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The New EU 2020 Innovation Indicator: A Step Forward in Measuring Innovation Output?

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Abstract

In October 2013, the European Commission presented a new output-oriented innovation indicator intended to "support policy-makers in establishing new or reinforced actions to remove bottlenecks that prevent innovators from translating ideas into products and services that can be successful on the market". This article aims to evaluate the usefulness of the new indicator against the background of the notorious difficulties in measuring innovation output. We propose a conceptual framework for measuring innovation output that distinguishes structural change and structural upgrading as two key dimensions. We conclude that the new indicator is biased towards a somewhat narrowly defined "high-tech" understanding of innovation output. We propose a broader set of output indicators capturing also structural upgrading and find that the results for the modified indicator differ substantially for a number of countries, countries, with potentially wide-ranging consequences for innovation and industrial policies.

Jelcodes:O33,O52

1 Introduction

In October 2013 the European Commission (EC) launched a new indicator for measuring the EU's progress in meeting the goals of the Europe 2020 Strategy and its Innovation Union flagship initiative (EC, 2013), henceforth the EU 2020 indicator. This new indicator is intended to measure innovation output and should complement the headline input indicator that had already been used in the Lisbon Strategy, the share of R&D expenditure in GDP. During the 2000s, this R&D intensity indicator strongly influenced research and innovation policy in Europe as the heads of state and government of EU member states agreed on a 3% target for this indicator at their Barcelona summit in 2002 (EC, 2002).

Over time, both policy makers and researchers recognised that the R&D intensity indicator had certain limitations in order to serve as the main indicator to monitor improvements of the EU in becoming the most competitive knowledge-intensive society. On the one hand, industry structure strongly determines R&D intensity (Mathieu and van Pottelsberghe de la Potterie, 2012; [Author]). On the other hand, the transformation of R&D inputs into innovation outputs is not captured in it, and this might result in overrating unproductive R&D investment (Edquist and Zabala-Itturiagagoitia, 2015). Based on the conclusions of a High-Level Panel on the Measurement of Innovation, the European Council asked the EC to develop "*a new indicator measuring the share of fast-growing innovative companies in the economy*"[1], to add an output dimension to the input dimension already provided by the R&D intensity indicator. In the following two years, the EC experimented with different approaches to develop and measure such an indicator and finally presented a new composite indicator, the EU 2020 indicator.

Since such tools are not only used as a purely informational basis but also feed into evidence-based policy advice, e.g. country specific recommendations within the Europe 2020 strategy (Innovation Union) or smart specialisation initiatives, the adequacy of the information provided becomes crucial. It is therefore critical to know whether the EU 2020 indicator measures innovation output in an unbiased way. Evaluating its informational content, we claim that the EU 2020 indicator implies a bias towards countries featuring high shares of

[1] Conclusion of 4/2/2011 (Council doc. EUCO 2/1/11 REV1).

knowledge-intensive sectors. The EU 2020 indicator therefore shares some of the weaknesses of the headline R&D intensity indicator used so far, as it also strongly focuses on the performance of sectors classified as knowledge-intensive and tends to ignore innovation – in particular in manufacturing - in less knowledge-intensive sectors. This somewhat surprising result reflects the fact that the indicator mainly measures structural (industrial) change towards knowledge-intensive sectors but neglects the possibility that innovation may occur as structural upgrading, when firms are moving closer to the technological frontier in less knowledge-intensive sectors. We conclude that the innovation output indicator may reflect reasonably well certain cases of innovative performance, but less well other cases. More specifically, it accounts reasonably well for the innovative performance of countries specialised in segments of knowledge-intensive sectors close to the technological frontier. It also reflects reasonably well the performance of countries specialised in segments of low-tech sectors far away from the frontier. For countries with a low share of knowledge-intensive sectors, the indicator may neglect relevant progress achieved through structural upgrading. We also find that the indicator tends to overrate innovation output in countries specialised in segments of high-tech sectors far away from the technological frontier.

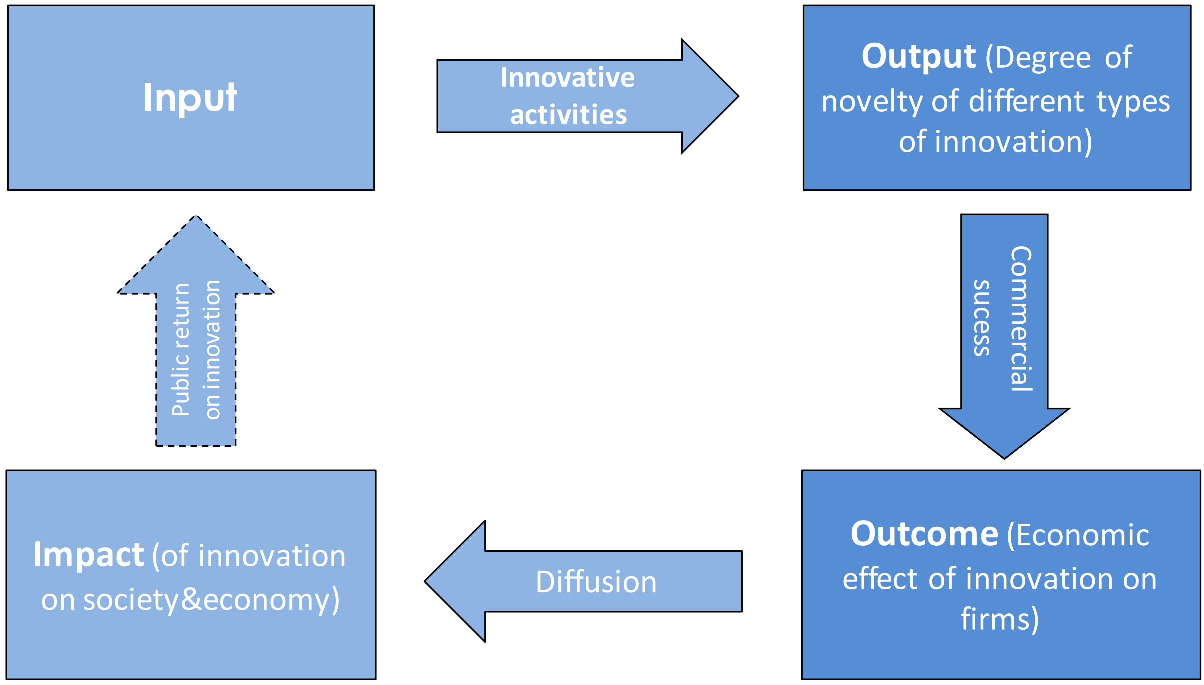
We start from a conceptual discussion of innovation output (section 2) and present existing approaches to measure the output of innovation at different aggregation levels (firm, sectors, countries). Section 3 analyses the strengths and weaknesses of the new indicator and its components. Section 4 compares the results of the new indicator with results of other output oriented innovation indicators. In Section 5 we conclude with an evaluation of the policy relevance of these biases and with suggestions for improving the measurement of innovation output at the country level.

2 Innovation Output and Outcome: a Conceptual Perspective

2.1. Innovation measurement: setting the stage

To conceptualise the transformation of innovation inputs into outputs, innovation production function models have been proposed in the literature (e.g., Pakes and Griliches, 1984; Bernstein and Singh, 2006; Roper et al., 2008; Chen and Guan, 2011). In addition, stage process models from the evaluation literature (e.g., the logic chain model) have been developed which include wider impacts of innovation activities on society and the economy and which specifically aimed to identify critical areas of performance measurement (e.g., McLaughlin and Jordan, 1999). Figure 1 shows a simplified chain of events which helps to delineate innovation inputs, outputs, outcomes and impacts for proper measurement[2].

Figure 1: Innovation outputs and outcomes in an innovation production process model



Innovation *inputs* consist of monetary, tangible and intangible, as well as human resources, such as R&D or innovation budgets, research infrastructures, the stock of existing knowledge, and skilled employees. Firms make use of these inputs in innovative activities which may either directly or indirectly lead to innovation *outputs*. Innovation activities may transform innovation inputs into new scientific and technological knowledge (potentially codified in publications and patents), and may add to the stock of tacit firm-specific knowledge, which in turn may result in innovation outputs in the form of different types of innovations (e.g., product or process innovations). The commercial success of these innovations and their economic effects on the firms which introduced them are referred to as innovation *outcomes*. The *impact* of innovation focuses on the economy-wide benefits of innovation such as productivity increases, and is often linked to the diffusion of an innovation from the firm- and industry-level to several industries and the economy as a whole.

