



Center for Collective Learning

Our mission

We are interested in understanding how knowledge moves, grows, and decays, from teams to nations, and from the past to the future.

We study how technology, geography, and culture impact the growth and diffusion of knowledge using machine learning and data science tools.



Who we are

Corvinus University, in Budapest



University of Toulouse

The Center for Collective Learning (CCL) is a multidisciplinary research center with offices at the Artificial and Natural Intelligence Institute (ANITI) of the University of Toulouse and at the Corvinus Institute of Advanced Studies (CIAS) at Corvinus University.

The CCL is internationally recognized for its work on economic complexity, economic geography, and data visualization.

What are we known for?



Economic Complexity:

For nearly 20 years we have pioneered the use of machine learning and network science tools to study economic development. This includes seminal concepts, such as the product space, the network of related economic activities used to anticipate and strategize industrial diversification strategies, and the economic complexity index (ECI), a popular international development statistics explaining international variations in future economic growth, inequality, and emissions.

Digital Democracy:

We have developed digital democracy platforms to scale nuanced deliberation and expand the boundaries of social choice theory.

Urban Perception:

We pioneered the use of crowdsourcing and machine learning methods to map and understand urban perception and physical urban change.

Data Visualization:

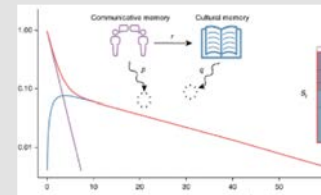
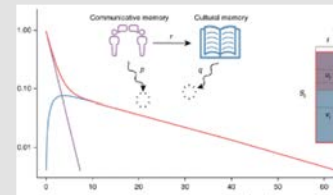
We have built dozens of data visualization platforms and experiences.

Collective Memory:

We have explored the role of languages, technology, and time on collective memory.

Perception of AI:

We have explored people's perception of AI in dozens of controlled experiments.



Who supports us

Our support comes from several European and National research projects.

Support for CCL at Corvinus University comes from the **European Research Executive Agency (ERA) Chair**. Support for CCL at the University of Toulouse comes from an **ANITI Chair** provided by the national french research agency (**ANR**) and from the **European Lighthouse of AI for sustainability (ELIAS) Horizon project** and **Obs4Sea (Horizon) project**.



European
Commission |

A large & growing multidisciplinary team



Philipp Koc



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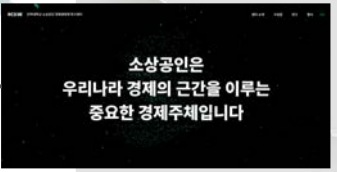
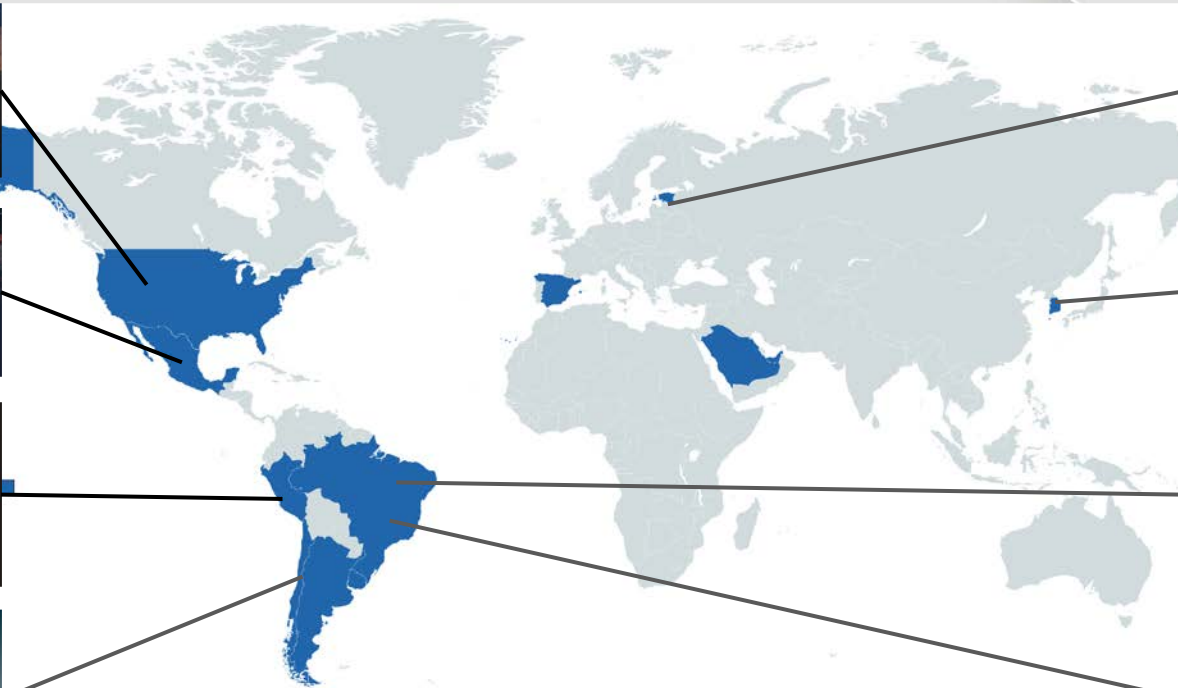


Touloudapest

4 postdocs, 2 PhD Students, 2 Assistant Professors, 1 Engineer, 1 Designer, 1 External Visiting Professor, 4 graduate students, 1 executive director, 1 director

Our impact

includes the creation, inspiration, and development of dozens of public data observatories around the world, visited by millions of people every month.



Created with maps

**What did we do between
2019 and 2023?**



Institutional building:

Went from 1 person and 1 project in 2019, to over a dozen people in two universities with several funded projects in 2023

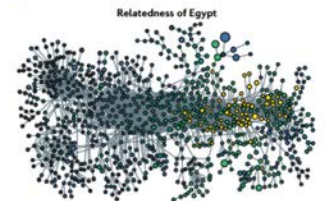
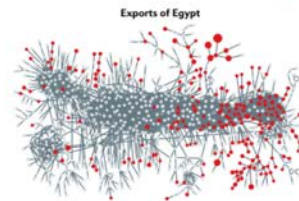


