Understanding the link between computational behavioral economics and the Big Data revolution. Towards a new paradigm in Macroeconomics?

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1. Introduction

2. Data, Information, Knowledge
   - The spectrum of data
     - Definitions of Big Data
   - Which Big Data for Economics?
   - The relationship between Data, Information and Knowledge

3. The computational turn and the emergence of a new paradigm in Macroeconomics
   - Paradigms’ evolution in Macroeconomics
   - Data as the new starting point for additional analysis and research

4. “More is different”: modeling behavioral heterogeneity and the quest for micro data
   - Improvement of the experimental method through the interplay with Big Data availability and production

5. Conclusions
The term Big data is ubiquitous
Despite its widespread usage, it seems that there is no mature discussion about BD in academia as well as no univocal definition for it → confusion regarding concepts as well as skepticism with respect its use in academic research.

Research questions:

- What are Big Data?
- Why are they important for economic research? (...why should economists care about them?)
- In presence of the Big Data revolution, is Economics (in particular, Macroeconomics) heading to a paradigm shift?
Aim of the paper

- Report how the debate on BD in social sciences is developing and potentially affecting research in economics, and, in particular, in Computational Behavioural Economics (CBE)
- By CBE we mean Agent-based computational models “informed” by findings reported by Behavioural Economics (see Akerlof, 2002; Colander et al., 2008; Velupillai and Kao, 2014, among others).
- Discuss the extent to which the increasing production and availability of BD for social researchers can make it possible a shift from data-scarce to data-rich investigations
Motivation of the paper

We highlight two main reasons for drawing the attention on this interlinkage:

1. Because from the interaction of BD and CBE, a new research paradigm is emerging in economics, and in particular in macroeconomics → **Agent-based computational economics offers the possibility to store and analyze large datasets, but also to use them and find hidden patterns**
Motivation of the paper

2 Because computational behavioral economic models need Big Data

- Since researchers lack micro level data to empirically microfound their models, BD can contribute to the improvement on the modeling of the behaviors of the agents that populate the micro level of Agent-based models (ABM).
- The massive sample size and the granularity that characterize BD increase the power of data in revealing individual features and/or actions.
- They can help researchers observing aspects of the human behaviour (e.g., social links, preferences and so on) beyond the traditional micro data availability.
- This in turn could help in solving the issue of limited observation we have in traditional statistics.
The spectrum of data

- **Observational data** (survey data) → Data collected from surveys can be very large and complex, but they are collected in a systematic way over a small sample of the entire population.

- **Experimental data** → similarly to observational data, are collected over a small known sample and in a systematic way because they respond to a specific investigation that aims at testing a specific (theoretical) hypothesis. Differently, from observational data, they are relatively small in size and this reduces the complexity of the data structure. → **partially true in case of proper Macroeconomic experiments (high number of participants)**

- **Big data** → different possible definitions
Definitions of Big Data (I)

a Ward and Barker (2013) try to collate the various definitions that have been developed in the past 4 years: “BD is a term describing the storage and analysis of large and or complex data sets using a series of techniques”

b Laney (2011)
1. *volume*: magnitude of data
2. *variety*: structural heterogeneity
3. *velocity*: rate at which data are generated

c Gandomi and Haider (2015):
1. *veracity*: unreliability of data
2. *variability (and complexity)*: variation in the data flow and different sources
3. *value*: low value with respect to the volume of data
Definitions of Big Data (II)

**d** Kitchin (2013):

1. **exhaustiveness**: the extent to which BD strive to capture the entire population or systems
2. **relationality**: because BD contain common fields that allow for the connection of different datasets
3. **scaleability**: because BD can expand rapidly in size

**e** Our view: The term Big Data entails a phenomenon which is based on the *interaction between technologies and data analysis development* and both *co-evolve* with the present technological frontier, i.e., the magnitude of the attribute “big” is related to the computational power currently available for research, data storage and processing
Definitions of Big Data (III)

The definition of BD should thus involve at least three concepts:

- the *size* (magnitude) of data
- the *complexity* of the data structure
- the increasing rate at which they are produced and stored thanks to the available *technologies*
Are Big Data a *panacea* for social scientists?

1. Having a **big** dataset composed of millions of observational points does not necessarily mean having a “good” dataset ⇒ *Quality* and *quantity* should go indeed hand in hand.

2. The **representativeness** of the sample is an issue that is often **not** canceled out by the big dimension of the sample (e.g. analyses carried out by considering the network “traffic” on Twitter and Facebook).

3. BD are usually rather **context-dependent** than generic.

4. Because BD are often **proprietary**, they are usually very expensive. This in turn implies high costs for getting the access to the datasets, which in turn may result in a new form of digital divide in the research community.

