Socio-Economic Review, 2025, Vol. 00, No. 0, 1–30
https://doi.org/10.1093/ser/mwaf018
Article

OXFORD

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The transition to the knowledge economy in advanced capitalist democracies: a new index for comparative research

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Abstract

This article sets out to develop a new index capturing advanced capitalist democracies' transition to the knowledge economy. Reviewing how the notion has evolved in the literature, the article proposes a definition of the knowledge economy based upon two key elements—technology and (high) skills. These are operationalized in six indicators and combined through Bayesian latent variable analysis to produce a new Knowledge Economy Index, covering twenty-two countries from 1995 to 2019. A descriptive exploration of the index provides important insights for the emerging body of work on the knowledge economy in comparative political economy. The index is the first to provide a comprehensive measure of the knowledge economy that accounts for both technology and skills across space and time. As such, it paves the way for future research examining the causes and consequences of the transition to the knowledge economy in advanced capitalist democracies.

Key words: knowledge-based economy; labour markets; skills; technological change.

JEL classification: O33 Technological Change: Choice and Consequences; Diffusion Processes; J240 Human Capital; Skills; Occupational Choice; Labour Productivity; P51 Comparative Analysis of Economic Systems

1. Introduction

The advanced capitalist democracies have undergone a period of profound transformation since the mid-1990s as they have transitioned into knowledge-based economies (Iversen and Soskice 2019; Thelen 2019; Hall 2020). This transition has been accompanied by major changes across many spheres of public policy, including industrial relations (Ibsen and Thelen 2017; Thelen 2019), social policy (Garritzmann, Häusermann, and Palier 2022; Garritzmann, Röth, and Kleider 2023), and skills policy (Bonoli and Emmenegger 2022). It has also reconfigured the politics underpinning such policy choices (Iversen and Soskice 2015; Kitschelt and Rehm 2023), as well as producing distinct socio-economic outcomes (Hope and Martelli 2019). Despite the centrality of the knowledge economy in recent research in comparative political economy (CPE), when reading across this nascent body of work, it becomes clear that scholars tend to mean different things when referring to the 'knowledge economy'. The term has also at times (implicitly or explicitly) been used interchangeably with other—closely related but arguably distinct—terms, including automation, cognitive capitalism, digitalization, digital(ized) capitalism, the digital economy, robotization, and technological change (Moulier-Boutang 2011; Boix 2019; Thelen 2019; Choi et al. 2020; Gallego, Kurer, and Schöll 2022; Kemmerling and Trampusch 2023; Van Overbeke 2023; Busemeyer et al. 2023; Seidl 2023a; Hall 2020, 2024; Staab 2024).

A natural consequence of this lack of a unified understanding of what the knowledge economy 'is' can be seen in the use of a range of different proxies that try to measure the phenomenon. These proxies have included the ICT (information and communications technology) capital stock per employee, the intensity of public and private expenditure on R&D (research and development), the number of patent applications across different sectors and technologies, the share of employment in knowledge-intensive sectors, or the share of ICT workers as a percentage of the total workforce (Powell and Snellman 2004; Hope and Martelli 2019; Thelen 2019; Brady, Huber, and Stephens 2020; Diessner, Durazzi, and Hope 2022; Gallego, Kurer, and Schöll 2022; Seidl 2023b), as well as country rankings of knowledge intensity developed primarily by international organizations like the World Bank (see Ojanperä, Graham, and Zook 2019) or the European Bank for Reconstruction and Development (EBRD 2019). As a result, we do not currently have a commonly agreed and robust measure that allows us to capture the transition to the knowledge economy in advanced capitalist democracies and to systematically track its evolution across time and space.

This article seeks to make progress on both the conceptual and empirical fronts, by providing a theoretically-informed conceptualization of what constitutes a knowledge economy, and then using that conceptualization to construct a novel composite index of the knowledge economy. To do so, we first systematize the debate around the transition to the knowledge economy by tracing the origins of the term and highlighting its evolution in the social sciences over time, with a particular focus on how the concept of knowledge in relation to economic growth has been drawn upon by economists, sociologists, and political scientists. This review leads us to propose that a concise conceptualization of the knowledge economy should focus on two key elements in particular—*technology* and *skills*—whose complementarity is crucial to the production strategies of leading firms and sectors in the knowledge economy.

We posit, therefore, that the knowledge economy should be understood as a mode of organization of the economy that is characterized by the co-production and co-deployment of technology and high-level skills. This article seeks to map the extent to which countries have transitioned to the knowledge economy as captured by the degree to which their labour markets combine technology with high-level skills. We are primarily interested in establishing *how far* advanced capitalist democracies have gone in the transition to the knowledge economy. By implication, we do not seek to capture the policies and institutions that have favoured or held back countries' transition to the knowledge economy. In other words, our goal is to create a measure of the knowledge economy that captures 'outputs' (i.e. levels of skills and technology) rather than 'inputs' (i.e. policies and institutions that may lead to certain skills and technologies being available in the labour market). We see the latter as a subsequent step building on the index developed in this article.

We operationalize technology and skills with the help of six indicators. The technology indicators measure the prevalence of information and communications technology, industrial robots, and patents, while the skills indicators measure the employment shares of highly-skilled occupations (i.e. managers, professionals, and technicians and associate professionals) in the labour market. We utilize Bayesian latent variable analysis to construct a novel Knowledge Economy Index based on these six underlying indicators, covering twenty-two Organization for Economic Co-operation and Development (OECD) countries from 1995 to 2019. The index presented in the article aims to make an important contribution to the growing CPE literature on the knowledge economy by providing a springboard for other scholars to push forward empirical research on the causes and consequences of the transition to the knowledge economy in the advanced capitalist democracies.

2. Between skills and technology: a short history and concise conceptualization of the knowledge economy

This section aims to provide a concise review of how different social scientific disciplines have conceptualized the role of knowledge in relation to economic growth and development. We choose this approach for two main reasons. First, while the term 'knowledge economy' itself was only popularized in the late-1990s by scholars and policymakers (see, e.g. Blair and Schröder 1999 and Stiglitz 1999; for an authoritative account, see O'Donovan 2022), the transformations that underpin the concept have a much longer pedigree, reaching back to the aftermath of World War II at the very least. In his seminal work on *The Technological and Economic Origins of the Information Society*, for example, James Beniger (1986) identified no less than seventy-four terms that had been coined since 1950 in order to describe the development away from the predominant Fordist model of production (including 'new economy', 'information economy', and 'post-industrial economy'). Second, and related, many of these terms—including the knowledge economy—tend to be deliberately vague so as to accommodate a wide variety of ideas, concepts, and indicators associated with the development and use of science and technology (Godin 2010; Hadad 2017). By contrast, what we aim for is a brief synopsis of the understanding of knowledge as a key ingredient of socio-economic transformations across different academic disciplines, which we believe is a more effective way to uncover the latent theoretical dimensions underpinning different ideas of the knowledge economy. Through this approach, we seek to arrive at a comprehensive yet operationally useful conceptualization.

It was in the second half of the twentieth century that economists first began to think of the knowledge economy as a distinct phenomenon. The first use of the term can be traced to Austrian economist Fritz Machlup (1962), who conceptualized knowledge as a commodity that can be produced and distributed in its own right, arguing that the growth in technical knowledge and the resultant productivity gains had become the dominant drivers of the American economy (see Godin 2010). Machlup also sought to provide one of the first empirical estimates of the size of 'knowledge industries', suggesting that nearly 29 per cent of the US gross national product was dedicated to knowledge-producing activities in 1958 already.

This early work was accompanied by a second strand of economics research in the human capital tradition, championed by Theodore Schultz (1963) and Gary Becker (1964), and were debated critically by organizational theorists and economic sociologists, including Peter Drucker (1967, 1993) and Daniel Bell (1973). According to the human capital school, knowledge should primarily be conceived of as the skills and abilities which individuals acquire through education, training, and on-the-job experience, thus representing an investment which can generate a return in the form of higher wages and productivity. Becker (1964) employed neoclassical economic theory to analyse the factors that determine the level of investment in human capital and the role of government policies in promoting that investment, such as subsidies for education and training programs. Economic sociologists, in turn, focussed primarily on the new types of work spawned by the post-industrial knowledge economy and its wider societal implications, distinguishing manual from knowledge workers as an emerging category of labour mainly carrying out intellectual tasks (Bell 1973; Powell and Snellman 2004; see O'Donovan 2020: 251).

