Methods to Assess Co-Benefits of California Climate Investments

Jobs

Center for Resource Efficient Communities, UC-Berkeley
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I. Background

Senate Bill 862 requires the California Air Resources Board (CARB) to develop guidance on reporting and quantification methods for all state agencies that receive appropriations from the Greenhouse Gas Reduction Fund (GGRF). Guidance includes developing quantification methodologies for greenhouse gas (GHG) emission reductions and other non-GHG outcomes. Non-GHG outcomes are the positive or negative social, economic, and environmental impacts of projects funded through GGRF (termed "California Climate Investments"), which are collectively referred to as "co-benefits."

This document is one of a series that reviews the available methodologies for assessing selected co-benefits at two phases of a given GGRF investment: (1) estimating potential project-level co-benefits prior to project implementation (i.e., prediction of co-benefits), and (2) measuring actual co-benefits after projects have been implemented (i.e., tracking of co-benefits). The assessment methodology at each of these phases may be either quantitative or qualitative. As with CARB's existing GHG reduction methodologies, these co-benefit methodologies will be developed to meet the following standards:

- Apply at the project level
- Align with the project types proposed for funding for each program
- Provide uniform methods to be applied statewide, and be accessible by all applicants
- Use existing and proven tools or methods where available
- Reflect empirical literature

CARB, in consultation with the state agencies and departments that administer programs that award GGRF funds, has selected ten co-benefits to undergo methodology assessment and development. This document reviews available empirical literature on the ***Jobs Co-benefit*** and identifies:

- the direction and magnitude of the co-benefit indicators,
- the limitations of existing empirical literature,
- the existing assessment methods and tools,

- knowledge gaps and other issues to consider in developing co-benefit assessment methods
- a proposed assessment method for further development
- an estimation of the level of effort and delivery schedule for a fully developed method

II. Co-benefit description

Direct investments of Greenhouse Gas Reduction Fund (GGRF) resources in the state economy are expected to create jobs as well as training opportunities, the number and location of which will depend upon the activities proposed by the applicant. Job creation is here defined to include not only the *direct* job creation resulting from the GGRF investment, but also *indirect* job creation in industries supplying goods and services to the directly affected industries, as well as *induced* job creation resulting from changes in local spending patterns that result from the increased income created by the first two types of job creation. Job training co-benefits can be cited by applicants or reported in ongoing project evaluation if it accompanies direct project employment, but existing methods do not project direct, indirect or induced job training effects.

Along with job creation, the quality of the jobs being created is also of interest to policymakers and society at large. Higher quality jobs can lead to higher rates of retention, improved career trajectories, better benefits for employees, improved access for disadvantaged communities, and other benefits.

This co-benefit and the proposed methods included in this memo are applicable to all of the programs within the GGRF.

III. Directionality of the Job Creation Co-benefit

As long as the proposed activity generates positive net investment/expenditure in the California economy, it can be expected to have a positive net employment benefit.[1]

IV. Magnitude of the co-benefit

The magnitude of the job creation co-benefit will vary with the absolute magnitude of the GGRF allocation and the specific composition of investment/expenditure activities. Some activities are more labor-intensive than others, and different activities will generate different kinds of occupational demand. Thus, the same GGRF funding commitment in two different programs can have very different employment impacts, both in terms of the number and type of jobs created. Investments in labor-intensive industries may be expected to result in more direct and induced job creation than in more capital-intensive industries.

[1] Autonomous or induced technological change could lead to lower net job creation, but we cannot estimate these effects with the data and methods available.

Indirect and induced job creation effects can be quite substantial and for some investments may be larger than the direct job creation effects, especially in the long term. Each of these relationships is industry-specific, suggesting the need for an estimation approach that distinguishes between the individual industries in which the GGRF is investing.