[2] The Figure is not meant to suggest that innovation processes are linear, but it serves as a framework to systematically collect evidence on the innovation process and its economic effects.

In terms of measurement, international standardisation of input measurement started early e.g. with the OECD's Frascati Manual on measuring R&D (OECD, 1963, 2015) and the Canberra Manual regarding human resources for innovation (OECD/Eurostat, 1995). These approaches have been successful in terms of delivering comparable international data. Given their statistical reliability, it comes as no surprise that for benchmarking and target-setting in innovation policy, innovation input indicators have been widely used[3]. Internationally comparable indicators on innovation outputs, outcomes, and impacts, however, are much more difficult to build[4]. This is particularly true for measuring the link between firm- or industry-level innovation and economy-wide performance through indicators. While econometric analyses have been conducted to measure the returns of R&D or innovative activity (Hall et al., 2010)[5], indicator-based approaches are still widely missing. This article focuses on difficulties and opportunities to build indicators for innovation outputs and outcomes. From an economic and policy perspective, we are most interested in innovation outcomes at the country level. However, as these outcomes are shaped by the quality and quantity of outputs at the firm level, we start by explaining how the latter lead to economy-wide outcomes.

[3] Recently, the quality of bibliometric data has improved significantly, making comparisons of countries' scientific output (as an input for innovative activity) more robust, as witnessed by the rising importance of university rankings.

[4] For the measurement of innovation activities and the innovation process itself, surveys of firms' innovation activities have been used, e.g., including questions on sources and cooperation partners for innovative activities. In the past 20 years, a large number of countries conducted innovation surveys inspired by the Oslo Manual (OECD, 1992; OECD/Eurostat, 2005). A prominent example is the Community Innovation Survey (CIS) coordinated by the European Commission's Statistical Office (Eurostat) and conducted since 1993. Innovation processes have also been measured using bibliometric and patent data (e.g., in terms of co-publications between firms and universities, or firm patent data citing academic science). In what follows, we will not consider innovation process measurement.

[5] Innovation survey data were also used to econometrically estimate the innovation impact on productivity (Crépon et al., 1998), employment (Harrison et al., 2006) and profits (Peters, 2008; [Author]).

2.2. Measuring innovation output

Outputs of innovation processes can be defined following the Oslo Manual (OECD and Eurostat, 2005). It distinguishes four types of innovations: product (new goods or services or significant improvements of existing ones), process (changes in production or delivery methods), organisational (e.g. changes in workplace organisation) and marketing innovations (e.g. changes in product design). A large literature has conceptualized differences in the degree to which innovations change products or processes, i.e. their novelty. A common distinction distinguishes "radical" innovations, describing completely new products or completely new technologies, and "incremental" innovations, relating to performance improvements of existing products or production processes which do not fundamentally alter their characteristics (e.g., Dosi, 1982; Freeman and Soete, 1987). In the perception of the public and of policymakers, a high level of innovation output is often associated with the development and introduction of radical innovation. Measuring the radicalness of innovation has been a substantial challenge for empirical research, though, and no standard framework has been established yet.

One approach to measure innovation output is the object-based approach, which tries to work out the improved technical characteristics at the level of individual innovations. Examples include technometrics or literature-based measures of innovation output, which collect information from technical and trade journals (Grupp, 1994; Kleinknecht and Reijnen, 1993; Coombs et al., 1996). While these approaches constitute a large step forward in sorting out issues of radicalness, they did not receive great acceptance, because their construction is time-consuming and ill-suited for yearly national comparative indicators. These methods also do not work properly for service innovation.

In contrast, the subject-based approach collects information on innovation output at the level of the firm, on whether it introduced an innovation or not. One advantage of this approach is that it also captures service innovation, though in a very generalized way. In this approach the measurement of novelty remains dissatisfactory: novelty is (e.g., in the CIS) judged by the target group for which the innovation is new: when the innovation is only new for the firm introducing it (thus reflecting technology adoption), there is supposedly less novelty than if the innovation is new for the entire relevant market. This new to market criterion is however quite remote from the question of whether this innovation may serve as a basis for developing new technological paradigms (Dosi, 1988). As an example, a new model of a car is by definition a market novelty but may not necessarily be technologically radical. Nevertheless, survey-based output indicators (e.g., from the CIS) are nowadays used frequently in indicator scoreboards such as the Innovation Union Scoreboard.

As a consequence of dissatisfactory measurement of novelty at the product and process level of innovation outputs, patent data – i.e. data on codified knowledge arising from innovative activities as a form of pre-innovation output - are very widely used as a proxy for output indicators. To the degree that citation weights are included, there are also possibilities to account for technological impact. Empirical work, however, has shown that these adjustments are poor in predicting either of technological radicalness or economic value (Gambardella and Harhoff, 2008, [Author]).

Conceptually more problematic is that it is not known whether patents actually develop into an innovation at all. As works on motives to patent have shown there are a variety of reasons to apply for patents and the intention to launch an innovation is not necessarily the most important in many cases (Blind et al. 2006). Many patents are on the contrary rather intended to impede innovations by competitors (Moser, 2013; Hall and Ziedonis, 2001). Vice versa, most innovations are actually not based on patents (Arundel and Kabla, 1998). Patent data are also not neutral in terms of industry structure: propensities to patent strongly differ by sectors (Arundel and Kabla, 1998), with some barely patenting at all (among them services). In that respect, strictly speaking patents are rather a (sectorally biased) measure of the capability to create new technological knowledge, a kind of pre-output or throughput indicator. In summary, measurement of innovation outputs remains dissatisfying in particular as regards novelty and in practice output indicators are often indicators of (technological) capability.

2.3. Innovation outcomes: structural change vs. structural upgrading

Incremental and radical innovations have also been associated with differences in outcomes. E.g., radical innovations may lead to higher productivity and growth effects as a higher degree of technological novelty can potentially allow for a more substantial change in production technology or performance characteristics of new products. Radical innovation may also be able to mobilise new demand by offering entirely new applications. If radical innovations generated superior economic effects, the difficulties of measuring the novelty of innovation output would also heavily impede the measurement of economic effects of innovation outputs, of the innovation outcomes.

Saviotti and Metcalfe (1984) however pointed out that the degree of change can alternatively apply to a product’s technical features, the services it performs and its methods of production.

Radical technical changes do not necessarily lead to radically new service characteristics (such as the change from propeller to jet aircraft technology, which provided only incremental service improvements in terms of faster travel times rather than creating new markets), while vice versa incremental technical changes may lead to radical innovations in terms of the services they provide to users. One such an example may be the smartphone, which at the time of its launch was based on incrementally improving and combining existing technologies, while changing the opportunities of communication and information processing for its users quite substantially (Vogelstein, 2013)[6].

From an economic perspective, incremental innovations may hence be as important as radical ones in terms of innovation outcomes. A large literature which looks at innovation patterns across time and industries provides support for this view: While the focus of the early innovation literature was clearly devoted to radical innovations (Schumpeter, 1961; Smith, 2005), the importance and frequent occurrence of incremental innovations (or inching up, as put by Darby and Zucker, 2003) has inter alia been outlined by Kline and Rosenberg (1986) and Lundvall (2010) not least because they mirror trends in both competition strategy and growing complexity of knowledge bases, both reinforcing path-dependence of technological progress at the firm level:

First, in countries close to the technological frontier, innovation is the dominant business strategy, and (incremental) innovation processes become routine elements of a firm's activities ([Author]). In many mature industries, own radical innovation could endanger the return on large sunk investments, with successful innovations mainly replacing the incumbent's old profit position (Arrow 1962, Reinganum 1983) so that moving forward by small steps may be the rational competitive strategy. Increasing competitive pressure by low-cost firms leads to technological upgrading of existing products and processes (Bloom et al., 2011)

Second, the growing complexity of knowledge bases leads to increasing specialisation of firms on core competencies based on their firm-specific knowledge, in turn contributing to

[6] Radical and incremental changes can also be intertwined. E.g., accumulation of incremental improvements over time may eventually constitute a radical (technological) innovation (e.g. as in the case of spark generators, the weight of which was reduced from 118kg to 2kg over a span of 30 years), while subsequent incremental (technical) innovations may be necessary for a preceding radical (technical) innovation to create radical new service characteristics (e.g., as in the case of Teflon; see Kline and Rosenberg, 1986).

increased path-dependency of technological progress at the firm level, i.e. more incremental rather than radical innovation (Pavitt, 2005): firms usually work and learn along their cumulative knowledge bases, guided by firm-specific routines (see Dosi and Nelson, 2010, for a recent survey).[7]

From a product life cycle perspective, the distinction between high-tech and low-tech industries is not so much that the in the former innovation occurs while in the latter it does not. Rather it is a shift in the type of innovation from product to process innovation (Klepper 1996; Tushman and Anderson, 1986; Abernathy and Suarez 1993). Accordingly, the empirical literature agrees that innovation outputs can be seen in all industries, including low-tech ones, significantly influencing economic performance either through product differentiation or costs reductions (Peneder, 2010; Kirner et al., 2009).

