Artificial Intelligence and the UK Labour Market: Questions, methods and a call for a systematic approach to information gathering

Tim Hinks

University of the West of England (UWE), Bristol

Economics Working Paper Series

1903

Artificial Intelligence and the UK labour market: Questions, Methods and a Call for a systematic approach to information gathering

Tim Hinks†

Abstract

Whilst much work has recently been produced on the impact robots will have on labour markets of rich countries there is no substantial body of work as yet into what impact artificial intelligence will have on labour markets. Recently Raj and Seamans (2018) have called for an urgent need to gather firm-level information on what AI is being used and how the use of AI is changing over time. In Felton, Raj and Seamans (2018) the authors use a measure of AI in US firms and map the areas in firms in which AI is used against a broad range of job requirements in occupations in order to ascertain the probability that occupations will be made redundant or which job requirements will become redundant. In the UK we currently have nothing comparable to the level of detail found in these data sources. This paper calls for a concerted and rigorous approach to gathering this information at individual and firm-level in order to give some idea of which jobs and job requirements are under threat from AI and crucially whether the quality of jobs is or will decline.

Introduction

Innovation and the impact of new technologies on the economy, society and institutions has a long and illustrious history within economics. The so called 4th industrial revolution or IR4.0 is happening today and is expected to impact on the global economy for the next 30-40 years. Whilst there is continued dispute about the impact robots are having and will have on society many mainstream and non-mainstream economists are predicting a new kind of labour market, one that will produce more lousy than lovely jobs (Goos and Manning, 2003), lower employment and wages (Acemoglu et al, 2017) and the continued and even speeding up of a lower wage share of output (Brynjolfsson and McAfee, 2014; Karabarbounis and Neiman, 2014; Elsby, Hobijn, and Sahin, 2013 – refs from Graetz and Michaels, 2015; OECD 2012 – Employment Outlook found on Freeman (2015)). Whilst the jury is out on whether these predictions are accurate the counter-argument often heard is that new jobs will be created, new products will be produced and that robots will allow people to focus on aspects of jobs that they are better at, that they may prefer or will extend their working lives (Alexopoulos and Cohen, 2016). At the heart of the debate is the substitutability between workers and capital and how robots have increased this substitutability thus making labour more vulnerable in the production process. To remain competitive workers will need to lower wages or reduce the hours they work, either way reducing income levels and contributing to the lower wage share observed in the last 30 years in developed countries. The prediction of consistently lower average working hours over time due to rising productivity is hardly new with John Maynard Keynes in his 1930 lecture titled *Economic Possibilities for our Grandchildren* arguing that by the 1970s the workers in the UK would be working a 15-hour week. Keynes saw this as a good thing driven by innovation and technology that increases productivity and economic growth. Recent examples of workers negotiating lower working hours to reduce the wage bill and retain employment is seen in Germany (Daily Telegraph, 2018) and there is a ground swell movement arguing for a 4-day working week in the UK.[1] Ownership of robots is of importance when considering the impact on workers. Freeman (2015) makes the simple argument that if workers are to benefit from new technologies that substitute for their skills then they need to own or at least part-own this technology. If the technology is not owned by the worker then they will be worse off,

† Senior Lecturer, Bristol Centre for Economics and Finance, University of the West of England, Coldharbour Lane, Bristol BS16 1QY. Correspondence e-mail: timothy.hinks@uwe.ac.uk

[1] A number of stories in the national media have highlighted the potential benefits of a 3 or 4-day working week, with trade unions in the UK calling for this if the productivity gains from new technologies is shared with workers and not simply kept by firms. See https://www.bbc.co.uk/news/business-45463868.

possibly working for lower wages and having to work longer hours. One obvious result of this would be increasing inequality. This raises a host of questions to do with maintaining and improving the quality of lives of people, whether work in any way increases the quality of life of people apart from simply selling one's labour, what kind of jobs people will do or want to do in the future and what impact this will have on different form of inequality (income, wealth, opportunity, expectations).