Academic Publications

nature reviews physics



REVIEWS

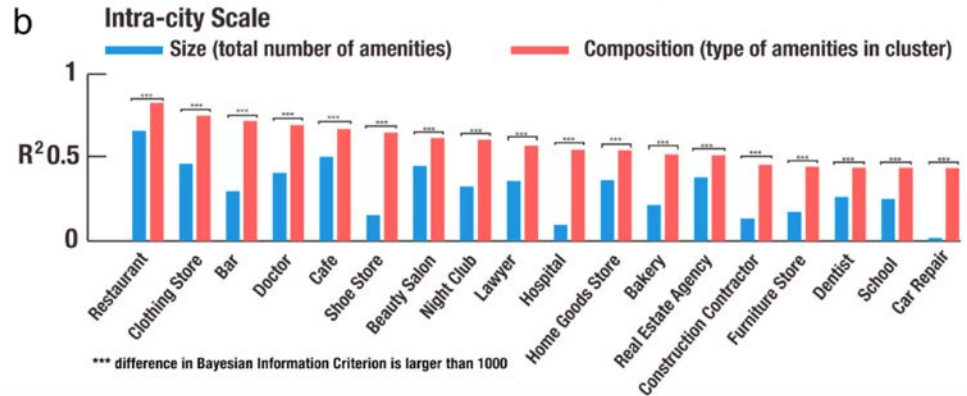
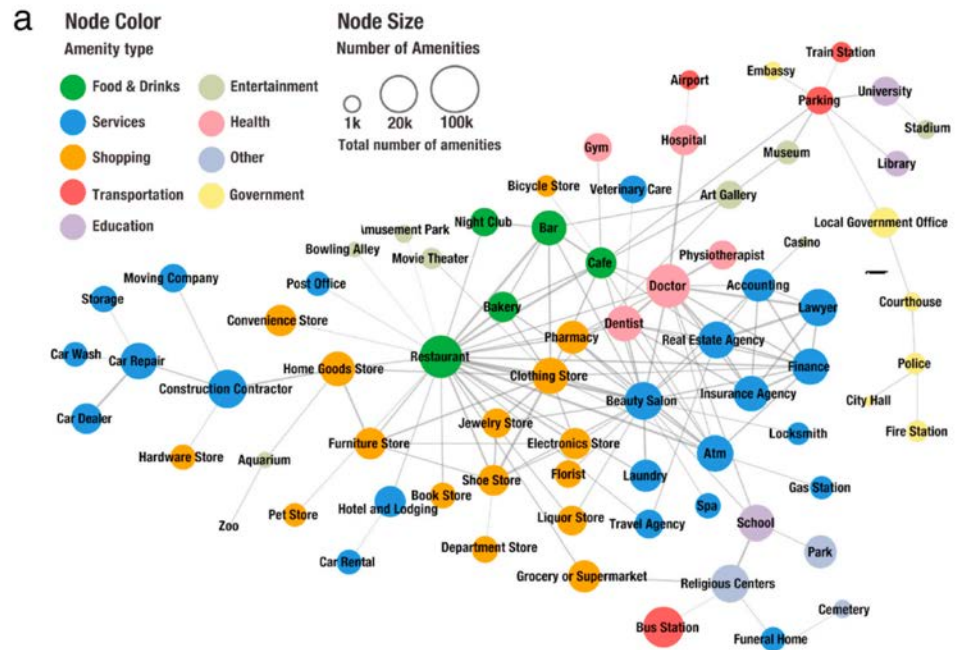
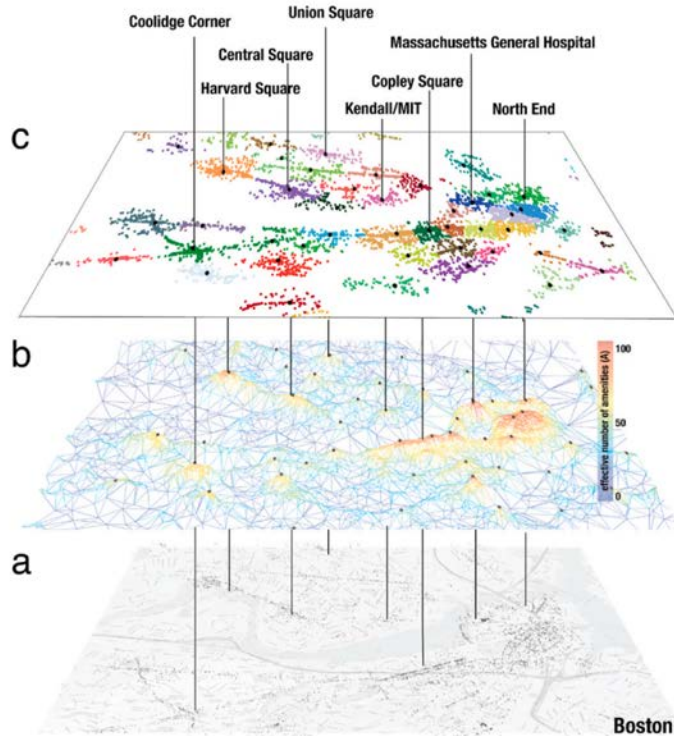


one billion USD and have a population of at least one million. Likewise, it is common to disregard products with small export volumes (for instance, <500 million in global exports at the four-digit level). These tricks of the trade are important to perform meaningful comparisons and are used in all data types (including products, patents or industries).

Relatedness
 Relatedness measures the affinity between a location and an activity. Yet, since a good measure of affinity is expected to predict changes in specialization patterns, relatedness can be defined as a predictor of changes in specialization that is specific to a location-activity pair and that goes beyond the naive prediction (no change).

The amenity mix of urban neighborhoods

César A. Hidalgo^{a,b,c,*}, Elisa Castañer^d, Andres Sevtsuk^e





Spillovers across industries and regions in China's regional economic diversification

Jian Gao^a, Bogang Jun^b, Alex 'Sandy' Pentland^c, Tao Zhou^d and César A. Hidalgo^e

ABSTRACT

Industrial diversification depends on spillovers from related industries and nearby regions, yet their interaction remains largely unclear. We study economic diversification in China during the period 1990–2015 and present supportive evidence on both spillover channels. We add to the literature by showing that these two channels behave as substitutes when explaining new entries and exits, and by using acceleration campaigns of high-speed rail to address some endogeneity concerns with regional spillovers. Our findings confirm the role of relatedness and geographical distance in the diffusion of economic capabilities and support the idea that improvements in transportation can facilitate the diffusion of productive capabilities.

KEYWORDS

economic development; industrial structure; economic complexity; spillovers; high-speed rail

JEL O11, O47, O53, R11

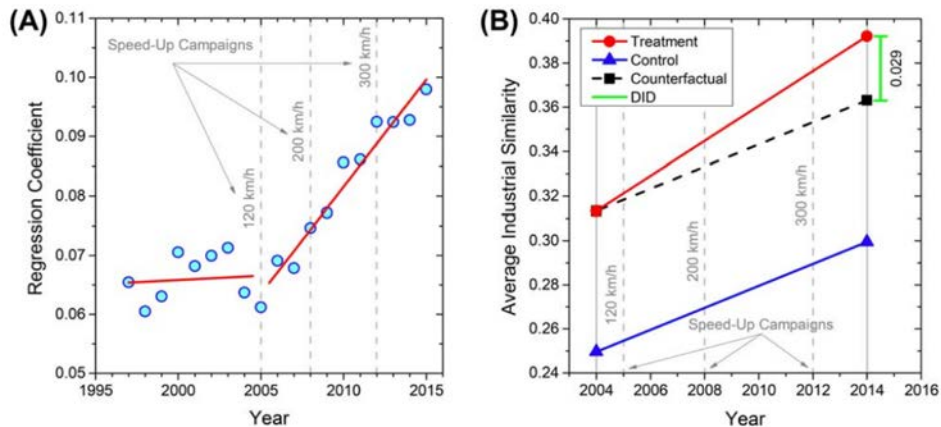
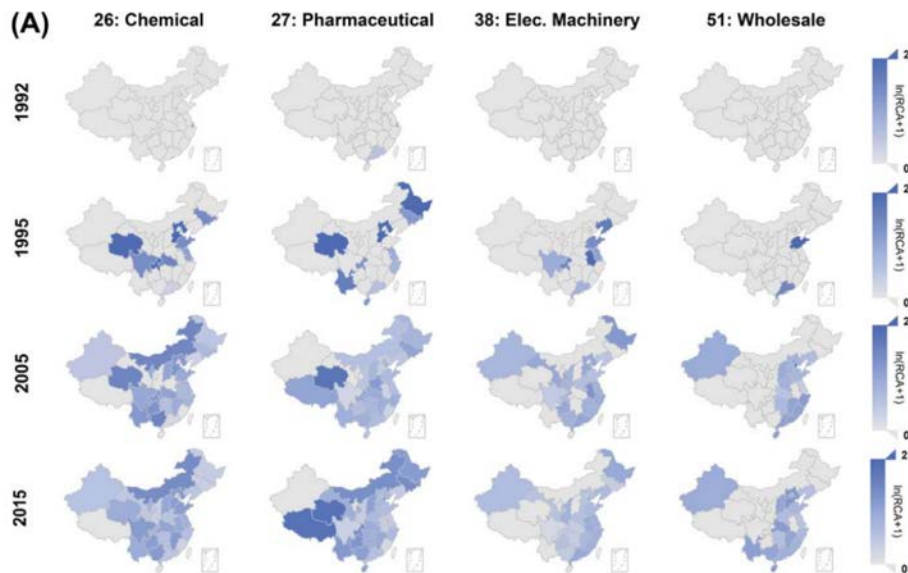
HISTORY Received 16 December 2019; in revised form 15 January 2021

INTRODUCTION

The pace and scale of China's economic expansion has no historical precedent (Eichengreen et al., 2012; Felipe et al., 2013; Song et al., 2011; Zhu, 2012). Between 1990 and 2015, China's overall gross domestic product (GDP) grew by a factor of 30, from less than US\$400 billion in 1990 to more than US\$10 trillion in 2015, and its GDP per capita (purchasing power parity – PPP) increased by a factor of nearly 10 (from US\$1516 in 1990 to more than US\$13,400 in 2015). But what explains China's remarkable economic success? Here, the literature provides multiple answers, from the advantages of backwardness (Gerschenkron, 1962), to government policies (Amsden, 1992; Evans, 2012; Leftwich, 1995; Lin et al., 2003; Wade, 2004), economic

reforms (Lin et al., 2003), financial development (Laurenceson & Chai, 2003) and institutional change (Qian, 2001).

