Monetizing the Value of Social Investments

THE METHODOLOGY BEHIND THE LOW INCOME INVESTMENT FUND’S SOCIAL IMPACT CALCULATOR

www.liifund.org/calculator  AUGUST 2014
In the area of affordable housing, we monetize the value of subsidized rental housing on discretionary income, and on human health—as a remedy for food insecurity, as a “vaccine” for homeless populations, and as vehicle to enable families to “buy health” by moving to a healthier location.

In the area of early care and education, we monetize long-term individual and societal benefits, including health improvements later in life.

In the area of charter school finance, we estimate societal benefits and long-term income boosts for students who attend high-performing schools.

In our health clinic financing, we estimate the economic value of producing better health outcomes, delivering more efficient forms of care, and preventing costly downstream hospitalizations and emergency room visits.

In the area of equitable transit-oriented development, we monetize the value of improved health generated by weight loss and increased physical activity.
INTRODUCTION

LIIF is committed to expressing the social value of the projects that we support. In most cases, however, we are not in the position to collect longitudinal data to track outcomes, let alone determine impact (i.e., answering the counterfactual question of what would have happened “but for” the intervention that LIIF supported). Still, high quality social science research exists that can help address many of the “but for” questions in the program areas where LIIF invests.

Our approach relies on leveraging the best available academic research in a commonsense manner. We estimate impact and monetized value based on output proxies that we can collect in the normal course of our business. We periodically update our approach to account for advances in research and our evolving understanding of the value of the projects that we support. LIIF focuses on social impact indicators that are central to our mission of poverty alleviation, and relate to our “impact pathways” or program areas: affordable housing, early learning, education, health, and equitable transit oriented development.

We fully recognize that our approach monetizing impact “by proxy” is imprecise and falls short of rigorous evaluation. In addition, most of our monetary estimates do not account for the time value of money. However, we think it is important to take a first step toward measuring the social value of community investments. Our approach is simple, but it is practical given our institutional setting and limitations. At the portfolio and sector level, we believe it is directionally accurate.

This document describes our approach to estimating a range of impacts—for the families we serve, and for society at large. We update our methodology on a periodic basis to account for changes in practice, advances in research, and our evolving understanding of the value of the projects that we support.
Affordable Housing

An outpouring of research over the past decade has helped us understand the particular value of affordable housing—for example, as a boost to discretionary income, as a platform for improving health through multiple pathways, and as a critical element to child cognitive and behavioral development. Long intuitive, we now have strong evidence that affordable, high quality, and stable housing located in safe, complete communities is critical for generative positive economic, educational, and health outcomes for families and individuals.

We have drawn upon some of this new evidence and extrapolated impacts to LIIF-supported affordable housing projects. LIIF supports affordable rental housing and affordable homeownership, and we use similar methodologies to estimate the impacts of both forms of support.

Discretionary Income Boosts from Affordable Rental Housing

LIIF’s approach is to estimate the monetary value of paying affordable rent, rather than a higher market rent. But for the affordable housing our financing supports, many families would be forced to pay higher, market rents that far exceed what is affordable for their budgets. Our methodology centers on calculating the difference between market rents (based on appraisal data collected for each project we finance) and the affordable rent planned for the project, for the period that affordable housing will be available to low income households. Since we do not know how long affordable units will remain in the housing supply, we assume the unit remains affordable for the longer of the rent restriction period or the term of LIIF’s financing.

**Step 1:** Determine the Annual Rent (AR) of the project’s rental housing. A project’s AR may be found in the terms of the subsidy or tax credit agreement, or the planned rents identified in the project pro forma at the time of underwriting.

**Step 2:** Determine the average Annual Market Rental Rates (AMRR) of similar rental housing in the area in which the project is located, per the project appraisal.

**Step 3:** Determine the Number of Housing Units (NU) supported.

**Step 4:** Determine the Restriction Term (RT) or the term of LIIF’s loan, i.e. the number of years during which rent will be affordable.

**Step 5:** Estimate household savings based on the inputs from Steps 1–4 using this formula:

\[(AMRR - AR) \times NU \times RT\]
Example

Let’s say that LIIF supports the development of 50 units of affordable rental housing in San Francisco, California, supported through the Low Income Housing Tax Credit program. The applicable tax credit agreement requires that rents remain affordable for the next 15 years. At the time of underwriting, the affordable rent is $1,000 per month, whereas similar rental housing units in the area rent for an average rate of $1,500 per month, per the project appraisal.

**Step 1:** On an annual basis, Affordable Rents are $12,000 per unit. Therefore, $AR = $12,000.

**Step 2:** We know from appraisal data that similar rental housing units in the area rent for an average rate of $1,500 per month. Since there are 12 months in a year, on an annual basis similar rental housing units rent for an average rate of $18,000. Therefore, $AMRR = $18,000.

**Step 3:** We know LIIF supported the development of 50 units of affordable rental housing. Therefore, $NU = 50$.

**Step 4:** Finally, since the tax credit agreement requires that rents be restricted for 15 years, $RT = 15$.

**Step 5:** We have all of our inputs so we’re ready to estimate impact! Let’s plug the inputs into our equation:

\[
\text{Discretionary income boosts} = (18,000 - 12,000) \times 50 \times 15 = 4.5 \text{ million}
\]

Buying a Healthy Location: Modeling How LIIF-Supported Affordable Housing in Low-Poverty Areas Generates Positive Diabetes and Obesity Outcomes

The U.S. Department of Housing and Urban Development’s Moving to Opportunity experiment provided groundbreaking evidence on the value of housing’s *location*. One of its major findings was that moving from public housing in a high-poverty area to a relatively low-poverty neighborhood for at least one year could yield dramatic health benefits. In particular, the prevalence of diabetes and extreme obesity among adult women who experienced these changes in location was much lower than the experiment’s control group. Mental health in the experimental group had also significantly improved for both adult and young females.
The MTO findings point towards a convergence of traditional fair housing priorities with an emerging understanding of the role of health in community development—where expanding housing opportunities in “healthier” environments for very low-income and minority populations whose housing choices are mostly limited to disinvested neighborhoods could be an effective way to generate returns in the area of health. In fact, the most common reason that families chose to enroll in MTO was to escape neighborhood violence—a frame of decision-making that HUD planners at the time did not interpret as being related to health, but which many now recognize as having been a conscious effort by heads-of-household to “purchase health” for their families in the form of a different location.

Applying the MTO health results to the LIIF portfolio is an imperfect science. For instance, differences between the two contexts’ design and strength of the “treatment,” as well as population characteristics, make this extrapolation inexact. One example of such a difference is that families who live in LIIF-supported units are likely not as high-needs, nor as low-income as the MTO population, nor are their counterfactual neighborhoods—the places they would live but for access to housing in low-poverty areas—likely as high-poverty or otherwise “unhealthy.” In other words, the LIIF-supported population might not be as primed to reap positive health benefits from a change in location.

On the other hand, the unit-based subsidies in low-poverty areas that LIIF supports constitute a stronger “treatment” than what MTO families experienced, from the perspective of helping them maintain stability in low-poverty areas and sustain access to whatever benefits they provide (in addition to avoiding exposure to risks in high poverty areas). MTO families with tenant-based vouchers faced the constant threat—and, often, reality—of involuntary moves, and they were only required to stay in low-poverty areas for one year.1 Many reverted to higher-poverty areas shortly thereafter—almost never due to a desire to return to their old neighborhood—which likely reduced the strength and lasting impact of the positive “neighborhood effects” that MTO was designed to test.

 Whatever the complexity and uncertainties around applying the MTO health results to non-MTO circumstances, data from the experiment do provide a path to make rudimentary estimates of health improvements from changing neighborhood circumstances. And although census tract poverty rate turned out to be an inadequate proxy for higher performing schools, MTO evaluators still found that area poverty had a linear relationship with most of the outcomes they tracked—including health improvements.2

1 The one-year requirement—and, perhaps more importantly, the lack of post-move support or second-move housing search assistance—has prompted some advocates to call the MTO program model a “weak” treatment. See, for example: Tegeler, Philip, and Hankins, Salimah. “Prescription for a New Neighborhood.” Shelterforce, Spring 2012. Website: http://www.shelterforce.org/article/2769/prescription_for_a_new_neighborhood/

In particular, a study by Ludwig et al. that focused on physical health impacts for adult women in MTO suggests a simple way to estimate reductions in diabetes and extreme obesity prevalence based on changes in neighborhood characteristics. The authors’ quasi-experimental instrumental variables analysis of the MTO data found that, over a 10–15 year period, a 10 percent drop in duration-weighted census tract poverty was associated the following outcomes (note that each of these percentage drops is absolute and not relative to baseline percentage):

- A 6.2 percentage point reduction in class II obesity prevalence (BMI ≥ 35)
- A 4.3 percentage point drop in class III obesity prevalence (BMI ≥ 40)
- A 3.2 percentage point drop in prevalence of diabetes prevalence (HbA1c ≥ 6.5%)

Although other recent MTO studies focused on “high dosage” households that stayed in lower-poverty areas for longer periods have suggested other positive impacts, such as health improvements and educational achievement for children, we feel that research on MTO sub-group effects is still nascent and not widely accepted. As such, we only derive impact measures from MTO studies with the strongest statistical power (such as the Ludwig et al. study on adult diabetes and obesity).