Studies of the job creation effects of the 2009 American Recovery and Reinvestment Act (ARRA; a.k.a. the stimulus package), for example, have found that each million dollars in public expenditure created or protected from 6 to 8.1 jobs in the first year (Wilson 2012, Feyrer and Sacerdote 2011). The ARRA included many different kinds of public expenditure, including education, health care, and local government employment. Previous studies of the job creation effects of public infrastructure spending have found even larger effects. The White House Council of Economic Advisors estimated that highway construction created 13 jobs per million dollars of highway expenditure, of which almost 65% were direct and indirect jobs and about 35% induced jobs (FHWA 2017). The U.S. Bureau of Labor Statistics (2008) found that each million dollars of expenditure in the construction industry in California in 2008 created 10.2 jobs (Copeland et al. 2011), somewhat lower than the national construction industry average of 11.3. The multiplier effect of a job created can vary due to several factors, primarily the industry in which the job is created, the skill profile of the job, and whether it is in a tradable or non-tradable sector (Moretti 2010; Bivens 2003). Therefore different regions can see different multipliers for similar projects based on differences along these dimensions.

The major sectors of the economy differ widely in their employment multipliers, or the number of indirect and induced jobs that are produced for every job directly created. Among the major sectors, multipliers for the U.S. economy range from 0.88 (or 88 indirect or induced jobs created per 100 jobs directly created) for the retail trade sector to 6.21 for the utilities sector. Of particular relevance to GGRF programs, the forestry sector has an estimated average multiplier of 0.94, the transportation sector has a multiplier of 1.67, the construction sector has a multiplier of 1.90, durable goods manufacturing sector has a multiplier of of 3.72, and the automobiles sector has a multiplier of of 4.64 (Bivens 2003).

Household energy efficiency measures instituted in California since the early 1970s have enabled California households to divert spending away from electricity bills and into a wide variety of other activities. Electricity supply chains are not very job-intensive, so diverting spending out of this sector and into others resulted in the creation of at least 1.4 million indirect and induced jobs in California between 1972 and 2007, and the energy efficiency measures associated with AB 32 have likely produced hundreds of thousands more since 2006 (Roland-Holst 2008). A review of the job creation effects of various energy technologies (Wei et al 2010) found that renewable energy and energy efficiency investments create more jobs than fossil fuels. For example, solar PV creates about 0.87 job-years (years of work) per GWh and energy efficiency about 0.38 job-years per GWh (referring to jobs that were created as a result of energy efficiency programs, comprised mainly of induced jobs due to household expenditure shifting made possible by energy efficiency). Coal and natural gas, by contrast, each create about 0.11 job-years per GWh. While energy efficiency enabled households and enterprises to divert expenditure to other goods and services, this resulted in slower job growth in the conventional energy supply chain. Because the former is more than 10 times as labor-intensive as the latter, the result of EE has been net job creation. More complex economic models evaluating both renewable energy and energy efficiency investments, accounting for job losses in the coal and natural gas sectors, clearly reveal net positive employment impacts (i.e., "net jobs created per unit energy saved" (Wei et al 2010, pp 924)).

Water efficiency investments in Los Angeles have also been found to have comparatively large job creation effects. Each million dollars in water conservation projects was found to create 16.6 jobs, of which 9.1 were direct jobs, 3.0 indirect jobs, and 4.5 induced jobs (Burns and Flaming 2011). Water efficiency created more jobs per million dollars of investment than other kinds of water projects (between 12.6 and 14.9) or other major regional job sectors in Los Angeles like housing construction (11.3 jobs per million dollars) or the motion picture industry (8.3 jobs per million dollars).

Ecological restoration activities, including forest restoration, have been found to produce between 6.8 and 39.7 jobs per million dollars invested, depending upon the location, scale and type of restoration (BenDor et al 2015). Forest and watershed restoration activities in Oregon have been estimated to create between 15.7 and 23.8 jobs per million dollars invested (Nielsen-Pincus and Moseley 2010). Restoration activities can vary from quite labor-intensive (e.g., vegetation planting) to more equipment-intensive (e.g., some watershed restoration projects), and direct job creation effects vary accordingly.

