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Evaluation of the Foster Care Hub Home Model: *Supplemental Benefit-Cost Analysis*

The hub home model is an approach to licensed foster care delivery wherein an experienced foster "hub home" provides activities and respite care for a group or "constellation" of foster homes. The Mockingbird Society has operated Washington's only hub home program, frequently referred to as the Mockingbird Family Model, on a small scale since 2004.

The 2016 Washington State Legislature directed the Washington State Institute for Public Policy (WSIPP) to evaluate the "impact and cost effectiveness" of the hub home model (HHM).[1]

In December 2017, WSIPP published an evaluation of the differences in child welfare outcomes for individuals served by HHM foster homes compared to those served in standard foster homes. These outcomes included new reports to Child Protective Services (CPS), new out-of-home placements, placement stability, permanency, child safety, sibling connections, runaways, and caregiver retention.

In this supplemental report we present benefit-cost results incorporating CPS reports and out-of-home placements along with a broader range of outcomes, including high school completion, arrests, behavioral health, and indicators of economic security.

Summary

The hub home model is an approach to licensed foster care delivery wherein an experienced foster "hub home" provides activities and respite care for a group or "constellation" of foster homes.

The program has operated on a small scale in Washington State since 2004.

The 2016 Washington State Legislature directed WSIPP to evaluate the hub home model (HHM). The study includes an outcome evaluation and a benefit-cost analysis to address the cost effectiveness of the HHM in comparison to traditional foster care delivery.

In this study we compare youth who were placed in an HHM foster home at any time to a group of similar foster youth who were not served by the HHM. In general, we find few statistically significant differences between HHM and comparison foster youth.

Based on the modest group differences that emerged we estimate that over the long run, the total economic benefits to society will exceed the cost of providing the HHM approximately two thirds of the time. These economic benefits do not represent savings to the child welfare system but rather consequences to participants, taxpayers, and others in society.

Suggested citation: Goodvin, R., Miller, M., & Hirsch, M. (2018). *Evaluation of the foster care hub home model: Supplemental benefit-cost analysis (Document Number 18-01-3901)*. Olympia: Washington State Institute for Public Policy.

[1] Second Engrossed Substitute House Bill 2376, Chapter 36, Laws of 2016, 1st Special Session.

The report is organized as follows: Section I briefly reviews our evaluation methodology and summarizes definitions for the outcomes presented in this report. Section II presents results of new outcome analyses. Section III details program costs and our benefit-cost analysis. Section IV summarizes key findings and limitations. An Appendix provides supplemental analysis and technical detail.

The primary purpose of this report is to present a benefit-cost analysis of the hub home model in comparison to traditional foster care. WSIPP has developed a standard approach to estimating the overall benefits and costs of interventions at the individual level, which we employ here to the best of our ability. We use estimates from that analysis to inform the potential long-term savings of the HHM, in accordance with the legislative assignment.

To conduct a benefit-cost analysis, we need two types of information. First, we need an estimate of the magnitude of the effects of an intervention. Typically, we assess the magnitude of effects by reviewing all of the available rigorous research evidence and statistically combining the results with a method called meta-analysis. This gives us a robust estimate of how effective we think a treatment will be on average, given evidence from a number of studies. In this report, we estimate the magnitude of outcomes associated with the HHM with results from a single evaluation (described in Sections I and II of this report). While there are limitations of a benefit-cost analysis based on a single evaluation with a small sample, WSIPP's evaluation is the only information currently available to address the legislature's request for an analysis of potential long-term cost savings associated with the HHM.

Legislative Assignment

...the Washington state institute for public policy [shall] evaluate and report to the appropriate legislative committees on the impact and cost effectiveness of the hub home model, a model for foster care delivery. The institute shall use the most appropriate available methods to evaluate the model's impact on child safety, permanency, placement stability and, if possible, sibling connections, culturally relevant care, and caregiver retention. ***The report shall include an analysis of whether the model yields long-term cost savings in comparison with traditional foster care...*** *The institute shall submit an interim report by January 15, 2017, and a final report by June 30, 2017.*

2ESHB 2376, Chapter 36, Laws of 2016, 1st Special Session.
Bolded emphasis added.

The WSIPP Board of Directors exercised its statutory authority to extend the due date of the final outcome analysis to December 31, 2017.

The second type of information we need is the monetary value of the measured outcomes. For our benefit-cost analysis of the HHM, we begin with standard WSIPP values for outcomes but modify certain assumptions so that our analysis is appropriate to this population of youth who have been in foster care. Details of these assumptions are described in the Appendix.

Background information on HHM operations in Washington State, full details of the methodology for our outcome evaluation, and results estimating HHM impacts on child welfare outcomes can be found in WSIPP's December 2017 report, *Evaluation of the foster care hub home model: Outcome evaluation.*[2]

[2] Goodvin, R. & Miller, M. (2017).

I. Review of Evaluation Methods

To evaluate the impact of the HHM, we must compare outcomes of youth in HHM placements to outcomes for a similar group of youth who were placed in foster homes that did not participate in a constellation. As described in WSIPP's December 2017 report, we used an advanced statistical technique called propensity score matching to identify a group of comparison youth who were as similar on a set of key observable factors as possible to youth in HHM placements.[3]

Propensity score matching allows us to approximate the comparability between groups that might have been achieved with a more ideal research design in which participants are randomly assigned to treatment or control groups.[4] However, we recognize that propensity score matching may not eliminate all differences in unobservable characteristics between the treatment and comparison groups that may affect outcomes.

In this report we used historical administrative data obtained from the Department of Social and Health Services (DSHS) Children's Administration (CA), the DSHS Integrated Client Database (ICDB), and the Education Research and Data Center (ERDC).[5]

Study Groups

The HHM "treatment" group includes all youth with at least one placement event between 2004 and 2016 in an HHM foster home. We identified a total of 802 youth who had at least one placement event, for any duration, in an HHM foster home. Some youth had multiple placements in an HHM foster home. We selected each youth's first HHM placement and defined that as the "index event."

Because the HHM was only implemented in five counties, we limited comparison youth to those in foster care in each of the five counties during the years of HHM operation but who were never placed in an HHM foster home.[6] For the comparison group, the index event was the first placement event for a youth in that county during the period of HHM operation.

Including youth with placement events between 2004 and 2016 maximizes sample size and allows us to observe a subset of participants after sufficient time has passed to capture impacts on outcomes in early adulthood. Samples for most outcomes presented in this supplemental report are thus limited to youth for whom we have adequate follow-up data.

To summarize, HHM youth were foster youth who had experienced any placement event in an HHM foster home, regardless of

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Evaluation of the foster care hub home model: Outcome evaluation (Doc. No. 17-12-3902). Olympia: Washington State Institute for Public Policy.

[3] For further information on the rationale for this approach, see Goodvin & Miller (2017).

[4] Austin, P.C. (2011). An introduction to propensity score methods for reducing the effects of confounding in observational studies. *Multivariate Behavioral Research, 46*(3), 399-424.

[5] The research presented here utilizes confidential data from ERDC, located within the Washington Office of Financial Management (OFM). Committed to accuracy, ERDC's objective, high-quality data helps shape Washington's education system. ERDC works collaboratively with educators, policymakers and other partners to provide trustworthy information and analysis. ERDC's data system is a statewide longitudinal data system that includes de-identified data about people's preschool, educational, and workforce experiences. The views expressed here are those of the authors and do not necessarily represent those of the OFM or other data contributors. Any errors are attributable to the authors.

[6] More detailed methods for identifying the treatment and comparison groups are included in Goodvin & Miller (2017), Appendix Section I.

the duration of that placement event. Comparison group youth were similar foster youth who had never been placed in an HHM foster home.

Matching Method

We used an iterative two-phase propensity score matching protocol to select a matched comparison group from youth in foster care who had not been placed in an HHM foster home.

We completed matching protocols within county to lessen the effect of geographical differences such as urbanicity and community resources. Our matching protocols also accounted for year of placement to reduce effects of historical trends in the child welfare system and outcomes over time.[7]

For the first phase, we matched HHM youth to the nearest three individuals with a similar propensity score—our sample was 802 HHM youth and 2,356 comparison youth.[8] Using this as our potential comparison pool for the second phase, we then matched to the nearest single individual with a similar propensity score. We retained 790 HHM youth and 790 comparison youth for the final sample.[9]

Sample sizes vary across outcomes presented in this report because of variability in both age at index event and year of index event, as well as duration of follow-up period.

