EMPLOYMENT STRATEGIES for Low-Income Adults *Evidence Review*

ESER ISSUE BRIEF

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The Right Tool for the Job: A Meta-Regression of Employment Strategies' Effects on Different Outcomes

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Policymakers, practitioners, and other officials want to be able to readily understand the evidence on what works to help low-income workers find and keep jobs. There is growing recognition, however, that the term "low-income workers" encompasses people with a wide range of educational and employment histories who live in diverse settings and face diverse challenges. Their needs vary, and so do the interventions that can improve their labor-market outcomes. As a result, it is important not only to understand the interventions that work best overall to improve employment outcomes for low-income workers, but also to determine which are most effective under which conditions and for which types of workers.

In this brief, we use a rigorous quantitative approach known as meta-regression to identify not only those interventions that seem successful on the whole, but also those that are effective for particular labor market outcomes and for particular types of low-income workers.

Because any given intervention typically comprises several employment strategies, we also examine the specific employment strategies that appear to be successful (1) overall, (2) for certain outcomes of interest, and (3) for certain types of low-income workers. Being able to identify the context in which particular strategies work best can help practitioners and policymakers make targeted and informed decisions about the types of interventions that could be most effective in their contexts. Specifically, it is important to understand:

- **What works in general?** Which interventions and employment or training strategies improve outcomes for low-income workers overall?

Highlights

- **Several interventions are effective at improving low-income adults' labor market outcomes.**
  - Although most of these effective interventions are associated with relatively small impacts, 10 are highly likely to improve outcomes by at least 5 percent.
  - Only one intervention causes significantly unfavorable impacts.
- **Most individual strategies, although effective, are associated with modest positive effects. No single strategy on its own is associated with substantial gains.**
  - The individual strategies that appear most effective are financial incentives and sanctions, education, work experience, and training. Each has over a 90 percent chance of improving outcomes across population and outcome types.
  - Interventions that *combine* several strategies to help low-income workers find and keep jobs appear more effective than any *single* strategy.
- **It is easier to improve education and training outcomes than it is to increase employment or independence from public assistance.**
  - Interventions' impacts on education and training outcomes were larger than impacts on employment or independence from public assistance, suggesting that the latter outcomes are more difficult to improve with employment and training interventions over the time period that the original studies examined.
- **The effect of an intervention is more than the sum of the effects of that intervention's strategies. In this context, implementation and other idiosyncratic factors become all the more crucial to our understanding of effectiveness.**

OPRE

MATHEMATICA Policy Research

WHAT IS ESER?

The Employment Strategies for Low-Income Adults Evidence Review (ESER) is a systematic review of the literature on the impacts of employment and training programs and policies for low-income people. Sponsored by the Office of Planning, Research and Evaluation (OPRE) in the Administration for Children and Families, ESER provides practitioners, policymakers, researchers, and the public with a transparent, systematic assessment of the quality of research evidence supporting approaches to improve the employment-related outcomes of low-income adults.

The ESER team searched the literature for relevant research published from 1990 to mid-2014 and then screened for eligible studies to review—those that used randomized controlled trials or comparison group designs.

Trained reviewers examined the strength of the causal evidence for each study—that is, they gauged how likely it was that any impacts reported in the study were *caused by* the intervention being studied, not by something else. They then rated each study based on its rigor (not on the effectiveness of the intervention):

High ratings were for randomized controlled trials with low attrition—that is, few people were missing from follow-up data collection efforts—and with no reassignment of people or cases after the original random assignment.

Moderate ratings were for two types of studies: (1) randomized controlled trials that, due to flaws in the study design or analysis (for example, high attrition), did not qualify for the high rating but satisfied other design criteria and (2) comparison group designs that were well executed and established equivalence between the two groups.

Low ratings were assigned to studies that did not qualify for a high or moderate rating.

This is one in a series of briefs that highlights results from this review. The briefs describe high-quality research on several strategies that promote employment for low-income adults.

The ESER team identified a "primary strategy" for each intervention. This was the employment or training strategy used most in the intervention—the service most treatment group members received and most comparison group members did not. The primary strategy was also the one that appeared integral to the theory of change tested by the study of that intervention.

The team determined the primary strategy for each intervention by having two reviewers independently read the description of each intervention, identify a primary strategy, compare their assessments, and discuss until they reached agreement.

For more details, see Assessing the Evidence Base: Strategies That Support Employment for Low-Income Adults

- **What works for particular outcomes?** Do some interventions and strategies have different effects for different outcomes? For example, job search assistance may help people find jobs but not ensure their independence from public assistance.
- **What works for particular workers?** Which strategies are most effective for particular types of low-income workers? For instance, basic skills training may be more effective for those lacking a high school diploma than it is for those who have a diploma or GED.

DATA

We used the information collected through the Employment Strategies for Low-Income Adults Evidence Review (ESER) to better understand what works best overall and for certain outcomes of interest. Specifically, we relied on the detailed ESER database of 235 high- or moderate-rated studies of 93 interventions testing employment strategies for low-income adults.[1] From those interventions, we identified each intervention's estimated impact on each outcome. We obtained a total of 1,162 intervention-outcome combinations for analysis. For each study, the database includes:

- The services each intervention offered to the treatment group and not to the comparison group[2]

THIS SERIES OF BRIEFS

This series of briefs offers a synthesis of the findings of the Employment Strategies for Low-Income Adults Evidence Review (ESER) for policymakers, practitioners, and others who seek to improve the employment and earnings outcomes of low-income adults through research-based interventions. This brief focuses on a quantitative synthesis—known as a meta-regression—of the research evidence across all the studies included in ESER to examine which employment services are most effective. Other briefs focus on an overall qualitative summary of ESER and its findings, financial incentives and sanctions interventions, work readiness interventions, primary service strategies, and gaps in the research base.