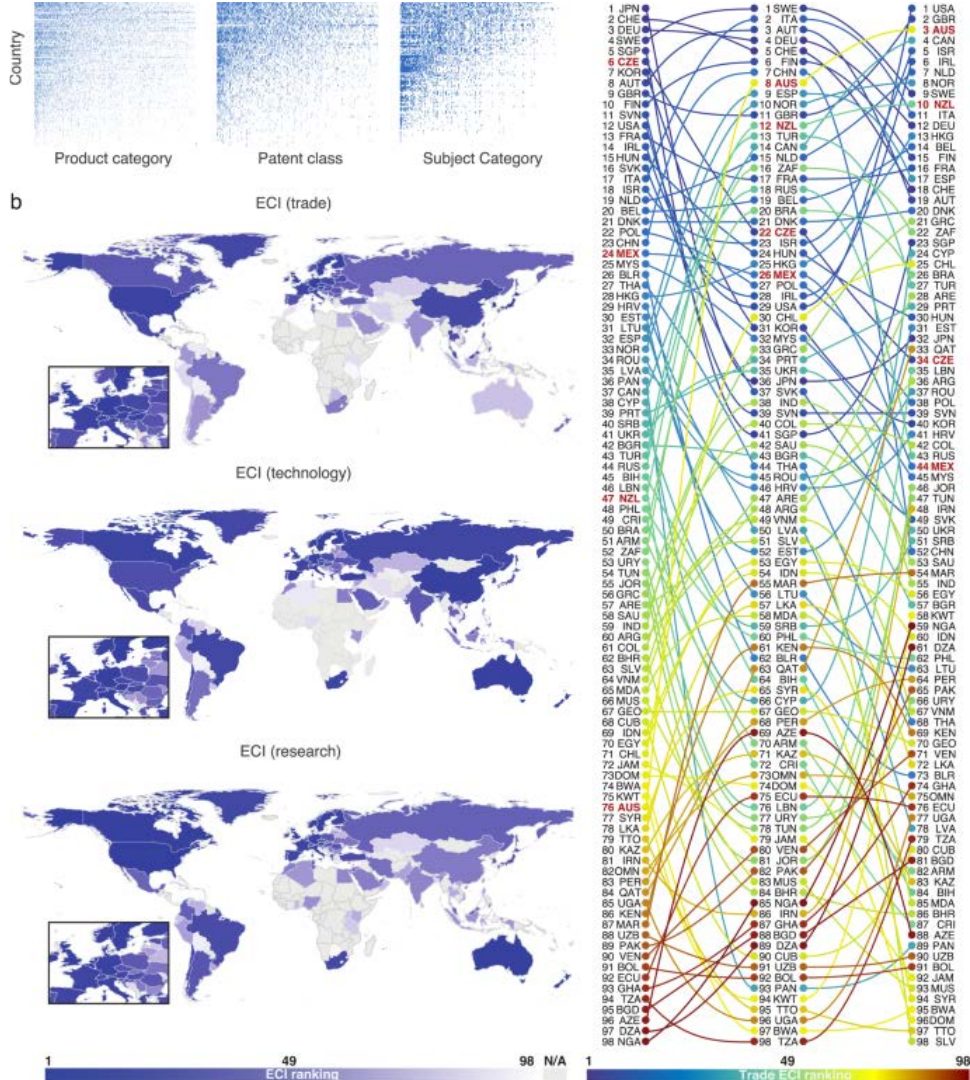
What is also evident from the data is that China's expansion relied on the export of products that were unusually sophisticated for its income level (Hidalgo & Hausmann, 2009; Lin, 2012). Rodrik (2006) estimated the level of sophistication of China's exports by calculating the average income per capita of countries exporting the same products. He showed that even in 1992, when China's GDP per capita at PPP and constant prices was US\$1844, its exports were associated with an average level of income of about US\$13,500 (China's GDP per capita in 2015). Rodrik argued that this high level of export sophistication drove China's great economic expansion, a finding that is supported by the literature on



Multidimensional economic complexity and inclusive green growth

Viktor Stojkoski^{1,2}, Philipp Koch^{1,3} & César A. Hidalgo^{1,4,5,6,7,8,9}

To achieve inclusive green growth, countries need to consider a multiplicity of economic, social, and environmental factors. These are often captured by metrics of economic complexity derived from the geography of trade, thus missing key information on innovative activities. To bridge this gap, we combine trade data with data on patent applications and research publications to build models that significantly and robustly improve the ability of economic complexity metrics to explain international variations in inclusive green growth. We show that measures of complexity built on trade and patent data combine to explain future economic growth and income inequality and that countries that score high in all three metrics tend to exhibit lower emission intensities. These findings illustrate how the geography of trade, technology, and research combine to explain inclusive green growth.



The policy implications of economic complexity

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ABSTRACT

In recent years economic complexity has grown into an active field of fundamental and applied research. Yet, despite important advances, the policy implications of economic complexity can remain unclear or misunderstood. Here I organize the policy implications of economic complexity in a framework grounded on 4 Ws: what approaches, focused on identifying target activities and/or locations; when approaches, focused on the timing of related and unrelated diversification; where approaches, focused on the geographic diffusion of knowledge; and who approaches, focused on the role played by agents of structural change. The goal of this paper is to provide a framework that groups, organizes, and clarifies the policy implications of economic complexity and facilitates its continued use in regional and international development.

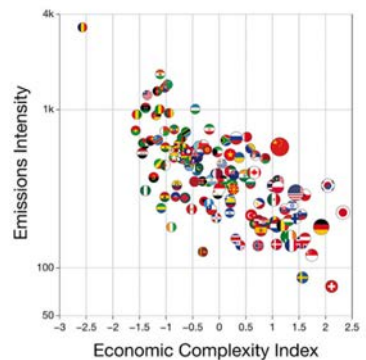
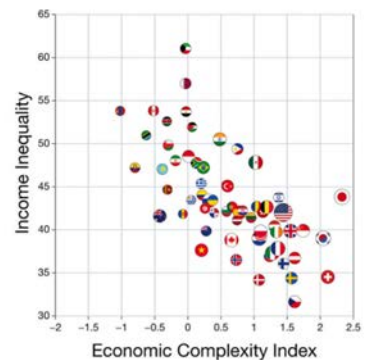
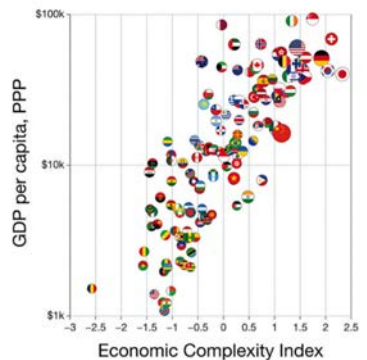
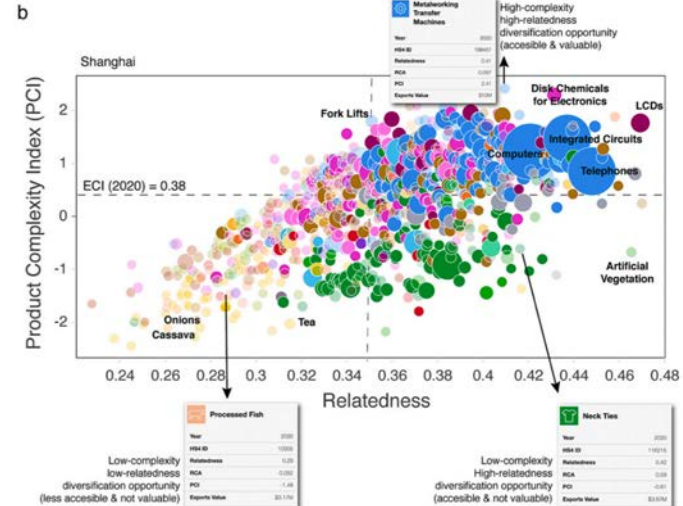
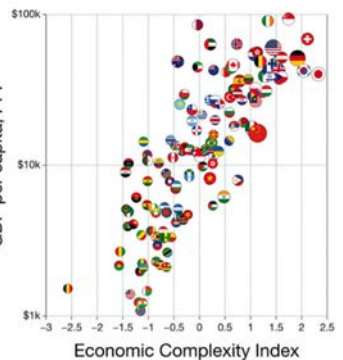
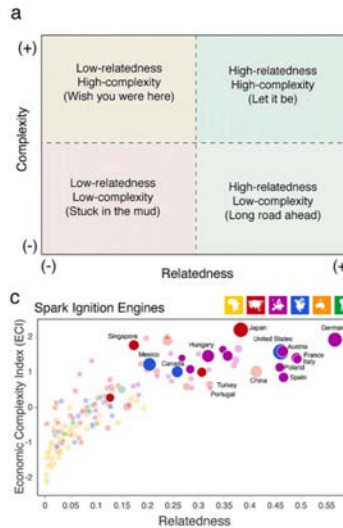
1. Introduction

