Causality Problems

Dead weight, net effects and the counterfactual

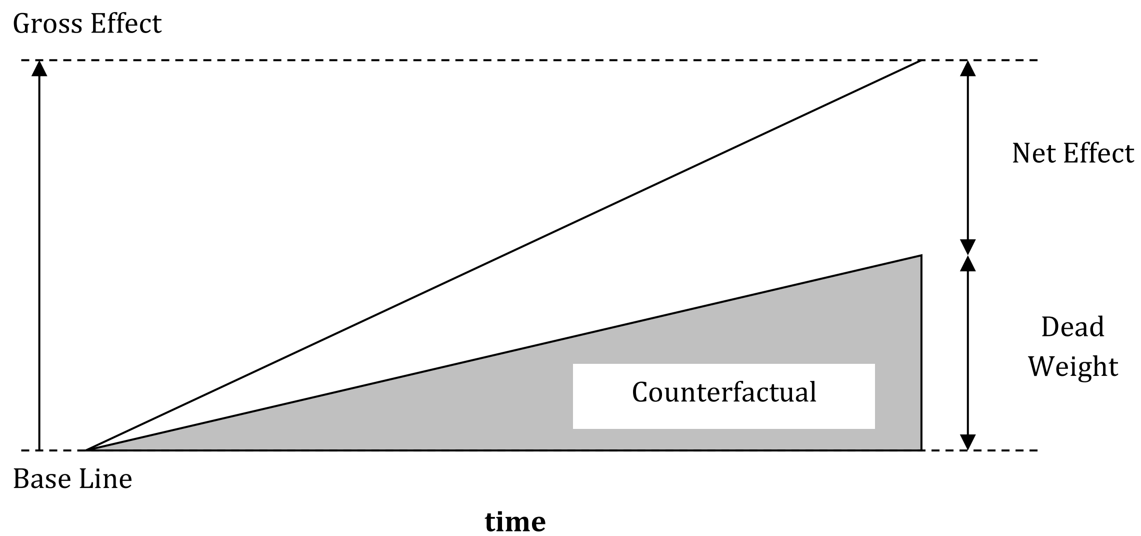
The central problem in impact analysis is to connect an intervention or activity with its effects: that is, to establish what it **caused**. But interventions take place in a dynamic context. Many changes are afoot and it is not always evident what happened if the intervention had not taken place.

In the ideal case, at the start of an intervention a **baseline** measurement exists or is taken – so that there is an adequate description of the state of affairs that the intervention is intended to change. Over time, the intervention appears to have an effect and if the baseline measurement is repeated the change in the baseline (represented by the arrow at the left of Figure 1) is the **gross effect**. Many evaluations and impact analyses report this as the effect of the intervention. In some cases, this is a reasonable simplification; in others, it involves a significant overstatement of impacts.

Often there are changes in the value of the variable(s) measured by the baseline that happen independently of the intervention. For example, an intervention to increase economic growth will be only one of many factors influencing such growth. The change that would have happened anyway is called **deadweight** – it is the change that would have happened in the so-called **counterfactual situation**, i.e. the situation without the intervention. The gross effect minus the deadweight is the **net effect** that we can attribute to the intervention[1].

[1] Deadweight can also be negative, as in the case of an intervention intended to increase economic growth that is launched in a period of economic decline. In such a case, the net effect could be a reduction in the rate of decline rather than having a positive slope

Figure 1. Deadweight, net effects and the counterfactual situation



While these concepts are simple in theory, they are very difficult to capture in practice – especially in complex systems like national research and innovation systems where many different causes often have to come together to effect change. In some impact analyses, it is possible to estimate the counterfactual situation by using a control group (sometimes referred to as a "non-treatment" group) or by using a range of other devices such as comparing the behaviour of those being analysed before and after the intervention.

Displacement or **substitution** effects can complicate the analysis, where the intervention causes activity to move between categories rather than to increase.

