Do Time-Limited Housing Subsidies Reduce Homelessness for Transition-Aged Youth?

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Executive Summary

This report shows that Time-Limited Housing Subsidies (TLS), often referred to as Rapid Rehousing, significantly reduce homelessness for Transition-Aged Youth (TAY) between the ages of 18 and 24 who use the subsidies to rent housing in Los Angeles. Recent research by the California Policy Lab found that enrollment in a TLS program was effective at reducing future homelessness among single adults over the age of 25 in Los Angeles County.[1] This report expands on that research by estimating the impact TLS programs have in reducing homelessness for TAY.

TLS provides short-term financial support, typically lasting 12 months with a maximum duration of 36 months, to help people afford housing in the private market. The hope is that by helping people stabilize their housing in the short-term, TLS will put them into a position to afford permanent housing in the longer term. TAY have unique needs (as compared to adults aged 25 and older) and receive homeless services from a different set of programs and funding streams. For these reasons, it is important to analyze the impact of TLS on homelessness among TAY separately from older, unaccompanied adults.

Our study focuses on 3,552 TAY who enrolled in homelessness services between 2016 and 2019 and were given a screening assessment. Of those, 528 enrolled in a TLS program and moved into a rental unit subsidized by TLS within six months of their assessment, a process referred to here as "leasing up." We compare homelessness rates over the following four years for those 528 TAY who leased up in TLS to the remaining 3,024 who were not housed with a subsidy within the six months following their assessment.

1 Brian Blackwell and Robert Santillano, "Do Time-Limited Subsidy Programs Reduce Homelessness for Single Adults?" (California Policy Lab, 2023), https://capolicylab.org/do-time-limited-subsidy-programs-reduce-homelessness-for-single-adults/.

Key Findings

- We estimate that leasing up with a TLS subsidy reduced homelessness for Transition-Aged Youth (TAY) by 39% over four years. Only 16% of TAY who leased up with TLS during the enrollment period experienced homelessness in the next four years, compared with 27% of those who did not lease up.[2] Looking year by year within that four-year period, we find TLS significantly reduced TAY's future homelessness in the first year following enrollment. We find mixed evidence of an impact in the following two to four years.
- TLS reduced homelessness for both Black TAY (10%) and Latinx TAY (13%). However, Black TAY who lease-up with TLS and Black TAY in the comparison group who did not lease up with TLS eventually enrolled in street outreach services or interim housing at higher rates than Latinx TAY in those groups. More research is needed to understand why these return rates are different.
- Seventy-two percent of TAY who are enrolled in TLS lease a rental unit with the subsidy. While this is higher than the lease-up rate for single adults (62%), increasing lease up rates for TAY enrolled in TLS could reduce homelessness.

Below, we provide background on Time-Limited Subsidies and Transition-Aged Youth experiencing homelessness in Los Angeles. We then provide an overview of our data and research methods.[3] Next, we describe our results. Finally, we discuss future avenues of research into the effectiveness of TLS at reducing homelessness and helping people remain stably, permanently housed.

2 The 39% reduction is the estimated impact of TLS lease-up with a subsidy, in contrast to the estimates in Blackwell and Santillano (2023) which are for the impact of TLS enrollment overall including those who did not lease up.

3 A more detailed discussion of our methods and findings can be found in the Technical Research Methods section.

Background on Time-Limited Subsidies

Over 75,000 people experience homelessness on any given night in Los Angeles County.[4] Transition-Aged Youth (TAY) — defined as youth aged between 18 and 24 who are not accompanied by children aged under 18 — comprise just over 3% of this population (2,300 individuals). The policy response to help these individuals is a mix of interim-housing (e.g. shelters), transitional housing, and interventions where the goal is to place individuals in long-term housing solutions. One of these long-term housing solutions — Time-Limited Housing Subsidy (TLS) programs, often referred to as Rapid Re-housing (RRH) — made up 83% of all permanent housing enrollments for TAY in the Los Angeles homeless services system in 2023. TLS programs were originally conceived as a strategy to quickly rehouse people who experienced homelessness due to a financial shock. However, program participants face challenges like documentation requirements, tight rental markets, or rejection by landlords, raising questions about the program's efficacy. In a working paper and policy brief released in 2023, the California Policy Lab found strong evidence that TLS reduces the number of single adults aged 25 and older who use homeless services in Los Angeles.[5] This policy brief extends that research to see if TLS also has an impact on homelessness among TAY.

Our study focuses on TAY enrolled in the Los Angeles homeless services system between January 1, 2016 and December 31, 2019. During this period, 22,515 TAY were enrolled in homeless services such as interim housing, street outreach, and permanent housing. Of those people, 8% were enrolled in TLS programs (1,812 individuals), and 72% of those enrollees (or 6% of all TAY enrolled in homeless services) went on to move into a rental unit. Our study focuses on TAY who were not only enrolled in homelessness services but who were also assessed with the Next Step screening tool, a questionnaire that was used to prioritize access to permanent housing during the study period. We limit our sample to TAY who were assessed with the Next Step tool because information gathered during the assessment is important to our research design, where we need to construct two groups of TAY who are similar in all observed characteristics except whether they received TLS. We also limit the sample to TAY without prior enrollments in permanent housing programs and who leased up in TLS within six months of their assessment.

4 "2024 Greater Los Angeles Homeless Point in Time Count" (Los Angeles Homeless Services Authority, 2024), https://www.lahsa.org/news?article=976-2024-greater-los-angeles-homeless-count-data.

5 Blackwell and Santillano, "Do Time-Limited Subsidy Programs Reduce Homelessness for Single Adults?"

The Next Step screening tool asks questions in a range of areas, including history of homelessness and prior risk factors such as hospitalization and criminal legal involvement, resulting in an acuity score from 0 to 17. The tool recommends that individuals with scores 8 and above be prioritized for long-term housing programs such as TLS and PSH. Scores of 4 to 7 are recommended for short-term housing programs such as interim or transitional housing, and scores of 0 to 3 are recommended for diversion and support services. However, Next Step tool scores are one of many factors — such as additional eligibility criteria and the availability of scarce housing resources — that influence whether or not an individual is placed in a permanent housing program. In practice, the score threshold functions as a flexible guideline rather than a guarantee of housing placement, with many individuals below the score threshold being placed in permanent housing programs and vice versa.

Of the 3,560 TAY in the study sample, 528 enrolled in TLS and moved into a rental unit subsidized by TLS within six months of their assessment, a process referred to as "leasing up." The remaining 3,024, who make up the comparison group, were not housed with any subsidy during the six months following their assessment. There are several reasons why this might occur. As discussed above, individuals receiving a Next Step tool score of 7 or below may have been directed towards less intensive interventions such as problem solving rather than being enrolled and leased up in TLS. In addition, individuals who scored 8 and above but did not receive permanent housing may have failed to satisfy eligibility criteria for specific programs, or there may simply have been no permanent housing placement available at the time of assessment due to the extremely resource-constrained nature of the homeless services system.