In less than two decades, economic complexity grew from a handful of papers into an active field of research (Hidalgo, 2021). Today, scholars and practitioners use economic complexity methods to explain variations in diversification patterns (Bustos et al., 2012; Hausmann et al., 2014; Hidalgo et al., 2007; Jara-Figueroa et al., 2018; Neffke et al., 2011; Neffke and Henning, 2013), economic growth (Chavez et al., 2017; Doğan et al., 2022; Dominici, 2019; Hausmann et al., 2014; Hidalgo and Hausmann, 2009; Koch, 2021; Lo Turco and Maggioni, 2020; Orens, 2012; Stojkoski et al., 2016; Stojkoski and Kocarev, 2017), inequality of income and gender, (Barza et al., 2020; Bastie and Ciccone, 2022; Ben Said and Assoumou-Ella, 2019; Chu and Hoang, 2020; Fawaz and Rahnama-Moghadam, 2019; Hartmann et al., 2017; Sbardella et al., 2017), and sustainability (Can and Gorgor, 2017; Dong et al., 2020; Dordmond et al., 2020; Fraccascia et al., 2018; Hamwey et al., 2013; Lapatinas et al., 2019; Mealy and Teytelyboym, 2020; Neagu, 2019; Romero and Gramkow, 2021; Sbardella et al., 2022) (Fig. 1). This has made economic complexity methods increasingly common in policy reports and national development strategies (Balland et al., 2018; Hausmann et al., 2011; Mealy and Coyle, 2021; Montresor and Quarato, 2019) and have motivated the creation of several data observatories by ministries of economy or production, or by national innovation or statistics agencies in Mexico, Chile, Brazil, Peru, and Estonia, among other places. But despite these advances, the policy implications of

economic complexity are sometimes misunderstood. This is due in part to the rapid growth of the field, and also, to the fact that—as an interdisciplinary endeavor—economic complexity builds on network science and machine learning methods that are uncommon in economic geography, international development, and science, technology, and innovation studies. The goal of this paper is to help fill this gap by organizing attempts to bring economic complexity into practice in a framework that integrates multiple approaches.

Before diving into the framework, we need to define economic complexity, both as an academic field and as a collection of methods. In brief, economic complexity is the use of network science and machine learning techniques to explain, predict, and advise changes in economic structures. The focus on economic structure is motivated by work showing that these structures explain and predict important macroeconomic outcomes, from economic growth to the intensity of greenhouse gas emissions and income inequality (For a recent review see: (Hidalgo 2021)). This work has helped formalize and expand intuitions that have for long been present in economic development, from Alexander Hamilton's Report on Manufactures, a document advocating for the industrial development of the United States (Hamilton, 1791), to more recent work on the importance of export structures in economic development (Hausmann et al., 2007; Imbs and Wacziarg, 2003; Rodrik, 2006; Saviotti and Frenken, 2008; Saviotti and Pyka, 2004).

But economic complexity is also a peculiar field involving contributions from scholars from a wide range of disciplines, from the



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The role of immigrants, emigrants and locals in the historical formation of European knowledge agglomerations

Philipp Koch^{a,b}, Viktor Stojkoski^{b,c} and César A. Hidalgo^{a,d,e}

ABSTRACT

Did migrants make Paris a *pecca* for the arts and Vienna a beacon of classical music? Or was their rise a pure consequence of local actors? We use data on more than 22,000 historical individuals born between the years 1000 and 2000 to estimate the contribution of famous immigrants, emigrants and locals to the knowledge specialisations of European regions. We find that the probability that a region develops or keeps specialisation in an activity (based on the birth of famous physicists, painters, etc.) grows with both the presence of immigrants with knowledge about that activity and immigrants with knowledge in related activities. In contrast, we do not find robust evidence that the presence of locals with related knowledge explains entries and/or exits. We address some endogeneity concerns using fixed-effects models considering any location, period, activity-specific factors (e.g., the presence of a new university attracting scientists).

KEYWORDS

migration; knowledge spillovers; relatedness; economic history; economic complexity

JEL N90, O15, R11

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1. INTRODUCTION

Migrants help carry knowledge across space (Cipolla, 1972; Kerr et al., 2017; Lissoni, 2018; Trippi & Maier, 2011; Williams, 2006), shaping the geography of cultural and economic activities (Elekes et al., 2019; Miguelez & Morrison, 2022; Morrison, 2023; Neffke et al., 2018; Puterman & Weil, 2010). But most studies documenting the role of migrants in the diffusion of knowledge use recent data on patents (Bahar et al., 2020; Bernstein et al., 2022; Bosetti et al., 2015; Breschi et al., 2017; Fassio et al., 2019; Hunt & Gauthier-Loisele, 2010; Miguelez & Morrison, 2022; Miguelez & Noumedem Temgoua, 2020; Miguelez & Moreno, 2013, 2015), research (Bosetti et al., 2015; Trippi, 2013) or product exports (Bahar & Rapoport, 2018), or analyse historical spillovers within activities (Borowiecki, 2012; Borowiecki & Graddy, 2021; Collins, 1974; Diodato et al., 2022; Ganguli, 2015; Hornung, 2014; Mitchell, 2019; Moser et al., 2014; Scoville, 1952a, 1952b; Waldinger, 2010, 2012), leaving questions about the role of migrants in the

historical formation of knowledge agglomerations relatively unexplored.

To explore the role of migrants in the historical formation of knowledge agglomerations we use geographical data on more than 22,000 famous individuals – artists, physicists, explorers, philosophers, etc. – living in Europe between the years 1000 and 2000. We use these data to investigate how immigrants, emigrants and locals explain the probability that famous individuals specialised in an activity – that was not yet present in a region – are born during the next century. That is, we study how the knowledge of migrants and locals contributes to explain, for example, Paris becoming the birthplace of painters and Vienna of composers.

We can explore these questions by creating measures of knowledge spillovers within and between locations and activities. Consider spillovers across locations within the same activity. The knowledge that migrants carry across borders may impact a location's ability to give birth to famous figures in the activity that the migrants specialise in. That is, immigrant mathematicians may increase the

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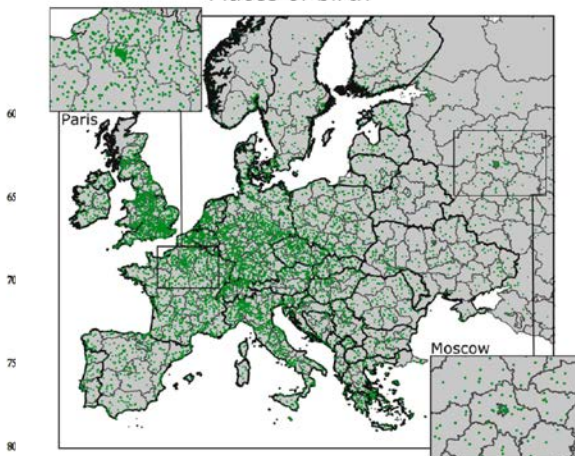
^cFaculty of Economics, University Ss. Cyril and Methodius in Skopje, Skopje, North Macedonia

^dAlliance Manchester Business School, University of Manchester, Manchester, UK

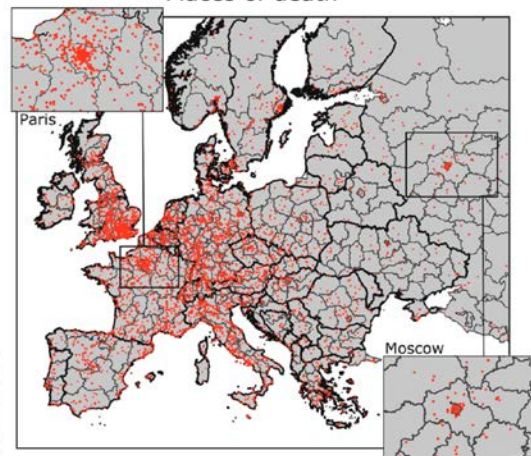
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Supplemental data for this article can be accessed online at <https://doi.org/10.1080/00343404.2023.2275751>.