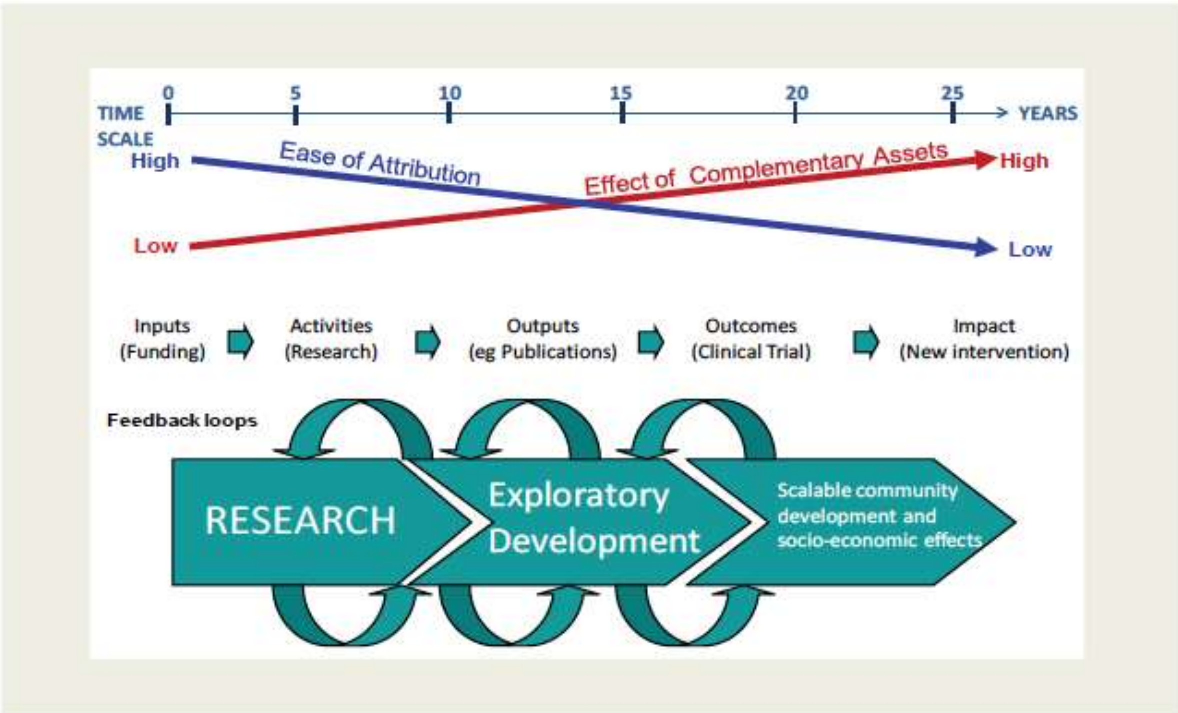
Attribution and multiple causality

The practice of impact analysis rests on insecure philosophical foundations, especially in relation to the idea of causation that is used. In everyday discourse, we operate with a naïve but operationally adequate philosophy of causation that deals in single causes. If I push open a door, there is no doubt that I caused it to open, just as surely as if I deliberately kill a man I am responsible for his death. For the door to open, it is **necessary** that someone pushes it (it will not open otherwise) and it is **sufficient** that I do the pushing. I do not need help and opening the door does not depend on additional actions by others. If I claim to open the door, few would contradict me.

Once we enter the world of joint action, things become more complex. Suppose that my friend and I kick someone to death. On a simple view, we are jointly and severally guilty of murder. The court is likely to want to know that my friend delivered the fatal blow and punish him more severely. But would that blow have been fatal if I had not already injured the victim? What if I had hurt the victim so badly that he would have bled to death from internal injuries if my friend had not pre-empted his slow demise by breaking his neck?

1. Almost all impact analyses, even those using linear impact models, involve multiple causes. If we look at impacts through the lens of innovation systems thinking, the number of causes goes up dramatically. As Hughes and Martin point out, the quicker the impact becomes obvious the easier it is to attribute causality (Figure 2). The further we move to the right in the Figure, the more additional causes are involved – or as Hughes and Martin put it with their focus on successful, research-based innovation, the greater the importance of "complementary assets" in achieving impacts. We quickly see that – as VINNOVA's summary of several years of experience in running long-term R&D impact studies shows, research or indeed any other relevant contributing factor in innovation success is at best a **necessary** condition for achieving impacts: it is never **sufficient** (Elg and Håkansson, 2011).