For two subsamples—those eligible for high school graduation and those 18 and older and discharged from care, for whom our indicators of economic stability are most relevant—we completed new propensity score matching protocols to ensure that the HHM and comparison groups remained balanced. For these subsamples we used one-to-one matching from our pool of potential comparison youth. For further detail, see the Appendix.

Outcome Measures

For this supplemental report on our benefit-cost analysis we used effects on new reports to CPS and subsequent out-of-home placements from our initial outcome evaluation. Although we also evaluated HHM effects on placement stability, permanency, placement with siblings, runaways, and caregiver retention, WSIPP is currently unable to attach a monetary value to these outcomes, making them ineligible for inclusion in this benefit-cost analysis.

To address the charge to evaluate long-term cost savings, we extended our evaluation to longer-term outcomes where foster youth have been shown to be at elevated risk compared to non-foster youth.[10] Outcomes include high school

[7] For full detail on our two-phase matching protocol, including all variables used, see Goodvin & Miller (2017), Appendix Section II. Matching was completed in two phases because it was not feasible to request data on all desired matching characteristics for all youth in foster care placements from 2004-2016. By first identifying the HHM treatment group and a potential comparison pool, we were able to appropriately limit the number of youth to be matched to ICDB records.

[8] Our initial 3:1 match resulted in 50 duplicate comparison youth who had placement events in more than one county, reducing our potential comparison pool.

[9] In 41 cases (12 HHM and 29 comparison pool), the RDA process for linking to Phase 2 data resulted in multiple matches resolving into the same FamLink ID from our analysis sample. To ensure accuracy, we dropped these cases. This resulted in an HHM sample of 790 and potential comparison pool of 2,327.

[10] Burley, M. (2013). *Educational outcomes of foster youth—updated benchmarks* (Doc. No. 13-06-3901). Olympia: Washington State Institute for Public Policy; Cawthon, L., Lucenko, B., Woodcox, P., & Felver, B. (2014). *Pregnant and parenting youth in foster care in Washington State: Comparison to other teens and young women who gave birth* (Report 11.202). Olympia: DSHS Research and Data Analysis

completion; criminal arrests; teen births; treatment for both mental health and substance use disorder; and indicators of economic security including employment, earnings, receipt of both TANF and food stamps, and homelessness.

New Reports to CPS

We examine new reports to CPS in two ways. In our initial evaluation, we examined new reports to CPS within two years of exit for youth who had exited care and had not yet turned 18. For the benefit-cost analysis, we also examined new reports to CPS within two years of starting the index placement event for all youth in the sample with at least a two year follow-up period. This analysis includes youth still in foster care.

New Out-of-Home Placement

We also examine new out-of-home placements in two ways. In our initial evaluation, we examined subsequent out-of-home placements within two years of exit for youth who had exited care to a permanent placement (adoption, guardianship, or reunification with parents). For the benefit-cost analysis, we also examined subsequent out-of-home placements within two years of starting the index placement event for all youth in the sample with at least a two year follow-up period. As with new reports to CPS, this analysis includes youth still in foster care.

High School Graduation

High school graduation status is derived from youths' last enrollment status as of June 2016—the end of the final school year available in our follow-up period. To account for variation in the time that students might take to graduate from high school, we focus on graduation by age 19. Students are categorized as a high school graduate if they graduated with a regular high school diploma. We completed this analysis with a propensity score matched sample of youth eligible to have graduated from high school. Our analysis excludes youth who were: [11]

- younger than 18 in June 2016 (as these youth would not yet have been expected to graduate from high school),[12]
- age 18 and still enrolled in high school, and
- confirmed in their last enrollment status to have transferred out of state.

Arrests

Youth were classified as having an arrest if they were arrested for a crime at any time after the start of their index event. This analysis includes only youth who were age eight or older at the start of their index event.[13]

Teen Births

Youth were defined as having a teen birth if there was record of them having given birth to or fathered a child between the ages of ten and 17 years old and if that birth occurred after the start date of the index

division; Pavelle, B., Lucenko, B., Hughes, R., & Felver, B. (2015). *Behavioral health treatment needs and outcomes among foster care children in Washington State.* Olympia: DSHS Research and Data Analysis division; Allwood, M.A., & Widom, C.S. (2013). Child abuse and neglect, developmental role attainment, and adult arrests. *Journal of Research in Crime and Delinquency, 50*, 551-578; and Currie, J., & Widom, C.S. (2010). Long-term consequences of child abuse and neglect on adult economic well-being. *Child Maltreatment, 15*, 111-120.

[11] Ten additional cases were excluded because the youth were not matched to any records in ERDC's data.
[12] Youth in our sample who were recorded as graduating from high school at age 17 were included in our analysis.
[13] Arrests were limited to youth age eight and older to maintain consistency with WSIPP's benefit-cost model. For more information, see WSIPP's Technical Documentation.

event.[14] All records of sample youth having a child were for births to females, so we excluded males from this analysis. Our analysis only includes youth who were age ten or older by January 1, 2017—the last date for which we have data.

Behavioral Health Treatment

For both mental health treatment and substance use disorder treatment we defined outcomes as having received any relevant inpatient treatment after the start of the index event.

Economic Security

We consider data on outcomes related to economic security to be most relevant to youth who have transitioned to adulthood. We therefore examined indicators of economic security only for youth who were age 18 or older by the end of our follow-up period. We conducted these analyses using a propensity score matched subsample of youth 18 or older by January 1, 2017 (see Appendix for further detail).

For food stamp receipt, TANF receipt, and homelessness, we further limited the sample to youth who had been discharged from care. Date of discharge from state custody was sometimes missing from our data. In the case of missing discharge date, we assumed that the case closed on the youth's 19th birthday. For all indicators of economic security, the duration of time for which we can observe outcomes varies based on when in our follow-up period an individual turned 18.

Employment. Youth were classified as having employment if the unemployment insurance wage file indicated that they had been engaged in paid employment during any quarter after turning 18.

Earnings. We calculated average quarterly earnings across all quarters between youths' 18th birthday and the end of our follow-up period.

Food Stamp Receipt. Youth were classified as receiving food stamp benefits if they received food stamps during any month after turning 18.

TANF Receipt. Youth were classified as receiving TANF benefits if they received TANF during any month after turning 18.

Homelessness. Youth were classified as having experienced homelessness if they were flagged as being homeless with or without housing during any month after turning 18.[15]

Analysis Method

For outcomes defined as yes/no (such as high school graduation and arrests), we typically used specialized logistic regression[16] controlling for the same characteristics used in the propensity score model and county. In the smaller sample used for economic security indicators, we instead used a fixed effects logistic regression that controlled for time "at risk;" that is, months between youth turning 18 and the last date for which we had information.[17] Similarly, for high school graduation we used a fixed effects logistic regression controlling for the matching characteristics and county.

[14] We set a lower limit of ten years because of several cases present in our data where youth were recorded as having had a child at an implausibly young age, and we assume that these records represent data match errors.

[15] This information comes from the DSHS Automated Client Eligibility System.

[16] We use the SAS program, Surveylogistic, specifying that cases were clustered by county.

[17] Last available dates varied by outcome. More information on these dates is provided in Appendix Section I.

For the outcome that was continuously measured, average quarterly earnings, we used a unique analytic approach. Paid employment was relatively uncommon in our sample, resulting in a high number of youth with zero earnings. To calculate the average quarterly earnings, we used a statistical approach referred to as a "two-part model."[18] The first part of the model estimates the likelihood of having any earnings. The second part calculates the average quarterly earnings per youth, accounting for the likelihood of earnings.

[18] Belotti, F., Deb, P., Manning, W.G., & Norton, E.C. (2015). Twopm: Two-part models. *The Stata Journal, (15)*1, 3-20.

II. Evaluation Findings

In this section we present results for analyses assessing the impact of HHM foster home placement on youth outcomes.

New Reports to CPS

In our initial report we analyzed the likelihood of a subsequent report to CPS for a subsample of youth discharged from the child welfare system before age 18. Seen in Exhibit 1, the rates of reports for HHM and comparison youth were not significantly[19] different within two years of exit. This approach produces the best estimate of the likelihood of new reports following exit from care.

To determine an appropriate effect size for our benefit-cost analysis, we examined the likelihood of a new report to CPS for the full sample with two years of follow-up past the start of the index event, regardless of permanency status. There was no significant HHM effect on the likelihood of a new report to CPS (see Exhibit 1).

When we include the full sample, we observe lower rates of subsequent CPS reports. This estimate of group differences more closely approximates a causal effect of the HHM on new reports for the average youth in care.

