP's efforts to reduce recidivism seem to fall under the **overall blanket** of its services: facilitating employment for, and teaching important life skills to, those who have previously offended. This makes sense; it is the mission of the organization. However, recidivism is a highly complex issue, and combating it requires a tailored approach.

TIP could benefit from evaluating its approach to reducing recidivism and identifying gaps in its underlying theory. From this internal assessment of TIP's programs, and from interviews with graduates who have reoffended, there may be some opportunities to build upon. Indeed, employment is just one of a variety of risk factors for recidivism, some crucial others being **substance abuse** and **antisocial attitudes** (Duwe & Henry-Nickie, 2021; Andrews, Bonta, & Wormith, 2006). While TIP requires its participants to stay clean throughout the program, and offers a lot of emotional support, it may be worth considering whether more intensive approaches–such as in-house therapy, referrals to outside services, or integration with other nonprofits–would be helpful.

To help provide more insight into major and moderate risk factors for recidivism, as well as related needs, we have included a chart from Andrews, Bonta, & Wormith (2006) in **Appendix IV**. The factors identified here are widely accepted in criminology research and are often a foundation for strategies to reduce recidivism.

5. **Target services for reducing recidivism to those with the highest risk of recidivism.**

If TIP creates more specific services for reducing recidivism, it may be the best use of resources to **target those with the highest risk of reoffending**. The three most predictive factors for recidivating–**age, number of previous convictions, and time since last offense**–should be available to TIP among participants' entry to the program.

We found in our literature review and in our own analyses that younger individuals are more likely to reoffend than older individuals (Bushway, 2024). Additionally, those with more prior convictions, and/or those whose last offense is more recent, have a higher probability of reoffending than their counterparts (Bushway, 2024; Stolzenberg et al., 2020). Ensuring TIP's efforts to curb recidivism are especially accessible to, or encouraged for, participants within these categories could **more effectively decrease its post-graduation recidivism rate**.

There are **many tools available** to estimate risk of recidivism that gauge and score these and other risk factors, if TIP would like to incorporate a more formal process of assessing the risk of its participants. There is no tool that is universally used, and they come at varying costs. If TIP has connections to participants' parole officers, it may be helpful to learn if they use a risk-measuring tool and, if so, which one. In any case, we have compiled a list of resources and information for selecting a tool in **Appendix V**.

Conclusion

We conducted two outcome analyses: one comparing TIP graduates to nongraduates and another comparing TIP graduates with prior offenses to a matched Allegheny County comparison group. Our outcome analyses indicate that, for its 2009 through September 2018 graduates, the TIP program had no causal impact on recidivism and did not operate as a signaling mechanism. Though these results may not be what we hoped or expected, we acknowledge that there were significant sample size and data limitations that affected them.

For next steps, we propose that TIP conduct further research using more current versions of its program; qualitatively interview past graduates on their post-TIP experiences; continue providing post-program support to its graduates; offer services for recidivism factors beyond employment; and target recidivism-reduction activities to its riskiest participants.

We know that TIP is dedicated to helping its students, and we are excited to see how the organization continues to grow.

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Appendix I: Matching Criteria, Weights and Methodology

	Variables	Weight Assigned
Static Demographics	Birth Year	1.5
	Race	1
	Gender	1
Census Tract Socio-Economic Indicators	Census Tract	0.1
	Poverty Rate	0.4
	Median Household Income	0.2
	Median Rent	0.2
	Percent Black	0.4
	Unemployment Rate	0.2
	Percent High School Or Less	0.4
Pre-TIP Criminal Justice Background	Offense within 1 year before TIP (OGS 3+ / OGS 6+)	1.25 / 1.25
	Offense within 1-2 year timeframe before TIP (OGS 3+ / OGS 6+)	2 / 2
	Offense within 2-5 year timeframe before TIP (OGS 3+ / OGS 6+)	1.5 / 1.5
	Offense within 5-10 year timeframe before TIP (OGS 3+ / OGS 6+)	1.5 / 1.5
	Any offense within 4 years of TIP, including misdemeanors (OGS 1+)	1

Matching Methodology:

The methodology for computing similarity scores involves both categorical and numerical data points to assess the similarity between individuals or entities based on specific attributes, each contributing differently according to assigned weights.

- **Categorical Columns:** Our algorithm analyzes categorical attributes like race, gender, and historical offense records. A match between the attribute values of two entities adds our assigned weights to the similarity score.
- **Numerical Columns:**
    - *Birth Year:* Small differences (within 2 years) add a full weight to the score, moderate differences (3 to 5 years) add half, and larger but still minor differences (6 to 8 years) add a quarter. Differences beyond this contribute nothing.
    - *Z-scored Socio-Economic Indicators*: All of the socioeconomic indicators were first standardized using Z-scores comparing all census tracts in Allegheny County. Variations up to 0.5 add full weight, between 0.5 and 1 add half weight, and between 1 and 2 add a quarter. Greater differences do not affect the score.