- The population(s) targeted by the intervention[3]
- Estimates of the intervention's impacts on employment, educational attainment, and independence from public assistance (that is, benefit non-receipt)[4]

The data set contained information on 9 population characteristics and 10 employment strategies (Table 1).

Table 1. ESER interventions' population characteristics and employment strategies

	Category	Number of studies
Population characteristic	Welfare population	225
	Parents	219
	General low-income population	51
	Employed	42
	Hard-to-employ	24
	Unemployed	20
	Men	12
	Women	10
	Young adults	8
Strategy	Case management	157
	Training	152
	Work readiness	140
	Supportive services	129
	Financial incentives and sanctions	120
	Education	116
	Work experience	62
	Job development	61
	Employment retention services	49
	Health services	35

*For ESER, a **study** is a publication that describes the implementation and impact of at least one, and often more than one, intervention. An **intervention** is a bundle of one or more strategies offered to a set of recipients; in this brief, we classify bundles of strategies administered to different populations as distinct interventions. A **strategy** is a service, like job search assistance, or an incentive structure, like a re-employment bonus, intended to promote improvement in labor market outcomes.*

Before conducting the analysis, we rescaled the impact estimates to be comparable across studies. To understand why rescaling is important, consider Study A and Study B, both of which found an impact of 5 percentage points on employment rates for the interventions they examined; that is, low-income workers who were offered either intervention had employment rates 5 percentage points higher than a comparison group of low-income workers who were not offered the interventions. If the comparison group in Study A had an employment rate of 50 percent, then that 5-percentage-point increase translates to a 10 percent improvement. But if the comparison group in Study B had an employment rate of only 10 percent, then the 5-percentage-point increase for the intervention group corresponds to a 50 percent improvement, making the intervention in Study B potentially much more effective than the one in Study A.

Unfortunately, with few exceptions, the studies reviewed by the ESER team did not provide enough information to calculate or estimate the appropriate rescaling for outcomes of interest on a continuous numeric scale: earnings and the amount of public assistance received. Therefore, we could not include those outcomes in the meta-regression.

The studies in the ESER database did include all the information needed to calculate rescaled impacts for the binary (yes/no) outcomes of interest: whether a person was employed, obtained an educational credential, or was independent from public assistance. For each binary outcome, we estimated the impact of the intervention as a percentage of the comparison group mean. In the example above, the rescaled impact on the employment rate in Study A would be 10 percent (a mean of 55 percent in the intervention group versus 50 percent in the comparison group), whereas the rescaled impact in Study B would be 50 percent (a mean of 15 percent in the intervention group versus 10 percent in the comparison group). Appendix A.1 provides more details on how we rescaled the impact estimates.

METHODS

Meta-regression

To conduct the analyses we report here, we used a rigorous quantitative approach called *meta-regression*. Meta-regression builds on regression—a statistical process for estimating the relationships among variables. In many studies in the ESER database, the original researchers used regression to estimate the relationship between exposure to an intervention and later outcome rates. A meta-regression analyzes outcomes from different studies rather than outcomes from different people. Meta-regression allows us to rigorously summarize the sizes of the impacts estimated from different studies and to determine whether certain intervention features, like specific strategies, are associated with larger or smaller impacts. Using this method we can identify strategies that are promising overall and for specific outcomes, such as employment; for specific populations, such as parents; and even for specific combinations of outcomes and populations. The outcome variable in our meta-regression is the estimated impact of each intervention as a percentage of the average outcome in the comparison group, as described above and in Appendix A.1.

In this case, we estimated the relationships between the rescaled outcomes and (1) the services offered and (2) population(s) targeted in different studies. To address the research questions motivating this analysis—what strategies work best for which workers?—we also estimated relationships between outcomes and combinations of strategies and populations. The regression equations and additional technical details are available in Appendix A.2.

We estimated the relationships between the outcomes from the ESER-reviewed studies and the services offered and populations targeted by each intervention to explore what combination of strategies works for employment-related outcomes, which individual strategies are associated with the greatest improvement in impacts, and which strategies work best for specific populations.

Like any quantitative technique, meta-regression can only estimate relationships among measured concepts—outcomes like whether a person was employed and factors like whether an intervention included a certain strategy. Meta-regression necessarily excludes unmeasured factors, like community attitudes or the prevailing policy context at the time the study took place, that may also affect a program's success. Given these limitations, the picture of intervention effectiveness derived from meta-regression—or any quantitative analysis—will be incomplete. Similarly, we were not able in our analysis to account for changes over time in the estimated relationships. Though the understanding of relationships among factors and outcomes we derive from meta-regression is simplified, this distillation of the available data can suggest important trends that in turn suggest promising policy directions. This brief describes the trends we identified through applying these meta-regression techniques to the interventions studied in ESER.

The Bayesian framework

We use a Bayesian statistical framework, which differs in important ways from the traditional, or frequentist, statistical framework. In a traditional framework, we can estimate relationships of interest well when many studies include a given combination of outcomes, services, and populations, but not as well for combinations that appear rarely in the data. In those cases we would not have enough information to draw precise conclusions about the relationships of interest. The ESER database contains many such cases; despite its scope, it includes few instances of many potentially informative combinations of strategies and populations, so we are less able to reach precise and compelling conclusions by using the traditional approach. The Bayesian approach strengthens our estimates for combinations of study features—outcomes, strategies, and populations—that appear only rarely in the data.