Whilst research into the impact of robots on the labour market continues to be highly sort after there is, as yet, no similar research into the impact artificial intelligence is having and is expected to have on the labour market and indeed wider society in the coming decades. In this paper we will ask a number of questions and how best to answer these questions with the current resources at our disposal. The main objective of the paper is to highlight where significant evidence gaps are in the current literature that is preventing a more rigorous answer to the questions raised and how best these gaps can be filled.

What will be the impact of AI on labour markets?

To answer this question we look first at recent empirical studies that ask what impact robots have on the labour market. Acemoglu et al (2017) use industry level robotic date from 1990 to 2007 to estimate the impact of observed robotic change on both employment and earnings in the US labour market. They find both effects are negative, consistent with any positive productivity effects of robots being outweighed by the displacement of workers. They estimate that in the time period considered, between 360,000 and 670,000 jobs have been lost because of robots, equivalent to a decline of between 0.18-0.34 percentage points in the employment to population ratio (ibid, p.36). Of course if the take-up of robots increases (e.g. due to subsidies, cost of robots decline further) then future impacts on employment and earnings will be greater. Dauth et al (2018) use the same robotic data set and undertake similar work for Germany between 1994 and 2014. They find that every robot destroys 2 manufacturing jobs equivalent to 23 per cent of the overall decline in manufacturing employment in the period. Incumbent manufacturing workers are no more likely to lose their jobs with the increase in robotics, with the number of jobs for new labour market entrants declining instead, suggesting a further decline in manufacturing employment over time. However incumbent workers have had to incur pay cuts in order to maintain their employment and employability. Both of these paper use the International Federation of Robotics date series that is based on yearly surveys of robot suppliers, and claims to capture around 90 per cent of the world market of robots. The data for each year and country locates robots into 3-digit industries providing a degree of granularity that helps with variation when conducting quantitative studies.

The first country-level comparison study to use the IFR data is Graetz and Michaels (2015) who consider the impact of robots on industries across countries by using the EUKLEMS data set (University of Groningen). With the price of quality-adjusted robots calculated to have fallen by 80 per cent between 1990 and 2005 the key findings from the paper are that robot densification increased growth and labour productivity by 0.37 and 0.36 percent respectively, that robot congestion results in diminishing returns and that aggregate hours worked in unskilled and medium skilled jobs decline in equal measure indicating that robots do not polarise the labour market as ICT has done (Michaels, Natraj, and Van Reenen, 2014; Autor, 2014). That this study covers 17 countries but cannot consider either China or Japan (two of the biggest users of robots) calls into question whether this can really be called an aggregate study in the first place. Further country-specific studies are instead called for.

At present there is nothing remotely similar available for undertaking equivalent studies that focus just on AI. A clear challenge to producing such a data set is that AI is not tangible, like a robot. Often when firms are asked about what AI they currently use they do not understand what the question is. A solution identical to the IFR data series is to instead ask suppliers of AI what industries they have supplied to and indicate what the use of AI is for. Then it would be possible to analyse what parts of current jobs AI is performing or could perform in the future, what job requirements can be performed or are expected to be performed by the AI thus reducing the need for human input and ultimately to have a more rigorous grasp of which jobs are possibly more likely to be under threat than others and estimate what the productivity effects are of AI that could result in job creation. Frey and Osbourne (2013) produce the first study that attempts to frame which jobs and aspects of jobs are most likely to be replaced by "..Machine Learning, including Data Mining, Machine Vision, Computational Statistics and other sub-fields of Artificial Intelligence (AI), in which efforts are explicitly dedicated to the development of algorithms that allow cognitive tasks to be automated" (ibid, p14). Using the Occupational Information Network (O*NET) that contains granular characteristics of occupations including technological skills, tasks, knowledge, skills, abilities, work activities, work context, education, work styles and work values they worked with experts in machine learning to identify occupations that were at risk from displacement. For the US they estimated that 47 percent of total employment was at a high risk of being automatable in the next decade or so. Following the same method Brzeski and Burk (2015) find that 59 percent of German jobs may be highly susceptible to automatability while in Finland the figure is estimated to be 35.7 percent (Pajarinen and Rouvinen, 2014).