A focus on the measurement of the economic effects of radical vs. incremental innovations may hence be of limited relevance, as various degrees of technological novelty may still lead to high novelty in terms of services for product users. Therefore, capturing innovation outcomes according to (technological) novelty would not be a main requirement for indicators of economic innovation performance. We see more potential for identifying and measuring innovation outcomes at the sectoral or industry level. Dosi (1988) calls the economic effect of innovations an asymmetry-creating effect which will improve the competitive position of a firm, e.g. through lower prices or better products. Dosi (1988) notes as a result that industrial structure is endogenous to innovative activity, i.e. that outcomes of innovation are reflected in changes of industry structure.

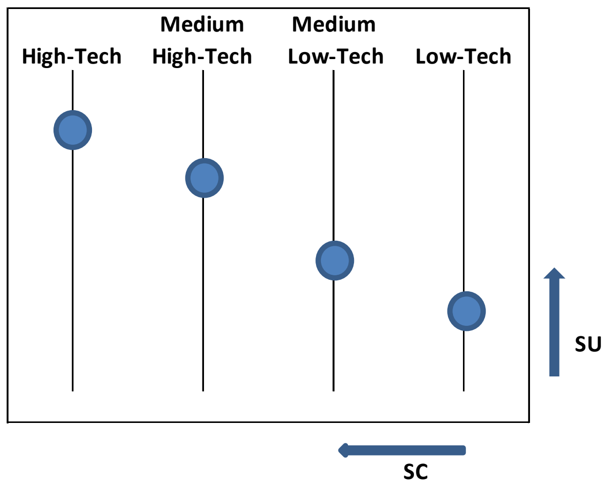
From a measurement perspective we propose that there are two possible ways for innovation outputs to show up in outcomes at the sectoral level, as economic benefits of innovation. The first we label **structural change**, i.e. differential growth of value added across industries, away from industries with lower levels of innovative activity or knowledge intensity to industries with higher innovative activity. By such a change, the share of innovative output in an economy's total output will increase.

[7] "It is precisely the paradigmatic cumulative nature of technological knowledge that accounts for the relatively ordered nature of the observed patterns of technological change… [ ] technological search processes in each firm are cumulative processes too. What the firm can hope to do technologically in the future is narrowly constrained by what it has been capable of doing in the past" (Dosi, 1988: 1129f.).

The second we call **structural upgrading**, featuring differential performance by firms within industries, without necessarily changing the overall composition of economic activities. This differential performance may be reflected in moving to industry segments with higher innovative activity, thereby defending competitive advantage. Dosi (1988) has conceptualised this intra-sectoral movement of firms triggered by innovation via changing distances to the technological frontier at the firm level. Such upgrading may not necessarily be reflected in differential value added growth at the firm level. The economic benefit of innovation may, e.g., consist in increasing product quality to be able to hold market shares constant in spite of higher prices when compared with low-cost competition; or in keeping costs down to stay competitive in spite of higher wages paid to a firm's workforce.

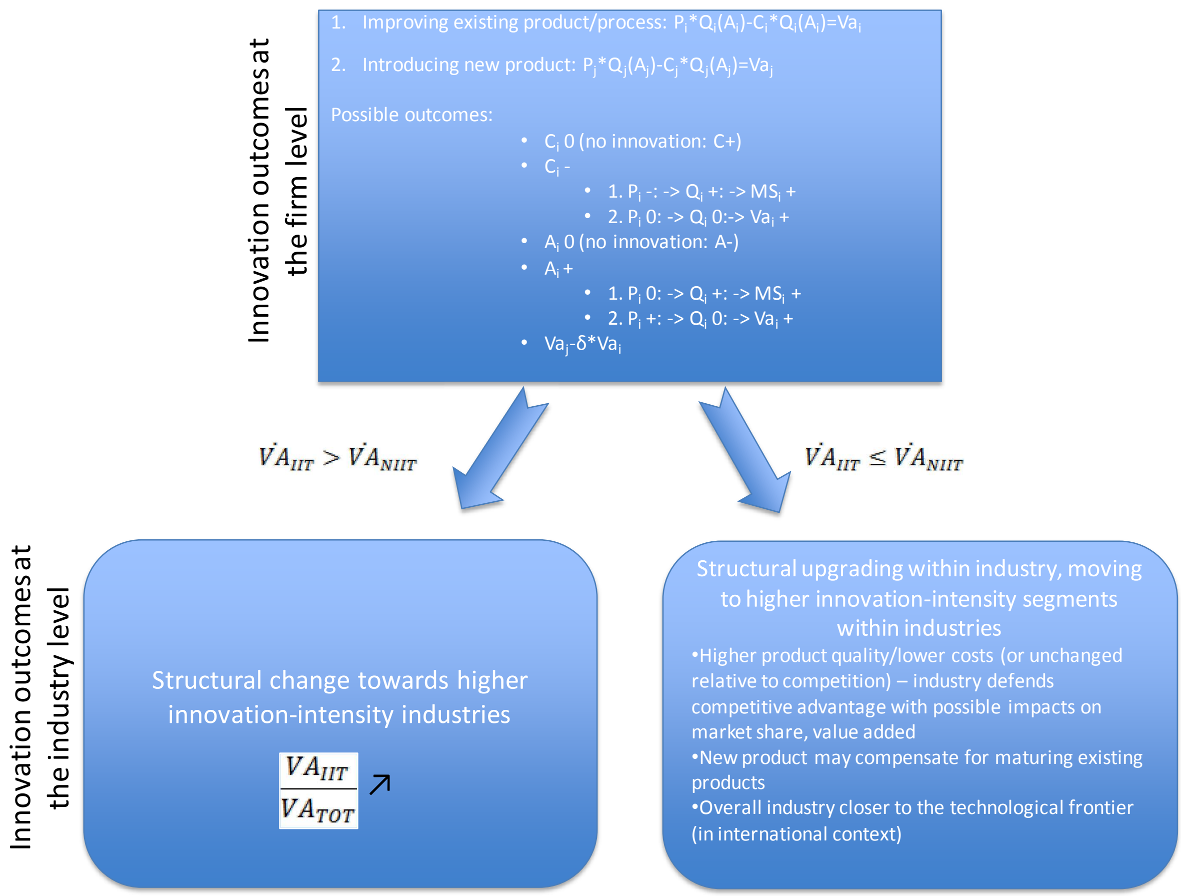
Both phenomena, structural change and structural upgrading, are shown schematically in Figure 2. Industries are roughly classified in four broad groups, which we call "-tech" for the sake of brevity. The blue circle for each group represents its average innovation or knowledge intensity, going from low-tech, on the right, to high-tech, on the left. Within each of the groupings, firms can be more or less knowledge-intensive, or display varying distances to the frontier in each grouping, sliding up or down the vertical axes. Structural upgrading (SU) then occurs when firms (and consequently industries composed of those firms in a country) move upward on the vertical axes. Structural change occurs (SC) when there is a horizontal move, from industries with lower levels of innovation activity, towards industries with higher innovation activity or knowledge intensity.