Our Approach

Using the Ludwig et al. study as a guide and starting point, we can model the health improvements that LIIF helps generate by providing access to “healthy” communities for low-income families whose housing choices we assume to be otherwise restricted to higher-poverty areas. It is also worth noting that our methodology can apply to both new construction and preservation projects, based upon the theory that low-income families would be displaced to higher-poverty areas were it not for access to subsidized units in low-poverty areas within the overheated coastal markets where LIIF invests. For preservation projects, then, our approach to estimating impact could be interpreted as avoided declines in health, rather than improvements in health.

Which Projects Qualify

Although the study suggests a way to model diabetes and extreme obesity impacts according to any given duration-weighted change in census tract poverty rate over an equivalent 10–15 year study period, we believe it is reasonable to only model improvements generated by LIIF-supported projects in areas that meet the same threshold that the MTO program model used for identifying low-poverty neighborhoods of “opportunity” to qualify as landing spots for families moving out of public housing—census tract poverty levels below 10 percent.

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4 Obesity is defined as having Body Mass Index (BMI) of 30 or higher. Obesity ranges above BMI of 35 are called extreme, morbid, or severe. We use the term ‘extreme’ as a catch-all for this sub-group.


6 We will monitor tract poverty rates on an annual basis to ensure that we do not “qualify” projects in areas with rapidly rising poverty rates.
In addition, even though obesity reductions were detected at the MTO interim impacts evaluation, the MTO data does not tell us when, within the 10–15 year study period, those positive health outcomes emerged. As a result, we assume that benefits emerge over a 10-year period in order to roughly correspond with the MTO study period.

**Health Outcomes vs. Health Expenditures**

It is worth noting that no existing research can confirm whether MTO families who moved to low-poverty areas actually generated lower medical expenditures—not to mention a specific dollar reduction—even if their health improved overall. It is even conceivable that in some cases, moving to a “healthier” area meant better access to medical care, which might have generated an *increase* in health costs. Researchers at Johns Hopkins University have set out to answer these questions by pairing Medicaid and other health care insurance claims data with MTO data, but results aren’t expected in the near term.

Our approach for now, then, is to base our modeling of reduced expenditures on those physical health outcomes that demonstrated statistically significant changes—diabetes and extreme obesity reductions—and on research associated with the incremental increase in medical costs associated with those conditions. Put differently, we assume that elimination of a medical condition such as diabetes means that the incremental costs associated with having that condition are also gone.

**Families’ Housing Careers**

Once we have a list of qualifying projects, we still need to make a few assumptions about families’ “housing careers” over the hypothesized 10-year period (again, corresponding to the MTO study period) in order to use the Ludwig et al study and other research on particular medical conditions to model health improvements and their cost savings. Each of these assumptions, and our rationale behind them, are explained in detail below. To see how these assumptions feed into the impact calculation, please jump ahead to the step-by-step calculation in the following section.

1. **Hypothesized counterfactual tract poverty rates for families living in LIIF-supported units in low-poverty areas**—where they would be living but for access to these units.

Although the concentration of low-income housing and those receiving tenant-based rental assistance in higher poverty areas suggests that the availability of subsidized units in low-poverty areas could represent an opportunity for low-income families to experience a significant reduction in neighborhood poverty levels, there is no way for us to know to what extent this takes place in LIIF-supported units in low-poverty areas—let alone what those reductions might be, on average.
Given this level of uncertainty, we believe it is reasonable to assume a constant counterfactual tract poverty rate equivalent to the average census tract poverty rate for all housing projects (not to be confused with housing units) for which LIIF has this data—all projects since 2005, and a handful from before this time—according to the then-most recent decennial census at the time LIIF helped finance the project. This average tract poverty rate is approximately 24 percent.

2. How long families who do lease up in LIIF-supported units in low-poverty areas are hypothesized to live in them before moving out.

It would be overly optimistic to assume that families who live in LIIF-supported housing in low-poverty areas will stay in these units for entire 10-year periods. Length of tenure is impacted by several factors, including demographics (e.g., families with children vs. seniors) and income amount. Research on length of stay in low-income housing programs has shown that, on average, families stay in subsidized units for several years—for example, one survey found an average of 4.4 years for non-senior units in LIHTC properties,\(^7\) and another analysis of HUD data showed an average of 3.4 years in public housing for families with children\(^8\)—but ranges are considerable. To be conservative, we estimate that families stay in LIIF-assisted low-poverty unit for 4 years.

3. Tract poverty rates for areas where families who lived in LIIF-supported units in low-poverty areas live once they move out.

We believe it is reasonable to assume that once families move out of their units in low-poverty areas, they will not be able to find housing in areas with similarly low poverty rates. Housing markets simply aren’t so kind, and the vast majority of families in LIIF-supported don’t have the benefit of tenant-based rental assistance that follows them to their next unit (and theoretically expands housing options), as do families who participate in traditional mobility programs.

However, researchers have found that families that participate in mobility programs and “revert” back to higher poverty areas often move to neighborhoods with poverty rates that still represent an improvement on their starting neighborhood (perhaps in an effort to keep some of the benefits of low-poverty areas, and/or due to newfound market savvy). With this in mind, our model assumes that for the remainder of the 10-year period where families did not live in low-poverty areas, they lived in an area with a poverty rate of 15 percent.


4. *When positive health outcomes first emerge in families’ housing careers, and how long they last.*

Unfortunately, even though obesity reductions were detected at the MTO interim impacts evaluation, the MTO data does not tell us exactly when positive health outcomes emerged. To be conservative, we model these benefits as appearing *at the end* of the 10-year “treatment” period after a family is first hypothesized to have moved from a tract with 24 percent poverty to that particular low-poverty property.

The MTO data also does not include information about whether health benefits were sustained over time, beyond the point-in-time measurements at the end of the study period. Although we do not have evidence to suggest whether our rationale is reasonable or not, we assume that for each family that is hypothesized to experience health benefits from living in LIIF-supported housing in low-poverty areas, these benefits accumulate for 5 years after the hypothesized 10-year “treatment” period ends—that is, we assume that if a person no longer has diabetes as a result of living in this unit, she will continue to avoid the condition for 5 additional years after positive health outcomes is hypothesized to have emerged at the end of the 10-year “treatment” period.

*Prevalence and Costs for Diabetes and Extreme Obesity*

Our methodology requires that we have estimates for diabetes and extreme (class II and class III) obesity costs, and population prevalence for each to serve as baselines and control comparisons for the hypothesized health improvements among the “treatment” population.

**Diabetes Prevalence**

Some context: diabetes can cause health complications such as heart disease, blindness, kidney failure, and amputations. It is also the seventh-leading cause of death in the country. Among adults, 90–95 percent of diagnosed cases of diabetes are type 2 diabetes—also known as adult-onset diabetes—which is associated with obesity. However, studies have shown that regular physical activity can significantly reduce the risk of developing type 2 diabetes.9

In 2012, 12.3 percent of adults 20 years and older were estimated to have diabetes (both diagnosed and undiagnosed),10 although this figure is significantly higher for minority populations that are more likely to be low-income, and thus overrepresented in LIIF-supported housing—for example, 18.7 percent of non-Hispanic blacks have diabetes,11 and this figure was 20 percent of the MTO control group. In addition, populations with lower socioeconomic status have also shown to have higher rates of diabetes.12

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12 See, for example: Baumann et al. 2002. “Clinical Outcomes for Low-Income Adults with Hypertension and Diabetes.” Nursing Research. Vol. 51, No. 3. May/June. Also note that diabetes prevalence is higher among those receiving Medicare and Medicaid, especially for “dual eligibles.”
Diabetes prevalence is also increasing at a rapid pace, and has been for some time. The rate has tripled since 1980, and researchers have projected dramatic increases in the coming decades. UnitedHealth Group, a health care company (that has begun to invest in low-income housing as an approach to reduce medical costs), projects that the prevalence of both diagnosed and undiagnosed cases will be 15 percent by 2020.\textsuperscript{13} Looking even longer-term, the Centers for Disease Control and Prevention (CDC) projects that between 20 and 33 percent of the U.S. population will have diabetes by 2050.\textsuperscript{14} A recent study projected that the lifetime risk of being diagnosed with diabetes for those born between 2000 and 2011 is around 40 percent, and these figures are even higher—over 50 percent—for Hispanic men and women, and non-Hispanic black women.\textsuperscript{15}

Considering the higher incidence of diabetes both lower-income and minority populations when compared to the rest of the country, and the projected increases in diabetes overall, we conservatively assume that 15 percent of adults in LIIF-supported housing have diabetes, either diagnosed or undiagnosed (before experiencing the “treatment” of living in a low-poverty area).

**DIABETES COSTS**

Our approach to monetizing the cost of diabetes does not account for indirect costs (e.g., disability, lost work productivity, premature death), but rather on shorter-term savings in annual medical expenditures. On average, people diagnosed with diabetes have annual medical expenditures that are approximately 2.3 times higher than what they would be in the absence of diabetes; in 2012 dollars, the average per capita annual medical costs attributable to diabetes alone was $7,900. This figure is higher for minority populations that are likely overrepresented in LIIF-supported housing—for example, the figure is $9,540 for non-Hispanic blacks.\textsuperscript{16}

Landing somewhere in the middle, we assume that, for the estimated 15 percent of adults who live in LIIF-supported housing and have diabetes, their annual medical expenditures associated with the condition are $8,500. As previously noted, our approach to modeling cost reductions assumes that elimination of the disease is associated with savings equivalent to this amount.