One of the lasting legacies of these debates has been a consensus on investment in education and research in order to promote skill formation and innovation in the pursuit of continued economic prosperity. These notions gained policy traction in the late 1990s on the back of 'new' or endogenous growth theory, which helped convince politicians and international organizations alike that economic growth was achieved by fostering human capital and R&D (Romer 1990; Crafts 1996). In Nick O'Donovan's (2020: 253–4) account of the political triumph of this set of ideas on both sides of the Atlantic, '[i]nvesting in human capital [had become] economically imperative' by the turn of the century, as policymakers sought to 'ensure that the education system provides a sustainable supply of appropriately-skilled individuals into the labour market' in order to reap the benefits of knowledge-based growth. An important extension of this argument went beyond the realm of education policy to encompass social policy at large by assigning a 'capacitating' ambition and 'skill-oriented' role to national welfare states (Morel, Palier, and Palme 2011; Garritzmann, Häusermann, and Palier 2022), in what has been discussed as a turn towards the social investment state (Hemerijck 2017; Hemerijck, Ronchi, and Plavgo 2023). The social investment perspective emphasizes the role of social policy as primarily 'preparing' individuals to thrive in contemporary labour markets rather than 'repairing' them from labour markets' adverse consequences (Morel, Palier, and Palme 2011). Accordingly, promoting human capital development throughout the life course lies at the heart of the social investment paradigm, which has been explicitly framed as 'the welfare state for the knowledge economy' (Garritzmann, Häusermann, and Palier 2022).

While diverse strands of the literature have focused on the role of skills and human capital as the key ingredient for sustaining economic growth in the knowledge economy, a parallel body of work, primarily in mainstream economics, has focussed on the productivity-enhancing effects of technology instead (see Powell and Snellman 2004: 206). Highlighting the 'astonishing productivity growth' of sectors reliant on computers and semiconductors, for example, this literature has maintained that the rollout of information and communications technology was the main driver behind the rebound in productivity observed in a number of advanced economies in the mid-1990s, most notably United States (Nordhaus 2001: 2, 2005). From this vantage point, the 'new economy' was seen as a consequence of technological progress, manifesting itself in productivity gains in technologically-advanced sectors and—from there—reverberating through the economy at large.

An adjacent literature in labour economics has looked at the transformation of labour markets in terms of *both* technological change *and* its relationship with different types of skills. Two perspectives have dominated this literature: skill-biased technological change (SBTC) (Katz and Murphy 1992; Acemoglu 1998; Autor, Katz, and Krueger 1998) and routine-biased technological change (RBTC) (Autor, Levy, and Murnane 2003; Goos and Manning 2007; Goos, Manning, and Salomons 2014). Both approaches maintain that the relationship between technology and skills is structured in an asymmetric manner. SBTC posits a linear relationship between skill levels and technology whereby technology has a complementary effect on highly skilled workers and a substitutive effect lower down the skills distribution. RBTC, instead, posits a U-shaped relationship, where the focus is not only on skill levels but also—and primarily—on the type of tasks that are associated with different occupations. From this perspective, technology boosts demand for workers who perform non-routine cognitive tasks, replaces occupations characterized by routine tasks, and leaves non-routine manual jobs largely unaffected—a development famously captured by Goos and Manning's (2007) notion of 'lousy' and 'lovely' jobs being created at the two ends of the labour market, while the middle hollows out. Hence, according to RBTC, the substitution effect of technology is concentrated in the middle of the labour market, rather than along its 'lower' tail as implied by SBTC.

Where the two perspectives overlap, however, is with regard to the upper end of the skills distribution, which represents the crucial segment of the labour market in the transition to the knowledge economy. Here, RBTC and SBTC concur that the spread of technology—primarily of ICT—boosts demand for highly skilled workers performing non-routine cognitive tasks. Such skills and tasks tend to be associated with high educational attainment, typically at the tertiary level. It is this complementary relationship between high-level skills and technology which sets the technological changes that have taken place in the late twentieth century apart from preceding waves: new technologies are more 'skill-complementary today than two centuries ago', which 'accounts for the steady increase in the demand for skills in the face of the rapidly increasing supply of skills' (Acemoglu 1998: 1058).

An important corrective to prevalent mainstream perspectives has been put forward by development economists in the heterodox tradition (Dosi 1982; Abramovitz 1993). Recent contributions in this mould have stressed the continued centrality of the manufacturing sector as a key site of knowledge development amid the ICT revolution (Hauge and Chang 2019), exemplified by the fact that the bulk of R&D spending remains tied to manufacturing activities (Andreoni and Gregory 2013). These contributions suggest that a singular focus on skills acquired through tertiary education misses important production-based capabilities that are fostered on-the-job at the plant- or firm-level (for a review, see Anzolin 2021)—a suggestion which is reflected in the specification of our index in Section 3.

These debates have travelled from labour and heterodox economics to CPE in recent years. CPE has grappled with how 'dynamic services' (such as finance and insurance), advanced manufacturing, and the ICT sector itself has thrived through the co-evolution of technological advancements and educational expansion (Wren 2013; Iversen and Soskice 2019; Hassel and Palier 2021; Diessner, Durazzi, and Hope 2022). Governments across the advanced democracies have nurtured the growth of these sectors in an effort to establish their position in high value-added segments of the global value chain (Hall 2020). In particular, they have deployed innovation and industrial policies to promote the development and adoption of new technologies (Thelen 2019; Lee 2024), while expanding the supply of highly skilled workers by means of upgrading vocational training systems and linking higher education policy with the demands of the most advanced sectors of their economies (Bonoli and Emmenegger 2022; Durazzi 2019, 2023).

The joint focus on (high) skills and technology informs our own conceptualization of the knowledge economy. As the preceding discussion suggests, it is in the complementarity between these two elements that knowledge economies thrive, and it is in their co-evolution that knowledge economies expand. Put simply, *we conceptualize the knowledge economy as a mode of organization of the economy characterized by the co-production and co-deployment of technology and high-level skills*. Knowledge economies, in other words, can be identified empirically by *the combination of technology and high-level skills that is present in a country's labour market*. We keep our definition of the knowledge economy intentionally broad to underscore our main contention that the relationship between technology *and* high-level skills is a defining feature of advanced capitalism.

This sets our conceptualization apart from other recent approaches in political economy and economic sociology that have sought to theorize digital capitalism and, in doing so, have focused primarily on the rise and implications of novel digital technologies (highlighting, among others, the ever-growing importance of big data and artificial intelligence, as well as the emergence of proprietary markets in which private platforms increasingly set and enforce rules) (Bradford 2023; Seidl 2022, 2023a; Törnberg 2023; Lehdonvirta 2024; Staab 2024). Conversely, our approach allows us to accommodate, at least indirectly, some of the more recent socio-economic developments that have been studied as part of the wider transition to the knowledge economy. For instance, although our proposed index does not capture specific developments in the realms of digital platforms or artificial intelligence, the index does remain sensitive to an increase in these sets of activities, by including a crucial enabler of both the platform economy and of AI in the form of ICT. Related to this, a clear limitation of our approach is that it remains silent on the implications of technological change for empowering certain actors over others (such as the power of multinational tech companies and their platforms over national governments, for example). At the same time, by tapping into two defining features of our times—technology and high-level skills—our index can still provide relevant contextual information for scholars of contemporary capitalism who seek to study some of these important questions on the political–economic implications of the transition to the knowledge economy.

Importantly, our conceptualization of the knowledge economy leaves room for different types of technology-skills combinations to be present in different political economies and, by implication, it allows for different pathways to knowledge-based growth (as we discuss and illustrate in detail further below). This is particularly important as it enables the indicator to capture developments in both the services and the manufacturing sectors, to the extent that these sectors combine high technology and high-level skills. This allows us to de-couple our conceptualization of the knowledge economy from structural shifts in the sectoral composition of national economies, in that our conceptualization is deliberately blind to which sectors undergo a transformation toward higher levels of technology and skills, thus allowing for different sectors to provide a different *relative* contribution to national knowledge economies.

We believe that this approach is empirically parsimonious, while retaining robust theoretical underpinnings in that it builds on important recent findings in both labour and heterodox economics as well as CPE that veer away from an exclusive focus on either human capital or technological change to place the emphasis, instead, on the symbiotic relationship between different types of technologies and high-level skills. Moreover, it allows us to place countries along a continuum and to trace their evolution, by tracking how levels of technology and high skills compare across different political economies and how they have evolved over time. The next section translates this theoretical discussion into a new measure of the knowledge economy, introducing six indicators through which we propose to capture the main dimensions of technology- and skill-intensity, before describing the Bayesian latent variable analysis we use to construct our composite Knowledge Economy Index.

3. Better measuring the knowledge economy

In the previous section, we established *technology* and *skills* as the two crucial features that should be considered when seeking to capture the extent to which advanced democracies have transitioned into knowledge economies. In this section, we discuss how we can draw on this conceptualization to better measure the knowledge economy.

