Setting and adjusting targets for ESF Operational Programmes

Background Paper

Client: EC, DG Employment, Social Affairs and Inclusion

Rotterdam, 26 May 2013

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Summary

In preparation of the ESF 2014-2020 multi-annual framework, the European Commission organised a learning seminar on setting and adjusting targets for ESF Operational Programmes. To account for expenditures, indicators on outputs (numbers of participants, entities) and results (numbers of participants finding employment, gaining a qualification etc.) are essential. This background paper discusses methodologies for setting and adjusting quantified cumulative employment targets.

According to a survey of the EC, two commonly applied methods in the 2007-2013 programming period were extrapolation from the past and a combined use of budget allocation and unit cost. Common challenges were accounting for external factors and lack of data.

This paper first discusses the combined use of budget allocation and unit cost per participant. This approach allows for an integrated setting of output and result targets to maximise the expected achievement of an objective. An objective could be to maximize the number of participants in employment (the result target). Another objective could be to maximize the total number in employment from both participants and non-participants. This may result in different output targets and higher employment levels overall (overall effectiveness) despite lower result targets (gross effectiveness). Another approach is a SWOT analysis, which allows an integrated approach of top-down setting of objectives and bottom-up allocation of budgets given unit costs. Methods to allocate budgets proportionally to target groups and by extrapolation are easier to apply but have the drawback that they are not result oriented.

When calculating unit costs from historical data, it is also preferable to use actual historical costs instead of historically committed costs because the actual number of participants may be different from the initially targeted number and this could result in distorted unit costs and output targets for the next programming period. In the case of on-going interventions, it is still preferable to use data on actual costs incurred and to add estimates of the remaining cost to be incurred, over using initially committed budgets for the whole period. Unit costs are also preferably calculated at a disaggregate level to calculate more accurate output targets. When gaps in disaggregate data exist, or perhaps when costs are influenced by factors that change in the future, a cost equation that relates unit costs to other factors can be used to estimate unit costs. However normative issues also play a role: are efficiency gains possible to reduce unit costs, if some projects achieve similar results for similar target groups at lower cost? Finally, in the complete absence of any data on unit costs, Eurostat LMP data can be used, but own judgement will still be needed.

The setting of result targets is as easy or as difficult as applying success rates to the output targets. More than unit costs, success rates depend on a large number of factors beyond the influence of an ESF Operational Programme, and a result equation can be used to predict future success rates. To predict the future success rates this way, the development of the other factors need to be predicted as well, or need to be indicated in scenarios of the future. Result equations could be tailor-made to specific interventions, but it requires advanced econometrics to estimate such equations. A Bartik (2009) type of model is linear and uses micro-data from individual participants and is less sensitive to assumptions underlying the model. As for unit costs, own judgement is needed as well to assess whether better success rates could be achieved in the future. Simply picking the project with the highest success rate is not a sound method, because this project may have been targeted at easier groups, where participants would have found a job without intervention as well. Randomized

experiments and matching are methods that help compare success rates for "similar groups and frontier analysis further helps choosing projects with higher result rates that should be achievable for other projects. In the end, allocating more budget to such projects make it more likely that (higher) result targets are achieved.

Finally, the result equation can also be used to adjust targets if at a certain moment during the programming period, the forecasts of the factors influencing the success rates change. In this case one needs to add the predicted results for the remainder of the programming period to the results that could have been expected up to that moment based on the previously set targets.

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1 Introduction

In preparation of the ESF 2014-2020 programming period, the European Commission organised a learning seminar on setting and adjusting targets for ESF Operational Programmes. To account for expenditures, indicators on outputs (numbers of participants, entities) and results (numbers of participants finding employment, gaining a qualification etc.) are essential. For a limited number of output and result indicators, quantified cumulative targets for the whole programming period need to be set. This background paper presents and discusses methodologies for setting and adjusting quantified cumulative employment targets.

Targets at Operational Programme level

In the ESF, Member States set national targets for outputs and results for the whole period 2014-2022 (up to two years beyond the ESF programming period). The results of an Operational Programme are the sum of the results of its investment priorities and ultimately the individual projects, as illustrated in Figure 1.1. If for example a combined total of 10,000 people participate in projects conducted in the framework of one investment priority, and out of them 30% on average are in employment upon, different projects under the Operational Programme may well have varying success rates. In the example of Figure 1.1, the success rates vary from 20% to 50%. Likewise, a target at Operational Programme level does not imply proportionate targets for each project.

Figure 1.1   Output and results at investment priority level
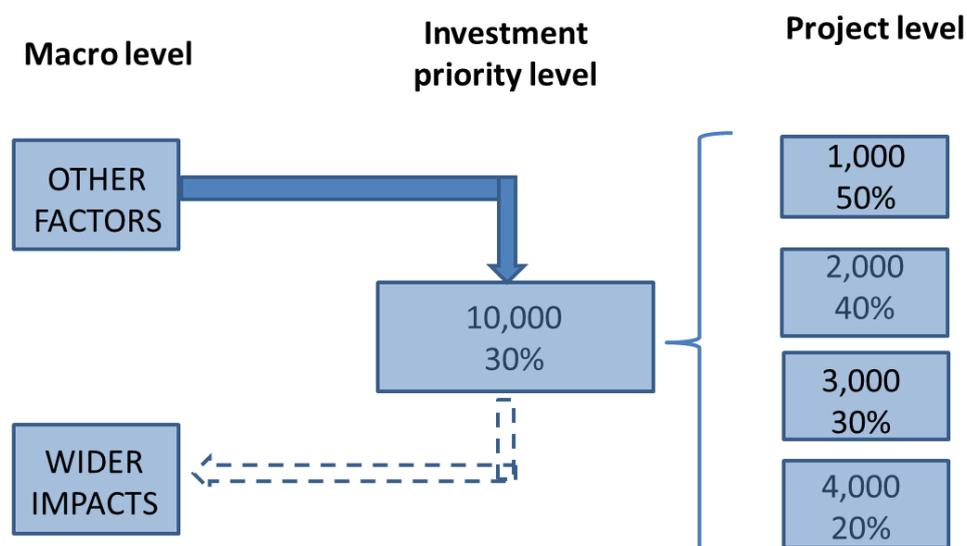
Source: Ecorys, prepared for the learning seminar on targeting of 14 March 2013.

Targets at the level of investment priorities are not only different from targets at project level, they are not targets at the macroeconomic level either. According to a survey of the EC discussed in the next chapter, macroeconomic performance indicators such as the employment rate and the unemployment rate are influenced by external factors beyond the control of ESF Operational Programmes, such as the business cycle and changes in national legislation. In addition, only part of the target population participates in ESF co-funded projects. The wider impact of ESF Operational Programmes on for example the unemployment rate are therefore hard to estimate.

However, the output and result indicators do not relate to wider impacts, and are not discussed in this background paper.

List of common indicators

The draft ESF regulation contains a provisional list of common indicators to be used for the period 2014-2020[1], which is also given in annex A in this paper.

The two types of indicators to be used are:

- Output indicators (numbers of participants or entities involved);
- Result indicators (mostly on the employment situation and training).

Positioning of the paper

This background paper builds on a 2011 methodological study[2] on performance targets for ESF Operational Programmes which focused on methodologies to adjust result targets. Compared to that study, this paper focuses more on practical issues and also broadens the scope to setting (besides adjusting) targets and to output indicators (besides result indicators).

The discussion of setting targets in this paper starts under the assumptions that historical average data are available, and ends with discussing possible approaches without such data. This paper discusses how to use data to set programme targets, but not how programme targets can be used to manage projects. This paper also discusses how to use estimates of macroeconomic factors for target setting, but does not discuss the wider impacts of the outputs and results at the macro level.

This background paper is further organized as follows:

- Chapter 2 summarizes results of a EC survey on targeting methodologies;
- Chapter 3 discusses methodologies for setting output targets;
- Chapter 4 discusses methodologies for setting result targets;
- Chapter 5 discussed methodologies for adjusting targets.

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[1] Regulation of the European Parliament and of the Council on the European Social Fund and repealing Council Regulation EC No 1081/2006; Proposal of 14.3.2012,
http://ec.europa.eu/regional_policy/sources/docoffic/official/regulation/pdf/2014/proposals/regulation/esf/esf_proposal_en.pdf
[2] Ecorys (2011), Performance Targets for ESF Operational Programmes. http://www.coprbm.eu/?q=node/494

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2 Survey on targeting methodologies

At the start of 2013, the European Commission conducted a survey on targeting methodologies used in the previous 2007-2013 programming period, in preparation of the learning seminar. From this survey, it became clear that the Member States applied different methodologies. Extrapolation of historical data was the most commonly applied method, by 10 out of 17 responding countries, see Table 2.1. However this method was always combined with other methods. Another frequently applied method was to calculate output targets from budgets and unit costs (7 countries). However, new Member States had less data from the past to extrapolate from and some newer Member States started from national strategic documents (5). Some countries explicitly indicated they adjusted targets from the past according to the new economic situation (2) or estimated social and labour market trends (3). Ex ante evaluations (3) and expert judgement (6) were also applied and one country explicitly mentioned the use of benchmarking.

Table 2.1   EC Survey on targeting – methods used

Method used (multiple choice)	Number of countries
Regression / extrapolation from the past	10
Output indicators – from budgets and unit costs	7
Expert judgement	6
Starting from national strategic documents	5
Ex ante evaluation	3
Adjusting targets to estimated trends	3
Adjusting targets to new economic situation	2
Benchmarking	1
Number of countries responding to the EC survey on targeting	17

Source: EC survey on targeting, summary by Ecorys

As Member States used different methodologies, they also faced different challenges. The most frequently mentioned challenge was the long time horizon of the ESF period, mentioned by 7 countries (Table 2.2). In the 2007-2013 programming period, external factors such as changes in the demand for labour, demographic changes and even changes in national legislation required adjustments of priorities and the associated targets.

Table 2.2   EC Survey on targeting – challenges

Challenge (multiple choice)	Number of countries
Long time horizon; external factors	7
Lack of historical data	5
Macroeconomic impact indicators	4
Realistic estimations	3
An intervention is a mix of activities	2
Regional / target group disparities	2
Coherence with national policies	2
Targets in percentages or absolute numbers?	2
Questions on result-based management	2
Coherence between indicators (output, result, impact)	1
Few or many targets	1
Inclusion of other targets besides ESF indicators	1

Challenge (multiple choice)	Number of countries
Methodology for baseline targets	1
Keep records of EC methodologies	1
Number of countries responding to the EC survey on targeting	17

Source: EC survey on targeting, summary by Ecorys

A lack of historical data is another frequently mentioned challenge (5 countries), and indicates that the most often applied methodology of regression / extrapolation from the past can be far from straightforward. Lack of data is mentioned in particular by newer Member States, but also by other countries, for new types of interventions.

Developing macroeconomic impact indicators was another challenge faced in the 2007-2013 programming period (4 countries). However, the list of common indicators for the ESF 2014-2020 period does not include macroeconomic impact indicators. Moreover, as for programme-specific indicators, the Commission does not recommend to use impact indicators for ESF programme monitoring. A more specific but nevertheless important question is whether to formulate output targets in percentages (percentage of the population) or in absolute numbers (2 countries).

A reality check was another challenge mentioned specifically by a few countries (3) – how realistic will it be to deliver the targets? Quantifying targets was also a challenge for interventions that consist of a mix of activities, in the situation of strong disparities between regions or target groups (2 countries each).

Two countries that extrapolated data from the past, mention the challenge to ensure coherence with national policies. Two countries question the application or even usefulness of targets in result based management. Related issues raised by countries are whether to formulate few or many targets, the coherence between indicators (if interventions have poor results – prioritizing other interventions to achieve better results implies that output targets for the original interventions are not met). Also, other targets besides ESF indicators may be important for specific interventions. The example given in the survey is "getting closer to the labour market". It can be noted in this respect that the list of common indicators for the 2014-2020 period includes "participants with an improved labour market situation 6 months after leaving."

Two specific methodological issues mentioned by countries concern the formulation of the baselines and the harmonization of methodologies with EC guidance. In this background paper the formulation of baselines with limited data is discussed in the concluding sections of the next two chapters (Sections 3.6 and 4.5). Harmonization of methodologies with EC guidance is mentioned by one country, but not further elaborated, nor in this background paper.

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3 Methodologies for setting output targets

3.1 Introduction

Annex 1 of the ESF Regulation for the programming period 2014-2020 distinguishes between two types of output indicators:

- Numbers of participants in specific target groups;
- Numbers of entities involved.

This chapter discusses setting output targets for participants. The main target groups are set out in the provisional list of common indicators (see Annex A). In the previous ESF programming period, objectives were to be set in National Action Plans (top-down approach), and unit costs were applied to calculate what outputs were feasible given the budget (bottom-up approach).

Ideally output targets are set in such a way that the result target (gross effect of the programme), or even better the number of persons in employment (overall effectiveness) is maximized and this method is discussed first. A SWOT analysis that the French government applied in the previous programming period combined both the top-down and bottom-up approach coherently. This method determined the budget allocation. Other countries applied different methods to allocate budgets. After determining the budget allocation, unit costs were applied to calculate output targets. All these methods are discussed in Section 3.2.

Section 3.3 discusses the calculation of unit costs which play such an important role in the setting of output targets. Output targets are set most accurately with disaggregate unit costs, but this requires accurate disaggregate data. To overcome some of the data requirements, Section 3.4 discusses how a cost equation can be estimated, which relates unit costs to characteristics of the target groups, interventions or regions. However, normative issues which are discussed in Section 3.5 also play a role: is it possible to reduce the unit costs in the future? Finally, a fall-back option for estimates of unit costs in the complete absence of data is discussed in Section 3.6.

3.2 Budget allocation as a first step

A commonly applied method for setting output targets is to allocate budgets and use unit costs (per participant) to calculate the number of participants. The following formula describes this method:

$$Number\ of\ participants = \frac{Allocated\ budget}{Unit\ cost}$$

The calculation of the output target therefore depends on how budgets are allocated and on the estimate of the unit cost which is discussed in the next section.

The allocation of the budget is an important issue, because the need for interventions and the effectiveness of interventions may change over time, in different ways for different regions and target groups. For example, when labour demand increases, job counselling is likely to be more effective. In times of crisis, occupational mobility tends to increase[3] and the same applies to

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[3]   Moscarini, G. and F. Vella (2008), Occupational mobility and the business cycle, NBER Working Paper, www.econ.yale.edu/~gm76/cps_nber_wp.pdf *(based on USA data)*

sectoral mobility,[4] and different measures may further support this mobility such as perhaps retraining workers.

For allocating budgets, the following methodologies are applied in Member States:
1. Ex ante analysis;
2. SWOT analysis;
3. Proportionally to the distribution of the population;
4. Extrapolation of trends.

1. Ex ante analysis

The ideal ex ante analysis compares the situation without intervention with the situation with interventions. This may result in a different solution compared to maximizing result targets. Maximizing result targets optimizes the result achieved <u>with</u> the interventions (gross effectiveness) whereas maximizing the total number in employment (among participants and non-participants) optimizes the result achieved <u>through</u> the interventions (overall effectiveness).[5]

The following hypothetical example illustrates the difference between gross and overall effectiveness. Suppose out of two interventions, intervention A has unit cost € 10,000 per participant and results in 70% of the participants in employment, and intervention B has unit cost € 5,000 and results in 40% of the participants in employment.[6] Without intervention, 20% of the unemployed would find employment. The target population is 20 and the budget is € 100,000. Table 3.1 illustrates the results of investing all in intervention A, intervention B or nothing:

A. If the budget is invested in A, it allows for 10 participants, and the remaining 10 persons of the target group do not participate. With success rates of 70% and 20% respectively, 7 participants and 2 non-participants find employment, or 9 in total.

B. If the budget is invested in B, the budget allows for 20 participants, which equals the whole target group. With a success rate of 40%, this means 8 participants find employment which is also the total number in employment.

C. If no budget is invested, 20% of the target group would be in employment or equivalently 4 persons.

Table 3.1   Simplified example of maximizing result target or numbers in employment

	Intervention A (maximizes numbers in employment)	Intervention B (maximizes the result target)	No intervention
Number of participants (= <u>output target</u>)	10	20	0
Number of non-participants	10	0	20
Target population	20	20	20
Participants in employment (= <u>gross effectiveness</u>) (= <u>result target</u>)	7	8	0
Non-participants in employment	2	0	4
Total in employment (= <u>overall effectiveness</u>)	9	8	0

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[4] Scheele, D., R. van Gaalen en J. van Rooijen (2008), Werk en inkomsten na massaontslag: De zekerheid is niet van de baan. *Verkenning van CBS en WRR*. (*Work and income after mass layoff: Certainty is not in the job. Study of CBS and WRR*), Amsterdam University Press.

[5] At the 14 March seminar the exercises maximized gross effectiveness because this can be done step by step.