[19] Statisticians often rely on a metric, the p-value, to determine whether an effect is significant. The p-value is a measure of the likelihood that the difference could occur by chance—values range from 0 (highly significant) to 1 (no significant difference). By convention, p-values less than 0.05 (a 5% likelihood that the difference could occur by chance) are considered statistically significant.

Exhibit 1

Regression-Adjusted Percent of Youth with a New Report to CPS

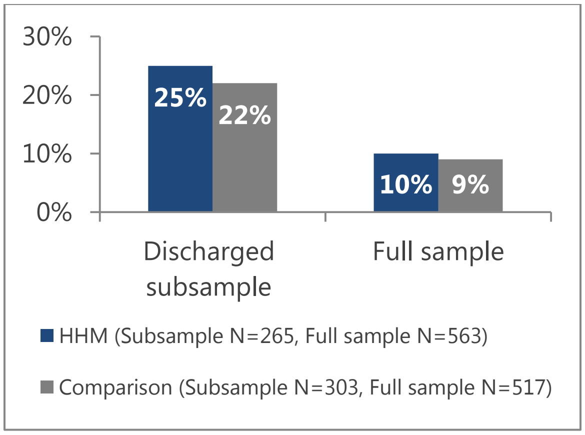
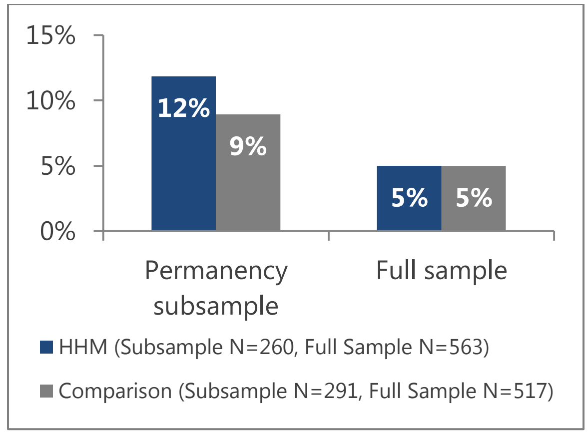


Exhibit 2

Regression-Adjusted Percent of Youth with a New Out-of-Home Placement



New Out-of-Home Placement

In our initial report, we analyzed the likelihood of a new out-of-home placement within two years for a subsample of youth who achieved permanency before turning 18. As shown in Exhibit 2, there was no significant difference between HHM and comparison youth for new placements within two years of permanency. This approach produces the best estimate of the likelihood of new out-of-home placements following exits to permanency.

To determine an appropriate effect size for our benefit-cost analysis, we examined the likelihood of a new out-of-home placement for the full sample with two years of follow-up past the start of the index event. The HHM and comparison groups did not differ in their likelihood of a new out-of-home placement (see Exhibit 2).

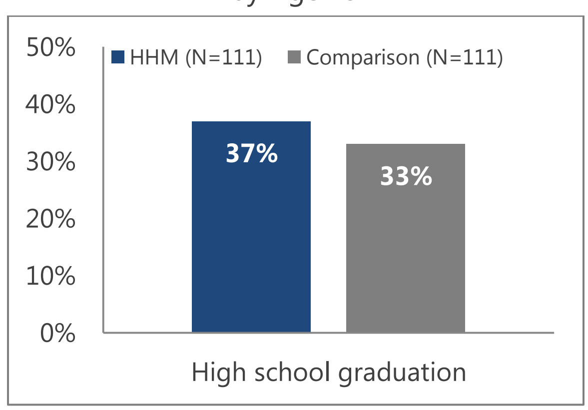
As with new reports, the between group difference for the full sample is a better estimate of the causal effect of the HHM for the average youth.

High School Graduation

For youth 18 and older by June 2016, we compared the likelihood of high school graduation in the HHM and comparison groups.[20] Although HHM youth were slightly more likely to have graduated from high school by age 19, this difference was not statistically significant (see Exhibit 3).

Exhibit 3

Regression-Adjusted Percent of Youth Age 18 and Older Graduated from High School by Age 19



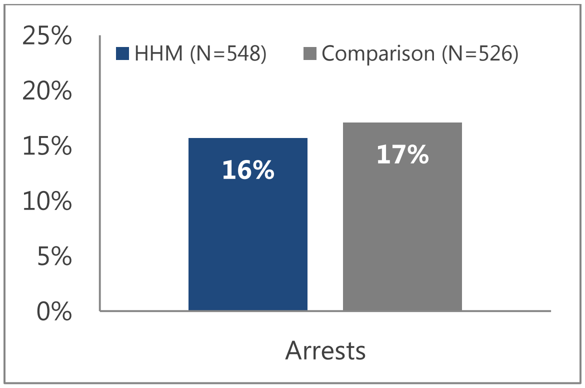
[20] We also included a small number of youth in our sample who graduated from high school at age 17.

Arrests

For youth age eight and older at the start of their index event, we compared the likelihood that HHM and comparison youth had been arrested for a crime at least once during our follow-up period. As shown in Exhibit 4, the likelihood of arrest was about the same in the two groups.

Exhibit 4

Regression-Adjusted Percent of Youth Age Eight and Older with an Arrest



Teen Births

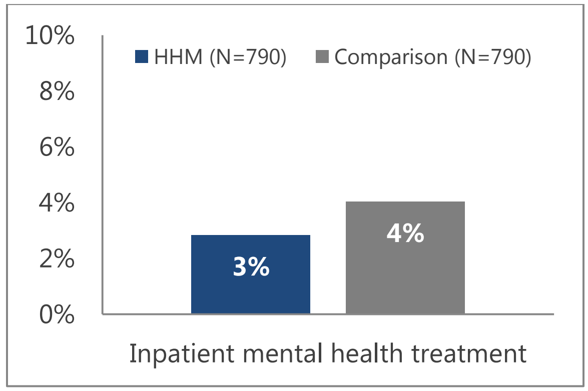
For females age ten and older at the end of our follow-up period, we examined births occurring after the start of the index event and before age 18. Teen births were so infrequent in our data that we could not meaningfully analyze differences between the HHM and comparison groups.

Behavioral Health Treatment

For all youth in our sample, we examined the likelihood of inpatient treatment for mental health and substance use disorder at any time after the start of the index placement. For mental health inpatient treatment, HHM youth had a slightly lower rate than did comparison youth, as seen in Exhibit 5. However, this difference was not statistically significant.

Exhibit 5

Regression-Adjusted Percent of Youth with any Inpatient Mental Health Treatment



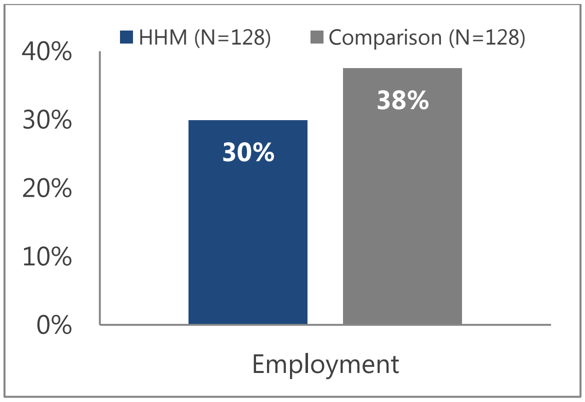
Inpatient treatment for substance use disorder was too infrequent in our data to meaningfully evaluate differences between the HHM and comparison groups.

Employment

For our sample of youth age 18 or older by January 1, 2017, we examined the likelihood of paid employment in any quarter during our follow-up period. The overall employment rate was relatively low. There are a variety of reasons why youth may not have been employed. For example, youth still in secondary school or continuing on to higher education may not have entered the labor force. HHM youth were slightly less likely to have had any paid employment, overall, than were comparison group youth. As presented in Exhibit 6, this difference was not statistically significant.

Exhibit 6

Regression-Adjusted Percent of Youth Age 18 and Older with any Paid Employment



Earnings

As indicated by our employment findings, only a small percentage of youth had any earnings recorded. We therefore applied a two-stage statistical model to account for the wide variability in average quarterly earnings. This approach allowed us to more accurately determine if average quarterly earnings differed for the HHM and comparison groups.

Exhibit 7 displays, for youth age 18 or older, the average quarterly earnings per participant across each quarter eligible for earnings. HHM youth had marginally higher earnings ($p = 0.08$).