The Bayesian framework borrows information from all the studies that offered a given strategy or targeted a given population when estimating the association between that combination of strategy and population and impacts. To leverage this information, we made some initial assumptions about the relationships among the impacts for each combination of outcome, strategy, and population. We began by assuming that all interventions in the database had similar impacts on all outcomes. That is, if most interventions with substantial information tended to have favorable impacts, we assumed that other interventions for which less information was available also tended to have favorable impacts. We made similar assumptions for strategies, populations, outcomes, and all their combinations. These assumptions were a starting point; we then checked whether the assumptions had support, allowing the data to contradict the assumptions. Appendix A.2, in which we describe the meta-regression model in full, contains the assumptions' exact specifications.

A Bayesian approach also offers interpretive advantages over the traditional approach because it allows researchers to make more policy-relevant conclusions. A traditional meta-regression uses a single summary value (*p*-value) to classify each estimated relationship as statistically significant or not—a thumbs-up or thumbs-down. This summary does not account for the magnitude of the relationship or whether it is meaningful in context—is an increase of 5 large, small, or moderate for a given outcome?—so a small magnitude that is negligible in context may be statistically significant, whereas a large one that is striking in context may not be statistically significant. Even when researchers seek to interpret estimates in the context of previous results or their understanding of the data, the frequentist approach offers no straightforward summary of the effect's magnitude and statistical significance.

In contrast, Bayesian analyses describe the *probability* that a result exceeds a meaningful threshold. Thus, we can make statements such as "There is an XX percent chance that training improved impacts on short-term employment rates by YY percent or more." These statements use intuitive language to convey both the strength and magnitude of the relationship.

Describing results

Meta-regression can estimate relationships between rescaled impacts and study features (outcomes, interventions, strategies, and populations). We describe the results as both: (1) estimates of the relationships ("relationship estimates") and their uncertainty intervals and (2) probabilities that these relationships meet certain practical significance thresholds.

- **Relationship estimates** use percentage terms to convey the magnitude of the estimated association between the impacts of each intervention and a given study feature; for instance, an estimate of 0.07 for work readiness activities indicates that impacts are, on average, 7 percent higher when work readiness activities are present than when they are absent. Along with each relationship estimate, we provide 95 percent uncertainty intervals, which represent the range of values in which we are 95 percent confident that the true relationship falls.
- **Probabilities** convey the likelihood that the estimated relationships fall into meaningful ranges. Thus, they measure both the strength and magnitude of the relationship between the estimated impacts and different study features. We calculated the probability that each relationship (1) exceeds 0.05, implying increases in impacts of 5 percent or more when the feature is present, and (2) exceeds 0.1, implying increases in impacts of at least 10 percent when the feature is present. When presenting probabilistic results, we consider a probability of greater than 90 or 95 percent to indicate a strong relationship.

Large, statistically significant estimates typically correspond to high probabilities. We describe both types of results to provide a more comprehensive picture of the meta-regression results; the estimates convey the magnitude of the relationship and whether it differs meaningfully from zero, while the probabilities summarize the strength of the relationship in a single metric focused on the research question of interest: how likely the intervention or strategy was to improve outcomes for low-income workers by specified amounts.

RESULTS

In this section we report our findings on all three research questions—on what interventions work best in general, for particular kinds of workers, and for particular outcomes. First, using the techniques outlined earlier, we examined the effectiveness of each intervention. Unlike in other ESER briefs, here we define an intervention as a unique set of strategies implemented for a specific target population to avoid confounding a strategy's effectiveness with the populations who undertake that strategy. We assessed the effectiveness of each intervention overall, across all types of outcomes, and by outcome type to learn whether specific interventions are particularly effective at improving specific outcomes. For example, an intervention might be associated with improvements in employment but not with independence from public assistance. As context for this analysis, we also considered whether certain outcomes are easier to improve than others. Finally, we examined each strategy independently, using the data to determine strategies' relationships with the outcomes across interventions.

HOW TO INTERPRET THESE RESULTS

Each rescaled impact is based on the difference in the predicted outcomes of the intervention and comparison groups as a percentage of the comparison group mean. An impact of zero implies that the outcome is just as likely to occur in the intervention group as in the comparison group; for example, that intervention and comparison group members are equally likely to be employed. Positive impacts mean the outcome is more likely for the intervention group; a 5 percent impact means that employment rates are 5 percent higher in the intervention group than in the comparison group. Conversely, negative impacts mean the outcome is less likely for the intervention group; for example, an impact of negative 5 percent means that employment rates are 5 percent lower in the intervention group than in the comparison group.

In a traditional analysis, a p-value determines whether an estimated relationship is statistically significant. There is no typical Bayesian substitute for the p-value, so in this analysis we consider an effect to be statistically significant if its 95 percent uncertainty interval does not contain zero, mirroring the traditional definition. Thus, we can be confident that that feature is associated either with:

- Significantly unfavorable outcomes, for effects less than zero
- Significantly favorable outcomes, for effects greater than zero

What works? Which interventions and strategies improve outcomes for low-income workers overall?