Appendix II: Similarities between Matched Group and TIP Graduates

Demographic Characteristics and Criminal Histories

Characteristic	TIP Graduates (n = 186)	Matched Group (n = 1860)
% Black	82%	83%
% Male	86%	91%
% without any offense X years before TIP		
0-1 years	84%	87%
1-2 years	74%	74%
2-5 years	50%	50%
5-10 years	57%	57%
% with no severe offense X years before TIP		
0-1 years	91%	92%,
1-2 years	88%	88%,
2-5 years	71%	71%
Mean Birth Year	1986	1986

Neighborhood Characteristics

Characteristic	Z-Score Differences
Income	0.01
Rent	0.05
% Black	0.14
Poverty Rate	0.02
Unemployment Rate	0.03
High School Education Rate	-0.09

Appendix III: Linear Regression Results

1-Year Reoffense Rates (any OGS3+ offenses)

```
Number of people with program_graduate == 1: 141
```

OLS Regression Results

Dep. Variable:	post_conviction_1_years_ogs3_and_up	R-squared:	0.037
Model:	OLS	Adj. R-squared:	0.034
Method:	Least Squares	F-statistic:	11.63
Date:	Sat, 27 Apr 2024	Prob (F-statistic):	4.82e-11
Time:	13:49:28	Log-Likelihood:	-299.80
No. Observations:	1532	AIC:	611.6
Df Residuals:	1526	BIC:	643.6
Df Model:	5		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.1632	0.051	3.195	0.001	0.063	0.263
program_graduate	0.0786	0.026	3.016	0.003	0.027	0.130
age_at_tip	-0.0040	0.002	-2.644	0.008	-0.007	-0.001
prior_3_year_ogs3_and_up	0.0417	0.017	2.461	0.014	0.008	0.075
prior_high_conviction_all_time	-0.0513	0.019	-2.692	0.007	-0.089	-0.014
num_priors_OGS3_and_up	0.0260	0.006	4.650	0.000	0.015	0.037

Omnibus:	759.943	Durbin-Watson:	1.986
Prob(Omnibus):	0.000	Jarque-Bera (JB):	3082.313
Skew:	2.524	Prob(JB):	0.00
Kurtosis:	7.775	Cond. No.	212.

1-Year Reoffense Rates (severe offenses)

```
... Number of people with program_graduate == 1: 141
```

... OLS Regression Results

Dep. Variable:	post_high_conviction_1_years	R-squared:	0.021
Model:	OLS	Adj. R-squared:	0.018
Method:	Least Squares	F-statistic:	6.554
Date:	Sat, 27 Apr 2024	Prob (F-statistic):	4.83e-06
Time:	14:42:44	Log-Likelihood:	443.23
No. Observations:	1528	AIC:	-874.5
Df Residuals:	1522	BIC:	-842.5
Df Model:	5		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.1131	0.031	3.595	0.000	0.051	0.175
program_graduate	0.0242	0.016	1.510	0.131	-0.007	0.056
age_at_tip	-0.0034	0.001	-3.672	0.000	-0.005	-0.002
prior_3_year_ogs3_and_up	0.0072	0.010	0.688	0.491	-0.013	0.028
prior_high_conviction_all_time	-0.0081	0.012	-0.684	0.494	-0.031	0.015
num_priors_OGS3_and_up	0.0099	0.003	2.870	0.004	0.003	0.017

Omnibus:	1488.006	Durbin-Watson:	1.952
Prob(Omnibus):	0.000	Jarque-Bera (JB):	39361.819
Skew:	4.923	Prob(JB):	0.00
Kurtosis:	25.832	Cond. No.	212.