**EXTREME OBESITY PREVALENCE**

Similar to diabetes, obesity is associated with premature death and a range of other medical complications. For example, BMI of 30-35 is associated with a lifespan reduction of 3 years, and BMI of 40-50 is associated


\textsuperscript{16} American Diabetes Association. 2013. “Economic Costs of Diabetes in the U.S. in 2012.” Website: http://care.diabetesjournals.org/content/early/2013/03/05/dc12-2625.full.pdf+html
with reduced life expectancy of 10 years.\textsuperscript{17} As noted earlier in this document, obesity is a risk factor for diabetes, and the two conditions are considered comorbidities.

As of 2010, the prevalence of class II and class III obesity for the total U.S. adult population 20 years and older was estimated to be 15.4 percent and 6.3 percent, respectively.\textsuperscript{18} However, similar to diabetes (for which obesity is a risk factor), prevalence of extreme obesity in low-income and minority populations is higher than general population averages.

For example, the 2010 prevalence of class II and class III obesity for non-Hispanic blacks was 26 percent and 13.1 percent, respectively; the rates for women in this sub-group was even higher, at 30.9 percent and 18 percent.\textsuperscript{19} Further, a CDC study of obesity trends from 2005–2008 found that obesity was 13 percentage points higher for low-income non-Hispanic black women, when compared to all low-income women. The gap between low-income people those with higher income was also substantial across nearly all racial/ethnic and gender breakdowns.

Extreme obesity is also similar to diabetes in that it is rapidly increasing, and is projected to impact a growing percentage of the population. Class III obesity (BMI of 40 and above) is the fastest growing category of obesity;\textsuperscript{20} between 2000 and 2010, its prevalence increased by 70 percent, and the rate of increase for BMI of 50 and above was even faster.\textsuperscript{21} Looking into the not-too-distant future, a National Bureau of Economic Research study projects that in 2020, class II and class III obesity will impact 21 percent and 14 percent of the population, respectively; for women, these figures are 25 percent and 18 percent.\textsuperscript{22}

Considering the higher prevalence of extreme obesity in both lower-income and minority populations when compared to the rest of the country, and the projected rapid increases in the outer ranges of obesity, we conservatively assume that the prevalence of class II and class III obesity in adults in LIIF-supported housing is 20 percent and 12 percent, respectively (before experiencing the “treatment” of living in a low-poverty area).


\textsuperscript{19} Flegal, et al. 2012.


As previously noted, obesity is a comorbidity with diabetes. Current research estimates that 15 percent of those with class II obesity and 26 percent of those with class III obesity have diabetes. For the purpose of not double-counting, we only calculate hypothesized obesity-related medical cost reductions for the percentage of adults living in LIIF-supported housing in low-income areas who we estimate to have class II and III obesity, but not diabetes. Specifically:

- We assume that only 85 percent of hypothesized reductions in class II obesity prevalence—and cost savings—resulting from the “treatment” of living in low-poverty neighborhoods will be among those who had previously had class II obesity without diabetes.
- We assume that only 74 percent of hypothesized reductions in class III obesity prevalence—and cost savings—resulting from the “treatment” of living in low-poverty neighborhoods will be among those who had previously had class III obesity without diabetes.

**EXTREME OBESITY COSTS**

Similar to our approach to diabetes, our approach to monetizing reductions in extreme obesity prevalence does not account for potential longer lifespans, but instead on shorter-term savings in annual medical expenditures. A systematic review of studies on the direct medical costs of obesity estimated that, based on the highest quality and most universally applicable studies available, the per-person annual medical costs of being obese was $1,723 in 2008 dollars ($1891 in 2014 dollars), and that the costs of having class III obesity was $3,012 in 2008 dollars ($3,306 in 2014 dollars). There do not appear to be good estimates for the cost of class II obesity in particular, although it is reasonable to assume that the costs associated with this condition would be higher than for all people with BMI of 30 and up, and lower than the figure for those with class III obesity.

Based on available research, we assume that, for those adults living in LIIF-supported housing who we estimate to have class II and III obesity, their annual medical expenditures associated with these two conditions are $2,000 and $3,300, respectively. As previously noted, our approach to modeling cost reductions assumes that elimination of these conditions is associated with savings equivalent to these amounts.

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Here is how we estimate medical cost savings generated by a project’s impact on diabetes prevalence among low-income adults:

**STEP 1:** Estimate the number of adults who had diabetes before moving into the property (which we also assume to be the counterfactual prevalence).

- Determine the affordability Restriction Term (RT) for the property.
- Divide RT by 4, to reflect the number of families who will be exposed to the “treatment” (since we assume they will each live there for 4 years)
- Assuming 1.5 adults per family, determine the number of adults who will live in the property.
- Determine how many of these adults are likely to have diabetes before moving to the property.
  - Multiply the total number by .15, since we assume that 15% of adults in LIIF-supported housing have diabetes, either diagnosed or undiagnosed.
  - Multiply this number by the total number of units restricted to low-income families in the property.

**STEP 2:** Estimate the average drop in duration-weighted census tract poverty over 10-year periods for families who initially gain access to a unit in this property.

- For each of the first 4 years where the family is hypothesized to live in the property, assume a drop in poverty rate equivalent to the difference between the average tract poverty rate of a LIIF-supported housing project (24 percent—the assumed ‘starting point’ for the family before it moved) and the tract poverty rate for the project.
- For the remaining 6 years of the 10-year period, assume a drop in poverty rate of 9 percent—the number that represents the difference between the assumed post-low-poverty tract poverty rate of 15 percent and the hypothesized counterfactual rate of 23 percent.
- Sum the drop for each year and then divide this total by 10. This number is the hypothesized reduction in duration-weighted tract poverty over the 10-year period.

**STEP 3:** Estimate the reduction in diabetes prevalence.

- The Ludwig et al study on MTO health results found that, over a 10–15 year period, a 10 percent drop in duration-weighted census tract poverty rate is associated with a 3.2 percentage point reduction in diabetes.
- The percentage point reduction in diabetes is thus equal to the duration-weighted drop in tract poverty rate times 0.32.

**STEP 4:** Estimate the number of adults associated with this drop in diabetes prevalence.

- Subtract the percentage reduction in prevalence (Step 3) from 15%, in order to find the prevalence of adults hypothesized to have diabetes, post-“treatment.”
- Multiply this number by the total number of adults hypothesized to have exposure to the “treatment” by living in the property, in order to find the number of adults hypothesized to have diabetes, post-“treatment.”
- Subtract the hypothesized post-“treatment” number from the pre-“treatment” number (from Step 1)
**STEP 5:** Estimate the medical cost savings associated with reductions in diabetes prevalence.

- Multiply the number of adults who will no longer have diabetes as a result of having lived in this property (Step 4) by $8,500, the assumed annual cost reduction from no longer being diabetic.
- Multiply this number by 5—the assumed number of years of “impact,” as described earlier in this document.

**Example**

Let’s say that LIIF supports the development of 100 units of affordable rental housing in a neighborhood in the San Francisco Bay Area with a census tract poverty rate of 8 percent, supported through the Low Income Housing Tax Credit program. The applicable tax credit agreement in California requires that rents remain affordable for the next 55 years.

**STEP 1:** 55 years divided by 4 years (the term per family), multiply by 1.5 (the number of adults in each household), multiply again by 15% (the percentage assumed to have diabetes), and then multiply by the 100 units restricted to low-income families. The number of low-income adults assumed to have diabetes upon leasing up at the property is 309 (out of 2,063 adults in total who are hypothesized to live there).

**STEP 2:** Per the rationale described earlier in this document—for the three years that the family is assumed to live at the property, the annual drop in tract poverty rate is 24 – 8 = 16 percent. For the remaining seven years, the assumed drop in tract poverty rate is 24 – 15 = 9 percent. The hypothesized average drop in duration-weighted census tract poverty rate over 10-year periods for low-income families who live in this property is \[
\frac{16 \times 4 + 9 \times 7}{10} = 12.7\%.
\]

**STEP 3:** 12.7 percent average duration-weighted tract poverty rate reduction over 10-year periods for low-income families × .32 = 4.06% absolute (not relative) reduction in diabetes prevalence.

**STEP 4:** 15% - 4.06% = 10.94% assumed diabetes prevalence in the property’s adult population after “treatment.” 2,063 total adults × .1094 = 226 adults with diabetes in total, or an 83-person reduction compared to the hypothesized control and “before” scenario.

**STEP 5:** 83 people × $8,500 annual medical cost savings × 5 years of impact = $3,527,500 in medical cost savings associated with reductions in diabetes prevalence.

Medical cost savings = $3,527,500
Here is how we estimate medical cost savings generated by a project’s impact on extreme obesity prevalence among low-income adults:

**STEP 1:** Estimate the number of adults who had diabetes before moving into the property (which we also assume to be the counterfactual prevalence).

