Workpackage 8

Policy Relevance of the Knowledge Economy Indicators Project

Deliverable 8.1

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http://europa.eu.int/comm/research/index_en.cfm
http://europa.eu.int/comm/resarch/fp6/ssp/kei_en.htm
http://www.corids.lu/citizens/kick_off3.htm
http://kei.puplicstatistics.net/

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1. Introduction

The ability of the European economy over the next few decades to provide economic growth and improvements to the quality of life of its citizens partly depends on the competitiveness of European firms, particularly in the face of low cost production of manufacturing and services in India and China and highly innovative countries such as the United States for high technology products. The construction of a European knowledge based economy (KBE) is often viewed as an essential element in European competitiveness, with the KBE leading to improved productivity and economic growth. Other aspects of a KBE are also of importance to policy, such as its effects on quality of life measures, including income dispersion, social cohesion, equality and the environment.

The Knowledge Economy Indicators (KEI) project provides a framework of metrics for measuring European progress towards a KBE. The main project goals were to identify policy relevant indicators for measuring the KBE and to use these indicators to explore different methodologies for constructing composite indices. A variety of methodologies for constructing composite indices at the national level were examined, including evaluation techniques for data quality, imputation methods for estimating missing data for specific countries, and different weighting methods for calculating a composite index. The methodological findings of this work are available in several technical reports.[1]

This brief report summarizes the policy relevant results of the KEI project. Since the project largely concerns methodologies for indicator development, most of the policy relevant results concern the types of indicators that should be collected in the future and how composite indicators can be used to assist policy. For the latter, the project constructed a composite index for the KBE for different European countries. However, this is an experimental index only. It should not be used to draw policy conclusions, such as to rank different countries on achieving a KBE.

The structure of this report is as follows. Section 2 discusses policy relevant results from the main indicators for a KBE and the use of scenario analysis to identify key indicators. Section 3 summarizes the policy relevant results of five in-depth studies that identify missing indicators or explore different methods for constructing composite indicators. Section 4 examines the policy issues from constructing composite indicators, including both quality issues and how a composite index can help inform policy development. Finally, Section 5 provides a short conclusion that also summarizes the policy impacts of the KEI project to date.

[1] In particular, see KEI deliverable *3.3: Quality of Knowledge Economy Indicators* and KEI deliverable *5.1: State of the Art on Composite Indicators*.

2. Indicators for the Main Dimensions of a KBE

Using the literature, the KEI project developed a framework for seven main dimensions of a KBE, as shown in Table 1, that were used in the construction of a composite index. These include four main drivers of a KBE (dimensions A1 to A4), two outcomes (dimensions B1 and B2), and a cross-cutting dimension of the internationalisation of activities (dimension C). For each dimension, several subcategories of indicators were identified. Several hundred indicators across these seven dimensions were evaluated, with 113 selected for further analysis.

Table 1. Indicator dimensions for the knowledge based economy

A1. Production and diffusion of information and communication technology (ICT)
- economic impacts
- internet use by firms
- internet use by individuals
- government ICT

A2. Human resources, skills and creativity
- general education
- human resources in S&T education
- skills
- creativity
- mobility

A3. Knowledge production and diffusion
- research and experimental development (R&D)
- patents
- bibliometrics
- knowledge flows
- total investment in intangibles

A4. Innovation, entrepreneurship and creative destruction
- entrepreneurship
- demand for innovative products
- financing of innovation
- market innovation outputs
- organisational innovation

B1. Economic outputs
- income
- productivity
- employment

B2. Social performance
- environmental conditions
- employment and economic welfare
- quality of life indicators

C1. Internationalisation
- trade
- knowledge production and diffusion
- economic structure
- human resources

The identification of dimensions and indicators began with a theoretical overview, but the end result also depends on data availability. As an example, the original framework includes a fifth dimension for the drivers, consisting of structural and organisational change.[2] This was deleted from the set of dimensions used to construct the composite index because of the paucity of available indicators. The few available indicators for structural and organisational change were added to the dimension "innovation, entrepreneurship and creative destruction".

The selection of dimensions and indicators also needs to capture structural changes that are ongoing and which are expected to continue into the future. These include 1) increasing use of global production chains for both goods and services, leading to shifts in the location of comparative advantages; 2) new centres of knowledge and innovation, 3) demographic changes such as ageing in European countries, 4) changes in the stocks and flows of skilled workers, and 5) technological shifts driven by new technology or environmental requirements.

2.1 Policy perspectives on indicators for a KBE[3]

Indicators need to be relevant to the efforts of policy analysts and policy makers to develop programmes to improve the 'KBE' capabilities of a country or region. In order to identify the types of indicators that policy analysts would like to have, face-to-face interviews were conducted with 40 policy experts and decision makers across Europe in 2005. The interviews focused on two themes: what policy issues are likely to develop over the next decade, and what indicators will be needed to support policy over the future? The latter theme also asked for opinions on the quality and adequacy of current indicators.

The main future priorities for indicators, in approximate order of priority, were better indicators for human resources and education, collaboration, ICT adoption and use, new technologies such as nanotechnology and biotechnology that will drive future innovation, energy and the environment, social welfare and ageing, venture capital and entrepreneurship, and globalisation. With the exception of new technologies, all of these future priorities are covered by the seven dimensions of a KBE, as summarized in Table 1.

In terms of the types of indicators that are currently used by policy analysts, there is a strong reliance on macro-economic indicators such as GDP and employment rates and other indicators for R&D expenditures, patents, citations and the supply of human

[2] Sub-categories for this group included worker responsibilities, off-shoring and outsourcing, e-work, organisational change, and social capital.
[3] Further details on this section are available in Chapter 5 of deliverable *1.3: Policies for a KBE.*

resources. Most of these indicators have been available for decades. The main concerns with these and other available indicators, as expressed in the interviews, were over comparability between countries and timeliness, with most respondents finding that most indicators often were several years out of date. Another problem was unease over poor definitions, leading to concerns over the reliability of indicators.