Interventions. We examined which interventions work in general, averaging across all outcomes (employment, education and training, and independence from public assistance), as well as analyzing whether some interventions are more likely to improve certain types of outcomes than others. In both the overall and outcome-specific effectiveness analyses, we controlled for the strategies each intervention implemented and the populations it targeted; for more details on the calculation, please see Appendix A.3.

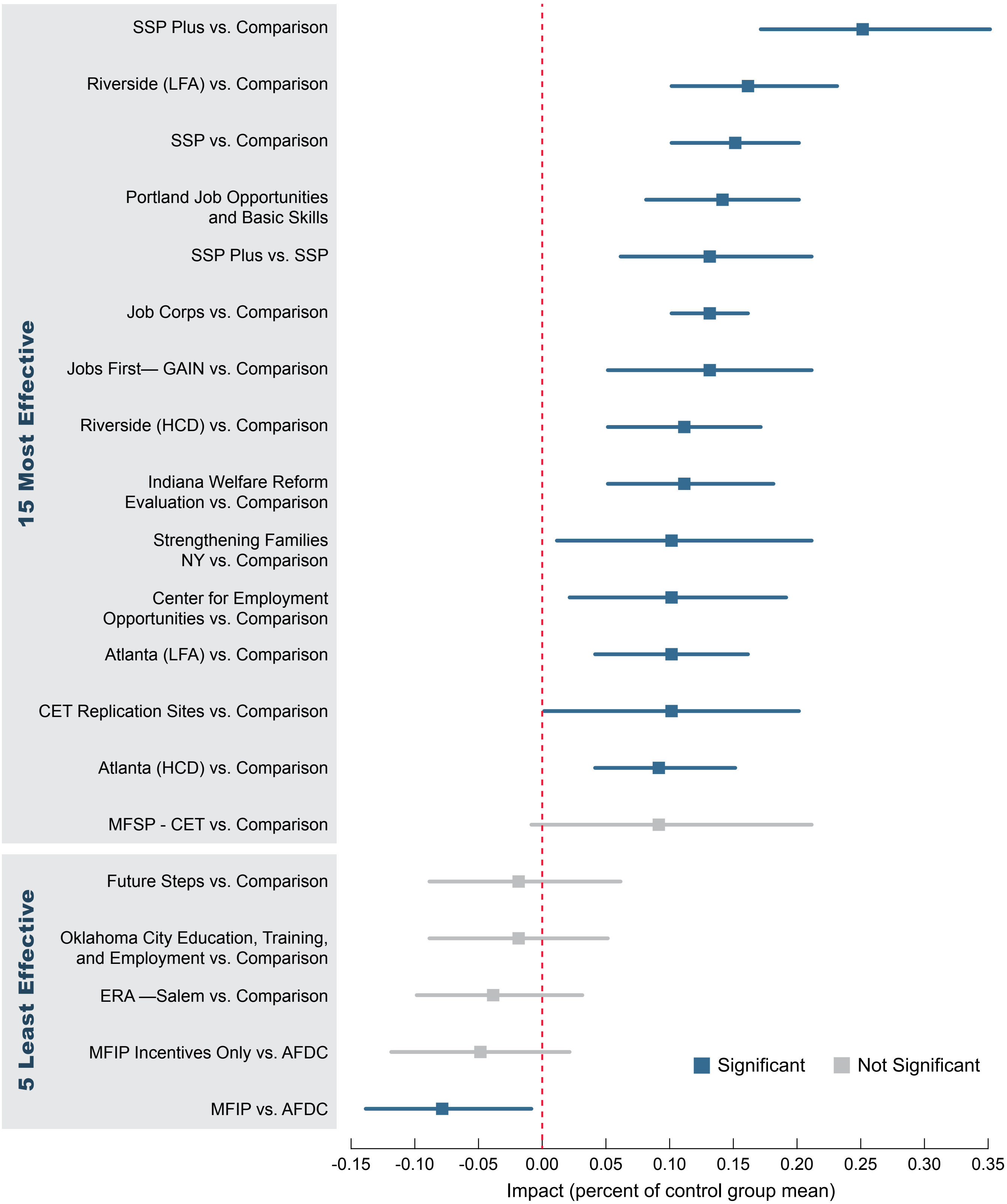
First, we tested what works overall. Defining an "effective" intervention as one with statistically significant and favorable estimated impact, we found that 19 of the 93 interventions were effective. The magnitudes of the expected impacts ranged from 7 to 25 percent of the comparison group means (Figure 1 shows results for the 15 most and 5 least effective interventions).[5] One intervention, the Minnesota Family Investment Project (MFIP)-which consisted of financial incentives for work, employment and training activities that emphasized rapid entry into the job market, and streamlined access to several public benefits-had statistically significant negative impacts when compared to standard Aid to Families with Dependent Children (AFDC).[6]

One in five interventions improved outcomes at least somewhat, and for about one half of those interventions the magnitude of the impact was likely to be at least 5 percent.

Second, we estimated the probabilities that the impacts surpass certain thresholds. Using this approach, we reached a similar conclusion. Figure 2 shows the 15 interventions with the greatest probability and the 5 interventions with the lowest probability of achieving favorable impacts. The interventions most likely to achieve favorable impacts align with those identified as statistically significantly effective based on the estimates. We also show the probability that each intervention achieves impacts of 5 percent or more and 10 percent or more. Large differences between the probability of impact (gray bar) and the probability of a 5 or 10 percent impact (light and dark blue bars) suggest that the intervention is very likely to improve treatment group outcomes but unlikely to improve them substantially.

