Inna Grinis[1]

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Email:	I.Grinis@lse.ac.uk	**Date of Birth:**	25th March 1993
Telephone:	(+44) 07549878193	**Citizenship:**	French

Education

2015 - present PhD in Economics - **London School of Economics**
Lead Supervisor: *Prof. John Van Reenen*
Field courses: *Topics in Advanced Econometrics for Research Students (mark: 81)*
Asset Pricing for Research Students (mark: 72)

2013 - 2015 MRes in Economics, *Merit* - **London School of Economics**

2010 - 2013 BA in Economics, *1st Class* - **University of Cambridge**, King's College

2009 Classe préparatoire ECE - Lycée Henri IV, Paris

2009 French Baccalauréat ES, *Mention "Très Bien", overall mark: 20.71/20*

Employment

Summer 2015 **Goldman Sachs International**, London. Global Portfolio Solutions, Off-cycle Intern

2014 - 2015 **LSE**, Graduate Teaching Assistant, EC317 Labour Economics (3rd year undergraduates)

Affiliations

2015 - present PhD Student (Growth), **Centre for Economic Performance** (CEP), LSE

2015 - present Research Associate, **Systemic Risk Centre** (SRC), LSE

2015 - present Associate Fellow, **UK Higher Education Academy**

Prizes & Scholarships

2013 - 2017 **ESRC Doctoral Training Centre Studentship** (Enhanced award)

2014 **Deutsche Bank Award in Financial Risk Management and Regulation** (Runner-up)
Title: *Credit Risk Spillovers, Systemic Importance and Vulnerability in Financial Networks*

2013 **Adam Smith Best Dissertation Prize**, University of Cambridge, Department of Economics
Title: *Spillover Effects in the European Sovereign Debt Crisis: a Network Approach*

2013 **LSE Economics Policy Challenge 2013**
Title: *Is a lost generation of young workers an evitable outcome of recession?*

2013 **James Prize Essay**, King's College (2nd Prize)
Title: *Does Beauty have a role in Art?*

2012, 2013 **King's College Scholarship**

2011 **DAAD University Summer Course Scholarship**

2009 **Concours Général des Lycées** - Economics & Sociology (2nd Prize), Russian (1st Accessit)
Title: *L'État doit-il intervenir dans la vie économique?*

Research Presentations

2016 1st IZA Workshop on the Economics of Education: Higher Education
Rimini Conference in Economics and Finance (RCEF) - "Innovation, Growth, Governance and Development"
8th International Oxford Education Research Symposium (OERS)
SRC Research Meeting, LSE Labour Work-in-Progress Seminar

2015 15th Society for the Advancement of Economic Theory (SAET) Conference - "Current Trends in Economics"
Lead Portfolio Managers Meeting (Global Portfolio Solutions, Goldman Sachs)

2014 Deutsche Bank / LSE Financial Markets Group event

2013 LSE Economics Policy Challenge

[1] Updated: November 2016

Working Papers

- "The STEM Requirements of 'Non-STEM' Jobs: Evidence from UK Online Vacancy Postings and Implications for Skills & Knowledge Shortages"
- "Trend Growth Durations & Shifts"

Publications (Refereed)

- "Credit Risk Spillovers, Systemic Importance and Vulnerability in Financial Networks", *Complexity Economics*, 2015(1), 1-22, doi:10.7564/14-COEC4, preprint: SRC Discussion Paper No. 27

Publications (Non-Refereed)

- "Is a lost generation of young workers an evitable outcome of recession?" *, Columbia Economics Review,* Spring 2013, Vol.III, No.2

Research Interests

Computational Economics; Labour Economics/Economics of Education; Growth; Networks; Finance/Systemic Risk

Computer skills

R, Stata, MatLab

Languages

Russian (native), French & English (fluent), Italian & German (advanced), Mandarin (basic)