[6] Methods to obtain such data from partial data or to estimate these data without historical data, are discussed in later paragraphs of this chapter and the next chapter.

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As can be seen from the above table, intervention B maximizes the output and result targets, with 8 participants in employment compared to 7 for intervention A. Nevertheless, intervention A results in the highest number of persons in employment: 9 compared to 8 for intervention B. In the above example the high success rate of intervention A offsets the lower reach because of the high costs, because a sufficiently high share of non-participants find employment, but this would not have been the case if the success rate of intervention B had been 60% instead of 40%.

Finally, one needs to compare the benefit of the additional number in employment through the intervention compared to no intervention, which is (9 – 4 = 5) for intervention A, with the cost. The cost per additional person in employment is 100,000 / 5 = € 20,000 for intervention A, and 100 / 4 = € 25,000 for intervention B. For comparison to judge these costs, an order of magnitude of € 50,000 can be given of an annual benefit of € 7,000, discounted 10 years at 5%.[7]

Whether one maximizes the result target or the total number of persons in employment in an ex ante analysis, the advantages and disadvantages are:
- Advantages:
    - Method is result-based (output and results in an integrated analysis).
    - The choice between interventions is integrated.
- Disadvantages:
    - The percentage of additional job-finders is hard to estimate;
    - Calculations are needed for every intervention that is considered.
- Needed:
    - Preferably, administrative data per participant / person in the target group;
    - Second best: survey data for a sample of participants / persons in the target group and aggregate statistics per intervention;
    - Data on macroeconomic factors that have an impact on interventions;
    - Expertise to estimate success rates with (and ideally also without) intervention, and to value one additional person finding work.
    - The analysis can be done in Excel.

The example to illustrate this method is taken from the first exercise of 14 March. 10,000 workers are threatened with unemployment, of which 50% would find a job without any intervention. The value per job-finder is € 50,000 and the budget is € 10 m. The data for three interventions are summarized in the table below. The last column reflects capacity constraints: maximum numbers of participants that can be reached through an intervention. However, the approaches illustrated below also work with other constraints, for example minimum numbers per region.

Alternative	Unit cost per participant	Success rate	Capacity
Job counselling	1,000	55%	5,000
Mobility scheme	4,000	60%	10,000
Retraining	16,000	90%	500

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[7] If the annual benefit € 7,000 and a job, if any, is found after 1 year, then the value of reduced expenditures in year 1-10 discounted at 5% per year is: $7{,}000/(1+5\%) + 7{,}000/(1+5\%)^2 + \ldots + 7{,}000/(1+5\%)^9 = €\ 49{,}755$.

Approach a: maximize the cost effectiveness per participant.

In this approach, the interventions is identified with the "best" result <u>per participant</u>, and all the budget is invested in that intervention until the budget or capacity is exhausted. Later it will be shown that this approach need not result in the highest overall employment that can be achieved with the budget.

First, the extra persons in employment through the intervention is calculated by subtracting the 50% that find employment without intervention from the above table (see column B in the table below, where cells shaded in green indicate already available data). The unit value per participant is found by multiplying this difference with the value of € 50,000 per person in employment (column C). Lastly, the interventions are ranked by the difference in unit value and unit cost (column D), compared to the unit cost. As the table below shows, each alternative has a positive value per job-finder when the value of reduced benefit expenditure is compared to the cost (column D).

Alternative	A: Unit cost per participant	B: Difference in success rate[a]	C: Unit value per participant[b]	D: Unit value-cost difference[c]
1. Retraining	16,000	+40%	20,000	+4,000
2. Job counselling	1,000	+5%	2,500	+1,500
3. Mobility scheme	4,000	+10%	5,000	+1,000

    a)   Calculated as the success rate minus 50% without intervention
    b)   Calculated as column B times € 50,000
    c)   Calculated as column C minus column A.

The budget of € 10 million can then be allocated in two rounds as follows. First, budget is allocated to the "best" intervention until the budget or capacity limit is exhausted, as illustrated in the table below.

Alternative	A: unit cost	B: Budget limit for participants [a]	C: Capacity limit	D: Participants [b] = min[B ; C]	E: Budget [c]
1. Retraining	16,000	625	500	500	8,000,000
2. Job counselling	1,000		5,000		
3. Mobility scheme	4,000		10,000		
Total				500	8,000,000

    a)   For the first intervention, the budget limit is 10 million divided by the unit cost (column A)
    b)   The lower value of the numbers from the budget limit and capacity limit (column B and C)
    c)   Column A times Column D.

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In the second round, the remaining budget is allocated to the "second-best" intervention until budget or capacity is exhausted, as shown in the table below.

Alternative	A: unit cost	B: Budget limit for participants [a]	C: Capacity limit	D: Participants [b]	E: Budget [c]
1. Retraining	16,000	625	500	500	8,000,000
2. Job counselling	1,000	2,000	5,000	2,000	2,000,000
3. Mobility scheme	4,000		10,000		
Total				2,500	10,000,000

a) For the second intervention, the budget limit is the remaining budget of 2 million divided by the unit cost (column A)

b) The minimum value of the budget and capacity limits

c) Column A times Column D.

The result targets are finally calculated by multiplying the number of participants (the output) with the success rates, in the table below. Retraining results in 90% in employment for 500 participants, or 450 persons and job counselling results in 55% in employment for 2,000 participants, or 1,100 persons. The total result target is then 1,550. This method maximizes the cost effectiveness <u>per participant</u> because step for step, budget is allocated to first the alternative with the highest cost effectiveness per participant, then the alternative with second-highest cost effectiveness per participant and so on. In the training, the exercise was built around maximizing the cost effectiveness per participant because it can be done step by step in Excel.

Alternative	A: Output	B: Success rate	C: Result target [a]
1. Retraining	500	90%	450
2. Job counselling	2,000	55%	1,100
3. Mobility scheme	0	60%	0
Total	2,500		1,550

a) Column A times Column B.

Approach b: maximize the number of employed among participants and non-participants

As the simplified example at the start of this section showed, maximizing the result per participant does not necessarily maximize the number of persons in employment, because this method does not take into account that a certain number of non-participants can find employment as well, or that a slightly lower success rate in one alternative can be compensated by a larger reach if the unit cost per participant is lower.

To find the optimum number in employment, one needs to solve a so-called linear programming problem under budget and capacity restrictions (or political restrictions of minimum numbers) and the population restriction which specifies that the sum of participants and non-participants is equal to the number of persons in the target group:

Maximize in employment = result%[1] * participants[1] + … + result%[n] * participants[n]
Subject to:

- Unit cost[1] * participants[1] + … + unit cost[n] * participants[n] ≤ available budget
- Participants[1] ≤ Maximum capacity[1]
- …
- Participants[n] ≤ Maximum capacity[n]
- Participants[1] + … + participants[n] + non-participants = target group.

This linear programming problem can be solved with an Excel add-in.[8] One feeds the data for the linear programming problem in an Excel sheet, and the add-in solves the optimal numbers of participants per intervention that maximize the number of persons in employment within the available budget. It is a "black box" approach which is illustrated step-for-step in Annex 2; but the add-in is easy to apply once the user is familiar with it. The result after solving the linear programming problem as in Annex 2 is given below.

Alternative	A: Budget	B: % job-finders	C: Output [a]	D: Result [b]
Non-participants	---	50%	4,688	2,344
Job counselling	5,000,000	55%	5,000	2,750
Mobility scheme	0	60%	0	0
Retraining	5,000,000	90%	313	281
Target	10,000,000		5,313	3,031
Total in employment				5,375

a) The output is calculated by the "black box" linear programming solver add-in.

b) The result target is also calculated by the "black box" linear programming solver add-in, but the results can be verified by multiplying columns B and C.

The total number of employment of 5,375 is higher than achieved by maximizing the cost-effectiveness per participant as in the first approach described above. In this approach, the number

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8 http://it.usu.edu/plugins/work/sitemaps/107/files/Linear_Programming_Using_Excel.pdf

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of participants is 2,500 and therefore the number of non-participants is 7,500. The total number in employment is therefore as given below.

The "black box" method of linear programming finds the maximum number in employment that can be achieved with the available budget, but does not indicate whether the "value" of the mix of interventions in terms of reduced benefit expenditures outweighs the cost. To do so, one can calculate the cost per additional person in employment compared to the situation with no intervention. In the above example, in the case of no intervention 50% of the population of 10,000 would find a job, or equivalently 5,000 persons. The above mix of interventions therefore results in (5,375 – 5,000) = 375 additional persons in employment. The cost of 10 million euro to achieve this result is then equivalent to € 26,667 per participant, which is less than the value of € 50,000 associated with each job-finder in terms of reduced benefit expenditures.

Alternative	Budget	Output	% job-finders	Result
Non-participants	---	7,500	50%	3,750
Job counselling	2,000,000	2,000	55%	1,100
Mobility scheme	0	0	60%	0
Retraining for new jobs in region B	8,000,000	500	90%	450
Target	10,000,000	2,500		1,550
Total in employment				5,300

The table below compares the outcomes between the output and result targets calculated after applying the above two methods. The first method maximizes the success rate per participant and the second method maximizes the number of employed with the same budget.

Table 3.2   Results of the exercise in maximizing gross or overall effectiveness

	a. Maximizing success rate (gross cost effectiveness)	b. Maximizing numbers in employment (overall effectiveness)
Output (a)	2,500	5,313
Result (b)	1,550	3,031
Success% per participant (a/b)	62%	57%
Non-participants (c)	7,500	4,688
Success% per non-participant	50%	50%
Non-participants in employment	3,750	2,344
Total in employment (b+d)	5,300	5,375

While the strength of the ex-ante analysis is that setting output and result targets happens in an integrated process as illustrated above, the weakness of this approach is that it requires quite a lot of information:

- success rates per type of intervention;
- success rate without intervention
- the value of each job-finder in terms of reduced benefit expenditures.

In reality, the success rate can vary over the business cycle. For the next programming period, the success rates of participants starting in 2014-2020 can be different for each year. How to set targets for the whole programming period, was illustrated on 14 March by the third exercise. In this exercise, only one intervention is considered. This exercise is elaborated in Chapter 5 on adjusting targets (for the business cycle).

2. SWOT analysis

A SWOT analysis compares strengths and weaknesses of interventions, and opportunities and threats (at the macro level) for these interventions.
It is a logical analysis that can be used to rank interventions qualitatively rather than quantitatively as in a full-blown ex ante analysis.

- Advantages:
    - A result-based approach to allocating budgets;
    - Policy priorities can be taken on board;
    - The choice between interventions is integrated;
    - Avoids exact calculation of extremely hard to calculate net unit gains;
    - Less strict data requirements.
- Disadvantages:
    - The analysis is partly subjective;
    - Strengths and weaknesses need to be determined for each intervention.
- Needed:
    - A mix of quantitative / qualitative data per intervention to identify strengths and weaknesses;
    - Macroeconomic data to identify opportunities and threats;
    - Actual target setting can be done in Excel.

An example of a SWOT analysis can be found in a document of the French government that is available on the internet.[9] It first identified at the macroeconomic level (for France)[10]:

- Strengths such as: a highly qualified workforce and regional business dynamics;
- Weaknesses such as: the gender pay gap and difficult target groups;
- Opportunities such as: jobs in personal services and jobs with durable perspectives;
- Threats such as: loss of human capital and competitiveness.

After elaborating the SWOT elements, a number of policy orientations were identified (page 18-20 of the document):

- Encourage access or return to work;
- Improve the functioning of the labour market;
- Invest in human capital;
- Stimulate work in jobs with growth potential.

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[9]   http://www.fse.gouv.fr/IMG/pdf/valuation_ex_ante_du_PO_FSE_version_definitive-2.pdf
[10]   Page 12 and 13 of the document for the full list of SWOT elements.

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Chapter 2 of the document elaborated how each priority axis of the ESF Operational Programme is expected to contribute to objectives falling under the above policy orientations. Chapter 3 of the document described the principles behind allocating budgets to regions, which depends on a mix of diagnostics as at the national level and budget negotiations. Another document explains how in France historical ESF (and Cohesion Fund) budgets were adjusted according to changes in SWOT elements in each region.[11]

Shift-share models can be used to adjust historical budgets while taking into account regional shifts in underlying variables; this model is usually applied in analysis of regional growth[12] but can be applied more widely.

3. Applying the distribution of the population

In this approach, the distribution of the population between regions and target groups is applied to budget.

- Advantages:
    - Allocation is objective and offers equal opportunities;
    - Less data requirements;
    - No comparison between interventions is required.
- Disadvantages:
    - The approach is not result-based;
    - The choice between interventions still needs to be made.
- Needed: Population data or reliable survey data (e.g. Labour Force Survey)
- Can be done in Excel.

A number of countries apply this method to allocate budgets between regions, even before target setting in countries where the Operational Programmes were already regionalised (for example, Italy).

The method of applying the distribution of the population is however also very useful as a reality check: can the outputs be delivered or is the targeted number of participants larger than the target group population in a region? To apply this method, the future population and its distribution have to be predicted.

Assuming that the ESF intends to support three different types of interventions helping school leavers (depending on the skill levels of school leavers) Table 3.3 informs which share of money should go to which type of intervention in the identified regions (also assuming that regions and interventions are equally important). If the total available budget were 100 million euro for interventions, this would imply that 4 million euro would be allocated to interventions for high educated school leavers in the North region.

Table 3.3   **Example of distribution of the population**

Target group	Region North	Central	South	Total per education level
Low educated school leavers	10%	10%	10%	30%
Medium educated school leavers	16%	18%	16%	50%

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11   The actual budgeting of ESF is integrated with the budgeting of the Cohesion Policy, see http://www.fse.gouv.fr/IMG/pdf/Cadre_de_Reference_Strategique_National-2.pdf

12   E.g. Zaccomer, G. and P. Mason (2011), A new spatial shift-share decomposition for the regional growth analysis: a local study of the employment based on Italian Business Statistical Register.

Target group	Region North	Region Central	Region South	Total per education level
High educated school leavers	4%	12%	4%	20%
Total per region	30%	40%	30%	100%

Source: Ecorys, example prepared for the learning seminar on targeting

If the population is predicted for the whole programming period 2014-2020, a different set-up of the table is more convenient, as illustrated in the table below.

Table 3.4   **Example of distribution of the population per year**

Region	Target group	2014	2015	…	2020
North	Low	10%	…	…	8%
	Medium	16%	…	…	16%
	High	4%	…	…	6%
Central	Low	10%	…	…	8%
	Medium	18%	…	…	18%
	High	12%	…	…	14%
South	Low	10%	…	…	8%
	Medium	16%	…	…	16%
	High	4%	…	…	6%
Total		100%	100%	100%	100%
N school leavers		1 mln	1.02 mln	…	1.12 mln

In the above example, one may allocate proportionally higher budget (in prices of 2014) to years for which a larger total target group population is predicted.

To set output targets, the allocated budget for each region and target group is divided by the average unit costs, preferably the average unit cost per region and target group.

4. Trend extrapolation

Trend extrapolation is another approach to allocate budgets. Trend extrapolation to set output targets consists of two steps: trend extrapolation per target group / region or type of intervention, and an adjustment to fit the allocation within the available budget.

- Advantages:
  - Limited data requirements;
  - Integrates expected changes in the future.
- Disadvantages:
  - The approach is not result-based;
  - The approach does not incorporate shifts in priorities;
  - Allocation of budgets is implicitly as objective or subjective as in the past.
- Needed: Population data or reliable survey data (e.g. Labour Force Survey)
- Can be done in Excel.

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For example if the available budget remains the same and three target group populations increase by +5%, +7.5% and +10% respectively, an adjustment will be needed as the populations increase more than the budget. Table 3.5 illustrates this principle, where the total budget for the next programming period remains the same. As before, the shaded cells indicate already available data.

Table 3.5   **Steps of budget allocation with trend extrapolation**

	A: Old Budget	B: Population increase	C: Preliminary budget a)	D: Final budget b)
Intervention 1	20 million	+5%	21 million	19.5 million
Intervention 2	40 million	+7.5%	43 million	39.8 million
Intervention 3	40 million	+10%	44 million	40.7 million
	100 million		108 million	100 million

a) Old budget (column A) times (1+population increase from column B)
b) The preliminary budget (column C) adjusted to the total budget (100 million).

In the first step, a preliminary budget is calculated per intervention by increasing the budget with the same percentage as the increase of the population. In the above example, historically 20 million euro was spent on the first intervention, and the target group of the first intervention increases by 5%. In a preliminary budget allocation, this results in 21 million euro (20 million + 5%). The preliminary budgets for interventions 2 and 3 are calculated in the same way.

In the second step to allocate the budget, the preliminary budgets are adjusted to the total budget. In Table 3.5, the preliminary budgets add up to 108 million euro, while the total available budget is only 100 million euro. Multiplying all preliminary budgets by $\frac{100}{108}$ suffices to adjust the preliminary budgets to the total budget of 100 million euro.