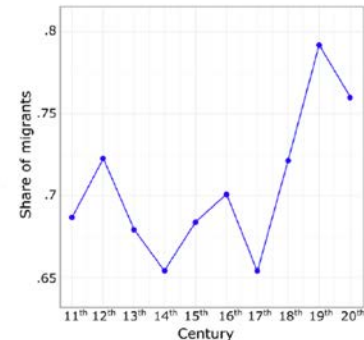
Places of birth



Places of death



Migration network

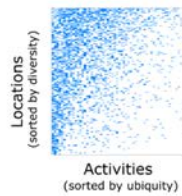


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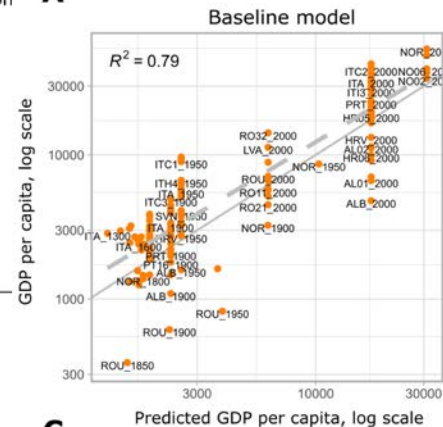
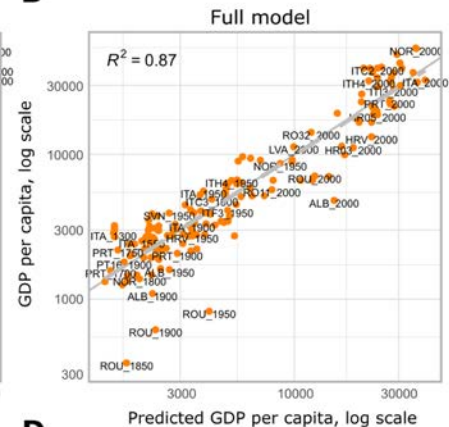
- Place of birth
- Place of death

Features derived from famous biographies:

- Place of birth/death
 - Migration
 - Occupation
 - Historical importance
 - Diversity of occupations
 - Average age
- Dimensionality reduction techniques:*
- Singular value decomposition
 - Economic complexity



Machine learning (Elastic Net)

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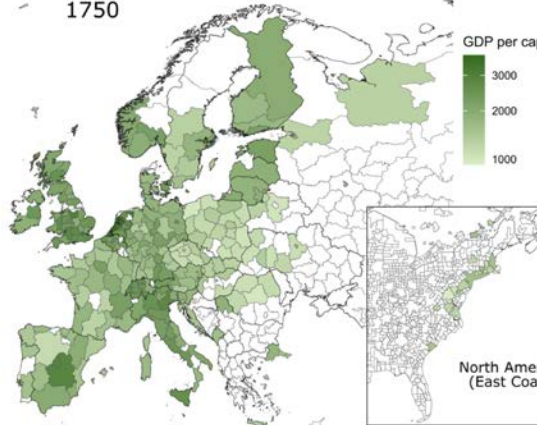
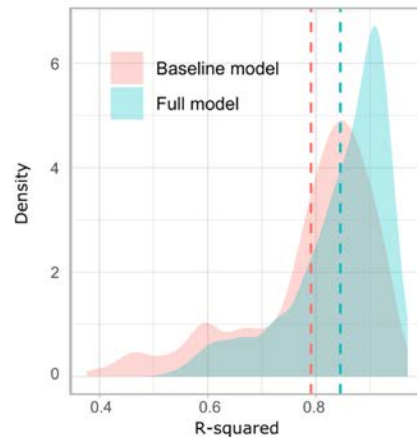
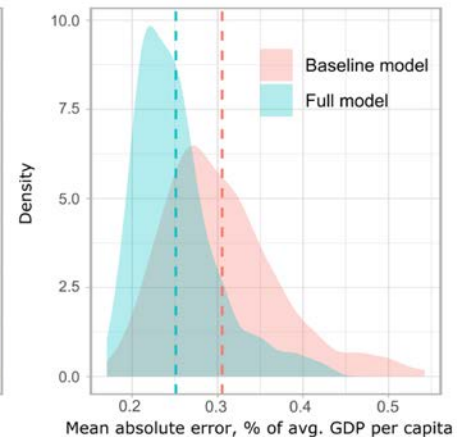
Country-level GDP per capita estimates

1300

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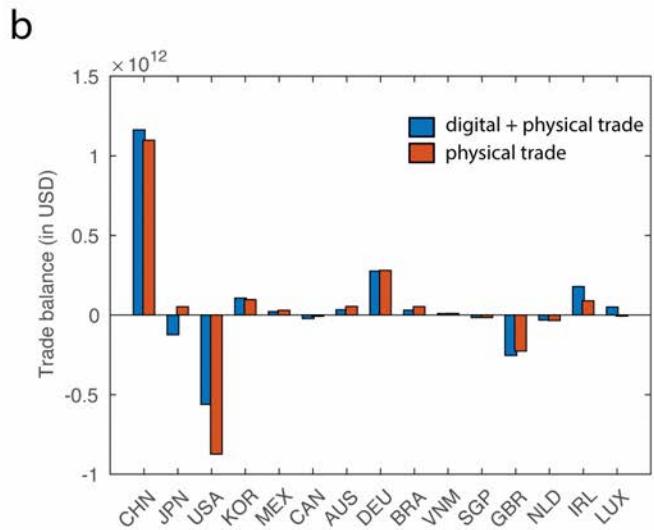
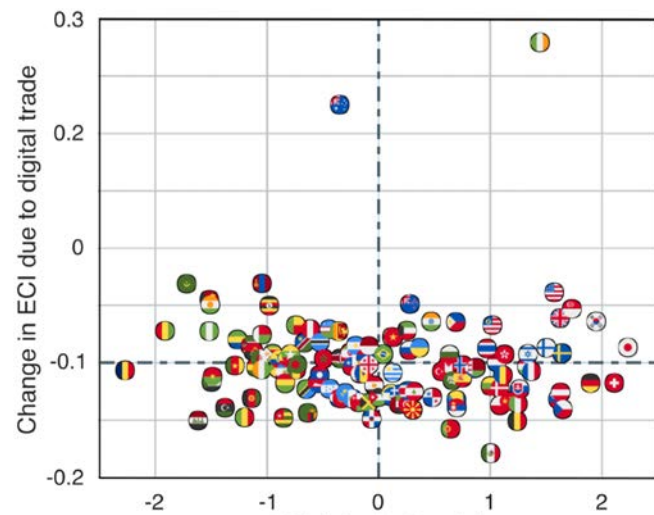
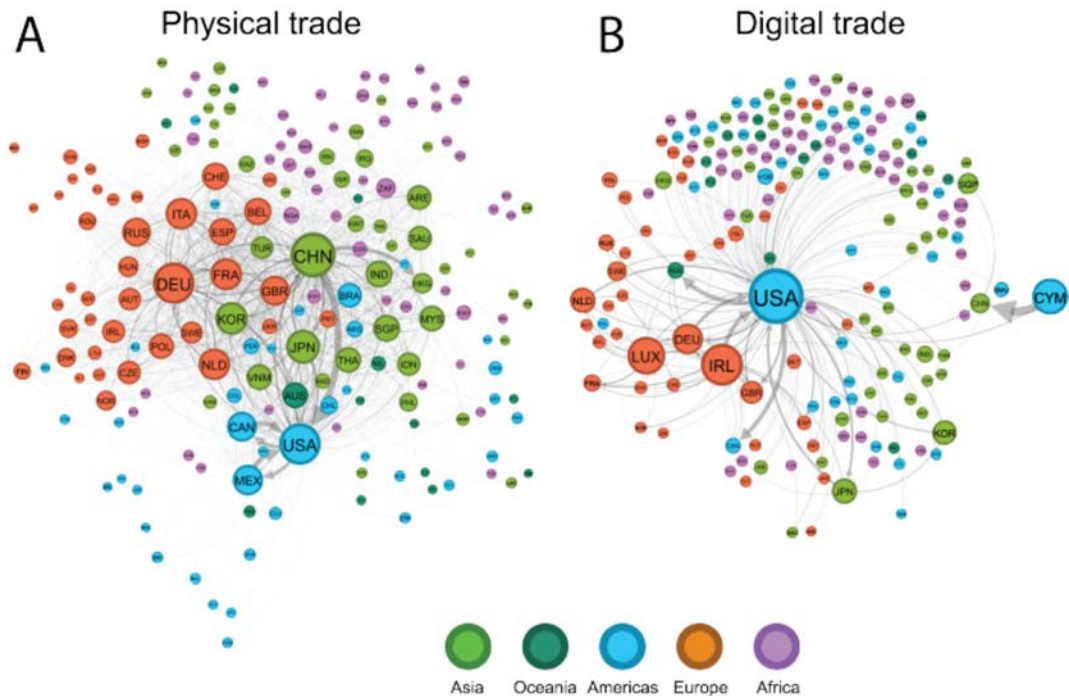
Regional GDP per capita estimates

1750

**C****D**

The Growth, Geography, and Implications of Trade in Digital Products

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Why people judge humans differently from machines: The role of perceived agency and experience

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[†]Centre for Creative Technologies and School of Psychology, University of Galway

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Abstract—People are known to judge artificial intelligence using a utilitarian moral philosophy and humans using a moral philosophy emphasizing perceived intentions. But why do people judge humans and machines differently? Psychology suggests that people may have different mind perception models of humans and machines, and thus, will treat human-like robots more similarly to the way they treat humans. Here we present a randomized experiment where we manipulated people's perception of machine agency (e.g., ability to plan, act) and experience (e.g., ability to feel) to explore whether people judge machines that are perceived to be more similar to humans along these two dimensions more similarly to the way they judge humans. We find that people's judgments of machines become more similar to that of humans when they perceive machines as having more agency but not more experience. Our findings indicate that people's use of different moral philosophies to judge humans and machines can be explained by a progression of mind perception models where the perception of agency plays a prominent role. These findings add to the body of evidence suggesting that people's judgment of machines becomes more similar to that of humans motivating further work on dimensions modulating people's judgment of human and machine actions.

