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INNOVATION ANALYTICS

A GUIDE TO NEW DATA AND MEASUREMENT IN INNOVATION POLICY

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Nesta...

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INTRODUCTION

What can new methods, and new sources of data, tell us about innovation and growth?

Measuring the economy for the purposes of innovation policy poses a number of challenges. It requires capturing novelty (such as new ideas, technologies, and industries), emerging from complex networks of people and knowledge. Our tools for making sense of these phenomena are often adapted from other economic tools: surveys, estimates, and standard industrial classifications. But traditional tools do not always make it easy to answer questions of interest to innovation policymakers, such as:

- What is the size and importance of new industries and technologies? Are they growing? How much investment do they attract?
- Are policymakers talking to the right people in those areas? Which skills are in greatest demand?
- What do business and knowledge networks look like in innovative parts of the economy? Are they connected or fragmented; resilient or fragile, and what can the rest of the economy learn from this?

In recent years, Nesta has been developing new techniques and making use of new sources of data to supplement what can be learned using traditional tools for measuring innovation. This short guide summarises some of this work and highlights the context and purpose behind each of these methods. First, we have developed an approach for using official data to measure new industries in a more accurate way. Second, we have been examining the potential of new data sources to measure business innovation. Third, we have been exploring new ways that policymakers can visualise and interact with data. In what follows we describe these approaches, and finish by presenting six case studies with more specific detail about each of the methods.¹

A NOVEL WAY TO USE OFFICIAL DATA

In order to understand emerging and other relevant sectors for innovation policy, we need to overcome a number of challenges with using official data. Administrative data sources such as the Inter-departmental Business Register (IDBR) and surveys like the Annual Business Survey and Labour Force Survey form the basis of official economic estimates that innovation policymakers use. In this section we describe our ‘dynamic mapping’ method, which has been developed to improve the classification of occupations and industries to more accurately measure the creative, hi-tech and information economies using official data.

The Standard Industrial (and Occupational) Classification, SIC (and SOC) codes are used to record and categorise industrial (and employment) sectors on a consistent basis across countries. They are, however, set irregularly (every ten years or so in the case of the SIC). In cases where the international consistency of metrics is important, or there is a need to use official data, this creates an obvious problem for innovation policy. Nesta’s dynamic mapping aims to optimise the use of SIC and SOC codes in these cases.

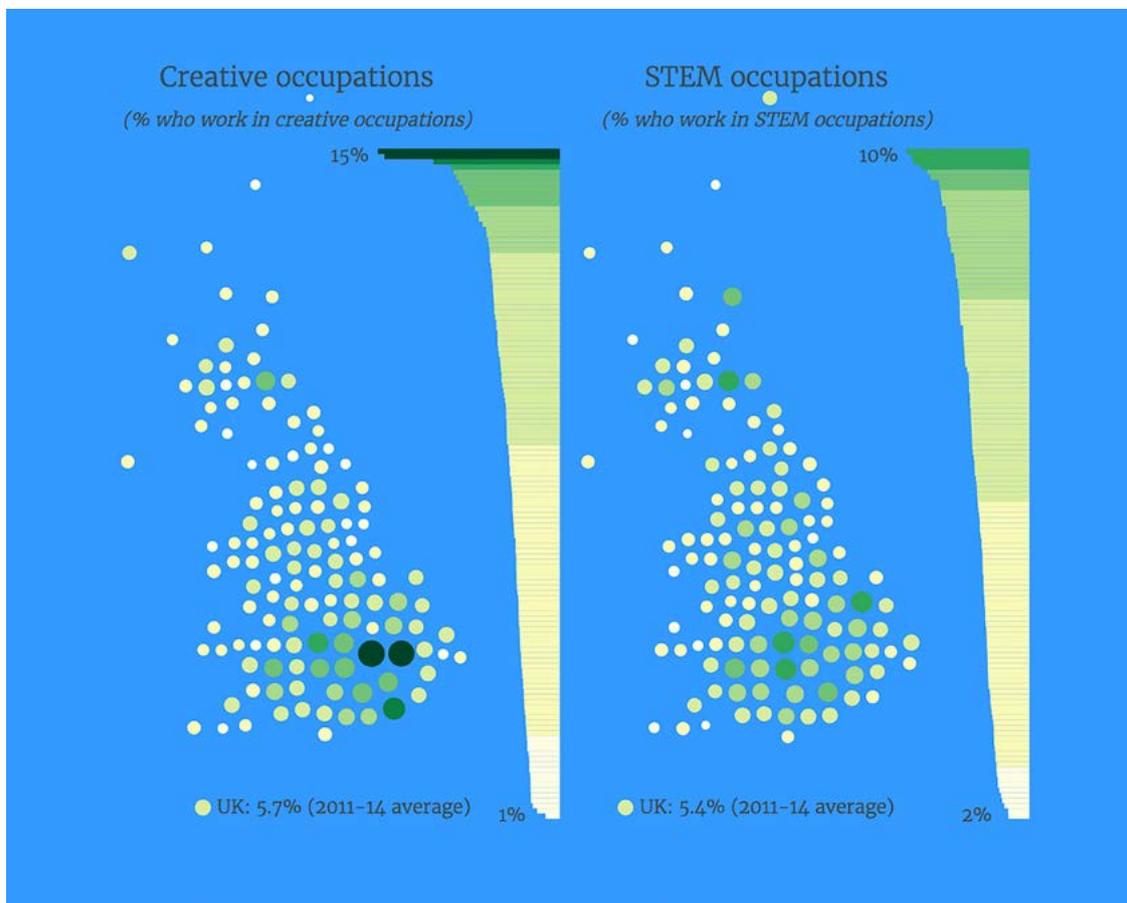
We first developed this for creative work and the creative industries. That is, which occupations and industries should be labelled as ‘creative’ (and which should not) for the purposes of the government statistics?