3.1 The rationale for constructing a composite index

The rationale for selecting multiple indicators to construct our Knowledge Economy Index aligns closely with our conceptualization of the knowledge economy set out in the previous section, which focuses on the interaction of skills and technology. As a result, we think of the knowledge economy as a multifaceted phenomenon, meaning that there is no single path to knowledge intensity. The CPE literature has already shown that the advanced capitalist democracies have transitioned to the knowledge economy in different ways. For example, Germany continues to specialize in (increasingly ICT- and robot-intensive) advanced manufacturing (Thelen 2019; Dauth et al. 2021; Diessner, Durazzi, and Hope 2022), the United Kingdom and United States have shifted more towards high-end, knowledge-intensive services (Wren 2013; Hope and Martelli 2019), while Sweden has branched out to knowledge-intensive services building on pre-existing core strengths in advanced manufacturing (Thelen 2019; Anzolin and Benassi 2024). Relying on a single indicator to measure the knowledge economy, which has been the standard approach in existing empirical studies in CPE (e.g., Kwon and Roberts 2015; Hope and Martelli 2019; Hope and Limberg 2022b), therefore risks missing an important part of the picture, as countries are likely to 'score' very differently on different indicators. A composite index thus has two crucial advantages over single indicators: firstly, it allows to comprehensively capture the transition to the knowledge economy by establishing an *overall level of knowledge intensity* over time (as we will show in Section 4); secondly, it allows to shed light on *distinct paths to the knowledge economy* by subdividing the composite index and focussing on *specific subsets of the underlying indicators* in line with theoretical priors (as we will show in Section 5).

Treating the knowledge economy as multidimensional also aligns with existing knowledge economy indices produced by international organizations such as the World Bank (see Ojanperä, Graham, and Zook 2019) and the European Bank for Reconstruction and Development (EBRD 2019). These indices, however, are typically constructed from a large number of underlying variables, many of which fall outside of our conceptualization, which focuses on technology and high skills (e.g. the EBRD Knowledge Economy Index is derived from a total of thirty-eight indicators, including measures of the business environment, economic openness, and governance). Importantly, these indices merely provide a snapshot in a given year (the EBRD index is only available for the years 2011 and 2018), which makes it difficult or impossible to track the evolution of knowledge economies over time and to conduct panel data analyses which we believe are particularly relevant to fully understanding the causes and consequences of the transition to the knowledge economy in the advanced capitalist democracies. Indeed, this is one of the key motivations for constructing our own index.

3.2 The underlying knowledge economy indicators

Table 1 presents the six indicators that, when combined, we believe can provide a novel and more encompassing index of the knowledge economy. The table groups the indicators into two categories—technology and skills—in line with our theoretical conceptualization.

The technology indicators are measures of ICT, industrial robots, and patents. ICT and robots have been central to the labour economics literature exploring the effects of technological change on the labour market (Autor, Katz, and Krueger 1998; Autor, Levy, and Murnane 2003; Acemoglu and Autor 2011; Acemoglu and Restrepo 2020; Dauth et al. 2021), as well as the political science literature on the political consequences of technological change (Anelli, Colantone, and Stanig 2021; Gallego, Kurer, and Schöll 2022; Schöll and Kurer 2024). We include indicators for both ICT and robots as previous empirical research has found them to be 'two distinct forms of technological change' (Schöll and Kurer 2024: 8). Robotization primarily captures automation in the manufacturing sector, whereas ICT is more evenly spread across sectors and is especially important in high-end services such as finance and the technology sector itself (Hope and Martelli 2019; Schöll and Kurer 2024).

The final technology indicator is patents, which have been widely used across the social sciences as a measure of innovation (Lee and Rodríguez-Pose 2013; Iversen and Soskice 2019; Powell and Snellman 2004). The OECD definition of patents states that they 'protect technological inventions (i.e., products or processes providing new ways of doing something or new technological solutions to problems)' (OECD 2019: 148). We use IP5 patent families for our measure of patents, which covers patents filed in at least two offices worldwide, including one of the five largest IP offices. Patents are a direct measure of innovation activity that offer important 'insight into the contribution of knowledge-intensive activities to economic growth' (Powell and Snellman 2004: 202). A key strength of patents as a measure of innovation is that—unlike other commonly used proxies such as R&D spending—they are an output from innovation rather than an input (Lee and Rodríguez-Pose 2013: 9). Taken together, our three technology indicators aim to capture both the frontier of innovation and technological change (through patents), as well as how widely new technologies have diffused and been adopted in production processes throughout the economy (through ICT and robots).

Table 1. The six knowledge economy indicators.

Indicator	Measure	Source
Technology		
ICT	ICT capital stock per employee (in thousands of 2015 €s)	EUKLEMS and INTANProd Database—release 2023, Luiss Lab of European Economics
Industrial robots	Industrial robots (per 1,000 employees)	International Federation of Robotics for number of industrial robots; EUKLEMS and INTANProd Database—release 2023, Luiss Lab of European Economics for number of employees
Patents	IP5 patent families (per 10,000 employees)	OECD Directorate for Science, Technology and Industry—Patent Database for number of patent families; EUKLEMS and INTANProd Database—release 2023, Luiss Lab of European Economics for number of employees
Skills		
Managers	ISCO–08 Major Group 1. Managers (as a share of total employment)	EU Labour Force Survey (LFS) for European countries; IPUMS Current Population Survey (CPS) for United States
Professionals	ISCO–08 Major Group 2. Professionals (as a share of total employment)	EU LFS for European countries; IPUMS CPS for United States
Technicians and associate professionals	ISCO–08 Major Group 3: Technicians and associate professionals (as a share of total employment)	EU LFS for European countries; IPUMS CPS for United States

Note: Additional information on the sources and calculation methods for each of the indicators can be found in Supplementary Appendix Part A. For the European countries in the sample, the skills indicators are constructed using the microdata from the EU LFS. We thank Eurostat for access to the data. The results and conclusions drawn from the data are those of the authors and not those of Eurostat, the European Commission, or any of the national statistical authorities whose data have been used.

On the skills side, we use three different indicators as well, which are constructed from labour force survey data and from the International Standard Classification of Occupations (ISCO) published in 2008 (ISCO–08). ISCO–08 classifies occupations into ten major groups. Each major group is also assigned a *skill level* from 1 to 4, which is 'defined as a function of the complexity and range of tasks and duties performed in an occupation' (International Labour Organization 2023: 15). Skill levels 3 and 4 represent the most high-skilled occupations and these apply to only the first three major groups: (1) Managers (skill levels 3 and 4); (2) Professionals (skill level 4); and (3) Technicians and associate professionals (skill level 3). For a full mapping of the ISCO–08 major groups to skill levels, see Supplementary Appendix Part A.

We therefore use the share of total employment in each of these occupational groups as our three skills indicators. To make these series comparable over time and across countries, we follow the existing labour economics literature (Goos, Manning, and Salomons 2014; Hardy, Keister, and Lewandowski 2018) and correct for structural breaks occurring due to the changing or revising of occupational classifications over time, as well as linearly extrapolating the small number of missing country-year observations (the index created without extrapolating these twelve missing observations is almost identical to the main index; see Supplementary Appendix Fig. B5). Details of these adjustments are explained in Supplementary Appendix Part A.

While the ISCO-08 skill levels take into account the level of formal education required in an occupation—skill levels 3 and 4 are typically associated with workers possessing tertiary education (International Labour Organization 2023: 50)—, the ILO define *skill* more broadly as 'the ability to carry out the tasks and duties of a given job' (International Labour Organization 2012: 11). Hence, the nature of the work and the amount of previous experience and/or informal on-the-job training needed for the job also form part of how the ILO assess the skill level of an occupation, in line with heterodox economists' emphasis on the importance of production-based capabilities. The tasks that the ISCO descriptors associate with occupations at skills levels 3 and 4 fit closely with the types of complex, non-routine cognitive tasks that the labour economics literature sees as complementary to new technologies (Autor, Levy, and Murnane 2003; Acemoglu and Autor 2011). Occupations at skill level 4 (hence professionals and partly managers) require 'complex problem-solving, decision-making and creativity based on an extensive body of theoretical and factual knowledge in a specialized field' as well as 'extended levels of literacy and numeracy, sometimes at a very high level, and excellent interpersonal communication skills' (International Labour Organization 2012: 13). Occupations at skill level 3 (hence technicians and associate professionals and partly managers) entail 'complex technical and practical tasks that require an extensive body of factual, technical, and procedural knowledge in a specialized field' as well as 'a high level of literature and numeracy and well-developed interpersonal communication skills' (International Labour Organization 2012: 13).