The respondents identified several 'gaps' in the ability of available indicators to meet both current and emerging policy needs. Table 2 summarizes the results. The most frequently cited requests for better indicators were for innovation flows, from creation to commercialisation. The respondents asked for more detailed information in terms of the fields of research, the types of innovation, innovation capabilities, new products, the number of firms doing research in a certain country, and the adoption and diffusion of innovations.

Table 2. Need for new indicators for a KBE: number of 40 interviewees that cited a specific type of indicator

Types of Indicators	Total	%
Innovation Flow	10	15.4%
Economic Impact	10	15.4%
Collaboration	9	13.8%
Human resources – researchers	7	10.8%
Human resources – role of youth	5	7.7%
ICT	5	7.7%
Social Impact	5	7.7%
Innovation Services	4	6.1%
Entrepreneurship /venture capital	3	4.6%
Human resources: employment/migration	3	4.6%
Broadband	2	3.1%
Organizational aspects	2	3.1%
Total	**65**	**100%**

Another area of concern is the need for better indicators on the economic impact of innovation in quantitative terms. The respondents wanted quantitative results for grants, subsidies and tax exemptions in order to evaluate innovations results.

Apart from the above, several other topics had substantive support. The respondents wanted improved indicators on collaboration, linkages, clustering and networks. There is a need for indicators on researchers, such as the number of researchers per institute, category of research, gender, term of contracts, type of financing and mobility. There are perceived needs for continuing indicators on type of education, number of students, mobility and job markets. ICT was also mentioned as lacking relevant information. Respondents would like to have data on both the usage and impact of ICT in both enterprises and households.

Apart from the economic impact of innovation, the respondents requested better indicators for social impacts, such as externalities as a consequence of innovation, an area that needs to be explored. More specifically, security issues and its impact on immigration, research and foreign scientists were stressed in particular. Moreover, there was concern with the involvement of consumers in the innovation process (both innovation demand and 'user-driven' innovation.

Service innovation and its related areas, such as e-government, e-health and e-commerce were also mentioned in the list of priorities for indicator development for future policy needs.

2.2 Scenarios to identify key indicators[4]

In addition to the problem of indicators that do not exist ('missing indicators'), the complexity of a KBE and the number of potential indicators can create problems for policy relevance. Complexity can be reduced by statistical techniques such as correlation analysis to identify redundant indicators, but these techniques are not reliable unless the problem is fully understood. A 'redundant' indicator can capture an essential, policy relevant activity. One solution is to use scenario analysis (see Box 1) to identify key indicators for the future. This method can identify both key indicators that exist and important missing indicators. This method was applied to three aspects of a KBE: the supply of highly skilled scientists and engineers for research and development activities (relevant to the dimension 'human resources, skills and creativity), environmental innovation (dimension 'social performance'), and the role of demand for innovative products in spurring firms to invest innovation (dimension 'innovation, entrepreneurship, and creative destruction'). These three topics were selected because of policy interest and because they were relevant to different dimensions of a KBE.

[4] This section draws on deliverable *1.4: Policy scenarios*.

2.2.1 Human resources scenario

The first step of constructing a scenario is to identify all factors that could possibly influence an outcome of interest. The research question for the human resources scenario is how to increase the stock of researchers and scientists in the EU to meet the requirements of the Lisbon Agenda's 3% target for R&D. The stock of researchers must grow in order to increase R&D from approximately 1.9% of GDP today to 3%, since researchers are the main R&D expense. Figure 1 shows the factors that can increase or decrease the stock of researchers and the linkages between them.

Box 1. What is a scenario?

A scenario is usually a 'thought experiment' conducted to investigate how the future might look if certain events did or did not take place. Such a scenario does not necessarily include any forecasted or estimated data.

However, in addition to involving 'what if' ideas, a scenario can include projections or simple simulations based on numerical data. Although these simulations must usually be based on a number of broad assumptions and simplifications and cannot account for unforeseen events, they do provide an idea of trends and possible outcomes. For example, how well would the European Union do in the future in terms of its stock of researchers, if it *didn't* succeed in attracting more foreign researchers, or, if it *did* manage to get more women into science? Such scenarios enable us to look at the effect of changes in one or more variables, and also importantly, to find out which variables, or factors, have the most effect on the outcome, and which are less relevant.