Exhibit 7

Average Quarterly Earnings

	N	Mean	SE
HHM	128	$299.52	$110.21
Comparison	128	$195.98	$64.61

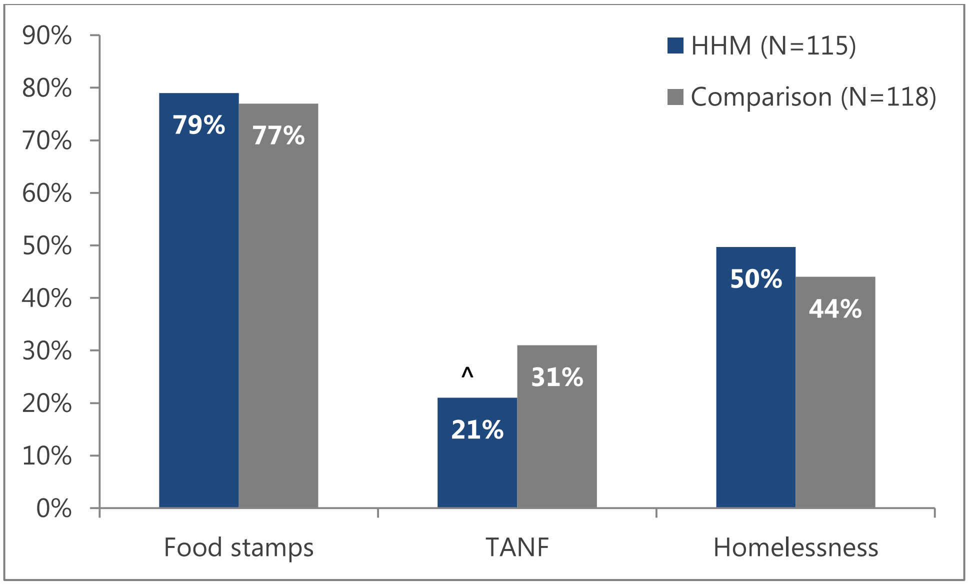
Basic Food Receipt, TANF Receipt, and Homelessness

For our sample of youth age 18 or older and discharged from care by January 1, 2017, we examined the likelihood of receiving basic food benefits, receiving TANF, or experiencing homelessness in any month during our follow-up period. Results are shown in Exhibit 8 on the following page.

HHM youth were slightly more likely to have received basic food benefits, but this difference was not statistically significant. HHM youth were slightly less likely to have received any TANF benefits, a difference that was marginally statistically significant. Finally, HHM youth were slightly more likely to have been identified as experiencing homelessness, but this difference was not statistically significant.

Exhibit 8

Regression-Adjusted Percent of Youth with any Basic Food Receipt or TANF Receipt, or any Homelessness



Note:
^ $p < 0.10$.

III. Program Costs & Benefit-Cost Analysis

We assess the potential economic consequences of the HHM using WSIPP's standard benefit-cost approach. In this approach we compare the costs of administering the program to the predicted monetary benefits to society associated with outcomes measured in our evaluation. This gives a very broad measure of whether, over time, we expect the total value to participants, taxpayers, and others in society to outweigh the cost of providing the program. To more specifically address the legislative assignment to review "long-term cost savings in comparison with traditional foster care," we also discuss potential costs and savings to Washington's publicly funded systems (e.g., child welfare, criminal justice, public assistance).

In typical applications of the benefit-cost model, we estimate the average effects of a program by analyzing the existing body of research evaluating that program. In this analysis, rather than using information from multiple studies, we relied on estimates from a single evaluation. These estimates are our effort to produce the best possible prediction of the monetary impact of the HHM considering the limited follow-up time and small sample sizes.

In addition, we adjusted our typical assumptions—described in WSIPP's Technical Documentation[21]—to better match the outcome rates for youth in the foster care system.[22] However, even with adjustments, the methods we use to value outcomes do not always fit such a specialized population. For all of these reasons, results presented here represent a stand-alone product, not comparable to other benefit-cost analyses published by WSIPP.

In our benefit-cost model, a program that, for example, produces a decrease in the probability of additional removals and foster care placements or an increase in the probability of high school graduation can lead to monetary benefits. These benefits accrue over time to program participants, taxpayers, and other people in society through reduced use of services provided by the child welfare system, increased employment, and greater tax revenue. An increase in the rate of high school graduation can also lead to reductions in the probability of crime and reductions in the use of publicly provided health care. These benefits can then be summed and compared to the cost of a program to estimate an overall return on investment.

We present our results using standard financial summary statistics including net present values and benefit-cost ratios. We also provide an estimate of risk that accounts for the uncertainty present in any individual statistical or benefit-cost estimate. Additional detail on our benefit-cost methods can be found in WSIPP's Technical Documentation.[23]

For this benefit-cost analysis we monetized child welfare outcomes—new reports to CPS and new out-of-home placements—using

[21] See WSIPP's Technical documentation.
[22] Adjustments are described in Section V. of the Appendix.
[23] See WSIPP's Technical documentation.

two different approaches. Our primary approach for the benefit-cost analysis used results from the full analytic sample with the requisite follow-up time. Given the minimal likelihood of a youth experiencing a new report to CPS or a new out-of-home placement while still in foster care, we completed an alternative analysis using effects for the subsample of youth who had exited care as a sensitivity check on our benefit-cost results.

In addition to new reports and new out-of-home placements, we included in the benefit-cost analysis effects on high school graduation, arrests, inpatient mental health treatment, food stamp receipt, and TANF receipt.[24]

Not all new outcomes evaluated in this supplemental report could be included in the benefit-cost analysis. Due to the small sample size available for this evaluation and the low rate of occurrence in the population, we were unable to examine the effect of the HHM on substance use treatment and teen birth. In other words, these events were so infrequent that any differences between the HHM and comparison groups would not be meaningful.

Additionally, WSIPP's benefit-cost model was designed to measure employment and earnings over the life course. We have several concerns about applying our typical techniques for this sample. In this study, earnings and employment are measured in a small sample over a short period during a time of life when many of these youths would not be expected to be in the labor force. This issue is exacerbated by the imprecise measurement information available. As a result, we do not presently have the capacity to provide accurate estimates of the long term value of employment and earnings for this unique population of foster youth during early adulthood. Finally, WSIPP is not currently able to monetize homelessness.

[24] Effect sizes and additional information for all outcomes included in the benefit-cost analyses are shown in Appendix Section V.

Cost Estimates

In our December 2017 report we provided detailed information on our approach to estimating the total per-participant cost to provide the HHM, over and above the cost of traditional foster care. In this section we summarize our estimate.

Using information on youth served in HHM foster homes between 2014 and 2016, we assume hub homes receive $2,400 per month for the additional services they provide. We calculated the average cost per day per youth to be $5.72, with an average length of stay of 319 days. Thus, we estimate the total cost per youth, in addition to the cost of foster care, to be $1,826.

This figure may underestimate the total cost of the HHM, as it does not include the cost of training hub home providers, support provided by The Mockingbird Society, or the cost of time for CA (or other HHM host agency) liaisons. On the other hand, our figure may be an overestimate, as we were unable to estimate potential savings from unbilled respite care. In certain hub homes (those supervised by CA), monthly payments to hub homes are intended to cover the cost of providing respite care. Data on respite care not billed to the state are not available, so we were unable to examine the magnitude of these potential cost savings.

Benefit-Cost Results

In Exhibit 9 (next page), we provide findings from the benefit-cost analysis. We estimate the lifetime benefits of the outcomes reported. Because we are interested in the effects and costs of the HHM over and above traditional foster care, we place the cost of the comparison group at $0.

Of the outcomes we can include in our estimate of long-term monetary benefits, we found no statistically significant differences between the HHM and comparison youth. Effects are small in magnitude. We include the effects in our benefit-cost estimates along with the estimated error in our measurements.

HHM youth were slightly more likely to graduate from high school, less likely to be arrested, less likely to experience inpatient mental health treatment, and less likely to receive TANF. All of these outcomes would lead to positive monetary benefits over the long term. On the other hand, HHM youth were slightly more likely to experience a subsequent CPS report and more likely to receive food stamps. These outcomes would lead to negative benefits over the long term.

We find the long term benefits of the HHM outweigh the cost of providing the HHM. We estimate the total net benefits (benefits minus costs) of the HHM to be $14,121. The total estimated benefits of the program outweighed the estimated costs. Based on the risk analysis, we would expect the benefits to exceed costs 67% of the time.

Exhibit 9 displays results from our primary analysis. For the two child welfare outcomes—new reports to CPS and new out-of-home placements—we used effects based on the full analytic sample (that is, the sample including youth still in foster care) to estimate effects of the HHM on these outcomes.