3-Year Reoffense Rates (any OGS3+ offenses)

```
Number of people with program_graduate == 1: 73
```

OLS Regression Results

Dep. Variable:	post_conviction_3_years_ogs3_and_up	R-squared:	0.047
Model:	OLS	Adj. R-squared:	0.041
Method:	Least Squares	F-statistic:	7.833
Date:	Sat, 27 Apr 2024	Prob (F-statistic):	3.29e-07
Time:	13:49:29	Log-Likelihood:	-423.07
No. Observations:	798	AIC:	858.1
Df Residuals:	792	BIC:	886.2
Df Model:	5		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.4214	0.095	4.444	0.000	0.235	0.607
program_graduate	0.0804	0.051	1.585	0.113	-0.019	0.180
age_at_tip	-0.0094	0.003	-3.231	0.001	-0.015	-0.004
prior_3_year_ogs3_and_up	0.0402	0.032	1.241	0.215	-0.023	0.104
prior_high_conviction_all_time	-0.0644	0.037	-1.750	0.081	-0.137	0.008
num_priors_OGS3_and_up	0.0452	0.011	4.062	0.000	0.023	0.067

Omnibus:	129.436	Durbin-Watson:	1.982
Prob(Omnibus):	0.000	Jarque-Bera (JB):	192.122
Skew:	1.191	Prob(JB):	1.91e-42
Kurtosis:	2.679	Cond. No.	204.

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

3-Year Reoffense Rates (severe offenses)

```
... Number of people with program_graduate == 1: 73
```

...

OLS Regression Results

Dep. Variable:	post_high_conviction_3_years	R-squared:	0.036
Model:	OLS	Adj. R-squared:	0.030
Method:	Least Squares	F-statistic:	5.883
Date:	Sat, 27 Apr 2024	Prob (F-statistic):	2.39e-05
Time:	14:44:55	Log-Likelihood:	-49.414
No. Observations:	794	AIC:	110.8
Df Residuals:	788	BIC:	138.9
Df Model:	5		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.2166	0.059	3.642	0.000	0.100	0.333
program_graduate	0.0390	0.032	1.229	0.219	-0.023	0.101
age_at_tip	-0.0063	0.002	-3.479	0.001	-0.010	-0.003
prior_3_year_ogs3_and_up	0.0116	0.020	0.571	0.568	-0.028	0.052
prior_high_conviction_all_time	-0.0115	0.023	-0.496	0.620	-0.057	0.034
num_priors_OGS3_and_up	0.0206	0.007	2.953	0.003	0.007	0.034

Omnibus:	508.193	Durbin-Watson:	2.020
Prob(Omnibus):	0.000	Jarque-Bera (JB):	3313.854
Skew:	3.069	Prob(JB):	0.00
Kurtosis:	10.906	Cond. No.	203.

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Appendix IV: Risk Factors for Recidivism (Andrews, Bonta, & Wormith, 2006)

TABLE 1 Major Risk and/or Need Factors and Promising Intermediate Targets for Reduced Recidivism

Factor	*Risk*	*Dynamic Need*
History of antisocial behavior	Early and continuing involvement in a number and variety of antisocial acts in a variety of settings	Build noncriminal alternative behavior in risky situations
Antisocial personality pattern	Adventurous pleasure seeking, weak self-control, restlessly aggressive	Build problem-solving skills, self-management skills, anger management and coping skills
Antisocial cognition	Attitudes, values, beliefs, and rationalizations supportive of crime; cognitive emotional states of anger, resentment, and defiance; criminal versus reformed identity; criminal versus anticriminal identity	Reduce antisocial cognition, recognize risky thinking and feeling, build up alternative less risky thinking and feeling, adopt a reform and/or anticriminal identity
Antisocial associates	Close association with criminal others and relative isolation from anticriminal others; immediate social support for crime	Reduce association with criminal others, enhance association with anticriminal others
Family and/or marital	Two key elements are nurturance and/or caring and monitoring and/or supervision	Reduce conflict, build positive relationships, enhance monitoring and supervision
School and/or work	Low levels of performance and satisfactions in school and/or work	Enhance performance, rewards, and satisfactions
Leisure and/or recreation	Low levels of involvement and satisfactions in anticriminal leisure pursuits	Enhance involvement, rewards, and satisfactions
Substance Abuse	Abuse of alcohol and/or other drugs	Reduce substance abuse, reduce the personal and interpersonal supports for substance-oriented behavior, enhance alternatives to drug abuse

NOTE: The minor risk and/or need factors (and less promising intermediate targets for reduced recidivism) include the following: personal and/or emotional distress, major mental disorder, physical health issues, fear of official punishment, physical conditioning, low IQ, social class of origin, seriousness of current offense, other factors unrelated to offending.
Thanks to Shad Maruna and colleagues (Maruna, Lebel, Mitchell, & Naples, 2004) for expansion of antisocial cognition to include the broader construct of personal identity.

Appendix V: Resources for Finding Recidivism Risk Measurement Tools

This appendix provides (1) resources and background information on choosing recidivism risk measurement tools and (2) links to popular recidivism risk measurement tools.

Resources and Background Information

PSRAC Tool Selector

The Bureau of Justice Assistance, with the Urban Institute, maintains a Public Safety Risk Assessment Clearinghouse (PSRAC). PSRAC provides information, resources, and training around criminal justice risk and needs assessments.

