DOI:
10.1016/j.techsoc.2022.102148

The impact of STEM on the growth of wealth at varying scales, ranging from individuals to firms and countries: the performance of STEM firms during the pandemic across different markets

Boris Podobnik

Zagreb School of Economics and Management, 10 000 Zagreb, Croatia
Faculty of Civil Engineering, University of Rijeka, 51 000 Rijeka, Croatia.
Faculty of Information Studies at Novo Mesto, SI-8000 Novo Mesto, Slovenia
Luxembourg School of Business, 2453 Luxembourg, Luxembourg

bpodobnik@gradri.uniri.hr
https://orcid.org/0000-0003-4270-1756
Marina Dabić*

University of Zagreb, Faculty of Economics and Business,
Department of International Economics,

Zagreb, Croatia
mdabic@efzg.hr

University of Dubrovnik, 20 000 Dubrovnik Croatia

University of Ljubljana, School of Economics and Business, 1000 Ljubljana, Slovenia

https://orcid.org/0000-0001-8374-9719

Dorian Wild

Zagreb School of Economics and Management

Zagreb, Croatia
dorian.wild7@gmail.com
ORCID ID: 0000-0002-9616-1989
Tiziana Di Matteo, Ph.D
Tiziana Di Matteo
Professor of Econophysics
Department of Mathematics

Faculty of Natural, Mathematical & Engineering Sciences

King's College London
Strand, London WC2R 2LS

United Kingdom
Room 524, Strand Building
Ph 44 (0)20 78482223 (direct line)
tiziana.di_matteo@kcl.ac.uk
ORCID: 0000-0002-5913-3268
***corresponding author**

Abstract

Researchers have not yet reached consensus on whether there is a difference in performance between STEM and non-STEM firms across different financial markets during economic expansion and through economic downturns, such as pandemics and recessions. It is unclear as to whether STEM or non-STEM firms, but also graduates with STEM or non-STEM education contribute more, less, or equally to economic inequality. By analysing total wealth at varying scales, ranging from individuals, to firms, to entire countries, we demonstrate that the Zipf exponent, serving as a proxy for wealth inequality, persistently ramps up as the scale of a system increases. At an individual level, analysing the Zipf plots separately for the world's richest individuals with STEM and non-STEM graduation, we begin by demonstrating that STEM education contributes more to inequality than non-STEM. At a firm level, in contrast to the DAX and CAC40 indexes, for firms comprising the S&P 500 index, the average growth rate of STEM constituents has been significantly higher than those calculated for non-STEM constituents during the most recent economic expansion and the coronavirus pandemic. This insight is particularly useful for the financial sector. Secondly, we demonstrate a functional dependence between a country's number of patents and its STEM graduates. Finally, motivated by the fact that the U.S. heavily surpasses the E.U. in terms of Venture Capital, we model wealth inequality at different scales of the economy.

The impact of STEM on the growth of wealth at varying scales, ranging from individuals to firms and countries: the performance of STEM firms during the pandemic across different markets.

“While it is important to invest in STEM education to ensure a future talent pipeline, it’s just as important to have a scientifically-literate population to understand why we need to do so“.

Ron Mobed, CEO, Elsevier

Source: *100 CEO Leaders in STEM*

I. INTRODUCTION

'STEM' stands for science, technology, engineering, and mathematics. STEM employees play a crucial role in continuing, sustaining, and maintaining the growth and stability of the economy across every nation (Bybee, 2010; Koonce et al., 2011; Human Capital Report, 2016; Cai & Winters, 2017; Deming & Noray, 2020). Greene et al. (2006, p. 53) pointed out that *the central principle for STEM education is to support and prepare students for successful careers and deliver the skills needed to meet the demands of a new STEM workforce to enable the United States to remain competitive in the global marketplace*. STEM fields are considered a crucial component when it comes to helping countries to achieve future success and dominance over others (Yildirim, 2016; Lloyd, C. Payne, 2019; Colombo & Piva, 2020).