Figure 2. Time, attribution, impact



Source: (Hughes & Martin, 2012)

This has two important implications. First, a cause in impact analysis is likely to be one among many and there is no sound logical calculus that can determine its relative importance. Some impact evaluation tries to overcome this problem by asking stakeholders to rate the importance of several parallel causes and uses the comparative ratings to allocate different proportions of the responsibility. (This may be democratic, but is no more logical than the children in the old joke who could not tell what sex a kitten was and who therefore decided to resolve the matter by putting it to a vote.) Others reduce their impact estimates by an arbitrary amount in order to be "conservative". (One might as well divide by the page number…). Most simply ignore the problem.

Ignoring the attribution problem leads to a second implication of multiple causality: multiple counting of benefits. This can occur either through multiple impact analyses within a single effect logic (for example, separate studies looking at "impacts" of research and the provision of venture capital on innovation) or though analysis of multiple but overlapping interventions. For example, innovation agencies and their programmes tend to be used multiple times by individual firms. Thus, simply adding up the impacts observed by analysing a number of support instruments offered in parallel will lead to multiple counting and to overstating benefits.

The "project fallacy"

The project fallacy overlaps with the problem of multiple causality.

In literary criticism, the "intentional fallacy" is the idea that it matters what the author of a literary work intended it to mean. The critical perspective is that what matters is how readers perceive the meaning. That is what determines everything from the way it is understood to the number of copies it will sell. By analogy, the "project fallacy" is the idea that with regard to impact it matters what a funding agency thinks it is funding – something that will be determined through a call for proposals, bounded by a contract, monitored, and so on. Rather, research and innovation performers tend to have a "real project", to which the formally funded project is at best a contribution. Impact analysis focusing on the **formal** project therefore significantly understates the input effort for many research and innovation activities.

Circular causality ("endogeneity")

In many circumstances it can be difficult to trace back the links running from the inputs to the outputs in a linear way, making the task of quantifying the causal impacts an especially challenging one. Econometric specifications of impact causality can easily suffer from endogeneity. This is a form of circularity, where there is feedback from the dependent to the independent variable. The assessment of the impact or of innovation policies on well-being, productivity or GDP growth proxies is a typical case of an analysis suffering from endogeneity problems.

A simple example would be a test of the hypothesis that at the national level R&D leads to economic growth, since increased economic output tends to trigger increases in R&D expenditure. (It is fairly well known that industrial R&D expenditure depends significantly on companies' recent profits. R&D is a sunk cost whose pay-off is hard to predict, so companies prefer to spend cash on it rather than to fund it through debt.)

Endogeneity seems most likely to be a problem where impact analysis aims to consider aggregate variables that are far to the right in the logic diagram that describes the intervention logic or programme theory. Inherently, these are affected by a comparatively large number of exogenous and endogenous variables not automatically considered in the intervention logic.

Macroeconomic studies have in the past tended to treat R&D as a stock of yearly investments, each of which has a limited lifetime during which it generates an annual return. This is loosely analogous to the idea of a stock of knowledge inherent in the non-linear innovation models. This type of approach is useful in that tends to mimic key sources of non-linearity in our qualitative understanding of innovation mechanisms. It is one of several areas where case-based micro research could usefully be conducted in connection with econometric modelling, in order to test the plausibility of the simplifications made in the econometric models

This document is based on: **OECD Directorate for Science, Technology and Innovation (2014), "Assessing the Impact of State Interventions in Research – Techniques, Issues and Solutions", unpublished manuscript.**

References

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Hughes, A. and B. Martin, (2012). Enhancing Impact: The Value of Public Sector R&D. Cambridge: UK-IRC, Hudge Business School.