Despite the fact that the UK Government had been publishing Creative Industries Economic Estimates using official data for over a decade, these estimates were based on a top-down selection of occupational and industrial codes.² Due to the absence of systematic criteria for which codes were selected, there was little basis on which to adapt the codes as the structure of the UK’s economy changed over time, not least associated with the disruptive impact of the internet. As such, the statistics lost credibility with users.

Nesta’s report *A Dynamic Mapping of the UK’s Creative Industries*³ addressed this problem by proposing a method whereby individual industry codes are identified as ‘creative’ based on their ‘creative intensity’: the proportion of total employment within the industry that is engaged in creative occupations (see Case Study 1). The method is called ‘dynamic’ mapping because the creative intensity of industries can change over time, meaning that some industries become ‘more’ or ‘less’ creative. The UK’s Department for Culture, Media and Sport consulted on the use of this method for producing the Creative Industries Economic Estimates and adopted it in 2014.

By making use of official Labour Force Survey data and the SOC and SIC codes, the method also allowed analysis of the geography and concentration of the UK's creative industries and occupations on a basis that is consistent with how other parts of the economy are measured. So, for example, we have learned that the creative workforce is heavily concentrated in and around London (approximately 15 per cent of workers or just under three times the national average). In comparison, STEM workers (where STEM refers to Science, Technology, Engineering and Maths) are more evenly spread across the UK. The most STEM-intensive areas are Oxfordshire, Cambridgeshire and Berkshire where approximately 10 per cent work in STEM occupations, which is around twice the national average (see Figure 1).⁴ We have subsequently adapted this method and applied it to measure other areas, such as a mapping of the UK's 'information economy', which was used in our 2016 Tech Nation analysis.⁵

FIGURE 1: VISUALISING AND COMPARING THE CREATIVE AND STEM WORKFORCE



Source: Visualisation by Nesta,⁶ based on data from the Annual Population Survey (2011 to 2014). Main jobs only. For the complete list of Creative and STEM occupations see pages 16 and 32 of *The Geography of the UK's Creative and High-Tech Economies*.⁷ Data was not available for regions in Northern Ireland.

Since the SOC and SIC are international standards and similar labour force surveys are conducted in other countries too, we have also used the dynamic mapping approach to produce internationally comparable statistics. For example, we have recently published mapping studies of the European, US and Canadian creative economies.⁸

NOVEL MEASUREMENT TECHNIQUES

In this section we describe new types of data collection and analysis that have become possible with improvements in digital technology and the internet, and how insights from these techniques can improve our understanding of business innovation. Specifically, we discuss: the data that can be harvested from websites; new insights from relational data (about the meetups, networks, and informal relationships behind innovation); and the ability to combine and interact with new datasets.

Supplementing official statistics

Notwithstanding the obvious attractions of using official data and international classification standards, there are cases where they are not fit for purpose. For example, where the innovative activity in question cannot adequately be captured using the SIC codes at all. Emerging technologies might be so disruptive to existing industry boundaries that they give rise to important new industries altogether. In such cases, policymakers do not have the luxury of waiting for the next round of SIC revisions to capture these activities. While it may be relatively easy to count firms and measure output using the SIC in a long-established sector like car making or oil, it is much more difficult to do so in a new field like edtech, health tech or cybersecurity.