As a sensitivity check on our benefit-cost results, we conducted a second benefit-cost analysis using the approach to these outcomes taken in our December 2017 report. As previously described, we examined new reports and new out-of-home placements for youth who had exited the child welfare system. Similar to our primary analysis, in the sensitivity analysis we again found that the estimated benefits exceeded the estimated costs. Estimated net benefits are $14,030, and benefits are predicted to outweigh costs 66% of the time.

Long-Term Cost Savings

The HHM is thought to potentially produce long-term cost savings to the child welfare system. These cost savings are predicted to accrue based on increased caregiver retention (leading to less turnover for HHM foster homes) and reduced use of respite care that is billed to the state. We are unable to comment on the potential cost savings associated with caregiver retention. Limited data availability prevents us from making an accurate causal estimate of the magnitude of the impact of the HHM on retention. Further, we are not currently able to assign a monetary value to caregiver retention.

We are able to estimate the value of respite care billed to the state. However, because we cannot observe how much respite care is being provided by most HHM homes as part of their HHM payment, we cannot estimate avoided costs to the system.

We can, however, estimate the overall costs and avoided costs to Washington's public systems. Exhibit 9 illustrates that over time, youth served by the HHM accumulate slightly higher costs than comparison youth in the child welfare system, the K–12 system, and the higher education system.

On the other hand, youth served by the HHM are predicted to *avoid* costs in the criminal justice, public assistance, and health care systems that comparison youth would otherwise be expected to incur.

If we add all of the public system costs and cost savings together over time, we expect that they would outweigh the initial HHM cost (or "break even") approximately 14 years from the initial investment.

Exhibit 9

Benefits and Costs per Participant for HHM vs. Comparison Group in 2016 Dollars

Program cost		
Cost per participant including as described in Part 1 of this report - Costs are in addition to the cost of foster care		($1,826)
	(1) Net Hub Home cost	**($1,826)**
Labor market effects		
Increased income to participants due to increased human capital from an increase in high school graduation		$7,872
Increased tax revenue due to increased human capital from an increase in high school graduation		$3,575
Positive externalities ("spillover effects") to society due to a larger number of high school graduates		$3,579
Decreased income to participants due to more child abuse and neglect		($1,513)
Decreased tax revenue due to more child abuse and neglect		($687)
Out-of-home placement effects		
Decreased cost to taxpayers due to decreased out-of-home placements		$1
Child abuse and neglect effects		
Increased cost to participants due to more child abuse and neglect		($30)
Increased cost to taxpayers due to more child abuse and neglect		($69)
Increased cost to others due to more child abuse and neglect leading to more alcohol use disorder		($0)
Value of mortality risk increase as a result of more child abuse and neglect		($26)
Education effects		
Increased K-12 education costs due to increased grade retention as a result of child abuse and neglect		($9)
Increased K-12 education costs due to increased special education as a result of child abuse and neglect		($43)
Increased postsecondary costs for participants due to increased probability of attending college		($333)
Increased cost to taxpayers due to increased probability of attending college		($221)
Increased cost to others due to increased probability of attending college		($100)
Health care-related effects		
Decreased costs to participants due to decrease in psychiatric hospital use		$3
Decreased costs to taxpayers due to decrease in psychiatric hospital use		$202
Decreased costs to private or employer provided insurance programs due to decrease in psyciatric hospital use		$45
Food assistance effects		
Increased food assistance received by participants		$383
Increased cost to taxpayers due to increased food assistance - including overhead		($424)
Public assistance effects		
Decreased public assistance received by participants		($1,229)
Decreased cost to taxpayers due to decreased assistance payments- including overhead		$2,893
Crime-related effects		
Decreased cost to taxpayers due to reduced probability of crime		$494
Decreased crime victim costs due to reduced probability of crime		$1,076
Deadweight cost of taxation		$510
	(2) Total benefits	**$15,947**
Bottom line:		
Net benefits (cost) per participant	(3) Net (benefits – costs)	**$14,121**
Benefit-to-cost ratio		**$8.74**
Probability of positive net benefits (risk analysis)		**67%**

IV. Summary

Findings

In our December 2017 report, we found that HHM youth were likely to have higher rates of placement stability. Of youth who achieve permanency, there were no significant differences in the rate of new out-of-home placements for HHM and comparison youth. Overall, for youth who exited the child welfare system, there was no statistically significant relationship between HHM placements and new reports to CPS. The HHM had no effect on placement with siblings. Youth in HHM placements were more likely to end their index placement by running away from care. Based on limited data, our results suggest that HHM caregivers are likely to remain licensed for a longer duration than their non-HHM counterparts.

In this report, we found no statistically significant effect of participation in the HHM on high school graduation, criminal arrest, mental health inpatient treatment, employment after age 18, receipt of basic food assistance, or homelessness.

We find marginally significant lower rates of receipt of TANF and higher average quarterly earnings among youth who had reached the age of 18 and exited from care.

Benefit-Cost Analysis

Based on the outcomes included in the benefit-cost analysis, we find that the total estimated benefits of the HHM program exceed the total estimated costs, and that benefits would be expected to exceed costs approximately 67% of the time.

The magnitude of the net benefit is largely due to downstream effects of greater labor market earnings caused by the slightly higher rates of high school graduation observed in the HHM group. We therefore urge caution in interpreting these results, as the effect of HHM on high school graduation is estimated in a relatively small sample.

If we restrict our perspective to Washington's taxpayer-funded public systems, we find that overall cost savings outweigh costs over time. The cost savings are not predicted to accrue to the child welfare system but rather to the criminal justice, public assistance, and health care systems. We expect these total savings to outweigh the HHM costs roughly 14 years after the initial investment.

Limitations

The main limitation of this study is the inability to randomly assign participants—both caregivers and youth—to the HHM or to standard foster care. This experimental approach would have allowed us to rule out the possibility that foster caregivers who elect to participate in the HHM differ in important ways from those who do not participate. Random assignment of youth would allow us to compare outcomes for HHM youth to youth from the same offices at the same time and would have increased our confidence that group differences observed were due to the HHM and not to other unobserved characteristics.

A second limitation is the small sample size available for this study. A small sample reduces the power to detect significant effects and reduces our overall confidence in determining whether the HHM program had effects on study outcomes.

A third limitation is the restricted time for follow-up for a large part of our sample. Nine new constellations were initiated in 2015-2016, and approximately 40% of HHM youth entered into their index event in 2015 or 2016. Data available at the time of our analyses included less than two years of follow up on these youth.

There were additional limitations specific to the benefit-cost analysis. Our benefit-cost approach allowed us to monetize a wide range of outcomes within a consistent framework. However, we were not able to monetize all outcomes we observed. For example, at this time WSIPP is unable to include placement stability or homelessness in our benefit-cost analysis. Further, due to the unique characteristics of this study sample, we were required to adjust the monetary values we typically assign to the outcomes we observed.

Finally, in benefit-cost analysis WSIPP typically uses average effect sizes drawn from a body of rigorous evaluations of a program. In this instance, the only available effect sizes come from WSIPP's own evaluation of a single small sample. Nonetheless, this study represents the best available information about HHM effects on youth outcomes.

If the legislature is interested in a more robust assessment of the HHM, it might consider another evaluation in several years that would increase the sample size and extend the available follow-up period for this larger sample.

Appendices

Evaluation of the Foster Care Hub Home Model: *Supplemental Benefit-Cost Analysis*

Appendices

A. I. Data and Identification of the Study Group

Data

For detailed information on the data and study groups, please see the Appendix of our previous report.[25] In summary, creation of the analysis data set involved a two-phase process. In Phase 1, we identified all youth in a hub home and created a comparison pool using a statistical approach called propensity score matching, using child demographics and welfare history. We then matched to youth in the same counties, in the same time periods, allowing three comparison youths for each youth in a hub home model (HHM) foster home. This sample was sent to the Research and Data Analysis Division (RDA) at the Department of Social and Health Services (DSHS). RDA then attached information on the need for mental health and substance abuse treatment prior to the index placement event, employment, arrests, mental health and substance abuse treatment after the index placement event, records of births to youth in our sample, and homelessness (individuals identifies as homeless in the DSHS Automated Client Eligibility System). RDA also sent identifiers for the comparison pool to the Washington State Education Research and Data Center (ERDC), who attached information on high school graduation year and other school exits to the file for each youth.

In Phase 2, we matched HHM youth to comparison youth (1:1), again using child welfare information as well as arrest history and need for mental health and substance abuse disorder treatment prior to the index event.