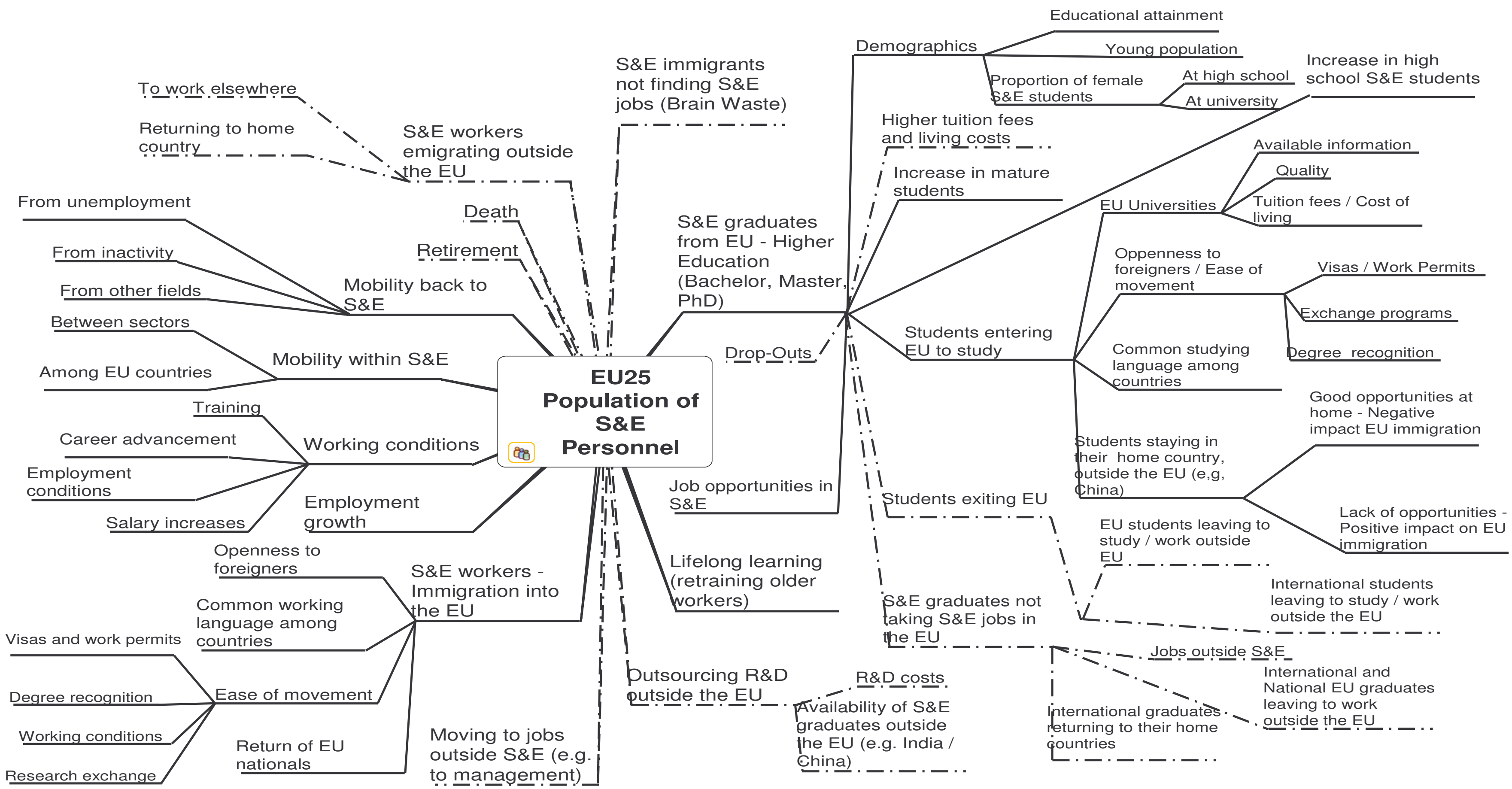
The second step that was used in this scenario was to run simulations to manipulate variables that might influence the stock of researchers. This method was used to identify 'key indicators' that have the greatest effect on these stocks. The simulations were run over time, with an end year of 2015. Nearly 90% of the total impact on the stock of scientists and engineers is due to only five factors, with 50% of the impact from the first two:

1. Increasing the average retirement age in the EU for scientists and engineers
2. Increasing the proportion of students choosing S&E studies
3. Increasing the proportion of S&E graduates getting S&E employment
4. Bringing in more scientists and engineers from countries like China and India (or even the United States)
5. Increasing the proportion of women studying S&E fields.

Consequently, indicators for these five main factors would be able to capture progress (or failure) over time in increasing the stock of researchers.

Estimates of the required numbers of scientists and engineers to meet the Lisbon R&D target vary from around 3.5 million to as much as 10 million. The simulations showed that the EU would not be able to meet the higher target domestically, even if it implemented realistic policies to substantially increase the number of students studying

Figure 1. Factors that influence the stock of science and engineering personnel



science and engineering. Europe could only meet this target by attracting more scientists and engineers from other countries. On the other hand, the lowest target estimate would be fairly easy to reach without depending on in-migration.

The exercise identified key indicators that are also unavailable across Europe, including data on the careers of graduates (relevant to factor 3) and the number of immigrants by educational level (relevant to factor 4).

2.2.2 Environmental innovation scenario

The second scenario on indicators for environmental innovation did not use simulation because a desirable 'end point' could not be identified. Instead, it first conducted a thought experiment to identify five relevant factors (drivers, facilitators, inputs, outputs, and effects of eco-innovation), identified 45 indicators for these five factors, and then used correlation analysis to remove redundant indicators. The exercise, summarized in Table 3, identified 15 key indicators, of which four are currently inadequate or missing.

Table 3. Summary table of key environmental innovation indicators

Indicator (indicator number in this study)	Indicator type	Results from this study	Future potential	Recommendations
Part I. Indicators for which data are currently available				
1. Environmental regulatory regime index (ERRI) on the stringency, clarity and stability of environmental regulations	Driver	Reasonable and strong correlations with several types of indicators.	Important driver, although captures only regulation related eco-innovation (but across sectors).	Regulatory indicators should be consistently available on a yearly basis.
2. Publications in specialized journals in 'environment/ ecology' in the EU per capita	Input	Some reasonable and strong correlations, especially with effect indicators.	Potentially good indicator, but mostly captures (intentional) product innovation.	Should be explored further.
3. Patent counts in the EGSS or outside it	Input	Some correlations, but data quality is poor, due to a small number of included countries (further data collection was not possible for this project).	Fairly established eco-innovation indicator, which also captured diffusion, but up-to-now mostly confined to the EGSS. Also, focus on product innovation.	Existing patent databases should be further developed to allow for easier access to eco-innovation related patents.
4. Intermediate material or energy inputs (IIM and IIE) at current purchasers' prices per GDP	Output	IIM correlated well with some, especially effect indicators.	Measures an important factor in the eco-innovation process between inputs, outputs and effects. Captures also unintentional eco-innovation.	Data collection should be maintained on a yearly basis and extended to all EU countries.
5. Exports in EU eco-industry products to large developing economies, such as China and India (as share of total exports to these countries)	Output	Reasonable and strong correlations with several types of indicators. However, the current product classification systems are not well designed to include only EGSS related exports.	Potentially a good indicator, also measuring diffusion. Confined to the EGSS and product innovation.	Further refinement of EGSS product code lists or product classification systems should be explored (already supposedly under way at the World Bank).