5. BD are **complex and unstructured**, implying challenge for statistics and potential new developments for econometrics (Varian, 2014)
Other features of Big Data

- **heterogeneity** → heterogeneity that stems from sub-population data and different sources. Sometimes the sub-population data in small samples are considered as outliers because of their insufficient frequency but they can also be considered as an opportunity to model differences in the sample.

- **noise accumulation** → accumulation of estimation errors due to the simultaneous estimation of several parameters at a time, so that some variables with significant explanatory power can be overlooked.

- **spurious correlation and incidental endogeneity** → in presence of big and complex datasets it can be that uncorrelated variables (because of their independence) are found to be correlated due to the high dimensionality of the dataset.
Methods to dig into “the wilderness” of BD (I)

- In presence of large datasets which could be composed of a very large number of observations (billions) and a large number of covariates (millions), resorting to machine learning could be thus the only option to dig into “the wilderness” of BD and carry out the empirical research.
- Machine learning is particularly gaining a lot of attention (Varian, 2014) because, caeteris paribus, of its ability to deal with large datasets and the possibility of continuous “retraining” of the algorithm over time as the environment changes.
- It does not exist a unified framework yet ⇒ large set of algorithms among which researchers could choose.
- Fan et al. (2014) suggest the adoption of new methods such as: penalized quasi likelihood, sparsest solution in high confidence set, independence screening.
Methods to dig into “the wilderness” of BD (II)

<table>
<thead>
<tr>
<th>MACHINE LEARNING ALGORITHMS</th>
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<tbody>
<tr>
<td><strong>Supervised learning</strong></td>
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<td>Regression</td>
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<td>- Linear regression</td>
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<td>- OLS</td>
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<td>- LOESS</td>
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<td>- Logistic Regression</td>
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<td>- Stepwise regression</td>
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<td>Decision tree</td>
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<td>- Classification and regression tree</td>
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<td>- Conditional decision tree</td>
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<tr>
<td>Random Forest</td>
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<td><strong>Unsupervised learning</strong></td>
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<tr>
<td>Clustering</td>
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<tr>
<td>- k-means</td>
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<td>- k-medians</td>
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<td>- hierarchical clustering</td>
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<td><strong>Supervised learning</strong></td>
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<td>Markov decision processes</td>
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<td>(deep learning)</td>
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<td>- Boltzmann Machine</td>
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<td>- Belief network</td>
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<td>Neural networks</td>
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<td>Bayesian learning</td>
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**Figure:** *Machine learning algorithms: an overview.* Source: Author’s elaboration.
Which Big Data for Economics? (I)

- **Government administrative data**
  - Data on education
  - Social insurance
  - Local government spending
  - Medicare
  - IRS (Internal Revenue Service): instituted in 1913 that offer a large micro-level dataset of tax revenues. It has been used by Piketty and Saiz (2003) to derive historical series of income shares for the top percentiles earners among US households

- Data that result from **online activity** (queries and/or social media)

- Data on **consumer spending and sentiment**: e.g., MasterCard distributes “SpendingPLus” that provides a real-time consumer spending data in different retail categories
Researchers engaged in financial agent-based modeling already make use of very complex and large datasets (LeBaron, 2000; Hommes, 2006).

- Over the past decades, extremely high frequency data has become available.
- Researchers have a detailed picture of exactly how the market is unfolding, as well as the exact dynamics of trade clearing.
- There are also series that show detailed holdings of institutions and that record the flows coming in and out of these funds.
- The availability of high frequency data, pricing and volume data from financial markets enhances the transparency of the trading behaviours of financial agents and allows for a detailed modeling (and/or calibration) of the features of artificial financial markets.
Towards a new empirical revolution

Even if Big Data present some drawbacks and are not a panacea . . .

The distinction among the different types of data available for social research lead us to claim that the process of diffusion and use of Big Data, thanks to the availability and development of new computational and storing technologies, could eventually lead to an empirical revolution akin to the Keynesian revolution that led to the availability of macro data (Patinkin, 1976).
The relationship between Data, Information and Knowledge

Data are unorganized and unprocessed facts about events, which constitute the prerequisites to information. Information can be considered as an aggregation of data (processed data) which implies a meaning and a purpose. From information we derive knowledge; i.e., human understanding of a subject matter that has been acquired through study and experience.
## Science paradigms: evolution and features