- Determine the affordability Restriction Term (RT) for the property.
- Divide RT by three, to reflect the number of families who will be exposed to the “treatment” (since we assume they will each live there for three years)
- Assuming 1.5 adults per family, determine the number of adults who will live in the property.
- Determine how many of these adults are likely to have class II obesity before moving to the property.
  - Multiply the total number by .2, since we assume that 20% of adults in LIIF-supported housing have class II obesity.
- Determine how many of these adults are likely to have class III obesity before moving to the property.
  - Multiply the total number by .12, since we assume that 12% of adults in LIIF-supported housing have class II obesity.
- Multiply each of these numbers by the total number of units restricted to low-income families in the property.

**STEP 2:** Estimate the average drop in duration-weighted census tract poverty over 10-year periods for families who initially gain access to a unit in this property.

- For each of the first 4 years where the family is hypothesized to live in the property, assume a drop in poverty rate equivalent to the difference between the average tract poverty rate of a LIIF-supported housing project (24 percent—the assumed ‘starting point’ for the family before it moved) and the tract poverty rate for the project.
- For the remaining 6 years of the 10-year period, assume a drop in poverty rate of 9 percent—the number that represents the difference between the assumed post-low-poverty tract poverty rate of 15 percent and the hypothesized counterfactual rate of 24 percent.
- Sum the drop for each year and then divide this total by 10. This number is the hypothesized reduction in duration-weighted tract poverty over the 10-year period.

**STEP 3:** Estimate the reduction in class II and class III obesity prevalence.

- The Ludwig et al study on MTO health results found that, over a 10–15 year period, a 10 percent drop in duration-weighted census tract poverty rate is associated with a 6.2 percentage point reduction in class II obesity, and a 4.3 percentage point reduction in class III obesity.
- The percentage point reduction in class II obesity is thus equal to the duration-weighted drop in tract poverty rate times 0.62, and the percentage point reduction in class III obesity is equal to the drop in tract poverty rate times .43.
**STEP 4:** Estimate the number of adults associated with this drop in class II and class III obesity prevalence (not counting comorbid cases with diabetes)

- Subtract the percentage reductions in class II and class III prevalence (Step 3) from 20% and 12%, respectively, in order to find the prevalence of adults hypothesized to have each condition, post-“treatment.”
- Multiply each of these percentages by the total number of adults hypothesized to have exposure to the “treatment” by living in the property, in order to find the number of adults hypothesized to have class II and class III obesity, post-“treatment.”
- Subtract the hypothesized post-“treatment” numbers from the pre-“treatment” numbers (from Step 1).

**STEP 5:** Estimate the medical savings associated with reductions in class II and class III obesity prevalence that are hypothesized to be independent of diabetes.

- Multiply the number of adults who will no longer have class II obesity as a result of having lived in this property (Step 4) by $2,000, the assumed annual cost reduction from no longer having class II obesity. Then multiply this number by .85 to reflect the assumption that 15 percent of the reduction would be attributable to adults hypothesized to have had both class II obesity and diabetes from the start.
- Multiply the number of adults who will no longer have class III obesity as a result of having lived in this property (Step 4) by $3,300, the assumed annual cost reduction from no longer having class III obesity. Then multiply this number by .74 to reflect the assumption that 26 percent of the reduction would be attributable to adults hypothesized to have had both class III obesity and diabetes from the start.
- Multiply each of these numbers by 5—the assumed number of years of “impact,” as described earlier in this document.
Consider the previous example of a LIIF-supported development of 100 units of affordable rental housing in a neighborhood in the San Francisco Bay Area with a census tract poverty rate of 8 percent, supported through the Low Income Housing Tax Credit program. The applicable tax credit agreement in California requires that rents remain affordable for the next 55 years.

**STEP 1:** 55 years divided by 4 years (the term per family), multiply by 1.5 (the number of adults in each household), multiply again by 20% (the percentage assumed to have class II obesity), and then multiply by the 100 units restricted to low-income families. Do the same calculation to find the number with class III obesity, assumed to be 12 percent of the adults. The number of adults assumed to have class II obesity without diabetes upon leasing up at the property is 413, and this number is 248 for class III obesity without diabetes (out of 2,063 adults in total who are hypothesized to live there).

**STEP 2:** Per the rationale described earlier in this document— for the three years that the family is assumed to live at the property, the annual drop in tract poverty rate is 24 – 8 = 16 percent. For the remaining seven years, the assumed drop in tract poverty rate is 24 – 15 = 9 percent. The hypothesized average drop in duration-weighted census tract poverty rate over 10-year periods for low-income families who live in this property is \([16 \times 4 + 9 \times 7] ÷ 10 = 12.7\) percent.

**STEP 3:** 12.7 percent average duration-weighted tract poverty rate reduction over 10-year periods for low-income families × .62 = 7.87% absolute (not relative) reduction in class II obesity prevalence. For class III obesity, the reduction is \(12.7 \times .43 = 5.46\) percentage points.

**STEP 4:** 20% - 7.87% = 12.13% assumed class II obesity prevalence in adult population after “treatment.” 2063 total adults × .1213 = 250 adults with class II obesity in total, or a 163-person reduction compared to the hypothesized control and “before” scenario. However, we assume that 15 percent of class II cases are also diabetic, so we only account for medical cost savings associated with the 85 percent of the total (139) who we hypothesize are not comorbid with diabetes.

12% - 5.46% = 6.54% assumed class II obesity prevalence in adult population after “treatment.” 2063 total adults × .0654 = 135 adults with class III obesity in total, or a 113-person reduction compared to the hypothesized control/“before” scenario. However, we assume that 26 percent of class III cases are also diabetic, so we only account for medical cost savings associated with the 74 percent of the total (84) who we hypothesize are not comorbid with diabetes.

**STEP 5:** 139 people × $2,000 annual medical cost savings × 5 years of impact = $1,390,000 in medical cost savings associated with class II reductions, independent of diabetes. 84 people × $3,300 annual medical cost savings × 5 years of impact = $1,386,000 in medical cost savings associated with class III prevalence reductions, independent of diabetes. Total medical cost reductions due to extreme obesity improvements, independent of diabetes = $2,776,000.

Medical savings cost = $3,527,500 + 2,776,000 = $6,303,500
Affordable Housing as a Remedy for Food Insecurity

Children who do not have adequate nutrition are less healthy, suffer developmental impairments, and have lower educational achievement. Further, recent studies have begun to uncover a strong correlation between housing costs and food insecurity. To estimate the impact of LIIF-supported housing subsidies on food expenditures, we draw from Bureau of Labors Statistics Consumer Expenditure Survey (CES) data, reported in the "State of the Nation's Housing by the Joint Center for Housing Studies of Harvard University. This report shows that families in the bottom expenditure quartile (a very conservative proxy for low-income) who live in housing that is affordable to them spend significantly more—around $123 per month more for families with children, and around $88 more for all renters—on food when compared to their counterparts who are more burdened by housing costs. We model this incremental increase in food expenditures over the term of each project's affordability restrictions using the following approach:

**STEP 1:** Determine the number of family-oriented (FU) and elderly or homeless-oriented (EHU) affordable units restricted to low- and very low-income households in a given housing project

**STEP 2:** Assume monthly per-FU increase in food expenditures of $123, and monthly per-SHU increased in food expenditures of $88.

**STEP 3:** Determine the affordability Restriction Term (RT) or the term of LIIF's loan, whichever is longer.

**STEP 4:** Calculate the boost in expenditures from affordable housing using this formula:

\[ RT \times (FU \times 123 \times 12) + RT \times (EHU \times 88 \times 12) \]

**Example**

Let's say that LIIF supports the development of 50 units of affordable rental housing targeted to very low-income families in San Francisco. The applicable tax credit agreement in California requires that rents remain affordable for the next 55 years.

**STEP 1:** The project provides 50 units affordable to very low-income families.

**STEP 2:** Using BLS data, we can estimate that, with the help of the rental subsidy, families living in this project will spend $123 more per month than they would if they did not have access to a housing subsidy.

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STEP 3: The project’s California Tax Credit Allocation Committee agreement requires that rents be restricted for 55 years.
Using the inputs from Steps 1–3 from the methodology, we can estimate the project’s impact:
Boost in food expenditures = $123 × 50 × 12 × 55 = $4,059,000

Housing as a Vaccine: Improved Health Outcomes and Medical Cost Savings from Permanent Supportive Housing for the Homeless

Thanks to solid research over the past decade, we can now make reasonable estimates of the medical cost savings generated by LIIF-supported permanent supportive affordable housing projects. Permanent supportive housing is an effective strategy for improving positive life outcomes for the chronically homeless—particularly those with chronic and complex illnesses—which in turn lead to significant public cost savings, the majority of which are related to reductions in health services.

We draw from the from a 2009 study\(^29\) by the Economic Roundtable, based on the quality of the data available to the authors, the comprehensiveness (across multiple risk factors such as mental health status, substance abuse problems, and HIV/AIDS) and size of the study population, and the fact that its savings figure falls somewhere in the middle of the ranges in medical cost savings quoted in other studies\(^30\). As such, it seemed to be a reasonable but conservative estimate to apply to the LIIF portfolio of permanent supportive housing projects. The study specifically found that monthly cost savings to public agencies (e.g., County health services outpatient clinics) and agency sub-departments (e.g., corrections medical services)\(^31\) providing physical and mental health services were $1,853 per month, or $22,242 per year, for those chronically homeless in permanently supportive housing, compared to those who were not. We use this figure to calculate medical cost savings over the course of a given project’s affordability restriction term.