Table 3. Summary table of key environmental innovation indicators

Indicator (indicator number in this study)	Indicator type	Results from this study	Future potential	Recommendations
6. Relative world shares (RWS) – relative position of a nation in international trade in EGS (export orientation), or revealed comparative advantage (RCA)	Output	Correlates well with the EGSS export indicator (see above), but otherwise not very many correlations found in this study.	Not as sensitive to the EGSS product code list issue discussed above. Include some measure of diffusion. Confined to the EGSS and product innovation.	Could be used instead of the EGSS export indicator, at least until the EGSS export classification is better developed.
7. Energy intensity of the economy - Gross inland consumption of energy divided by GDP	Effect	Strong and mostly reasonable correlations with several types of indicators.	Important effect indicator on energy use. Measures also effects from unintentional eco-innovation.	Essential indicators.
8. Resource productivity of the economy – GDP per direct material consumption (DMC)	Effect	Strong and mostly reasonable correlations with several types of indicators. However, the data used were for 2000, and therefore old.	Important effect indicator. Measures also effects from unintentional eco-innovation, as well as decoupling of economic growth from resource use.	This indicator should be developed further, also so that annual data would be available.
9. Survey data on the effects from product or process innovation in terms of reduced materials and energy per produced unit, or highly improved environmental impact	Effect	The impact question includes improved impact for health and safety.	Potentially valuable indicators, as the data are collected at the sector level. Can capture unintentional eco-innovation across sectors, as well as process innovation.	Further development of the CIS survey, improvement in response rates. Environmental effects should be separated from health and safety effects in the questionnaire.
10. Weighted emissions of greenhouse gases per capita	Effect	Almost no relevant correlations in this study. However, actual consistent reductions in greenhouse gases still mostly to take place.	Important effect indicator for the future. Measures also effects from unintentional eco-innovation.	A longer time lag may be needed to see the effects from intentional eco-innovation to reduce greenhouse gases.
11. Weighted emissions of acidifying pollutants per GDP	Effect	Strong and reasonable correlations with many indicators from all types.	Important effect indicator. Measures also effects from unintentional eco-innovation.	Essential indicator.
Part II. Indicators for which data are not currently available				
12. Venture capital for firms in the EGSS	Driver	Not used in correlations, as no data are available for Europe.	Important driver, although confined to the EGSS.	Data collection should be improved.
13. Business environmental R&D, as a share of total business expenditure on R&D	Input	Not included in correlations. No data are available for most European countries.	Uuseful eco-innovation indicator, with a link to regulation.	Data collection should be further developed.
14. Sales or profits from environmentally beneficial innovation across sectors	Output	Not included as no data are available at an international level.	Potentially very valuable indicator, as would measure eco-innovation across sectors (including unintentional eco-innovation).	Data collection should be developed. The topic could be included in the CIS.

Table 3. Summary table of key environmental innovation indicators

Indicator (indicator number in this study)	Indicator type	Results from this study	Future potential	Recommendations
15. Foreign direct investment in EGSS (outside the EU)	Output	Not included, as FDI data are only available by aggregate sectors, and therefore identification of EGSS not possible at the moment.	Potentially a good indicator, and would also measure diffusion. However, this indicator is confined to the EGSS.	Data availability should be developed based on a sectoral identification of the EGSS, if possible.

Note: EGSS = environmental goods and services sectors

2.2.3 Innovation demand scenario

The third scenario concerns the effect of demand on innovation. Demand as a driver for innovation activity has attracted increasing policy interest. The European Commission report "*Creating an Innovative Europe*", for example, proposes several policy actions to improve demand as a driver of innovation investments, including the creation of a single market. Other demand related policies could also influence innovation.

The scenario identifies three main factors: domestic demand, foreign demand and the role of government. Domestic demand is further divided into quality and quantity aspects while the role of government is divided into regulations and standards and procurement. Eighteen key indicators were identified.

The exercise found that demand conditions are influenced not only by the quality of domestic demand, such as the existence of lead users made up of sophisticated buyers, but also by quantitative aspects including the actual numbers of consumers in such markets. Highly skilled and educated people, whose higher incomes are a reflection of their level of education, constitute the sophisticated buyer. Furthermore, this share of the population consists of prime age adults with the disposable income and interest to purchase sophisticated products.

Not only domestic demand is relevant for local firms, but also foreign demand. Reaching new markets can be decisive for firms that lack large domestic markets. Domestic markets may not be large enough to permit firms to recoup their investments in innovation. Government also plays an important role, by not only consuming innovative products through procurement, but also by creating regulations and standards that can free up demand, both by reducing uncertainty and improving quality.

3. Missing Indicators for a KBE

The KEI project investigated the problem of missing indicators through five in-depth studies on the 1) globalisation of R&D (relevant to the KBE dimension *Internationalisation*), 2) knowledge transfer from public science institutes to firms

(*Knowledge production and diffusion*), 3) new indicators from the CIS (*Innovation, entrepreneurship and creative destruction*), 4) organisational innovation (*Innovation, entrepreneurship and creative destruction*), and 5) human resources (*Human resources, skills and creativity*). The first two studies explored options for collecting entirely new data. The third study explored methods for constructing new indicators from analysing existing data sources. The final two studies link composite indicators created from different data sources to explore policy relevant questions, such as the relationship between innovation and the organisation of work.

3.1 Globalisation of R&D[5]

Large firms increasingly distribute R&D in a number of locations around the world. The drivers are to seek lower costs, specialised expertise, or to serve local manufacturing or services. These activities are not captured by official R&D surveys, which only provide data on national R&D expenditures.

Better information on the location of R&D expenditures by multinational enterprises (MNEs) is of relevance to both policies to respond to inward flows of R&D and outward flows. Inward flows are relevant to policies to attract R&D units from abroad and to innovation policies to encourage domestic firms to acquire and absorb foreign knowledge. Outward flows are relevant to policies to keep R&D expertise at home. Both types of flows are relevant to policies to improve the competitiveness of domestic firms and to support the mobility of skilled individuals, including accessing foreign talent.