On top of the close alignment with our conceptualization of the knowledge economy, we see several other advantages of our operationalization of skills over measures that focus on formal education alone such as enrolment in tertiary education. First, our operationalization that focuses on skills levels of *occupations* is better aligned with our goal to create a measure of the knowledge economy that focuses on 'outputs' rather than 'inputs'. Focusing on measures of skill supply, such as enrolment in tertiary education, would risk pushing us into 'inputs' territory, as they are closely tied to national education policies. Our operationalization also allows for different skill 'inputs' (i.e., national configurations of education and training systems) to potentially lead to similar skill levels. In other words, our skill measure captures high-skilled workers beyond those that have gone through traditional three-year degree programmes. We believe that this is conceptually important in light of recent research which suggests that, in the context of the transition to the knowledge economy, countries may opt for and be able to pursue an upskilling strategy based on either the expansion of the higher education sector or on an upgrade of their vocational education and training system (see Emmenegger, Bajka, and Ivardi 2023). This is corroborated by Durazzi and Tonelli (2024), who show that some vocational training systems—chiefly, collective skill formation systems—can provide an effective route for workers *without* tertiary education to be employed in non-routine, cognitive occupations, particularly in contexts of high technological intensity.

Second, our measures are less likely to be affected by 'skill mismatch' (Ansell and Gingrich 2017), as they avoid picking up workers with high levels of formal education whose jobs do not utilize those skills (such as university graduates working non-graduate jobs). The problem of skill mismatch has recently been addressed by Garritzmann, Häusermann, and Palier (2022: 273) who combine demand for skilled labour (through an occupational measure analogous to ours) with supply of skilled labour (through a measure of expansion of higher education). This allows the authors to distinguish between knowledge economies (characterized both by strong demand and supply of skilled labour); non-knowledge economies (characterized by neither); over-education (characterized by strong supply and weak demand); and skilled-labour scarcity (characterized by strong demand and weak supply) (Garritzmann, Häusermann, and Palier 2022). While this categorization is very helpful for dealing with the issue of skill mismatch, we prefer to operationalize skills in a way that is blind to their supply, for two main reasons. On the one hand, as spelled out in the previous paragraph, we believe it is important to theoretically allow for the possibility of 'functional equivalence' between higher education and training systems in providing high-level skills (in line with Emmenegger, Bajka, and Ivardi 2023). On the other hand, our operationalization of the knowledge economy seeks to remain firmly within the domain of 'outputs' (in this case: skill levels) in order to enable future research to assess more systematically which kinds of 'inputs' (in this case: education policy) can explain different levels and types of transitions to the knowledge economy.

Lastly, our operationalization of skills is also in line with that of Fleckenstein, Saunders, and Seeleib-Kaiser (2011), who associate the ISCO occupational groups with three different categories of skills: high-general, low-general, and specific. The only occupational groups that the authors allocate to the high-general category are ISCO groups 1–3, which they see as post-industrial jobs, as per Esping-Andersen's (1993) hierarchy of occupations. This grouping is primarily driven by the similarity of tasks involved, as workers in these occupations typically have high educational attainment and skills that are not bound to specific firms or industries (Fleckenstein, Saunders, and Seeleib-Kaiser 2011). It is precisely these high-level general skills that have become central to the production strategies of leading firms in the knowledge economy (Iversen and Soskice 2019; Diessner, Durazzi, and Hope 2022).

3.3 Constructing the index

To construct a composite Knowledge Economy Index from our six underlying indicators, we use Bayesian latent variable analysis (Lee 2007). This approach has become increasingly popular in the social sciences, with applications in recent years including the creation of indices for state capacity (Hanson and Sigman 2021) and taxes on the rich (Hope and Limberg 2022a, 2022b).

A latent variable is an 'unobserved or not directly measurable variable whose values can be inferred from the observed or measurable variables' (Black, Hashimzade, and Myles 2009). In this case, we are inferring the latent construct of the knowledge economy from our six underlying (measurable) knowledge economy indicators. Modelling the knowledge economy as a latent variable has two key advantages. First, the index is constructed solely based on the common variance of our six indicators (i.e., the extent to which they move together). The index construction is therefore data-driven and avoids the researcher having to make (arbitrary) decisions about how to weight the different components. Second, using this approach allows for the creation of an index that is comparable across countries and over time (even though the underlying indicators are in different units). This means the index not only allows us to track the changes in knowledge intensiveness across the OECD countries over time, it is also well-suited for panel data analysis, which can help further advance our understanding of the socio-economic causes and consequences of the rise of the knowledge economy.

We estimate the latent variable estimated using a Bayesian Markov–Chain Monte Carlo (MCMC) approach with a single dimension, diffuse normal priors, three MCMC chains and 1,000 burnin iterations, and the means of the observed variables enter the model (Lee 2007; Merkle and Rosseel 2018; Hope and Limberg 2022b). For all estimations of the MCMC, we use the *blavaan* package in R. Merkle and Rosseel (2018) provides detailed information on Bayesian latent variable analysis and its implementation. The Knowledge Economy Index we construct runs from 1995 to 2019 and covers twenty-two OECD countries (Fig. 1 in Section 4 shows the specific countries and years that the index covers). The index is available to download from: www.knowledge-economy-index.com. The website also contains data for the underlying knowledge economy indicators and the R code used for constructing the index.

We focus on OECD countries as we are looking to capture the transition to the knowledge economy in a set of comparable advanced capitalist democracies. Beyond that, the coverage of the index is determined by data availability. The country coverage is constrained to twenty-two countries due to the limited availability of the EU KLEMS data for non-European countries (EU KLEMS stands for EU level analysis of capital (K), labour (L), energy (E), materials (M) and service (S) inputs). The coverage over time is dictated by a number of our knowledge economy indicators having limited or no coverage before the mid-1990s. The index beginning in 1995 means that it cannot pick up earlier stages of the growing importance of knowledge to economic growth (as outlined in the first part of Section 2). It is the post-1995 period, however, that aligns most closely with our conceptualization of the knowledge economy as a mode of organization of the economy characterized by the co-production and co-deployment of technology and high-level skills, in line with extant CPE scholarship on the knowledge economy. Peter Hall's (2020, 2024) influential work on growth regimes, for example, identifies the late 1990s as the onset of the 'era of knowledge-based growth' across the advanced capitalist economies.

4. The Knowledge Economy Index

This section explores our composite Knowledge Economy Index descriptively, providing new insights into how the advanced democracies have transitioned to the knowledge economy, before presenting a number of tests to check the validity of the novel index.

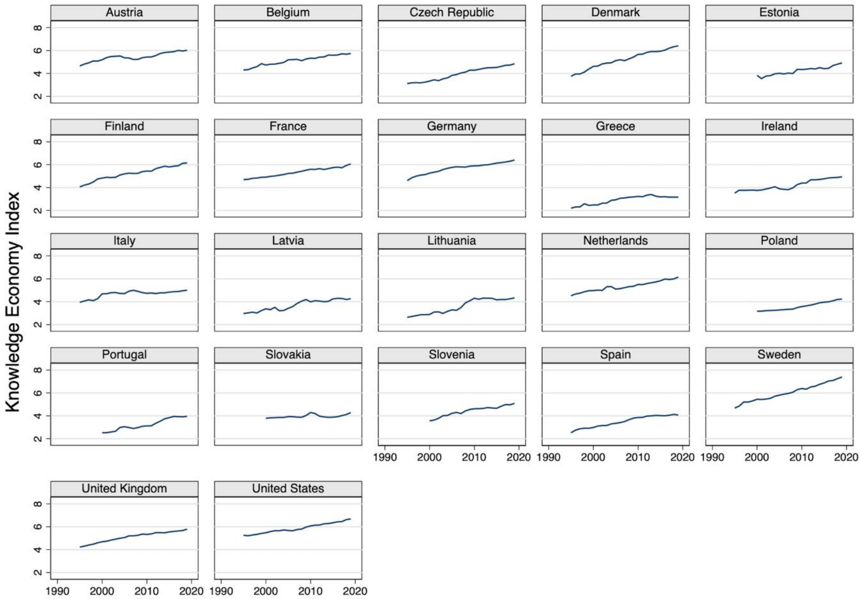

Figure 1. Knowledge Economy Index for twenty-two OECD countries, 1995–2019.

Figure 1 displays the development of our Knowledge Economy Index across the advanced democracies between 1995 and 2019. Higher scores on the index represent greater levels of knowledge intensiveness of an economy. The values themselves do not have substantive meaning, since they are a latent construct. However, and crucially, they are comparable not only across countries but also over time. This allows us to assess the relative knowledge intensiveness of the countries in our sample over the past two and a half decades. There are three key takeaways from the figure: first, all countries in the sample have become more knowledge intensive over the sample period; second, there is substantial cross-national variation in the level of knowledge intensiveness; and third, there does not seem to be one single path to knowledge intensiveness. To illustrate the latter, three of the countries that score very highly on the index—Sweden, United States, and Germany—are typically portrayed as very different political economies in the CPE literature (Esping-Andersen 1990; Hall and Soskice 2001; Thelen 2014; Baccaro and Pontusson 2016).