Other activities

2013 - present	London School of Economics Orchestra (violin)
2011 - 2012	Chief coordinator & Researcher, Marshall Economics Research group (MERG)
2010 - 2013	Cambridge University Symphony Orchestra
2010 - 2013	King's College (Cambridge) Music Society (orchestra, violin)
2009	Certificate in Musical Education (violin), *Mention "Très Bien"* - Conservatoire of music, Nice

Research Proposal: NBER Post-Doctoral Fellowship on Innovation Policy

Inna Grinis

November, 2016

I am a PhD student at the London School of Economics. A large part of my research focuses on working with a big dataset containing information on all online vacancy postings in the UK (33m between January 2012 and July 2016) collected and processed by the labour market analytics company Burning Glass Technologies (BG). Where available, BG collects job titles, occupation and industry identifiers, employers' names, geographical locations, education, experience and degree discipline requirements, wages, and transforms the vacancy description text into a set of keywords, e.g.: *"Adobe After effects - E-Learning - Multi-Tasking - Audio Editing"*.

This research proposal first summarizes the work I have been doing with the BG data so far, then discusses research projects related to Innovation Policy that I would like to undertake with it in the future.

Summary of current research with BG data: "*The STEM requirements of 'Non-STEM' jobs"*

Many governments in developed economies are concerned about the existence of STEM (Science, Technology, Engineering, Mathematics) skills and knowledge shortages because STEM human capital is very important for the creation and use of new products and technologies and therefore for innovation and growth.

The debate often focuses exclusively on STEM shortages within *STEM occupations* (e.g. Engineers, Scientists, Programmers, …). However, do certain jobs that belong to *non-STEM occupations* (e.g. Graphic Designers, Artists, Economists…) also require advanced STEM human capital, i.e. knowledge and skills that are typically taught within STEM disciplines (e.g. C++, Systems Engineering, Relational Databases…)? Addressing this question is important not only for correctly quantifying the labour demand for STEM and therefore assessing the existence of STEM shortages, but also for proposing adequate education policies that will help alleviate them.

My paper *"The STEM requirements of 'Non-STEM' jobs: Evidence from UK online vacancy postings and Implications for Skills & Knowledge shortages"* proposes a new approach to identifying STEM *jobs* directly, by inspecting the keywords found in corresponding vacancy descriptions, and not, as is typically done, by first defining a set of STEM *occupations*, then considering all the jobs belonging to these occupations as STEM and the rest as non-STEM, and therefore automatically ignoring all the jobs that belong to non-STEM occupations but also require STEM knowledge and skills.

The approach, illustrated in Figure 1, relies on first classifying thousands of keywords into STEM and non-STEM using a statistical learning algorithm called "context mapping", then labelling as STEM the jobs whose vacancy descriptions contain STEM keywords.

"Context mapping" employs the sample of vacancies for which we observe both the keywords and the specific degree discipline requirements, e.g. Chemistry, Economics, English… (12% of all postings) to classify keywords depending on the discipline "contexts" in which they appear. Intuitively a proper STEM skill, knowledge, task should rarely appear together with a non-STEM discipline because it requires a proper STEM education and a STEM qualification, and vice versa. The idea is illustrated in Figure 2 and further examples of STEM and non-STEM keywords are given in Figure 3.[1]

[1] Out-of-sample tests on the subset of vacancies with both keywords and discipline requirements show that "context mapping" classifies around 84% of vacancies correctly (as STEM if the recruiter specifies a STEM discipline and as non-STEM if he specifies a non-STEM discipline).