This makes it hard for policymakers to see if innovation policy is working. How can you tell if your attempts to promote, say, cleantech companies, are working if your data cannot identify which companies are involved in cleantech? It also makes innovation policymaking more of an act of faith. The previous government made a number of investments and initiatives in specific technology areas, from the Graphene Engineering Innovation Centre, to the Catapult Centres, to the Eight Great Technologies; but there was little quantitative evidence they could rely on to pick these areas of focus, which is a barrier to good policy. A better approach to innovation policy would be experimental, where government uses robust and timely data to learn and inform policy design.⁹

Where official datasets have a problem capturing aspects of economic activity that matter to innovation policy, we can increasingly fill existing innovation gaps by mining new 'big' data sources from the web and using machine learning techniques to develop alternative industrial classification schema.¹⁰

For example, large-scale data harvesting – or 'web-scraping' – of unstructured information located on company websites allows us to predict the sector where a company operates, and can help us spot new innovative industries and places as they emerge, even when these do not respect traditional sectoral boundaries. Examples of this include our mapping of the videogames industry¹¹ (Case Studies 2 and 3); or a Nesta-funded study that extracted information about technologies and products of graphene SMEs from their websites, since publications and patents do not fully capture these firms' economic activities.^{12, 13}

We also believe that datasets constructed from alternative sources should be transparent if they are to be used by governments for making innovation policy. Otherwise there is a risk of a proliferation of competing sector estimates whose relationship cannot be understood. The digital tech economy is a case in point. In two studies we have worked with big data companies that have developed algorithms for classifying businesses into new

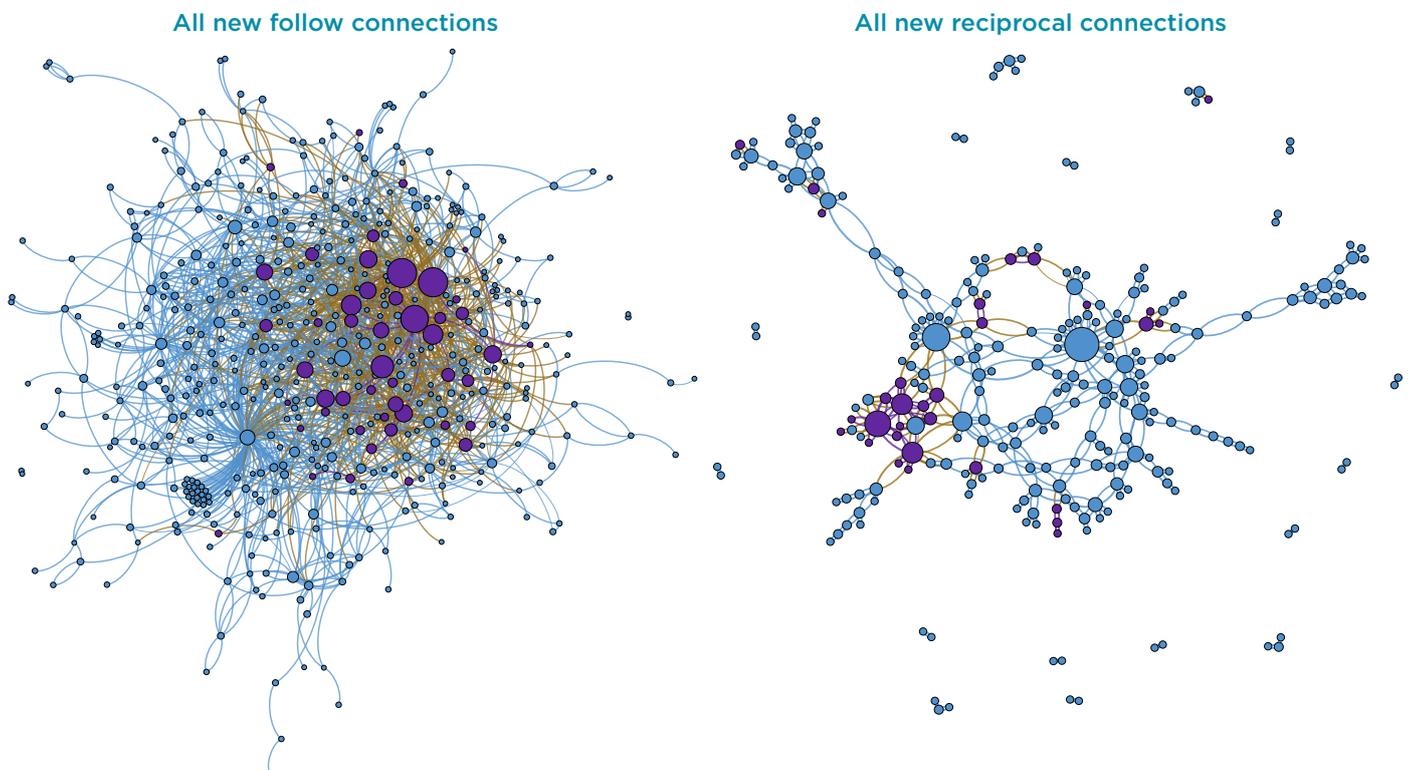
sectors.¹⁴ However, as the algorithms are proprietary, there are naturally limitations on the methodological detail which has been made publicly available. In the longer term, short of a radical reform of the international SIC review process, the statistical authorities may need to develop a more open industrial classifier for policy use.