TLS participants are eligible to receive flexible financial assistance to support their tenancy for up to 36 months, and up to 24 months of supportive services such as education services, employment assistance, job training, transportation, and housing-focused case management that works with participants to determine an appropriate end date for the subsidy. For our study sample, the average total amount of financial assistance documented by caseworkers is $5,531. Participants stayed enrolled in the program for an average of 353 days, with 95% of participants enrolling in the program for three years or less.

Overview of Data and Research Methods

The data for the study is an anonymized, linked administrative dataset called the Information Hub, and is provided by the Los Angeles County Chief Executive Office — Chief Information Office (CEO-CIO). The Information Hub contains over 10 years of data from Los Angeles County agencies covering a wide range of characteristics, including demographic data like race, ethnicity, and gender; detailed service histories in health and social safety-net programs; criminal legal involvement; and prior histories of homelessness.

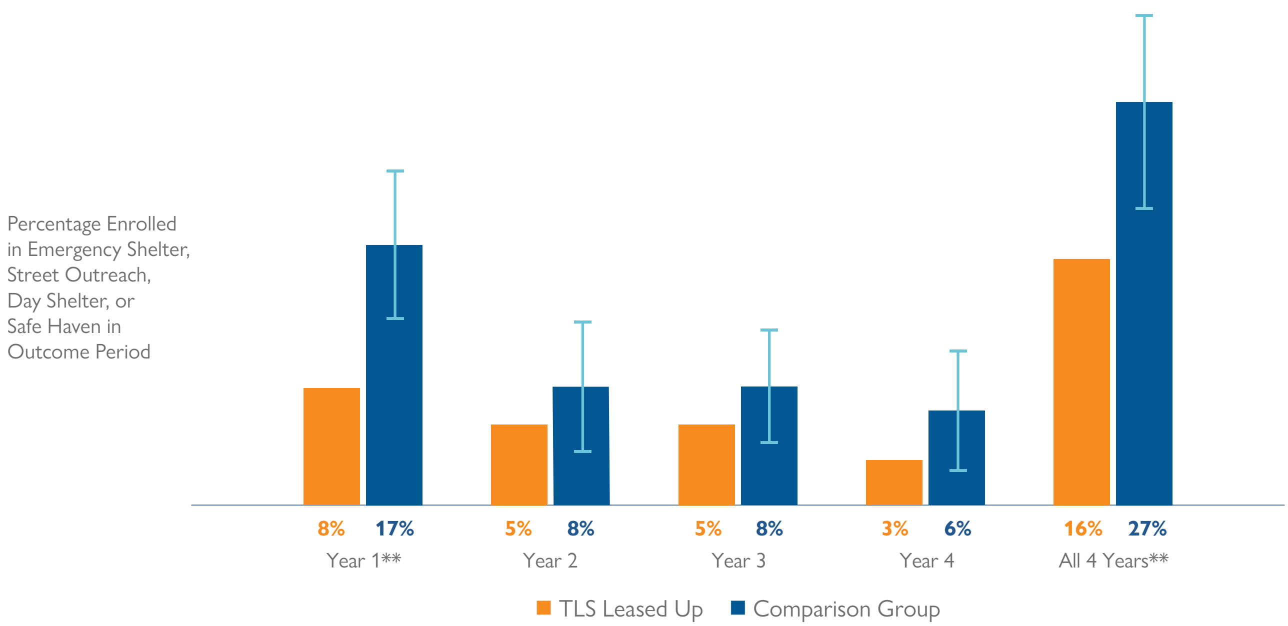
To estimate whether TLS reduces future homelessness — defined as enrollment in emergency shelter, street outreach, day shelter, or safe haven projects — we compare outcomes for TAY who received a Next Step triage tool assessment and who successfully leased up with TLS to outcomes for a comparison group of TAY who were also assessed but who did not lease up with TLS. The goal of the research design is to compare homelessness outcomes for two groups that are similar in all relevant aspects, except for whether they leased up with TLS. To make sure the two groups are the same, we use the long histories of participant-level data available in the Information Hub to adjust for differences in individual characteristics across the two groups. This helps to ensure that we are isolating the impact of TLS on homelessness, and not mistakenly attributing the outcome to the program when it could be attributed to other, "confounding" factors, such as one group being on average older or being served by different providers.

For our primary analysis, we estimate impacts using Ordinary Least Squares (OLS) regression, controlling for observed individual characteristics along with the site and time when the participant was enrolled in TLS. We also perform three supplementary analyses in order to address the concern that the OLS regression estimates may be biased by unobserved confounding factors, such as interpersonal skills or having necessary documents completed and in hand. We find that the estimates from the supplementary analyses are similar to those produced by the main OLS regression analysis, which provides evidence that the primary OLS regression analysis is not substantially affected by unobserved confounding. A more detailed presentation of the data and research methods, including results of the supplementary analyses, can be found in the Technical Research Methods section.

Key Findings

1. **Leasing up with TLS reduces future homelessness among TAY over the next four years by 39%.** Only 16% of TAY who leased up with TLS during the enrollment period experienced homelessness in the next four years, compared with 27% of those who did not lease up. Looking year-by-year within that four-year period, TLS's largest impact was in the first year, reducing homelessness by 54% (8% of TAY who leased up with TLS experienced homelessness compared with 17% of those who did not). We find mixed evidence that TLS has an impact on TAY's homelessness in the two to four years following their assessment.[6]

FIGURE 1. Rates of future homelessness for 528 Transition-Aged Youth (TAY) leased up in Time Limited Housing Subsidy (TLS) programs versus a comparison group of 3,024 TAY who were assessed without receiving permanent housing (regression adjusted).



**: $p < 0.01$; *: $p < 0.05$. Blue bars represent 95% confidence intervals.

6 See the Technical Research Methods section for more details.

2. **TAY who did not lease up with TLS were more likely to receive other types of housing assistance in the four years following their assessment than those who did lease up.** Although we excluded from our analysis people who received other types of housing interventions in the six months following their assessment, 5% of the people who did not receive TLS eventually enrolled in permanent supportive housing (PSH) and 6% in transitional housing (TH) in the following four years, compared with 1% (PSH) and 2% (TH) of those who leased up with TLS during the enrollment period. In addition, 7% of those who did not lease up with TLS during the enrollment period (within six months of their assessment) eventually leased up in TLS at some point in the following four years. We do not observe any significant differences between the two groups for enrollments in supervised independent living placements (SILP) in the foster care system.