This in-depth study focused on measuring outward R&D, or R&D conducted by the foreign affiliates of domestic firms. The study involved a detailed survey of large firms that asked about the location of their R&D expenditures and the reasons for conducting R&D abroad. The survey found that firms could answer the questions, but they were difficult, creating response burden. A main problem was that the accounting system for many MNEs was based on business units instead of the location where R&D is performed. Some MNEs found it easier to report the location of R&D by personnel, while others preferred reporting R&D expenditures.

The study evaluated several options for collecting data on foreign R&D. One option was to add a few questions on outward R&D to R&D surveys. Another option was to develop a rough estimate by using currently available data such as the EU R&D scoreboard, which provides global R&D expenditure data obtained from the national reports of MNEs. National R&D expenditures for the head office country of these firms, obtained from

[5] This section is based on deliverable *6.1: Role of Multinational Enterprises for Information on R&D*.

official R&D surveys, could be subtracted from the total, giving an estimate of domestic R&D spending. This would estimate outward R&D, but it would be unable to provide results for specific countries or explanations of the drivers of outward R&D. In addition, these indicators must be created by national statistical offices with access to confidential national R&D data.

3.2 Knowledge transfer metrics[6]

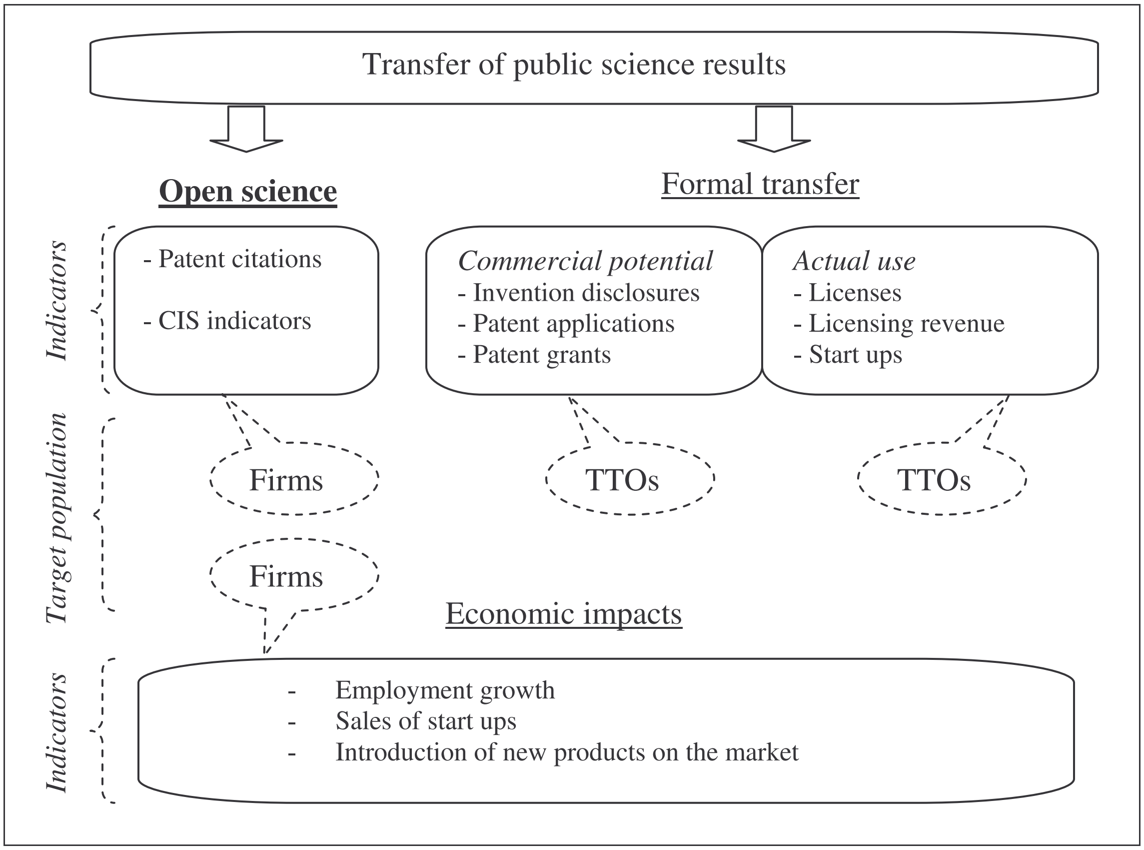
Over the past decade, innovation policy in many OECD countries has stressed the need to improve the commercialization of research results from 'public science' institutions such as universities and government research institutes. European governments have introduced policies to promote commercialization, such as university courses on entrepreneurship for future academics and a range of other programmes to encourage technology transfer by promoting formal contractual relationships between the business sector and public science. These include subsidies for the establishment of technology transfer offices (TTOs) at universities, changes in IPR regulations to encourage universities to patent and license inventions, and requirements for universities to obtain a higher share of their research funding from the private sector.

Several pathways are available for transferring knowledge from universities and government research institutes to firms, as shown in Figure 2. Indicators are already available for open science from the European Community Innovation Survey (CIS) and from patent or publication citations. However, there are no consistent and comparable indicators in Europe for formal transfer methods via TTOs.

This in-depth study looked at the types of indicators that could be collected from TTOs and how to create comparability across Europe. Several organizations already collect such data in Europe, including HEFCE in the UK and ASTP and ProTon in several EU countries. The study recommended that governments provide support to collect annual data for three indicators of the commercial potential of public science discoveries (invention disclosures, patent applications, and patent grants) and three indicators of the actual use of public science discoveries (the number of licenses executed, the number of start-ups established, and license revenues). Given that there are less than 1,000 research universities in Europe, a full survey of TTOs would not be very costly.