I. INTRODUCTION

Do people judge human and machine actions equally? Recent empirical studies suggest this is not the case. In fact, several studies have shown that people make strong differences when judging humans and machines.

Consider the recent experiments from Malle et al. (2015) asking people to judge a trolley problem [10], [15]. In a trolley problem, people can pull a lever to deviate an out-of-control trolley sacrificing a few people to save many. Malle et al. (2015) found that people expected robots to pull the lever and act utilitarianly (sacrifice one person to save four) compared to humans (which were not judged as severely for not pulling the lever) [21]. This idea was expanded by [14]. Using a set of over 80 randomized experiments comparing people's reactions to the actions of humans and machines, the authors concluded that people judge humans and machines using different moral philosophies: consequentialist philosophy (focused on outcomes) for machines and a moral philosophy focused more on intention when it comes to humans.

But why do people use different moral philosophies to judge humans and machines? Psychology suggests that people may perceive the minds of machines and humans differently

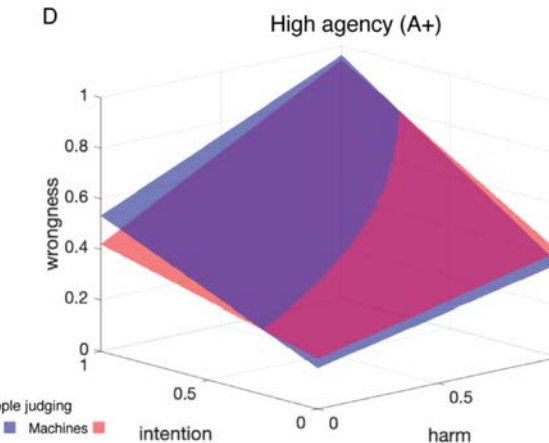
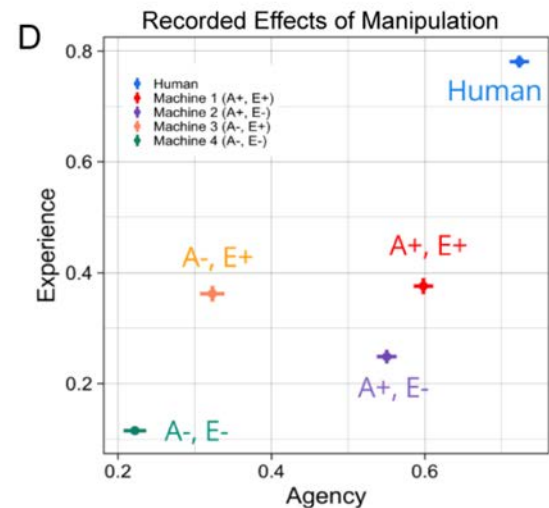
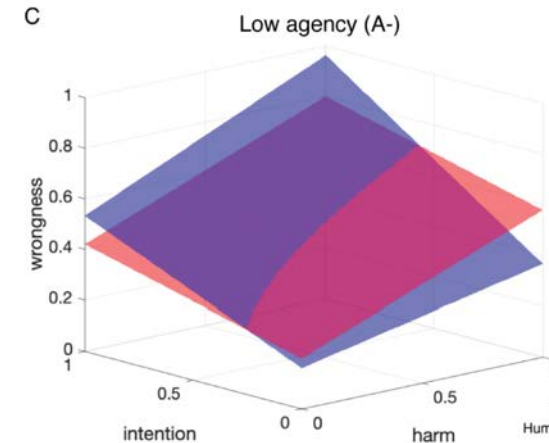
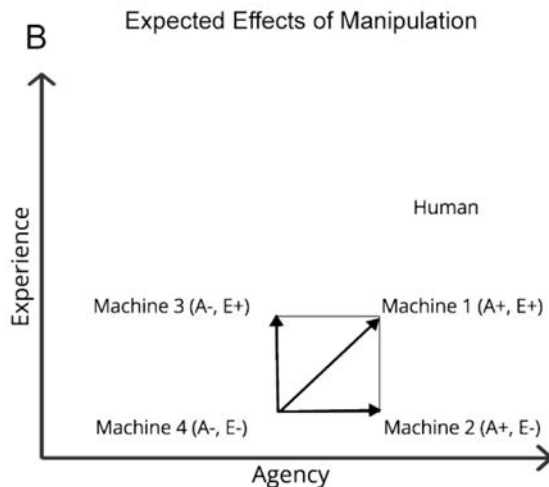
[8], [11], and therefore, may treat more human-like robots more similarly to the way they treat humans [9]. This idea is related to various experiments where robots were endowed with human-like features [19], [27], [16], [24], [22], [28], [29], [23]. For instance, Powers and Kiesler (2006) used a robot with tunable chin length and tone of voice to explore the connection between the robot's appearance and its perceived personality [24]. Waytz et al. (2014) compared anthropomorphized and non-anthropomorphized self-driving cars to show that people trust the anthropomorphized self-driving cars more [27]. Malle et al. (2016) explored the impact of a robot's appearance in people's judgment of moral actions (trolley problem), finding that people judge more human-like robots more similarly to the way they judge humans [22]. Yet, these experiments did not provide an explicit quantitative mind perception model explaining people's judgment of more and less human-like machines.

Here we explore how perceived agency and experience, two key dimensions of mind perception [11], affect people's judgments of machines.

Agency is related to an agent's ability to plan (e.g., to create a strategy for action that considers potential consequences) and to act (e.g., the capacity to affect or control the immediate environment). Thus, agency is related to moral responsibility for performed actions (higher agency, higher expected responsibility) [17].

Experience, in the context of this paper, is used to describe the ability to feel (e.g., the ability to experience sensations such as pain, sadness, guilt, or anger). It is, thus, related to the concept of moral status (not to be confused with the idea of expertise) and to the right of an agent to be treated with dignity.

These two dimensions represent a basic mind perception model that has been used previously to explain the cognition and behavior of alters using representations of their perceived mental abilities [3], [4], [8], [11]. Usually, mind perception models involve low dimensional representations of an alter's characteristics, such as the warmth and competence model used to explain stereotypes [5]. That model, for instance, says that people tend to protect those high in warmth and low in competence (e.g., babies) but fear those high in competence and low in warmth (e.g., killer robots).



Understanding political divisiveness using online participation data from the 2022 French and Brazilian presidential elections

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Digital technologies can augment civic participation by facilitating the expression of detailed political preferences. Yet, digital participation efforts often rely on methods optimized for elections involving a few candidates. Here we present data collected in an online experiment where participants built personalized government programmes by combining policies proposed by the candidates of the 2022 French and Brazilian presidential elections. We use this data to explore aggregates complementing those used in social choice theory, finding that a metric of divisiveness, which is uncorrelated with traditional aggregation functions, can identify polarizing proposals. These metrics provide a score for the divisiveness of each proposal that can be estimated in the absence of data on the demographic characteristics of participants and that explains the issues that divide a population. These findings suggest that divisiveness metrics can be useful complements to traditional aggregation functions in direct forms of digital participation.