Relational data

While most data sources focus on businesses as the ‘innovation unit’, the internet also captures relational data; the networks or ‘hidden wiring’ underpinning successful innovation. Although researchers in the field of scientometrics use citations and authorship data in patents and papers to map some of these innovation networks, this covers only those (relatively rare) industries that patent and publish.

New insights into innovation networks are, however, possible by extracting data from websites such as Meetup.com, a website to organise networking events (see Case Study 4); GitHub, a website where coders collaborate on software projects; or Twitter, a social networking site.¹⁵ The diffusion of digital know-how also happens when skilled individuals move between firms – we can look for evidence of this in online labour market data, including from job advertisement websites (for example Case Study 5). Another potential advantage of these data is that they can be more timely than official datasets that take a lot of time to collect and publish.

FIGURE 2: DATA-DRIVEN INSIGHT INTO THE EFFECTIVENESS OF CONFERENCES AT CONNECTING PEOPLE



Source: Nesta.¹⁶ Before and after the LeWeb’12 tech conference held in London, we tracked 702 attendees on Twitter for the development of new and ‘reciprocal’ follows, the latter suggesting a more meaningful measure of connectivity. The purple nodes are speakers and the blue nodes are attendees. The size of the nodes represents the in-degree of each node (how many new follows it gained).

Detailed data

If you want to encourage tech clusters, promote new technologies, or understand how high-growth firms are doing, your data need to be specific. A characteristic of big data is that it tends to be available at a higher degree of resolution than the traditional sources of data that policymakers use. This is particularly attractive when disclosure constraints mean that official data is not accessible, even if it is in principle available, to policy analysts at a sufficiently granular level.¹⁷

Interactive data

This brings us to a further point: the importance of interactive data. Big data sets can be matched, republished, and therefore made more readily useable and insightful to users. This opens up the possibility of using the data for interactive data applications like visualisations or dashboards. We discuss this in the following section.

CONNECTING, COMMUNICATING AND USING DATA

Having improved measurement using official data, and mined novel data sources for new insights, how can we communicate these in helpful and intuitive ways? In this section we present some of the ways Nesta is bringing datasets together to help policymakers and other users extract value from data.

Two recent Nesta projects have involved combining and presenting data to map the conditions for innovation across cities in particular. CITIE, a partnership with Accenture and OneFineStay, creates an online tool to standardise and compare policy frameworks and infrastructures for innovation across 40 cities globally. As part of the European Digital Forum, a Brussels-based think tank we run with the Lisbon Council, we have also constructed a detailed online scoreboard of Europe's major cities, where users can see how they are ranked according to policies conducive to digital entrepreneurship.¹⁸

Questions also arise with how we utilise the web's connectivity to build new, live measurement tools. Innovation is a networked phenomenon, spanning industries, geographies and knowledge. Attempts to understand innovation also requires breaking down data silos, bringing datasets together, and merging, linking and mashing datasets, often automatically with Application Programming Interfaces (APIs), the data connectors that allow websites to talk with each other.

We can use this connectivity to pragmatically fill gaps across datasets – for example, in partnership with Ukie (a non-profit trading body for the UK games industry), our map of the video games industry combined economic activity data from official sources with business counts based on web data to study clusters of video games companies. We can also benchmark unproven (web) datasets, with quality-assured (official) ones, many of which are now open or available via APIs.¹⁹

The interactivity of the web also opens up new possibilities. It empowers users to find the information they are looking for in complex, multi-dimensional datasets, and to explore questions in ways that the people who originally collected and analysed the data had not intended. Interactivity also helps to visualise complex innovation datasets in ways that are easier to understand for non-technical users (see Case Study 6).

We believe there are opportunities here to systematically combine these approaches in ways of use to innovation policymakers. In particular, this could help them to:

- Identify emerging technology areas and industries when setting policy priorities and formulating strategies, linking Intellectual Property data, business data and relational data between individual innovators.
 - Find new business communities to consult with during policy design and implementation.
 - Locate 'gaps' in innovation networks that hinder collaboration.
 - Monitor the evolution of innovative industries, and inform the evaluation of the policies to support them.
-

Nesta is experimenting with the development of these tools.²⁰

A final point: policy analysis is only valuable insofar as it is of use.²¹ Sophisticated research reports and beautiful data visualisations are of little use if they do not address questions that policymakers need answering. (And, unfortunately, the early days of the 'big data for policy' movement have seen their fair share of impressive but useless outputs.) However, at the same time, the questions policymakers need answering partly build on what evidence exists. This means that the process of developing new measurement tools and the process of working out how policymakers can use them go hand-in-hand. Government will need new capabilities²² – and in some cases new organisations²³ – to extract value from data.