Figure 2. Schematic display of structural change and structural upgrading



A simple conceptual model may illustrate both channels. Figure 3 starts with innovation outcomes at the firm level, which relate to the characteristics of innovation output: First, changes to existing products and processes can affect production costs C of product i (e.g., through increased process quality), decreasing C or keeping C constant relative to competing firms, which are also trying to reduce costs. Depending on the amount of relative cost reduction and ensuing price setting, value added Va and market shares MS generated by product i may remain unchanged or increase following changes in quantities sold Q. Innovations can also change product quality A, keeping product quality unchanged relative to competitors or increasing it, with impacts on value added or market shares as a function of corresponding price setting. Second, a new product j generates value added levels net of any substitution effects with the older product i it may replace, indicated by an elasticity of substitution δ.

Figure 3: Innovation outcomes at the firm and industry levels: a conceptual model



These outcomes of innovative activity at the firm level translate either into economic effects of innovation changing the sectoral composition of activities (structural change through higher value added growth of industries characterised by high innovation intensities (VA_{IIT}) relative to industries showing lower innovation intensities (VA_{NIIT})); or into changing the intra-sectoral composition of activities, by moving towards segments of higher innovation intensity within the same industry. While radical innovations (i.e. entirely new products) may be more likely than incremental innovations to trigger structural change, Figure 2 shows that structural change can well be the result of incrementally improving products and processes, e.g. when the firm is already active in a very innovation-intensive industry (e.g., iterations of the latest smartphones); whereas an even radically new product in a low-tech sector may merely prevent the decline of the industry (see, e.g. the development of breathable and waterproof textiles). Put differently, developments along a technological trajectory may not just lead to structural upgrading, but also to structural change at the industry level, while a new technological paradigm may not necessarily initiate structural change towards more innovation-intensive industries.

Whereas public attention is often focused on new products creating new markets (structural change), empirical evidence shows that structural upgrading as an outcome of innovation is equally relevant for economic performance. Kline and Rosenberg (1986) point to the example of the US electric power generation industry, which achieved very high rates of total factor productivity growth without any single major innovation, but rather due to constant upgrading in the form of slow, cumulative improvements in the efficiency of centralised thermal power plants[8]. Robertson et al. (2009) observe that the development of both higher-quality products and new products can offset the maturation of older industries, limiting declines in demand for products of low- and medium-technology sectors. In a firm-level analysis of the global paper industry, Ghosal and Nair-Reichert (2009) find that the impact of investments in modernisation builds up over time to create significant performance differences as regards productivity and competitive position between firms.

The international trade literature also provides empirical evidence on the importance of structural upgrading. It conceptualises differences between products within sectors using the term “quality ladder”. In Grossman and Helpman’s (1991) North-South trade model, every traded product exists on such a quality ladder; its production will move to the ‘South’ once the ‘South’ is able to imitate its technology. As a result, firms from the ‘North’ are forced to

[8]“… it is a serious mistake (increasingly common in societies that have a growing preoccupation with high technology industries) to equate economically important innovations with that subset associated with sophisticated technologies” (Kline and Rosenberg, 1986: 278).

innovate and bring out the next generation of higher quality products in order to escape low cost competition. The empirical literature on the quality of exports has shown that such phenomena have indeed been widespread as advanced countries try to cope with the adjustment pressure from rising emerging economies. Schott (2008) finds that trade between China and developed countries overlaps in terms of export mix, but that over time this overlap decreases in terms of export prices, suggesting that developed (high-wage) countries compete with developing (low-wage) countries by raising the quality of their exports. Martin and Mejean (2014) find that one fifth of the increasing specialization of France in high quality goods can be attributed to the competition with low-wage countries, limiting the market share loss of France in international trade. Bloom et al. (2011) show that Chinese import competition leads to two distinct effects among European firms, a "within"-effect of productivity increases at the firm level and a "between"-effect of employment reallocation towards more innovative and technologically advanced firms.

In summary, the available evidence points to the fact that both structural change (i.e. differential growth at the firm level changing the composition of activities towards more innovative activities) and upgrading (i.e. moving up the quality ladder of industries, or getting closer to the frontier of an industry) are important types of innovation outcomes. They indirectly inform also on trends in innovation output determined by competitive strategy and path dependency and should both be considered in attempts to measure innovation outcomes.

The measurement of outcomes of innovation at the industry level has several benefits in comparison with measurement at the firm level. One is the spread of benefits from individual firms to other firms, possibly located in different industries. A general framework of structural change and upgrading is in principle able to capture innovation outcomes wherever they originated. Measuring outcomes rather than outputs also alleviates the problems faced with identifying the degree of novelty of an innovation: Eventually, from an economic perspective, the degree of novelty of an individual innovation – be it related to technological or service characteristics - matters less than the economic benefits of this innovation.

From a practical measurement perspective building suitable indicators of outcomes is more difficult than indicators of inputs, but more straightforward than output indicators. There are a variety of indicators of structural change towards more knowledge-, R&D- or innovation-intensive sectors (e.g. Peneder, 2010; Hatzichronoglou, 1997). They build international averages of sectors and then calculating the shares of these sectors in national output. This approach is also used e.g. in the Innovation Union Scoreboard. "Change"-indicators are therefore usually employed to measure current levels of shares. They usually show countries featuring high shares of R&D-intensive ("high-technology") sectors in national output at the top.

There is much less in terms of upgrading. So far, the most commonly used innovation outcome indicator from innovation surveys which could be seen as referring to upgrading (when weighted by industries' shares in total output) is the sales share of product innovations. This indicator has been used both in analyses on sector and country performance in innovation (particularly by the Innovation Union Scoreboard, see European Commission, 2014) and in firm-level studies on innovation success (Mairesse and Mohnen, 2002; Laursen and Salter, 2008; Leiponen and Helfat, 2010; [Author]). While the sales share of product innovations is useful to quantify the outcome of a firm's innovation efforts, comparability across firms and consequently across sectors and nations is limited (Kleinknecht et al., 2002; Knell and Srholec, 2009). First, perception by firms of what constitutes an innovation is subjective. Though a distinction between new to market and only new to firm novelties is made, it turns out that product innovations new to a firm's market may refer to a wide variety of regional or sectoral markets, depending on the firm's delineation of markets, so that product sales may be registered as being from an innovation by some firms (e.g., from catching-up countries) whereas other firms would not count these sales towards innovation outcomes (e.g., from frontier countries). Second, comparison between industries is complicated by the fact that the sales share of new products is strongly driven by product life time. For this reason, the first and second edition of the Oslo Manual suggested collecting data on the average or typical length of the product life in order to control for this interference, but only a few innovation surveys took up this idea. Potentially related to life-cycle aspects, but also to changing perceptions of innovativeness and technical survey issues such as sampling, the indicator is also quite volatile.

Upgrading indicators which are not based on firm survey data are more difficult to build. [Authors] use both structural change and upgrading indicators to assess industrial performance of EU Member States. They find that in particular structural change indicators related to manufacturing are suffering in their accuracy from the fragmentation of international value chains: as the knowledge intensity of industries is calculated on international averages rather than on country-specific data, a country can have high shares in knowledge-intensive sectors even when it hosts only less knowledge-intensive parts of the value chain, such as final assembly (an example being Hungary; see also Srholec, 2007). This then penalises countries specialised in the high quality or knowledge-intensive segments of more low- to medium-technology sectors (e.g., Austria and Denmark). Upgrading indicators can correct for this by showing a country's position on different knowledge-intensity or quality segments within industries.

[Authors] suggest two indicators: one measuring export quality, or the share of low-, medium- and high-quality exports of an industry, and the other measuring R&D intensity of countries by correcting for industrial structure. The first is now becoming more commonplace, in different methodologies (e.g. Vandenbussche, 2014). Here, "actual" quality is measured by detailed export data on prices and weight (enabling calculations of unit values), whereby unit values are a proxy for quality. This proxy will of course not work under all conditions (see Aiginger, 1997, for a discussion). The second indicator, R&D intensity of a country's business sector corrected for industrial structure, is not per se an outcome indicator. However, knowing whether a country – relative to an average of R&D intensive benchmark countries – is R&D intensive or not given its industrial structure, allows for an assessment of its position on the segments of an industry in terms of its knowledge intensity, and this could be used as a weighting scheme for structural change indicators ([Author]). Both indicators empirically perform well in explaining performance differences between countries, complementing the information obtained from structural change indicators. They can also be used both in terms of changes over time as well as reflecting current levels.