Many of the above findings were derived with national-scale models that capture job creation effects in supply chains that in many cases may extend throughout the United States. Analyses that seek to identify only the job creation effects inside of a specific state, as the GGRF co-benefit analyses seek to do, will produce lower estimates, since the supply chain job-creation effects occurring outside of the state's boundaries are not included. This issue will also alter the relative proportions of indirect and induced jobs created to direct jobs created (i.e., the employment multipliers) for a given investment, since virtually all of the direct jobs are likely within state borders while many of the indirect and induced jobs may not be.

Overall, despite the sizable variation in job creation impacts of various types of public investments, three general rules apply to the assessment of local or state job creation:

1. Direct and induced job creation effects are likely to be higher on a per-dollar basis for investments in more labor-intensive activities, because a higher proportion of each dollar invested goes toward employing people, and those people then create more jobs by spending more money elsewhere in the economy. Indirect job creation is not necessarily larger per unit of labor-intensive jobs, but due to greater numbers of direct and induced jobs

created, the overall job creation effect is likely to be larger for investments in labor-intensive industries.

2. Local and in-state job creation effects are likely to be higher for services than for goods, because services are more often provided by local or in-state firms, whereas goods may be much more easily imported from out of state.

3. Among goods production activities, in-state job creation effects are higher when the proportion of their in-state content or value-added is higher, because this entails greater use of local labor, and therefore larger total employment effects. For example, a forest restoration project that involves planting tree seedlings will create more indirect (and induced) jobs in California if the seedlings are sourced from a nursery in California rather than one from out of state. Similarly, if a transit project involves the purchase of new low-emission buses, the more components of the bus that are manufactured or assembled in California, the larger the indirect (and induced) job creation effects of the project will be.

V. Limitations of current studies

Along with job creation, the quality of the jobs being created is also of interest to policymakers and society at large. Higher quality jobs can lead to higher rates of retention, improved career trajectories, better benefits for employees, improved access for disadvantaged communities, and other benefits. However, measuring the success of employment initiatives with respect to these metrics is difficult due to intensive data and analysis requirements. As a result, the economic literature has typically used employment, wages, and occupation categories as the main proxies for job quality (see e.g., Nekoei & Weber, 2015).

For example, Cazes and Saint-Martin (2015) lay out a useful framework for measuring job quality in OECD countries. Specifically, to measure quality of work environment, they recommend measuring time pressure and physical health demands and effects. To apply this to GGRF applications, however, potential employers would need to forecast and record working hours, work intensity, flexibility of work time, physical health risk factors, and work strain, as well as training opportunities for new jobs created. Each of these is measured separately on a scale, and calibrations require detailed comparison to the OECD Job Quality database.

While there are many studies measuring the impact of job training as a dedicated activity (e.g., Andersson et al., 2013; Autor, Houseman and Kerr, 2017), studies attempting to measure the level of on-the-job training conferred by given jobs are rare and not yet methodologically sound. If the level or quality of on-the-job training can be proxied by the number of registered apprenticeships – a measure that is reported by the Department of Labor quarterly and annually – then these figures could be used to estimate the level of job training produced from a particular economic activity. For example, in fiscal year 2016 the five industries to offer the most registered apprenticeships (excluding the military) were construction, manufacturing, public administration, transportation, and utilities. (The agriculture, forestry, fishing and hunting industry was in the top 15.) The top five occupations for the same metric were electrician, plumbers/pipefitters/steamfitters, carpenter, construction laborers, and heavy and tractor-trailer truck drivers. (US Department of Labor, 2017)

Similarly, other important job metrics, such as job retention and its impacts, are also difficult to isolate, measure, and identify with individual sectors or investments. Applicants can enunciate goals/targets about these, but they can only be validated with ongoing program evaluation. Attempts to forecast such qualitative outcomes have not generally been successful. Analysis of job turnover (another way of measuring job retention) usually takes place at the national level at which a large panel study tracking workers (the National Longitudinal Survey of Youth, NLSY) is available. These data have been used to study job turnover rates among large groups such as welfare recipients or low skilled workers (see for example, Hershey and Pavetti, 1997; Holzer and Lalonde 2000 and Holzer, Stoll and Wissoker, 2004). It is not easy to study metrics like job retention at sub-regional levels, especially with smaller sub-groups affected by a particular investment, because long-run panel data on employment is not collected and maintained at, for example, the county level. The national long-run surveys are also not representative at more local levels. There is a surprising dearth of such measurements at more local levels in the impact analysis literature, offering negligible guidance for self-evaluation or survey design by GGRF applicants.