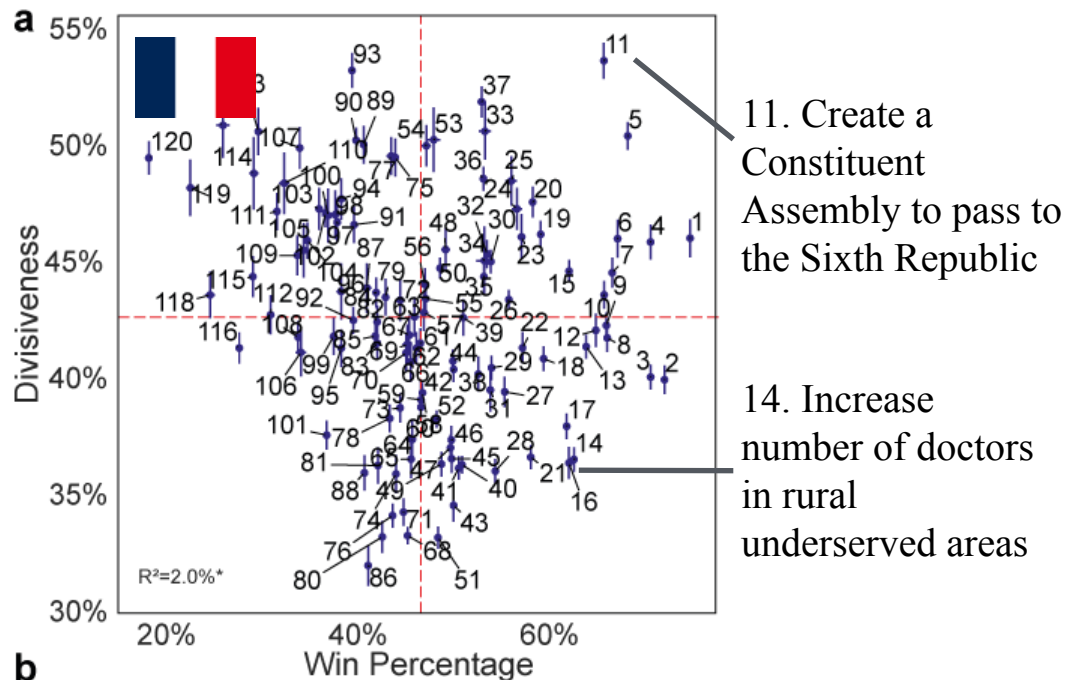
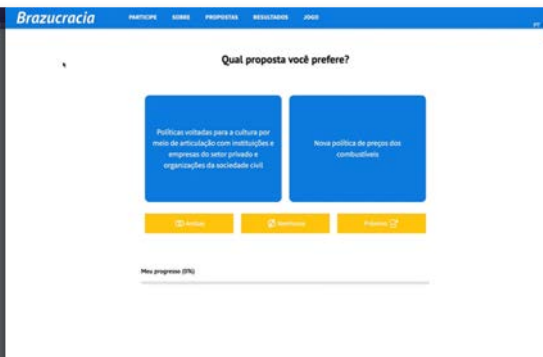
Digital technologies provide an opportunity to unbundle participation by allowing citizens to express their preferences over fine-grained alternatives. Yet, despite this opportunity, there has been relatively little work exploring the use of digital participation platforms^{1–5} to understand citizens' preferences over many alternatives. Here we use the 2022 French and Brazilian presidential elections as an opportunity to help explore this gap by conducting an organic direct democracy experiment. For this experiment, we developed two digital participation platforms (monprogramme2022.org and brazucracia.org) that allowed users to build personalized government programmes by combining proposals from the 12 candidates of the 2022 French presidential election and the six candidates of the 2022 Brazilian presidential election. We used this information to explore agreements, using traditional

aggregation functions, and disagreements, by constructing a metric of divisiveness. The latter complements the former by distinguishing among similarly ranked proposals. For instance, two proposals ranked 50 and 51 out of 100 alternatives could score similarly because participants do not have a strong preference for either of them, or because some participants strongly support the proposal while others strongly reject it. This difference, which traditional aggregation functions fail to capture, is important to separate tepid proposals that citizens are relatively indifferent about, from controversial proposals that are strongly supported or rejected by distinct segments of the population.

In this Article, we show that divisiveness metrics can be constructed as complements for any aggregation function—the aggregates used to identify winners in an election—and provide information about

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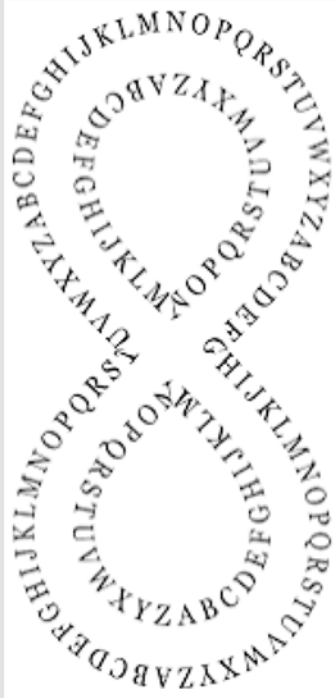
Penguin
Random
House

The Infinite Alphabet

and the laws of knowledge

(signed January 2023, due Dec 2024)

The Infinite Alphabet



What makes the study of knowledge difficult is the fact that it is non-interchangeable, or non-fungible (e.g you cannot replace a pianist with a surgeon).

Non-fungibility limits factor mobility among sectors, and the use of aggregation in its analysis.

The Infinite Alphabet

Book Structure:

The book is organized around three parts focused on three principles (laws) governing:

1. The growth (& decay) of knowledge (time).
2. The diffusion of knowledge (space).
3. The valuation of knowledge (value).

The Infinite Alphabet

Part I

During the twentieth century the study of knowledge focused on learning curves which explore the accumulation of knowledge in a narrow domain.



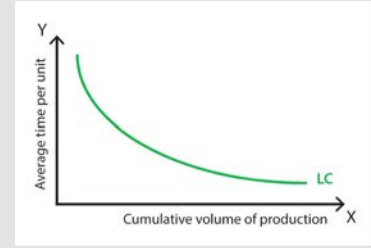
Leon Thurstone's 1919
PhD Thesis on individual
learning curves



Theodore Wright's 1935
article on the cost of
manufacturing airframes



Rapping 1965 Liberty
Ships study

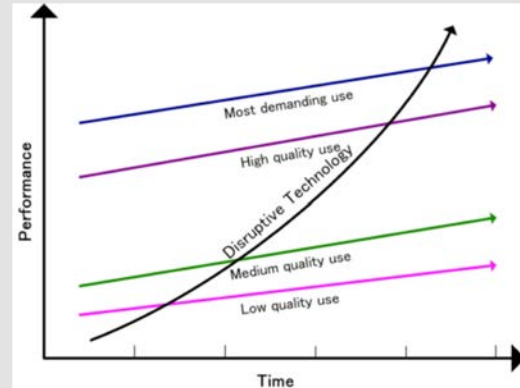
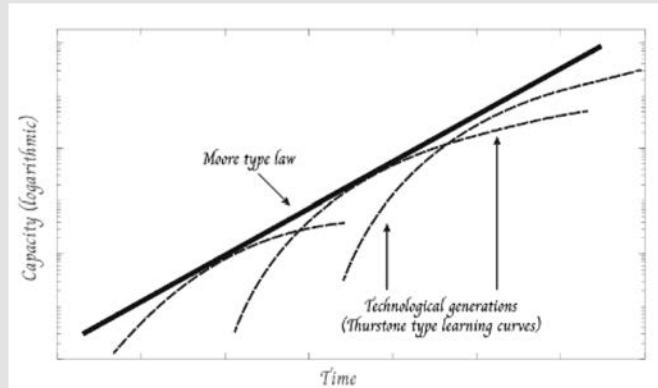


Learning curve of cost as
a function of volume

The Infinite Alphabet

Part I

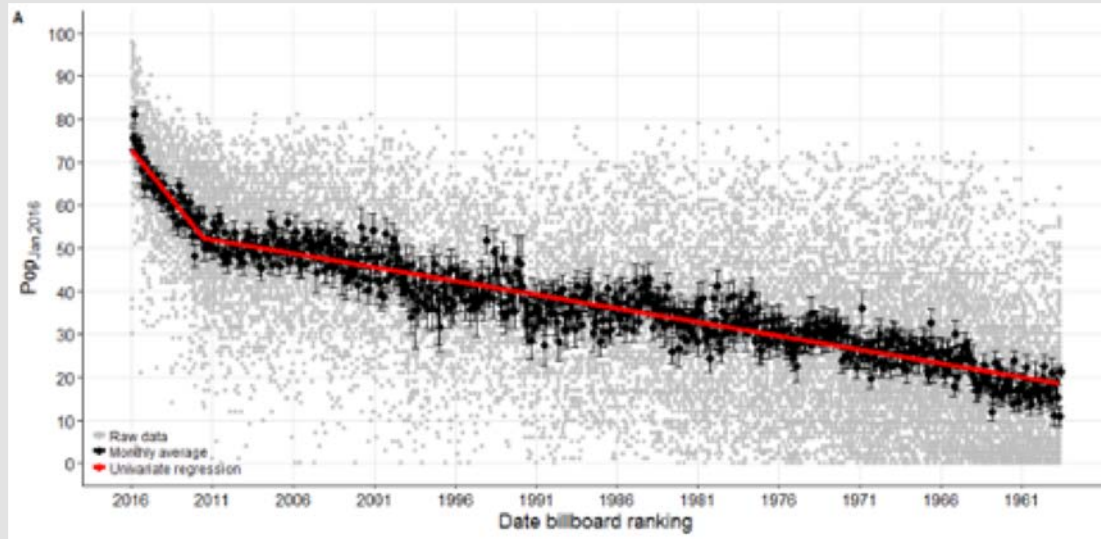
With the introduction of Moore's law in 1965, the study of knowledge moved from learning to experience curves, the latter describing the growth of knowledge at the industry scale. Later, this provided room for the creation of theories of disruptive innovation.