[6] This section is based on section 3.3 of deliverable *4.2: Missing KBE key indicators*.

Figure 2. Pathways for transferring of public science results to firms.



3.3 New indicators from the CIS[7]

The European Community Innovation Surveys (CIS) provide a wealth of data on innovation activities, but the policy interviews discussed above in section 2 found that the CIS data are relatively under-used in comparison to indicators for R&D or patents. The effect of the CIS is largely diffuse, influencing general policy perspectives rather than the development of concrete policy actions. This is unfortunate, as the CIS can fill important gaps in indicator availability, particularly on *how* firms innovate and the role of diffusion in innovation activities. However, further understanding of these two topics requires using the CIS data to construct composite indicators, based on analyses of two or more CIS questions. This in-depth study constructed examples of possible new indicators, using data from the third CIS survey. Two examples are given here: indicators for knowledge diffusion and how firms innovate.

Knowledge diffusion activities can be divided into two groups: active knowledge diffusion in which firms primarily obtain their innovations through collaboration with

[7] This section is based on section 3.4 of deliverable *4.2: Missing KBE key indicators*.

other firms or institutions, and non-interactive knowledge diffusion in which firms only obtain external knowledge through open sources or through purchasing technology. In the former case firms need to interact with other firms or institutions and sometimes collaborate on their innovation projects. In the latter case almost all innovative activity occurs in-house.

Active knowledge diffusion can be defined as a positive response to one or more of three CIS questions: the firm's *product* innovations were developed mainly in cooperation with other enterprises or institutions, or the firm's *process* innovations were developed mainly in cooperation with other enterprises or institutions, or the firm had one or more cooperation arrangements on innovation with other firms or institutions. The indicator is simple to calculate because it only uses 'yes or no' questions with high response rates.

The CIS defines a firm as innovative if it has introduced at least one product or process that was new to the firm itself. This means that a firm can be innovative even if it purchases new technology off-the-shelf with minimal effort on its own part, while other respondent firms might have extensive in-house R&D projects to develop innovations. The consequence is that the widely available indicator for the percent of firms that innovate is of minimal value to policy because it provides no information on innovative capabilities. An increase or decrease in this indicator does not necessarily mean that innovation support policies have failed or succeeded – a net increase could be due to a decline in the share of firms with highly developed innovative capabilities combined with an increase in minimally innovative firms.

One solution is to develop mutually exclusive indicators that describe *how* innovative firms innovate, using a methodology that assigns all CIS firms to one and only one category. An example is given in Figure 3. The first axis is whether or not the firm is involved in active knowledge diffusion based on collaboration (defined above), while the second is whether or not the firm has formal in-house creative activities, as measured by a positive response to one of two questions: the firm performs R&D or the firm has applied for at least one patent. These are defined as 'inventive' firms that are most likely to produce innovations with a major technical advance. The alternative is informal innovators that could develop innovations on an ad hoc basis, such as through production engineering. Many other options are possible for defining how firms innovate.

Figure 3: How innovative firms innovate

Percentages in bold sum to 100% of all innovative firms

Formal in-house creative innovation

Non-collaborators			Collaborators
	A *Inventive non-collaborative innovators* **24.7%**	**B** *Inventive collaborative innovators* **18.1%**	
	D *Informal non-collaborative innovators* **41.4%** *(8.9% are technology adopters)*	**C** *Informal collaborative innovators* **15.8%**	

Informal or no in-house creative innovation

Source: CIS-3 micro-aggregated data referring to innovative activities in 1998-2000. Limited to innovative firms (non-innovators are excluded).

3.4 Organisational innovation[8]

It is widely recognised that while expenditures on R&D and the skills of scientists and engineers with tertiary education are important inputs to successful innovation, these are not the only inputs. Developing new products and services also depends critically on the skills developed by employees on-the-job in the process of solving problems encountered in testing, producing, implementing and marketing new products and processes. Developing these sorts of skills in turn depends not just on the quality of formal education, but also on having the right organisational structures and work environments. Work environments need to be designed to promote learning through problem solving and to encourage the effective use of these skills for innovation.

This in-depth study linked national composite indicators on *how* firms innovate, drawn from CIS-3, with composite indicators constructed from the European Survey of Working Conditions on the organizational practices of employers. The study finds that in nations where work is organised to support high levels of discretion in solving complex problems, firms tend to be more active in terms of endogenous innovation, i.e. innovation developed, at least to some degree, in house. In countries where learning and problem-solving on the job are more constrained, and little discretion is left to the employee, firms tend to engage in a supplier-dominated innovation strategy. Their technological renewal reflects, almost exclusively, absorption of innovations developed elsewhere. These results raise new

[8] This section is based on section 3.2 of deliverable *4.2: Missing KBE key indicators*.

questions about the link between work organisation, learning and innovation. For example, they raise doubts about whether the use of organisational practices such as job rotation and teamwork are relevant indicators for how far firms engage in learning and innovation.

3.5 Human resources[9]

The slow growth of high- and medium-high technology industries (HMHT) in Europe has been associated with weak science and technology linkages that can be explained, in part, by a lack of a strong scientific base. Very few studies have explored the strength of the scientific base. This in-depth study evaluates the problem by linking data on the scientific base of industries and the stock of human resources in specific scientific disciplines. This work represents a valuable addition to the indicator family of innovation, technology and scientific performance and human capital.

Although indicators of scientific performance include some measures of human capital (e.g. degrees in science and technology, labour force level of educational attainment, R&D personnel, science and technology occupations, etc.), measures of scientific and technical performance continue to focus on a core group of indicators, and within this group R&D expenditures and R&D intensity are key. Indicators on human capital are analyzed but they are not linked to other indicators that are used to analyze scientific performance.