In the battle for dominance and survival, for individuals, firms, and countries, the STEM disciplines in world economies play a crucial role. Firstly, it is worth mentioning that the fields of economics and management share some common origins with biology in that humans are at the very top of the food chain. Competition, dominance, and survival are fundamental controlling processes on different scales, ranging from biological scales to human societies. According to Darwin's theory of natural selection, a species that randomly mutates to better adapt to its surroundings increases its chances of surviving and dominating less competitive species by taking their territory (Frank, 2012). Similar generalized selection principles may hold, not only for other species, but also for high-level human organizations, such as firms and countries. Adam Smith observed that self-interest pushes producers to introduce new innovations to accommodate changing economic environments and capture rivals' market shares, equivalent to stealing territory in biology (Aghion & Howitt, 1992).

However, in contrast to living beings, both firms and countries intentionally – and thus non-randomly – introduce innovations, mainly related to STEM fields, in an attempt to dominate their competitors. To this end, over the years, the largest countries have become aware that the nation's well-being and national security depend on STEM technologies, such as cyber, robotics, AI, and quantum research. These fields have led to huge advancements, such as driverless cars, the diagnosis of varying diseases (Esteva et al., 2017), speech recognition (Artificial Intelligence Index Report, 2021), and financial simulations which adequately evaluate financial risk (Dunis et al., 2016). The Committee on Prospering in the Global Economy of the 21st Century (2007) and the World Economic Forum (World bank, 2021) argue that STEM disciplines are essential for economic growth worldwide. More than sixty years ago, Nobel Laureate Robert Solow reported that *more than half of the U.S. growth during the first fifty years of the last century was due to progress in knowledge*, most likely with a focus on technology and, thus, involved STEM (Solow, 1957). Moreover, STEM innovations are responsible for the emergence of fast-growing innovative superstar companies (Jones & Kim, 2018; Gabaix et al., 2016) which, ultimately, are more efficient. These companies dominate others, taking most of the market share (Dorn et al., 2017; Autor et al., 2020). We know that superstar firms generally have a lower fixed cost and, therefore a substantially smaller labor share (Dorn et al., 2017). Generally, as technologies have become more important to economics, this has led to a steady reduction in the proportion of countries' GDP (gross domestic product) attributed to labor (Karabarbounis & Neiman, 2014), questioning the widely known Kaldor *"stylized facts"* of countries' growth (Kaldor, 1961).

Superstar firms such as Tesla and Amazon not only require less labor, but they also require substantially lower physical capital than the top firms of fifty years ago. Alderman et al. (2022) revealed that CEOs with STEM backgrounds are better equipped to help companies handle the ambiguity inherent in innovation. Furthermore, the diminishing need for workers in the modern economy implies that money is distributed between fewer people, indicating that (STEM) technological innovations could also lead to increased inequality (Jones & Kim, 2018; Gabaix et al., 2016; Stiglitz, 1969; Piketty & Saez, 2003; Jones, 2015). As stated in Stiglitz's book (Stieglitz, 2019), *a substantially small percentage of companies in the U.S. economy control the entire economy's sect*ors *and contribute to skyrocketing inequality*. Although it is clear that nowadays STEM fields mainly drive innovation, we are not yet fully aware of how STEM education quantitatively contributes to economic inequality and how STEM and non-STEM firms behave during economic downturns, such as recessions and pandemics. These considerations are vital when it comes to portfolio fund analyses.

STEM and non-STEM education affects our propensity for innovation in contradictory ways. In contrast to Tsang, who reports that *humanities students are more inclined to innovation (*Tsang, 2017), Brunow et al. report that firms that employ STEM graduates are more innovative than competing firms that do not (Brunow et al., 2018). A study shows that Georgia's HOPE Scholarship reduced the chances of individuals enrolling onto STEM degrees (Sjoquist & Winters, 2015). Another study reported that students' decisions to choose a STEM degree were highly dependent on their ethnicity, high school reputation, gender, and SAT math score (Crisp et al., 2009). Wang similarly found that a STEM major can be affected by a variety of factors, such as students' 12th-grade math results, their exposure to STEM courses (particularly science and math) during their prior education, and also by receipt of financial aid (Wang, 2013). Mativo et al. (2016) investigated the extent to which integrative science, technology, engineering, and mathematics (STEM) education programs impacted high school students in the South-East region of the U.S.