As in all other methods discussed above, output targets are calculated as the budget divided by the unit cost per participant. The following section discusses the calculation of the unit costs which play such an important role in setting output targets.

3.3   Calculating unit costs

In this section, a number of aspects of calculating unit costs are discussed. The selection of aspects is based on the survey of challenges Member States reported for the previous programming period:

- Using aggregate versus disaggregate unit costs;
- Estimating costs of uncompleted interventions;
- Using actual versus committed costs;
- Price inflation needs to be added to historical unit costs.

Aggregate versus disaggregate unit costs

Preferably, different unit costs per participant are calculated for all regions, target groups and types of interventions that are budgeted. The reason is that if the budget is adjusted for different regions, target groups or types of intervention, this affects the average unit cost. This is illustrated with a simplified example below.

Suppose that historically, 10 and 12 million euro were budgeted to interventions A and B respectively, with respectively 1,000 and 3,000 participants. Then the unit cost per participant is respectively € 10,000 and € 4,000 (budget divided by the number of participants). The average

historical unit cost is the total budget of 22 million euro divided by the total number of 4,000 participants, or € 5,500, as shown in the table below.

	Intervention A	Intervention B	Total
Budget	10,000,000	12,000,000	22,000,000
Unit cost	10,000	4,000	5,500
Participants	1,000	3,000	4,000

Now suppose that in the next programming period, the total budget remains the same but 6 million euro is allocated to intervention A and 16 million to intervention B. If one uses for each intervention the historical average unit cost across all interventions (€ 5,500), then the output target changes proportionally to the total budget, regardless of the budget allocation.

In the example, if the number of participants of both interventions A and B is calculated by dividing the new budget by the historical average across both interventions, this results in 6 million / 5,500 = 1,091 participants in intervention A and 16 million / 5,500 = 2,909 in intervention B, adding up to 4,000. The number of participants is the same as the historical number, because the total budget has remained the same in the example.

	Intervention A	Intervention B	Total
Budget	6,000,000	16,000,000	22,000,000
Unit cost	5,500	5,500	
Participants	1,091	2,909	4,000

However if the historical unit costs per intervention is used, this results in 6 million / 10,000 = 600 participants in intervention A and 16 million / 4,000 = 4,000 participants in intervention B, adding up to 4,600 participants, see the table below. The reason that more participants can be reached with the same budget, is that more budget is allocated to an intervention with lower unit costs. By allocating more budget to lower-cost interventions, the average unit costs across interventions decreases, from € 5,500 to 22 million / 4,600 = € 4,783 in this example.

	Intervention A	Intervention B	Total
Budget	6,000,000	16,000,000	22,000,000
Unit cost	10,000	4,000	
Participants	600	4000	4,600

The advantage of using disaggregate unit costs is that the output targets can be set more accurately, but the data requirements are large and certain disaggregate data may be missing. How to deal with a situation of partially missing disaggregate data, is discussed in the Section 3.4.

Estimating costs of still running interventions
If an intervention is fully completed, one can simply divide the actual expenditures by the total number of participants. However, if an intervention is still running, one may assume that all expenditures have been incurred for those participants who have left the programme, but not for those who are still in the programme. Figure 3.1 illustrates this situation, where 9 euros have been spent, and the number of participants is 5. Naively dividing the spent budget of 9 by the number of participants would result in an estimated unit cost of 1.8 per participant. However, recognizing that one euro still needs to be spent for those participants who are still in the program, the unit cost is calculated by dividing 10 by 5, resulting in a unit cost of 2.

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Figure 3.1   Unit costs for running interventions
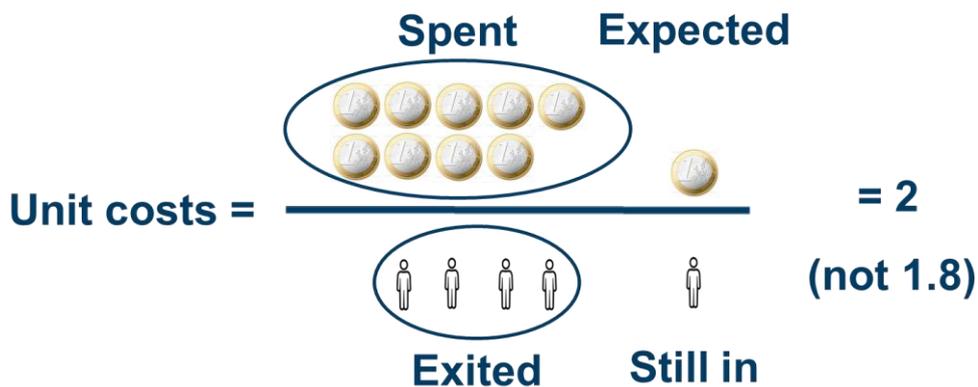
The unit cost in the situation of running intervention can be calculated by assuming that for those participants still in the program, only a percentage "p" of the unit cost need to be incurred. This can be done by solving the equation:

$$Unit\ cost = \frac{spent\ budget + expected\ budget}{exited\ participants + participants\ still\ in}$$

In the above equation, one fills in the assumed expected budget:

$$Expected\ budget = p \times unit\ costs \times participants\ still\ in$$

The resulting formula for the calculation of unit cost of still running interventions is then:

$$Unit\ cost = \frac{spent\ budget}{exited\ participants + (1-p) * (participants\ still\ in)}$$

This generalization of the unit cost calculation reduces to the standard formula when the intervention is completed and 100% of the costs are incurred, because then p=1.

Actual versus committed cost

A pragmatic solution for still running interventions might seem to calculate the unit cost from historically committed budgets and historically targeted numbers of participants. However, this is not preferred because the actual number of participants could be quite different from the targeted number whereas the actual cost is likely to be closer to the committed costs because some costs are fixed, such as start-up costs and overhead.

Figure 3.2 illustrates this situation, where 8 million euro is committed for a targeted number of 4,000 participants. Based on this committed budget and output the unit cost would be € 2,000. However if actually 6 million euro is actually spent on an actual number of 2,000 participants, the unit cost is in reality € 3,000.

Figure 3.2   **Unit costs based on committed versus actual costs**
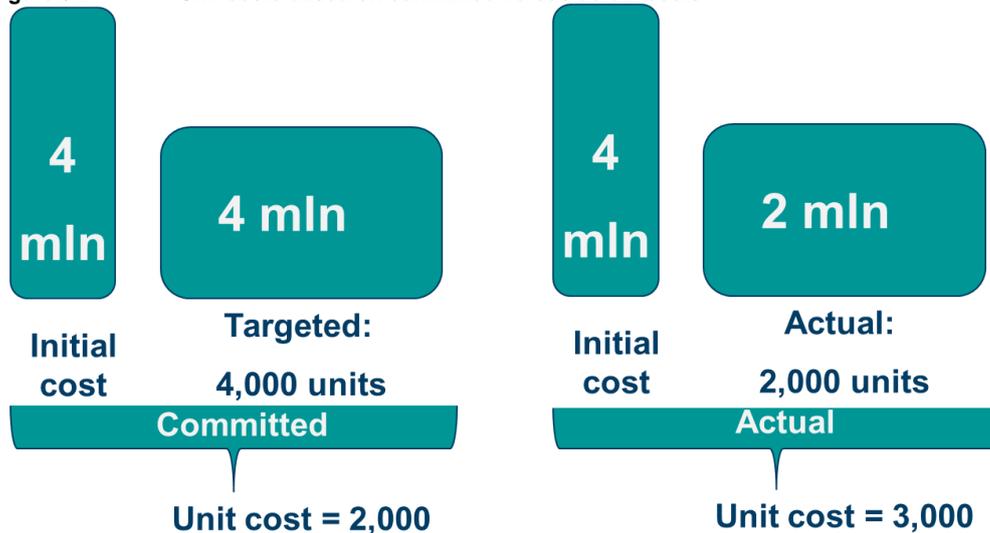
Whether the historically committed or the historical actual unit costs are used for setting output targets, matters substantially in the above example. In the first case, the budget allocated for the next programming period would be divided by € 2,000 and in the second case it would be divided by € 3,000. The method to estimate the costs that still need to be incurred for those participants who are still in the program results in more reliable estimates of the unit cost because it uses more actual data.

Price inflation

The average unit costs of the 2007-2013 ESF programme need to be inflated to prices of 2014 and beyond for the 2014-2020 ESF programme. In formula, if expenditure[t] is the expenditure of year t and pi[t] is the price inflation in year t, then the average unit costs in prices of 2014 is calculated as follows:

$$\text{Unit cost[2014]} = \frac{Expenditure[2007] \times pi[2008] \times ... \times pi[2014] + \cdots + Expenditure[2013] \times pi[2014]}{partipants[2007] + \cdots + participants[2013]}$$

For example if prices increased by 2% each year in 2008-2012 except in 2009 when prices remained constant, and for 2013 and 2014 an inflation of 2% is expected, the unit cost in prices can be calculated as illustrated in Table 3.6.

Table 3.6   **Illustration of the use of price inflation**

		In prices of…							
		2007	2008	2009	2010	2011	2012	2013	2014
Expenditures	2007	100	102.0	102.0	104.0	106.1	108.2	110.4	112.6
	2008		102	102.0	104.0	106.1	108.2	110.4	112.6
	2009			104	106.1	108.2	110.4	112.6	114.8
	2010				106	108.1	110.3	112.5	114.7
	2011					108	110.2	112.4	114.6
	2012						110	112.2	114.4
	2013							112	114.2
	2007-13								799.1

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In Table 3.6, the shaded cells indicate the actually incurred expenditures, in prices of the going year. Expenditures were only 100 in 2007 compared to 112 in 2013. However when the inflation of 2008-2014 is accumulated for the expenditures of 2007, the expenditures of 100 in 2007 amount to 112.6 in expected prices of 2014. The expected expenditures of 112 in 2013 needs to be inflated by only the expected price index of 2014 (1.02) which results in 114.2 in prices of 2014. In prices of 2014, the total expenditures of 2007-2013 is therefore not

100 + … + 112 = 742 (sum of shaded cells in Table 3.6) but
112.6 + … + 114,2 = 799.1 (sum of last column in Table 3.6).

If the total number of participants were 100 over the period 2007-2013, then the unit cost in prices of 2014 should in the above example be calculated as 7.991 instead of 7.420.

For the period 2014-2020, future price inflations should be forecasted and applied to both receipts of ESF funds and expenditures, but this matter of financing goes beyond the scope of this paper.

3.4   The cost equation

A large number of projects will be conducted under a certain investment priority, differing between regions, target groups, scales of magnitude, types of intervention and years. This raises the question how valid historical unit costs are when different circumstances have developed in any of these aspects. In addition, projects can run in multiple regions, et cetera, and data may be lacking.

Together, these difficulties create a multi-dimensional problem, and the question is how to effectively calculate appropriate unit costs. One approach is that of a *cost equation*, which relates the cost of a project to a number of factors. A cost equation is a tool that can be used to greatly reduce the dimensionality of calculating unit costs, and to estimate costs of projects for which no historical data are available.[13]

Attention should be paid to ensure that the estimated relation applies to a whole range of projects. To this end, it should be avoided that one large project dominates the estimation. One solution is to relate unit cost rather than total cost to a number of factors. But even then, a particular project can have extremely high unit costs, for example business start-up support, if a business loan is included. To further scale unit costs of different projects, experts calculate the logarithm of costs and after their analysis transform the logarithm of costs back into normal values. To illustrate the principle of using a cost equation to differentiate unit costs in an efficient way, the following example illustrates a cost equation without such transformations.

The following formula gives an example of a cost equation for the unit cost per participant:

$$\begin{aligned}
Unit\ cost = a_0 + a_1 \times (\text{Number participants}) + \\
b_2 \times Region2 + b_3 \times Region3 + \cdots + \\
c_2 \times Targetgroup2 + c_3 \times Targetgroup3 + \cdots + \\
d_2 \times Activity1 + d_3 \times Activity2 + \cdots + \\
N(0, \sigma^2)
\end{aligned}$$

In this formula, the value a_0 reflects "fixed costs" such as start-up costs and overhead that are incurred even when there are no participants. The unit cost per participant can be related to the

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number of participants if economies of scale exist: projects with more participants may have lower unit costs, although unit costs tend to increase again for very large projects. In the above formula, the unit cost is assumed proportional to the number of participant, with value a_1.

The formula further explained:

- The variable: "Region2" takes on the value 1 if the project is active in Region2, and otherwise the value 0
- The values b_2, b_3 … indicate euro mark-ups for regions compared to a reference region (Region1 in this example) which must <u>not</u> be included in the equation.
- The values c_2, c_3, … are euro mark-ups for target groups targeted by the project, compared to the reference target group
- The values d_2, d_3, … are euro mark-ups for the activities of the project.

The last term is the prediction error of the formula, where σ^2 indicates the variance of the difference between the actual unit cost (left hand side of the equation) and the predicted unit cost (right hand side of the equation).

If there are 30 regions and 10 target groups, this means that 40 values must be estimated to relate unit costs to these factors. However, often many values need not to be used to calculate unit costs:

1. Values that are virtually zero;
2. Values that are statistically not reliable;
3. Values in a close range.

The principle of "Ockhams razor" in econometrics is to remove variables with zero, unreliable or similar values, to greatly reduce the number of variables. For example, consider a cost equation for unit costs per project, with the following estimated values, with the error margin given below the estimate (the example abstracts from different activities)[14]:

$$
\begin{aligned}
\text{Unit cost} = 6{,}000 &- 10 \times \text{Number participants} + \\
\pm 500 \qquad &\pm 1 \\
+3 \times R2 + 50 \times R3 + 290 \times R4 + 270 \times &R5 + 310 \times R6 - 500 \times R7 + \\
\pm 1 \qquad \pm 100 \qquad \pm 50 \qquad \pm 50 \qquad &\pm 50 \qquad \pm 100 \\
100 \times Targetgroup2 + 200 &\times Targetgroup3 \\
\pm 20 \qquad\qquad \pm 20 &
\end{aligned}
$$

Then the value for the second region may be neglected because the mark-up of € 3 is very small. The value for the third region may be neglected because the error margin (±€ 100) is larger than the value of the percentage mark-up (€ 50). This implies that regions 1, 2 and 3 can be grouped together as the reference region. The euro mark-ups for regions 4, 5 and 6 may all be assumed to be € 300, because for all three regions, € 300 is within the error margin of the estimated values. The unit cost in the last region is € 500 lower than for equally large projects for the same target groups in the reference region. After applying "Ockhams razor" the equation becomes (ignoring the error margins of the estimated values):

$$
\begin{aligned}
\text{Unit cost} = 6{,}000 &- 10 \times \text{Number participants} + \\
&+300 \times (R4 + R5 + R6) - 500 \times R7 + \\
100 \times &Targetgroup2 + 200 \times Targetgroup3
\end{aligned}
$$

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[14]   Usually the error margin is determined as the 95% range of values that would be estimated for random selections of the population which can be calculated as 2 times the standard deviation of the estimate.

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Table 3.7 illustrates how with the previous formula, the unit cost of one region (R3) with missing data for some projects can be calculated. The example is simplified by assuming that all projects in one region have the same target group, but similar calculations apply for "real life" data:

$$Unit\ cost\ R3 = \underset{constant}{6000} \underset{economies\ of\ scale}{-\ 10 \times 200} \underset{R\ markup}{+\ 0} \underset{TG\ markup}{+\ 200} = 4200$$

Table 3.7   **Estimating unit cost**

Region	Target group	Number projects	Historical participants per project	Historical unit cost	Estimated unit cost
R1	1	20	50	7500	5500
R2	2	20	100	4000	5100
R3	3	20	200	?	4200
R4	1	20	50	8000	5800
R5	2&3	20	100	5000	5600
R6	3	20	200	3500	4500
R7	3	20	400	2000	2000
Total excl. R3		120	18,000	63,500,000	66,700,000
R3		20	4,000	+4000 x ?	16,800,000
Total incl. R3		140	22,000	?	83,500,000

Source: Ecorys, example prepared for the learning seminar on targeting

The cost equation provides an objective estimate for projects with missing data, but can also be used for projects that have a mix of target groups, as in region 5 in the above example, or for new target groups in new regions (not illustrated in the above example). Without estimating the cost equation, arbitrary choices would have to be made. For example:

- The average cost of all other projects = 63,500,000 / 18,000 = 3,528
- The average cost of other projects for target group 3 = 2,750.

However, the power of the cost equation lies not in correctly predicting the unit cost of each and every project. In the above example, the estimated unit cost is too low for projects in region 1 and too high for projects in region 2. The power of the cost equation lies in the ability to correctly estimate the <u>average</u> unit cost over all projects, taking account of differences between regions, target groups and activities, economies of scale and whatever else is relevant. In the above example, the total cost exclusive region 3 are estimated at 66.7 million, which is 5% higher than the actual total cost of 63.5 million; a difference that is generally considered acceptable.