This in-depth study develops a method to link the scientific and technological base of HMHT intensive manufacturing industries and scientific disciplines as defined by education. The linkage was conducted for seven countries. The analyses find that people, measured in terms of the number of PhDs in science and technology, matter more than R&D expenditures as determinants of technological performance (measured by patents). This result also holds across a range of industries, with a positive relationship between technological outputs and the number of relevant PhDs.

The preliminary results of this work establishes the viability of the methodology and shows that existing data can be used to develop new indicators for human capital and scientific and technological performance. The results also show that it is important for policy analysts not to focus on R&D expenditures alone – human resources matter more. Furthermore, the results suggest that the time frame to improve scientific and technological performance may be longer than anticipated, since it takes time to develop

[9] This section is based on section 3.1 of deliverable *4.2: Missing KBE key indicators*.

human capital. This requires investing in education and waiting three to four years after new PhDs graduate to see a measurable impact on technological productivity.

4. Constructing Composite Indicators for a KBE

Economics abounds in composite indicators. Both R&D expenditure data and GDP are composite indicators, although all components use a single denominator measured by the local currency, while other widely used measures such as the Human Development Index (HDI), the Global Competitiveness Index (GCI) or the Summary Innovation Index (SII) of the European Innovation Scoreboard create composite indicators out of disparate data sources with different denominators. Many of these composite indicators are widely used to benchmark national performance. However, as shown in Section 3 above, composite indices are much more powerful and can provide insights into the different dimensions of a KBE[10].

The acceptance of composite indices by policy analysts for both benchmarking and for economic analysis depends on solving two problems: establishing the reliability of these indices and ensuring that results are comparable across countries, regions, or sectors. For instance, the interviews with policy analysts showed a high level of concern over the reliability of indicators for a KBE, which is partly responsible for a preference for 'tried and tested' indicators based on R&D (such as R&D intensities), patents, and educational achievement.

Research by the KEI project on data reliability and comparability is summarized below.

4.1 Data quality[11]

The first challenge for developing composite indicators for a KBE is to improve data quality and to weed out poor quality indicators. Unfortunately, the quality of many of the proposed KBE indicators is poor or varies across countries. Furthermore, assessment of data quality is difficult due to the difficulty for end users to access country specific metadata and other information necessary to evaluate quality.

There are seven main aspects of data quality that can affect composite indicators:

1. ***Accuracy:*** The closeness of computations or estimates to the unknown exact or true values. This is affected by the construction of survey questions (do the

[10] For a full explanation of the potential uses of composite indices, see deliverable *8.2: An overview of the KEI achievements*.
[11] This section is based on deliverable *3.3: Quality of knowledge economy indicators*.

respondents to a survey understand the question and give the relevant answer (validity)), by the ability of respondents to provide an accurate answer to the question (specificity), by comparability across sampling units (is the indicator accurate and consistent (reliability)), and by sampling and other factors that can reduce accuracy when results are aggregated to reflect national or sector conditions.

2. ***Missing values:*** When data for a specific indicator by year or country are unavailable. This problem can sometimes be solved by imputation methods.
3. ***Relevance***: The degree to which statistics meet current and potential user needs. This can be assessed by interviewing users, are discussed in section 2.1 above.
4. ***Comparability***: The level of error in data quality between geographical areas, non-geographical domains such as sectors, or over time. The goal is to maximize comparability by minimizing different types of errors for accuracy.
5. ***Coherence:*** The ability to reliably combine statistics in different ways and for various uses. When originating from a single source, statistics are normally coherent in the sense that the data can be reliably combined to produce more complex results.
6. ***Timeliness:*** The length of time between data availability and the event or phenomenon it describes.
7. ***Availability****:* The availability of data by unit of interest (country, sector, region etc)

It is frequently difficult to obtain enough information to assess each of these seven factors in data quality, particularly for accuracy, comparability and coherence. This can reduce the credibility of composite indices which are constructed from multiple indicators of varying or unknown quality. The construction of composite indicators should therefore, as far as possible, exclude indicators of questionable quality.

4.2 Robustness analysis for a composite index[12]

Data quality problems for a composite index can be minimized but are unlikely to ever be solved. Due to these problems and others, the construction of a composite index requires subjective judgements, such as over data imputation methods or the weight assigned to each specific indicator. Consequently, a second step is to test the accuracy and reliability of indicators under different realistic assumptions. This includes analysing the robustness

[12] This section is based on deliverables *7.1 and 7.2: State of the art on simulations and indicators* and *Simulation results for indicators for the KBE.*

of composite indicators to various policy scenarios, data quality aspects, and weighting schemes.

The robustness analysis tries to answer the following questions:

1. By how much do uncertainties affect the results of the composite indicator?
2. Which countries (or sectors or regions) have large uncertainty bounds in their rankings and which factors create these uncertainties?

Uncertainties can be caused by the selection of component indicators, data quality, weighting schemes, and the method used to normalise indicators with different denominators. These can be tested by examining the effects on the composite index across countries of including or excluding specific indicators, using different imputation techniques for missing values, different normalisation techniques, different weighting schemes, etc. In general, normalization and imputation methods are significantly less important as drivers of different results than the choice of component indicators and the weighting scheme. This suggests that robustness checks for all composite indices should examine the effects both of these factors on country rankings. In particular, weightings should be evaluated using Monte Carlo random generation methods. As shown below, the use of this method can substantially increase confidence in the robustness of a specific composite index. For this reason, this technique has been adopted for the Summary Innovation Index of the European Innovation Scoreboard.

4.3 Constructing a KBE index[13]

The KEI project developed an experimental KBE, drawing on up to 115 component indicators. Missing values were estimated by multiple imputation. Approximately 2000 simulations tested the robustness of the composite index, using different combinations of the imputation method, numbers of sub-dimensions, normalisation methods, weighting methods, etc. The results give a frequency matrix of the ranking of each country. For example, Sweden is ranked in first place in 54% of the simulations and in second place in 46% of the simulations. This strongly indicates that the results for Sweden are highly robust, with little variation due to different methodologies. Conversely, the ranking for Estonia varies between the 16th and 21st place, showing much greater sensitivity to different methodologies.