Here is how we estimate health-related cost savings generated by LIIF-supported permanent supportive housing for the homeless projects:

**STEP 1:** Determine the number of permanent supportive Housing Units for the homeless (HU) supported (assume one person per household)

**STEP 2:** Determine the affordability Restriction Term (RT) or the term of LIIF’s loan, whichever is longer.

**STEP 3:** Assume annual per-person medical cost savings (MCS) of $22,242.

**STEP 4:** Estimate medical cost savings using this formula: MCS × HU × RT

\(^{29}\) Economic Roundtable. 2009. “Where We Sleep: Costs when Homeless and Housed in Los Angeles.”


\(^{31}\) A nominal percentage of health-related costs for this population (2-3 percent) was tracked to private hospitals.
Example

Let’s say that LIIF supports the development of 50 units of supportive, affordable rental housing targeted to the chronically homeless in San Francisco. The applicable tax credit agreement in California requires that rents remain affordable for the next 55 years.

**Step 1:** Based on the unit mix (single-room occupancy), we can estimate that 50 homeless adults will live in this property.

**Step 2:** Based on the study, we can estimate that this project will generate annual per-person medical cost savings of $22,242.

**Step 3:** The project’s California Tax Credit Allocation Committee agreement requires that rents be restricted for 55 years.

Using the inputs from Steps 1–3 from the methodology, we can estimate the project’s impact:

Medical cost savings = \( $22,242 \times 50 \times 55 = $61,165,500 \)

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**EARLY CARE AND EDUCATION**

LIIF estimates the value of affordable early care and education (ECE, or “child care”) in terms of its long-term individual and societal benefits, including improved health. In this program area, LIIF makes grants with terms ranging from one to several years. Although the ECE centers that we support likely continue to operate and remain affordable for low- and moderate-income families beyond the term of our grants, we take the conservative approach of only calculating impact based on those terms.

### Societal Benefits from Early Care and Education

Several recent studies have used data from multiple random assignment experiments to propose estimates for early care and education’s long-term societal benefits—ranging from $7 to $20 in societal returns per dollar invested. We take a conservative approach and assume $7 in returns per dollar invested—the figure that President Obama cited in his State of the Union address in 2013—generated by a combination of increased family income, educational attainment, and reduced societal costs such as incarceration and special education. This figure is roughly in line with Nobel Laureate James Heckman’s calculations that the Perry Preschool program and the Chicago Child-Parent Centers had benefit-cost ratios of 9:1 and 8:1, respectively, and that the Perry Preschool program’s return on investment was in the range of...
7–10 percent. We calculate impact over the term of LIIF’s grant to the child care center—a conservative assumption, since the centers usually continue to serve children from low- and moderate-income families for many years after our grant term ends. Here is how we draw upon this research to estimate societal benefits of our investments in early care and education:

**STEP 1**: We assume that every dollar invested in child care programs generates $7 in societal benefits.

**STEP 2**: Determine the Annual Operating Expenses (AOE) of the child care program supported.

**STEP 3**: Determine the contract term (CT) that these spots are required to remain affordable to children from low- and moderate-income households.

**STEP 4**: Estimate societal benefits using this formula: $\text{AOE} \times \text{CT} \times 7$

**Example**

Suppose that LIIF helps to support a child care center in Los Angeles that has annual operating expenses of $100,000.

**STEP 1**: We’ll assume conservatively that for every dollar invested in early child care, $7.00 is saved in downstream social costs.

**STEP 2**: We know that the Los Angles child care center has annual operating expenses of $100,000. Therefore, AOE = $100,000.

**STEP 3**: Since we have the inputs we need, we can now estimate the downstream social savings attributable to the Los Angeles child care center’s investment in child care:

Societal benefits = $100,000 × 3 years × $7.00 = $21,000,000

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**Buying Adult Metabolic Health With Early Childhood Education**

To estimate health benefits of early childhood education, we draw on a study published in early 2014 that is the first to provide experimental evidence demonstrating that high quality early education can produce substantial physical health benefits that persist into adulthood. The study uses data from the Carolina Abecedarian Project, which randomly assigned 111 disadvantaged children living near Chapel Hill, NC in between 1972 and 1977 to either a “treatment” group that included early education, or a “control” group that received no treatment. The treatment was divided in two stages: one for early childhood (ages 0–5),

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and one for school-age (ages 6–8), and the children were randomly reassigned to either the treatment or control group before each of the two stages—that is, they could have been assigned to treatment for the early childhood stage, but to the control group to the school-age stage (or vice versa).

The study finds no long-term health impacts from the school-age treatment, but it does find substantial physical health benefits that were sustained into adulthood for the cohort that was assigned to the treatment group for the early childhood intervention. By their mid-30s, this group—particularly the males—had significantly lower prevalence of risk factors for cardiovascular and metabolic diseases, when compared to the control group.

One of the most dramatic outcomes was that, by their mid-30s, no males from the early education treatment group had the cluster of conditions known as “metabolic syndrome,” which is associated with greater risk of heart disease, stroke, and type 2 diabetes. The National Institutes of Health notes that metabolic syndrome has emerged as a “coequal partner” to cigarette smoking as a contributor to premature coronary heart disease, and its increasing prevalence threatens to partially reverse the reduction in heart disease risk over the past three decades that had resulted from a decline in serum low-density lipoprotein cholesterol (“bad” cholesterol) levels. It is also one of the underlying causes of type 2 diabetes.\(^{34}\)

By contrast, one quarter of the males in the early childhood control group was affected by metabolic syndrome by their mid-30s. The drop in prevalence for metabolic syndrome, then, was 100 percent. Further, the “conditional treatment effect” for metabolic syndrome among males—controlling for factors such as cohort, the number of siblings, mother’s IQ, and high-risk index at birth—was calculated to be an even more dramatic reduction of 189 percent when compared to the control group. The unadjusted reduction in prevalence among females from the early education treatment group was 67 percent, and the conditional treatment effect was 30 percent—noteworthy, but not statistically significant at the 10 percent level.\(^{35}\)

Adults from the early childhood treatment group also experienced sustained improvements in several other health categories, such as higher “good” cholesterol, lower prevalence of prediabetes, lower vitamin D deficiency, lower prevalence of “severe” obesity (BMI at or above 35), and significantly lower risk of experiencing “total” coronary heart disease. However, most of these and other conditions are either components of a diagnosis of metabolic syndrome diagnosis or are otherwise related to the condition, and it is difficult—even for medical professional and researchers—to disaggregate each of their contributions to premature heart disease and type 2 diabetes. For this reason, we use metabolic syndrome as an umbrella condition for our (conservative) estimation of early childhood education’s long-term health impacts.\(^{36}\)

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\(^{35}\) Campbell, et al. 2014.

\(^{36}\) The research team that authored the study that is the basis of our calculation plans to publish a follow-up study on the actual medical cost savings associated with long-term health impacts from the Carolina Abecedarian Project. Once these results become available to us, we will revise our impact methodology accordingly.
Existing research on medical costs associated with metabolic syndrome is limited. However, one study estimates that those diagnosed with metabolic syndrome incur annual medical costs that are, on average, about $2,000 higher than those without the syndrome ($5,732 vs. $3,581). In addition, costs increase by an average of 24 percent per additional risk factor, and certain clusters of risk factors, or conditions, that comprise a diagnosis of metabolic syndrome—particularly those clusters that included diabetes—are more costly.\(^{37}\)

The research team that authored the Carolina Abecedarian Project health study did not have access to data to adequately quantify diabetes risk, so relying on the $2,000 figure could be an underestimate of the costs associated with observed improvements in metabolic syndrome. However, using a more conservative figure fits our overall approach to impact assessment, so we choose to rely on it for our estimation of the monetary value of health improvements resulting from early childhood education.

Unfortunately, no existing research can help us determine the appropriate term of impact. If a person has not developed metabolic syndrome by her mid-30s, it is conceivable that she could remain syndrome-free for much longer, and it could make sense for us to assume several decades of impact. However, for the sake of being conservative, we assume 10 years of impact.

Although the unadjusted and conditional reductions in metabolic syndrome prevalence for males (100 percent and 189 percent, respectively) and females (67 percent and 30 percent, respectively) were quite different, we believe it is reasonable and conservative to assume that, if the gender breakdown in LIIF-assisted early education facilities is approximately even—and if LIIF provides an intervention equivalent to the Carolina Abecedarian Project, with a similar cohort of disadvantaged children—approximately 50 percent fewer these children will have developed metabolic syndrome by their mid-30s than would be the case in absence of this intervention (which is highly probable, as nearly all child care slots in LIIF-assisted facilities are subsidized in some way, and as such they are a service to which families would not have typically had access).

In addition, the prevalence of metabolic syndrome among both males and females in the Carolina Abecedarian Project control group (25 percent and 19 percent, respectively) closely approximates current figures for the U.S. males and females over age 20 (23 percent and 22 percent, respectively) and the for the total U.S. population over 20 (23 percent).\(^{38}\) As such, we believe it is reasonable to assume that, if LIIF provides an equivalent intervention to a similar cohort of disadvantaged children, we could expect a percentage point reduction in metabolic syndrome prevalence equivalent to 50 percent of 23 percent (11.5 percent, rounded up to 12).