Overall, the data and methodology requirements for measuring these metrics could be costly and of uncertain veracity, especially at the application (i.e., pre-award) stage. Applicants would have to gather a lot of information, design their own surveys, and develop/implement forecasting and analysis tools. These requirements of time, expertise, logistics, and funding could have an adverse impact on the inclusiveness of the GGRF program.

With respect to “green jobs” objectives, the data resources available for calibrating job creation estimation tools do not identify such occupations. Such an effort is underway with the Bureau of Labor Statistics “Green Jobs Metrics” initiative (BLS: 2012), but this effort is still aimed at post-investment estimation of the prevalence of green jobs in the US economy. With the current structure of the GGRF program and available data, it will only be possible to ask applicants about direct creation of jobs meeting an agreed-upon definition of a “green job,” and then estimate indirect and induced impacts for existing occupational categories.

VI. Existing quantification methods/tools

There is an extensive literature on employment impacts of investment, both for private investment and more targeted investments like GGRF projects (see for example, Berck and Hoffmann, 2002; Miller and Blair 2009; Bergman, 2005). The overwhelming majority of work in this area relies on large economic models using publicly available standardized data.

Table 1. Common methods for estimating job creation effects of public investments.

Analysis methods	Pros	Cons	Data requirements	Suitability
Single-market analysis[2]	Useful and cost effective for small investments that don't affect other industries	Does not capture induced job creation effects in other industries	Simple data inputs required of applicants; research team must model numerous supply-demand relationships	Will substantially underestimate job creation co-benefits of CCIs
Multi-market analysis	Incorporates selected linkages to other industries beyond the one subject to a CCI	Likely to underestimate job-creation effects of large investments	Simple data inputs required of applicants; research team must model numerous supply-demand relationships	Likely to underestimate job creation co-benefits of CCIs
Input-output models	Relies on empirical data, not models; flexible, easy and quick to use; draws upon standard national datasets, with comparability to other similar studies; can analyze investments of widely varying scope and scale; enables county-level analysis	Cannot incorporate changes in relative prices or non-linear relationships between industries	Simple data inputs required of applicants; research team must build tool based on national IMPLAN database	Will estimate job-creation co-benefits effectively with simple data inputs and easy-to-use tool
Computable General Equilibrium models	Incorporates changes in relative prices and non-linear relationships between industries; good for estimating long-run effects of policy changes	Much more complex models than above options; not well suited to estimate short-run effects of individual investments; expensive to maintain and update	Complex data inputs required of users; complex model must be built by research team	Not well suited for project-level estimation of job creation co-benefits of CCIs
Time series analysis	Estimates long-run job creation effect assuming stable relationship between past and current industry behavior; can analyze multiple relationships simultaneously	Very data- and knowledge-intensive; not well suited to estimate short-run effects of individual investments; expensive to maintain and update	Complex data inputs required of users; complex model must be built by research team; time-series data needed by research team to build models may not be available for all CCI industries	Not well suited for project-level estimation of job creation co-benefits of CCIs

[2] Single market methods confine assessment to only one industry or service sector, which in this case means only considering direct project employment. In fact, qualifying projects are likely to create significant indirect and induced employment spillovers, which should rightly be considered as co-benefits.

The employment effects of policies and investments are assessed in several ways in these studies. The most common approaches are shown in Table 1, with discussion of their pros and cons, data requirements, and potential fit for analysis of CCIs.

These approaches differ in how they model interactions across markets and industries and how they identify effects. The decision to use a particular method should take into account the type of proposed action (e.g., whether it affects supply/availability of a factor, or whether it changes production costs) and its scope (restricted to immediate market(s) or economy-wide). Other considerations include time and resources, data availability, and technical capacity. Generally speaking, complexity improves realism and detail, but this must be weighed against financial and technical knowledge requirements. Given the diversity of GGRF projects and the need to ensure equity in application processes, any method suitable for use by the GGRF must be accessible to applicants both small and large, technically proficient and nontechnical.