What makes the above model easy to apply, is that a linear cost function is assumed. One drawback of a linear cost function is that projects with very high unit costs ("outliers") have a disproportionate impact on the estimated cost of projects with no data (historical or future): they "elevate" the average. To overcome the disproportionate effect of outliers, one option is to identify them and remove them from the data, and another is to scale the unit cost, for example by taking logarithms. However if the cost equation is specified in logarithms:

$Log(unit\ cost) = a + b{*}x + N(0,\sigma^2)$

One needs to be aware that then the expected cost is not:

$exp(a + b{*}x)$ but
$exp(a + b{*}x + \frac{1}{2}\ \sigma^2)$.

Non-linear functions for unit costs have in turn the drawback that estimates are very sensitive to the exact function that is used, and the expected cost can be complex to calculate. For practical reasons, the linear model, with possibly removing outliers from the data, and applying Ockham's razor to keep the model transparent and accessible, should be considered first.

3.5   Normative issues – cost efficiency

An alternative to using historical unit costs is to set *normative unit costs*. Projects that have exceptionally high unit costs compared to similar projects are then excluded from the calculation. Again, the cost equation helps to take into account multiple factors influencing the unit costs. To set the normative unit costs, the historical unit cost is compared with the estimated unit cost. If the ratio is very high, it can be considered to require a lower unit cost for future projects. To continue from the previous example, the historical unit costs are highest compared to the estimated unit costs for projects in regions R1 and R4.

Table 3.8   **Estimate of cost efficiency**

Region	Historical unit cost	Estimated unit cost	Ratio historical to estimated unit cost
R1	7500	5500	1.36
R2	4000	5100	0.78
R3	?	4200	
R4	8000	5800	1.38
R5	5000	5600	0.89
R6	3500	4500	0.78
R7	2000	2000	1.00

Source: Ecorys, example prepared for the learning seminar on targeting

Both regions have in common that projects are relatively small: only 50 participants per project compared to 100 and above in other regions. One might then consider procuring projects with 100 or more participants only. According to the cost equation, the unit cost should then be 500 euros less, because the cost decreases by 10 euro for every extra participant from 50 to 100.

However, whether to actually require lower unit costs remains a normative choice, because lean and mean projects are not necessarily the best; comparing historical and estimated unit costs is a tool to identify potential cost inefficiencies, but not more than that.

3.6   Setting output targets with limited or no data

All the methodologies described above assume more or less accurate knowledge of unit costs, and methods to complete partially known unit costs.

If no historical data are available at all, for example because a new type of intervention is programmed, aggregate historical unit cost for that type of intervention can be used. Such data exist for all 27 Member States, for all types of interventions. All Member States contribute the relevant data to the Eurostat Labour Market Policy database, which is available from the following web-link:

http://epp.eurostat.ec.europa.eu/portal/page/portal/labour_market/labour_market_policy/database

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From this database, the following tables can be downloaded:
- Expenditures per Member State per intervention;
- Number of participants per Member State per intervention: entrants and average stock per year.

The unit cost can be calculated by dividing the expenditures by the number of participants. For the number of participants, the larger value of the number of entrants and the average stock per year can be used. Figure 3.3 illustrates the costs of training calculated with the above Eurostat database: typically, the costs of training are in the € 3,000 - € 8,000 range.

Figure 3.3   **Costs of training per participant**
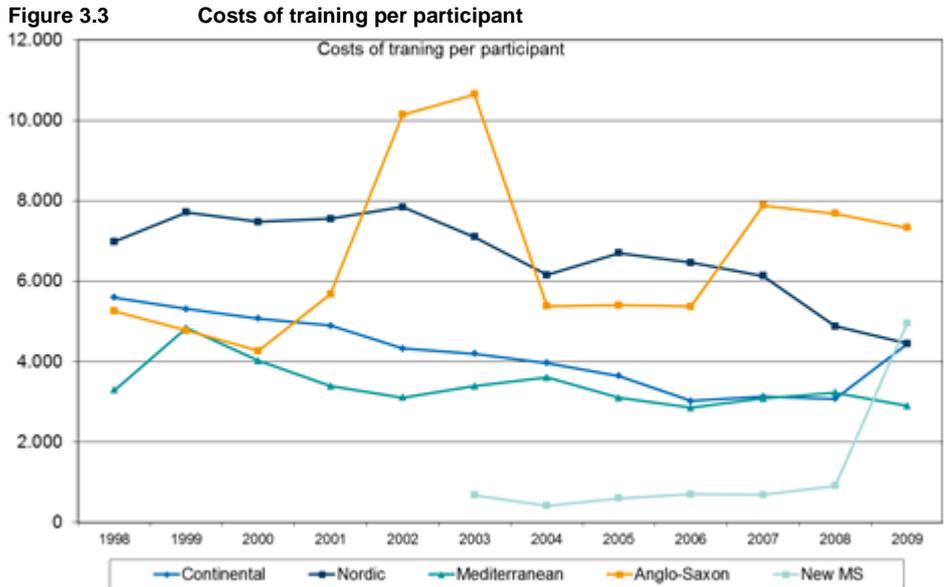
Source: Ecorys and IZA (2012), in Euro prices of 2009.[15]

The database can help to estimate unit costs in the absence of any data on ESF projects. However if a Member States experiments with more effective and expensive interventions, or a lighter than average intervention, one still needs judgement in the estimate of the cost for the new type of intervention.

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[15]   Ecorys and IZA (2012), Analysis of costs and benefits of active compared to passive measures, Final report, Rotterdam.

4 Methodologies for setting result targets

4.1 Introduction

Setting result targets is as easy or as difficult as applying success rates to the output targets. The previous Chapter 3 discussed methods for setting the output targets, ideally integrated with setting result targets.

The success rate can in principle be calculated as the percentage of participants leaving successfully, in particular the participants leaving and finding employment. However, the success rates depend on many factors which are likely to change in the future, including:

- The business cycle;
- The characteristics (composition) of the target group;
- Wages and their role in the matching of supply and demand;
- Labour market regulation;
- Changes in skills needs;
- Other structural changes in the demand for labour;
- …

Because all of the factors which influence the success rates are likely to change in the future, applying historical success rates to output targets does not necessarily result in achievable result targets. A result equation relates the success rates to such underlying factors. Once these factors are forecasted, the result equation can be used to predict future success rates, as discussed in Section 4.2.

Another aspect is whether higher success rates would be achievable if "best practices" were adopted in all projects, where the "best practice" should be defined as the practice that results in the highest success rates, highest cost efficiency or ideally the highest overall effectiveness. Benchmarking is the general method to identify best practices. However, a project aimed at a more difficult target group may have a larger overall effect than a project aimed at persons who would have found a job without intervention as well. Benchmarking is only useful after controlling for differences in the composition of the target group and other relevant effects. Techniques for controlling for these effects include, with references to empirical literature:

- Randomized experiments[16];
- Matching[17].

Randomized experiments have to be set up before the intervention, and consist of randomly (blindly) assigning some persons to the one or the other intervention, or no intervention at all: the random assignment ensures that effects of other factors average out, and the intervention with the highest success rate can arguably be attributed to the intervention itself. Matching consists of comparing the success rates of one group of participants in the one intervention with a "similar" group in the other intervention (or with a "similar" group of non-participants). The project with the highest success rate for that group, is arguably the "best practice" for that group.

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[16] Gautier, P., P. Muller, B. van der Klaauw, M. Rosholm and M. Svarer (2012), Estimating equilibrium effects of job search assistance, working paper, http://www.oecd.org/els/emp/DanishExperiment.pdf.

[17] Ecorys and IZA (2012), Analysis of costs and benefits of active compared to passive measures, Annex F provides references to studies based on matching techniques in Austria, Germany, the Netherlands, Poland and the UK.

The first method requires large efforts in setting up interventions, whereas the second method requires detailed data on individual participants. Still, both instruments are strongest in providing ex post information on the net-effect of an intervention in the past.

Instead, Section 4.4 discusses the frontier analysis, which can be applied after controlling for other effects, whether through the result equation, randomized experiments or matching. Section 4.5 concludes the chapter with discussing practical methods in the absence of data on historical success rates for particular groups.

4.2 Result equation

The result equation relates observed results to relevant variables such as target groups, regions and the phase of the business cycle (impact variables) and a variable that captures the effect of the participation. In its most abstract form, the result equation reads:

$$Result = a + b \times (impact\ variables) + c \times (participation\ variable)$$

The value "a" would be the average result if all other values "b" and "c" were zero, and in general is needed to ensure the average result for average values of the other factors. The value "b" controls for the impact of relevant factors such as the business cycle, composition of the target group etcetera. The value of real interest in this equation is the third value "c". If the value "c" is greater than zero, than the programme is effective towards the result.

- Advantages:
  - Method is direct;
  - Observations from all programmes are used to estimate likely results in specific situations;
  - Knowing what the result would have been in specific situations in the past enables setting attainable result targets for such a situation in the future.
- Disadvantages:
  - No wider impacts beyond the results are taken into account;
  - The target setter still needs to judge whether better results in the future compared to the past are realistic.
- Needed:
  - Preferably, administrative data per participant / person in the target group;
  - Second best: survey data for a sample of participants / persons in the target group and aggregate statistics per intervention;
  - Data on macroeconomic factors that have an impact on interventions;
  - Statistical software such as Stata, Eviews or SAS[18];
  - Expertise to estimate unit results.

With regard to the disadvantage that the result equation does not take into account wider impacts beyond the results, it should be noted that the estimates of wider impacts are not part of the target setting procedures for the ESF 2014-2020 period. Macroeconomic models could in theory be used to explore wider impacts, including:
- Substitution effect (employers replace non-participants with participants);
- Displacement effect (employers without participants lose jobs to those with participants).

However, macroeconomic models have shortcomings as well, in particular:

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[18]   Gauss and TSP cannot handle large datasets well, the Excel add-in only serves for basic regression analysis and SPSS has no convenient programming options to use estimated values in further analysis.

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- Modelling macroeconomic effects in the labour market is difficult;
- Macro-models tend to treat all target groups equal.

In the micro-based approach, the result is typically an improved likelihood of employment. Two standard forms of the result equation are:
- A model of binary outcomes (found a job: yes or no);
- A duration model (time till job is found, if any).

The model of binary outcomes is relatively safe, because relatively few modelling assumptions are required, compared to for example a duration model. In the standard model of Bartik,[19] the probability "P_{it}" to find a job is defined for every individual "i" in a given period "t", and is related to personal characteristics "X_i", the business cycle "X_t" and a participation variable "I_{it}".

$$P_{it} = a_0 + a_1 \times X_i + a_2 \times X_t + a_3 \times I_{it} + N(0, \sigma^2)$$

Historical values of P_{it} are defined as 0 for all periods "t" in which the individual "i" did not find a job, until the moment at which the individual did find a job in which case P_{it} is defined as 1. The values a_0, a_1 and a_2 are estimated by choosing the values that minimize the difference between the left-hand side and the right-hand side of the above equation.

For example, consider a minimalist dataset below with data for six participants (indicated with 1) and six nonparticipants (indicated with 0, in column C in the print-out below). The impact variable is the regional unemployment rate, which is 6%, 7% or 8% depending on the region (column B in the print-out below). Finally, the first column indicates whether the person found employment (indicated with 1) or not (value), in column A of the print-out below. In reality, other factors should be included and a far larger number of observations is needed, time series effects may need to be taken account of etcetera; the example only serves to illustrate the principle of estimating a regression equation.

[19] Bartik, T. J., R. W. Eberts and W.-J. Huang (2009), Methodology for adjusting GPRA workforce development program performance targets for the effects of business cycles. Upjohn Institute Working Paper No. 09-154. Kalamazoo, MI: W.E. Upjohn Institute for Employment Research.

In the above example, half of the participants find employment compared to two-third of the nonparticipants. This might suggest that the intervention is counterproductive, however the participants are in regions with a slightly higher unemployment rate (7.0% on average) compared to non-participants (6.8% on average), and the question is whether the higher unemployment rates in regions of participants can account for the negative effect of participation in the intervention.

After installing the Data Analysis add-in, in a similar way as the Solver add-in as discussed in Annex 2, one can go to the tab "Data" and click on "Data Analysis" in the ribbon and choose the option "Regression"
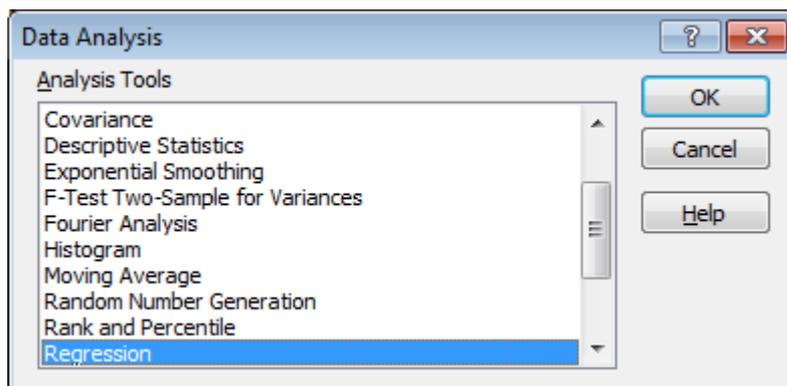
And select the Y range (the first column including the header), the X range (the second and third column including the header), indicate the labels (the headers) are included and that the constant (the value "a") needs to be included (is not zero).

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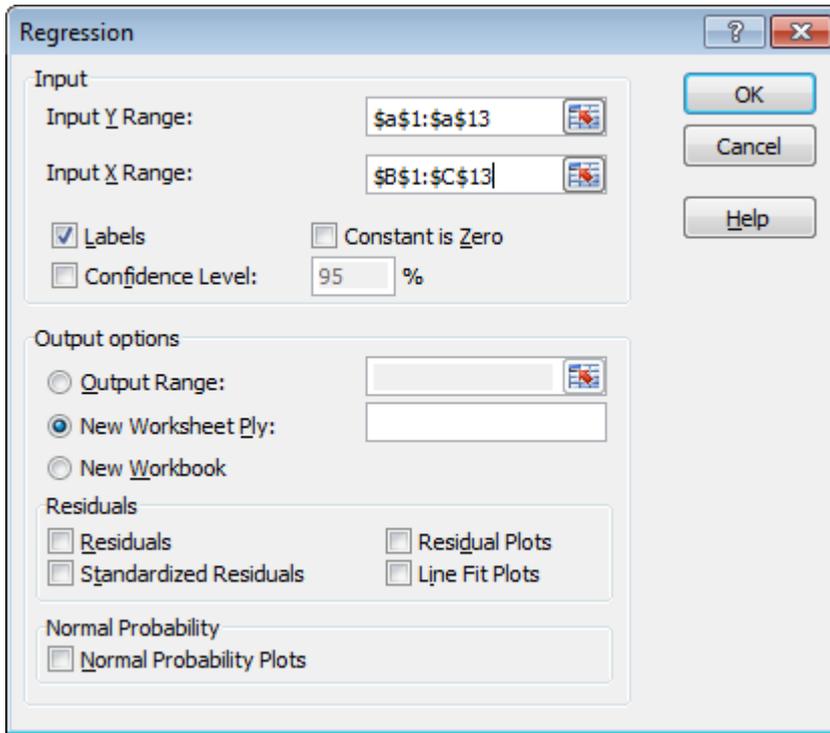
The result of the regression appears in a new sheet as shown in the print-out below.

SUMMARY OUTPUT

Regression Statistics	
Multiple R	77%
R Square	59%
Adjusted R Square	49%
Standard Error	0.37
Observations	12

ANOVA

	df	SS	MS	F	Significance F
Regression	2	1.7093	0.8547	6.371	1.9%
Residual	9	1.2073	0.1341		
Total	11	2.9167			

	Coefficients	Standard Error	t Stat	P-value	Lower 95%	Upper 95%
Intercept	4.0	0.97	4.1	0.3%	1.81	6.19
Regional unemployment rate	-0.49	0.14	-3.5	0.7%	-0.80	-0.17
Participant	-0.09	0.21	-0.4	69.8%	-0.57	0.40

The adjusted R square is a measure of the goodness of fit, and is an adjustment of the R square for small numbers of observations as is the case in the above example. In reality relations are not so strong and an (adjusted) R square of 15% can be considered as very good.

The intercept in the above example is 4.0. With an average unemployment rate of 6.9%, this implies for non-participants an average result percentage of 4.0 – 0.49 x 6.9 = 61.9%, which is somewhat less than the actual 66.7% (four non-participants find work and two do not in the example). The P-values of 0.3% and 0.7% indicate that the value "a" and the regional unemployment rate are different from 0 with high certainty (more than 99%).

However, the estimated effect of participation in the intervention is negligible (between -0.57 and +0.40 with an average value of -0.09), after controlling for the unemployment rate. Hence the intervention is not counterproductive as seemed at first sight, but does not improve the success rate either.