The Infinite Alphabet

Part I

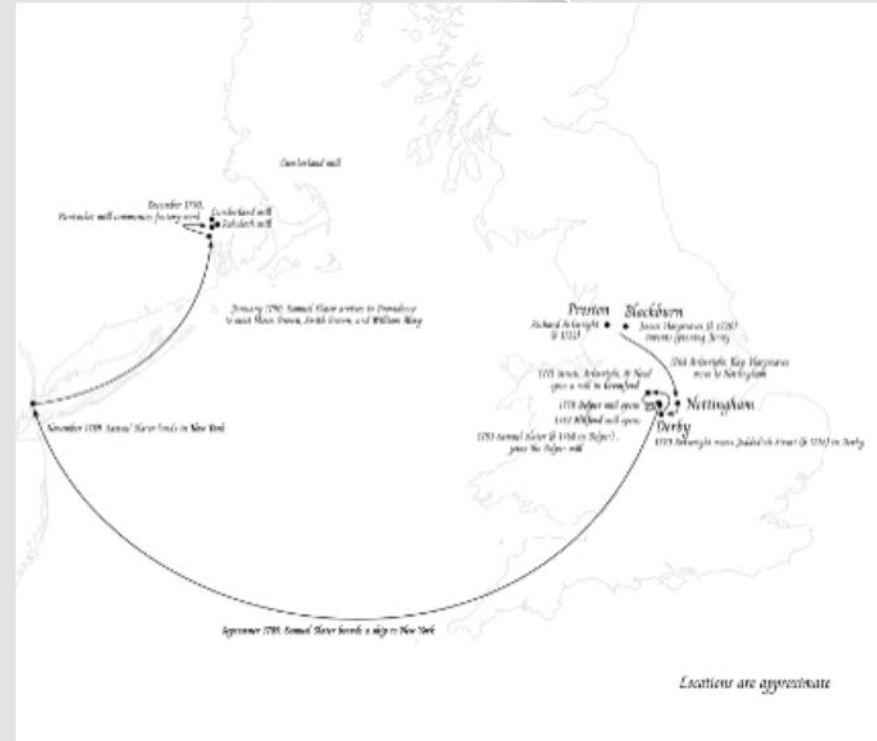
More recently we started making progress on the understanding of forgetting, describing the decay of knowledge.



The Infinite Alphabet

Part II

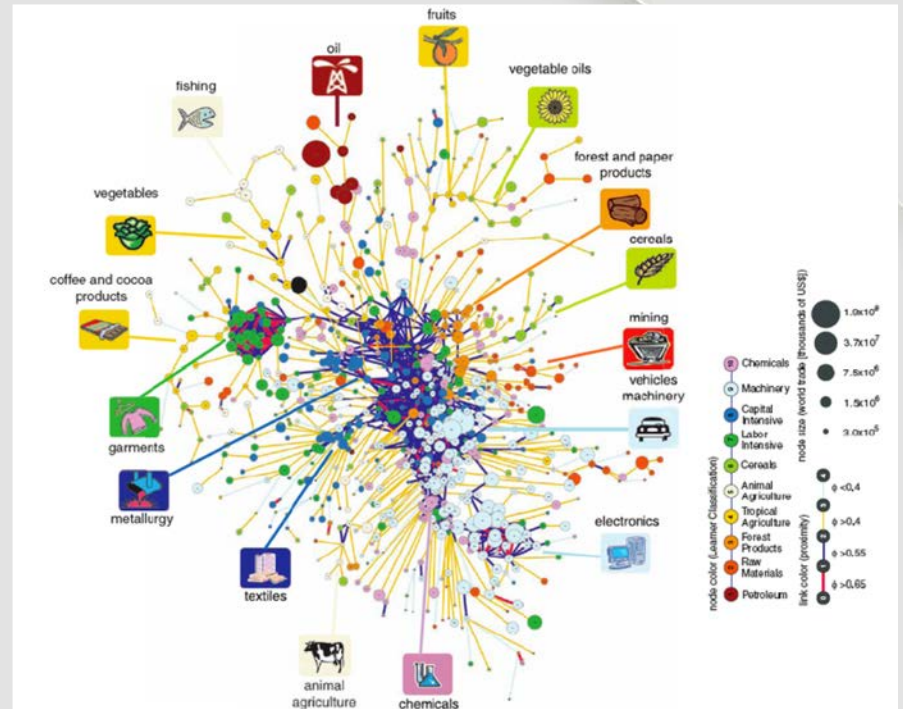
Late in the 20th century people began studying the spatial diffusion of knowledge, using mostly patent citations. But again, the focus remained on narrow domains (where non-fungibility plays a limited role).



The Infinite Alphabet

Part II

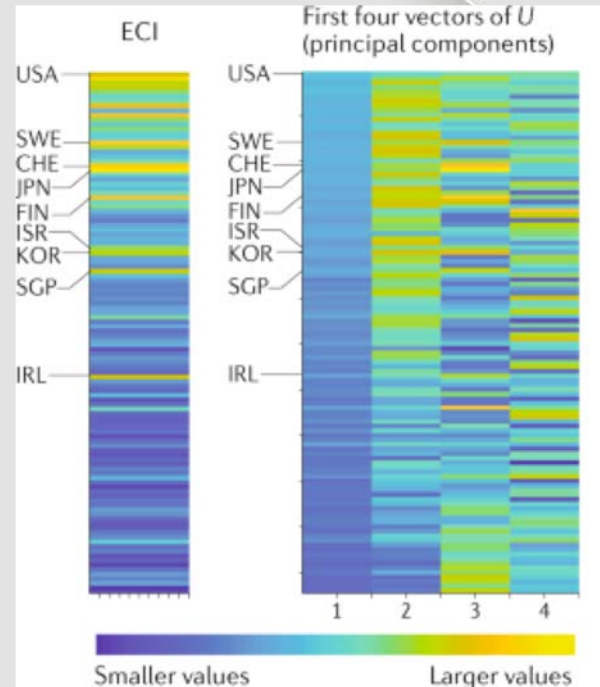
In the 21st century the use of big data and network science tools helped us map patterns of relatedness, and study the intricate and non-trivial networks of intersector factor mobility. This was finally a way to incorporate non-fungibility into the literature.



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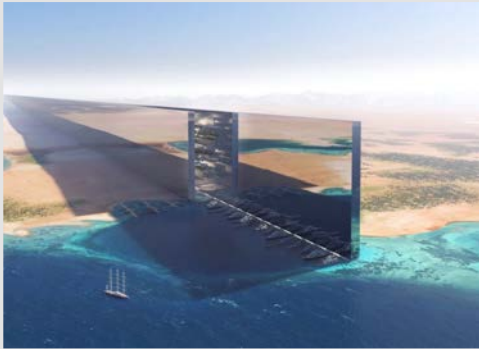
Part III

This led to the development of economic complexity metrics, which can take non-fungibility into account by using matrix factorization techniques to measure the value of geographic concentrations of knowledge. These metrics explain future economic growth, inequality, and emissions, among other things.



The Infinite Alphabet

Understanding the laws of knowledge is important because the world is no stranger to multiple failed attempts to engineer cities of knowledge. Attempts that blatantly ignore these principles.



Plan for NEOM, Saudi



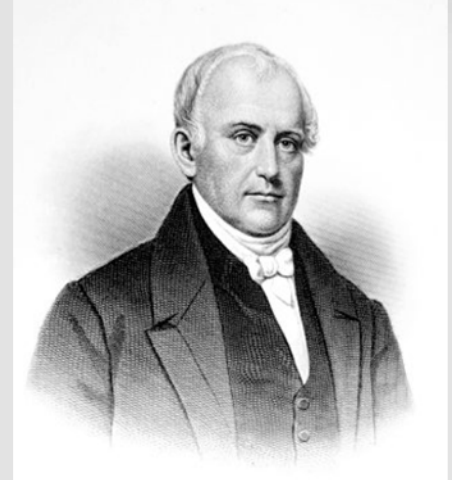
Plan for Yachay, Ecuador



Plan for Masdar City, UAE

The Infinite Alphabet

The book is written by matching biographical stories on the scientists, inventors, and entrepreneurs illustrating key parts of these principles, with the academic literature that validates each of these principles.





A large, light gray, stylized logo consisting of the letters 'C' and 'L' is positioned in the background on the left side of the image. The 'C' is formed by three concentric semi-circles, and the 'L' is a solid vertical bar with a horizontal base. The background features a light gray color with a pattern of thin white lines forming a network of triangles and polygons.

Center for Collective Learning