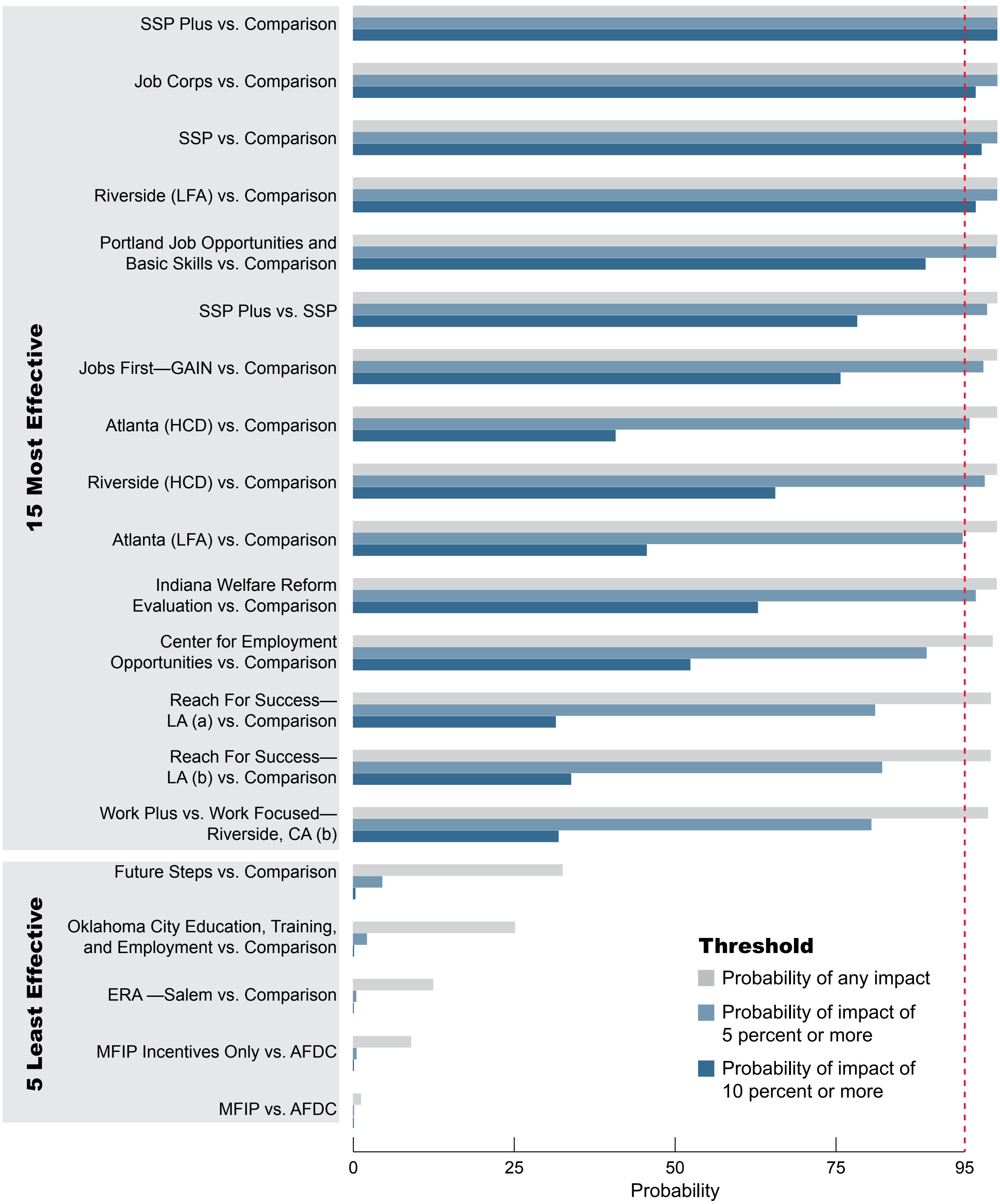
Of the 19 effective interventions, 10 have over a 95 percent chance of improving intervention group outcomes by at least 5 percent. Four are especially likely to have non-negligible effects, with a 95 percent chance of improving intervention group outcomes by at least 10 percent: (1) the Self Sufficiency Project (SSP), (2) SSP Plus, (3) the Labor Force Attachment intervention tested in Riverside, California as part of the National Evaluation of Welfare to Work Strategies, and (4) Job Corps. See Appendix Table B.2 for details.

Figure 1. Magnitude of effects for most and least effective interventions



Note: This figure depicts the estimated impact and associated 95 percent uncertainty interval for the 15 most effective interventions and the 5 least effective interventions. The dashed vertical line denotes no impact. Results for all interventions are presented in Appendix Table B.1. Intervention names are abbreviated to conserve space; please see Appendix C for a full list of interventions and the corresponding evaluations.

Figure 2. Interventions with highest and lowest probabilities of achieving impacts



Note: The bars in this figure give the probability that each intervention is effective. We define effectiveness using three thresholds: any impact, an impact of 5 percent or more, and an impact of 10 percent or more. The dashed vertical line at 95 percent corresponds to a one-tailed test of statistical significance; interventions with bars that cross this line are highly likely to be effective.

Individual strategies. Each intervention implemented several strategies in combination, but decision makers may want to know whether particular strategies are especially effective across outcomes, interventions, and populations. To examine this aspect of effectiveness, we quantified the effect of each strategy as the percent change in the impact associated with offering the strategy as compared to not offering it. We found that several strategies are associated with increased impacts, but none of these relationships is statistically significant. Moreover, each strategy is expected to increase impacts by no more than 2 percent; for specific results, please see Appendix Table B.3.