Standard individual characteristics that are generally found to have an impact on the probability to find a job are for example educational level and age, and standard time-variables are for example the unemployment rate and the activation/benefit expenditure ratio.

The result equation estimated above is a minimalist model, which does not take account of time series effects, which are discussed in the next Chapter 5. Also, the appropriate model to estimate depends on the type of intervention, because different types of interventions influence the likelihood of employment in different ways. Two examples are given below.

Modelling employment incentives

The intervention variable depends on the type of intervention. For employment incentives, this could be a tax credit for job-finders. According to the econometric literature, the impact of financial incentives on the probability to find a job is not always significant. [20] However, if gain in household income is used instead of the wage, the impact of financial incentives is much more likely to be significant, as is evident from the empirical literature. The example below illustrates the difference between wages and changes in net household income:

$$\Delta net\ household\ income = wage - \Delta taxation\ of\ worker - \Delta\ taxation\ of\ spouse$$

Where Δ indicates the difference between the new situation (participant finds a job) and the old situation (participant does not have a job). For example if without the job the husband will have a monthly unemployment benefit of € 1,000 and the wife has a part-time job earning another € 1,000 per month which is taxed at 20%, and the husband finds a job earning € 2,000 per month causing the wage of both husband and wife to be taxed at 30%, then the gain in net household income is not € 2,000 but only € 300:

Wage	+ 2000
Tax of worker	600 -/-
Lost benefit	1000 -/-
Extra tax of spouse	100 -/-
Net gain	= 300

On an annual basis, this worker stands to gain € 3,600 (12 times € 300) and a one-time tax credit of € 1,200 would increase this gain by one third, which is far more substantial than the gain of 5% compared to the annual wage of € 24,000.

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[20] This discussion is based on Ecorys (2004), Benefit systems and their interaction with active labour market policies, *ec.europa.eu/social/BlobServlet?docId=3195&langId=en.* This report describes estimates of micro-models for employment incentives for six EU15 countries.

Since the net gain is roughly $1/7^{th}$ of the wage in the above example, the estimate of the value a_3 should be roughly 7 times as large if net gain is used as the financial incentive variable instead of the wage, and the estimate of the impact of the tax credit should also be roughly 7 times as large.

To model employment incentives, it is important to compare future alternatives instead of benefits and wages from the past. Future benefits can be calculated given the national tax benefit system. For those unemployed that find a job, the wage of the future job is also known. However, for those that do not find a job, the wage of potential future jobs is unobserved and needs to be estimated. These unobserved wages are estimated through a wage equation, relating observed wages to relevant characteristics, in a similar way as the cost equation described in the previous chapter.

Modelling training

For modelling training, the intervention variable has value 1 for participants and value 0 for non-participants. While modelling training, the one complication is to take account of the so-called lock-in effect. This lock-in effect implies that during the training, participants have a lower probability of finding employment. It is only after the training that the chance of finding employment should be improved. Table 4.1 illustrates that if training lasts six months (including waiting time till the training starts), a comparison of the results of participants and non-participants would be extremely negative for the intervention, while positive result of the training could be evident in the longer run.

Table 4.1   **Illustration of the lock-in effect on results of training**

Region	Employed on 1 January	Employed on 1 July	Employed on 31 December
Non-participants	0%	50%	60%
Participants	0%	10%	65%

Source: Ecorys, example prepared for the learning seminar on targeting

If one estimates the impact of training with a binary probability model (found employment, yes or no), it suffices to compare the employment of participants and non-participants in the medium term. If a duration model is estimated, it is important to include both an intervention variable for the chance of employment during the training, and an intervention variable for the chance of employment after the training. If training has various durations, even assuming the average duration for all participants improves the quality of the estimates.

If only one training variable instead of both is used, for example "has attended training", the effect of training tends to be overestimated. It is not intuitive to see why, but the following factors play a role:
- The probability of employment diminishes over time;
- The long period after training contributes more to the fit of the model than the short period of training;
- After the period of training, the probability of participants just starting to look for a job is compared with the already diminished probability of non-participants who started looking for job earlier. Apparently, a high value of one single training variable to predict employment correctly after training, contributes more to the overall fit than a low value to predict employment correctly during training. The solution is, to use two training variables, for during and after training.

4.3   Application in setting targets

To illustrate the use of a Bartik-type result equation, consider an intervention for minority group unemployed school leavers, for which the value "b" of the youth unemployment rate is -2, indicating that for each percentage point of higher youth unemployment rate, the probability of finding a job decreases by 2 percentage points. In the example below, it is estimated that 40% of the participants would find employment in 2014, at a youth unemployment rate of 20%. Furthermore, the youth unemployment rate is forecasted to decrease in the period 2014-2020 as indicated below.

The budget allows for 10,000 participants for the whole programming period, which is 10% of the target group population of 100,000 minority group unemployed school leavers over the period 2014-2020. The number of participants is targeted at 10% of the target group in each year.

All the above data are summarized in Table 4.2 below. The question is how to use the relationship between the success rate and the youth unemployment rate to set result targets for the period 2014-2020?

Table 4.2   Basic data for setting result targets

	2014	2015	2016	2017	2018	2019	2020	Sum
Youth unemployment rate	20%	20%	16%	14%	12%	10%	8%	
% in employment 6 months after leaving	40%							
Number minority group unemployed school leavers	20,000	20,000	16,000	14,000	12,000	10,000	8,000	100,000
N participants	2,000	2,000	1,600	1,400	1,200	1,000	800	10,000
N in employment 6 months after leaving								

The answer is to first add 2% to the success rate for each percentage lower youth unemployment rate, to predict the success rates for 2015-2020. Secondly, these success rates are multiplied with the numbers of participants in the respective years to calculate the number in employment (6 months after leaving) in each year. The sum of the participants in employment 6 months after leaving over all years gives the final result target.

First step: predicting future success rates
The formula to use in this example is:

Success%[t] = success%[2014] – 2*(youth unemployment rate[t] – youth unemployment rate[2014])
Success%[t] = 40% - 2*(youth unemployment rate[t] – 20%).

Table 4.3 shows the results. As before, the shaded cells indicate values that already are provided or have been calculated. For example, the success rate of 2020 is

64% = 40% - 2*(8% - 20%) = 40% + 2 * 12%.

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Table 4.3   **Predicting future success rates with Bartik-type equations**

	2014	2015	2016	2017	2018	2019	2020	Sum
Youth unemployment rate	20%	20%	16%	14%	12%	10%	8%	
% in employment 6 months after leaving	40%	40%	48%	52%	56%	60%	64%	
Number minority group unemployed school leavers	20,000	20,000	16,000	14,000	12,000	10,000	8,000	100,000
N participants	2,000	2,000	1,600	1,400	1,200	1,000	800	10,000
N in employment 6 months after leaving								

Calculating participants in employment per year

In the second step, the predicted success rates are multiplied with the numbers of participants in each year. In the above example, this means multiplying the success rates in the second row with the respective numbers of participants in the fourth row. Table 4.4 shows the results of this calculation in the last row. For example, the number of 512 for 2020 is 64% of the 800 participants of 2020.

Table 4.4   **Predicting participants in employment with Bartik-type equations**

	2014	2015	2016	2017	2018	2019	2020	Sum
Youth unemployment rate	20%	20%	16%	14%	12%	10%	8%	
% in employment 6 months after leaving	40%	40%	48%	52%	56%	60%	64%	
Number minority group unemployed school leavers	20,000	20,000	16,000	14,000	12,000	10,000	8,000	100,000
N participants	2,000	2,000	1,600	1,400	1,200	1,000	800	10,000
N in employment 6 months after leaving	800	800	768	728	672	600	512	

Lastly, the result target for 2014-2020 is the sum of the results of each years, which add up to 4,880 as indicated in Table 4.5: 4,880 = 800 + 800 + … + 512.

Table 4.5   **Setting the result target with Bartik-type equations**

	2014	2015	2016	2017	2018	2019	2020	Sum
Youth unemployment rate	20%	20%	16%	14%	12%	10%	8%	
% in employment 6 months after leaving	40%	40%	48%	52%	56%	60%	64%	
Number minority group unemployed school leavers	20,000	20,000	16,000	14,000	12,000	10,000	8,000	100,000
N participants	2,000	2,000	1,600	1,400	1,200	1,000	800	10,000
N in employment 6 months after leaving	800	800	768	728	672	600	512	4,880

4.4   Normative issues – frontier analysis

To set target results, it helps to use historical data from various projects to assess which results are attainable. With a result equation, success rates can be calculated to adjust for changes in underlying factors that influence the success rates. Another aspect which needs to be judged is whether better results could be achieved in the future, compared to the past.

In this section, we illustrate the issues of assessing attainable results and setting result targets for different situations in the future with the method of frontier analysis, also called data envelopment analysis. First, issues of assessing attainable results are illustrated in the (unlikely) case of many observations in a comparable situation. Then, issues of applying estimates to new situations are illustrated.

Even for comparable target groups, in the same region and the same phase of the business cycle, different projects can achieve different results, for example due to differences in the services provided or the scale of the project. If there is a large group of projects with similar results, the result of those projects could be used as an estimate of attainable results in the future. Figure 4.1 illustrates that with an example where the result is plotted against the output (number of training participants). The majority of the results in this example lie on one line, and the solid line provides an estimate of attainable results.

The solid line connects the best results at given output levels and reflects the "frontier" of attainable results. Projects with poorer results such as bottom left in Figure 4.1 are not taken into account. Single projects with results far above or below the frontier should be considered as "outliers" – unique projects that may be difficult to replicate in the future.[21]

A normative issue – even when comparing projects in "similar" situations (with respect to impact variables such as target group, region, business cycle), is how to treat isolated clusters of projects with very good results – should these determine the target for the future? In Figure 4.1 this situation is illustrated with the dashed line. The dashed lines connects higher result levels (around 4.5) given a number of training participants around 10, ignoring other projects with lower result levels (around 3.2) given the same number of training participants around 10. If the dashed line is applied to target results in the future, the target levels are in fact set higher than for most projects in the past.

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[21]   Stochastic frontier analysis is a method that identifies such "outliers" and leaves them out of the calculations, but this is beyond this background paper.

Whether the dashed or the solid line should be used, is a normative issue, based on judgement. However, the dashed line has the advantage of being based on evidential information and in that sense helps in setting higher targets.

Figure 4.1   Use of frontier analysis as an aide in the decision whether to set higher targets
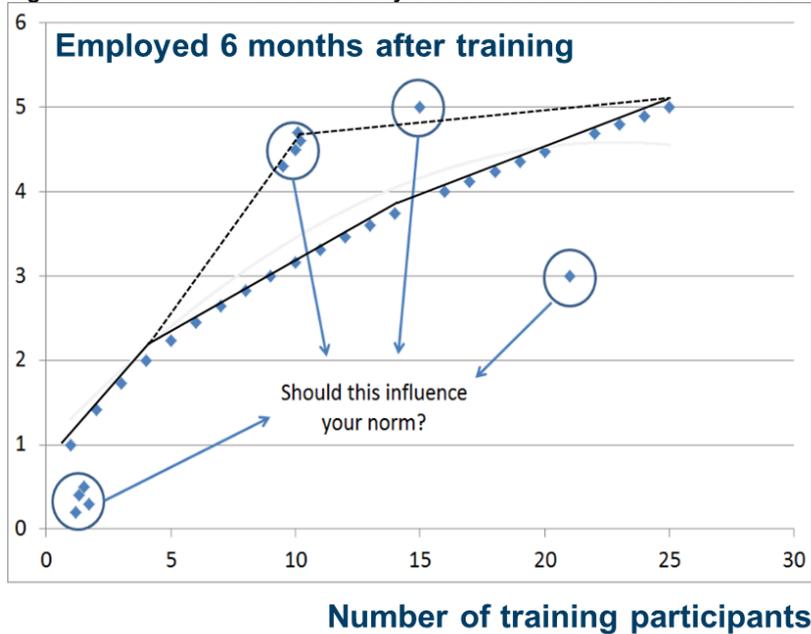
In the above example it was assumed that the situation was comparable for all projects. In reality impact variables such target groups, regions or the phase of the business cycle will have been different between projects. The result equation discussed in the previous section helps to control for differences in impact variables. Figure 4.2 illustrates how the result equation can be used to set targets for new groups (actually, a group with very few observations).

In Figure 4.2, the lower red dashed line connects the three observed results for a new group "y". The results are poorer than for the old group "x" of Figure 4.1, but the reason might be that the new group has a lower likelihood of employment with or without the programme. The result equation can be used to predict the results for the new group "y", by replacing the relevant impact variables with the characteristics of group "y". In the example of Figure 4.2 the predicted result levels for group "y" are below the observed levels for group "x" but above the observed level for group "y".

Again, it is a normative issue based on judgement whether to set higher result targets for the new group based on higher predicted values than the observed results – and again the frontier analysis has the advantage of being based on evidential information (in combination with the result equation).

Figure 4.2   Use of frontier analysis to set targets for a new group "y"
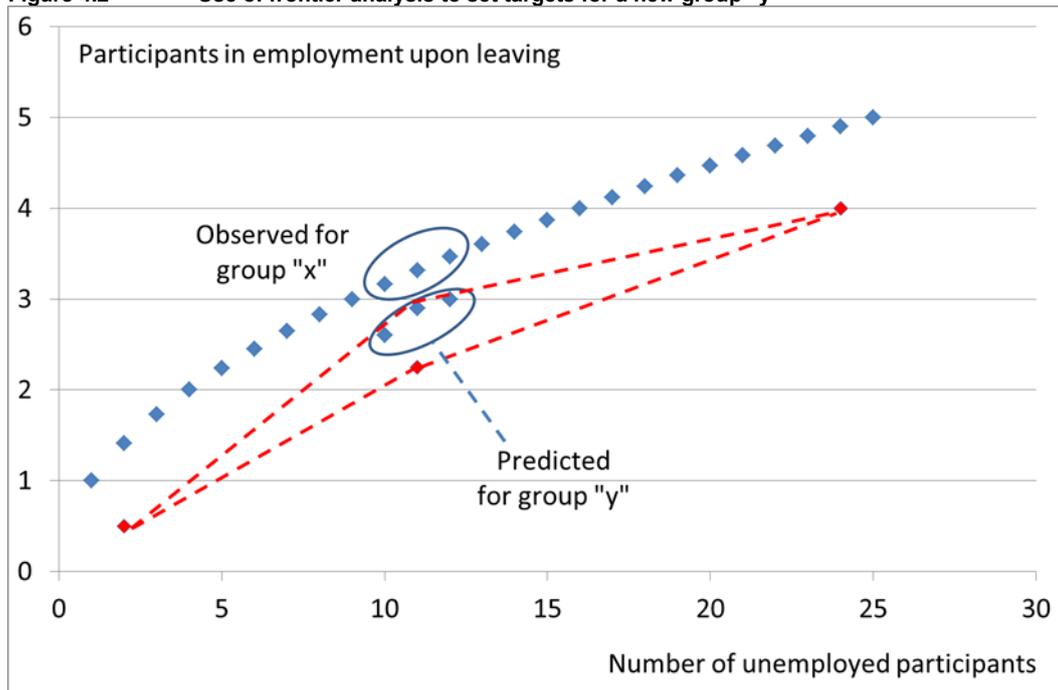
4.5   Setting result targets with limited or no data

In the case there are limited or no data available, one needs to apply practical solutions. In this
section, two practical solutions are discussed:

- One solution assumes that historical results are available for the relevant target group in the
  situation without the programme (the baseline) – although not for the situation with the
  programme;
- The other solution assumes that no historical results are available for the relevant target group
  at all, whether with or without the programme.

Limited availability: historical results for baseline and unit costs but not for the programme
In the first case the result for the target group is known for the situation without intervention, for
example 25% of the older unemployed find employment within one year of becoming unemployed.
Then this "no policy" result can serve as a starting point (first step) for target setting.

In a second step, one estimates what minimum result is needed to justify the cost of the programme
– and this would be the target level. The cost of the programme would be justified if the unit gain is
greater than or at least equal to the unit cost. The unit cost is assumed to be known (see Section
3.6 for the case no data on unit costs are available), for example € 5,000 per participant. To
calculate the minimum result needed to justify the cost, one also needs to assign a value to a unit
result, for example € 50,000 per job-finder.

The requirement that the unit gain is at least the unit cost, can be expressed in a formula:
        [Percentage extra job-finders] * Unit value ≥ Unit cost

Or equivalently:
        Percentage extra job-finders ≥ [Unit cost] / [Unit value].

In the above example, the minimum percentage of extra job-finders to justify the cost of the
programme is therefore 5,000 / 50,000 = 10%.

Lastly, the minimum percentage of extra job-finders is added to the baseline result to set a minimum target percentage, in the above example 25% + 10% = 35%. If the output target would be 10,000 older unemployed participants, then the result target would be 3,500 participants in employment upon leaving in this example

No historical results available at all, nor unit costs

The previous method uses unit costs. If unit costs are missing, as well as historical results, only "rules of the thumb" remain. A rule of the thumb from the author of this background paper is:

- 75% of the new unemployed find a job the first year;
- 25% of the long-term unemployed (≥ 1 year) find a job after their first year.