Table 2 shows the compound annual growth rate (CAGR) of the Knowledge Economy Index over the period under investigation to explore how rapidly countries have transitioned towards the knowledge economy.

The country with the fastest growth over the period is Portugal, whose Knowledge Economy Index grew at an average rate of 2.4 per cent per year. Portugal, along with Greece and the Central and Eastern European countries in the sample, however, did begin the period with comparatively low levels of knowledge intensiveness. Denmark and Lithuania are other countries that saw knowledge intensiveness grow particularly rapidly, with annual growth rates of 2.25 per cent and 2.1 per cent, respectively, between 1995 and 2019. At the other end of the scale are countries that saw knowledge intensiveness expand much more glacially—for example, Slovakia and Italy displayed average yearly growth rates

Table 2. Growth rate of the Knowledge Economy Index, 1995–2019.

Country	1995	2019	CAGR (%)
Austria	4.66	6.02	1.08
Belgium	4.31	5.74	1.21
Czech Republic	3.12	4.85	1.85
Denmark	3.76	6.41	2.25
Estonia	3.84[a]	4.92	1.31
Finland	4.06	6.16	1.75
France	4.70	6.07	1.07
Germany	4.61	6.41	1.39
Greece	2.20	3.17	1.52
Ireland	3.51	4.94	1.43
Italy	3.95	5.01	0.99
Latvia	2.97	4.26	1.52
Lithuania	2.64	4.34	2.10
Netherlands	4.52	6.15	1.29
Poland	3.17[a]	4.24	1.54
Portugal	2.52[a]	3.96	2.40
Slovakia	3.78[a]	4.28	0.65
Slovenia	3.56[a]	5.09	1.89
Spain	2.52	4.07	2.02
Sweden	4.68	7.39	1.92
United Kingdom	4.22	5.79	1.32
United States	5.25	6.68	1.01

[a]Data points are for the year 2000.
Note: Growth rates calculated as CAGRs.

of just 0.65 per cent and 0.99 per cent, respectively. Most countries in the sample grew in knowledge intensiveness between 1 per cent and 2 per cent a year, respectively, over the period. It is worth noting that countries that started the period with comparatively low scores on the Knowledge Economy Index appear to have grown faster than those starting with higher scores: a significant, moderate–strong negative correlation between the initial score on the Knowledge Economy Index and the annual growth rate over the period can be observed in our sample ($r = -0.56$, P-value < 0.01).

Despite evidence of a 'catch-up' process between knowledge economy laggards and leaders, the ranking of countries on the index has remained largely stable over time (the Spearman correlation coefficient for the index rankings for the twenty-two countries in the sample in 2000 and 2019 is 0.92), and the cross-country variation in scores on the Knowledge Economy Index remains substantial at the end of the sample period. This is highlighted in Fig. 2, which shows the stark differences in knowledge intensiveness across the OECD countries in 2019. We can see that the leading knowledge economies are Sweden, United States, Denmark, and Germany, all with scores well over 6. At the bottom end are Greece and Portugal, with values below 4. It is also worth noting that the countries that score highly on the Knowledge Economy Index score highly on the underlying indicators for *both* technology and skills (see Supplementary Appendix Figs B1–B4), which aligns

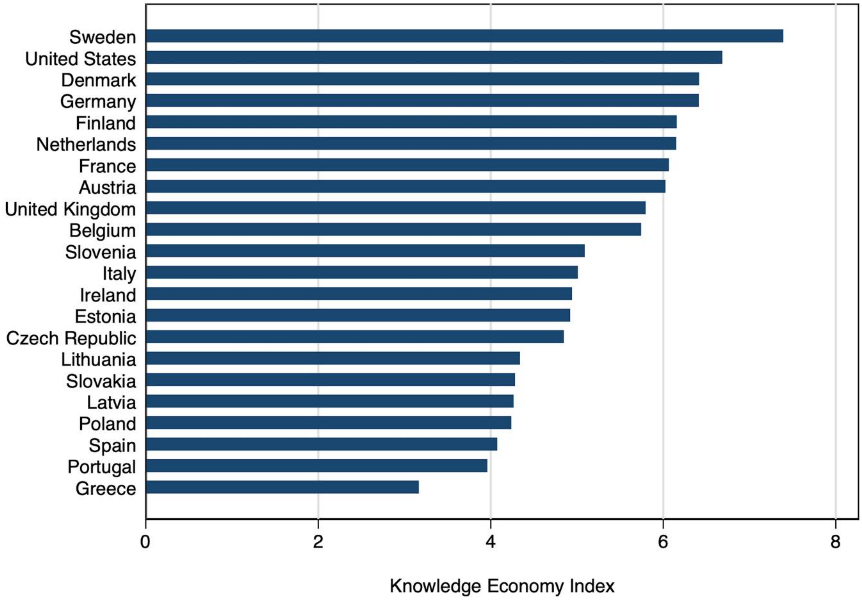

Figure 2. Knowledge Economy Index in 2019.

with our conceptualization of the knowledge economy that centres on the complementarity between technology and (high) skills.

Now we have explored the Knowledge Economy Index descriptively, we move on to look at which factors drive the index by examining the correlations between the index and the six underlying knowledge economy indicators. The pair-wise correlations and *P*-values are shown in Table 3. We can see that five of the six indicators are strongly positively correlated with the index, with patents ($r = 0.82$), technicians, and associate professionals ($r = 0.79$), and ICT ($r = 0.74$) being the most strongly associated. These three variables alongside industrial robots and professionals all correlate with *P*-values < 0.0001, meaning the correlations are highly statistically significant.

The only indicator that is not strongly correlated with the Knowledge Economy Index is managers. The correlation coefficient is close to zero ($r = 0.05$) and it fails to reach conventional levels of statistical significance. If the manager's indicator is removed from the estimation of the index, however, the results remain substantively unchanged. The correlation of the resulting index with our Knowledge Economy Index is 0.969 (*P*-value $<$ 0.0001) (see Supplementary Appendix Fig. B6). There are moreover plausible theoretical arguments to retain managers in the index, since this occupational group is assigned to skill levels 3 and 4 in the ISCO–08 classification (see previous section) and the tasks performed in managerial jobs are typically seen as complementary to new technologies in the labour economics literature (e.g., Autor, Levy, and Murnane 2003; Acemoglu and Autor 2011). In the ISCO-08 classification (International Labour Organization 2023), there are also several managerial occupations that sit firmly at the intersection of technology and high skills such as Research and Development Managers (ISCO-08 code 1223) and

Table 3. Correlation of Knowledge Economy Index with the six underlying indicators.

Indicator	*r*	*P*-value
Patents	0.82	<0.0001
Technicians and associate professionals	0.79	<0.0001
Information and communications technology	0.74	<0.0001
Industrial robots	0.60	<0.0001
Professionals	0.59	<0.0001
Managers	0.05	0.28

Note: r = pair-wise correlation coefficient.

Information and Communications Technology Service Managers (ISCO-08 code 1330). Taking into account these empirical and theoretical considerations, we decided to keep this indicator in our models.

We next compare our Knowledge Economy Index to other measures of the same or closely related concepts that were not included in the estimation of our latent variable. Following a similar logic to Hanson and Sigman (2021: 1505), this is to assess the validity of our measure and the extent to which it 'accurately taps the intended concept' of the knowledge economy. If our measure is valid, we should find that it is strongly correlated with other measures of the knowledge economy.

The first alternative measure we look at is the employment share in knowledge-intensive (i.e. ICT-intensive) services (Wren 2013; Hope and Martelli 2019; Hope and Limberg 2022b). Our index is strongly positively correlated with the employment share in knowledge-intensive services ($r = 0.717$; P-value < 0.0001) over our sample period (see Supplementary Appendix Fig. B7). While the strong correlation bodes well for the validity of our measure, it is also reassuring that the two measures are not picking up exactly the same thing (i.e. they are not close to being perfectly positively correlated). Our index has been purposely designed to stretch wider than knowledge-intensive services and to also pick up the growing knowledge intensity of other parts of the economy, especially in advanced manufacturing. As such, it aims to remove the service sector bias inherent in many of the previous measures used by scholars to capture the knowledge economy.