However, we are forced to confront the fact that we do not know whether the facilities that LIIF supports provide interventions that are stronger or weaker, on average, than what the Carolina Abecedarian Project provided. On the one hand, most of the early education programs we support do not start as early in children’s lives, nor do they last as long. On the other hand, it is possible that programs in LIIF-supported facilities have taken advantage of four decades worth of learning on how to run more effective early education programs, and as a result they are able to deliver more impact over a shorter “treatment” period. Further, we are uncertain whether children in LIIF-supported programs are more or less disadvantaged, in multiple dimensions, than those who participated in the Carolina Abecedarian Project—let alone how variability in this regard might result in specific differences in long-term health benefits, in comparison to the study’s findings.

Given these uncertainties (and probably others) around applying the study’s health impacts to our portfolio of early education, we take the admittedly rudimentary approach of assuming a linear relationship between the age groups covered—the “term” of the intervention—and its impact. For example, if a cohort of children attends an early education program from age 0 to 3, the hypothesized impact among this cohort would be three-fifths of the level of impact from Carolina Abecedarian Project cohort, which covered ages 0–5. Taking this logic a step further, we assume that each year of exposure to the “treatment” is equivalent to one-fifth of the level of impact found in the study.

Here is how we estimate medical cost savings generated by an early education program’s impact on long-term adult health.

**STEP 1:** Determine the number of early education (ages 0–5) slots for children from low- and moderate-income households. On an annual basis, this is the number of children that we hypothesized will experience the equivalent of one-fifth of a dosage of the Carolina Abecedarian Project “treatment.” Let’s call this the number of “student-years” of exposure to the treatment of early childhood education for each year.

**STEP 2:** Determine the contract term that these spots are required to remain affordable to children from low- and moderate-income households.

**STEP 3:** Determine the number of children hypothesized to avoid metabolic syndrome by their mid-30s as a result of having had access to early childhood education at this center.

- Multiply the annual number of “student-years” of exposure to the equivalent of one-fifth of the level of treatment of the Carolina Abecedarian Project (Step 1) by the total number of years that the program is required to remain affordable to children from low- and moderate-income families (Step 2). This number is the total number of “student-years” of treatment equivalent to one-fifth of a dosage of the Carolina Abecedarian Project treatment.
• Multiply this number by 0.12, signifying the assumed 50 percent reduction of the 23 percent of children who we hypothesize would have developed metabolic syndrome as adults, were it not for access to an early education treatment equivalent to that provided to children in the Carolina Abecedarian Project. Then divide this number by five, signifying that we expect one-fifth the impact for each “student-year” of exposure to the treatment.

**STEP 4:** Estimate medical cost savings generated by improved metabolic syndrome outcomes

• Multiply the number of students hypothesized to avoid metabolic syndrome as adults, as a result of having had access to early childhood education (Step 3) by $2,000 (to signify annual medical cost savings) and then by 10 (to signify the assumed years of impact)

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**Example**

Let’s imagine that LIIF supports an early education center in San Francisco with 30 slots for children from low- and moderate-income families. The program will serve three and four year olds, and the facility’s contract requires that the 30 slots remain affordable to children from low- and moderate-income families for five years.

**STEP 1:** There are 30 slots affordable to children from low- and moderate-income families.

**STEP 2:** Slots are required to remain affordable for five years.

**STEP 3:** $30 \times 5 = 150$ “student-years” of exposure to the treatment. $150 \times .12 = 18$. Then divide by 5.

3.6 (rounded up to 4) children hypothesized to avoid metabolic syndrome by their mid-30s as a result of having had access to early childhood education

**STEP 4:** $4 \times \$2,000 \times 10 = \$100,000$ in medical cost savings generated by improved metabolic syndrome outcomes.

Medical cost savings = \$80,000
Lifetime Earnings Boosts and Societal Benefits from High Performing Schools

In addition to supporting early learning and education (pre-K), LIIF helps finance the development and expansion of charter elementary, middle, and high schools (grades K–12). There is a robust and growing literature on the relationship of education to other social areas, such as child development, labor market outcomes, and health—both as a contributor to outcomes in those areas (e.g., educational attainment influences a child's lifetime earnings potential), and as an outcome itself, where factors in other realms are inputs into education (e.g., educational attainment is influenced by children's family poverty status and exposure to early-life trauma).

Researchers are still unpacking the complexity and potential causality around these relationships, and most existing studies are not easily transferrable to LIIF's approach to impact estimation because they have not offered simple ways to leverage easy-to-collect data from schools to estimate long-term social outcomes. Further, we do not collect data on post-secondary outcomes for students who attend LIIF-supported schools, so we must rely on educational attainment data from grades K–12 in order to evaluate these schools' performance and estimate their societal impact.

Still, there is enough quality research around the particular value of the terminal degree (graduating high school) of the grade range that we do cover. In particular:

**Lifetime Earnings.** Earnings data for adults with different levels of educational achievement from 1965 to 2005 showed that, over a 45-year career, high school dropouts could have expected to earn approximately $700,000 in adjusted 2004 dollars less than those with high school degrees (not including those with post-secondary years of education and/or degrees). However, current projections place this figure lower, in the $200,000–300,000 range—perhaps reflecting the declining value of a high school degree, relative to post-secondary degrees.

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If we were only to compare the earnings potential of those whose education ends with a high school degree vs. those who drop out, we might hypothesize a lifetime earnings difference of around $300,000. However, we believe it is reasonable to assume that when high-performing schools boost high school graduation rates, some percentage of that boost also translates to an increase in years of post-secondary education for some students.\(^43\) Considering the significant earnings potential associated with each year of post-secondary education—especially four-year college degrees and beyond—when compared to merely earning a high school degree, we believe it is reasonable to assume that an incremental boost to high school graduation rates translates to $500,000 in increased lifetime earnings, per student.

**Lifetime Avoided Social Costs.** Multiple estimations exist for lifetime avoided social costs to taxpayers (e.g., higher tax revenues, lower incarceration rates, lower government medical expenditures) of graduating high school as opposed to dropping out. The studies we found place this value in the range of $200,000.\(^44\)

**Elementary School Test Scores as a Proxy for High School Graduation Rates.** A recently published study using longitudinal data on around 4,000 students found that students who did not meet standards for “proficiency” for 3rd reading scores were four times more likely to eventually drop out of school without a high school diploma than those with proficient scores on an assessment comparable to the National Assessment of Educational Progress (NAEP) test—16 percent compared to 4 percent. These figures were even direr for students who did not even score as having mastered “basic” reading skills, if had experienced poverty in their lives, or both.\(^45\), \(^46\), \(^47\)

It is worth noting that high school graduation rates might not be the ideal proxy to estimate the social value of schools that we support. For instance, the U.S. labor market continues to devalue the high school degree.

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\(^43\) Researchers have also shown that one of the educational impacts of charter schools is higher levels of AP exam participation and college attendance. Source: Angrist, et al. 2013. “Stand and Deliver: Effects of Boston’s Charter High Schools on College Preparation, Entry, and Choice.” Funded by the U.S. Department of Education.


\(^46\) As of May 2014, we do not yet collect 3rd grade reading scores from the elementary schools we support—but we plan to begin asking for this data soon.

\(^47\) While testing criteria vary according to standards set by each state government, the Department of Education has administered the NAEP test to a representative sample of students from across the country, allowing them to approximate the relative rigor of each state’s assessment system. Based on the 2009 NAEP assessment, four states in LIIF’s primary charter school lending markets (CA, DC, NY, and RI) had scores that indicated reasonably competitive standards, though not among the highest. Two other LIIF charter school markets (CO, TN) had significantly lower scores. These differences in standards indicate that improved proficiency on some exams may not translate to comparable gains in skill level, which might undermine long-term earnings for some students. However, there is considerable debate about the level and nature of the NAEP standards, and changes for curriculum since 2009 should be incorporated into current analysis. Source: U.S. Department of Education, National Center for Education Statistics. 2009. “Mapping State Proficiency Standards Onto the NAEP Scales: Variation and Change in State Standards for Reading and Mathematics, 2005-2009.”
and shift towards jobs that require some kind of higher education. 48 Absolute earnings for both dropouts and high school graduates has decreased over the past several decades, while it has stagnated for those with four-year college degrees; the largest gains have been among those with advanced degrees. 49

On the other hand, the vast majority of students in LIIF-supported schools are from low-income families—a demographic whose children, on average, attend lower performing schools than their middle- and higher-income peers. 50 In addition, as noted above, we assume that at least some of the boost in high school graduation rates generated by high-performing schools translates to increased years of post-secondary education. As such, high school graduation rates could at least be useful proxy to indicate the extent to which the schools that we support buck trends and outperform others in the district—if not capture the full range or extent of positive social outcomes that good school generate. 51

OTHER NOTES:

• We assume four years of impact (four graduating classes) for each school that we support. This assumption is quite conservative because these schools will likely operate for much longer periods. 52
• We do not control for selection bias or other potential differences in student characteristics in LIIF-supported schools compared to the rest of the district—such as the percentage of low-income or special needs students. However, it should be noted, again, that the vast majority of students in LIIF-supported schools are from low-income and otherwise disadvantaged families.

Here is how we estimate the extent to which a LIIF-supported secondary school increases lifetime earnings for its students.