The above rule of the thumb is based on long experience with Dutch unemployment data and international meta-studies. However the author has no such rule of the thumb for other target groups, except for his home country. This is because a reasonable target percentage for other groups depends on national institutional settings including for example:

- Wage cost of older workers;
- Equal pay enforcement for minorities;
- …

As an alternative for other target groups besides the long-term unemployed, the unemployment distribution of the target group can be combined with the above "rule of the thumb" percentage for short-term and long-term unemployed. For example if 20% of the older unemployed is short-term unemployed and 80% is long-term unemployed, then:

- The 75% of the target percentage for short-term unemployed is weighted by 20%.
- The 25% of the target percentage for long-term unemployed is weighted by 80%.

As a result, the target percentage for the whole group of unemployed older workers is in this example: target% = 20% * 75%   +   80% * 25%   =   35%. As in the previous example, if the output target is 10,000 older unemployed participants, then the result target would be 3,500 participants in employment upon leaving.

Table 4.6   **Application of rule of the thumb to a new target group.**

	Short-term	Long-term	Total
Distribution	20%	80%	100%
Result %	75%	25%	35%

5 Methodologies for adjusting targets

5.1 Introduction

This chapter briefly discusses methodologies for adjusting output targets and result targets. When outputs are adjusted by reallocating a given year budget between different target groups, one can simply adjust the output targets to the most recent developments, in a similar way as the trend extrapolation discussed in Section 3.2. Only when budgets are reallocated between years according to the situation of the labour market, a methodology needs to be developed in advance.

For adjusting result targets, the micro-model of Bartik described in Section 4.2 can be used again, but then focusing on the variables capturing the impact of external factors on the results.

5.2 Adjusting output targets

To reallocate budgets between years, according to the needs and the size of the target group population, a model needs to be developed that predicts the target group population. Similar to the unit cost and wage equations discussed in previous chapters, a target group equation can be formulated to relate the target group population to external factors.

While the author has advised against estimating a macro-economic model for results with annual data, it is quite different for estimating the size of target groups based on monthly data. Estimating such a relationship with macro-economic data quickly involves time series aspects.

Macro-economic time series models
- Advantages:
  - The required data are usually available, for example from national accounts and PES data;
  - The model is very suitable for predicting developments over time;
  - The model can be flexibly specified.
- Disadvantages:
  - The limited number of observations allows inclusion of only a limited number of explanatory variables (relevant factors);
  - Time series estimations come with a number of pitfalls (which are discussed below);
  - Basic software such as the Excel add-in is not sufficient to estimate these models.
- Needed:
  - Econometric expertise;
  - Statistical software such as Stata, Eviews, TSP, Gauss.

A set of equations for the size of target group (say, the unemployed in group "i") in month "m" can be formulated as follows:

$$Unemployed[i, m] = Share[i, m] \times Unemployed[m]$$
$$\Delta Unemployed[m] = a_0 + a_1 \times \Delta GDP[q] + a_2 \times \Delta Unemployed[m - 1] + N(0, \sigma_a^2)$$
$$\Delta Share[i, m] = b_0 + b_1 \times \Delta Unemployed[m] + N(0, \sigma_b^2)$$

Here, the symbol Δ represents a change compared to the previous period, the values a_0, a_1, a_2, b_0 and b_1 are coefficients to be estimated by running a regression, and $N(0,\sigma^2)$ indicates Normally distributed white noise with variance σ^2.

For the number of unemployed, monthly data is typically available. For GDP, typically quarterly data is available. To predict the development of a target group population, the above set of equations needs to be estimated, and the development of GDP needs to be predicted.

The second equation of the above set is a time series equation, because the development of total unemployment is partly related to the development of total unemployment in the previous month, which in econometrics is called a "lagged" variable.

The main pitfalls of time series equations are in general:

- A correlation does not indicate causality;
- The "unit root" problem: the coefficient of the "lagged" variable is roughly 1;
- Autocorrelation: the prediction error of one month is correlated with the prediction error of the previous month;
- Multi-collinearity: the estimated values of external variables are mutually correlated;
- End-point bias.

These problems and the solutions are briefly discussed below.

Correlation versus causality

In the second equation, the value a_2 does not imply that a given change of GDP *causes* unemployment to change by a_2 times the GDP change. The causality might equally well be the other way round: if there are more unemployed, employment is lower, and fewer employed produce lower output (GDP). The idea behind using predictions of GDP to predict the development of unemployment is that perhaps GDP is easier to predict based on the demand of consumers, imports, exports, and investments. The impact of all these factors on unemployment is implicit through their impact on GDP, if GDP and unemployment are strongly correlated. In fact, the target group equation can be used to predict unemployment regardless of the actual causality. The causality is more of a concern when predicting the results of an intervention, because then naturally the causal relation from the intervention to the result is of primary interest.

Unit root and autocorrelation

The practical problem of a unit root is that in that case the last observation is the best predictor. The standard assumption of independent prediction errors is not applicable in the case of a unit root, and even the standard assumption of normally distributed prediction errors is no longer applicable.

The practical problem of autocorrelation is that the prediction error of the last observation carries over to the prediction for the subsequent period; autocorrelation is a milder version of the unit root problem.

For both problems, the solution is to formulate an equation for the change of the variable that is to be explained, instead of the variable to be explained itself (on the left-hand side of the equation). In the above set of equations, the equation is already formulated for the change of unemployment, exactly to solve the potential unit root and autocorrelation problems.

Multi-collinearity

The practical problem with multi-collinearity is that a strong mutual correlation between explanatory variables (on the right-hand side of the equation) causes the weights a_1, a_2, … to be extremely large. While this may result in a perfect fit of the past observations, it also is likely to result in extremely large (and implausible) predictions. The solution to this problem is to use fewer explanatory variables. The above set of equations already has few explanatory variables.

Multi-collinearity can be identified through the correlation matrix of the estimates of a_1, a_2, …, but practically speaking, one can already conclude multi-collinearity if the estimates are extremely large.

Endpoint bias

The endpoint bias refers to the fact that in a single time series, the first and the last values have a disproportionate weight in the estimated of time series coefficients. To illustrate the endpoint bias, Figure 5.1 shows a series with two extreme values, at the 25th in the middle of the time series and the 50th data point at the end of the time series. If a linear line is estimated based on all 50 data points, then the estimated 51st data point would be 7.6 instead of 8.1 if both extreme values were ignored, an error of 6%. If the 50th data point would be ignored but the extreme value in the middle of the time series is included in the estimation, then the estimated 51st data point would be 8.0, an error of only 1% compared to 8.1.

To correct for the endpoint bias, one judges by sight and leaves out the first or the last observation if necessary. In statistical software, the so-called Hodrick-Prescott filter automatically corrects for an endpoint bias. Correcting for the endpoint bias can be important in short time series. However if the time series is jointly estimated for a large number of regions, it is unlikely that the endpoint bias is the same in all regions, and the issue of the endpoint bias can be ignored.

Figure 5.1   Illustration of the endpoint bias
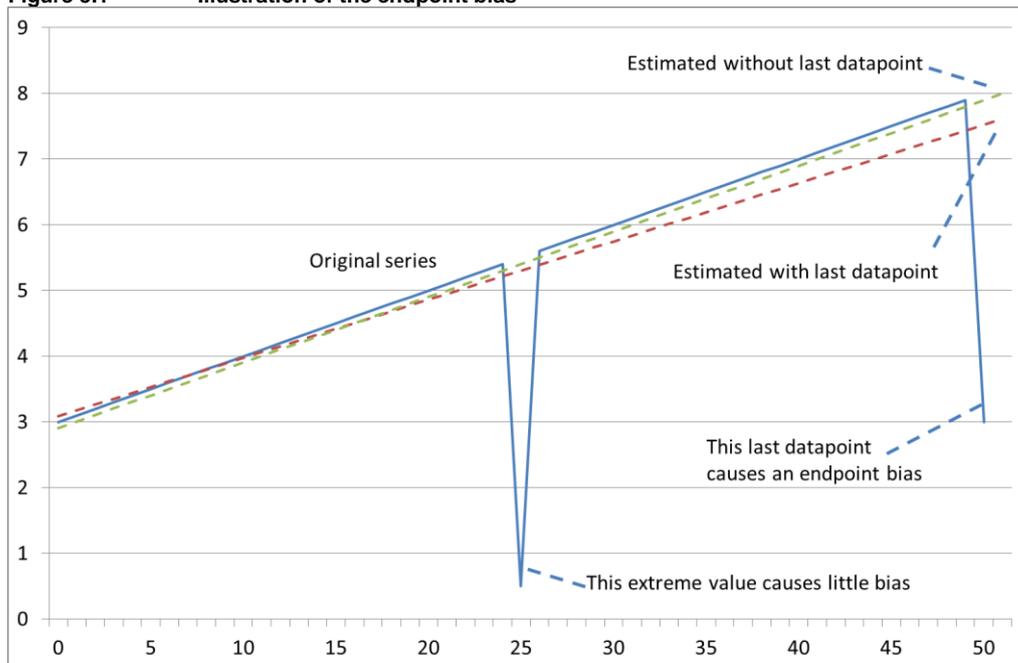
5.3 Application of time series models in setting output targets

Examples of estimating macroeconomic time series models are not provided as this paper is about target setting. However, the example below illustrates how the results of a macroeconomic time series can be used in setting output targets.

Suppose that the following equations have been estimated:

$$\Delta Unemployed[m] = -0.5 \times \Delta GDP[q] + 0.3 \times \Delta Unemployed[m-1]$$
$$\Delta Share[high, m] = 0.5 \times \Delta Unemployed[m]$$
$$\Delta Share[medium, m] = 0$$
$$\Delta Share[low, m] = -0.5 \times \Delta Unemployed[m]$$

Unemployment tends to decrease if the economy (GDP) grows and its estimated coefficient of -0.5 reflects this. But unemployment also has its own dynamics, perhaps because it takes time to find a new job. The estimate of 0.3 for the effect of a change in the number of unemployed in the previous month reflects this. The unemployment rate tends to decrease with educational level, but also tends to be more sensitive to the business cycle as reflected by the coefficient of +0.5 in the second equation. Among the low educated unemployed a relatively large core may exist that remains unemployed throughout the business cycle, "stabilizing" the unemployment rate among this group at a relatively high minimum level. Thus if the share of high educated unemployed increases, the share of low educated unemployed decreases. The coefficient for medium educated unemployed may be insignificant and is set at 0 in this example, implying that the share of medium educated unemployed is constant.

Table 5.1 provides the base data for setting output targets using the above set of equations. The four quarterly GDP growth rates for 2014 add up to 1.15%, a "realistic" GDP growth for 2014 as a whole. The initial unemployment forecast for January 2014 is also provided.

Table 5.1   Base data for setting output targets with macroeconomic time series data

	2014											
	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12
Δgdp	0.25%	0.25%	0.25%	0.50%	0.50%	0.50%	0.30%	0.30%	0.30%	0.10%	0.10%	0.10%
Δu	-1.00%											
%[high]	10%											
%[medium]	50%											
%[low]	40%											
Unemployed	100,000											
… High	10,000											
… Medium	50,000											
… Low	40,000											

To apply the above model, first the change in the number of unemployed needs to be forecasted, based on the change in the preceding month and the quarterly GDP growth. For example for February 2014 this gives:

Δu[February 2014]   = -0.5* Δgdp[First quarter 2014] + 0.3* Δu[January 2014]
                                       = -0.5*0.25% + 0.3*(-1%) = -0.43%.

Δu[March 2014]   = -0.5* Δgdp[First quarter 2014] + 0.3* Δu[February 2014]
                                       = -0.5*0.25% + 0.3*(-0.43%) = -0.25%.

The number of unemployed in February 2014 is therefore the 100,000 of January minus the predicted 0.43% decline or equivalently 99,575 persons. The number of unemployed in March 2014 is the 99,575 of February minus the predicted 0.25% decline or equivalently 99,324 persons. Continuing in this way for the other months of 2014 gives the result in Table 5.2 below.

Table 5.2   Base data for setting output targets with predicted changes in unemployment rates

	2014											
	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12
Δgdp	0.25%	0.25%	0.25%	0.50%	0.50%	0.50%	0.30%	0.30%	0.30%	0.10%	0.10%	0.10%
Δu	-1.00%	-0.43%	-0.25%	-0.33%	-0.35%	-0.35%	-0.26%	-0.23%	-0.22%	-0.12%	-0.08%	-0.08%
%[high]	10%											
%[medium]	50%											
%[low]	40%											
Unemployed	100,000	99,575	99,324	99,000	98,656	98,306	98,054	97,832	97,618	97,506	97,423	97,350
… High	10,000											
… Medium	50,000											
… Low	40,000											

The forecasts of Δu in Table 5.2 are in turn used to forecast the shares of high, medium and low educated unemployed. For February 2014, the predicted change in the share of high educated unemployed is:

Dshare[high] = +0.5* -0.43% = -0.21%

This results in a share of high educated unemployed of 10% - 0.21% = 9.79% (in Table 5.3 the rounded figure 9.8% is shown), and applying this percentage to the total number of unemployed in February 2014 (which is 99,575) gives 9,746 high educated unemployed. Continuing in this way for the other educational levels and the other months of 2014 gives the table below.

Table 5.3   Base data for setting targets broken down by educational level

	2014											
	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12
Δgdp	0.25%	0.25%	0.25%	0.50%	0.50%	0.50%	0.30%	0.30%	0.30%	0.10%	0.10%	0.10%
Δu	-1.00%	-0.43%	-0.25%	-0.33%	-0.35%	-0.35%	-0.26%	-0.23%	-0.22%	-0.12%	-0.08%	-0.08%
%[high]	10%	9.8%	9.7%	9.5%	9.3%	9.1%	9.0%	8.9%	8.8%	8.7%	8.7%	8.7%
%[medium]	50%	50%	50%	50%	50%	50%	50%	50%	50%	50%	50%	50%
%[low]	40%	40.2%	40.3%	40.5%	40.7%	40.9%	41.0%	41.1%	41.2%	41.3%	41.3%	41.3%
Unemployed	100,000	99,575	99,324	99,000	98,656	98,306	98,054	97,832	97,618	97,506	97,423	97,350
… High	10,000	9,746	9,596	9,403	9,199	8,992	8,844	8,713	8,587	8,521	8,473	8,430
… Medium	50,000	49,788	49,662	49,500	49,328	49,153	49,027	48,916	48,809	48,753	48,712	48,675
… Low	40,000	40,042	40,066	40,097	40,129	40,161	40,183	40,203	40,222	40,232	40,239	40,245

The average numbers of unemployed in 2014 can then be used to set output targets for the subgroups of unemployed, for example assume:
- a total budget is available for 10,000 participants,
- costs per participant are equal for all groups and
- subgroups are targeted proportionally to the population.

Table 5.4 gives the results. In the second column, the average numbers of unemployed are calculated by averaging the numbers of January up to December. In the third column, the shares of high, medium and low unemployed are calculated from the second column. In the fourth and last

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column, the number of participants is targeted by applying the shares to the total number of participants for which budget is available.

Table 5.4   Initial target setting

Educational level	Average number	Share	Participants (=output target)
High	9,042	9.2%	919
Medium	49,194	50.0%	5,000
Low	40,152	40.8%	4,081
Total	98,387	100%	10,000

Now suppose that in June, the forecasts for the second half have been adjusted significantly downward. The new situation is then given as in Table 5.5.

Table 5.5   Base data for <u>adjusting</u> output targets with macroeconomic time series data

	2014											
	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12
Δgdp	0.25%	0.25%	0.25%	0.50%	0.50%	0.50%	-0.70%	-0.70%	-0.70%	-0.90%	-0.90%	-0.90%
Δu	-1.00%	-0.43%	-0.25%	-0.33%	-0.35%	-0.35%						
%[high]	10%	9.8%	9.7%	9.5%	9.3%	9.1%						
%[medium]	50%	50%	50%	50%	50%	50%						
%[low]	40%	40.2%	40.3%	40.5%	40.7%	40.9%						
Unemployed	100,000	99,575	99,324	99,000	98,656	98,306						
… High	10,000	9,746	9,596	9,403	9,199	8,992						
… Medium	50,000	49,788	49,662	49,500	49,328	49,153						
… Low	40,000	40,042	40,066	40,097	40,129	40,161						

Repeating the same calculations as for Table 5.2 and Table 5.3 results in Table 5.6 where due to the downward adjusted GDP forecasts, the unemployment level and the share of high educated unemployed people increase.