<table>
<thead>
<tr>
<th>PARADIGMS</th>
<th>FEATURES</th>
<th>TIMING</th>
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<tbody>
<tr>
<td>I: Experimental</td>
<td><strong>Empiricism</strong></td>
<td>before XVIII century</td>
</tr>
<tr>
<td>Science</td>
<td>“data speak for themselves, free of theory”</td>
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<td></td>
<td>(induction)</td>
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<td>II: Theoretical</td>
<td><strong>Knowledge-Driven</strong></td>
<td>before advent of computational power</td>
</tr>
<tr>
<td>Science</td>
<td>Modeling, abstraction (deduction)</td>
<td></td>
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<tr>
<td>III: Computational</td>
<td><strong>Simulation of complex systems</strong></td>
<td>before Big Data</td>
</tr>
<tr>
<td>Science</td>
<td>(induction+deduction)</td>
<td></td>
</tr>
<tr>
<td>IV: eScience</td>
<td><strong>Data-intensive</strong></td>
<td>present</td>
</tr>
<tr>
<td></td>
<td>(abduction+deduction+induction)</td>
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**Figure:** Source: author’s elaboration based on Hey et al. (2009) and their report of Jim Gray’s speech on eScience.
Paradigms evolution in Macroeconomics (I)

- Even if paradigmatic accounting is usually problematic - and this especially true in the case of Economics - a similar evolution in research and methodology as the one sketched in Figure 2 can be found also in the Economics research field.

Taking an evolutionist perspective . . .

macro methodology has been climbing a fitness landscape, where recombination, which is a key feature in evolution, has been playing an essential role in the development of new methodologies in macroeconomics.
We follow Colander, Howitt, Kirman, Leijonhufvud, Mehrling (2008) Beyond DSGE Models: Towards an Empirically Based Macroeconomics, AER that offer an overview of the evolution of the research methodology in Macroeconomics.

1. *Up until the 40s and 50s*, macroeconomics proceeded without a formal theory: macroeconomics policy was based on a loose and largely empirical understanding of the macro economy. The *models* used by economists were *simple and not formalized in rigours mathematical terms*: this phase relied mainly on *induction*.

⇒ Paradigm I.
2. With the development of macro-econometric models in the 50s, many of the Keynesian models were presented as having formal underpinnings of microeconomic theory; then in the 70s, the formal modeling began in the spirit of General Equilibrium theory with the aim to build a general equilibrium model of the macro economy based on explicit and fully formulated micro foundations: research methodology based mainly on the use of deduction
⇒ Paradigm II.
3 However, since analytical models are technically difficult and constrained by the mathematical strait-jacket, it is not clear which, if any, will provide a meaningful advance. Colander et al. maintain that, in order to progress, macro theory should move on to models that take agents’ heterogeneity and interaction into account: thanks to the *increase in computing power* over the past decades, there is an alternative approach that can cut the *Gordian analytical knot*; it uses *agent-based computational economics (ACE)* and *simulations* to analyze the macro economy
⇒ Paradigm III.
Simulations as a third way of doing science

Simulation **differs from standard deduction and induction** in both its implementation and its goals. (Axelrod and Tesfatsion, 2006)

- Scientists use deduction to derive theorems from assumptions, and induction to find patterns in empirical data.
- Simulation, **like deduction**, starts with a set of explicit assumptions; but **unlike deduction**, simulation does not prove theorems with generality.
- Instead, simulation generates data suitable for analysis by induction; but **unlike typical induction**, the simulated data come from a rigorously specified set of assumptions regarding an actual or proposed system of interest rather than direct measurements of the real world.
- Simulation thus permits **increased understanding of systems through controlled computational experiments**.
4 The *data revolution* (Kitchin, 2014) is recently leading to the so-called “computational turn” (Berry, 2011) ⇒ implies *alternative epistemologies in humanities and social sciences and changing of research practices*, also in Economics.
Paradigm shift in Macroeconomics

In the Economics field, we emphasize that a paradigm shift (IV) implies a further shift from the mainstream deductive approach as well as the inductive approach (Lawson, 1989; Arthur, 1994), to an even more articulated shift where induction and deduction, together with abduction will contribute to the understanding of an economic complex phenomenon. 
⇒ this is at the core of agent-based computational economics where theory, experiments and simulations are the essential elements of the research methodology.
Figure: Macroeconomic agent-based model: building methodology. Author’s elaboration.
Because of their features, ABMs are thus suitable tools to study complex systems: *systems with many interacting entities and non-linear interactions among them.*

The value added, in term of modeling approaches and economic insights, of ABMs is that the dynamics of aggregate variables are the result of complex, continuously and endogenously changing *micro-structure* (Epstein, 2007) ⇒ they allow for modeling a large range of economic behaviors
Behavioral heterogeneity

- Standard Macroeconomics relies on *microfoundations*: the gap between the micro behavior and the macro “flavor” is filled by resorting to the *representative agent* assumption and to the process of *aggregation*.