Figure 1: Approach to identifying STEM jobs

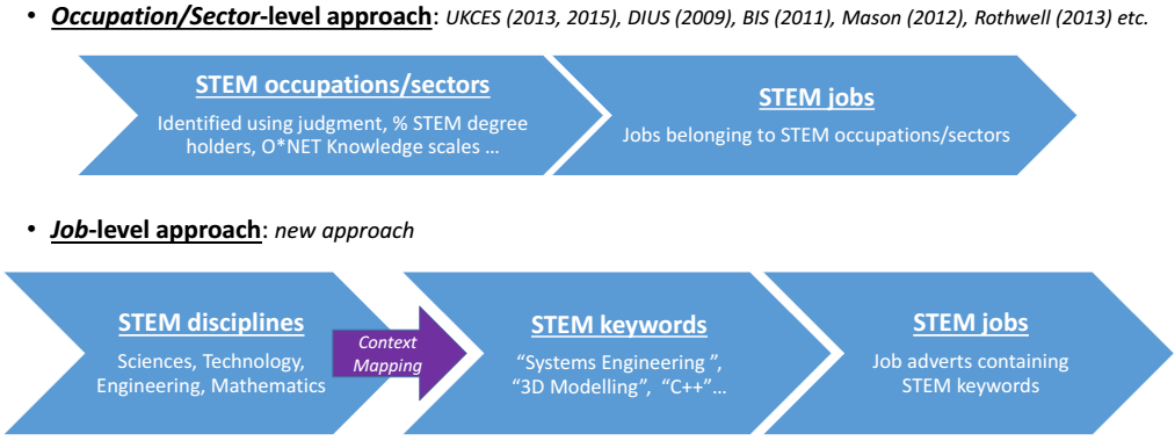
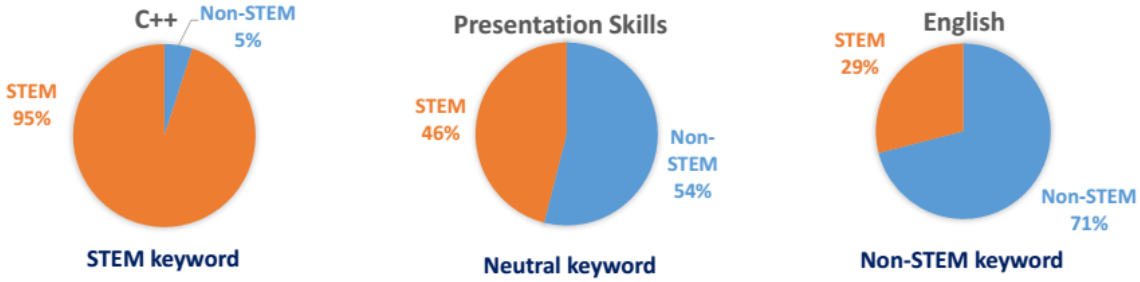


Figure 2: Intuition behind "context mapping"



Note: *Percentages of STEM and non-STEM discipline requirements with which a given keyword appears in the sample of vacancies where we observe both disciplines and keywords.*

Empirically, I find that 30% of the 6.7m UK online vacancies in 2014 are STEM jobs. 80% of these STEM jobs are positions for which a college education is typically required – "high-level" STEM jobs. One third of these high-level STEM jobs belong to non-STEM occupations.

I further use the subsample of vacancies with wage data to show that STEM jobs are associated with higher wages even after controlling for detailed occupations, industries, education, experience requirements, etc. This finding is consistent with a shortage of STEM knowledge and skills across the economy and not only within STEM occupations as previously found.

To understand the implications of these findings for the design of education provision policies that could help alleviate STEM shortages, I construct a simple abstract framework and employ it to illustrate two ideas that are rarely mentioned in the debate on STEM shortages:

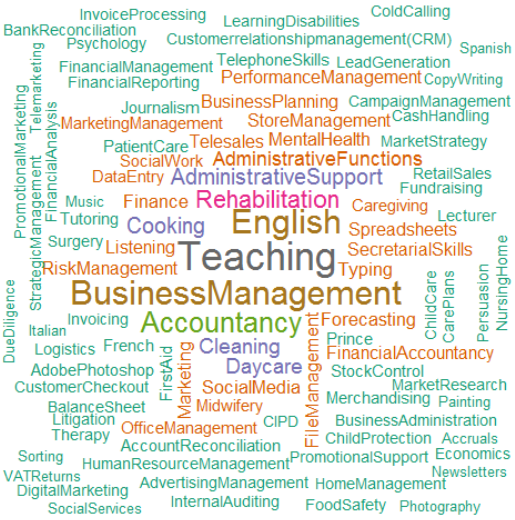
1. In assessing the existence of shortages we need to take into account the interdependence of all vacancies and job seekers in the economy, i.e. go beyond STEM graduates/STEM occupations and also incorporate non-STEM graduates and non-STEM occupations into our assessment;
2. Shortages can be solved by modifying the skills and knowledge composition possessed by "not-in-shortage" graduates. In particular, by increasing the amount of STEM knowledge & skills taught in non-STEM disciplines, we could reduce overall STEM shortages in the economy.