3. **There is no statistically significant difference in the impacts of TLS on homelessness for Black TAY vs. Latinx TAY. However, Black TAY who leased up with TLS and Black TAY in the comparison group returned to homelessness at roughly twice the rate of Latinx TAY in those groups.** There was not enough data for TAY in other race and ethnicity groups to estimate the impact of TLS on their future homelessness.

4. **More than one in four TAY who are offered TLS do not lease up within six months of their assessment.** Although the rate at which TAY lease up is higher than single adults in TLS programs (72% vs. 62%), 28% of TAY did not move into a rental unit. Although unobserved in the data, there could be multiple reasons why individuals fail to lease up, such as an inability to find a suitable rental unit, failure to satisfy documentation requirements, or self-resolution of the participant's homelessness without assistance.

Future Research Needs

Research using a randomized or quasi-experimental design would provide stronger evidence for the effectiveness of TLS at reducing homelessness for TAY. While we take care to use rigorous causal inference methods, estimating the impact of TLS using experimental or quasi-experimental methods would give us greater confidence that our estimates are not influenced by characteristics of participants we do not observe. Such methods could include randomly assigning some participants to TLS and others to non-permanent housing resources, or assigning participants strictly based on their score from a screening tool and analyzing the difference between those who are assigned just above the score threshold with those who fall just below it. These methods are ethically justifiable in a context like Los Angeles where demand for permanent housing far exceeds supply and program evaluations could meaningfully inform how policymakers decide to allocate limited resources to best serve people who experience homelessness.

We highlight three specific areas for further research:

First, more research is needed on the long-term impacts of TLS. In our year-by-year analysis, we find strong evidence that TLS reduces homelessness in the first year following lease up. However, we find mixed evidence that TLS is effective at reducing homelessness among TAY in the following two to four years. Although we estimate positive impacts for years 2 and 4 in two of our supplementary analyses as described in the Research Methods section, we do not find statistically significant differences in years 2 through 4 in our primary analysis. These results are in contrast to our analysis of the effectiveness of TLS at reducing homelessness among unaccompanied adults, which finds that TLS significantly reduced homelessness each year for four years after enrollment.[7] This may be due in part to the smaller sample size available for our TAY study. Future research should investigate the long-term effects of TLS on TAY's future experience of homelessness.

Second, it's important to understand how TLS can better serve people from different racial and ethnic groups. In particular, further research is needed to understand why Black TAY in TLS return to homelessness at higher rates than Latinx TAY, and how this can be addressed. There is also a need for research into TLS among TAY from racial and ethnic groups whose sample size in this study was too small to estimate impacts.

7 Blackwell and Santillano, "Do Time-Limited Subsidy Programs Reduce Homelessness for Single Adults?"

Third, research is needed on the housing needs of TAY overall. Compared to TAY who did lease up, TAY who did not lease up during the enrollment period were more likely to enroll in other housing assistance programs over time. However, their overall rate of enrollment into substantive housing interventions was still low (18% over four years). This finding is consistent with CPL's prior research into TAY exiting the foster care system, which found significant gaps between housing need and the availability of housing interventions.[8] More comprehensive research into the effectiveness of a range of housing interventions for TAY could help inform decision-making about how to serve the housing needs of TAY.

8 Janey Rountree et al., "Aging Out of Foster Care in Los Angeles: Opportunities to Prevent Homelessness Among Transition-Aged Youth." (California Policy Lab, 2024), https://capolicylab.org/aging-out-of-foster-care-in-los-angeles/.

Conclusion

TLS is an important intervention for people experiencing homelessness and it is less subject to high construction costs and scalability challenges associated with more intensive interventions such as permanent supportive housing. However, there are also areas for improvement, such as increasing lease-up rates and investigating the higher rates of return to homelessness for Black TAY. Our research shows that the positive impacts observed in CPL's previous work on TLS for single adults can be generalized to TAY. We recommend that future research builds upon these insights by incorporating experimental or quasi-experimental designs, investigating longer-term impacts and racial disparities, and exploring the overall housing needs of TAY.

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Technical Research Methods

Data Sources

The data source used for the study is an individual-level linked administrative dataset from LA County's Chief Information Office (CEO-CIO), referred to as the Information Hub. The origins of the Information Hub lie in a CEO-CIO project started in 2006 to link health services and benefits receipt data for adults in LA County. In subsequent years, the CEO-CIO and County agencies have worked intensively to forge legal agreements and build data-engineering pipelines to link administrative data from 11 LA County agencies. The resulting dataset is a critical piece of data infrastructure for both operational and analytical use cases in LA County, and includes health, mental health, social service benefits, sheriff arrests, probation, and homeless service records for millions of individuals from 2010 onwards. We supplement the Information Hub data with a de-identified copy of Homeless Management Information System (HMIS) data received separately from the LA Homeless Services Authority (LAHSA). This supplemental HMIS data provides information for data elements currently unavailable in the Information Hub, such as amounts of financial assistance received.

Sample Definition

We use the following criteria to define the study samples for the TLS and comparison groups:

Treatment Group (TLS Leased Up) Sample Definition (N=528)

1. Assessment with the Next Step Tool between January 1, 2016 and June 30, 2019,[9] using the first assessment when a person has multiple assessments in the study period;
2. Enrollment in a TAY TLS program and move-in to a rental unit within a six-month enrollment window following their assessment date;
3. No history of enrollment in TLS, permanent supportive housing, transitional housing, or Supervised Independent Living Placement (SILP) programs in the foster care system prior to their assessment date;
4. No enrollment in permanent supportive housing, transitional housing, or Supervised Independent Living Placement (SILP) programs in the foster care system during the six-month enrollment window.

9 The date range is chosen based on the coverage of the Information Hub and HMIS data to allow for five years pre-assessment and four years post-assessment outcomes.

Comparison Group Sample Definition (N=3,024)

1. Assessment with the Next Step Tool between January 1, 2016 and June 30, 2019, using the first assessment when a person has multiple assessments in the study period;

2. Enrollment in an HMIS project (aside from permanent supportive housing or transitional housing) in a six-month enrollment window following their assessment date;

3. No history of enrollment in TLS, permanent supportive housing, transitional housing, or Supervised Independent Living Placement (SILP) programs in the foster care system prior to their assessment date;

4. No enrollment in TLS, permanent supportive housing, transitional housing, or Supervised Independent Living Placement (SILP) programs in the foster care system during the six-month enrollment window.