[13] This section draws on the deliverables for WP 5 and WP7 and summarised in deliverable *D5.8etal: Final report on simulation results for indicators*.

Confidence in a composite index can be improved by providing a frequency table for simulations. This addresses one of the main criticisms of composite indicators: rankings are presented as accurate point data, when it is well known that they are only approximate. Readers can then see at a glance which countries are susceptible to a wide variation in results. The results for the KBE index are given in Figure 4.[14] The example in Figure 4 combines simulations for multiple factors, which may not be necessary. At a minimum, however, frequency graphs for simulations should be provided for data imputation and the weighting method.

Figure 4. Frequency results for 2000 simulations of the KBE index

Knowledge Economy Index

	Rank 1	Rank 2	Rank 3	Rank 4	Rank 5	Rank 6	Rank 7	Rank 8	Rank 9	Rank 10	Rank 11	Rank 12	Rank 13	Rank 14	Rank 15	Rank 16	Rank 17	Rank 18	Rank 19	Rank 20	Rank 21	Rank 22	Rank 23	Rank 24	Rank 25	Rank 26	Rank 27	Rank 28	Rank 29
Sweden	54	46																											
Denmark			55	30	14																								
Luxembourg	36	4	14	25	4	7	7	4																					
Finland		18	23	29	9	11	11																						
USA	11	32	2	4	39	9	4																						
Japan			4	7	18	32	36			4																			
UK			2	5	16	38	39																						
Netherlands								86	4		4			7															
Ireland							4		61	14	4	9	9																
Austria									18	50	18	7		7															
Belgium								11	4	11	57	16	2																
France						4			14	18	11	54																	
EU15											4		57	39															
EU25										4	4	14	32	39	7														
Germany														7	79	4	7	4											
Slovenia															7	41	38	14											
Estonia																4	36	25	21	11	4								
Malta															7	13	9	21	23	27									
Cyprus																36	7	4	23	23	7								
Spain																4	4	32	25	29	7								
Czech. Rep.																			4	7	30	39	5	7	7				
Latvia																					20	36	11	21	7		5		
Italy																					29	18	9	29	9	7			
Greece																				4	4	4	29	18	21	7	14		
Lithuania																						4	41	13	32	11			
Hungary																							2	13	13	57	2	14	
Portugal																			4				4		7	11	61	14	
Slovakia																									4	7	18	71	
Poland																													100

Legend:
Frequency lower 15%
Frequency between 15 and 30%
Frequency between 30 and 50%
Frequency greater than 50%

Separate frequency graphs can also be constructed for specific dimensions. For KEI, these were produced for each of the seven dimensions listed in Table 1. These also

[14] An alternative to the example of a frequency diagram in Figure 4 is to provide a chart giving the median value and 5th and 95th percentiles for the rank distributions for each country.

provide policy relevant results. For example, there is much less variation in the rankings for dimension A1 (production and diffusion of ICT) and for A2 (Human resources, skills and creativity) than for A4 (Innovation, entrepreneurship and creative destruction).

In addition to benchmarking, the overall composite index and the indices for each dimension have many other policy relevant uses. For example, simple correlations between indices and other types of data can help identify national strengths and weaknesses (particularly using radar diagrams of the dimensions) or factors that are positively or negatively correlated with the composite index. The identification of a relationship does not imply causality, but can identify topics for further research. Correlations between the composite index for a KBE and an indicator for lifelong learning found a positive relationship, implying that the factors that lead to continued learning might be important for KBE performance.[15]

4.3.1 Reducing the number of indicators

The use of a hundred or more indicators can create problems for data interpretation. One option to solve this problem is to create composite indicators for each major or even minor dimension, as illustrated in Table 1. Alternatively, the number of indicators can be reduced through statistical techniques to identify indicators that make a significant contribution to the composite index. This can be achieved using forward and backwards stepwise regression. As an example, only 23 out of 115 indicators explain 97.4% of the variation in the KBE composite index. The drawback is that this method can remove indicators that are of high interest to policy. In the end, the choice of indicators is subjective, with component indicators maintained in a composite index because of their policy relevance.

5. Conclusions

This brief report summarizes the policy relevance of over 25 deliverables of the KEI project. Of note, the KEI project focused on developing methodologies for identifying indicators of relevance to a KBE, identifying methods for addressing the problem of many missing indicators, and refining a methodology for constructing robust and credible composite indices. The primary policy relevance of the project has been to strengthen the development of a European Statistical System that can better serve policy needs over the next decade or more. As shown in Table 4, the project results have already had a notable impact on the collection, analysis and presentation of KBE indicators, with the results taken up in different projects by the European Commission and by the OECD.

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[15] More examples of how to use a composite indicator are provided in deliverable *8.2: An overview of the KEI achievements*.

Table 4. Policy relevant impacts of the KEI project

KEI activity	Impact
Environmental innovation scenario (2.2.2)	The results were incorporated into work by the MEI (Measuring Environmental Innovation) project for DG Environment and the design of the eco-innovation module of CIS 2008.
Globalisation Of R&D (3.1)	Results used by an OECD/EU project on developing indicators for the globalisation of R&D.
Knowledge transfer metrics (3.2)	Study results used by the European Commission's *Expert Group on Knowledge Transfer Metrics* to identify key indicators.
New indicators from the CIS (3.3)	Concepts for new indicators were explored by the NIND project (Policy Relevant Nordic Innovation Indicators) and by the OECD.
Organisational innovation (3.4)	Concepts used by the MEADOW Framework project on measuring organisational innovation and work.
Robustness analyses and methodology for constructing a KBE composite index (4)	Recommendations widely adopted by producers of composite indices, including the European Innovation Index, part of the Pro Inno Europe project of DG Enterprise.

Numbers in parentheses in column 1 refer to the relevant sections of this report.