In this paper, we examine the impact of STEM with regard to varying levels of economic complexity, ranging from individuals and firms to countries. Firstly, we analyse the Forbes lists (Forbes, 2018) to identify the richest individuals in the world over the last two decades. For the Zipf plot (Zipf, 1949) of the world's billionaires, we demonstrate that the ξ exponent for top STEM billionaires is systematically larger than for top non-STEM billionaires, implying that billionaires with STEM education contribute more to inequality than non-STEM billionaires. Over time, the Zipf ξ exponent for STEM billionaires steadily increases and becomes higher than the Zipf exponent for the top non-STEM richest.

At a firm level, for the S&P500 index that is a representative of the U.S. financial market, consistently, for each period equal to 1y, 3y, and 5y, taking market capitalization (MCAP) as a proxy for the total wealth of a company, the average growth rate for STEM companies is higher than the average growth rate for non-STEM companies. MCAP is the value of a company commonly calculated by multiplying the total number of stocks by the current stock price

Here, the 1y time span aligns with the 2020 pandemic year, to test whether the performance between STEM and non-STEM companies changes during the pandemic. To this end, for the U.S. market, we show that the differences between STEM and non-STEM companies exist not only during an economic expansion (for either 2014-2019 or 2016-2019), but even for the 2020 pandemic year. To test whether or not the previous findings stand up worldwide for varying financial markets, we analysed the constituents of the German DAX index and the French CAC40 index. For the CAC40 index, during an economic expansion, the growth rate is significantly higher for STEM than for non-STEM firms. This contrasts with the DAX index, for which we find no difference in performance between STEM and non-STEM firms. Surprisingly, in contrast to the S&P500 index, we found no difference in the performance of STEM and non-STEM constituents of the CAC40 and the DAX indexes during the pandemic. Furthermore, at a firm level, for both STEM and non-STEM companies, we found larger Zipf exponents than those uncovered for the top billionaires with STEM and non-STEM education.

At a national level, the Zipf plots of countries' MCAP and GDP exhibit an exponent larger than those calculated for individuals and firms. In short, the more complex the system, the higher the degree of inequality. The results uncovered motivate us to propose a model for firm growth. We also posit that the U.S. attracts more global high-tech companies than the E.U., due to its substantially larger Venture Capital market. The model combines Simon's traditional 'rich-gets-richer' model with what we propose as the 'rich-gets-richer competition mechanism'. In the model, we establish that U.S. STEM-orientated companies perform better than non-STEM.

II. DATA

Every year, the business magazine Forbes (Forbes, 2018) reports the list of the world's richest individuals, providing information on which businesses created their wealth. In the Forbes lists, royalty (such as the British Monarch) and dictators are not included. We analyse data between 2013 and 2019. In 2018, there were 2,208 people on the list, with an average net wealth of $4.1 billion. An astonishing Oxfam report revealed that the top eight richest billionaires possess the equivalent combined wealth of the world's poorest half. The Forbes list includes the world's richest individuals engaged in various sectors of the economy, ranging from the banking and financial sector (Warren Buffet, Michael Bloomberg), to communication and civil engineering (Carlos Slim), and computer software (Jeff Bezos, Bill Gates, Mark Zuckerberg). It also covers a variety of traditional non-STEM businesses, such as the chemical and oil industry (the Koch family), the retail industry (the Walmart family, the Walton family), and the fashion industry (Bernard Arnault, Amancio Ortega), and others.

There are many variations of the STEM definition and, in this manuscript, we use *the International Standard Classification of Education (ISCED) (UNESCO-UIS, 2012) to define STEM education* (Podobnik et al., 2020) Within this standard, a person *has STEM academic qualification if graduated in (i) mathematics, statistics, and natural sciences, (ii) communication technologies and information, or (iii) construction, manufacturing, and engineering* (Forbes, 2021). In this study, as STEM-educated individuals, we also include famous "STEM superstar dropouts", such as Bill Gates and Mark Zuckerberg (Figure 1), who have no formal degree.

Insert Figure 1 about here

FIG. 1. Net Worth over time for a set of STEM billionaires.

In our daily analysis of Venture Capital (V.C.) data, the data on V.C. investments was obtained from the international commercial Zephyr database. This data is widely used in scholarly work and has extensive worldwide coverage on IPO and V.C. transaction data.