Table 5.6   Data for adjusting targets with unemployment forecasts and educational breakdown

	2014											
	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12
Δgdp	0.25%	0.25%	0.25%	0.50%	0.50%	0.50%	-0.70%	-0.70%	-0.70%	-0.90%	-0.90%	-0.90%
Δu	-1.00%	-0.43%	-0.25%	-0.33%	-0.35%	-0.35%	0.25%	0.42%	0.48%	0.59%	0.63%	0.64%
%[high]	10%	9.8%	9.7%	9.5%	9.3%	9.1%	9.3%	9.5%	9.7%	10.0%	10.3%	10.6%
%[medium]	50%	50%	50%	50%	50%	50%	50.0%	50.0%	50.0%	50.0%	50.0%	50.0%
%[low]	40%	40.2%	40.3%	40.5%	40.7%	40.9%	40.7%	40.5%	40.3%	40.0%	39.7%	39.4%
Unemployed	100,000	99,575	99,324	99,000	98,656	98,306	98,547	98,964	99,436	100,026	100,654	101,297
… High	10,000	9,746	9,596	9,403	9,199	8,992	9,133	9,381	9,663	10,017	10,396	10,786
… Medium	50,000	49,788	49,662	49,500	49,328	49,153	49,273	49,482	49,718	50,013	50,327	50,648
… Low	40,000	40,042	40,066	40,097	40,129	40,161	40,141	40,101	40,055	39,996	39,931	39,863

Suppose that in the first 6 months 5,000 unemployed have participated in the intervention, of which 460 were high educated; 2,500 were medium educated and 2,040 were low educated. Then the

analysis for M7-M12 in the new situation can be repeated as was done above for M1-M12 in the old situation. This gives the result of Table 5.7.

In June 2014, the participants of the first six months of 2014 are given. The remaining 5,000 participants for which budget is left for the second half of 2014, are allocated proportionally to the new forecasts of the unemployed in the second half of 2014. Lastly, the adjusted target for the whole of 2014 is the sum of the participants who already have entered the programme in the first half of 2014, plus the adjusted target for the remainder of 2014.

Table 5.7   Adjusted targets based on new mid-2014 GDP forecasts

M1-M6		M7-M12			M1-M12
	Participants	Unemployed	Shares	Participants	Adjusted target
High	460	9,896	9.9%	496	956
Medium	2,500	49,910	50.0%	2,500	5,000
Low	2,040	40,015	40.1%	2,004	4,044
Total	5,000	99,821	100%	5,000	10,000

Comparing the targets of Table 5.4 and Table 5.7 shows that in this case, the adjustment of output targets would be small. In the course of years instead of months, adjustments may be larger, but the underlying calculations are the same as illustrated above.

5.4 Adjusting result targets

To adjust result targets, the same model as the Bartik model of Section 4.2 can be used, but now the values of the macroeconomic variables are used to adjust result targets. Table 5.8 illustrates the adjustment of a result target (the percentage of unemployed participants finding employment within 6 months after leaving) to the business cycle.[22] In this example, the chance to find employment is estimated to decrease by 1.1 percentage point for every per cent point of unemployment rate. In this example, every per cent point of unemployed corresponds to 20,000 persons. Over the period 2014-2020 the implied numbers of unemployed in Table 5.8 add up to 1 million. If the ESF budget covers 200,000 participants over this seven-year period, per year one fifth of the unemployed can be covered by the ESF Operational Programme. For 2014, this means the output would be targeted at 32,000 participants (one fifth of the population of 160,000 unemployed).

Table 5.8   Illustration of adjusting result targets

	2014	2015	2016	2017	2018	2019	2020	Sum
Unemployment rate	8%	10%	9%	8%	6%	5%	4%	
Share of job finders	76.7%	74.5%	75.6%	76.7%	78.9%	80.0%	81.1%	
Number of unemployed	160,000	200,000	180,000	160,000	120,000	100,000	80,000	1,000,000
Number of participants	32,000	40,000	36,000	32,000	24,000	20,000	16,000	200,000
Targeted job-finders	24,544	29,800	27,216	24,544	18,936	16,000	12,976	154,016

The question is, how to adjust the result targets if the chance to find employment decreases by 1.1 percentage point for every per cent point of unemployment rate? One first needs to set a target norm, for example at a 5% unemployment rate, 80% of the unemployed participants should find a

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[22]   This example is slightly modified from Ecorys (2011), Performance targets for ESF Operational Programmes.
        http://www.coprbm.eu/?q=node/494

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job within a six months after leaving an ESF-supported project. If that is the norm, then the adjusted share of job-finders for higher and lower unemployment rates can be calculated as follows:

$$Share\ jobfinders[t] = 80\% + (5\% - unemployment\ rate) * 1.1$$

For example for 2020 the predicted unemployment rate is 4% and the above formula gives a share of job-finders of 81.1% and in 2018 the predicted unemployment rate is 6% and the above formula gives a share of job-finders of 78.9%.

Once the share of job-finders is calculated, the result target is easy to calculate:

$$Number\ jobfinders = Number\ participants \times share\ of\ jobfinders$$

In 2019, this formula gives that 80% of the 20,000 participants should find a job, or equivalently 16,000 persons. Repeating this for each year and taking the sum over the period 2014-2020 finally gives the result target of 154,016 participants who should find a job, which is naturally rounded to 154,000. Of course, since the ESF programming period ends in 2020 and the result target is that the unemployed find a job within a year, the result target actually applies for the period 2014-2021, since the last unemployed of 2020 that find a job, will likely find that job in 2021.

A   List of common indicators

In this annex a list of common indicators is presented. The list of common indicators can be found in the annex to the draft ESF regulation.[23] Further definitions can be found in the 2013 draft ESF monitoring and evaluation guidance.[24]

(1) Common output indicators on participants
Participants refer to persons benefiting directly from an ESF investment and who can be identified and asked for their characteristics, and for whom specific expenditure is earmarked. Other beneficiaries should not be counted as participants.
- unemployed, including long-term unemployed
- long-term unemployed
- inactive
- inactive, not in education or training
- employed, including self-employed
- below 25 years
- above 54 years
- with primary (ISCED 1) or lower secondary education (ISCED 2)
- with upper secondary (ISCED 3) or post-secondary education (ISCED 4)
- with tertiary education (ISCED 5 to 8)
- migrants, people with a foreign background, minorities (including marginalised communities such as the Roma)
- disabled
- other disadvantaged

The total number of participants is calculated automatically on the basis of the output indicators. These data on participants entering an ESF supported operation are to be provided in the annual implementation reports. All data are to be broken down by gender.

(2) Common output indicators for entities
- number of projects fully or partially implemented by social partners or non-governmental
- organisations
- number of projects targeting public administrations or public services
- number of micro, small and medium-sized enterprises supported

These data are to be provided in the annual implementation reports.

(3) Common immediate result indicators on participants
- inactive participants newly engaged in job searching upon leaving
- participants in education/training upon leaving
- participants gaining a qualification upon leaving
- participants in employment upon leaving

These data are to be provided in the annual implementation reports. All data are to be broken down by gender.

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[23] http://ec.europa.eu/regional_policy/sources/docoffic/official/regulation/pdf/2014/proposals/regulation/esf/esf_proposal_en.pdf

[24] European Commission, Programming Period 2014-2020, Monitoring and Evaluation of European Cohesion Policy, European Social Fund, Draft Guidance document, 9 January 2013, http://ec.europa.eu/social/main.jsp?catId=701&langId=en

(4) Common longer-term result indicators on participants

- participants in employment 6 months after leaving
- participants in self-employment 6 months after leaving
- participants with an improved labour market situation 6 months after leaving

These data are to be provided in the annual implementation reports. They are to be collected based on a representative sample of participants within each priority axis. Internal validity of the sample should be ensured in such a way that the data can be generalised at the level of priority axis. All data are to be broken down by gender.

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B   Target optimization with Excel

In Microsoft Excel, a standard built-in add-in can be of great help in optimizing the result targets subject to economic (and perhaps political) constraints. This annex illustrates how to install this add-in in Excel 2010 and how to use it for the first exercise. This add-in is called Solver and solves linear programming problems. This is very useful for maximizing result targets under budget, capacity and minimum investment constraints, because budgeting is essentially a linear programming problem.

The Excel add-in can be found behind "Options" under the tab "File", as shown in the screen-print below.
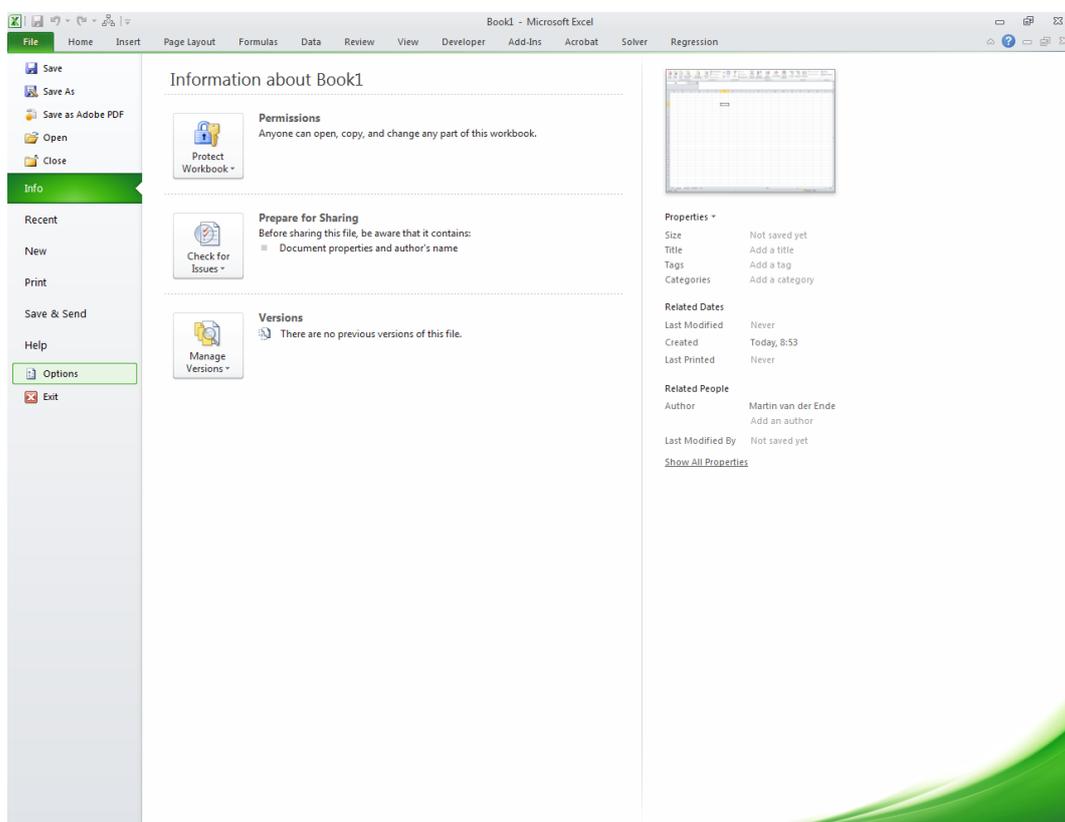
In the Excel Options screen, go to the option "Add-Ins". Another screen will then pop up as illustrated below. In this popup-screen, choose "Solver Add-in" and then click on "Go…" at the bottom, and then OK.
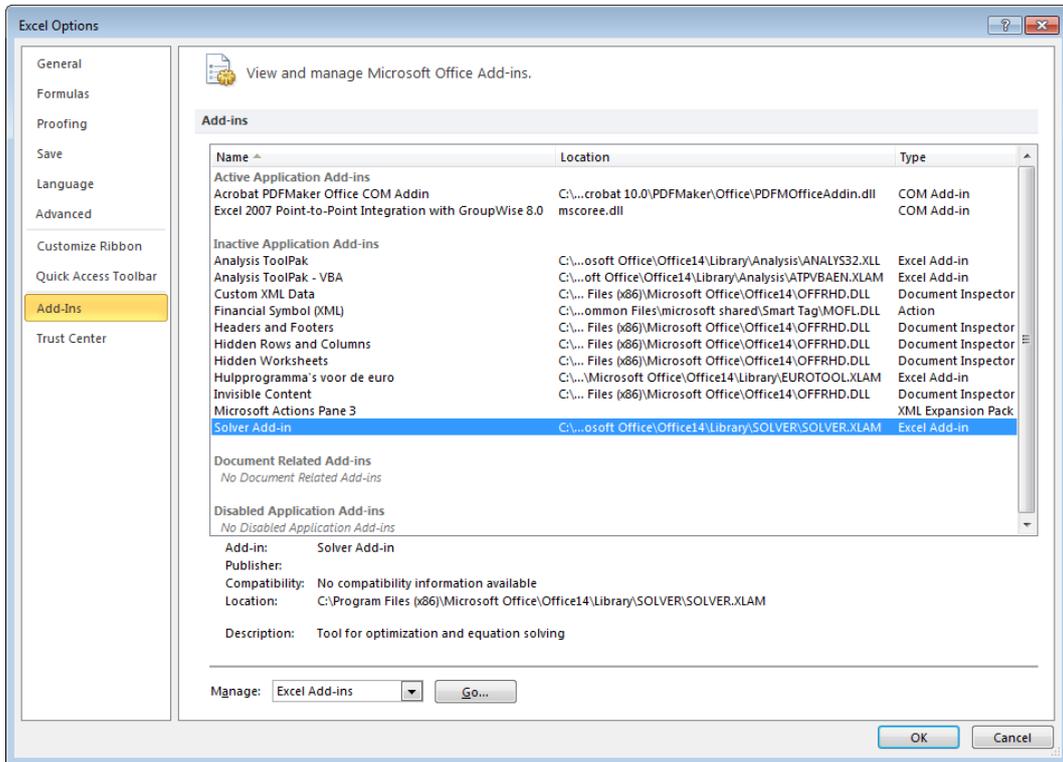
Finally, under the tab "Data" the Solver add-in is now available.

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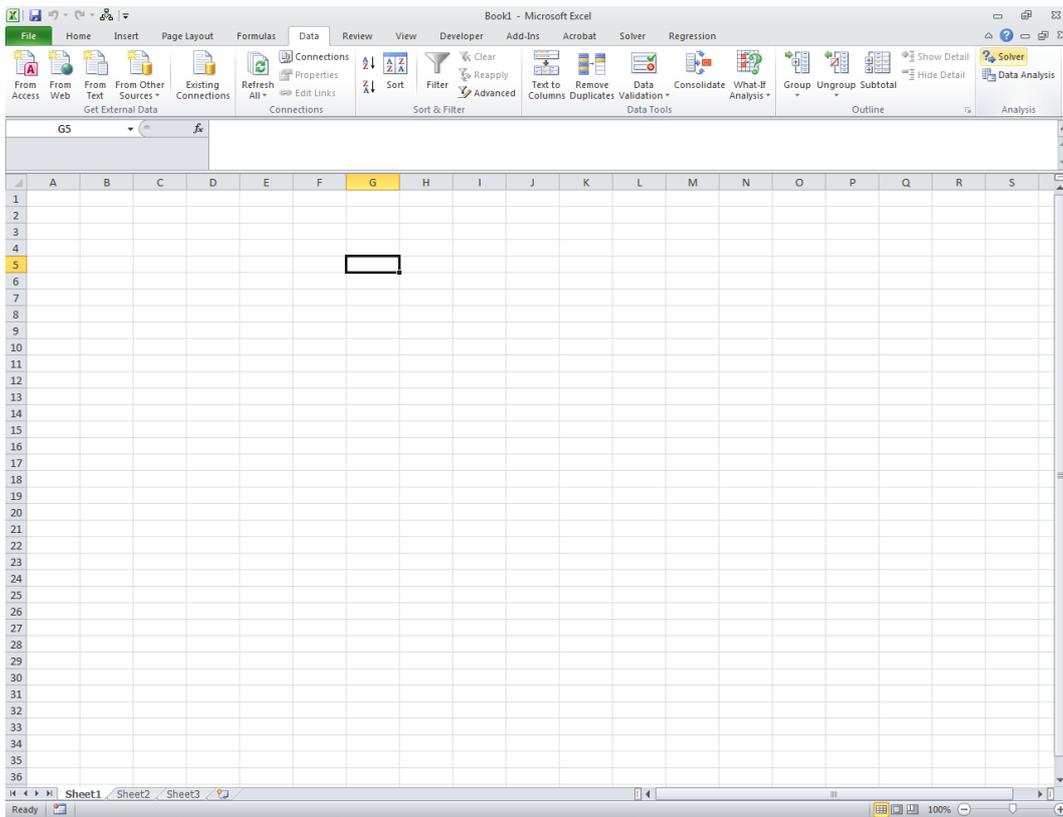
To use the Solver add-in, the unit costs, maximum budget and other constraints need to be specified, as well as the contribution of each alternative to the target. For Exercise 1, the screen print below shows how this information can be prepared. Besides the policy alternatives (counselling, mobility scheme, re-training in this example), the contribution of the no-policy alternative to the result needs to be specified (50% of the non-participants are in employment in this example). The cells for the numbers of participants are left blank for the moment, these will be filled by the Solver add-in in such a way that the result (persons in employment) is maximized.