Condition (1) for both groups is motivated by the fact that the Next Step triage tool assessment functioned as an important decision point for housing prioritization during the study period, and also allows for the definition of a common index date between the treatment and comparison groups. Condition (2) for the comparison group, requiring an HMIS enrollment excluding permanent housing or transitional housing, is intended to strengthen the similarity of the two groups by ensuring that both groups received some kind of homeless service as opposed to an assessment without any kind of documented service receipt. Conditions (3) and (4) are intended to improve the interpretability of the impact estimates by minimizing the extent to which both groups receive housing interventions of similar intensity to TLS. However, the design allows for both groups to receive housing interventions after the six months immediately following a person's assessment.[10]

The choice of a six-month enrollment window following assessment is in line with guidance received from local policymakers, who suggested that we define "sustained homelessness" in terms of new HMIS enrollments after a six-month window following assessment.[11] In our sensitivity analyses described below, we show that the OLS impact estimates are robust to alternative 3-month and 12-month enrollment windows. We also show that the OLS impact estimates are robust to a maximally inclusive sample which drops conditions (3) and (4) for the treatment group and conditions (2), (3) and (4) for the comparison group.

10 We do not filter for future housing enrollments in order to avoid conditioning on a post-treatment outcome. While there are causal methods for controlling for post-treatment interventions and confounding, they add considerable complexity and are outside the scope of this study.

11 Specifically, this was the advice received from the advisory group of local policymakers for the Coordinated Entry System Triage Tools Research and Refinement (CESTTRR) project. See E Rice et al., "CESTTRR: Coordinated Entry System Triage Tool Research and Refinement" (USC Center for AI in Society, 2023).

Outcome Definition

To measure future homelessness, we use enrollments in emergency shelter, day shelter, safe haven, and street outreach projects in the four years following the enrollment window. These projects represent LAHSA's interim housing and street outreach categories with the exception of Transitional Housing, which is a comparatively high-intensity housing intervention for TAY in Los Angeles. These projects are chosen because they are most likely to imply that an individual has experienced homelessness again as opposed to receiving continuing services in the Coordinated Entry System (CES). We encode the outcome as a cumulative binary indicator for all four years, where 1 indicates that a person experienced future homelessness in the four years following the enrollment window and 0 indicates they did not, and annualized binary indicators for each of the four years following the enrollment window, where 1 indicates that a person experienced future homelessness in a given year and 0 indicated they did not.

Methods

Primary analysis: selection-on-observables (OLS)

Our primary analysis employs a selection-on-observables assumption, using Ordinary Least Squares (OLS) regression to estimate impacts. The selection-on-observables assumption is motivated by the wide range of background covariates available in the Information Hub data, which include demographics, geography (proxied by assessment provider and SPA fixed effects), CES intake survey questions, and prior histories of encounters with County agencies across homelessness, health, mental health, social safety net, and the criminal legal system. The OLS regression is estimated using equation (1):

$$y_i = \beta T_i + X_i'\theta + \delta_{psm} + \varepsilon_i$$

where y_i is an outcome for individual i, T_i is a binary indicator for TLS move-in for individual i; X_i' is a vector of individual-level covariates for individual i; δ_{psm} is a vector of fully interacted fixed effects for assessment provider, SPA, and month; and ε_i is an error term.

Supplementary analyses

OLS impact estimates could be biased if characteristics that are not observable in the Information Hub data affect both whether a person leases up with TLS and whether they experience homelessness in the future. For example, an individual's interpersonal skills may help them in the negotiation process with landlords to successfully lease up, and may also help them maintain housing and avoid the need for future homeless services use. Another example is a poor credit history or history of eviction that may make it more difficult for a person to lease up with TLS and find future housing, putting them at increased risk of homelessness. Although the wide range of observed covariates could proxy for some of these unobservables, it is preferable to have some strategy to deal with these concerns explicitly. We therefore supplement the OLS estimates with the following three analyses.

1. Event study

Our first supplementary analysis is an event study ("staggered adoption differences-in-differences") design. The advantage of this design is that it can control for unobserved confounders, such as interpersonal skills, on the assumption that those confounders do not vary over time (the "parallel trends" assumption). We estimate the event study using the following model:[12]

$$y_{it} = \eta_i + \gamma_t + \sum_{t\,!=-1} \tau_t \times T_i + \varepsilon_{it}$$

where y_{it} is a binary indicator for an outcome for individual i in time period t, η_i is an individual fixed effect, γ_t is a time fixed effect, τ_t is a time-period impact of leasing up with TLS relative to one year before enrollment, T_i is a binary indicator for TLS lease-up, and ε_{it} is an error term. In this specification, pre-enrollment values of τ are used as tests of the parallel trends assumption, and values after the enrollment date reflect annualized impacts.

12 There is an active literature on the methodological issues with event studies, or 'staggered adoption difference-in-differences' designs (Sun and Abraham, 2021; Borusyak, Jaravel, and Spiess, 2021; Baker, Larcker, and Wang, 2022). The problem arises from using a two-way fixed effects regression including lags and leads of the treatment, where the coefficient on lags and leads can be contaminated by effects from other periods, potentially leading to a range of issues including false affirmation or rejection of the parallel trends assumption and biases in effect estimates. Our study avoids these issues by using only 'clean controls' — observations which never receive the treatment at any point in the study period — and thus ruling out 'forbidden' comparisons between newly-treated and already-treated units. For more detail see Liyang Sun and Sarah Abraham, "Estimating Dynamic Treatment Effects in Event Studies with Heterogeneous Treatment Effects," *Journal of Econometrics* 225, no. 2 (2021): 175–99; Kirill Borusyak, Xavier Jaravel, and Jann Spiess, "Revisiting Event Study Designs: Robust and Efficient Estimation," *arXiv Preprint arXiv:2108.12419*, 2021; Andrew C Baker, David F Larcker, and Charles CY Wang, "How Much Should We Trust Staggered Difference-in-Differences Estimates?," *Journal of Financial Economics* 144, no. 2 (2022): 370–95.

The event study design has some limitations. First, it can only estimate impacts year-by-year, not cumulatively over the following four years, as we do in our primary analysis. Second, event studies assume that outcomes for both the treatment and comparison group are similar in the time before treatment is assigned. Given that homelessness is a rare binary outcome, assessing impacts in pre-treatment years may provide limited empirical support for that assumption, since outcomes are bounded at 0 for both treatment and comparison groups. Finally, it may be unrealistic to assume that unobserved characteristics that impact both a person's likelihood of leasing up with TLS and of experiencing future homelessness do not vary over time, especially considering the time-sensitive nature of the events that precipitate homelessness. Despite these limitations, we regard the event study design as providing important support for the credibility of the primary analysis.

2. Positive selection bounding analysis

Our second supplementary analysis is motivated by the idea that selection into TLS may be affected by unobserved confounders that change over time. For example, people who lease up with TLS may have better credit scores or lack a criminal record or eviction history, which would also make them more likely to resolve their homelessness on their own and remain stably housed, reducing their likelihood of future homelessness. We therefore create alternative "positive selection bounding" estimates by comparing TAY who leased up with TLS with TAY from the comparison group who resolved homelessness on their own.[13] TAY who resolve their homelessness on their own are less likely to use homeless services again, in part because they have exited homelessness and in part because they have demonstrated they may be capable of finding and maintaining housing on their own. Therefore, our estimates from comparing TAY who leased up with TLS to TAY who resolved their homelessness on their own is a lower bound of the impact of TLS on people's future homelessness.