Single Market Analysis

Single market analysis is a good fit for studying smaller investments that are unlikely to have significant spillover effects into other parts of the economy. In such cases, it suffices to model impacts on the single industry or service activity represented by the project. Employment impact assessment in this only captures direct employment, which applicants are already required to estimate. Larger qualifying projects are likely to create significant indirect and induced employment spillovers, however, and these should rightly be considered as co-benefits.

Berck and Hoffmann (2002) provide an example of the effect on employment from a regulation restricting ozone from aerosol coatings, i.e., a regulation requiring reformulated spray paint. The Initial Statement of Reasons (ISOR) developed by the California Air Resources Board states that the industries affected by the regulation employ less than 1 percent of manufacturing employment in California. Therefore, given the limited scope of the regulation, it is fair to assume it will have negligible economy-wide effects. To account for the lack of California data on prices and quantities of spray paint, analysts used demand and supply elasticity from national studies. They estimated that the regulation would have quite small net job impacts.

Multi-Market Analysis

Multi-market analysis improves upon single-market analysis by incorporating selected market linkage effects of a policy change. Unlike the single market approach, this method can incorporate adjustments made by suppliers and consumers toward substitute or competing goods. This method is suitable for small-scale changes with job effects that are adequately captured by studying primary and secondary markets. As Sadoulet and de Janvry (1995) demonstrate for irrigation investments in agriculture, multi-market models expand analysis to include interactions between product supply and input demands. However, if the policy change is large enough to shift macro variables (like wages) that can affect many industries, then multi-market analysis will also underestimate overall effects.

Input-Output

Input-Output (I-O) models are by far the most widely used for analyzing economic impacts of policy changes. Unlike the single or multi-market analyses, I-O analysis relies on detailed empirical data on inter-industry linkages to map out the effects of changes in one sector or industry on another. Detailed and easy-to-manipulate databases exist for the US nationally, at the state level, and even at sub-state and county levels, making it suitable for estimating impacts of investments that will have regional-scale effects as well as investments that may have market-wide, structural impacts. Unlike many of the time series methods described below, I-O analysis also has a relatively strong theoretical component, allowing for policy recommendations based on economic mechanisms, and longer-run extrapolations using economic modeling. By including input and output information for individual industries and sectors, the I-O model is able to determine which industry is engaged at each stage of the production process.

Many I-O models are based upon the IMPLAN database. IMPLAN is derived from the System of National Accounts for the United States, based on data collected by the U. S. Department of Commerce, the U.S. Bureau of Labor Statistics, and other federal and state government agencies. Data are collected for 528 distinct industry or activity sectors of the national economy, corresponding to the Standard Industrial Categories (SICs), and are classified at the four or five-digit level of the North American Industry Classification System (NAICS). Industry sectors are classified on the basis of the primary commodity or service produced.

IMPLAN data sets are also produced for each county in the United States, allowing analyses at the county level and for individual states. Data provided for each industry sector include outputs and inputs from other sectors, value added, employment, wages and business taxes paid, imports and exports, final demand by households and government, capital investment, business inventories, marketing margins, and inflation factors (or deflators). Data on the technological mix of inputs and levels of transactions between producing sectors are taken from detailed input-output tables of the national economy. National-, state-, and county-level data are the basis for IMPLAN calculations of input-output tables and multipliers for local areas.

The structural detail of the IMPLAN database allows for calculation of multipliers for projects of very diverse scope and scale. Analysis using I-O models is popular because it is rapid and computationally inexpensive. Because of this popularity, the I-O approach has been “road-tested” for countless public and private investments, including those targeting environmental remediation. Compared to the more complex and more technically demanding CGE models described below, the data and modeling requirements of the I-O method are modest enough to be accessible for applicants with more limited information, technical skills, time, and finances, supporting more inclusive GGRF eligibility.