Several individual strategies are associated with improved results for low-income workers, but no strategy's expected improvement was large—no greater than 2 percent—or statistically significant.

Probabilities confirm the pattern of these findings: each employment strategy has at least an 80 percent chance of improving the intervention group's outcomes to some degree. Financial incentives and sanctions, education, work experience, and training are the strategies most likely to improve outcomes, with probabilities of improvement exceeding 92 percent. However, the magnitudes of the improvements are small, and no strategy has even a 2 percent chance of improving intervention group outcomes by 5 percent or more, as we show in Table 2. Though individual strategies are somewhat associated with improved labor market outcomes, the gains are small. Several strategies working in concert may facilitate larger improvements, as we see in our analysis of effective interventions.

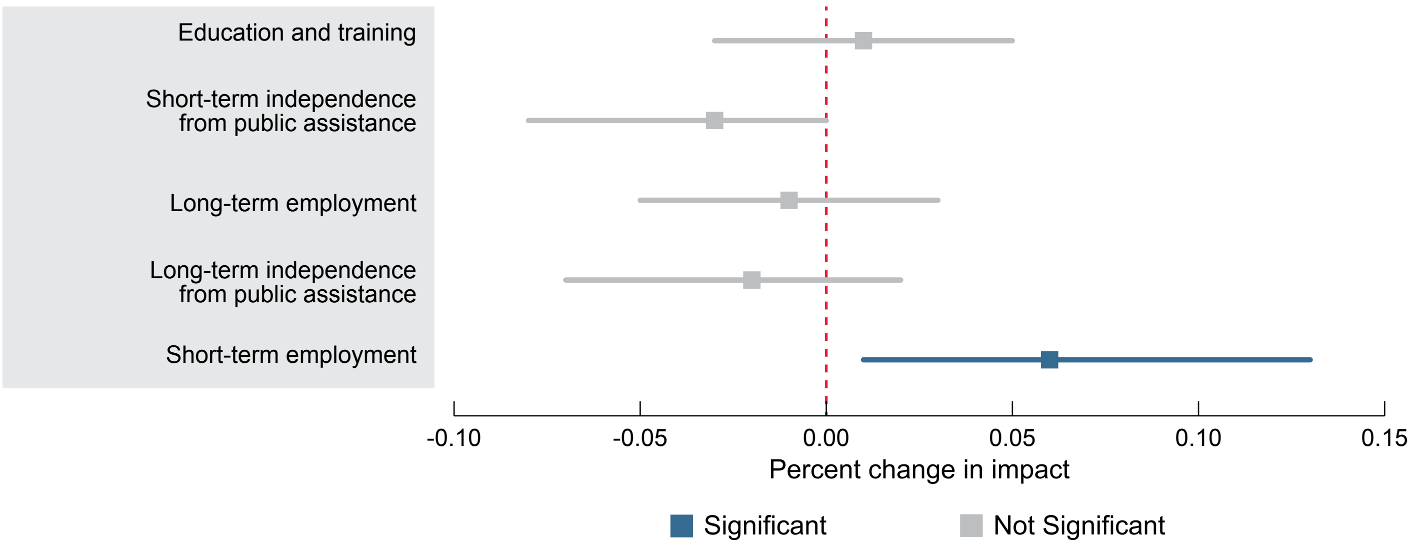
Outcomes. As part of the meta-regression, we analyzed whether, on average, impacts were larger or smaller for certain outcomes—education and training, short- or long-term employment, or short- or long-term independence from public assistance—than for others. We found that across interventions, strategies, and populations, impacts in education and training outcomes are on average 6.2 percent larger than impacts of other types, a statistically significant margin. In contrast, impacts for short-term employment outcomes are only 1.1 percent larger on average than other outcomes, a difference that is not statistically significant. The remaining outcome types are also associated with smaller impacts that are not statistically significantly different from zero. See Appendix Table B.5 for details. These findings suggest that it is easier to improve education and training outcomes than it is to increase employment or independence from public assistance.

This finding contrasts with the findings presented in an earlier summary brief from this project (Assessing the Evidence Base: Strategies that Support Employment for Low-Income Adults), in which we concluded that long-term outcomes were more likely to be favorable than were short-term outcomes. The difference in the two sets of findings stems from their distinct but complementary analytic approaches: the narrative summary relies primarily on the impacts' statistical significance in the original studies to determine which effects are meaningful, whereas the meta-regression emphasizes the magnitude of the difference between intervention and comparison group outcomes. Different analytic emphases suggest a possible explanation for differences in results: where impacts are statistically significant in the original studies but not necessarily large, we would expect the two approaches to produce different results, as they do here.

Table 2. Strategies' probabilities of improving impacts

Strategy	Any improvement	Improvement of 5% or more	Improvement of 10% or more
Financial incentives and sanctions	93.02	1.40	0.01
Education	92.77	0.69	0.00
Work experience	92.59	1.20	0.00
Training	92.19	0.73	0.00
Work readiness activities	89.63	0.25	0.00
Job development	88.73	0.41	0.00
Case management	88.33	0.33	0.00
Health services	88.13	0.64	0.00
Employment and retention services	81.59	0.18	0.00
Supportive services	81.05	0.05	0.00

Figure 3. Outcomes' effects and associated uncertainty intervals



Note: This figure depicts the estimated impact and associated 95 percent uncertainty interval for each outcome type, denoting whether the outcome type is generally easier or more difficult to improve than other outcome types. The dashed vertical line denotes average impact. Numerical results are presented in Appendix Table B.5.