There are several other measures of the knowledge economy that have been produced in the past but their coverage, particularly over time, is much poorer than for the employment share in knowledge-intensive services. To compare our index to a wider range of related measures, we therefore focus on correlations in a single year (2011 or 2012, depending on the measure). Table 4 shows the correlation coefficients and P-values. We can see that the Knowledge Economy Index is positively and statistically significantly correlated with all five of the alternative measures (as further highlighted by the scatterplots in Supplementary Appendix Fig. B8).

Our index is particularly highly correlated with the composite indices of the knowledge economy constructed by the EBRD ($r = 0.94$) (EBRD 2019) and the World Bank ($r = 0.86$), as well as the closely related Digital Knowledge Economy Index ($r = 0.85$) (Ojanperä, Graham, and Zook 2019). This offers further validation of our index. As discussed in Section 3.1, a major weakness of the EBRD and World Bank measures for comparative

Table 4. Correlation of Knowledge Economy Index with other measures of the knowledge economy in 2011/12.

Indicator	*r*	*P*-value
EBRD Knowledge Economy Index (2011)	0.94	<0.0001
World Bank Knowledge Economy Index (2012)	0.86	<0.0001
Digital Knowledge Economy Index (2012)	0.85	<0.0001
Economic Complexity Index (2012)	0.69	<0.001
Employment share of knowledge-intensive services (2012)	0.67	<0.001

Note: r = pair-wise correlation coefficient. For the EBRD Knowledge Economy Index, the data is for 2011 and coverage is limited to thirteen countries (Czech Republic, Estonia, France, Germany, Greece, Lithuania, Latvia, Poland, Slovenia, Slovakia, Sweden, the UK, and the USA). For the other four measures, the data is for 2012 and covers all twenty-two countries in our sample. The employment share in knowledge-intensive services is calculated from the same EU-KLEMS database used in our main analysis. We follow the approach in Hope and Limberg (2022b) by summing the employment shares in the ICT-intensive service sectors of finance and insurance, information and communication, and professional, scientific, technical, administrative and support services.

research is that they are only available in certain years and use many more variables in their construction than our index. It is encouraging that our more parsimonious approach using just six underlying indicators, which allows for the construction of an annual index covering twenty-two countries and running from 1995 to 2019, tallies so closely with the more data-intensive EBRD and World Bank indices.

The Knowledge Economy Index is slightly less correlated with the other two measures in Table 4: The Economic Complexity Index ($r = 0.69$) and the employment share in knowledge-intensive services ($r = 0.67$). This is unsurprising, however, for one and the same reason. As discussed above, the latter measure is solely focused on the service sector and therefore misses important parts of the knowledge economy that are encompassed in our index. The Economic Complexity Index, in turn, is taken from the Harvard Growth Lab's Atlas of Economic Complexity (available from: https://atlas.cid.harvard.edu/rankings) and assesses the state of a country's productive knowledge by looking at the number and complexity of the products it exports. In contrast to the previous measure, the Economic Complexity Index is more focused on advanced manufacturing, and hence, it is less well-suited than our index to picking up the knowledge intensiveness of *both* services *and* manufacturing.

A final validity check that we perform on our index is to look at its relation to GDP per capita. In our theoretical discussion (Section 2), we conceptualized the role of knowledge in relation to economic growth and development. Hence, we have strong theoretical reasons to believe that GDP per capita will be positively correlated with our index. Figure 3 shows exactly that. The correlation between the Knowledge Economy Index and GDP per capita is 0.769 (P-value < 0.0001), and the strength of the correlation has increased over time (see Supplementary Appendix Fig. B9). Again, the extent of the correlation (of around 0.8) is encouraging, as it shows that the rise of the knowledge economy is clearly associated with economic development, but also that the Knowledge Economy Index is capturing something distinct from GDP per capita.

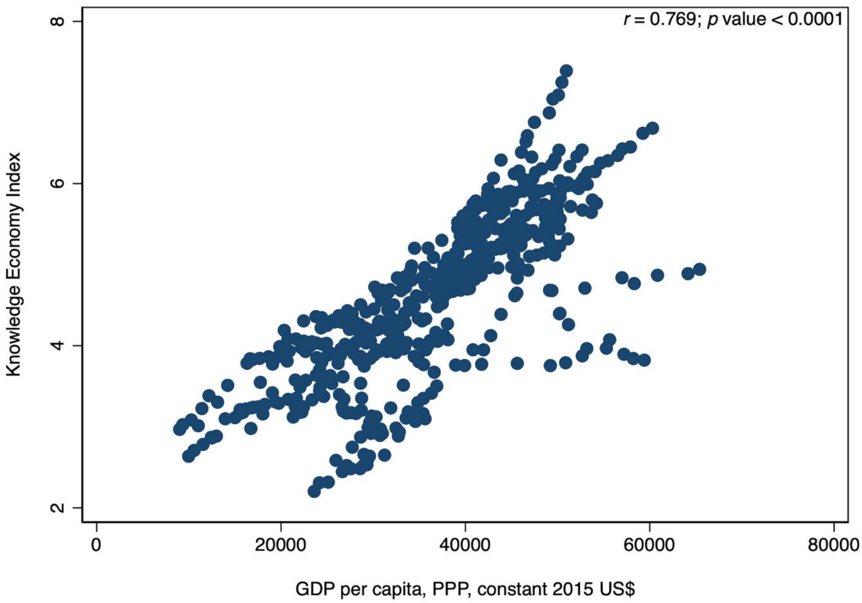

Figure 3 Scatterplot of Knowledge Economy Index vs. GDP per capita (PPP, constant 2015, USD), 1995–2019.

Source: GDP per capita (PPP, constant 2015, USD) data is from the OECD Annual National Accounts.

Note: Ireland's GDP per capita has been scaled to reflect the adjustments made by the Irish Central Statistics Office when calculating Modified Gross National Income, which is an indicator they have specifically designed to measure the size of the Irish economy *excluding* globalization effects (including the net income of re-domiciled companies).

5. Varieties of the knowledge economy: an example of using the underlying indicators of the Knowledge Economy Index in CPE research

This section provides an illustration of how not only the overall Knowledge Economy Index but also its underlying components can yield useful insights for scholars of comparative capitalism. The starting point for this empirical illustration is the Varieties of Capitalism (VoC) literature (Hall and Soskice 2001) that shifted the CPE paradigm in the early 2000s by pointing at the idea that different models of capitalism can achieve equally successful economic outcomes. The two ideal-typical models of VoC—famously captured by the labels of Liberal Market Economies (LMEs) and Coordinated Market Economies—suggested that countries can succeed in certain economic sectors and pursue distinct product specializations through different sets of complementary institutions (Hall and Soskice 2001). We do not intend to revisit the vast VoC literature here. What we seek to do, instead, is to build on one key insight from that literature—namely, the economic viability of more than one model of capitalism through the second half of the twentieth century—to explore the extent to which it may still apply to knowledge economies in the twenty-first century.

To do so, we select two countries—Germany and the USA—that score similarly in the overall Knowledge Economy Index and that locate firmly near the top of the 'ranking', but that are commonly identified in the CPE literature as representing two radically different models of organizing the national political economy. Both are frequently brought up to showcase different VoC (Hall and Soskice 2001), worlds of welfare (Esping-Andersen 1990), and growth models (Baccaro and Pontusson 2016). In the most recent five-year period of our index, the average scores of both countries are almost identical, standing at 6.3 for Germany and 6.5 for USA. However, when looking through the six underlying components of the index, we notice remarkable differences in how the two have arrived at similar levels of knowledge intensity. Assessing the six components separately, it is striking to note how their respective values mirror one another, in that Germany scores significantly higher than the USA as far as industrial robots, patents, and technicians and associate professionals are concerned, while the USA clearly 'outperforms' Germany in terms of ICT, managers, and professionals, as highlighted in Table 5.

A plausible interpretation of Table 5 is that—in the spirit of VoC—there is systematic variation in the ways in which national knowledge economies are organized. Indeed, reading Table 5 through the lens of existing literature would suggest that the six underlying indicators 'split' between the two countries with a degree of coherence that can be understood in light of the predominant sectoral configuration of national knowledge economies. Recent literature has documented how Germany's transition to the knowledge economy has been characterized by an upgrading of its 'traditional' manufacturing strengths in the direction of high-technology manufacturing (Iversen and Soskice 2019; Thelen 2019; Diessner, Durazzi, and Hope 2022). From this perspective, it seems plausible that concerted public–private efforts (e.g. under the headline of 'Industrie 4.0') have resulted in above-average adoption and utilization of robotics in German firms (Thelen 2019) and in a plentiful supply of highly-skilled technicians (Diessner, Durazzi, and Hope 2022; Durazzi 2023), creating the conditions for technological advancements and significant patenting activity (Anzolin and Benassi 2024) anchored in high-technology manufacturing. Conversely, the

Table 5. Comparison of Germany and the United States on the underlying components of the Knowledge Economy Index, 2015–19 averages.