From the comparison group, we identify 516 people who did not lease up with TLS but exited homelessness to temporary or permanent housing in the six-month enrollment period as indicated by their HMIS exit destination. By contrast, only 56% of people who leased up with TLS reported exiting homelessness to temporary or permanent housing. Focusing on this subset of the comparison group, we re-estimate the OLS regression and interpret the results as lower bound estimates of the impact of TLS on TAY's future homelessness.

13 We are indebted to David Phillips for suggesting this analysis as a strategy for addressing concerns about positive selection. See Rebecca Brough, David C Phillips, and Patrick S Turner, "High Schools Tailored to Adults Can Help Them Complete a Traditional Diploma and Excel in the Labor Market," *American Economic Journal: Economic Policy* 16, no. 4 (2024): 34–67.

3. Caseworker analysis

Our final supplementary analysis exploits exogenous variation in assignment of caseworkers in a manner similar to Cohen (2024).[14] This approach leverages the fact that homeless services in Los Angeles — and especially the staffing of such services — are extremely resource-constrained. Anecdotally, caseworkers in the homeless services system are assigned on a near-random, "first come, first served" basis, with staffing shortages and scheduling logistics making it difficult for either participants to cherry-pick caseworkers or vice versa. Additionally, caseworkers may differ in their ability to help their participants complete the TLS lease-up process. We find strong empirical evidence for both of these claims (conditional random assignment of caseworkers, and variation in caseworker lease-up rates), which can be used as the basis for inferring causality using a research design commonly known as "caseworker fixed effects" or "caseworker leniency."

However, whereas caseworker fixed effects designs traditionally use caseworker treatment propensities as an instrument for the treatment, this requires a strong exclusion assumption that caseworkers only influence individuals' outcomes through the intervention of interest, in this case TLS. While this kind of assumption might be plausible in settings such as criminal court — where the only way the judge can affect a defendant's outcomes is through sentencing — it is less likely to hold in the homeless services context, where caseworkers provide a wide range of services for their clients in addition to helping them lease up with TLS. Furthermore, many of those services may not be documented in HMIS. We therefore restrict our application of the design to a "reduced form" analysis, where we use OLS regression to estimate the causal impact of being assigned to a caseworker with a higher TLS lease up rate. While this does not specifically isolate the effect of leasing up with TLS from other caseworker services, we nonetheless believe that it provides evidence in support of our primary and other supplementary analyses, which do estimate the direct impact of TLS.

We implement this design using the standard approach of constructing a leave-one-out caseworker treatment assignment rate C_i, defined as the percentage of individuals assigned to individual *i*'s caseworker (excluding *i*) who leased up with TLS. To strengthen the relationship between and leasing up with TLS, we restrict the caseworker analysis sample to caseworkers who serve a minimum of 5 individuals, and to months where providers assessed at least 2 individuals in the SPA, resulting in an sample of N=386 TAY who leased up with TLS and N=2,296 TAY who did not.[15] For interpretability, we apply standard scaling to C_i

14 Elior Cohen, "Housing the Homeless: The Effect of Placing Single Adults Experiencing Homelessness in Housing Programs on Future Homelessness and Socioeconomic Outcomes," *American Economic Journal: Applied Economics*, no. forthcoming (2023).

15 For the entire N=3,552 analytic sample for the main analysis, the relationship between the caseworker assignment rate and TLS move-in was too weak to provide meaningful information, with an F-test value of 10.

so that regression coefficients can be interpreted as an increase of one standard deviation. We argue that assignment to caseworkers is conditionally random within a provider at a given month, so all regressions which test for relevance and conditional random assignment include fully interacted assessment provider, SPA, and month fixed effects.

Table 1 presents evidence that being assigned to a caseworker who is more successful at placing other clients in TLS-subsidized housing increases a person's likelihood of leasing up with TLS. We estimate a model predicting whether or not a person will lease up with TLS based on their caseworkers' success rate C_i at placing other clients into TLS, including the provider, Service Planning Area (SPA), and month of assessment as interacted fixed effects. We find that a person's likelihood of leasing up with TLS is strongly related with the success rate of their caseworker at placing other clients. Specifically, an increase in their caseworker's success rate of one standard deviation (14.2 percentage points from a baseline of 10.6 percentage points) increases TLS lease up by 10.8 percentage points from a baseline of 14.4 percentage points, with an F-test value of 28.

TABLE 1. **Relationship between caseworker leave-one-out TLS lease-up rate and individual TLS lease-up rates.**

F-test is from an OLS regression of the individual TLS lease-up indicator on the caseworker leave-one-out TLS lease-up rate plus fully interacted fixed effects for provider, Service Planning Area (SPA), and month of assessment. Values are given as percentages (apart from F-test). Standard errors are clustered at the caseworker level.

	VALUE	STD
Caseworker leave-one-out TLS lease-up rate (%)	10.6	(14.2)
Individual lease-up rate (%)	14.4	(35.1)
F-test	28.23	
Impact on individual lease-up rate of one SD increase in caseworker leave-one-out lease-up rate (p.p)	10.8	(2.0)

Table 2 provides evidence that clients are randomly assigned to caseworkers with varying success rates C_i conditional on the provider, SPA, and month of assessment. We regress caseworkers' success rate C_i on the 29 covariates related to an individual's demographics and service use history (controlling for interacted provider, SPA, and month fixed effects) and find only three significant differences at $p < 0.05$, a result consistent with conditional random assignment. This result can be contrasted with the strong selection seen when directly comparing TLS leased-up participants with the comparison group in Table 3, where there are 14 significant differences at $p < 0.05$.

TABLE 2. Evidence for conditional random assignment of caseworkers.

Rows represent OLS regressions of the caseworker leave-one-out TLS lease-up rate on each characteristic plus fully interacted fixed effects for provider, Service Planning Area (SPA), and month of assessment. Values are given as percentages. Standard errors are clustered at the caseworker level.