An extension of this work has recently been undertaken by Felton, Raj and Seamans (2018) who use information from the Electronic Frontier Foundation (EFF) AI Progress Measurement dataset to link advancements in AI and ML from 2008 to present day (as expressed by experts in the field of ML and AI) and the abilities they are most likely to replace. As the authors state, focussing on abilities and skills is a new way of thinking about labour rather than simply classifying as occupational groups and something that is important to recognise when discussing labour markets in the future. Given these abilities are more important for some occupations and industries than others it is then possible to gauge which jobs are most under threat of displacement from ML and AI.

1. **Research Gap:- Undertake similar studies to those of Frey and Osbourne (2013), Brzeski and Burk (2015) and Pajarinen and Rouvinen (2014) that estimate the impact of ML and AI on employment and earnings that, as yet, has not been undertaken for the UK.**

*Method:- Use O*NET to identify tasks and abilities and other aspects of jobs (e.g. work values, work styles and social skills) that are at risk from AI and ML. Identify AI and ML by talking to experts in the UK or using EFF. There is also scope to use patent data (see Mann and Püttmann, 2018 below) as a more objective measure. However all current available AI and ML data remains to some extent subjective and prone to human biases. Another possibility is to understand better how the buying and selling of ML and AI is monitored by asking suppliers of ML and AI to log which industries (3-digit level or even more granular) they sell to. This is identical to what the IFR data series does for advanced robots sales. Through this research it will become clearer what current jobs are affected by AI and ML, but also where younger people are finding jobs and whether 'new' jobs in at risk occupations or with at risk job requirements are declining.*

An extension of this research would be analyse what impact AI and ML would have on the wage distribution of workers. Goos and Manning (2007) found robots to be helping polarise the UK labour market into well paid, highly skilled jobs (lovely) and poorly paid, low skilled and infrequent hours jobs (lousy). Theoretically this fits into the old literature of dualistic labour markets that are disconnected which then restricts movements into higher paid jobs. The predicted hollowing out of middle-skilled jobs by robots (Brynjolfsson and McAfee, 2014) may be slowing being borne out but it maybe that AI and ML are having a larger effect on a wider number of jobs and the job requirements within jobs, since the nature of this technology is more general than specific to certain occupations and industries.

2. **Research Gap:- The need to test whether ML and AI is impacting on labour market inequality in the form of the earnings distribution.**

*Method:- Use O*NET to identify tasks and abilities and other aspects of jobs (e.g. work values, work styles and social skills) that are at risk from AI and ML. Identify AI and ML by talking to experts in the UK or using EFF. Once particular jobs have been ranked into different risk groups then we can observe earnings trends and test whether hollowing out is occurring and whether a dualistic labour market is forming or is likely to firm.*

Whilst the impact of AI and ML on employment, earnings and the earnings distribution are important research questions, the impact of this technology on workers themselves through observing their job satisfaction is something that is equally important given the argument that quality of jobs will improve (e.g. Alexopoulos and Cohen, 2016). While previous questions will analyse the impact on employment and new employment in 'at threat' jobs, there is the need to research more whether jobs in which AI and ML are likely to be adopted or have been adopted have resulted in any change in job satisfaction. If AI and ML is being used to free up time for people to do less mundane aspects of jobs or has created the opportunity to branch out into a different jobs (at the same firm, same industry, different firm, different industry) then this may result in higher job satisfaction. Of course there is also the prospect that AI and ML are seen as a threat (whether this is true or not) to job security (a large part of job satisfaction). What role trade unions play in the displacement of jobs by AI and ML is also something that needs analysing with under threat workers perhaps more likely to seek union representation.