- However, the reduction of the behavior of a group of heterogeneous agents to the behavior of a single representative agent can lead to *misleading* - or even wrong - conclusions (Kirman, 1992).
Behavioral heterogeneity

The theoretical debate and investigation on the issues arising from the use and implementation of rational expectations (RE) representative agent models has gradually led to the “behavioral revolution” (starting from (Simon, 1957)): has provided models with more realistic psychological foundations (Thaler, 1994; Akerlof, 2002; Kahneman, 2003; Camerer and Loewenstein, 2004; Camerer et al., 2004) and “practical” ways in which behaviors can be incorporated in them.
Open issues in the “alternative” microfoundation of Agent-based models

- Economists are still tangled up with several competing options in the choice of the microeconomic model (Chen and Wang, 2011).
- When the researcher wants to bring his model to the data, the building of the empirical microstructure still suffers from the paucity of individual micro data compared to aggregate (field) data.
The contribution of experimental economics

- By observing human subjects behaviors in the experimental laboratory, experimental economics has been helping in bridging the gap between the micro and the macro level in economic models.
- The use of experimental micro data to calibrate artificial agents is among the most important innovations that helped improving the self-referential nature of macroeconomic models (Duffy, 2006).
Improvement of the experimental method through the interplay with Big Data availability and production

Critiques to the experimental method are usually related to the so-called internal and external validity of experiments.

Advances:

1. Thanks to the possibility of collecting and storing big datasets from several realistic contexts, allows researchers to consider the field as their own experimental laboratory and themselves as “consumers of data” (Fan et al., 2014, p.293)

⇒ There is a wide digital landscape: collect data on users’ opinions from online questionnaires, on consumers preferences via online buying, online auctions, social networks, etc.
Improvement of the experimental method through the interplay with Big Data availability and production

Example: the Billion Prices Project (BPP)

Developed by Alberto Cavallo and Roberto Rigobon: provides an alternative measure of \textit{retail price inflation} relying on data from hundreds of online retail websites in more than fifty countries and data are used to construct price indices that can be updated in real time. The authors then use the data gathered to \textit{construct the BPP index to document patterns of price changes} in the same way that researchers have used the data underlying the CPI (Cavallo, 2015).
b Compared to the “standard” experimental lab, in the case of BD the researcher can work in a more natural experimental environment where

a **his direct action is hidden to the agents**; this is potentially very important because it helps in avoiding that agents’ - directly or indirectly - try to meet the expectations (about the results’ of the experiment) of the researcher,

b **framework effects** no longer exist because there is no need to ask questions (regarding e.g. preferences) directly to the subjects; preferences are just tracked in data,

c **sample size, sample bias** and **representativeness** are no more an issue the researcher should be concerned about

d for some cases, there is no need to have testable hypothesis of the **theory** (as required in standard experiments); the researcher observes data and grasps possible theoretical insights after the discovery of recurring **patterns**,
Concluding remarks

The different types of data used in social research represent

- noticeable opportunities in specific areas of investigation
- they co-evolve with the different scientific paradigms that have been developing and unfolding over the last decades.
Implications of the *Big Data revolution* for Computational Behavioral Economics

- It implies a **deep epistemological change** which will lead (is leading) economists to consider (or re-consider)
  - the process of research
  - the way in which they engage with data analysis, data processing and data gathering
  - the constitution of knowledge.
- “Inanimate data can never speak for themselves, and we always bring to bear some **conceptual framework**, either intuitive and ill-formed, or tightly and formally structured, to the task of investigation, analysis, and interpretation” (Gould, 1981, p.166).
- Computational (behavioral) economics provides researchers with a set of tools that enables the transition towards a **new scientific paradigm**, which is based on the availability of new kind of data, new analytic tools and new research methodology.
Conclusions

Data as the new starting point for additional analysis and research

- CBE allows researcher to take into account the specific context and contingency and BD can be used to refine the understanding of some features (e.g., agents’ preferences) or network structures.

- The massive sample size and high dimensionality of BD collected from various sources could be exploited to provide a very detailed and empirically-grounded specification of the agents’ behaviors ⇒ allows for a more complete and empirical heterogeneity of agents already at the initialization of the model, while heterogeneity is usually treated as an emergent property of computational agent-based models.
Improvements of the experimental (economic) method

- The field becomes the experimental lab and researchers become “consumers of data”
- Researchers can work in a more natural experimental environment and potentially mitigate the internal and external validity critiques
Thank you for your attention!

Comments are particularly welcome!

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