**STEP 1:** We assume that an incremental boost in high school graduation rates translates to an average of $500,000 of increased lifetime earnings per student.

**STEP 2:** Determine the graduation rate of the supported charter high school.

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51 It is also worth noting that our approach to estimating a school’s “impact” is different than the one we take in some other LIIF program areas in that we do not seek to extrapolate output or program-level data (e.g., number of units) to outcomes and impact with the help of research on evidence-based practices—which, in this case, could perhaps be a certain educational philosophy to which researchers have attributed high educational attainment. Instead, we take outcomes data (e.g., high school graduation rate), however they were achieved, and use research to extrapolate to an even larger outcome/impact.

52 We anticipate that LIIF will be able to offer more patient, longer-term capital to support schools and other community facilities at some point in the near future. In addition to filling a capital need, these products will allow us to defensibly assume longer periods of social impact.
**Step 3:** Determine the district average high school graduation rate.

**Step 4:** Determine the number of graduating students over the assumed four-year term of impact.

**Step 5:** With the inputs from Steps 1–4, we can estimate the monetary value of increased lifetime earnings using this formula: \((\text{Step 2} - \text{Step 3}) \times 500,000 \times \text{Step 4}\).

Here is how we estimate the extent to which a LIIF-supported secondary school generates long-term societal savings.

**Step 1:** We assume that over a lifetime, graduating from high school as opposed to dropping out is associated with $200,000 in societal savings.

**Step 2:** Determine the graduation rate of the supported charter high school.

**Step 3:** Determine the district average high school graduation rate.

**Step 4:** Determine the number of students over the assumed four-year term of impact.

**Step 5:** With the inputs from Steps 1–4, we can estimate the monetary value of societal savings of avoided dropouts or “bonus” graduates using this formula: \((\text{Step 2} - \text{Step 3}) \times 200,000 \times \text{Step 4}\).

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**Example**

Let’s say LIIF supports a charter high school in Oakland, California attended by 200 students. On average, 60 percent of district students graduate from high school. In contrast, the charter high school has a graduation rate of 90 percent.

**Step 1:** We assume that over a lifetime, a high school graduate will earn $500,000 more than a high school dropout. We also assume that graduating from high school generates lifetime societal savings of $200,000, as compared to dropping out.

**Step 2:** We know that the Oakland charter has a 90 percent graduate rate.

**Step 3:** We also know that on average in Oakland, 60 percent of students graduate from high school.

**Step 4:** The school will attempt to graduate 200 students over the assumed four-year term of impact.

**Step 5:** Using the inputs from Steps 1–4, we can estimate the Oakland charter’s impact on students’ lifetime earnings potential, as well as its societal savings, via avoided dropouts or “bonus” graduates:

- **Earnings Boosts =** \(.9 - .6 \times 500,000 \times 200 = 30,000,000\)

- **Societal Savings =** \(.9 - .6 \times 200,000 \times 200 = 12,000,000\)
As noted above, a recent study showed that those in the longitudinal sample who did not meet standards for “proficiency” for 3rd reading scores were four times more likely to eventually drop out of school without a high school diploma than those with proficient scores.

Here is how we use these findings to estimate the extent to which a LIIF-supported elementary school generates long-term earnings increases and societal savings.

**STEP 1:** We assume that over a lifetime, graduating from high school as opposed to dropping out is associated with $500,000 in increased earnings and $200,000 in societal savings.

**STEP 2:** Determine the percentage of 3rd grade students at the school reading at a “proficient” level, according to standardized tests.

**STEP 3:** Determine the district percentage of 3rd grade students reading at a “proficient” level.

**STEP 4:** Determine the district average high school graduation rate (Note: we assume that the district percentage of 3rd grade students reading at a “proficient” level corresponds with the district’s average graduation rate—and any higher proficiency rate above district averages would correspond with higher high school graduation rates, per the study).

**STEP 5:** Determine the number of students over the assumed four-year term of impact.

**STEP 6:** Determine the number of students at the school reading at a proficient 3rd grade level beyond what would be expected, per district averages.

- Multiply the school’s reading proficiency percentage (Step 2) by the number of students over the four-term period of impact (Step 5). This is the number of students reading at a proficient level.
- Multiply the district average proficiency percentage (Step 3) by the number of students over the four-term period of impact (Step 5). This is the number of students expected to be reading at a proficient level, per district averages.
- Subtract the previous number by the one prior to it, to get the number of “bonus” students reading at a proficient level at this school.

**STEP 7:** Determine the number of avoided dropouts (or “bonus” graduates) due to projected higher-than-expected graduation rates, compared to district averages. (Recall that students reading at a proficient level in 3rd grade are four times more likely to graduate from high school than those who are not reading at a proficient level.)
• Multiply the number of students at the school reading at a proficient 3rd grade level beyond what would be expected, per district averages (Step 6) by the district-wide dropout rate (valued at 1 minus Step 4). This is the number of them that would have been expected to drop out, per district averages, if they were not reading at a proficient level.

• Multiply the number of students at the school reading at a proficient 3rd grade level beyond what would be expected, per district averages (Step 6) by one quarter of the district-wide dropout rate. This is the number of them that are expected to graduate, since they are reading at a proficient level.

• Subtract the previous number by the one prior to it. This is the number of avoided dropouts or “bonus” graduates.

**STEP 8:** Determine the long-term earnings increases and societal savings from the avoided dropouts, or “bonus” graduates, using these formulas:

• Increased earnings: Step 7 × $500,000

• Societal savings: Step 7 × $200,000

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**Example**

Let’s say LIIF supports a charter elementary school in Oakland, California attended by 200 students. On average, 60 percent of district students graduate from high school, and 50 percent of them read at a “proficient” level in the 3rd grade.

**STEP 1:** We assume that over a lifetime, graduating from high school as opposed to dropping out is associated with $500,000 in increased earnings and $200,000 in societal savings.

**STEP 2:** We know that 75 percent of the students at the Oakland charter read at a proficient level in the 3rd grade.

**STEP 3:** We know that on average in Oakland, 50 percent of 3rd graders read at a proficient level.

**STEP 4:** We know that on average in Oakland, 60 percent of students graduate from high school.

**STEP 5:** The school will attempt to graduate 200 students over the assumed four-year term of impact.

**STEP 6:** \([.75 \times 200] - [.5 \times 200]\) = 50 students at the school reading at a proficient 3rd grade level beyond what would be expected, per district averages.

**STEP 7:** \([50 \times .5] - [50 \times .5 \times .25]\) = 19 (rounded up from 18.75) “bonus” graduates

**STEP 8:** Using the data from the previous steps, we can estimate earnings increases and societal savings from the “bonus” graduates:

Earnings Boosts = 19 × $500,000 = $9,500,000

Societal Savings = 19 × $200,000 = $3,800,000
COMMUNITY HEALTH CENTERS

Economic Value of Community Health Centers

Community Health Centers (CHCs) generate health system cost savings by producing better health outcomes, delivering more efficient forms of care, and preventing costly downstream hospitalizations and emergency room visits. The best available evidence suggests that patients who access care at CHCs generate at least $1,000 less in annual health care expenditures relative to people who do not use CHCs.\textsuperscript{53} We take the conservative approach of assuming that LIIF-supported CHCs serve the same patients every year, so we only count the number of people served per clinic. To estimate monetary value, we assume that the clinic is providing services to the same number of people, irrespective of whether they are the same individuals, each year. We multiply the value of the CHC savings by the term of LIIF’s capital, because we are confident that the clinic will remain in service at least for this period.

**STEP 1:** We assume that users of CHCs generate $1,000 less in annual health care expenditures relative to people who do not use CHCs.

**STEP 2:** Determine the Number of Patients (NP) served annually by the supported CHC.

**STEP 3:** Determine the Term (T) of the loan in years, as a conservative estimate of the period of impact.

**STEP 4:** Estimate a CHC’s economic value—in the form of medical cost savings—using this formula:

\[1,000 \times NP \times T\]

**Example**

*For example*, let’s say that LIIF supports a CHC in San Jose, California with a seven year loan. The clinic serves 1,000 people each year.

**STEP 1:** We’ll assume conservatively that patients of the San Jose CHC save $1,000 per year on health care expenditures.

**STEP 2:** We know that the San Jose CHC serves 1,000 people each year. Therefore, NP = 1,000.

**STEP 3:** We know that the term of the loan is seven years. Therefore, T = 7.

**STEP 4:** We can now estimate impact:

Medical cost savings = $1,000 \times 1,000 \times 7 \text{ years} = $7,000,000

\textsuperscript{53} Leighton Ku, Patrick Richard, Avi Dor, Ellen Tran, Peter Shin & Sara Rosenbaum, The George Washington University School of Public Health and Health Services, Using Primary Care to Bend the Curve: Estimating the Impact of Health Center Expansion on Health Care Costs (2009), pg. 6-7.
**EQUITABLE TRANSIT-ORIENTED DEVELOPMENT**

**Healthier Commutes: Equitable TOD as a Strategy to Increase Physical Activity and Boost Health**

Transit-oriented development (TOD) can generate positive human health outcomes through multiple pathways—for example, by increasing physical activity and reducing sedentary lifestyles by lowering dependence on cars for transportation needs, or by increasing the number and share of trips made on foot due to higher building densities and mix of land uses and pedestrian-friendly urban design features. Many TOD projects also take the approach of developing “complete communities” around transit stations where—in addition to living in close proximity to affordable and healthier transportation options—families and individuals are afforded easy access to a range of services and amenities that can positively influence health, such as health care, fresh food, and recreation.