3. **Research Gap:- The need to test whether ML and AI is impacting on the job satisfaction of the current workforce in the UK.**

*Method:- Use O*NET to identify tasks and abilities and other aspects of jobs (e.g. work values, work styles and social skills) that are at risk from AI and ML. Identify AI and ML by talking to experts in the UK or using EFF. Once particular jobs have been ranked into different risk groups then we can observe job satisfaction levels in these occupations. Using Understanding Society (1990-2016) panel data in which we have job satisfaction data we can analyse whether those whose jobs are at risk from AI and ML or aspects of jobs are at risk from AI and ML report lower job satisfaction or higher job satisfaction.*

As highlighted previously one glaring gap in the research into what impact AI and ML is having and may have in the future on the labour market but more broadly on work itself is that we cannot presently quantify what AI and ML is being used by which firms and in which industries. The best we can do presently is to ask experts in the field of AI and ML about what this new technology could mean for work. The call by Raj and Seamans (2018) for an urgent need to gather firm-level information on what AI is being used and how the use of AI is changing over time is something that needs doing now. They highlight a report from McKinsey Global Institute that interviewed over 3,000 executives of international firms and industry experts about the perceived impact of one particular aspect of AI to produce an aggregate report when analysis of the interviews themselves would produce a rich addition to the literature on how employers are using AI in their firms.

4. **Research Gap:- There is then a clear gap in the current research into which firm's are using AI and ML (by sector, size, region and tenure), why they are using ML and AI or not using ML and AI, the impact it has had on firm performance, employment, earnings and job satisfaction, how jobs have changed, what are the likely changes to job requirements in the future and what impact AI is having on "firm re-imagining"[2]. Recognizing different path dependencies**

Method:- (i) The most obvious way to begin filling this gap if to ask firms directly about their usage of AI and ML in the form of face to face interviews with owners, CEOs and the like. As part of this, firms could then offer their updates of AI and ML (actual, expected) and a panel date series that captures what firms are actually doing can be produced. One way to identify firms investing in AI and ML is to work with colleagues from the Robotics, Science and Technology and AI and ML who are working alongside firms interested in adopted or developing new AI and ML so as to ask these participants the questions raised above. Clearly this could be highly sensitive information but overcoming this hurdle is not insurmountable.

(ii) A quicker and cheaper alternative is to ask more detailed questions on AI and ML in the UK Innovation Survey. The initial aim of this survey in 1994, produced by the then Department of Trade and Industry was…

[2] A term take from Wilson and Daugherty (2018), available at https://hbr.org/2018/07/collaborative-intelligence-humans-and-ai-are-joining-forces

" to gather up-to-date information ***on*** *the levels and characteristics of innovation activity in UK firms. This will benefit business by allowing DTI to more effectively target its science and technology policies. The information collected will also form part of the European Community Innovation Survey (CS). The surveys aims to cover all of your firm's products and services"*

(Front Cover of the UKIS Questionnaire, UKIS)

While changing over the years (notably being reduced in length) the questions about innovations are broad in their nature and focus on where innovations came from and what (if anything) they resulted in regarding the production process and in the impact on current products and new products. With regard to ML and AI the most detail we have is whether innovation was in advanced machinery and equipment, computer hardware or computer software (See Table 1 below). Information on computer software could capture elements of ML and AI but clearly a more granular approach is required to understand the specific impact ML or AI is having and will have on the firm's performance as well as employment and earnings for year to come.