	Germany	USA
Technology		
ICT	3.3	11.9
Industrial robots	5.1	1.8
Patents	6.2	3.3
Skills		
Managers	4.7	11.5
Professionals	17.7	22.9
Technicians and associate professionals	22.5	17.5
Knowledge Economy Index	6.3	6.5

Source: See Table 1 for list of sources for underlying knowledge economy indicators.
Note: Values in bold indicate the highest scoring country on each underlying indicator.

transition to the knowledge economy in the USA has been characterized to a greater extent by the expansion of high-end services, and in particular so-called FIRE services, encompassing finance, insurance, and real estate (Wren 2013). From a technological standpoint, these are sectors in which ICT intensity is particularly pronounced (Hope and Martelli 2019), and this has been coupled with a strong influx of workers with high-level general skills, as embodied by the ISCO major groups of managers and professionals (Ansell and Gingrich 2013).

Based on these observations, we suggest that variation in national knowledge economies may be usefully organized—both theoretically and empirically—in a two-dimensional space, with each dimension capturing a different sectoral specialization related to either advanced manufacturing or high-end services. To pursue this line of thought further, we create two dimensions from our six underlying indicators. Dimension 1 includes ICT, managers, and professionals, while Dimension 2 comprises patents, industrial robots, and technicians, and associate professionals. Similar to the main Knowledge Economy Index, we construct the two dimensions using Bayesian latent variable analysis (Lee 2007; Merkle and Rosseel 2018). As shown in Supplementary Appendix Table B1, each of the two dimensions are positively and statistically significantly (P-value < 0.0001) correlated with all three of their underlying components.

Figure 4 shows how countries rank along the two dimensions for the most recent year of our Knowledge Economy Index, 2019. Traditional manufacturing powerhouses like Germany, Austria, or Italy rank high on Dimension 2 and relatively low on Dimension 1. Conversely, countries with large knowledge-intensive service sectors like the USA, the UK, or the Netherlands perform better on Dimension 1 than on Dimension 2. A subset of countries—chiefly the Scandinavians—rank close to the top in both dimensions, testifying to their ability to cultivate competitive advantages in both macro-sectors.

To further probe the hypothesized affinity between the two dimensions of the Knowledge Economy Index and countries' sectoral specializations, we plot each country's score on Dimension 1 (Dimension 2) against its share in gross value added (GVA) of knowledge-intensive services (advanced manufacturing). The results are reported in Fig. 5 and provide strong support for the reasoning developed in this section: Dimension 1 correlates strongly and statistically significantly with countries' reliance on knowledge-intensive services, while Dimension 2 is tightly linked with the contribution of the advanced manufacturing sector to national economic output. Importantly, and further corroborating our argument, the opposite does not hold true: Dimension 1 does not correlate with GVA share in advanced manufacturing ($r = -0.040$; P-value $= 0.864$), and neither does Dimension 2 correlate with GVA share in knowledge-intensive services ($r = 0.264$; P-value $= 0.236$). Tracing the sectoral foundations of countries' knowledge economy is a substantively important point. Figure 3 demonstrates that knowledge intensity correlates with countries' economic performance, as expressed by GDP per capita. Yet, different configurations of the knowledge economy in terms of sectoral compositions are likely to have *different* distributive implications at *similar* levels of economic performance (Ansell and Gingrich 2021). Thus, while our overall Knowledge Economy Index can be an important source of information for scholars interested in the relationship between knowledge intensity and economic development, the underlying dimensions of the index speak to scholarship aiming to understand the socio-economic implications of different pathways to the knowledge economy.

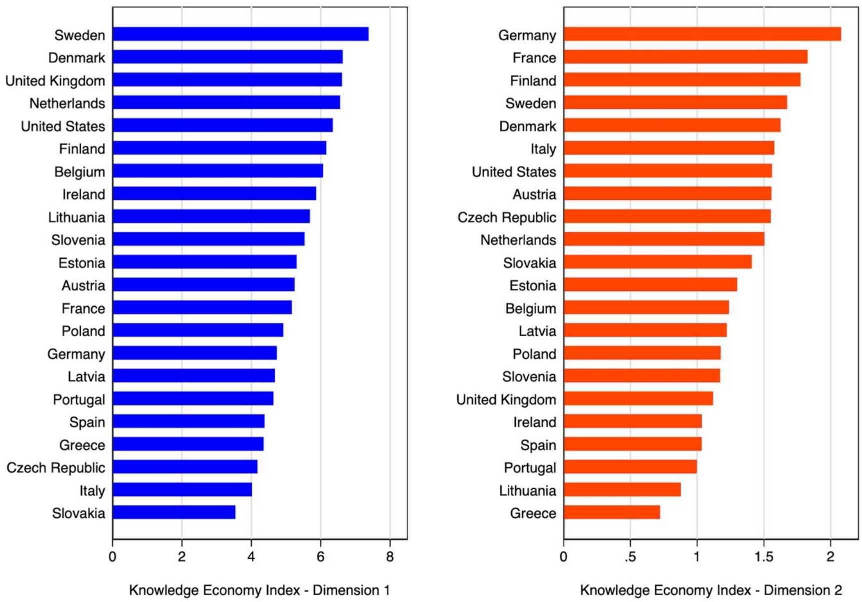

Figure 4 Ranking of countries on the two dimensions of the Knowledge Economy Index in 2019.
Note: Dimension 1 is constructed from the series for ICT, managers, and professionals. Dimension 2 is constructed from the series for robots, patents, and technicians and associate professionals.

Having demonstrated that breaking down the Knowledge Economy Index into two dimensions can help us capture interesting variation between knowledge economies in terms of their core sectoral specializations, we proceed to plot the two dimensions against each other. This allows us to locate national knowledge economies across four different quadrants, as outlined in Fig. 6. The figure provides insights into how different configurations of the knowledge economy have emerged across countries. We start from the bottom right quadrant, which features countries that do well on Dimension 2 and relatively poorly on Dimension 1. These are countries whose knowledge economies stand out for their advanced manufacturing, covering first and foremost Germany, Austria, and France. While Italy, the Czech Republic, and Slovakia also locate in this quadrant, they score less highly on Dimension 2, suggesting that their economies are integrated into advanced manufacturing value chains, but potentially in a position of the value chain that is less technologically- and skill-intensive compared to that of Germany, for example.

At the opposite end of the spectrum, in the top left quadrant, we find countries such as the UK, Ireland, and Belgium that do particularly well on Dimension 1 but much less so on Dimension 2. These are countries that rely more strongly on knowledge-intensive services, with relatively little contribution from the advanced manufacturing sector to the knowledge economy. At the top right, we find countries such as Denmark and Sweden that combine strengths on both dimensions. This is consistent with Thelen's (2019) account of Sweden managing to 'branch out' into high-end services, for instance in the realm of ICT, while retaining some of its traditional strengths in manufacturing. Another country in this quadrant is the USA, which locates between other LMEs and the Scandinavian countries.

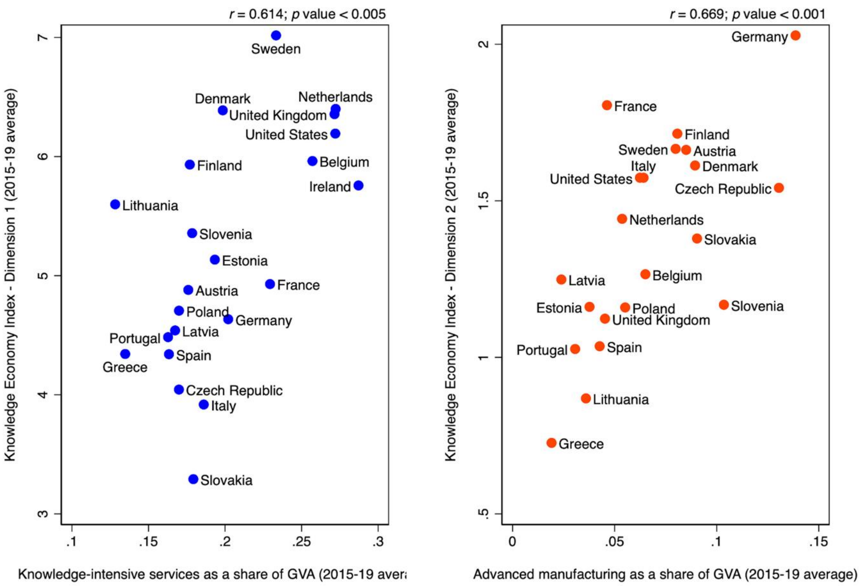

Figure 5 Scatterplots of the two dimensions of the Knowledge Economy Index vs. GVA shares in leading knowledge economy sectors.