Data for our analyses were extracted monthly (or quarterly for employment information) from January 2004. However, the final dates available varied by outcome. Exhibit A1 displays that last date for which data were available.

[25] Goodvin & Miller (2017).

Exhibit A1

Data Availability by Outcome

Outcome	Last available date
Arrest	January 2017
Homelessness	January 2017
Employment	Fourth quarter, 2017
High school graduation	2015-2016 school year
Teen birth	May 2017
Mental health inpatient treatment	March 2016
Substance use disorder inpatient treatment	March 2016

Subsamples

Some outcomes—receipt of TANF and food stamps, employment, earnings, homelessness—were only relevant for youth who had turned 18. When we created a subsample of youth meeting these criteria from our Phase 2 match, we found the HHM and comparison samples were no longer balanced on some variables that predicted outcomes. Thus, for these analyses, we created a new sample using the entire HHM sample (who had reached age 18) and matching to the comparison pool of youth meeting the same criteria we used in our Phase 2 match. Because this group was heavily weighted to King County (about 95% of youth were in King County) we completed only one matching protocol, controlling for King County. HHM and comparison youth were then well matched.

To evaluate the effect of HHM experience on high school graduation by age 19 it was again necessary to create a subsample, since not all youth would have been able to graduate by June 2016 (the last year for which we had data). When the sample was reduced to include only those youth who would have been expected to graduate (18 or older by June 15, 2016, and not still enrolled in school), the HHM sample and the comparison group were unbalanced on several measures. For this analysis, we matched HHM youth who were 18 or older by June 15, 2016 and not still enrolled in schoo with youth from the comparison pool. We excluded from the HHM sample and potential comparison pool all youth who had a school exit code indicating that they had transferred out of Washington State or were deceased,.

A. II. Matching Procedures

In an ideal research design, both caregivers and youth would be randomly assigned to either the HHM or traditional foster care model. With a successfully implemented random assignment, any observed differences in outcomes could be attributed to the effect of the HHM. Unfortunately, as is the case in many real world settings, random assignment was not possible for this evaluation.

Instead, we used observational data and relied on a quasi-experimental research design. To infer causality from this quasi-experimental study, selection bias must be minimized. To do so, we implemented a variety of research design methods and statistical techniques that provided the ability to test the sensitivity of our findings. In this section of the Appendix, we describe the study groups and statistical methods we used to arrive at estimates of the effects of the HHM.

Propensity Score Matching

Propensity score matching allowed us to match HHM youth with similar youth to obtain balance on observed covariates. This method has many benefits over standard regression analysis, which is often used to control for differences between treated and comparison groups.

First, the match is based on characteristics before the treatment occurs. That is, the outcome plays no part in matching the treated and comparison groups. This emulates an experimental design by separating the research design stage—where we test various matching procedures to obtain a sufficiently matched sample—from the analysis stage—where we estimate the effect of the treatment using our matched sample. Second, matching can limit the importance of functional form in regression analysis.[26] Finally, by conducting a logistic regression on the matched sample using the covariates from the matching model, we further reduced any residual bias that may remain after matching and account for any correlation between matched pairs.

Information on our initial two phase matching protocol is detailed in the Appendix of our previous report.[27] Here, we present results of matching protocols for the two new matched subsamples used for outcome analyses in this supplemental report. Exhibit A2 reports the results from the coefficients for subsample matching.

The table also provides the area under the receiver operating characteristic curve (AUC) for each model. AUC is a measure of how well the model predicts the outcome—in this case, whether youth would be in the HHM group. Values of AUC can range from 0.05 to 1, with 1 indicating perfect prediction. AUCs of 0.7 or greater are considered good predictive models.

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[26] Ho, D.E., Imai, K., King, G., & Stuart, E.A. (2007). Matching as nonparametric preprocessing for reducing model dependence in parametric causal inference. *Political analysis, 15*(3), 199-236.
[27] Goodvin & Miller (2017).

Exhibit A2

Subsample Logit Models Estimating the Likelihood of HHM Participation
Those over 18 January 1, 2017 and Those Meeting Criteria for Graduation by Age 19

	18 and over sample			High school grad sample		
Covariate	**Coefficient**	**p-value**	**SE**	**Coefficient**	**p-value**	**SE**
Age (reference group 5 to 10 years old)						
11-14 years old	-0.552		0.394	-0.392		0.460
over 15 years old	-0.670		0.431	-0.407		0.507
Male[a]	-0.294		0.231	-0.392		0.249
Race (reference group is White/undetermined)						
Black	0.026		0.274	-0.407		0.287
Asian/Pacific Islander	0.359		0.525	0.366		0.541
Native American	0.022		0.412	-0.320		0.457
Hispanic	0.664		0.410	0.656		0.428
Child placing agency	1.229	***	0.261	1.185	***	0.273
Exceptional rate payment[a]				0.241		0.266
No. of removal episodes to date	0.017		0.098	0.035		0.098
No. of prior placement events in removal	-0.022		0.015	0.001		0.013
No. of prior CPS reports	-0.017		0.031			
Year of index placement (reference group is 2009-2011)						
2003-2005	-0.099		0.371	0.003		0.417
2006-2008	-0.451		0.314	-0.386		0.336
2012-2014	0.319		0.344	0.866	*	0.372
2015-2017	0.557		0.509	0.754		0.588
Any prior arrests	1.390	***	0.373	-0.651	^	0.336
Any prior runaway event	0.980	*	0.427			
Prior mental health treatment need	0.651	^	0.332	0.678	^	0.359
Prior SUD treatment need	-0.580	^	0.323	-0.345		0.332
King County	1.214	*	0.546	1.014		0.578
N	528			433		
AUC	0.748			0.693		

Notes:
^ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$.

In Exhibits A3 and A4 we present descriptive statistics on all matching variables for HHM and comparison youth. We used various diagnostics to determine the extent to which the propensity score matching improved balance between the treated and comparison groups. A common measure of balance is the standardized difference (or bias) calculated as the difference in the mean/proportion for the treated and comparison groups, divided by the pooled standard deviation for each covariate prior to matching. This measure is preferred to traditional t-tests as the standardized difference is not influenced by the study's sample size. Additionally, t-tests are used for making inferences about a population based on a sample; balance, on the other hand, is an in-sample property. Standardized bias values greater than 0.10 usually indicate moderate imbalance while greater than 0.25 indicates severe imbalance.[28] Exhibits A3 and A4 also display the percent standardized bias for each covariate in the propensity score model before and after matching as well as the p-value as a reference. After matching using Austin's criteria,[29] in the sample of all youth over 18 by January 1, 2017 we found moderate imbalance in one characteristic—the percent of youth who were ages 5 to 10 at the beginning of the index event. In the sample of those eligible for high school graduation by June 15, 2016, we observed two characteristics with moderate imbalance after the match—the percent of youth who were Native American and average number of prior reports to CPS. Finally we used logistic regression, controlling for the same variables used in the propensity score match. This last step is used to "clean up" residual covariate imbalance between groups.[30]

[28] Austin, P.C. (2009). Balance diagnostics for comparing the distribution of baseline covariates between treatment groups in propensity-score matched samples. *Statistics in Medicine, 28*(25), 3,083–3,107 and Stuart, E.A. (2010). Matching methods for causal inference: A review and a look forward. *Statistical Science: A Review Journal of the Institute of Mathematical Statistics*, *25*(1), 1–21.
[29] Austin (2009).
[30] Stuart (2010).

Exhibit A3

Subsample of Youth 18 and Older Characteristics Before and After Matching

Variable	Means and proportions after matching			Absolute standardized difference (d)	
	HHM youth (n = 128)	Comparison youth (n = 128)	p-value	Before matching	After matching
Percent age 5-10	14%	9%	0.243	0.12#	0.12#
Percent age 11-14	38%	38%	1.000	0.03	0.00
Percent over 15	48%	53%	0.452	0.00	0.05
Percent male	41%	42%	0.795	0.04	0.02
Percent White/undetermined	27%	34%	0.273	0.04	0.08
Percent Black	46%	39%	0.257	0.01	0.08
Percent Asian/Pacific Islander	6%	6%	1.000	0.09	0.00
Percent Native American	9%	7%	0.490	0.08	0.08
Percent Hispanic	11%	14%	0.439	0.12#	0.08
Percent child placing agency	36%	41%	0.366	0.23#	0.06
Percent with exceptional rate payment	50%	45%	0.452	0.04	0.05
No. of removal episodes to date	1.75	1.83	0.668	0.02	0.05
No. of prior placement events in removal	7.44	7.38	0.957	0.03	0.00
No. of prior reports	4.93	4.77	0.757	0.00	0.04
Percent before 2009	43%	42%	0.900	0.01	0.01
Percent 2009-2011	28%	30%	0.673	0.06	0.03
Percent 2012-2014	19%	20%	0.754	0.07	0.03
Percent 2015-2017	8%	9%	0.648	0.03	0.05
Any prior arrests	22%	18%	0.438	0.34^	0.06
Any prior runaways	17%	13%	0.290	0.30^	0.10
Prior mental health treatment need	85%	84%	0.859	0.10	0.02
Prior SUD treatment need	19%	16%	0.621	0.08	0.04

Notes:

\# Indicates moderate imbalance, |d| > 0.1.