Interventions' impacts on education and training outcomes were larger than impacts on employment or independence from public assistance, suggesting that the latter outcomes are more difficult to improve with employment and training interventions over the time period that the original studies examined.

What works for which outcomes? Which interventions and strategies are most effective at improving particular types of outcomes?

Decision makers may wish to focus on the most effective approach to improving a specific outcome type, like employment. In this section we present the interventions and individual strategies that appear most promising for particular outcome types: education and training, short- and long-term employment, and short- and long-term independence from public assistance. Throughout this discussion, it is important to recall based on the findings above that, whatever the intervention or individual strategy, education and training outcomes are easier to improve than are other outcome types.

Interventions by outcome type. We summarize the most effective interventions for each outcome type in Table 3 on page 10. For each outcome, we cite the number of statistically significantly effective interventions according to the meta-regression results and name the five most effective interventions. Three interventions appear among the most effective in all five outcome types: Riverside (Labor Force Attachment), SSP, and SSP Plus. Unsurprisingly, these three interventions are also among the most effective overall. Three other interventions—Job Corps, Public Health Nursing, and the Indiana Welfare Reform Evaluation—appear only among the most effective interventions for a single outcome type. These interventions are more likely to be highly effective at improving one outcome type than to be generally effective.

Individual strategies by outcome type. Individual strategies were roughly equally effective across outcome types. Every combination of employment strategy and outcome type is associated with improved impacts, but the associations are relatively weak—no more than a 3 percent increase in impacts—and none are statistically significant. However, four combinations were associated with increases of 2 percent or more in the impacts and had approximately a 95 percent chance of improving outcomes:

- Work experience improves short-term impacts on independence from public assistance
- Education improves impacts on education and training outcomes
- Education also improves impacts on long-term independence from public assistance
- Financial incentives and sanctions improve impacts on short-term employment

Table 3. Most effective interventions by outcome type

Outcome type	Number of interventions effective for this outcome	Most effective interventions
Education and training	46	• Job Corps • Public Health Nursing • Riverside (Labor Force Attachment) • Self-Sufficiency Project • Self-Sufficiency Project Plus
Short-term employment	23	• Indiana Welfare Reform Evaluation • Portland JOBS • Riverside (Labor Force Attachment) • Self-Sufficiency Project • Self-Sufficiency Project Plus
Long-term employment	14	• ERA Chicago • Jobs-First—GAIN • Riverside (Labor Force Attachment) • Self-Sufficiency Project • Self-Sufficiency Project Plus
Short-term independence from public assistance	8	• Jobs-First—GAIN • Portland JOBS • Riverside (Labor Force Attachment) • Self-Sufficiency Project • Self-Sufficiency Project Plus
Long-term independence from public assistance	10	• Jobs-First—GAIN • Portland JOBS • Riverside (Labor Force Attachment) • Self-Sufficiency Project • Self-Sufficiency Project Plus

Note: Effective interventions are those associated with statistically significantly higher outcomes for the intervention group relative to the comparison group in the meta-regression, defining statistical significance at the 0.05 level. See Appendix Table B.6 for results for all interventions.

However, these effects were small and perhaps not reliable (Figure 4): none of these strategies had more than a 15 percent probability of improving even the most affected outcome by 5 percent or more. Appendix Tables B.7 and B.8 provide more details on this analysis.

Individual employment strategies were associated with roughly equal improvements in impacts across outcome types, with small (a 2.5 percent increase at most), non-significant gains.

What works for whom? Which strategies are most effective for which types of low-income workers?

Although some strategies are effective in general, they may not affect the members of different populations in the same way. The meta-regression framework allows us to examine this variation to see which population types are most sensitive to which strategies. In the ESER review, we classified each intervention into a given population category if the entire sample was in the category; for example, an intervention administered exclusively to parents would fall into the "parents" category. This approach ensures that the meta-regression is not biased by decisions authors may make to report results from subgroups only if the findings are striking. Otherwise, we would expect to see more statistically significant results for specific populations than are plausible simply because authors tend only to report statistically significant subgroup results.

No specific strategy had striking impacts for any specific population. Although each strategy was associated with very slight increases in impacts for each population, these increases are not statistically significant. Probabilistic analysis confirms this result; no combination of employment service and population has over a 90 percent chance of improving impacts at all. See Appendix Tables B.9 and B.10 for details.

No specific strategy had striking impacts for any specific population.

Figure 4. Effective strategies' probability of improving outcomes

Note: The bars in this figure give the probability that each combination of employment strategy and outcome is effective. We define effectiveness using two thresholds: any increase in impacts and an increase in impacts of 5 percent or more. The dashed vertical lines at 95 percent correspond to a one-tailed test of statistical significance; combinations that cross these lines are highly likely to be effective.

When interpreting these results, it is important to recall how population characteristics are defined in the ESER database. For ESER, an intervention only receives a population characteristic if the entire sample has that characteristic. We adopted this approach to ensure that our results are robust to selective reporting of subgroup results. However, this approach masks some differences between populations. For example, an intervention with a fully female sample would fall into the "women" category, but one in which 98 percent of the sample was female would not. Defining specific populations in this way makes it difficult to tell whether strategies are more effective for some populations than others because two interventions with different population labels may target effectively the same population. Our results, which do not point to any differences in strategy effectiveness by population, conform to this limitation.