In the following chapter, we will discuss the new EU innovation output indicator against the background of our framework. As a takeaway, lack of differentiation between radical and incremental innovation should not overly matter if one is more interested in the economic effects of innovation; but any indicator trying to capture outputs and outcomes should integrate dimensions of structural change and upgrading.

3 Strengths and Weaknesses of the EU 2020 Innovation Indicator

The EU 2020 innovation indicator is a composite indicator that consists of four components. Some of these components in themselves are made up of subcomponents. We will first briefly describe each of the four components and then discuss their advantages and shortcomings with respect to measuring innovation output and outcome. More technical details on how the various indicators are derived can be found in Vértesy and Tarantola (2014). The various components are shown in Table 2.

3.1. Composition of the EU 2020 Innovation Indicator

The first component (PCT) uses the number of patent applications per billion GDP. The numerator is the number of applications filed under the Patent Cooperation Treaty which name the European Patent Office (EPO) as designated office in the international phase of the application procedure. The denominator is GDP in Euro-based purchasing power parities. The goal of the European Commission is to use this component as an indicator of technological innovation, "*showing the ability of an economy to transform knowledge into technology*" (European Commission, 2013, pp. 3). EU member states differ widely with respect to this first component (see Table 2)

With the purpose of measuring how highly skilled labour feeds into the economic structure of a country, the European Commission advanced as the second component (KIA) the number of people employed in knowledge-intensive industries as a proportion of the total number of employees in the business enterprise sector. The criteria for considering an industry (measured at NACE 2-digit level) as knowledge-intensive is that, for the whole of Europe, at least one third of the employees in this industry have a higher education degree (i.e. ISCED 97, levels 5 and 6). In order to establish whether an industry is knowledge-intensive, EU-27 employment data from the European Labour Force Survey is used. Once the knowledge-intensive industries have been identified, the same data source is used to calculate country-level employment in these industries and in the business enterprise sector as a whole. The score for this indicator is approximately 14% for the EU as a whole (see Table 2), with the vast majority of countries having between 10 and 20 percent of business industry employees being employed in knowledge-intensive industries.

The third component (COMP) was selected to represent the competitiveness of knowledge-intensive goods and services. It consists of the average score of two subcomponents: (1) the share of medium-high and high-tech products in total exports (GOOD), and (2) the share of knowledge-intensive services in the total services exports (SERV). As for products, the Standard International Trade Classification Revision 3 (SITC, Rev. 3) is used. As for services, the sum of credits in the Extended Balance of Payments Services Classification (EBOPS) is used. The definition of high-tech and medium-high-tech products and knowledge-intensive services is the same for all countries. A positive contribution of high-tech and medium-high-tech products to the trade balance is an indication of specialisation and competitiveness in these products, and the same goes for services. The competitiveness component ranges between twenty and seventy percent (see Table 2).

A fourth component was developed to represent dynamism and reflects the employment in fast-growing firms of innovative sectors at NACE 3-digit level (DYN). It is measured as the sum over all sectors of the product of (a) the innovativeness of a specific sector, (b) the knowledge intensity of that sector, and (c) the number of employees in fast-growing firms in that sector as a percentage of total employment in the sector. The innovativeness of a sector is constructed based on the score of the EU-27 member states as well as Iceland, Norway, Serbia and Turkey for 33 variables from the Community Innovation Survey (CIS). These variables are arranged into four groups. For each group of variables, all business sectors receive an average score with respect to the variables within this group. The arithmetic average of a sector's score for each of these four groups, results in the overall sector score. Sectors are ranked according to this overall average and are given a score (between 0 and 1) proportional to their position in the ranking. The knowledge intensity of a sector is measured as the share of tertiary-educated persons employed in the sector for the whole of Europe (based on Labour Force Survey data for 19 EU member states) normalised by the highest share among all sectors. The third subcomponent, i.e. the share of employees in fast growing firms, is measured at the country level. Fast-growing firms are firms with ten or more employees and an average employee growth of 10% per year over three years. The indicator uses national employment data from the European Labour Force Survey on a 2-digit NACE level.

In order to arrive at the composite EU 2020 Innovation Indicator, its four components are weighted in such a way that the composite indicator is statistically equally balanced in its underlying components (Paruolo, Saisana & Saltelli, 2013). The weights are also chosen by the European Commission such that the composite score for the EU28 in one particular year (i.e. 2010) is 100, and individual member states can be benchmarked against this EU28 score.

3.2. Advantages and limitations of the EU 2020 Innovation Indicator

With the launch of the EU 2020 Innovation Indicator, the European Commission underlines its commitment to improving innovation performance at the EU and national level. In particular, the indicator is developed to measure performance in innovation output and outcomes. Although the European Commission includes a variety of output and outcome measures in the indicator, it is highly debatable whether the selected components actually give a good representation or coverage of a country's overall innovation output and outcome.

Whereas in general, patent indicators in general have their limitations and advantages (as explained in section 2.2.), the patent component of the EU 2020 Innovation Indicator particularly reflects the development of inventions to be used on global markets. In many industries, and particularly in SMEs, innovations are not targeted towards global but rather to national or regional markets. As a result, firms often seek patent protection at national or regional (European) patent offices and do not go through a costly PCT application process. The current PCT component of the EU 2020 Innovation Indicator hence does not capture innovation outputs targeted at these national or regional markets.

The KIA component of the EU 2020 Innovation Indicator consists of the number of people employed in knowledge-intensive industries as a proportion of the total number of employees in the business enterprise sector. As explained above, the knowledge intensity of industries is calculated based on European averages rather than on country-specific data. An industry is labelled knowledge-intensive if, for the whole of Europe, at least one third of the employees in this industry have a higher education degree. As a result, countries can only improve their score on this indicator by employing more people a specific, pre-specified set of knowledge-intensive industries. Increased employment in sectors that are not regarded as knowledge-intensive will lead to a decreased score even if this increased employment is due to productivity increases resulting in turn from significant investments in innovation.

A similar remark can be made when it comes to the DYN component which reflects employment in fast-growing firms in innovative sectors, where innovativeness is calculated for Europe as a whole. As a result, countries can only improve their score on this indicator through fast-growing firms in sectors that are, on average across EU-members, highly innovative. This is the case even if the local firms in that sector are not at all innovative. Similarly, highly innovative, fast-growing firms in sectors which are on average in the EU less innovative, will not lead to a higher score.

The fourth and final component of the EU 2020 indicator consists of the average score of the share of high-tech and medium-tech products in the total trade (GOOD), and the share of knowledge-intensive services in the total service exports (SERV). Attributing equal weight to both subcomponents implies that a country's specialisation on either services or manufacturing is not considered. Moreover, as with the indicators on the employment share in knowledge-intensive sectors and high growth firms, the innovativeness of exports is determined through international averaging, so that it is not known for a specific country how knowledge-intensive or technology-intensive the products and services in question really are. For example, high-tech products are identified through international classifications, rather than through real information on the technological content of real country exports. Note that countries with a high share of tourism services exports will also be penalised, as any knowledge-intensive services will get a comparatively lower score, even if e.g. the share of knowledge-intensive services in GDP between two countries would be the same.

We noted in section 2.3 that innovation outputs can result in two types of innovation outcomes, namely structural change (i.e. away from industries with lower levels of innovative activity to industries with higher innovative activity) and structural upgrading (increased performance of firms within industries, moving closer to the frontier, without changing the overall composition of economic activities). Overall, the three last components (KIA, DYN, and the average of GOOD and SERV) of the EU2020 innovation indicator reward member states that reallocate resources to a pre-specified set of knowledge-intensive, innovative sectors which is the same for all European member states. As such, these components are indicators of structural change, i.e. of the reallocation of economic activities away from industries with lower levels of innovative activity to industries with higher innovative activity. They fail to capture path dependent evolutions and structural upgrading in sectors that are on average less innovative and less knowledge-intensive, but that may be crucial for the economic development of a country or region. The patent indicator indirectly also favours certain industrial structures over others, as sectors of activity differ strongly by propensity to patent (e.g., Arundel and Kabla, 1998).

This measurement approach also goes against the European Commission's new policy concept of "smart specialisation", the goal of which is to boost regional innovation and economic growth by enabling regions or countries to focus on their relative strengths. A smart specialisation reasoning argues (a) that a region or country should not spread its scarce resources over a too wide range of activities, and (b) that a region or country should diversify not by focusing on the same ‘popular’ activities (cf. the vast number of regions attempting to become world class biotech players), but by instead building on its own relative strengths. The three last components of the EU 2020 innovation indicator fail to capture such specialisation efforts in established sectors, inciting all regions and countries to reallocate their resources and activities to the exact same set of sectors.