Figure 3: STEM (Computer Sciences cluster) vs. non-STEM keywords

Computer Sciences keywords



Non-STEM keywords



Note: *Random samples of around 100 keywords colored and weighted by frequency of being posted.*

Future research with BG data:

Around 30% of all UK vacancy postings also contain the employer's name. In future work, I would like to link this subsample to firm-level productivity and patent data in order to investigate which firm practices and worker requirements lead to improved productivity and innovation.[2] Here are two concrete projects that I would like to pursue:

- *Bigger Data – Smaller Ideas?*

There is no doubt that the use of data analytics transforms business and management practices and leads to better firm decisions and enhanced productivity (e.g. Brynjolfsson, Hitt, and Kim (2011), Brynjolfsson and McAfee (2014), Tambe (2014)).

However, a recent paper by Hitt and Wu (2016) challenges the view that the use of data benefits innovations. The authors employ a survey of 331 firms to show that when a firm is *process*-oriented, using data analytics can help the firm improve its existing business processes (e.g. by drawing insights from data on consumer behaviour and choices) and become more productive. By contrast, having data skills seems to worsen the productivity of firms that use *innovation*-oriented practices (e.g. new product development).

In other words, data analysis is a complement to small, incremental innovations but not to creative breakthroughs. Intuitively, if consumer analytics are good at reflecting preferences among *existing* products but limited in signalling the value of *imagined* ones, overreliance on them could reduce

[2] A recent paper by Deming and Kahn (2016) takes an important first step in this direction with the US BG data. However, the classification proposed by the authors is incomplete and does not exploit the main advantage of the BG data which is the granularity of the worker requirements and job tasks at the vacancy level. They distil the over 10,000 keywords and phrases in the BG taxonomy by selecting around 30 commonly occurring words and phrases and regrouping them into 8 categories in addition to using the pre-existing computer/software category created by BG.

breakthrough inventions. An anecdotal example here is Steve Jobs – the genius entrepreneur refused to undertake any marketing research when creating the first iPad.

As bigger datasets become more and more available to managers, the relation between data and innovation needs to be investigated further as it could have important implications for how businesses should employ it.

The BG sample offers a rich source of information about both:

- *the intensity of data use:* we can look at the firm-level percentage of vacancies requiring data analytics skills as well as distinguish between the firms that use advanced big data software (PIG, Hadoop, Apache Hive…) from those that undertake lower scale data analysis with software like R, Stata, Matlab, SAS …
- *the purpose of data use:* if data is being used for market research, the vacancy advert would also include keywords like "Consumer Trends", "Market Conditions", "Competitive Analysis", "Market Research" … If it is used for strategy deployment, we would find, e.g., "Strategic Analysis", "Financial Strategy" ...

Making the latter distinction is important as the negative impact of data skills on the productivity of innovation-oriented firms that appears in the Hitt and Wu paper may be due to overreliance on market research rather than data skills per se.[3]

To see this, consider a simple model where firms may require data skills for two different purposes: conduct experiments in the creation of new products and market research. Further, suppose that firms that over-rely on market research end up with a lower probability of coming up with an innovation. If firms A and B require the same level of data skills for the role of product creation itself, but firm B requires more data skills for the market research role than A, we will indeed observe that overall more data skills at the firm level lead to lower innovation. However, if we had made the distinction between the activities for which data is being used, we would see that the problem is too much market research and not data analysis per se.