So, in addition to giving policymakers important insights about innovation, our goal is that Nesta's ongoing analytics work also teaches us more generally about how innovation policymaking needs to change to take full advantage of the opportunities that the big data era affords.

NEXT STEPS

We are actively looking for partners in this ambitious programme of work. We welcome potential collaborators to get in touch, including anyone with:

- Interesting datasets that can be analysed to help us better understand innovation.
- Policy-relevant research questions that can be addressed with these methods.
- Research funds to support this work.
- Analytical skills to extract and communicate information from these complex datasets.

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CASE STUDIES

Case Study 1: Dynamic mapping with official statistics

We initially developed the dynamic mapping method for identifying creative industries in a way that recognises the important creative work that happens in all sectors of the economy.²⁴

The approach is made up of three steps: In step one, judgements are made on which occupations in the workforce should be labelled as 'creative'. In the original dynamic mapping report we based these judgments on a subjective, theoretically grounded scoring of each SOC code in the UK workforce.²⁵ In another paper, we have used detailed data on job task descriptions and machine learning techniques to label (a wider set of) occupations as creative.²⁶ Armed with this list of creative occupations, in step two we compute the percentage of the workforce that is in a creative occupation for all industries in the UK economy (in other words, its 'creative intensity'). And in step three, we analyse how this creative intensity is distributed across

different sectors, and on this basis partition industries into 'creative' and others (creative industries are those with exceptionally high creative intensities). We then define employment in the 'creative economy' as employment in the creative industries plus those working in creative jobs in sectors outside of the creative industries.

It turns out that there are a relatively small number of industries in the UK sharing the common characteristic of employing proportionately large numbers of individuals in creative occupations, of above 30 per cent. This compares with the vast majority of other industries in the UK with single-digit creative intensities. This result is important, as it suggests there is a strong statistical basis for considering 'creative' sub-sectors with otherwise very different cultures, business and operating models as a coherent group for policy purposes.

Case Study 2: Mapping the video games industry with big data

The video games industry is recognised as a highly innovative part of the UK economy, but it did not have dedicated SIC codes until 2007, and many of its companies remain hard to classify using standard codes.

To overcome some of these limitations, we leveraged the digital footprint of the sector by scraping information from gaming websites like MobyGames and review sites like GameSpot, which contain a wealth of information about games products and companies. We then established which of these companies are UK based, and extracted information about them (including their postcode and, where available, financial data) from Companies House. This allowed us to identify companies through their creative outputs (revealed by the consumers and journalists maintaining the websites we use

as data sources) rather than the box they tick in the business register when they get started. Official SIC codes covered just over one-third of our dataset.

It also resulted in a detailed, timely dataset with interesting information that is not available from official data sources. For example, we were able to understand what platforms are driving the development of the games industry (we found that iPhones and iPads were the main growth platforms for the sector). Linking our data to other openly available datasets we found further relationships between the prevalence of local games clusters and, for example, an area's broadband availability (data from Ofcom) or the delivery of specialist university games courses (data from the UCAS web portal).²⁷

Case Study 3: Mapping digital clusters with big data

In Tech Nation 2016, we worked with partner GrowthIntel to develop a dataset of the UK’s digital technology businesses. To do this, we combined machine learning and web scraping from company websites to build a more timely and detailed picture of digital tech than official data sources allow.