We also analyse the daily data on the U.S., French, and German stock markets. As the U.S. representative, we use the S&P500 stock market index, which comprises 500 large-cap companies, covering approximately 80% of the U.S. equity market with regards to capitalization. We also analyse the CAC40 stock market index as a representative French index. The French index comprises 40 stocks from the 100 largest firms concerning market capitalization. Finally, we analyse the German DAX index, comprising the 30 largest German companies.

To analyse patents worldwide, we apply the yearly collected data provided by a U.N. agency: the World Intellectual Property Organization (WIPO) (Klass et al., 2007). This organisation is tasked with several activities, the most important of which include: providing global services that register and protect intellectual property (I.P.) in different countries; and offering services for protecting I.P.s, such as inventions and trademarks. The WIPO also provides reports and statistics on I.P. protection. These statistics include information on patent applications and patent grants for residents, non-residents, and those abroad.

Insert Figure 2 about here

FIG. 2. Individual Level. Zipf coefficient ζ vs. time for billionaires with (a) STEM and (b) non-STEM graduations contributing to wealth inequality. Plots are shown for the 70, 50, and 25 richest billionaires (from top to bottom).

III. STEM AFFECTS WEALTH INEQUALITY AT AN INDIVIDUAL LEVEL

The fractal nature of the wealth data across different scales of the economy, from individuals to companies, would assume that there is a unique exponent calculated analysing wealth data for each scale. This fractal assumption seems reasonable between individuals and firms because it is reasonable to assume that STEM-orientated businesses have predominantly been founded by STEM-educated individuals, as is the case with Steven Jobs, Mark Zuckerberg, and Bill Gates. Note that, for the future of education, it seems particularly odd that some brilliant college dropouts became billionaires without formal education. Here, we hypothesize that STEM and non-STEM wealth, defined at different levels of the economy, roughly exhibit fractal behavior. To test this hypothesis, this analysis gradually moves from the smallest (individual) to the largest (country) scale.

The fractal notion is closely related to power laws describing empirical data, in which dynamics are self-similar or fractal over many orders of magnitude (scales). To this end, it is worth noting that Jones and Kim (in Baybe, 2010) report that the U.S. income X follows a probability distribution with fat tails, $P(X)\ X^{-1-1/\xi}$, where the index ξ for the U.S. income from 1980 to 2000 increased from ≈ 0.4 to ≈ 0.6. Unfortunately, similar analyses on individuals at an international level still fall short due to a lack of income data. Nevertheless, internationally, a good proxy for income data is the total wealth of the world's rich individuals. Accordingly, for the list of the top 400 wealthiest Americans, Klass et al. (2006) report that the tail of the U.S. wealth distribution comprising the country's top billionaires follows distribution $P(X)$, with power-law tails $X^{-1-\alpha}$ (Pareto, 1964).

Extending this examination from the U.S. to the rest of the world, we analyse the richest billionaires globally, focusing on how the world's top STEM billionaires have emerged over time and have begun to exert dominance over traditional non-STEM billionaires. Forbes and Bloomberg were used as sources of data with regards to billionaires' formal (graduate) and informal educational levels.

Because the number of billionaires collected between 2013 and 2019 varies over time, in our analysis, we always analyse the same number of billionaires - the 300 richest billionaires. To quantify the distribution of the richest individuals, we do not analyse the Pareto distribution of wealth – where wealth is defined as net worth (Zipf, 1949) – but rather its alternative representation: the Zipf plot of net worth vs. rank (Zipf , 1949; Forbes, 2021; Klass et al., 2006; WIPO, 20211; Pareto, 1964), wherein billionaires' net worth is ranked from largest to smallest. Suppose power-law scaling asymptotically exists in the far tail of the probability distribution of net worth with exponent α. In this case, the same scaling equally exists in the tail part of the Zipf plot of net worth vs. rank R, where the Pareto exponent α relates to the Zipf exponent ξ (Gabaix & Ibragimov 2011; Podobnik et al., 2011).

$$\xi = 1/\alpha. \tag{1}$$

In economics theory, the exponent α commonly serves to quantify the level of economic inequality (Pikety & Saez, 2003) where, generally, *the smaller the index value α, the fatter the far tails* or, alternatively, the larger the wealth gap between the rich and the poor (Gabaix & Ibragimov 2011). For example, for the Pareto distribution of income, Jones and Kim (Cai et al., 2011) show that the percentage of income for the top p percentiles equals $(100/p)\xi{-}1$. Consequently, changes in the power-law parameter directly contribute to changes in income inequality, as previously reported with regards to individual wealth data on an international scale. Hereafter, to fit the Zipf log-log plots, in order to estimate exponent ξ, we employ a method proposed by Gabaix and

Ibragimov: the so-called $R - 1/2$ method (Gabaix & Ibragimov 2011).