Moreover, as with ICT investments, the use of data may have an impact on the organization of firms (Bloom, Garicano, Sadun, and Van Reenen (2014)) and firms may need to make some organizational changes to reap all the benefits of data analytics usage (Bresnahan, Brynjolfsson, and Hitt 2002). The existing literature already suggests, for instance, that having more autonomous employees may enable firms to reap greater benefits from data analysis (Bakhshi et al. 2014).

Once again BG data would allow us to go much further in the investigation of complementarity between data skills and work styles since it distinguishes between collaboration ("Team Work/Collaboration", "Team Building" …), autonomy ("Initiative", "Self-Starter" …), creativity, leadership … We could also study the relation between data and other types of skills: e.g. Bakhshi et al. (2014) show that simply amassing data has no effect on firm productivity. What is really needed is data analysis and reporting. Hence, at the firm level, we could find that communication and presentation skills, reporting … are all complementary to data skills.

This exercise would allow us to draw some managerial implications on how to manage people working with data most efficiently.

More generally, in investigating the relation between firm practices and firm productivity/innovation, BG data offers several advantages relative to surveys that have usually been employed for this purpose so far:

- *size*: the surveys mentioned above are relatively small (e.g. 179 in Brynjolfsson, Hitt, and Kim (2011), 331 firms for Hitt and Wu (2016) and 500 firms for Bakhshi et al. (2014)), while BG contains the universe of online recruiters;

[3] To measure firm level data skills, Hitt and Wu (2016) use a database of over 6 million resumes and classify the skills collected from these resumes into data-related and non-data related. They then aggregate the number of employees with data-related skills at the firm level without distinguishing between consultants, financial analysts, systems engineers, etc.

- *time span*: most surveys are conducted in one specific year, whereas BG data spans several years and can therefore be used to construct time varying indicators of firm practices. We could then employ panel techniques to go beyond correlation analysis conditional on controls and establish causal relationships. Moreover, assuming that data analytics activities remain constant over several years (e.g. Bakhshi et al. (2014)) is problematic since advances in data software appear every year.

- *Does diversity of work styles improve firm performance?*

If everyone in a team has a big-picture, strategic, intuitive approach, the resulting work may lack structure and be behind schedule. By contrast, if everyone has an analytical, well-planned approach, the work may lack creativity and innovation. Despite the growing interest in social skills and work styles (e.g. Heckman & Kautz (2012), Deming (2015)), the question of whether there exists an optimal mix of work styles at the firm level does not seem to have been addressed in the academic literature, despite being often discussed by practitioners (e.g. Tate, 2015).

BG data contains detailed information on the work style requirements: "Self-Starter", "Building Relationships", "Creativity", "Detail-Orientated", "Leadership", "Meeting Deadlines", "Team Building", "Time Management", "Business Acumen", "Energetic", "Positive Attitude", "Quick Learner"… and could therefore be a great source of information for addressing this question.

References:

- Hasan Bakhshi, Albert Bravo-Biosca and Juan Mateos-Garcia (August 2014), "The analytical firm: estimating the effect of data and online analytics on firm performance", *Nesta Working Paper No. 14/05*
- Nicholas Bloom, Luis Garicano, Raffaella Sadun and John Van Reenen (January 2014), "The Distinct Effects of Information Technology and Communication Technology on Firm Organization", *Management Science*, p. 2859 – 2885
- Bresnahan, T. F., Brynjolfsson, E., & Hitt, L. M. (2002). "Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm-Level Evidence.", *The Quarterly Journal of Economics*, 117(1), 339-376
- Erik Brynjolfsson, Lorin Hitt, and Heekyung Kim (2011), "Strength in Numbers: How Does Data-Driven Decision-Making Affect Firm Performance?"
- Erik Brynjolfsson and Andrew McAfee (2014), *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*. WW Norton & Company.
- David Deming (August 2015), "The Growing Importance of Social Skills in the Labor Market", *NBER Working Paper No. 21473*
- David Deming and Lisa Kahn (June 2016), "Firm Heterogeneity in Skill Demands"
- James J. Heckman and Tim D. Kautz (June 2012), "Hard Evidence on Soft Skills", *NBER Working Paper No. 18121*
- Lorin Hitt and Lynn Wu (February 2016), "How Do Data Skills Affect Firm Productivity: Evidence from Process-driven vs. Innovation-driven Practices"
- Prasanna Tambe (January, 2014), "Big Data Investment, Skills, and Firm Value", *Management Science*, Forthcoming
- Carson Tate (April 2015), "Differing work styles can help team performance", *Harvard Business Review*