We can conclude that the four components of the EU 2020 indicator provide a rather limited coverage of the range of innovation outputs and outcomes discussed in our conceptual model. While the PCT component captures technological capabilities or innovation (pre-)outputs to some extent, and the three other components cover structural changes, innovation outcomes in the form of structural upgrading are barely represented in the indicator, even though structural upgrading is a major innovation outcome, reflecting firms’ efforts to stay ahead of low-cost competition and technological path-dependency.

4 A Modified Version of the EU 2020 Innovation Indicator

In the preceding sections we argued that the EU 2020 Innovation Indicator has a strong focus on structural change as a mediator of promoting innovativeness at the country level, while it neglects structural upgrading. We furthermore highlighted that this most likely is at the detriment of countries starting off from a structure with a focus on low- to medium-tech sectors (either countries close to the frontier or catching-up ones). In order to evaluate these claims we compare the EU 2020 indicator with an indicator, called SU indicator in what follows, that consists of the two variables we proposed on structural upgrading in section 2.3. We also present the results for a modified EU 2020 indicator which is calculated as the arithmetic average of all the indicators used in the EU 2020 indicator and the SU indicator.[9] If our arguments are valid, we should observe that countries with a focus on sectors classified through international averaging as high-tech or knowledge-intensive perform better in the EU 2020 indicator than in the modified EU 2020 indicator when they are further away from the frontier in these sectors. Table 1 shows countries’ shares in knowledge-intensive sectors in

[9] As the focus of the current paper is more conceptual, we will not go into the issue of weights used in composite indicators, and will use one of the simpler weighting methods. The problem of weights used in composite indicators has been discussed elsewhere (e.g., [Author]; OECD, 2008)

technology driven manufacturing industries[10] and of knowledge-intensive activities KIA as defined above (including both manufacturing and services) along with the EU 2020 indicator rank and GDP per capita. We show two different industry classifications because some countries such as Luxembourg, Malta and Cyprus achieve very high shares in KIA mainly due to a (less R&D intensive) large financial services sector (also contributing to their SERV score), whereas other countries such as Hungary, Slovakia and the Czech Republic achieve relatively large shares of R&D intensive technology-driven industries due to their integration in global value chains of innovation-intensive industries such as automobiles (affecting also their DYN and GOOD scores). Comparison with the EU rank and GDP per capita leads to a couple of observations

- Some countries with relatively large shares of knowledge-intensive sectors (e.g., catching up countries such as Hungary, Slovakia, Czech Republic, in technology-driven manufacturing, but also advanced countries such as the UK, in education-intensive sectors) achieve relatively high innovation output scores compared with their level of GDP per capita
- Some countries with relatively lower shares of knowledge-intensive sectors achieve better GDP per capita compared to their innovation output scores (e.g., Spain, Italy, Portugal, but also the Netherlands and Austria, in particular in technology-driven manufacturing)

If innovation output is a future predictor of GDP growth, then policy-wise clearly the second group of countries should be very worried. Given markets are open and globally competitive, one wonders how these countries achieve their GDP performance given their average innovation outputs and relatively high wages. We suspect that in some instances, the first group of countries may not be at the top end of quality ladders (with the exception possibly of countries benefitting from large financial services sectors), or further away from the frontier in knowledge-intensive sectors, while in the second group, countries are closer to the frontier in less knowledge-intensive sectors.

[10] We use an updated version of the classification developed by Peneder (2002), which is based on a cluster analysis of economic variables (labour intensity, capital intensity, advertising sales ratio, R&D sales ratio) obtained from the US manufacturing industry in the period 1990-1995. Technology oriented manufacturing industries include chemicals and biotechnology; new information and communication technologies; and vehicles for transport. Using e.g. the OECD's high-tech classification (Hatzichronoglou, 1997), however, we obtain similar results.

Table 1: Sectoral specialisation in knowledge-intensive industries, EU 2020 indicator rank and GDP per capita, sorted by GDP per capita, 2012

	Share of education intensive sectors (KIA) - total economy	Share of technology-driven industries in manufacturing	EU 2020 Indicator Rank	GDP per capita in PPS (EU28=100)
Luxemburg	25.4	1.0	4	264
Netherlands	15.2	13.4	10	133
Ireland	20.1	56.9	3	130
Austria	14.2	13.8	9	129
Sweden	17.6	21.7	2	126
Denmark	15.5	25.7	6	125
Germany	15.8	24.9	1	123
Belgium	15.2	20.4	11	120
Finland	15.5	7.1	5	116
UK	17.8	22.6	7	107
France	14.3	22.6	8	107
Italy	13.2	13.2	17	101
EU28	13.9	20.0		100
Cyprus	16.9	7.5	18	94
Spain	11.9	13.5	21	94
Malta	17.0	0.0	16	85
Slovenia	14.1	16.2	14	82
Czech Republic	12.5	15.4	13	82
Portugal	9.0	7.5	24	76
Greece	12.3	5.9	23	74
Slovakia	10.1	15.2	15	74
Estonia	10.8	4.8	19	71
Lithuania	9.1	3.3	28	69
Poland	9.7	9.4	20	66
Hungary	12.5	23.8	12	65
Croatia	10.4	8.7	25	61
Latvia	10.3	0.9	27	60
Romania	6.5	6.4	22	53
Bulgaria	8.3	6.6	26	45

Source: Eurostat, European Commission, Peneder (2002)

Table 2 shows the country values for the two indicators outlined in section 2.3, the quality of exports ([Author]) and the sectorally-adjusted R&D expenditures ([Author]).[11], that will be used in the structural upgrading indicator. The original values can be found in Table 2. Both are supposed to shed more light on the phenomenon of structural upgrading, or moving closer to the frontier within sectors. They are shown next to the four indicators that are the underlying components of the EU 2020 indicator. We see that some countries with relatively high or close to average shares of knowledge-intensive sectors show very negative values in

[11] We are very grateful to the authors of the cited papers for providing us with the data, in particular Irene Langer and Susanne Sieber.

the indicator for sectorally-adjusted R&D intensity, implying that they are active in the less R&D or innovation intensive segments of these activities, possibly focusing on product assembly (e.g. Hungary, Czech Republic, Slovakia or Malta).[12] Some countries with relatively lower shares of knowledge-intensive sectors show less negative adjusted R&D intensity (e.g., Portugal, Spain, Italy) than the group above, others even very positive values, implying specialisation in the top R&D-intensive segment of less knowledge-intensive sectors (E.g., Austria, Belgium, Netherlands). In export quality as well, some countries such as Italy and Portugal achieve relatively high values, while other countries such as Luxemburg and the Czech Republic – which are above Italy and Portugal in the EU indicator – achieve only medium values. Some top performers such as Denmark and Sweden are good in all indicators, suggesting that they are both specialised in knowledge-intensive industries as well as at the top of the quality ladders within those activities.

[12] We refer again to the two taxonomies used in table 1, "KIA" and the technology-driven manufacturing sectors.