In applying this method, Podobnik et al. (2020) recently revealed that STEM graduate education contributes to the prosperity and inequality of the world's richest individuals. For each of the two deliberately chosen years, the Zipf plots showed that the richest STEM graduates had significantly fatter tails than their non-STEM counterparts (Podobnik et al., 2020), indicating that, at an individual level, among the richest, STEM education contributes more to inequality than non-STEM. However, because the analysis was accomplished in just two years, a crucial question about the trend of wealth inequality remains unanswered.

To this end, for the 70, 50, and 25 richest billionaires chosen each year, Figures 2(a) and (b) show how billionaires who are STEM and non-STEM graduates contribute to wealth inequality. Specifically, Figures 2(a) and (b) vividly demonstrate that, for the world's top billionaires, the average ξ is well in agreement with the index ξ value (Jones & Kim, 2018) calculated with regards to U.S. income from 1980 to 2000 (Bybee, 2010).

Relative to non-STEM's top richest in Figure 2 (b), for STEM's top richest individuals in Figure 2 (a), the Zipf ξ exponent steadily increases faster than the one that corresponds to the top non-STEM richest individuals. Here, the upward trend in ξ exponent implies that the corresponding α of Eq. (1) decreases, implying that with small fluctuations the wealth inequality for STEM graduates persistently increases over time. Additionally, by comparing Figures 2(a) and (b), regardless of how many billionaires are analysed, we see that the ξ exponent is consistently larger for top STEM billionaires than for top non-STEM billionaires. For each year in Figure 2(b), we find that the α value is within a range $\alpha \in (0, 2)$ characteristic for Levy distributions. The results align themselves with the outcomes reported in scholarly literature on finance and economics (Gabaix & Ibragimov, 2011), which argues that a small fraction of outliers substantially skew the distribution and violate Gaussian assumptions. The fact that the far tail of the wealth distribution follows a power-law distribution at an individual level implies that, if we find similar exponents at different levels of the economy, wealth inequality is roughly fractal (Bybee, 2010).

To statistically test the null hypothesis that the growth rates of non-STEM and STEM billionaires display the same distribution, we use standard statistics; specifically, the Mann-Whitney U test (Podobnik et al., 2020), which was designed to quantify the difference between two populations or subgroups. Here, identifying the two subgroups as STEM and non-STEM, based on the graduate education of billionaires, the test quantifies the distinction between the ranks of growth rates with regards to billionaires' wealth. Precisely, for each billionaire in the 2018 Forbes list, we determine when they were initially listed. Then, using the initial (W_1) and final wealth (W_2), and the time span T, we calculate the annual wealth growth rate as $ln(W_2/W_1)/T$. Here, the null hypothesis of the statistical test is that the distributions corresponding to the two subgroups are equal. Table 1 examines the top billionaires, varying the number of the richest, and rejects the null hypothesis. It therefore confirms that there is a significant difference in wealth growth between STEM and non-STEM billionaires.

Insert Table 1 about here

In summary, STEM and non-STEM billionaires perform differently, implying that graduate education seems to be linked to the speed at which they accumulate wealth – at least for the richest individuals. At the 5% confidence level, STEM billionaires increased their wealth significantly more quickly than non-STEM billionaires. However, this study does not address whether or not STEM graduate education impacted upon the profiles of the companies created (whether they were STEM or non-STEM) even though – for the top richest individuals at least – we know that rich STEM individuals created STEM firms. This serves as sufficient motivation for the following analysis.