Massachusetts Institute of Technology

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MIT Economics

November 5th 2016

Dear NBER,

I am delighted to have the opportunity to write a letter in support of Inna Grinis.

I have known Inna since I started supervising her in the second year of her PhD in 2014.

She is an extraordinarily impressive candidate with a glittering array of prizes and talents (such as the Adam Smith dissertation prize, a Cambridge First and a Merit in her MRes). Unusually, she is a very talented mathematician (and now computer scientist) as well as a first rate economist who can do top rate theory and empirical work.

She has driven her own course very strongly, being determined from the start to consider the important policy issue of skill mismatch. The work on "over-education" is generally extremely poor and loose. Inna's first task (in her MRes dissertation) was to bring some intellectual order to this by developing a novel theoretical framework. She conceptualized jobs and people as bundles of skills and considers the (imperfect) matching between them. This is kind of a cross between a generalized Roy model, Rosen and mathematical lattice theory.

Having developed the framework, her job market paper seeks to empirically implement it. She successfully negotiated access to the Burning Glass (BG) data: a very rich source of information on online job vacancies. BG strips keywords from tens of millions

of descriptions from UK online vacancies. These keywords can be used to characterize job vacancies in a richer way that has ever been done before.

Inna is particularly interested in using this data to understand whether there is a problem with STEM (Science, Technology, Engineering and Mathematics) jobs. The UK has often been perceived to be relatively weak in generating people with the skills needed to satisfy growing demands from the STEM sector. But the concept of what is a STEM job itself is unclear and somewhat arbitrary. The good news is that it is possible to classify keywords into those that are STEM related or not and once this is done every jobs can be given a STEM index. This requires using many machine learning techniques for "Big Data" (her particular approach draws on "context mapping").

One of her important findings is that STEM skills are used in many occupations that are not typically classified as STEM at all. Many professional jobs in finance (e.g. quants) and business services use significant amounts of STEM skills. About 30% of the 6.7m vacancies in 2014 have some STEM skills demanded. Not only can vacancies be more precisely classified, but so can areas of the country and industries.

Since the BG data also has wage information, she can examine how informative is STEM in determining earnings. She shows that there is much more explanatory power using her method than simply relying on occupation or other observables (such as education, experience, etc.). STEM keywords are associated with much higher wage premiums, suggesting that such skills are in high demand.

Her work is clearly critical for understanding innovation as high quality human capital is a crucial complement to innovation. Further, in terms of policy, understanding supply and demand for STEM is high on the agenda.

Inna has also made contributions in finance and in growth empirics. I know these lines of work less well, as these have been developed since I moved from LSE to MIT. But they also seem interesting and of high quality. The growth paper is a contribution to the statistical literature of trying to extract medium/long-run trends in cross country growth rates (using data from 153 countries). It uses an extension of the “fit and filter” method exploiting a mixture of discrete and continuous time techniques to identify “growth spurts.” Cross-country macro is not my area of speciality, but better identifying long-run growth trends is an important issue and arbitrarily using start and end points to calculate the long-run is clearly unattractive. So Inna’s contribution here may well be a major one.

Already, she has been giving international seminars at a young stage in her research life. I have heard her speak several times and she is a very clear communicator, even though the material she is dealing with is often extremely complex.

I would recommend her to any institution and I am sure she will have a stellar career.



John Van Reenen, Professor of Economics, MIT Economics and Sloan School.