	DIFF	STD
Demographics		
Race/ethnicity: Latinx	-0.5	(0.5)
Race/ethnicity: Black	-0.4	(0.5)
Race/ethnicity: White non-Latinx	0.6	(0.5)
Gender: female	0.5	(0.6)
Age	-0.1	(0.1)
CES Intake		
Next Step Tool score	0.0	(0.1)
Income any source	0.7	(0.7)
Lived outside of home on court order	0.6	(0.3)
Disability	-1.2	(1.0)
Prior Homelessness		
Emergency shelter or street outreach in year -5	-2.1	(1.5)
Emergency shelter or street outreach in year -4	-0.3	(1.1)
Emergency shelter or street outreach in year -3	-0.5	(0.6)
Emergency shelter or street outreach in year -2	0.2	(0.6)
Emergency shelter or street outreach in year -1	-1.5	(0.6)*
Other HMIS enrollment in last 5 years	0.0	(0.4)
DPSS Homeless Flag in year -1	-1.3*	(0.6)*

	DIFF	STD
Encounters with County agencies		
DHS Emergency/Inpatient in last 5 years	-0.6	(0.5)
DHS Outpatient in last 5 years	0.4	(0.4)
DMH Crisis Stabilization in last 5 years	-0.4	(0.5)
DMH Non-Crisis in last 5 years	-0.4	(0.6)
DHS/DMH Diagnosis Related to Serious Mental Illness in last 5 years	-0.1	(0.5)
DHS/DMH Diagnosis Related to Substance Use in last 5 years	-2.0	(1.1)
Misdemeanor booking in last 5 years	-0.7	(0.5)
Felony booking in last 5 years	-0.5	(0.5)
Probation Spell in last 5 years	-0.2	(0.7)
CalFresh (SNAP) in last 5 years	-0.9	(0.5)
CalWORKs (TANF) in last 5 years	-0.6	(0.5)
General Relief (GR) in last 5 years	-1.1	(0.5)*
DCFS in last 5 years	1.6	(0.9)
Dependent variable (caseworker leave-one-out TLS lease-up rate %)	10.6	(14.2)
Joint F-Test	0.791	
Joint F-Test P-Value	0.769	

**: $p < 0.01$; *: $p < 0.05$.

Based on these analyses, we can be confident that assignment of TAY to caseworkers is conditionally random, and that their caseworkers' success at placing other people in TLS means they are also more likely to lease up with TLS. We can therefore use a person's caseworker as a proxy for the impact of leasing up with TLS on their risk of future homelessness.

Sample Characteristics

We find evidence that individuals who do and do not lease up with TLS are significantly different along a number of demographic and service use characteristics. Table 3 gives sample characteristics for the 528 individuals who leased up with TLS during the six-month enrollment window following assessment, the comparison group of 3,024 individuals who only received an assessment during the enrollment window, and the difference between the two.

TABLE 3. Sample characteristics.

Values (apart from Age and Next Step Tool Score) are given as percentages.

	TLS LEASED UP		COMPARISON GROUP		
	MEAN (%)	STD	MEAN (%)	STD	DIFF
Demographics					
Race/ethnicity: Latinx	31.3	(46.4)	30.9	(46.2)	0.4
Race/ethnicity: Black	58.1	(49.4)	55.1	(49.8)	3.1
Race/ethnicity: White non-Latinx	11.6	(32.0)	15.5	(36.2)	-4.0*
Gender: female	49.1	(50.0)	41.6	(49.3)	7.4**
Age (years)	22.1	(2.7)	21.8	(2.8)	0.3*
CES Intake					
Next Step Tool score (0–17)	5.6	(2.6)	6.9	(3.1)	-1.2**
Income any source	57.2	(49.5)	43.9	(49.6)	13.3**
Lived outside of home on court order	32.2	(46.8)	41.5	(49.3)	-9.3**
Disability	2.3	(14.9)	3.5	(18.3)	-1.2
Prior Homelessness					
Emergency shelter or street outreach in last 5 years	22.0	(41.4)	25.7	(43.7)	-3.8
Street outreach in last 5 years	10.0	(30.1)	11.3	(31.7)	-1.3
Emergency shelter or street outreach in year -5	0.9	(9.7)	1.0	(9.9)	0.0
Emergency shelter or street outreach in year -4	0.9	(9.7)	1.6	(12.4)	-0.6
Emergency shelter or street outreach in year -3	1.5	(12.2)	2.8	(16.4)	-1.3
Emergency shelter or street outreach in year -2	2.8	(16.6)	3.7	(19.0)	-0.9
Emergency shelter or street outreach in year -1	19.3	(39.5)	20.8	(40.6)	-1.4
Other HMIS enrollment in last 5 years	9.8	(29.8)	9.2	(28.9)	0.7
DPSS Homeless Flag in year -1	53.0	(50.0)	56.1	(49.6)	-3.1

	TLS LEASED UP		COMPARISON GROUP		
	MEAN (%)	STD	MEAN (%)	STD	DIFF
Encounters with County agencies					
DHS Emergency/Inpatient in last 5 years	8.1	(27.4)	16.1	(36.7)	-7.9**
DHS Outpatient in last 5 years	22.2	(41.6)	26.6	(44.2)	-4.4*
DMH Crisis Stabilization in last 5 years	4.7	(21.3)	13.7	(34.4)	-9.0**
DMH Non-Crisis in last 5 years	27.3	(44.6)	39.8	(49.0)	-12.5**
DHS/DMH Diagnosis Related to Serious Mental Illness in last 5 years	8.5	(27.9)	19.2	(39.4)	-10.7**
DHS/DMH Diagnosis Related to Substance Use in last 5 years	0.6	(7.5)	4.1	(19.9)	-3.6**
Misdemeanor booking in last 5 years	16.3	(37.0)	19.0	(39.3)	-2.8
Felony booking in last 5 years	13.6	(34.3)	17.8	(38.2)	-4.1*
Probation Spell in last 5 years	5.3	(22.4)	6.8	(25.1)	-1.5
CalFresh (SNAP) in last 5 years	70.5	(45.7)	68.7	(46.4)	1.8
CalWORKs (TANF) in last 5 years	10.8	(31.1)	9.6	(29.5)	1.2
General Relief (GR) in last 5 years	36.9	(48.3)	37.7	(48.5)	-0.8
DCFS in last 5 years	3.0	(17.2)	5.8	(23.4)	-2.8**
Future Service Receipt					
Time-Limited Subsidies (TLS) move-in in next 4 years	100.0	(0.0)	6.7	(25.0)	93.3**
Permanent Supportive Housing (PSH) in next 4 years	1.1	(10.6)	5.0	(21.8)	-3.9**
Transitional Housing in next 4 years	2.1	(14.3)	6.3	(24.3)	-4.2**
Supervised Independent Living Placement in next 4 years	0.4	(6.1)	0.5	(7.3)	-0.2
N	528		3,024		

**: $p < 0.01$; *: $p < 0.05$.

Table 3 shows strong demographic selection into TLS. TAY who leased up with TLS are less likely to be White (12% vs. 16%), more likely to be female (49% vs. 42%), and slightly older on average (22.1 years old vs. 21.8).