DISCUSSION

Key findings

Employment and training strategies and interventions demonstrate effectiveness both overall and for specific outcome types. Nineteen of the 93 unique interventions in the ESER database caused significantly favorable impacts, while one caused significantly unfavorable impacts. Most strategies are associated with modest positive effects. No single strategy on its own is associated with substantial gains. This finding suggests that combining different employment and training strategies, as most interventions do, can have positive and significant impacts on outcomes for low-income individuals. However, these combinations do not fully explain the effectiveness of an intervention: the effect of an intervention is more than the sum of the effects of that intervention's strategies. In this context, implementation and other idiosyncratic factors become all the more crucial to our understanding of effectiveness.

Although no strategy is statistically significantly more effective than any other, whether in general or for specific populations or outcome types, all strategies are generally effective.

Although no strategy is statistically significantly more effective than any other, whether in general or for specific populations or outcome types, all strategies are generally effective—that is, they are associated with increased impacts. Four strategies, financial incentives and sanctions, education, work experience, and training, have over a 90 percent chance of improving outcomes across population and outcome types.

These four employment strategies are associated with marginally better—between 2 and 3 percent increases—outcomes for some outcome types. Work experience is associated with improved impacts on short-term independence from public assistance; education is associated with improved impacts on both education and training outcomes and long-term independence from public assistance; and financial incentives and sanctions are associated with improved impacts on short-term employment rates.

Directions for future program development and research

Our findings indicate that some intervention strategies are more likely to improve outcomes of some types, suggesting that interventions should be designed with specific desired ends in mind. This finding points to the importance of developing a logic model and considering the principles of implementation science when developing an intervention.

The limitations of our analysis also point to some opportunities for future research.

- **Continuous outcomes.** Due to limitations in the available data, we could only examine binary (yes/no) labor market outcomes in this analysis. Further work involving non-binary outcomes, like earnings or the amount of public assistance received, would enhance decision-makers' understanding of interventions' effects across the full spectrum of labor market outcomes.
- **Implementation features.** As noted in the methods section, the original studies in the ESER database did not present sufficient implementation data for us to include these crucial features in our analysis. A more complete analysis would also attempt to account for engagement, enthusiasm, and other aspects of implementation that could be associated with improved impacts.
- **Population characteristics.** ESER's strategy for attributing population characteristics to outcomes severely constrained our ability to describe whether and how strategies affect different populations differently. The question of how best to tailor strategies to different populations' needs remains vital to decision-makers and therefore represents an important avenue of future inquiry.

In sum, the meta-regression results indicate that several interventions, and the strategies that they employ, are effective at improving low-income adults' labor market outcomes, though they are associated with relatively small impacts. The weak associations between particular strategies and the outcomes only underscore the important role that other factors, such as implementation, may play in improving outcomes for these populations and reaffirms the importance of further qualitative and quantitative investigation.

In sum, the meta-regression results indicate that several strategies, and the interventions that employ them, are effective at improving low-income adults' labor market outcomes, though they are associated with relatively small impacts.

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ENDNOTES

[1] In this brief, we cover fewer studies and count more interventions than in previous ESER briefs. We cover fewer studies because some studies covered in previous briefs reported only outcomes, such as earnings, that we do not include in this analysis. We count more interventions in this brief because we treat each combination of target population and set of strategies as a separate intervention, whereas in earlier briefs an intervention referred to a given set of strategies regardless of the population served. Some strategies may be more helpful for some populations than others; to identify these nuances, it is essential in the meta-regression context to treat the same set of strategies as two distinct interventions if they are administered to different populations.

[2] Defining the intervention strategies in this way controls for variation in the set of strategies available to the comparison population.

[3] In the ESER review, we attributed a population characteristic to an intervention only if all sample members had that characteristic. For that reason, some groups in Table 1 are smaller than expected; women, for example, predominate in most study samples, but only the 10 studies that targeted exclusively women are eligible to receive this label.

[4] Sample members deemed "independent from public assistance" are those who do not receive public assistance benefits; for more details on this modeling decision, see Appendix A.1.

[5] Most interventions had positive coefficients in the meta-regression, which means that they caused improved impacts. With a Bayesian lens, the fact that the vast majority of point estimates were positive suggests the overall effectiveness of these interventions. However, those coefficients are only statistically significant for 19 of the 93 interventions.

[6] This result may seem surprising, given that a previous ESER brief about the effects of interventions that focused on financial incentives and sanctions identified MFIP as promising. The MFIP study contained two sub-studies, one in which the study authors compared MFIP to AFDC and one in which they compared MFIP to a pared-down treatment, MFIP Incentives Only, that offered only financial incentives. Compared to MFIP Incentives Only, MFIP appears prom- ising – this is the sub-study that the previous ESER brief highlighted, given the topical focus of that brief. The meta-regression contains both sub-studies and suggests that when compared to AFDC, MFIP appears less promising and, in fact, possibly harmful.

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ESER publications referenced in this brief

- Sama-Miller, Emily, Alyssa Maccarone, Annalisa Mastri, and Kelley Borradaile (2016). Assessing the Evidence Base: Strategies That Support Employment for Low-Income Adults, OPRE Report #2016-58, Washington, DC: Office of Planning, Research and Evaluation, Administration for Children and Families, U.S. Department of Health and Human Services.

Additional publications

- For a list of studies included in the meta-regression, please see Appendix C.