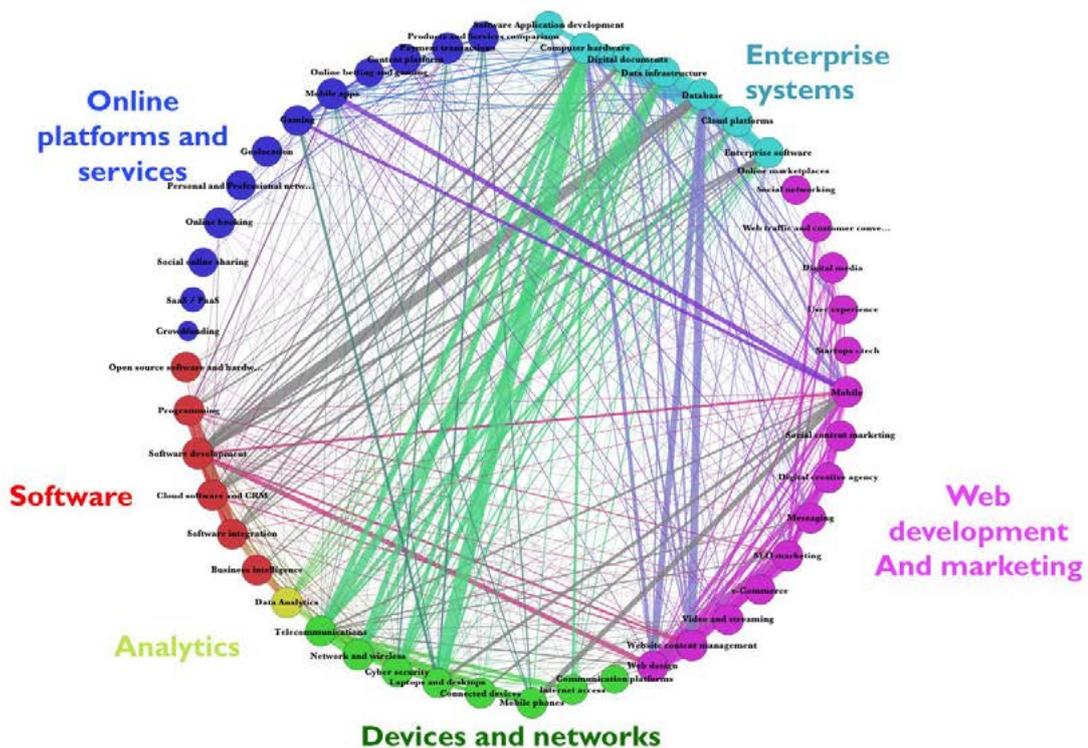
The main data collection process included an unsupervised text clustering approach, which extracted a total of 500 ‘tags’ about businesses’ areas of activity from the text in their websites. Any business that had been assigned at least one digital tag was defined as a ‘digital tech business’ (58,000 were identified out of a total of 320,000).²⁸

This data allows us to not only study the sector in which a business operates (for example, ‘financial services’) but also to determine if its ‘core capabilities’ are digital (for example, if it is a ‘fintech’ firm). This distinction is not easy to make with official data-sources that lump business into mutually exclusive

categories. Analysing the digital capabilities of ‘non-digital sectors’, for example, we learn that the web and online content are not the only drivers of digitisation in the economy. Sectors like Science and Aerospace also have large numbers of digital companies, probably reflecting the digitisation of their business processes.

We can also use this high-resolution information to measure and map the similarities and differences between digital tech businesses in interesting and novel ways. Using the GrowthIntel business tags, it is possible to explore which specific capabilities ‘co-occur’ within digital businesses. The diagram below highlights the importance of data, mobile and software capabilities that are highly interconnected to many other capabilities. It also highlights the fact that Digital Tech Industries are themselves networks of capabilities that can be recombined to generate even more innovation.²⁹

FIGURE 3: INDUSTRIAL NETWORK ANALYSIS BASED ON DIGITAL TAG CO-OCCURRENCE



Source: GrowthIntel

Case Study 4: Capturing relational and network data from tech meet-up data

Websites like Meetup and EventBrite have emerged to make it easier for people to create and manage meetups. When registering, users express interest on particular topics (like ‘data science’ or ‘online marketing’) and are shown information about groups near to them that focus on those topics (or similar ones). We have analysed the data generated by these platforms to help us understand when and where new technology communities emerge and evolve, and how they connect to each other.

We queried the Meetup API for groups in the ‘Tech’ category in UK cities, and extracted 1,391 groups based in 160 unique locations in the UK, with a gross total of 434,826 members; 2,569 group topics had to be arranged into a smaller set of ‘tech fields’ containing interrelated topics. To do this, we followed a ‘data-driven’ approach based on scientometrics principles (the quantitative

analysis of science and technology metrics, such as academics papers and patents). We then used community detection algorithms to look for densely connected ‘clusters’ of tech fields and the relationships between them.³⁰ In another analysis of Meetup data for Tech Nation, we expanded the method to reveal the geographical patterns of networking between tech clusters across the UK. Among findings, we detected a large amount of informal networking between tech clusters, particularly in the North West, and along the M4 corridor. This challenges the notion that digital tech clusters operate in geographical silos or that digital tech clusters in some areas develop at the expense of others.³¹

These are insights of obvious interest for policymakers, entrepreneurs, businesses and investors who want to identify where and how to identify communities of innovators to work with, and the right technologies to target.

Case Study 5: A low-cost approach for tracking innovative jobs in real time

For benchmark information on employment, researchers and policymakers rely on government statistics (often released annually) or they will pay for time-consuming and expensive surveys, with limited geographical specificity.

Online help-wanted advertisements (want-ads) provide an enormous amount of publicly available employment information, updated in real time. They also include much more detailed location and skill content data than is available from government statistics. We supported a preliminary study to see if using wants-ads could produce a low-cost and flexible way to track innovative employment. The study built keyword lists to search on

job websites – including Indeed.com and the Conference Board’s HWOL database – and then translated want-ad counts into employment estimates for IT, big data and medtech occupations.³²

The method shows potential for future work to aggregate this type of information into a real-time online tool. We have begun work in this area using Burning Glass labour market data (see the following case study). Given the nature of the data, future tools could be adaptable to the needs of individual local policymaking bodies looking to assess the impact of a particular investment or policy decision on local jobs.