Table 2: Original values for the EU 2020 indicators and the SU indicators, 2012

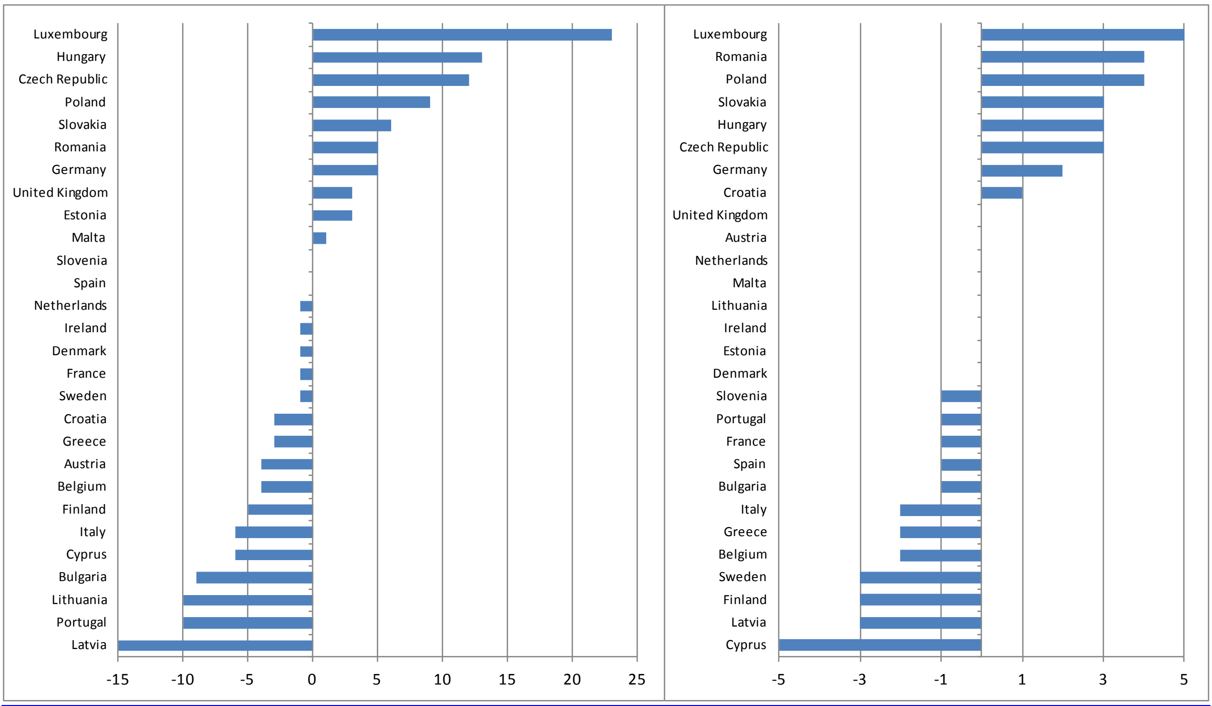
	PCT	KIA	COMP	DYN	Sectorally adjusted R&D intensity	Export quality
EU28	4.0	13.9	5.8	17.9	-0.13	85.8
Austria	5.4	14.2	5.1	17.2	0.48	88.6
Belgium	4.0	15.2	5.1	15.6	0.30	88.5
Bulgaria	0.4	8.3	3.4	16.2	-0.72	72.1
Croatia	0.8	10.4	3.5	15.0	-0.67	..
Cyprus	0.3	16.9	4.5	16.7	-0.52	86.0
Czech Republic	0.7	12.5	5.6	18.7	-1.05	66.0
Denmark	6.6	15.5	6.2	18.5	0.84	93.0
Estonia	2.3	10.8	4.8	14.7	0.36	46.3
Finland	10.5	15.5	4.9	17.1	1.42	90.0
France	4.2	14.3	5.6	20.8	0.43	87.9
Germany	7.8	15.8	6.9	19.1	0.00	94.9
Greece	0.4	12.3	4.2	16.8	-0.43	65.8
Hungary	1.5	12.5	5.5	19.1	-1.57	77.4
Ireland	2.4	20.1	6.9	21.8	..	94.4
Italy	2.1	13.2	4.8	15.3	-0.64	76.2
Latvia	0.5	10.3	3.9	11.3	-0.89	87.0
Lithuania	0.4	9.1	3.0	12.3	-0.90	73.9
Luxembourg	1.7	25.4	7.1	18.8	..	62.0
Malta	0.7	17	4.5	17.5	-1.89	92.4
Netherlands	5.5	15.2	4.4	16.2	0.12	79.4
Poland	0.5	9.7	4.8	19.3	-1.15	57.7
Portugal	0.6	9	4.2	14.7	-0.25	70.1
Romania	0.2	6.5	5.6	16	-1.57	47.7
Slovakia	0.5	10.1	5.4	19.2	-1.61	79.9
Slovenia	3.2	14.1	4.7	15.3	0.08	61.5
Spain	1.7	11.9	4.5	15.9	-0.57	67.8
Sweden	10.1	17.6	5.3	18.9	1.20	90.8
United Kingdom	3.3	17.8	6.6	18.6	-0.15	91.3

Note: no data for Ireland and Luxembourg in the sectorally-adjusted R&D intensity, no data for Croatiafor export quality; export data for very small countries such as Malta, Cyprus or Latvia to be interpreted with caution as very small volume data.

In the next step, we build a simple linear average of the two indicators and call this the "SU-indicator", for indicator of structural upgrading, and compare it to a linear average of the EU 2020 indicators. To gain a first impression of the data we plot in the left panel of Figure 4 the ranks resulting from their values, as the ranks are often the most important policy information triggering further analysis.[13]

[13] Note that due to the different weighting, the ranks for some countries are slightly different than in table 1 for the EU 2020 indicator, but the direction of change is unaffected.

Figure 4: Change in ranks: SU-indicator vs EU 2020 (left panel), modified EU 2020 vs. EU 2020 (right panel)

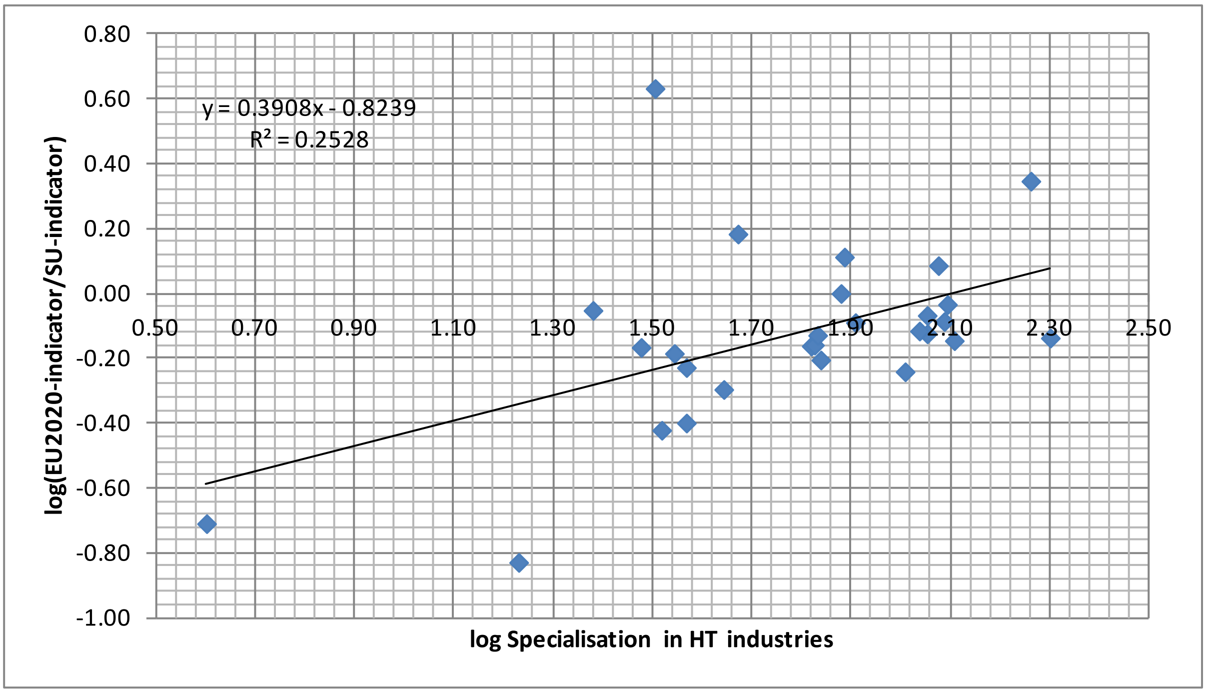


Note: a full set of normalised actual values is in the annex.

The comparison between the upgrading indicator and the EU 2020 indicator (focusing more on structural change, as outlined) reveals that several countries outlined above as showing relatively high specialisation in knowledge-intensive sectors, without necessarily being at the frontier in these activities, perform worse in the upgrading indicator in terms of losing several ranks (e.g., Hungary, Czech Republic, but also Luxembourg, which profits from large financial services). Among the "winning" countries are several which were said to focus on less knowledge-intensive sectors, but at a higher position on the rungs of the quality ladder (e.g., Portugal, Italy, Belgium and Austria). Some countries are barely affected, doing equally well on both dimensions of innovation outputs and outcomes (e.g., Sweden, France, Denmark).