The budget constraint states that the sum of participants weighted with their unit costs must be less than 10m euro in the example of exercise 1:

1,000 * (counselling) + 4,000 * (mobility scheme) + 16,000 * (re-training) ≤ 10,000,000.

As well as the unit costs for the alternative, the zero unit costs for nonparticipants need to be filled in.

The capacity constraint for counselling is that one times the number of participants in the counselling alternative must be less than 5,000, and so on for the other alternatives. Finally, it needs to be specified that the numbers of participants and non-participants add up to the total, 10,000 in the example of exercise 1:

1*(nonparticipants) + 1*(counselling) + 1*(mobility scheme) + 1*(re-training) = 10,000.

After the ground work is done, the result needs to be specified. The number of persons in employment is:

50%*(nonparticipants) + 55%*(counselling) + 60%*(mobility scheme) + 90%*(re-training).

This formula needs to be filled in in cell B6 in the sheet of the screen print below, where the cells B3:E3 refer to the expected result per participant, and the cells B4:E4 to the numbers of participants that will be solved by the add-in.

	A	B	C	D	E	F	G
1		Alternatives					
2		Nonparticipants	Counselling	Mobility scheme	Re-training		
3	Result%	50%	55%	60%	90%		
4	Participants						
5							
6	Persons in employment	+sumproduct(B3:E3;B$4:E$4)					
7							
8		Nonparticipants	Counselling	Mobility scheme	Re-training		Limits
9	Budget constraint	0	1,000	4,000	16,000	<=	10,000,000
10	Counselling capacity	0	1	0	0	<=	5,000
11	Mobility scheme capacity	0	0	1	0	<=	10,000
12	Re-training capacity	0	0	0	1	<=	500
13	Count restriction	1	1	1	1	=	10,000
14							
15		Lefthand side formulas	Righthand side limits				
16	Budget constraint		10,000,000				
17	Counselling capacity		5,000				
18	Mobility scheme capacity		10,000				
19	Re-training capacity		500				
20	Count restriction		10,000				
21							
22							

The formula for the budget constraint needs to be filled in in cell B16 in the sheet of the screen print below. Here, the cells B9:E9 refer to the unit costs and the cells B4:E4 to the numbers of participants.

The same is done for the capacity restraint of counselling as in the screen print below. Here, cell B10:E10 refer to the specification that the capacity limit applies to the numbers of participants in counselling (value 1) and not to the other alternatives (value 0).

After filling the similar formulas for the capacity constraints of the mobility scheme and re-training in cells B18 and B19, the formula for the count restriction is filled in in cell B20 in the screen-print below.

In cells C16:C20 the right hand side values of cells G9:G13 are copied, but this is purely cosmetic. After all the formulas have been specified as above, the Solver add-in can be applied to find the numbers of participants that maximize the result of persons in employment. For this, one needs to go to the tab "Data" and then click on the "Solver" add in at the top right side of the screen, as illustrated in the screen below.

In the pop-up screen of the Solver add-in, the user can specify which cells contain the required information:

- Set objective: cell B6 for the formulas for the result target (persons in employment);
- Indicate that the result target needs to be maximized (choose option "Max");
- By changing variable cells: B4:E4 (numbers of participants).
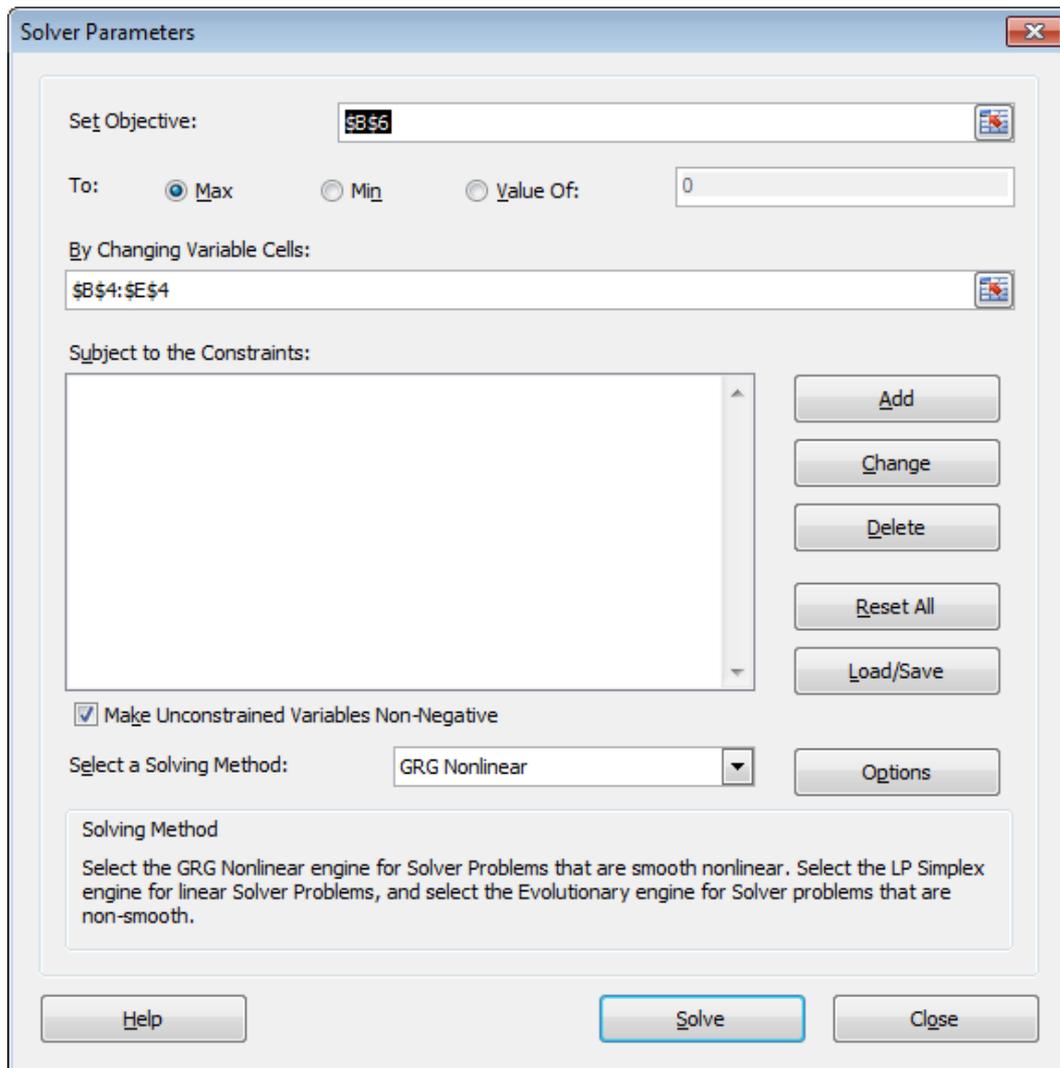
To add a constraint, one needs to open another popup screen by clicking on the "Add" button. The budget and capacity constraints are all subject to maximum limits and can be grouped together as illustrated in the pop-up below. Reference needs to be made to the cells with the formulas (B16:B20), not the cells with the numbers that are used in the formulas (B9:E12).
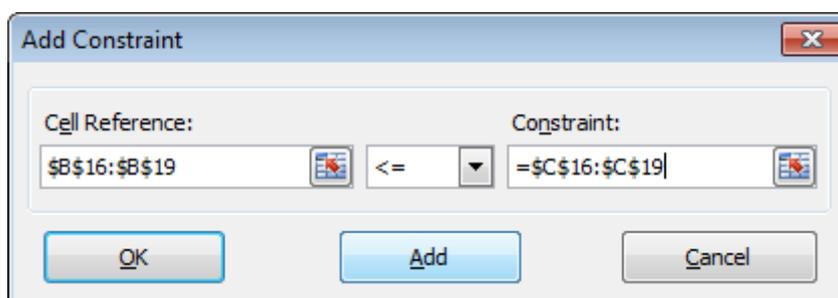
The count restriction is an equality and this constraint needs to be added as well.

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After specifying the constraints, the "Add Constraint" window can be exited by clicking on "Cancel".

The Solver window then should look as illustrated below.
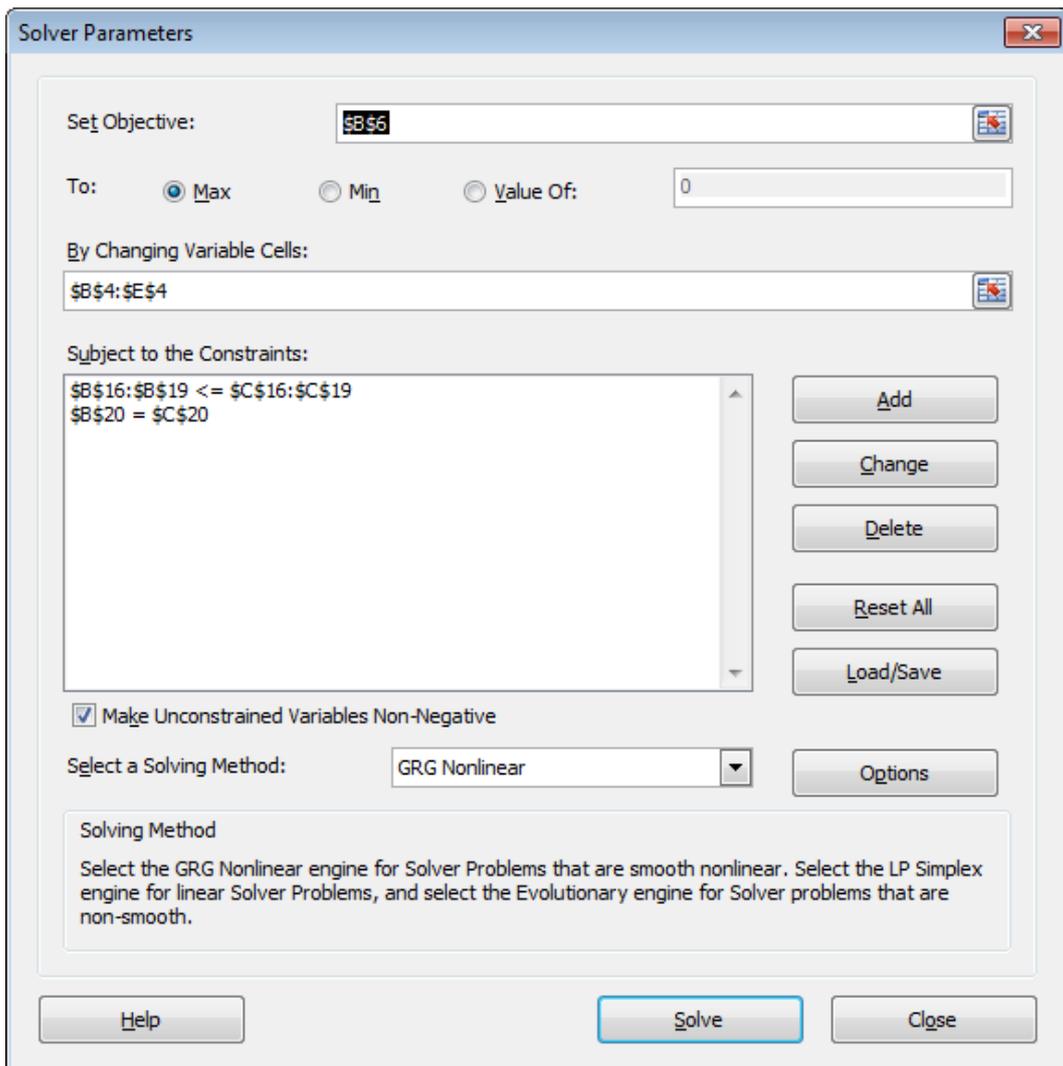
Lastly, a Solving Method needs to be specified; in this case the Simplex Linear Programming method is most appropriate, because the number of persons in employment is a linear function of the numbers of participants.
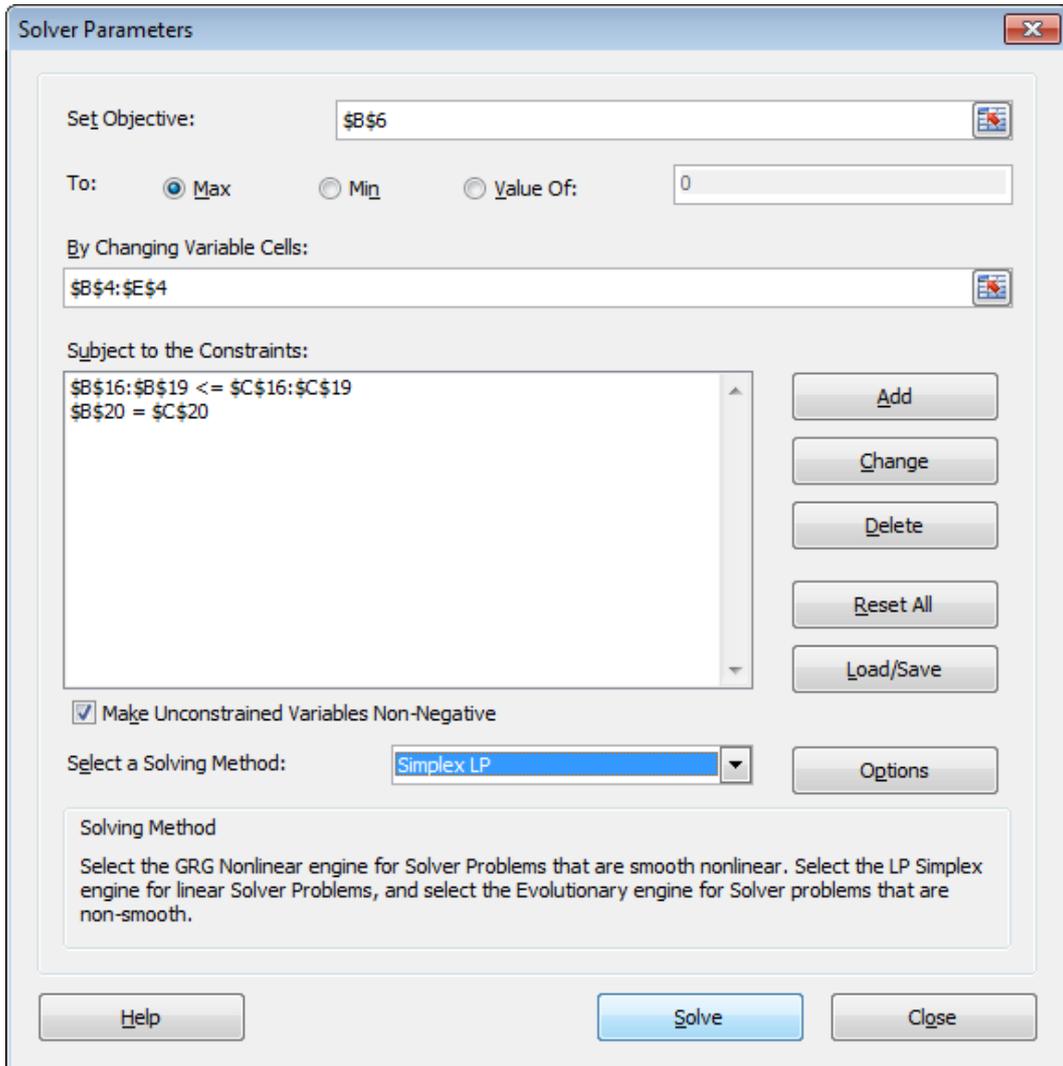
Clicking on the "Solve" button makes the Solver add-in calculate the numbers of participants (=output target) and the numbers of persons in employment (= result target).

After clicking on "Solve", a message should pop up to indicate that a solution is found which satisfies all the constraints and one can exit this message by clicking on "OK".

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The results should look as in the screen print below.

According to the linear programming solver, it is optimal to target 5,000 participants in counselling (exhausting the capacity constraint for counselling) and 313 participants in re-training. Together with the 50% of nonparticipants in training who are in employment, this results in 5,375 persons in employment.

The solver identifies the optimal allocation of participants, but still one final check is needed: is benefit per additional job-finder sufficient to justify the cost per additional participant? Without any intervention, 50% of all 10,000 persons threatened with job loss would have found a job in this example, resulting in 5,000. Hence the additional number of job-finders attributable to the mix of alternatives in this example is (5,375 – 5,000) = 375 persons.

The cost per additional job-finders is therefore the budget of 10m euro divided by 375, which is € 26,667. In this exercise, each additional job-finder is valued at € 50,000, which justifies the cost of € 26,667.

Finally, the output target is calculated as the sum of participants over all alternatives, namely:
- Output target = 5,000 + 313 = 5,313.

The result target is calculated as the sum of participants weighted with the result% per participant:
- Result target = 5,000*55% + 313*90% = 3,032.

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