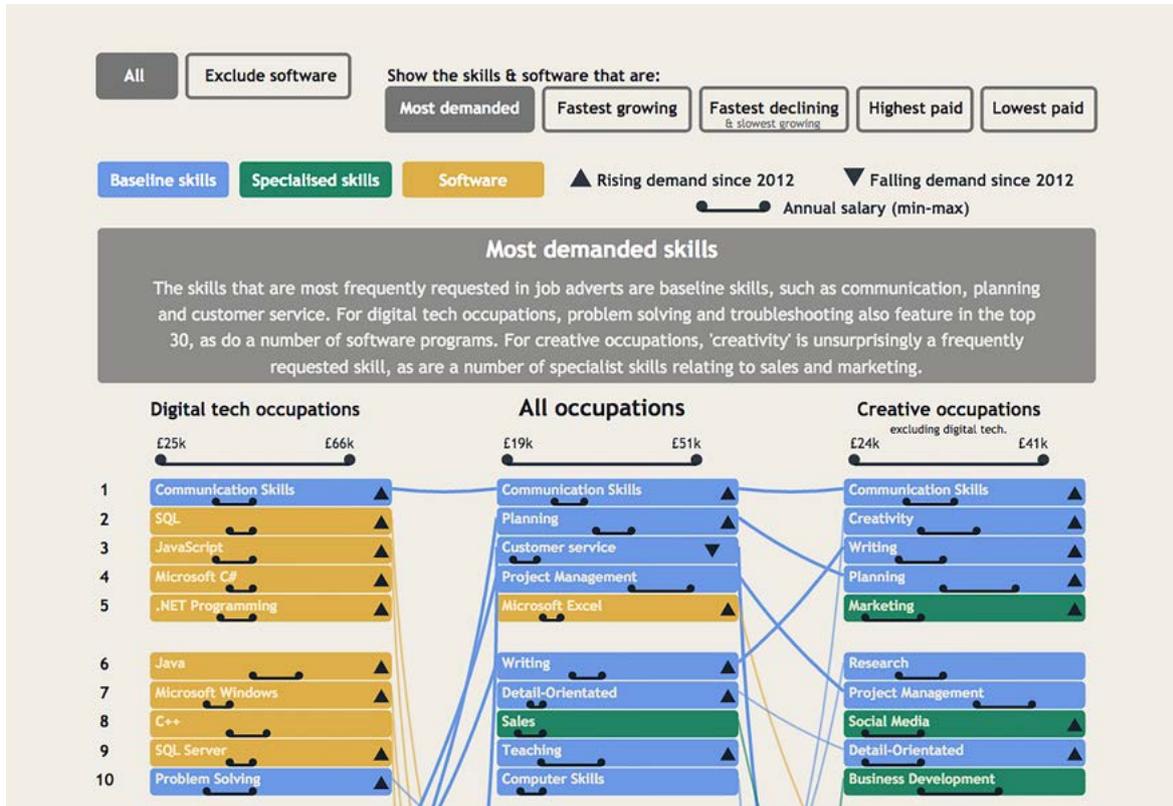
Case Study 6: Novel ways of interacting with data: data visualisations

A data visualisation lets users ‘see the data’. Visualisations can range from simple line charts to fantastic interactive creations. The strength of a data visualisation lies in its ability to show data efficiently. This efficiency takes two forms. The first is efficient use of our visual strength, and more specifically our ability to rapidly detect differences in features such as colour, size and shape, without the need for focused attention. These features are called ‘preattentive’ and they form the building blocks of data visualisation.³³ In contrast, text is not preattentive and this is the reason it is often difficult to quickly see patterns in large tables filled with numbers.³⁴ Data visualisations also make efficient use of space. By using preattentive features, visualisations can contain much more information than a single page of text. This allows a visualisation to convey both micro and macro detail within the same

space. By using variations in features such as colour and shape, they can comfortably contain multiple data series, enabling the viewer to draw a story from the data. The aforementioned properties make data visualisation an essential tool in the age of ‘big data’.

We have used data visualisation in a variety of projects. The example below summarises the skills requested in millions of job advertisements that were collected by Burning Glass. The dataset contains several million job advertisements for a single year and over 8,000 distinct skills. The data visualisation presents the most salient elements of the dataset, and lets users select and see the charts change according to highest demand by employers, as well as uncovering which skills are growing fastest and those that are most highly paid.