To further investigate the hypothesis that primarily countries specialized in high-tech industries perform better in the EU 2020 indicator as compared to the indicator on structural upgrading, we present a scatter plot with the logged ratio of the EU 2020 indicator and the SU-indicator on the y-axis and a logged specialization in technology-driven industries on the y-axis in Figure 2. The specialization index is based on the taxonomy introduced by Peneder (2002). If the hypothesis is correct that specialisation in high-tech industries is associated with a higher performance in the EU 2020 indicator relative to the structural upgrading indicator, there should be a positive relationship.

Figure 5: The relative performance in the EU-2020 indicator and the specialisation in HT industries.



We indeed find that countries with higher specialisation in high-tech industries perform better in the EU 2020 indicator relative to the SU indicator. Moreover, the log-log-representation allows giving an intuitive interpretation of the size of the coefficient in the regression line, which can be interpreted as an elasticity. In particular, if specialisation increases by 1% the performance in the EU 2020 indicator relative to the SU indicator increases by 0.39%.

This suggests that indeed the EU 2020 indicator favours countries that have sectoral compositions more oriented towards R&D or knowledge-intensive sectors. With respect to our main conjectures these descriptive figures support the view that an indicator set that ignores elements of structural upgrading consistently understates dimensions of innovative performance that are more pertinent in countries focusing on low or medium tech-sectors.

We will now evaluate the strength of the influence of the bias resulting from the omission of the structural upgrading component. For this end we compare the results for the ranking and the indicator for the EU 2020 and the modified EU 2020-indicator in the right panel of figure 1. The results of the ranking confirm that primarily countries with a relative specialisation in knowledge-intensive sectors, but further away from the frontier perform worse under the modified EU 2020-indicator. Examples include Hungary (13 instead of 10), the Czech Republic (16 instead of 13) and Slovakia (18 instead of 15). Countries with large financial sectors but few other innovation outputs (the EU indicator implies that the size of financial services contributes to innovation outputs) lose out as well (e.g., Luxemburg ranks 8 instead of 3). Among the countries that would gain under the modified version of the EU 2020 indicator are countries specialised in less knowledge-intensive sectors, focusing on high quality there, such as Italy (17 instead of 19), Spain (19 instead of 20), and Portugal (18 instead of 22). Some countries that already did well in the original EU 2020 indicator even improve on their position when structural upgrading is taken into account (e.g., Finland, Sweden).

It should be noted that some data problems are still present in our analyses. For example, in small countries the small export volumes observed make data for export quality less robust for them (e.g., Cyprus, Latvia). No sectorally adjusted R&D data for Ireland and Croatia are available. If available, we conjecture they would be quite negative, given Ireland's overall low R&D intensity and specialisation in generally knowledge-intensive sectors. Our analyses should be understood as a first attempt at shedding more light on the process of structural upgrading, with clear room for further improvement.

In summary, we find that the neglect of components measuring structural upgrading leads to a characterization that is too pessimistic of the innovation outputs for countries that are close to the frontier (or at the top of the quality ladder) in generally less knowledge-intensive sectors. This results in lower rankings for these countries. In contrast, countries that feature large financial sectors, or that have entered international value chains in generally knowledge-intensive sectors from the less innovation-intensive part (e.g., assembly), obtain higher rankings, that to some extent reflect too optimistic a picture. Countries that perform equally well (or equally poorly) on both dimensions are less affected.

5 Conclusions

The EU 2020 Indicator is an important step in taking the output and outcome dimension of innovation into account. European research and innovation policy over the past decade focused considerably on increasing inputs to innovation. In 2002 the Barcelona goal was announced, aimed at bringing R&D expenditure in the EU to 3 percent of GDP by 2010. When this target wasn't reached, 2020 was set as the new target date. In order to evaluate the efficiency of increasing inputs, a thorough understanding and monitoring of the outputs and outcomes to be achieved by these inputs is needed. We tried to show that the EU 2020 Indicator does make an attempt in this direction, but find that it falls short in terms of the dimensions of innovation output and outcome it captures.

Measuring innovation outputs and outcomes properly is difficult for the purpose of indicator-based country comparisons. Not surprisingly, the EU 2020 Indicator neither measures the quantity nor the quality of innovation output (with the exception of a patent indicator and its well-known drawbacks). We don't see this as a major problem of the indicator, however, as we contend that if one is interested in the economic benefits of innovation, then information on quantity and quality of innovation output (e.g., how many innovations introduced, how path-breaking they are from a technological perspective) matters less than information on innovation outcomes, i.e. the commercial success of innovation outputs.

In this paper, we propose that outcomes can be captured at the meso-level, focusing both on structural change (facing growing economic activity in more knowledge-intensive sectors) and structural upgrading (getting closer to the frontier in activities countries are already specialised in). The latter is certainly a major innovation outcome, reflecting trends in competitive strategy – defending competitive advantage against low-cost competitors pushing from below, requiring firms to carry out innovative activities to climb up quality ladders – but also mirroring the increased path dependency of technological progress due to more complex knowledge bases. Yet it has so far been widely neglected in innovation outcome indicators and is barely integrated in innovation performance rankings, including the EU 2020 output indicator, where three of the four components primarily focus on structural change as an outcome of innovation while the indicator widely ignores structural upgrading.

The EC's choice of focussing on indicators of structural change comes with some surprise given the current focus of EU policy on smart specialisation, which acknowledges the merits of strengthening industries that have comparative advantages regardless of being high-tech or low-tech, knowledge-intensive or capital-intensive. Indicators of structural change are necessary, but rely on a pre-specified set of sectors formed through international averaging, which in the case of the EU indicator unfortunately also includes financial services. Structural change indicators in manufacturing also heavily suffer from the fragmentation of international value chains, where research and innovation activities may take place in one country, but the associated production of goods (and services) in another. Even the patent indicator favours inventions destined for global markets, underrating regional or national markets which could be important for smart specialisation.

As a result, the EU 2020 Indicator tends to be biased in terms of innovation output and outcome measurement. It systematically favours countries specialised in industries classified as more knowledge-intensive, even if that knowledge intensity is in reality not pronounced, due to fragmentation of value chains or large financial sectors, while important innovation outcomes in terms of upgrading are neglected, underrating countries that are specialised and close to the frontier in less knowledge-intensive activities.

For policy makers, the EU 2020 Indicator will be of little additional value as it does not address sufficiently well the questions that are typically posed to a policy-oriented innovation indicator: How successful is my country in terms of outputs? Does my country invest enough given its specific situation? How well are inputs transformed into outputs? In fact, the indicator may even mislead policy makers and discourage from further investment. If higher investment in R&D and innovation is not mirrored in higher output when consulting an indicator that is intended to measure output, innovation policy makers will find it difficult to argue for higher budgets, particularly in a situation of tight government budgets and calls for cuts in government expenditure. A proper and comprehensive measurement of innovation outputs and outcomes is hence critical for demonstrating the importance of higher investment into the generation and exploitation of new knowledge.

We believe that measuring innovation output and outcome in a comprehensive way based on indicators requires a more balanced approach than those chosen by the European Commission. In this paper, we proposed a conceptual framework that stresses the differences between structural change and structural upgrading as two important dimensions of innovation output and outcome and showed that results can differ quite substantially for some countries if structural upgrading is considered. In terms of innovation policy strategy, countries at the top of the quality ladder in less knowledge-intensive sectors and low shares of knowledge-intensive activities may prioritise efforts to diversify into new areas of strength, using tools such as fostering fast growing spin-offs from academic research. By contrast, countries further away from the frontier in knowledge-intensive sectors may aim at upgrading through increased innovation intensity of existing firms, e.g. through R&D subsidy programmes or increased cooperation of firms with universities.

In terms of innovation output and outcome measurement, more work is still needed as several aspects were neither captured by the EU 2020 Indicator nor by our extension. One aspect is clearly upgrading in services; our measure of export quality is restricted to manufacturing, and the sectorally-adjusted R&D measure focuses on manufacturing as well, as R&D intensities in services are generally low. Another is the diffusion rate of new technologies/innovations applied throughout the economy and related employment gains due to innovation. Especially the latter are usually of particular interest to policymakers. For both dimensions, proper metrics to measuring them in a comparative way across countries are widely lacking. There is hence a clear need for further research on appropriate indicators for outputs and outcomes.

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