^ Indicates severe imbalance, |d| > 0.25.

Exhibit A4

Youth in the High School Graduation Subsample Characteristics Before and After Matching

Variable	Means and proportions after matching			Absolute standardized difference (d)	
	HHM youth (n = 111)	Comparison youth (n = 111)	p-value	Before matching	After matching
Percent age 5-10	9%	12%	0.511	0.08	0.08
Percent age 11-14	41%	39%	0.667	0.00	0.03
Percent over 15	50%	50%	1.000	0.03	0.00
Percent male	41%	38%	0.579	0.06	0.04
Percent White/undetermined	25%	26%	0.878	0.04	0.01
Percent Black	44%	47%	0.686	0.00	0.03
Percent Asian/Pacific Islander	5%	6%	0.771	0.08	0.04
Percent Native American	13%	8%	0.271	$0.13^{\#}$	$0.13^{\#}$
Percent Hispanic	13%	12%	0.835	$0.14^{\#}$	0.02
Percent child placing agency	36%	37%	0.902	$0.24^{\#}$	0.01
Percent with exceptional rate payment	48%	48%	1.000	0.04	0.00
No. of removal episodes to date	1.84	1.77	0.707	0.00	0.05
No. of prior placement events in removal	7.24	7.51	0.833	$0.48^{\wedge}$	0.03
No. of prior reports	5.12	4.59	0.300	$0.37^{\wedge}$	$0.14^{\#}$
Before 2009	50%	50%	0.766	0.04	0.01
Percent 2009-2011	32%	32%	1.000	0.06	0.00
Percent 2012-2014	19%	18%	0.861	$0.14^{\#}$	0.02
Percent 2015-2017	7%	5%	0.581	0.04	0.08
Any prior arrests	18%	20%	0.732	$0.15^{\#}$	0.03
Any prior runaways	22%	19%	0.617	$0.13^{\#}$	0.04
Prior mental health treatment need	80%	85%	0.368	0.05	0.08
Prior SUD treatment need	17%	19%	0.730	$0.11^{\#}$	0.03

Notes:

$^{\#}$ Indicates moderate imbalance, |d| > 0.1.

$^{\wedge}$ Indicates severe imbalance, |d| > 0.25.

A. III. Methods to Estimate HHM Effects

Dichotomous (Yes/No) Outcomes

For outcomes of interest defined as dichotomous (high school graduation, arrests, employment, TANF receipt, food stamp receipt, homelessness, and behavioral health treatment), we conducted logistic regression analysis. Because the vast majority of youth in the samples of youth over 18 or graduated from school were from King County, we used a fixed effect for whether a youth was in King County.

Continuous Outcomes

For outcomes of interest defined as continuous (earnings) we conducted a two-part model, again using a fixed effect for King County youth.

Outcome Analysis: Logistic Regression on Matched Samples

Our preferred analysis used logistic regression on the matched samples to estimate the effect of the HHM on youth outcomes. Our outcome models used most of the same covariates included in the matching model. Covariates used in the various models were not all the same. In some cases, small cell sizes resulted in multi-collinearity or quasi-complete separation. A group of variables provided various measures of a youth's behaviors and conditions. These included exceptional foster care payments, history of arrest and runaway, and the DSHS-identified need for mental health and substance abuse treatment. In some cases these were so highly correlated that we eliminated one or more of these indicators from the analysis. When we controlled for the years in which events began some subsets had so few children that we substituted "before 2009" for the years 2003-2005 and 2006-2008.

Calculating Earnings

Fewer than 40% of youth in our age 18 and older sample had any recorded earnings. For that reason we used a two-part model to calculate the average quarterly earnings per youth. The first part of the model used logistic regression to estimate the likelihood that a youth had any earnings. The second part calculated earnings given the likelihood that youth had any earnings. We used the Stata program, twopm, with a fixed effect for King County youth. We used the same covariates in the analysis that we used in the propensity score matching. Results of the analysis are summarized in Exhibit A5 below.

Exhibit A5

Average Quarterly Earnings

	N	Mean	SE
HHM	128	$299.52	$110.21
Comparison	128	$195.98	$64.61

A. IV. Results of Outcome Analyses Estimating HHM Effects

Results of the logistic regression analysis of high school graduation by age 19 are reported in Exhibit A6.

Exhibit A6

Logistic Regression Estimating Effects of the HHM on High School Graduation by Age 19

	High school graduation		
Covariate	**Coefficient**	**p-value**	**SE**
HHM	0.178		0.314
Age at event (reference group 0-10)			
11-14	-1.277	*	0.583
Over 15	-0.664		0.672
Male	-0.574		0.352
Race (reference group is White/undetermined)			
Black	-0.236		0.415
Asian/Pacific Islander	0.024		0.707
Native American	0.035		0.612
Hispanic	0.440		0.553
Child placing agency	0.646	^	0.368
Exceptional child payment	-0.073		0.361
No. of removal episodes to date	0.000		0.133
No. of prior reports	-0.013		0.048
No. of prior placement events in removal	-0.008		0.023
Before 2009	-0.642		0.435
King county	0.038		0.715
Any prior arrests	-0.707		0.518
Prior mental health treatment need	-0.377		0.429
Prior SUD treatment need	-1.897	**	0.612
N	222		
AUC	0.738		

Note:
^ $p < 0.10$, * $p < 0.05$, and ** $p < 0.01$.

Results of the logistic regression analysis of having been arrested any time after the start of the index event, for youth age eight and older at the start of the index event, are reported in Exhibit A7.

Exhibit A7

Logistic Regression Estimating Effects of the HHM on Arrests for Youth Age Eight and Older

	Arrests		
Covariate	**Coefficient**	**p-value**	**SE**
HHM	-0.090		0.109
Age at event (reference group is 0-10)			
11-14	1.639	***	0.128
Over 15	1.858	***	0.100
Male	0.090		0.103
Race (reference group is White/undetermined)			
Black	0.381	***	0.112
Asian/Pacific Islander	-0.309		0.355
Native American	-0.343	^	0.188
Hispanic	-0.023		0.191
Child placing agency	0.034		0.093
Exceptional child payment	1.330	***	0.184
No. of removal episodes to date	0.151	***	0.018
No. of prior placement events in removal	0.016	^	0.009
Year of index placement (reference group is 2009-2011)			
Before 2009	0.157		0.102
2012-2014	-0.251	**	0.080
2015-2017	-0.270		0.223
Any prior arrests	1.526	***	0.089
Any prior runaways	1.137	**	0.350
Prior mental health treatment need	-0.119		0.114
Prior SUD treatment need	1.195	***	0.334
Months at risk (months since 18)	0.023	***	0.003
N	1,074		
AUC	0.908		

Note:
^ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$.

Results of the logistic regression analysis on receiving inpatient mental health treatment at any time after the start of the index event are reported in Exhibit A8.

Exhibit A8

Logistic Regression Estimating Effects of the HHM on Inpatient Mental Health Treatment

	Mental health treatment		
Covariate	**Coefficient**	**p-value**	**SE**
HHM	-0.362		0.292
Age at event (reference group is 5-10)			
Under 5	-1.407	*	0.597
11-14	0.220		0.365
Over 15	0.719		0.467
Male	-0.035		0.297
Race (reference group is White/undetermined)			
Black	-0.020		0.367
Asian/Pacific Islander	1.071	^	0.610
Native American	0.652		0.430
Hispanic	0.017		0.551
Child placing agency	-0.851	*	0.417
Exceptional child payment	1.279	***	0.319
No. of removal episodes to date	0.092		0.119
No. of prior placement events in removal	-0.048	^	0.027
Year of index placement (reference group is 2009-2011)			
Before 2009	2.508	***	0.515
2012-2014	1.108	*	0.491
2015-2017	0.647		0.541
Prior mental health treatment need	0.477		0.407
Prior SUD treatment need	0.523		0.451
N	1,580		
AUC	0.863		

Note:

^ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$.