FIGURE 3: INTERACTIVE DATA VISUALISATION: A TOP 30 SKILLS CHART



Source: Nesta.³⁵

ENDNOTES

1. Although the focus here is on our quantitative data work, we believe that the relationship between knowledge, networks and innovation cannot be understood by quantitative data collection alone; qualitative evidence plays an important role, which is why Nesta sets so much store by the use of mixed methods. See for example: Nesta/Tech City UK (2016) 'Tech Nation 2016: Transforming UK Industries.' London: Nesta/Tech City UK, p.118.
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13. These new techniques should still be regarded as experimental. They require dealing with messy data, which often has not been created for analytical purposes or quality assured by statisticians. As suggested in our video games study, it's important that researchers openly share new techniques and methodologies for using these data so that they can be replicated, or the results reproduced and scrutinised.
14. Nathan, M., Rosso, A. and Bouet F. (2014) 'Mapping Information Economy Business with Big Data: Findings from the UK.' Nesta Working Paper 14/10. London: Nesta.
15. A current project, working with Endeavour - a New York based non-profit promoting high impact entrepreneurship - will also combine scraped information from CrunchBase (a store of startup news and information), and AngelList (a website for angel investors and startup job seekers) with interviews from over 600 tech startup founders and co-founders in Oxford, Cambridge and London. See Gaillard, E. and Mocker, V. (2016) 'Connecting the dots in the tech ecosystem' [online]. London: Nesta. Available from: <http://www.nesta.org.uk/blog/connecting-dots-tech-ecosystem> [Accessed 4 April 2016.]
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17. There are, of course, also a large number of important data ethics issues to be considered. See Windsor, G. (2014) 'Striking a balance: Data protection vs. Data Driven Innovation' [online]. London: Nesta. Available from <https://www.nesta.org.uk/blog/striking-balance-data-protection-vs-data-driven-innovation> [Accessed 23 March 2016.]

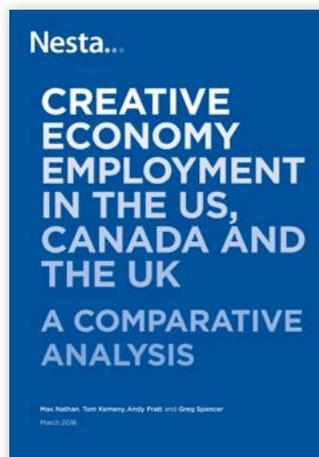
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33. See <http://www.csc.ncsu.edu/faculty/healey/PP/#Preattentive> [Accessed 23rd March 2016.]
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SELECTED AND FURTHER WORK BETWEEN NESTA AND PARTNERS



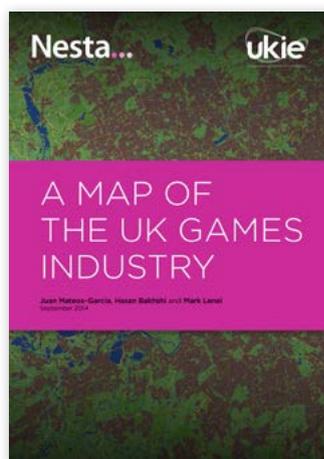
A Dynamic Mapping of the UK's Creative Industries (2012)

Our 'dynamic mapping' of the creative economy including an initial explanation of the methodology.



Creative Economy Employment in the US, Canada and the UK: A comparative analysis (2016)

An extension of the dynamic mapping methodology to provide a basis for international comparison of US, Canadian and UK creative economies.



A Map of the UK Games Industry (2014)

Using a 'big data' approach to measure and map the UK games industry and track its evolution over time.



Tech Nation 2016: Transforming UK Industries (2016)

Combining a range of techniques and new data, including dynamic mapping, job advertisement data, and Meetup and Github data, to map, analyse and understand the UK's digital tech businesses.



European Digital City Index (2015)

An interactive tool that combines a range of data to map the conditions for digital entrepreneurship across European cities.



'Full STEAM Ahead' (2015)

An interactive data visualisation showing the popularity of Science, Technology, Engineering, Arts and Mathematics (STEAM) subjects and other subject combinations among Scottish Highers students.

Further work

- City Initiatives for Technology, Innovation and Entrepreneurship (2015)
- Creativity vs. Robots: The creative economy and the future of employment (2015)
- Creative Economy Employment in the EU and the UK: A Comparative Analysis (2015)
- State of Uncertainty: Innovation policy through experimentation (2011)
- The Geography of the UK's Creative and Hi-Tech Economies (2015)
- 'Who hires the creatives?' [data visualisation] (2015)

Working papers

- A Low-Cost and Flexible Approach for Tracking Jobs and Economic Activity Related to Innovative Technologies (2015)
- Graphene Research and Enterprise: Mapping Innovation and Business Growth in a Strategic Emerging Technology (2015)
- Mapping Information Economy Business with Big Data: Findings from the UK (2014)

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