Table 1

Innovation Investment

4.1 During the 3 year period 1 January 2012 to 31 December 2014, did this business invest in any of the following, for the purposes of current or future innovation? Please X all that apply

a. Internal Research and Development Creative work undertaken within your business that increases knowledge for developing new and improved goods or services and processes	X	1310
b. Acquisition of Research and Development Same activities as above, performed by companies, including other businesses within your group, or by public or private research organisations and purchased by your business	X	1320
c. Acquisition of advanced machinery, equipment and software for innovation		
Advanced machinery and equipment	X	1331
Computer hardware	X	1332
Computer software	X	1333
d. Acquisition of existing knowledge Purchase or licensing of patents and non-patented inventions, know-how and other types of knowledge from other businesses or organisations	X	1340
e. Training for innovative activities Internal or external training for your personnel, specifically for the development and / or introduction of innovations	X	1350
f. All forms of design Engagement in all design activities, including strategic, for the development or implementation of new or improved goods, services and processes.	X	1360
g. Market introduction of innovations		
Changes to product or service design	X	1371
Market research	X	1372
Changes to marketing methods	X	1373
Launch advertising	X	1374

4.2 If 'Internal Research and Development' was selected at question 4.1, in which of the following years did this business invest in it? Please X all that apply

a. 2012	X	2675
b. 2013	X	2676
c. 2014	X	2677

Source: Taken from the 2012-2014 UK Innovation Survey, available from UKIS 2012-14 Questionnaire

A natural extension of the research questions posed above is to focus on particular industries, occupations and regions within a country to understand which are likely to be more and less affected by AI and ML. Focussing on these areas using quantitative methods is straight forward and could reveal sectors which appear to be more likely to adopt certain types of AI and ML. This work could then lead to sector-specific or regional –specific studies that encompass data collection, qualitative evidence from various agents (e.g. workers, executives, sector-experts, trade unions, owners, AI and ML experts in the field) that can contribute to the wider public debate about what is, what will and what could happen in particular sectors and regions which appear more likely to adopt AI and ML. To date in the UK we only have the Topol Review (2019) of what impact robots and AI can potentially have on the NHS and within this report there is a call to arms for more research to be done in this area. The Topol review highlights the impact of AI on freeing-up time for health professionals to do their job better. The key finding of the report in this regard is the administrative cost per worker being reduced so face-to-face care and contact time, that many have been trained in and think the job is about, increases – what Topol calls the "gift of time". Specific to the potential impact of AI on freeing-up time the report states,

"Well-designed AI can reduce administrative burdens, giving clinicians more time for patient-clinician interaction and highlighting the positive impact of AI technologies."

(Topol Review, 2019, p.56)

Given other public services such as education, welfare, police and fire services are also likely to be affected by AI and ML there is a need for research in these sectors too as to the extent to which AI and ML will augment workers or replace workers.

5. **Research Gap:- Sector-specific and regional-specific research that follows the impact of AI and ML on particular jobs and job requirements. Focus on public services first but with a view to then focus on private sector industries.**

*Method:- The need to work with AI and ML experts to understand what technologies in these areas will be useful in improving the quality of public services. Question professionals in public services to understand how hours worked are distributed between different tasks, which tasks are preferred based on rankings, what they would like to do more of and less of. Quantitative analysis again using O*Net and Understanding Society data could focus on public services but this will likely produce small samples. The nature of people who work in public services e.g. vocation-minded, may have some impact on attitudes towards robots, AI and ML. Workers might be more likely to accept new technologies (given the necessary training and buy-in) as they can spend more time with people and perhaps feel less threatened by the new technologies due to having more power (e.g. trade unions) in public sector jobs than in private sector jobs.*

Conclusion

The paper calls for more research activities into how AI and ML is impacting on work in the UK labour market. It is currently feasible to undertake quantitative work in this area. In keeping with the small literature in this area to date, this relies on working with AI and ML research leaders to understand what previous developments in these technologies have meant for job requirements and jobs and what current and near-future developments will mean. The research does not call for more information on what AI and ML is being sold to firms in the UK and other countries as currently exists for robotics. This is mainly because much AI and ML is hard to quantify. More qualitative information is required as to which firms are using AI and ML, what AI and ML they are using, what their motivations are for using this technology (e.g. cost reduction, new product development) and whether there have been changes in jobs and job requirements.