TAY who leased up with TLS also gave significantly different answers to CES intake questions and had different county service histories prior to their assessment. Overall, these differences suggest that TAY with less intensive service needs were more likely to enroll in TLS and successfully complete the lease-up process. TAY who leased up with TLS have lower Next Step Tool scores (5.6 vs. 6.9) than those who did not, are more likely to report income from any source (57% vs. 44%), and are less likely to report living outside the family home on a court order, a proxy for prior foster care involvement (32% vs. 41%). TAY who leased up with TLS are also less likely to have prior visits to a Department of

Health Services emergency room in the last 5 years (8% vs. 16%), less likely to have a prior Department of Mental Health crisis stabilization episode (5% vs. 14%), less likely to have a diagnosis related to serious mental illness (9% vs. 19%), less likely to have a diagnosis related to substance use (1% vs. 4%), less likely to have a felony arrest (14% vs. 18%), and less likely to have foster care involvement in the last 5 years (3% vs. 6%).

Table 3 also shows differences in future enrollments in housing programs. TAY who did not lease up with TLS were more likely to enroll in other housing programs in the four years following their assessment than those who did lease up with TLS. They were more likely to enroll in PSH (5% vs. 1%) and transitional housing (6% vs. 2%) in the next four years. Also, 7% of those who did not lease up with TLS (in the six months following assessment) subsequently enrolled in TLS and moved into a subsidized rental at some point in the next 4 years. However, our results suggest that TAY who leased up with TLS in the six months following their assessment experienced less future homelessness in the following four years than those who did not lease up within the six months of their assessment.

Table 4 provides data on the experiences of TAY who leased up with TLS during their enrollment in the program. We trim the sample to the 5th and 95th percentiles when calculating means and standard deviations in order to exclude outliers which may be data entry errors. On average, TAY who leased up with TLS took 77 days (median 69) to complete the lease-up process and move into a subsidized unit; they received $5,531 in documented financial assistance (median $4,828),[16] and were enrolled in the program for 353 days (median 316). Each of these characteristics has a large standard deviation, indicating considerable variation in program experiences and services received.

TABLE 4. **TLS program experience for 528 leased-up participants.**

Mean and standard deviation are trimmed at the 5th and 9th percentiles.

	MEAN (TRIMMED)	STD (TRIMMED)	MIN	5TH	25TH	50TH	75TH	95TH	MAX
Days from TLS enrollment to lease-up	77	(59)	0	3	23	69	118	282	1,459
Days enrolled in TLS	353	(220)	0	29	166	316	513	864	1,579
Documented financial assistance ($)	5,531	(5,138)	0	0	1,492	4,828	9,128	23,618	106,327

16 Financial assistance amounts are from HMIS and are dependent upon caseworker data entry. Because these amounts are not integrated with financial systems which disburse checks, they are likely to be an undercount of true financial assistance amounts.

Impact Estimates

Table 5 presents impact estimates for the primary OLS analysis and each of the supporting analyses, including: the event study, the positive selection bounding analysis, and the caseworker impacts analysis. Taken together these results give us confidence that leasing up with TLS significantly reduces TAY's future homelessness.

TABLE 5. **Impact estimates.**

OLS regressions control for all covariates in the sample characteristics table (excluding Future Service Receipt), and fully interacted fixed effects for provider, Service Planning Area (SPA), and month of assessment. Event study regressions include individual and year fixed effects (regression equation given in the Methods section). Values are given as percentages. Standard errors for the OLS caseworker analysis are clustered at the caseworker level. Base rate is the estimated base rate for the comparison group, defined as the base rate for the TLS leased-up group minus the percentage point impact. The sample for estimate (4) is restricted to caseworkers who have at least 5 cases, and months where at least 2 peoples were assessed at a given provider/SPA.

	(1) OLS (PRIMARY)			(2) EVENT STUDY			(3) OLS (POSITIVE SELECTION)			(4) OLS (CASEWORKER IMPACT)		
OUTCOME	BASE RATE (%)	IMPACT (P.P)	STD ERR	BASE RATE (%)	IMPACT (P.P)	STD ERR	BASE RATE (%)	IMPACT (P.P)	STD ERR	BASE RATE (%)	IMPACT (P.P)	STD ERR
Emergency Shelter or Street Outreach												
Year -5				-0.5	1.4	(2.0)						
Year -4				0.1	0.8	(2.0)						
Year -3				1.3	0.2	(1.9)						
Year -2				2.3	0.6	(2.1)						
Year -1												
Year 1	17.5	-9.5	(2.5)**	19.5	-11.5	(2.3)**	14.4	-6.4	(3.8)	19.8	-2.3	(1.2)
Year 2	8.0	-2.5	(2.2)	12.1	-6.6	(2.3)**	8.0	-2.5	(3.3)	8.9	-0.9	(0.7)
Year 3	8.0	-2.5	(1.9)	8.4	-2.9	(2.3)	9.0	-3.5	(2.9)	8.3	-0.3	(1.0)
Year 4	6.4	-3.5	(1.8)	7.3	-4.5	(2.2)*	5.2	-2.3	(3.0)	7.8	-1.5	(0.7)*
All 4 Years (Cumulative)	27.1	-10.6	(2.9)**				28.8	-12.3	(4.6)**	30.9	-3.9	(1.4)**
N (Leased Up)	528			528			528			386		
N (Comparison Group)	3,024			3,024			516			2,296		

**: $p < 0.01$; *: $p < 0.05$.

Primary analysis

Our primary OLS analysis finds that leasing up with TLS significantly reduced (by 10.6 percentage points, to 16.5%) TAY's future homelessness in the four years following their assessment as compared to a rate of 27.1% of homelessness for those who did not lease up. We also find evidence that TLS significantly reduced TAY's future homelessness in the first year after the six-month enrollment period to 8.0% of those who leased up with TLS from 17.5% of those who did not. Future homelessness among the TLS leased-up group was also estimated to be lower than the comparison group in years 2 through 4, although these estimates were not significant at the $p < 0.05$ level.

Event study

The event study gives us confidence that positive impacts of TLS lease-up are not substantially biased by unobserved confounding factors that do not vary over time. The event study design allows us to look at homelessness rates year by year to check whether TAY who did and did not lease up with TLS experienced homelessness at different rates in the years before their assessment.

As demonstrated in Table 5, there were no significant differences in rates of homelessness in any of the four years before the assessment among TAY who did and did not lease up with TLS during the enrollment period, providing evidence for the parallel trends assumption. However, similar to the primary OLS analysis, the event study finds evidence that leasing up with TLS significantly reduced homelessness among TAY in the first year following the enrollment period (-11.3 percentage points). The event study also finds evidence that TLS significantly reduced homelessness in the second year following the enrollment period (-6.6 percentage points) and some evidence that it reduced homelessness in the fourth year (-4.5 percentage points).