Results of the logistic regression analysis of having been in paid employment any time starting at age 18, for our sample of youth age 18 and older, are reported in Exhibit A9.

Exhibit A9

Logistic Regression Estimating Effects of the HHM on Paid Employment for Youth Age 18 and Older

	Employment		
Covariate	**Coefficient**	**p-value**	**SE**
HHM	-0.342		0.280
Age at event (reference group is Before 11)			
11-14	-0.325		0.468
Over 15	-0.396		0.520
Male	-0.353		0.305
Race (reference group is White/undetermined)			
Black	0.166		0.351
Asian/Pacific Islander	0.459		0.605
Native American	0.615		0.552
Hispanic	0.794	^	0.462
Child placing agency	-0.170		0.322
Exceptional child payment	-0.660	*	0.305
No. of removal episodes to date	-0.058		0.107
No. of prior placement events in removal	-0.020		0.019
Year of index placement (reference group is 2009-2011)			
Before 2009	0.195		0.377
2012-2014	-0.039		0.438
2015-2017	-0.628		0.670
King County	-0.083		0.663
N	256		
AUC	0.696		

Note:
^ $p < 0.10$ and * $p < 0.05$.

Results of the logistic regression analyses for receiving food stamps or TANF and for homelessness at any time starting at age 18 and discharge from care, for our sample of youth age 18 and older, are reported in Exhibit A10.

Exhibit A10

Logistic Regression Estimating Effects of the HHM on Food Stamp Receipt, TANF Receipt, and Homelessness after Age 18 and Discharge from Care

	Food stamps			TANF			Homelessness		
Covariate	**Coefficient**	**p-value**	**SE**	**Coefficient**	**p-value**	**SE**	**Coefficient**	**p-value**	**SE**
HHM	0.111		0.36	-0.488		0.33	0.227		0.30
Male	-1.008	*	0.39	-1.506	***	0.39	0.555	^	0.32
Race (reference group White/undetermined)									
Black	-0.664		0.47	0.320		0.41	-0.009		0.36
Asian/Pacific Islander	-2.109	*	0.71	-0.229		0.71	0.210		0.64
Native American	-1.715		0.69	0.812		0.63	-0.096		0.60
Hispanic	-0.925		0.61	0.432		0.56	0.871		0.55
Exceptional child payment	0.327		0.40	0.220		0.37	-0.258		0.33
No. of removal episodes to date	-0.011		0.14	-0.073		0.13	-0.016		0.10
No. of prior placement events in removal	0.072	*	0.03	0.005		0.02	-0.034	^	0.02
Year of index placement (reference group is 2009-2011)									
Before 2009	0.350		0.46	-0.262		0.43	-0.016		0.38
2012-2014	0.105		0.55	-0.591		0.56	0.260		0.47
2015-2017	-0.171		0.79	1.166		0.79	0.323		0.77
King County	0.256		0.72	0.840		0.86	0.194		0.71
Months at risk (months since 18)	0.026	**	0.01	0.019	**	0.01	-0.025	***	0.01
N	233			233			233		
AUC	0.806			0.755			0.762		

Note:
^ p<0.1 * p < 0.05, ** p < 0.01, and *** p < 0.001.

A. V. Benefit-Cost Analysis

Exhibit A13 shows all effects entered into the benefit-cost analysis for our primary model, using the full analytic sample with a minimum two-year follow-up period from the start of the index event to examine new reports to CPS and new out-of-home placements. Exhibit A14 shows all effects entered into the benefit-cost analysis for our alternative model, using the sample who exited the child welfare system, with a minimum two-year follow-up period after exit, to examine new reports to CPS and new out-of-home placements.

Exhibit A13

Effects Entered in the Primary Benefit-Cost Analysis

Outcome	Effect size	SE	Tx N	p-value
New reports to CPS	0.134	0.126	563	0.286
New out-of-home placements	-0.007	0.166	563	0.965
High school graduation by age 19	0.108	0.170	111	0.528
Arrests	-0.059	0.100	548	0.554
Inpatient mental health treatment	-0.220	0.169	790	0.195
Food stamp receipt	0.067	0.192	115	0.728
TANF receipt	-0.295	0.184	115	0.109

Exhibit A14

Effects Entered in the Alternative Benefit-Cost Analysis

Outcome	Effect size	SE	N	p-value
New reports to CPS	0.090	0.120	265	0.450
New out-of-home placements	0.191	0.170	260	0.261
High school graduation by age 19	0.108	0.170	111	0.528
Arrests	-0.059	0.100	548	0.554
Inpatient mental health treatment	-0.220	0.169	790	0.195
Food stamp receipt	0.067	0.192	115	0.728
TANF receipt	-0.295	0.184	115	0.109

In our standard approach to benefit-cost analysis,[31] WSIPP estimates what the effects and monetary consequences of a program would be in Washington, given what we know about the characteristics of people in Washington. For the analysis described in this report, we look at the observed outcomes for a very specific population of youth who lived for at least some time in HHM foster homes in comparison to a similar group of youth who lived in traditional foster homes. Rather than use what we know about the Washington population at large, we instead used information specific to our study population.

For example, the foster youth in our study were much less likely to graduate from high school than the average Washington youth. While we would normally set our expected outcomes to match the average Washington youth, for the purposes of this study we adjusted expected educational achievement levels, the percent of people receiving inpatient mental health treatment, and the likelihood of child abuse and

[31] See WSIPP's Technical Documentation.

neglect and out-of-home placement to reflect outcomes observed for youth in our study population. These adjustments are described in the paragraphs below.

High School Graduation
Previous work by WSIPP on the foster care population[32] indicated youth in the foster care system are substantially less likely to graduate from high school. For our benefit-cost analysis of the HHM, we made an adjustment to the expected rate of high school graduation. Rather than relying on the graduation rate for all Washington students, we used information from our comparison group of foster youth. This reduced the expected high school graduation rate of 78% to the 33% graduation rate observed in our comparison sample.[33]

Postsecondary Education
Foster youth can be considered to face a different set of barriers than non-foster youth in attaining higher education. We adjusted our percent of students who pursue higher education[34] using information from an analysis of foster youth outcomes in Washington.[35] We proportionally reduce the likelihood of continuing beyond high school (by attaining some college education or completing college) by the ratio (47%) of enrolling in higher education for foster youth as compared to the overall population.

Inpatient Mental Health Treatment
We used the rate of acceptance into inpatient mental health treatment in the comparison group (4.1%) instead of the general Washington base rate for psychiatric hospitalization (8.3%).[36]

Subsequent Reports of Child Abuse and Neglect
WSIPP's Technical Document displays the population assumptions for the cumulative likelihood of subsequent recurrent substantiation by follow-up year for an indicated population.[37] We adjust our estimates for the overall rate of subsequent Child Protective Services interaction by multiplying the rate in each year by the ratio of comparison group subsequent interaction (8.7%) to that in the overall population (32.7%), measured at two years of follow-up. In our alternative benefit-cost scenario, we used the ratio of subsequent interaction following permanency (22.4%) to that in the overall population up (32.7%), measured at two years of follow-up.

Out-of-Home Placement
WSIPP's Technical Document displays the population assumptions for the likelihood of subsequent out-of-home placement after a subsequent child protective services event.[38] We used our estimates for the "indicated" population but adjust them for the overall rate of subsequent out-of-home placement given a subsequent Child Protective Services interaction. We multiply the expected rate in each year by the ratio of subsequent placement in the comparison group (5.2%) to that in the overall population (1.0%) measured at age ten. In our alternative benefit-cost scenario, we used the ratio of out-of-home placement following permanency given a subsequent child protective services interaction in our comparison group (8.9%) to that in the overall population (1.1%) measured at age ten.

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[32] Burley, M. (2013). Educational outcomes of foster youth—updated benchmarks (Document Number 13-06-3901). Olympia: Washington State Institute for Public Policy.
[33] For more detail see Exhibit 4.7.1 of WSIPP's Technical Document.
[34] Ibid, Exhibit 4.7.5.
[35] Sharkova, I., Luckenko, B., & Felver, B.E.M. (2015). Transition to adulthood: Foster youth at 19: An analysis of the 2013 National Youth in Transition Database Survey for Washington State. DSHS RDA Report 7.107.
[36] For more detail see Exhibit 4.9.10 in WSIPP's Technical Document.
[37] Ibid, Exhibit 4.3.1.
[38] Ibid, Exhibit 4.3.4.

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