Computable General Equilibrium Modeling

Computable General Equilibrium (CGE) models build on input-output model databases to simulate the market responses, but unlike I-O models, they allow for relative prices to change and for non-linear economic relationships between industries. This yields a more flexible but technically much more complex model. CGE models include substitution of input factors as well as goods in response to changes in relative prices, and allow for movement of labor across industries and impacts on inter-industry wages. CGE models also include equations on labor force participation and migration, thereby accommodating changes in overall employment. By allowing for substitution among factors of production, CGE is well suited for analyzing the long run effects of a policy change, but it is less able to simulate more immediate effects.

To use CGE models, applicants must model each detailed structural and behavioral characteristic of the economy. CGEs typically include five to fifty production sectors and at least one household sector (International Institute for Labour Studies, 2011). Unlike I-O models, CGEs add in behavioral assumptions and specifications expressing the availability of markets. Unlike the I-O method, CGE models are not suitable for rapid assessment, and can be very computationally demanding. CGE models are not suitable for analyzing the impact of small to medium scale changes (Berck and Hoffmann, 2002). Large CGE models are expensive to maintain and update, and are therefore cost-effectively utilized for large investments and policy changes that are instituted over long time periods.

Another general concern with CGE models is the lack of transparency regarding assumptions and parameters driving the models. The mathematical functions and model parameters used are often not derived purely from existing data, but are influenced by the modeler's understanding and assumptions regarding economic forces. Such decisions are often made ad-hoc to make the complicated CGE setup solvable (Bergman, 2005; International Institute for Labour Studies, 2011). Based on the quality of the modeler's knowledge, these estimates and behavioral assumptions may not be an improvement upon linear input-output assumptions. On the other hand, CGE models can be improved and adapted as parameters are refined over time.

Time Series Analysis

Time series analysis uses long-run data to estimate a long-run job multiplier of specific economic sectors. It is performed with the assumption that there is some stable, reliable relationship between past and current observations, but otherwise, this method frequently imposes very little or no economic theory on the data (Berck and Hoffmann, 2002). Analysts can estimate several equations simultaneously where each equation represents a time series evolution of a specific sector of interest. Simultaneous estimation allows the time series method to capture the effects of one sector on another, which can evolve into a subsequent effect on the initial sector (feedback).

This method requires considerable econometric knowledge and is not comparable to the more general purpose IMPLAN model. For example, Berck et al. (2000) use a vector autoregressive (VAR) panel model to study the long run impact of timber harvest restrictions on local employment and poverty in California. They developed a two-sector (timber and non-timber) structural model and used monthly, multi-county time series data to test whether local timber employment determined poverty in the region. To model both sectors and the key relationships in question, they specified five equations defining equilibrium in the timber and non-timber local markets, local poverty, local population, and local migration. Each equation was set up to incorporate relationships across equations by, for example, allowing migration to determine local poverty and vice versa, and to allow for relationships over time by including lagged variables. This helps estimate feedback effect. Unfortunately, this approach is very data- and knowledge-intensive, and could be reliably implemented only by a handful of larger state agencies and corporations.

VII. Knowledge gaps and other issues to consider in developing co-benefit quantification methods

The models described above do not generate estimates of more detailed quality-related characteristics of jobs and, as noted above in section four, generating these estimates would require extra effort on the part of applicants. From a pre-award perspective, this would increase information requirements for applicants and entail forecasting of very uncertain reliability. This is more than an issue of econometric technique and data gathering, but relates to core knowledge gaps that are endemic to the market economy. Small businesses can reasonably be asked how they intend to spend project funds, but it may not be within their capacity to predict even their own hiring outcomes. Applicants will have a specific intended job description and numerical recruitment goals, but they cannot forecast the tenure, effort, productivity, workplace dynamics, and other job metrics that will result from hiring for that position. Moreover, there is no reliable and general empirical method for estimating job-quality characteristics of indirect and induced employment impacts, and it is unclear how applicants could be evaluated on the basis of these linkage effects since they have limited control over the management practices of others. As noted above, indirect and induced employment gains may in some cases be larger than the direct employment effects of a given GGRF investment, but apart from this quantity effect, little is predictable.