Sector-specific studies are required so is to feed into expected reviews of how the digital economy can be used in public services. The Topol Review represents the first of these reviews and has already resulted in new jobs being created in NHS Digital (established 2013) such as Chief Clinical Information Officer, Digital Analyst, Software Development Digital Degree Apprentice and Primary Care Digital

Transformation Nurse Champion. Whether similar posts will appear in other public services in the near future is unclear at this point and is why research in these sectors is urgently needed.

References

Acemoglu, D., and Restrepo, P., (2017) "Robots and Jobs: Evidence from US Labor Markets," *National Bureau of Economic Research Working Paper No. w23285.*

Alexopoulos, M., and Cohen, J., (2016) "The Medium Is the Measure: Technical Change and Employment, 1909–1949." *Review of Economics and Statistics*, Vol. 98(4), pp. 792–810.

Autor, D. H. (2014): "Polanyis Paradox and the Shape of Employment Growth," NBER Working Papers 20485, National Bureau of Economic Research, Inc.

Brynjolffson, E., and McAfee, A., (2014) *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*. New York, NY: W.W. Norton.

Brzeski, Carsten and Inga Burk (2015) "Die Roboter Kommen," ("The Robots Come,") *ING DiBa Economic Research.*

Dauth, Wolfgang, Sebastian Findeisen, Jens Südekum, Nicole Wößner (2017) "German Robots – The Impact of Industrial Robots on Workers." *IAB Discussion Paper.*

Daily Telegraph, (2018), "German Workers win right to 28-hour Working Week", https://www.telegraph.co.uk/news/2018/02/07/german-workers-win-right-28-hour-working-week/

Elsby, M., Hobijn, B., and Sahin, A., (2013): "The Decline of the U.S. Labor Share," Brookings Papers on Economic Activity, 47(2 (Fall)), 1–63.

Felten, Ed, Manav Raj, and Rob Seamans (2018) "Linking Advances in Artificial Intelligence to Skills, Occupations, and Industries." *AEA Papers & Proceedings*. Forthcoming.

Freeman, R., (2015), "Who owns the robots rules the world:Workers can benefit from technology that substitutes robots or other machines for their work by owning part of the capital that replaces them", *IZA World of Labor: Evidence-based policy making.*

Frey, Carl B. and Michael A. Osborne (2017) "The Future of Employment: How Susceptible Are Jobs to Computerisation?" *Technological Forecasting and Social Change*, Vol 114, pp. 254–280.

Goos, M.., and Manning, A., (2007): "Lousy and Lovely Jobs: The Rising Polarization of Work in Britain," *The Review of Economics and Statistics*, 89(1), 118–133.

Graetz, G and Michaels, G., (2017), "Is Modern Technology Responsible for Jobless Recoveries?", IZA Discussion Papers, No. 10470

Karabarbounis, L., and Neiman, B., (2014): "The Global Decline of the Labor Share," *The Quarterly Journal of Economics*, 129(1), 61–103.

Keynes, J.M., (1930), "Economic Possibilities for our Grandchildren", Scanned from John Maynard Keynes, *Essays in Persuasion*, New York: W.W.Norton & Co., 1963, pp. 358-373, available from http://www.econ.yale.edu/smith/econ116a/keynes1.pdf

Manav, R and Seamans, R., (2018), "AI, Labor, Productivity and the Need for Firm-Level Data", NYU Stern School of Business.

Michaels, G., Natraj, A., and Van Reenen, J., (2014): "Has ICT Polarized Skill Demand? Evidence from Eleven Countries over Twenty-Five Years," *The Review of Economics and Statistics*, 96(1), 60–77.

OECD. *OECD Employment Outlook 2012*. Paris: OECD, 2012.

Pajarinen, Mike and Petri Rouvinen (2014) "Computerization Threatens One Third of Finnish Employment," *ETLA Brief No. 22*.

The Topol Review (2019), "Preparing the healthcare workforce to deliver the digital future: An independent report on behalf of the Secretary of State for Health and Social Care", National Health Service.