PSRAC has an online tool selector that helps organizations determine which tool fits their needs best. The tool selector allows you to filter on functionality, outcome, service population, whether a training is needed, and whether an interview is needed. It also previews the costs of each tool. A policy brief to help in using the tool is here.

PSRAC also records the most popular recidivism risk measurement tools at different levels of justice system interaction for each state. The most popular tool in Pennsylvania through most levels of the justice system is the Level of Service Inventory-Revised (LSI-R), which is included in the links below.

Issue Brief: Using Risk/Needs Assessments in Reentry Services

The Department of Labor and Mathematica created an issue brief on the use of risk/needs assessments in reentry programs. Though TIP is not a reentry program, it may still have some helpful insights. Some key takeaways include:

- Risk/needs assessment tools consider static (unchanging) and dynamic (changeable) factors to score and categorize likelihood to recidivate.
- Most of the organizations surveyed for the brief used assessments that fit in the following categories:
    - **Risk-Need-Responsivity (RNR) framework**: "The RNR framework's three key principles say providers should plan responsive services that target the needs of people at highest risk for recidivism. It is the basis for some of the most widely used assessments,

including the Level of Service Inventory-Revised and the Level of Service/Case Management Inventory."

    - **Resource Allocation and Service Matching Tool**: "The tool has three steps: assess risk of reincarceration, assess job readiness, then deliver targeted services based on risk and readiness scores. It uses the RNR framework to calculate risk in its first step."
- Risk/needs assessment tools have the potential to (1) perpetuate racial and ethnic biases in the criminal justice system; (2) have unreliable predictive validity; (3) operate with little explanation as to how they derive their results. Suggestions to avoid these issues include:
    - Seeking validation (in other words, testing) from tool developers or outside researchers that risk categorization does not differ across race or ethnicity;
    - Completing a local validation to ensure that the tool does not differ across race or ethnicity and that it predicts well for your population;
    - Ensuring implementation of the tool is correct by using specially trained staff and doing fidelity reviews;
    - Choosing tools that are transparent about how they calculate scores

Resource Brief: Risk Assessment and Racial Equity: Making Your Reentry Program Evaluation Part of the Conversation

RTI and Center for Court Innovation developed a resource brief on how to use a risk/needs assessment tool while being mindful of any racial biases. Key highlights include:

- Look toward external validation, or complete your own internal validation, of the tool to ensure it has predictive validity for your population.
- If applying the tool at different points in the program, ensure that the tool is sensitive to changes in dynamic risk factors to an equal degree across racial and ethnic subgroups. You can either find previous studies for the tool on the topic or complete an evaluation yourself.
- Use the tool, if reliable, to determine how your program affects people in different risk categories differently.
- Interview staff and participants on their perceptions of the risk assessment tool.

Book: Handbook of Recidivism Risk/Needs Assessment Tools

Described as "ideal for correctional, probation and parole, and behavioral health professionals," this book, written by criminologists and other professionals, covers a variety of risk/needs assessment tools and reviews related research. It is meant to help organizations decide which tool is right for them.

Popular Tools (and Strategies)

The following is a list of risk/needs assessment tools that came up various times in the research and appear to be fairly popular in the field:

- Level of Service Inventory-Revised (LSI-R): "Designed for ages 16 and older, the LSI-R helps predict parole outcome, success in correctional halfway houses, institutional misconducts, and recidivism. The 54 items included in this tool are based on legal requirements and include relevant factors needed for making decisions about risk and treatment."
    - Tool used throughout Pennsylvania's legal system, according to PSRAC
    - One of the most commonly used tools by the Reentry Project (RP) grantees, as measured in the Department of Labor Issue Brief above
- Level of Service/Case Management Inventory (LS/CMI): "The Level of Service/Case Management Inventory (LS/CMI) is a fully functioning case management tool and an assessment that measures the risk and need factors of late adolescent and adult offenders. This single application provides all the essential tools needed to aid professionals in treatment planning for and management of offenders in justice, forensic, correctional, prevention, and related agencies."
    - The more recent version of the LSI-R
    - One of the most commonly used tools by the Reentry Project (RP) grantees, as measured in the Department of Labor Issue Brief above
- Resource Allocation and Service Matching Tool: Uses risk tools like the ones above in its first step, but puts them within a separate framework designed specifically to help those with offenses become employed.
- Prisoner Assessment Tool Targeting Estimated Risk and Needs (PATTERN): This is a tool developed for the First Step Act to determine early release. It is for people currently incarcerated but could be tailored to those post-release.