Generating additional quality-related job information as part of post-award tracking is feasible, but would also increase program costs and should be standardized both in terms of objectives and methods. While evidence on job quality is of intrinsic interest, the diversity of GGRF fund applications will introduce challenges in generalizing from the experiences of individual funding awards or in using the information to target GGRF allocation in the future. Given these challenges and the need to preserve equitability and inclusivity of GGRF participation, developing general objectives and standardized metrics for progress according to quality-related characteristics will require substantial additional thought and discussion. Overall, post-award tracking of job quality characteristics will entail additional administrative costs and effort for both the state and GGRF funding recipients that will need to be balanced against the benefits of such tracking, but it can likely be achieved with careful assessment tool design.

In terms of potential significance, it is clear that job creation will be a significant co-benefit for virtually all GGRF programs. Even programs that fund projects that may be more capital-intensive (such as major transit system upgrades) or those that fund consumer rebates (such as the Low Carbon Transportation program) may still result in significant indirect and induced job creation co-benefits in the supply chains of the purchased vehicles and equipment. Programs with relatively small individual projects, such as the Low Income Weatherization, State Water Efficiency and Enhancement, and Woodsmoke Reduction programs, may report modest job creation effects at the project level but will still likely generate significant job creation co-benefits at the program level. An exception to these conclusions is the Sustainable Agricultural Lands Conservation program, which conserves farmland in its existing uses and therefore does not create new jobs apart from the labor effort required to plan and execute the conservation easements.

VIII. Proposed method/tool for use or further development, schedule, and applicant data needs

Given these findings, we offer the following recommendations for methods and tools for assessment of job creation co-benefits, schedule for development of guidance documents, and applicant data needs.

Methods for estimation prior to award of GGRF funds (Phase 1)

In light of our review of available models and their reliability and information requirements, we propose the use of an I-O modeling approach based on the IMPLAN dataset that supports the majority of similar studies across the US. This approach will be adapted to address specific characteristics of the GGRF context, including the following:

1. Input information requirements are general enough to account for the diversity of GGRF applicants. This means we only ask about investment and direct employment commitments across standardized economic activity classes and job occupations.

2. Input requirements are relatively simple and appropriate for projects of all scales. Below, we list in four steps what information applicants need to enter into the Jobs Tool. If GGRF is to be an inclusive program, it must not present high information barriers for applicants. For this reason, we only request information

that could be estimated by a small enterprise professional with reasonable financial and technical knowledge of their proposed project.

3. Comparability of inputs and outputs across applicants improves coherence and fairness of evaluation, as well as reporting and interpretation of program outcomes. For the sake of comparability, we request estimated direct job creation within a small set of standard occupational categories, using FTE annual employment as the job metric. Likewise, we report cumulative (direct, indirect, and induced) job impacts according to transparent and standardized classifications.

UCB will develop a non-technical, user-friendly interactive Jobs Tool, designed for use in both pre-award and retrospective assessment of GGRF job co-benefits, using a suite of 20 indicators reflecting quantitative and qualitative aspects of job creation within the state of California, as these would be affected by a given project. Most indicators are based on applicant inputs, for which a detailed instructional manual will be developed.

For Phase 1, as part of their application for funding, public agencies, private enterprises, and individuals would use this tool to estimate an employment co-benefit that would result from their intended use of funds, based on standard econometric methods. The basic technique underlying the job co-benefit tool is multiplier analysis, calibrated to county and state-level information from the IMPLAN database. Using IMPLAN accounts, the tool would estimate multiplier effects of changes in final demand for one industry on all other industries within a local economic area. Job multipliers are estimated for individual counties and for the entire state of California. They measure total changes in employment, as these would be caused or induced by changes in demand attributed to the intended use of GGRF monies.