Source: Sectoral GVA shares (as a percentage of total GVA) calculated from EUKLEMS and INTANProd Database—Release 2023, Luiss Lab of European Economics. Underlying GVA series in current prices, millions of national currency.

Note: Knowledge-intensive services comprise finance and insurance activities, information, and communication, and professional, scientific, technical, administrative, and support services (as in Hope and Limberg 2022b). Advanced manufacturing comprises the seven 2-digit NACE Rev. 2 sectors that Eurostat defines as high-technology or medium-high-technology, which are sectors C20, C21, C26, C27, C28, C29, and C30. Ireland is not included in the right-hand figure, as GVA data is not available after 2015 for a number of the manufacturing sub-sectors used to construct the advanced manufacturing measure.

The USA's score on Dimension 1 is in line with other LMEs, denoting a significant presence of knowledge-intensive services. But unlike countries such as the UK or Ireland, the USA also features significant—although geographically circumscribed—areas of successful advanced manufacturing, for example, the semiconductor industry in California. This may not characterize the US knowledge economy at large, in line with the more general tendency to spatial concentration of the US knowledge economy (Ansell and Gingrich 2021), but it is nonetheless a cluster of manufacturing activities so technologically advanced that, even if territorially-bounded, allow the USA to score higher compared to other LMEs on Dimension 2. Lastly, the bottom left quadrant features a group of countries—chiefly from Southern and Central and Eastern Europe—that do not score well on either of the two dimensions. These are, in other words, countries that have not yet fully transitioned into a knowledge-based economy and that are relying on activities characterized by relatively lower levels of skills and technology instead.

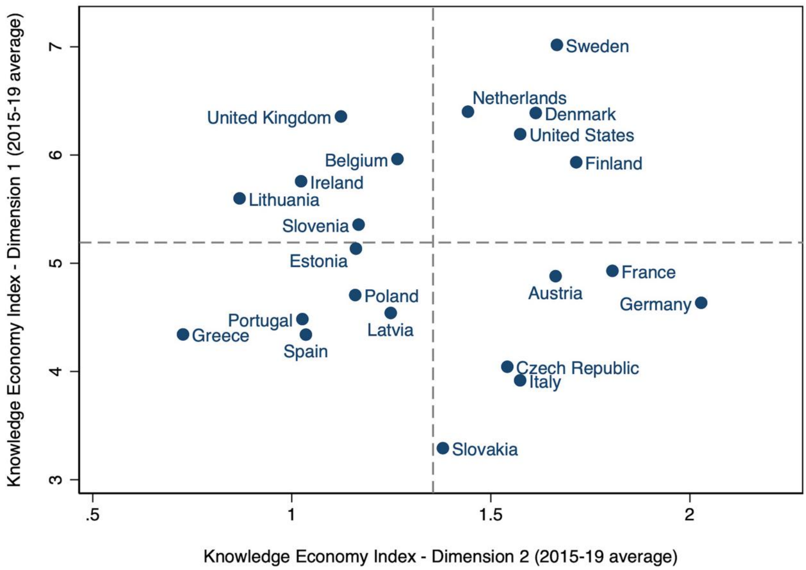

Figure 6 Scatterplot of countries on the two dimensions of the Knowledge Economy Index, 2015–19 averages.

Note: Horizontal dotted line shows the average value on Dimension 1 of the Knowledge Economy Index for the twenty-two countries in our sample from 2015 to 19. Vertical dotted line shows the same for Dimension 2.

6. Conclusion

In recent years, scholars of comparative capitalism have turned their attention to the rise of the knowledge economy, seeking to explain both the causes and consequences of the phenomenon. Yet, a unified understanding of what the knowledge economy is, and crucially, how its evolution across time and space can be measured, has been lacking. This article fills these conceptual and methodological gaps. By tracing the history of the term and its underlying concepts, we have demonstrated how—with changing emphases over time—two elements have traditionally been central to discussing the knowledge economy: skills and technology. We have noted in recent years an emerging consensus in both labour economics and CPE on the complementary and symbiotic relationship between skills and technology as the defining feature of the knowledge economy.

In line with this emerging consensus, the article conceptualizes the knowledge economy as a mode of organization of the economy that is characterized by the co-production and co-deployment of technology and high-level skills. Accordingly, we propose an operationalization of the knowledge economy that allows us to capture technology and skill levels across time and space, mobilizing three indicators on the technology side (namely, ICT, industrial robots, and patents) and three indicators on the skill side (namely, the share of total employment of managers, professionals, and technicians and associate professionals). Through Bayesian latent variable analysis, we create a new Knowledge Economy Index covering twenty-two countries over twenty-five years. An extensive validation exercise shows that the new Knowledge Economy Index is positively and statistically significantly correlated with existing indices that seek to capture cognate phenomena, greatly strengthening our confidence that the index is tapping into the 'correct' concept. Yet, the Knowledge Economy Index also presents distinct advantages compared to existing measures on both theoretical and empirical grounds. Theoretically, it offers a comprehensive assessment of national knowledge economies, capturing both knowledge-intensive services and advanced manufacturing sectors, while most existing indices tend to be biased toward either macro-sector. Empirically, the parsimonious construction of the index, which relies on six underlying indicators, allows us to construct a much longer time series than other composite indices that rely on a larger number of underlying indicators.

Next to introducing an overall Knowledge Economy Index, the article also provides an empirical illustration of how the six underlying indicators can be fruitfully employed for comparative research. Grouping the indicators into two dimensions, the article took a first step toward identifying national 'varieties of the knowledge economy', based on whether countries perform relatively well in advanced manufacturing, knowledge-intensive services, neither, or both. Throughout this article, we have highlighted *between*-country differences in overall levels of knowledge intensiveness and in the relative importance of economic sectors that contribute to national knowledge economies. Mapping such cross-national variation is meaningful on the grounds that national-level policies and institutions have played a crucial role in enabling—or holding back—countries' transition to the knowledge economy (Thelen 2019; Hall 2024).

At the same time, gaining a better understanding of *within*-country variation in knowledge intensiveness is of critical importance as well, not least since advanced sectors do not distribute homogeneously across national territories but tend to concentrate in specific locations (such as core urban areas) (Iversen and Soskice 2019; Lee 2024). The important literatures on regional VoC (e.g. Crouch, Schröder, and Voelzkow 2009) and policymaking in multi-level systems (e.g. Garritzmann, Röth, and Kleider 2021) would also suggest that sub-national variation in knowledge intensiveness is likely to be shaped by institutions and policies below the national level (e.g. regional education policies). While the approach that we have pursued in this article cannot easily be transposed to the sub-national level for reasons of data availability, we strongly encourage future research to hone in on within-country variation in the knowledge economy, including by studying how sub-national administrations appropriate and employ resources granted by national policies and institutions in support of local knowledge clusters.

Finally, it is worth noting that we do not seek to take a normative stance on the desirability of transitioning to a knowledge-based economy. While various policymakers and international organizations have associated the knowledge economy with the promise of 'good' jobs and sustainable growth, ample evidence suggests that adverse socio-economic outcomes, including mounting disparities in income and wealth, have persisted and in many cases deepened in the era of knowledge-based growth, including in countries that come towards the 'top' of our Knowledge Economy Index (Kristal and Cohen 2017; Hope and Martelli 2019). Instead, our aim is precisely to facilitate these vital debates on the promises and perils of the knowledge economy—both within and beyond CPE—by means of putting them on a more solid conceptual and empirical footing. By developing a theoretically informed new index that is able to chart the evolution of the knowledge economy across time and space, we hope to pave the way for scholars of comparative capitalism to further our understanding of the institutional–political roots of different levels and types of the knowledge economy, as well as the socio-economic outcomes associated with them.

Acknowledgements

We would like to thank Patrick Emmenegger, Matthias Haslberger, Cecilia Ivardi, Julian Limberg, Angelo Martelli, Toon van Overbeke, and Olaf van Vliet for their extensive feedback on previous versions of the article, as well as the participants at the ECPR General Conference 2024, the Europe@LSE Seminar at the London School of Economics, the Decision-Making and Policy Theme Group Meeting at the Institute of Public Administration at Leiden University, and the Master of Public Policy Research Seminar Series at University College Dublin.

Supplementary data

Supplementary data is available at *Socio-Economic Review Journal* online.

Funding

This research was supported by the Leverhulme Trust through Research Project Grant RPG-2022-151 on 'The Political Economy of Knowledge-Based Growth'.

Data availability

The knowledge economy index is available to download from: www.knowledge-economy-index.com. This website also contains data for the underlying knowledge economy indicators and the R code used for constructing the index.

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