Further, real estate values near transit stations tend to be inflated in metropolitan areas with tight housing markets and limited rail transit infrastructure. In this context, developing and preserving affordable housing near these stations is a way to prevent displacement of low-income families and individuals to neighborhoods that are underserved by transit, where they will be unable to benefit from the particular health benefits of TOD. As such, we believe equitable transit-oriented development—which incorporates housing and services targeted to lower- and moderate-income households—to be a critical strategy for addressing health disparities between socioeconomic and racial/ethnic groups living in the same metropolitan regions.

The evidence directly linking TOD to health improvements is, in the current moment, strongly suggestive—particularly in the area of increasing physical activity—but still limited. For example, studies have revealed correlations between neighborhood walkability indexes and a range of health outcomes, but most research in this area is not experimental in nature, nor is it easily extrapolated to the LIIF context. However, a 2010 pre-post longitudinal study of people living near the South Corridor Light Rail line in Charlotte, North Carolina (before and after it became operational—setting the stage for a “natural experiment”), provides the first experimental evidence demonstrating that increasing access to transit can mitigate some environmental barriers to daily physical activity, and generate reductions in body mass index and obesity.

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In particular, the study finds that, after adjusting for “treatment” and “control” group characteristics, taking light rail to work on a daily basis was associated with an average drop in body mass index (BMI) of 1.18—equivalent to 6.45 pounds for a person whose height is five feet, five inches—12-18 months after follow-up, and 81 percent of participants reduced their odds of becoming obese during this period.\textsuperscript{55a}

If we make a few assumptions, we can apply this study's findings to LIIF-supported equitable TOD contexts to give a rough estimate of these projects' short-term health impacts specifically due to their proximity to transit. In particular, we need to decide: 1) which projects or units qualify; 2) what percentage of individuals we hypothesize experience similar health benefits to those in the Charlotte study; 3) the period of impact for these benefits; and 4) how to monetize these benefits. Our rationale behind each of these assumptions is provided below:

**Which Projects Qualify?**
We can only defensibly extrapolate the findings from the Charlotte study to LIIF-supported equitable TOD projects in markets where access to regionally serving transit is similarly limited—meaning that their counterfactual housing locations would not likely be transit-accessible.

To this end, we only assume health impacts for LIIF-supported affordable housing projects that obtain financing specifically targeted to equitable TOD projects, such as the Bay Area Transit-Oriented Affordable Housing (TOAH) Fund, or which are located within ½-mile of either a rail (light or heavy) or bus-rapid-transit station in a housing market other than New York City—where transit infrastructure is much stronger than other core LIIF markets, and where people of all incomes have reasonably good access to transit for commuting purposes (much more so than in Charlotte, for example). Although the Charlotte study included households living within one mile of transit stations, the ½-mile distance is more commonly accepted as a TOD "zone," and the evidence around ridership that we can use to form the basis of our impact estimates appears to be limited to the ½-mile radius.

Further, the health improvements revealed in the Charlotte study were associated with using light rail to commute to work on a daily basis (as opposed to any other modal distribution). We cannot defensibly apply these results to LIIF-supported TOD housing projects whose residents are unlikely to have a reason for a daily commute. For this reason, we do not qualify units within otherwise “qualifying” TOD projects (those within ½-mile mile of a transit station) that target special needs populations—such as the formerly homeless, those with chronic illnesses, or the elderly—where such regular commutes are less likely.

Who Benefits?

Once we have established a list of qualified LIIF-supported TOD housing projects—and qualified units within those projects, per the discussion above—we still need to determine how many residents are likely experience similar health benefits as those adults in the Charlotte study’s “treatment” group—whether via preserved access to transit (i.e., avoiding the “costs” of displacement to a non-TOD location) or via newly obtained access to transit (i.e., reaping health benefits of moving from a non-TOD location to this property).

To arrive at this number, we need to hypothesize how many people living in qualified units take transit on a daily basis. The Charlotte study does not provide data on distances between residences and transit stations for those commuters who became frequent transit users after light rail became operational. However, evidence on ridership near transit stations provides a basis for estimating how many adults in LIIF-supported TOD projects use transit at a similarly high rate as those in the Charlotte study.

The vast majority of qualified TOD projects that we support are in California. For this reason, we draw from the evidence on transit ridership in the state. However, as previously noted, we estimate impact for all LIIF-supported TOD projects in markets with similar levels of transit infrastructure—including in markets outside California, but not including New York City, because it is so thoroughly served by public transit.

Among workers living within ½-mile of rail transit in Los Angeles County and the San Francisco Bay Area, around 31 percent and 41 percent of workers earning less than $25,000 per year, respectively, of workers commute by transit or by walking. These figures are a bit lower for households of all incomes—around 22 percent and 34 percent, respectively.56

Since the vast majority of unit in LIIF-supported TOD projects are reserved for low-income households—and many of these projects are located within ¼-mile of transit stations, where evidence has shown that ridership is even higher 57—we assume that 35 percent of daily commuters living in LIIF-supported TOD projects commute via transit on a daily basis.

In addition, the 2009 National Household Travel Survey found that there were 1.41 workers per household in the western region of the United States, where most LIIF-supported TOD projects are located.58 We thus conservatively assume 1.25 daily commuters per household.


57 Transit ridership in California is between 50 and 75 percent higher among those living within ¼-mile of a transit station, when compared to those within ½-mile. Source: TransForm and the California Housing Partnership Corporation. 2014. “Why Creating and Preserving Affordable Homes Near Transit is a Highly Effective Climate Protection Strategy,” May

58 U.S. Department of Transportation, Federal Highway Administration. 2009 National Household Travel Survey. Website: http://nhts.ornl.gov/
**Period of Impact**

The Charlotte study analyzed health impacts over a relatively short-term—only 12–18 months after the South Corridor Light Rail line became operational—and the authors specifically recommend that future studies examine longer-term health impacts of increased access to transit. Although we do not have information on the duration of benefits, they could conceivably be sustained over time—at least for the period that families continue to live in a transit-accessible location. For this reason, we assume a period of impact that is the same as the project's housing restriction term, as required by subsidy sources. This period is the term that we can reasonably assume that the project will remain operational.

**Monetizing Health Improvements**

We base our monetization of hypothesized health improvements associated with LIIF-supported TOD housing projects on the Charlotte study's finding that commuting daily via transit was associated with lowering BMI by 1.18, when compared to not taking transit. Although the predominance of research to date on the relationship between body mass and medical expenditures has focused on differences between groups defined by BMI ranges (e.g., those who are overweight vs. those with class III obesity), there is some evidence on the relationship between medical expenditures and each BMI unit. In particular, a study based on 36,000 employees and their spouses in a United States auto manufacturing company found that, within the 25-45 BMI unit range (which comprises the vast majority of adults), each unit increase of BMI was associated with increased annual medical and pharmaceutical expenditures equivalent to $202 in 2004 dollars ($253 in 2014 dollars, which we round down to $250). We use this study as the basis to make estimates of medical expenditure savings associated with health improvements from LIIF-supported TOD housing projects.

We estimate weight loss and associated medical cost savings generated by qualifying LIIF-supported TOD housing projects with the following step-by-step calculation:

**STEP 1:** Determine the number of qualifying housing units—those that are not targeted to special needs populations. Multiply this number by 1.25 to get the assumed total number of daily commuters in the project.

**STEP 2:** Determine the term that the property is required to remain affordable to low-income households.

**STEP 3:** Determine the number of daily commuters in qualifying units who we assume will commute by transit. Multiply the number of commuters at any given time (Step 1) by 0.35, representing that we estimate that 35 percent of daily commuters will use transit.

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59 Consistent with our approach to monetizing health benefits across LIIF program areas, we only account for reduced medical expenditures and do not account for other positive results such as improvements in worker productivity and fewer disability claims.

**STEP 4:** Estimate medical cost savings generated by hypothesized health improvements each year:

- Multiply the number of transit commuters (Step 3) by 1.18—the drop in BMI per commuter.
- Multiply the number from the previous step by $250, to reflect the annual reduction in medical expenditures associated with this BMI reduction.

**STEP 5:** Estimate medical cost savings generated by hypothesized health improvements over the total term of impact. Multiply the annual cost savings (Step 4) by the housing restriction term (Step 2).

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**Example**

Let’s say that LIIF supports the development of 50 units of rental housing for low-income families adjacent to a BART station (less than ½-mile) in Berkeley, CA. The applicable tax credit agreement in California requires that rents remain affordable for the next 55 years.

**STEP 1:** There are 50 units targeted to low-income families that are not special needs.

  Assuming one commuter per unit, we assume that 62.5 (rounded up to 63) commuters live in the property at a given time.

**STEP 2:** The project’s California Tax Credit Allocation Committee agreement requires that rents be restricted for 55 years.

**STEP 3:** 63 commuters × .35 = 22 transit commuters.

**STEP 4:** 22 commuters × 1.18 BMI lost × $250 = around $6,500 in medical cost savings per year.

**STEP 5:** $6,500 × 55 years = $357,500 in total medical cost savings over the expected life of the project.