Wilson, H.J., and Daugherty, P.R., (2018), "Collaborative Intelligence: Humans and AI Are Joining Forces", July–August issue (pp.114–123), *Harvard Business Review*.

Recent UWE Economics Papers
See https://www1.uwe.ac.uk/bl/research/bcef/publications.aspx for a full list.

2019

1901 **Education and the Geography of Brexit**
Robert Calvert Jump and Jo Michell

1902 **Robots and Life Satisfaction**
Tim Hinks

2018

1807 **Learning, Heterogeneity, and Complexity in the New Keynesian Model**
Robert Calvert Jump, Cars Hommes, and Paul Levine

1806 **DSGE Models and the Lucas Critique. A Historical Appraisal**
Francesco Sergi

1805 **A new approach to estimating interregional output multipliers using input-output data for South Korean regions**
Malte Jahn, Anthony T. Flegg and Timo Tohmo

1804 **Urban food security in the context of inequality and dietary change: a study of school children in Accra**
Sara Stevano, Deborah Johnston and Emmanuel Codjoe

1803 **The use of differential weighting and discounting in degree algorithms and their impact on classification inflation and equity: A further analysis**
David O. Allen

1802 **Unambiguous inference in sign-restricted VAR models**
Robert Calvert Jump

1801 **Degree algorithms, grade inflation and equity: the UK higher education sector**
David O. Allen

2017

1706 **Internal rationality, heterogeneity and complexity in the new Keynesian model**
Cars Hommes, Robert Calvert Jump and Paul Levine

1705 **The regionalization of national input□output tables: a study of South Korean regions**
Anthony T. Flegg and Timo Tohmo

1704 **The impact of quantitative easing on aggregate mutual fund flows in the UK**
Iris Biefang-Frisancho Mariscal

1703 **Where are the female CFOs?**
Gail Webber, Don J Webber, Dominic Page and Tim Hinks

1702 **Mental health and employment transitions: a slippery slope**
Don J Webber, Dominic Page and Michail Veliziotis

1701 **SMEs access to formal finance in post-communist economies: do institutional structure and political connectedness matter?**
Kobil Ruziev and Don J Webber

2016

1611 **Curriculum reform in UK economics: a critique**
Andrew Mearman, Sebastian Berger and Danielle Guizzo

1610 **Can indeterminacy and self-fulfilling expectations help explain international business cycles?**
Stephen McKnight and Laura Povoledo

1609 **Pricing behaviour and the role of trade openness in the transmission of monetary shocks**
Laura Povoledo

1608 **Measuring compliance with minimum wages**
Felix Ritchie, Michail Veliziotis, Hilary Drew and Damian Whittard

1607 **Can a change in attitudes improve effective access to administrative data for research?**
Felix Ritchie

1606 **Application of ethical concerns for the natural environment into business design: a novel business model framework**
Peter Bradley, Glenn Parry and Nicholas O'Regan

1605 **Refining the application of the FLQ Formula for estimating regional input coefficients: an empirical study for South Korean regions**
Anthony T. Flegg and Timo Tohmo

1604 **Higher education in Uzbekistan: reforms and the changing landscape since independence**
Kobil Ruziev and Davron Rustamov

1603 **Circular economy**

Peter Bradley

1602 **Do shadow banks create money? 'Financialisation' and the monetary circuit**
Jo Michell

1601 **Five Safes: designing data access for research**
Tanvi Desai, Felix Ritchie and Richard Welpton

2015

1509 **Debt cycles, instability and fiscal rules: a Godley-Minsky model**
Yannis Dafermos

1508 **Evaluating the FLQ and AFLQ formulae for estimating regional input coefficients: empirical evidence for the province of Córdoba, Argentina** Anthony T. Flegg, Leonardo J. Mastronardi and Carlos A. Romero

1507 **Effects of preferential trade agreements in the presence of zero trade flows: the cases of China and India**
Rahul Sen, Sadhana Srivastava and Don J Webber