For each GGRF applicant, the tool will present three component pathways of total employment creation:

1. Direct effects based on the applicant's stated commitment to job creation.
2. Indirect effects based on changes in inter-industry transactions as supplying industries respond to increased demand from the investment commitments.
3. Induced effects based on changes in local spending that result from income changes in the directly and indirectly affected industry sectors.

Job creation effects thus obtained would measure the number of Full Time Equivalent (FTE) jobs created per dollar of GGRF investment. All three types of job impact are additive, calculated at both county and state level (excluding the county in question), with total in-state job creation comprising the sum of all six components.

In addition to identifying jobs by the three pathways and location (in-county or elsewhere in California), the tool would enable accounting of types of jobs across the following 22 occupation categories, to provide greater specificity on the types of jobs being created. A relevant extension for the GGRF fund would be to identify the specific employment impact on the subset of green jobs in these categories. However, as discussed in section V, the current approach does not allow for the estimation of indirect and induced employment effects for green jobs. What is possible is an estimate of the direct effect, if applicants are asked in Phase 1 to classify which of their created jobs in each occupation category will fall under the domain of green jobs.

1. Management occupations
2. Business and financial operations occupations
3. Computer and mathematical science occupations
4. Architecture and engineering occupations
5. Life, physical, and social science occupations
6. Community and social services occupations
7. Legal occupations
8. Education, training, and library occupations
9. Arts, design, entertainment, sports, and media occupations
10. Healthcare practitioners and technical occupations
11. Healthcare support occupations
12. Protective service occupations
13. Food preparation and serving related occupations
14. Building and grounds cleaning and maintenance occupations
15. Personal care and service occupations
16. Sales and related occupations
17. Office and administrative support occupations
18. Farming, fishing, and forestry occupations
19. Construction and extraction occupations
20. Installation, maintenance, and repair occupations
21. Production occupations
22. Transportation and material moving occupations

Implementation of the tool can take the form of either a stand-alone Excel workbook or an interactive webpage. The advantage of the latter would be integration with a complete GGRF database and uniform standards/upgrades. However, a webpage would also need to be hosted and maintained within existing or new GGRF web infrastructure.

Methods for measurement after award of GGRF funds (Phase 2):

The tool developed for Phase 1 can also include evaluation sheets for ongoing tracking of job creation in Phase 2. This component would produce a set of accounts based only on user inputs from direct project experience. No reliable method is available to directly monitor or report indirect and induced jobs impacts on an ongoing basis, though estimated multiplier effects from Phase 1 can be applied to Phase 2 data on actual (as opposed to expected) job creation.

Phase 2 will also assess the qualitative characteristics of the jobs created by project-level GGRF expenditures. The job quality characteristics can be assessed using a questionnaire for GGRF funding recipients.

Schedule

The Jobs Tool will be custom-built for this purpose, and we anticipate providing a working prototype with a guidance document on the assessment methodology for CARB review. Based on CARB review and feedback, we envision delivering a distribution version with complete user documentation by 2018, with subsequent additional availability for transfer and training support, stakeholder engagement, and results communication.

Data needs

Use of the Jobs Tool by applicants would entail four steps:

1. We have already obtained comparison data needed for the Jobs Tool from IMPLAN and the Bureau of Labor Statistics.[3]

2. Applicant chooses their economic activity from a drop-down menu listing (100) International Standard Industrial Classification (ISIC) 3-digit codes.

3. Applicant enters their county of operation. If operation is in more than one county, pass on this option.

4. A menu of (10) ISIC codes is then presented to the applicant, who enters two estimates into an electronic table:

   a. the intended level of direct FTE job creation, by occupation type,
   b. the intended investment/expenditure level for each activity (e.g., construction, office equipment, etc.)

   Both estimates should be provided on an annual average basis over the term of their project.

5. The tool then calculates job statistics for the county and the rest of California, estimating direct, indirect, and induced job creation impacts for the 22 occupation classes. Applicants with multi-county activities will receive state results only.

[3] IMPLAN was obtained by the UCB research team in a separate project and will be made available for this activity at no cost to CARB.

6. Applicants are asked to report a series of indicators to assess the quality of jobs provided.

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