Positive selection bounding analysis

The positive selection bounding analysis gives us confidence in the results of our primary OLS analysis by demonstrating that those who leased up with TLS were less likely to experience homelessness even when compared to those who resolved their homelessness on their own. This analysis compares future homelessness among those who leased up with TLS to the 516 TAY who found temporary or permanent housing without TLS during the six-month enrollment period after their assessment. The results of this analysis are similar in direction and magnitude to our primary OLS analysis. We find that leasing up with TLS reduced future homelessness by 12.3 percentage points over four years, even when compared to those who found housing on their own. However, in this analysis, we do not find evidence that TLS significantly reduced homelessness year over year (which may partially be due to the smaller sample size when compared with the primary analysis).

Caseworker analysis

Consistent with our primary OLS analysis, we find evidence that being assigned to a caseworker who is more successful at leasing up their clients with TLS significantly reduces TAY's future homelessness in the four years following the enrollment period (-3.9 percentage points). We also find that being assigned to a caseworker with a better TLS lease-up rate significantly reduces a person's future homelessness in the fourth year after the enrollment period (-1.5 percentage points). These estimates are smaller than those from our primary analysis, likely because we are estimating the impact of being assigned to a caseworker with a higher lease-up rate rather than estimating the impact of a person actually leasing up. Still, these findings lend further evidence that the impact of TLS on TAY's future homelessness cannot be explained solely by differences between those who did and did not lease up.

Sensitivity analyses

Table 6 contains results for sensitivity tests which show that the OLS impact estimates are robust to different durations of the post-assessment enrollment window and to the removal of sample definition criteria discussed above.

TABLE 6. Sensitivity analyses.

OLS regressions control for all covariates in the sample characteristics table (excluding Future Service Receipt), and fully interacted fixed effects for provider, Service Planning Area (SPA), and month of assessment. Base rate is the estimated base rate for the comparison group, defined as the base rate for the TLS leased-up group minus the percentage point impact. Values are given in percentages.

	(1) FULLY INCLUSIVE SAMPLE			(2) 3-MONTH ENROLLMENT WINDOW			(3) 12-MONTH ENROLLMENT WINDOW		
OUTCOME	BASE RATE (%)	IMPACT (P.P)	STD ERR	BASE RATE (%)	IMPACT (P.P)	STD ERR	BASE RATE (%)	IMPACT (P.P)	STD ERR
Emergency Shelter or Street Outreach									
Year 1	17.9	-9.2	(1.9)**	17.0	-9.4	(3.2)**	14.8	-6.7	(2.2)**
Year 2	10.0	-4.0	(1.6)*	10.2	-5.4	(2.7)*	8.7	-3.0	(1.8)
Year 3	7.8	-2.1	(1.4)	7.6	-3.7	(2.3)	7.5	-2.6	(1.7)
Year 4	6.9	-3.6	(1.4)**	5.4	-2.1	(2.2)	6.5	-2.9	(1.7)
All 4 Years (Cumulative)	27.3	-9.3	(2.2**)	26.5	-10.1	(3.6)**	25.2	-9.5	(2.7)**
N (Leased Up)	717			355			630		
N (Comparison Group)	5,851			3,391			2,625		

**: $p < 0.01$; *: $p < 0.05$.

The first results in Table 6 are from an analysis of all TAY whose needs were assessed with the Next Step triage tool, including those who received other forms of housing assistance during the six-month enrollment period. Including these other TAY in the analysis does not change the results substantively. We still find that leasing up with TLS during the enrollment period significantly reduces TAY's future homelessness over the following four years. When analyzing year-by-year outcomes, we also find evidence that leasing up with TLS significantly reduced TAY's future homelessness in most of the four years.

Next, we consider whether varying the enrollment window from six months to three or twelve months affects our results. We find that changing the length of the enrollment period does not substantively change the results of the analysis. With either a three-month or twelve-month enrollment period, TAY who leased up with TLS are significantly less likely to experience future homelessness than those who did not.

Racial Equity Analysis

Table 7 provides subgroup impacts for Black, Latinx, and White race and ethnicity groups. The table provides evidence that leasing up with TLS significantly reduced homelessness for both Black and Latinx TAY. While we do not find evidence that TLS significantly reduced future homelessness for White TAY, these results should be interpreted with caution. There are likely too few White TAY in the analysis to estimate a significant impact of TLS on their future homelessness, which is suggested by the large standard errors we estimate.

TABLE 7. **Impact estimates by race and ethnicity.**

Race and ethnicity groups include any individuals with the corresponding HMIS Client indicator ("Black African American", "Ethnicity (Hispanic/Latino)", or "White"), with the exception of the White group which is non-Latinx (i.e. excluding individuals with the "Ethnicity (Hispanic/Latino)" indicator). These variables represent participants' self-reported identity at program intake as recorded by caseworkers on the Coordinated Entry System survey packet. Base rate is the estimated base rate for the comparison group, defined as the base rate for the TLS leased-up group minus the percentage point impact. Values are given as percentages. OLS regressions control for all covariates in the sample characteristics table (excluding Future Service Receipt), and fully interacted fixed effects for provider, Service Planning Area (SPA), and month of assessment. No statistically significant differences were found between impact estimates across groups (tests performed using 1,000 bootstrap iterations).

	(1) BLACK			(2) LATINX			(3) WHITE		
OUTCOME	BASE RATE (%)	IMPACT (P.P)	STD ERR	BASE RATE (%)	IMPACT (P.P)	STD ERR	BASE RATE (%)	IMPACT (P.P)	STD ERR
Emergency Shelter or Street Outreach									
Year 1	21.7	-12.3	(3.7)**	11.5	-4.9	(4.9)	21.0	-11.1	(11.2)
Year 2	9.5	-2.3	(3.2)	3.4	-1.0	(4.2)	17.4	-10.8	(10.5)
Year 3	6.6	-0.8	(2.7)	9.1	-6.7	(3.6)	16.9	-7.0	(8.9)
Year 4	5.9	-2.0	(2.7)	8.6	-8.0	(3.7)*	4.6	0.3	(7.8)
All 4 Years (Cumulative)	29.9	-10.4	(4.2)*	22.9	-13.2	(6.0)*	25.4	0.8	(13.8)
N (Leased Up)	307			165			61		
N (Comparison Group)	1,665			933			470		

**: $p < 0.01$; *: $p < 0.05$.

In addition, we tested whether there were significant differences in the impact of TLS on future homelessness between Black and Latinx TAY by running the OLS estimates across 1,000 bootstrap iterations. We did not find evidence that there was a significant difference in the impact of TLS on Black and Latinx TAY's risk of future homelessness. However, we did find that Black TAY who leased up with TLS returned to homelessness at a significantly higher rate (19.5%) than Latinx TAY who leased up (9.7%).

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