IV. STEM AFFECTS WEALTH INEQUALITY AT A FIRM LEVEL

One should expect that the STEM/non-STEM scaling behavior we found at an individual level exists even at a firm level. For example, Zuckerberg made his fortune by developing Facebook, whereas Bill Gates became rich because a company he launched – Microsoft – became a powerful technology company. STEM dominance among the top largest world companies presumably occurs because the marginal costs for STEM-orientated firms are significantly lower than in traditional industries. As long as their technology dominates, these firms are natural monopolies. It seems reasonable that, if STEM graduates start to exert dominance over non-STEM graduates among the richest individuals, a similar STEM dominance might appear at a firm level as well.

To this end, analysing the companies comprising the S&P500 in 2018, (Podobnik et al., 2020) found that, over a three-year period of economic expansion, STEM firms on average had larger growth rates than non-STEM. However, insights on the performance of STEM and non-STEM firms during economic downturns, such as the pandemic and recessions, are still unclear. It is still not adequately understood (a) whether STEM firms generally exhibit better performance than non-STEM firms in terms of MCAP growth rates not only in the U.S., but worldwide and across different financial markets; (b) how STEM and non-STEM firms perform during economic downturns, such as pandemics and recessions; and (c) whether STEM or non-STEM firms contribute more to economic inequality.

Insert Figure 3 about here

FIG. 3. Firm Level. To test the robustness of our results on different definitions, the S&P500 index over the last (a) five years, (b) three years, (c) and during 2020 reveal the growth rates for STEM and non-STEM companies, randomly presented.

To this end, we begin our analysis of the U.S. market. Here, for each company within a representative U.S. financial index – the S&P500 index – we calculate the growth rate as the log difference during (a) the five-year period between 01/01/2015 and 01/01/2020, and (b) the three-year period between 01/01/2017 and 01/01/2020; both of which occurred during economic expansion. Choosing different time spans helps to confirm the robustness of our findings and reveals that our results are relevant irrespective of the time span chosen. For each company from the S&P500 index, Figures 3(a) and (b) show the growth rate calculated over the five and three years. We demonstrate that, for STEM companies, the average growth rate is significantly larger in comparison to non-STEM firms both over the last five and three years. However, it is especially important to determine where money should go during economic downturns. To this end, performing (c) an analysis for the pandemic year (2020), we obtain the same result. As such, the STEM sector can be seen to perform better than the non-STEM sector, as shown in Figure 3(c). This information is important for financial fund managers, as it reveals how varying sectors behave during different economic stages. Next, the dominance of the STEM sector is confirmed using a statistical test.

Insert Table 2 about here

To this end, applying the Mann-Whitney test for the right tail test for varying time spans, where H_0: *STEM = non-STEM* and H_1: *STEM > non-STEM*, Table 2 shows that, for each time span, we obtain p-value = 0.00, implying that a randomly selected STEM firm population performs better than a randomly selected non-STEM firm population. We see in Tables 3 and 4 that, relative to non-STEM sectors, new STEM industries exhibit more promising results than old STEM industries. We find that one of the newest STEM industries - the software industry - has the largest z value relative to non-STEM industries. In the test for this example, the larger the z value, the higher the STEM performance superiority relative to non-STEM industries.

Insert Table 3 about here

Insert Table 4 about here

For the S&P500 constituents at 2020, to test how STEM and non-STEM firms contribute to economic inequality, Figure 4(a) is used as a baseline. It reports a Zipf plot with $\xi = 0.69$ calculated for all firms. We also depict the Zipf plots of non-STEM and STEM firms, revealing that there is a substantial and significant difference in Zipf exponents calculated for STEM ($\xi = 0.79$) and non-STEM firms ($\xi = 0.6$), implying that, relative to non-STEM firms, STEM firms contribute more to economic inequality (see Equation 1).

To test for universality in the previous inequality analysis, we perform the scaling analysis at an international level. Considering the largest companies internationally, Figure 4(b) shows the Zipf plot of MCAP for the world's 100 largest companies for 2020 with exponent $\xi = 0.63$, a value very similar to the Zipf exponent $\xi = 0.68$ obtained for the MCAP of SP500 constituents. The result is expecting regarding the fact that U.S. firms remain dominant among the world's 100 largest firms. However, these two exponents are significantly larger than the exponents calculated for the wealth data of the world's richest individuals, implying the existence of approximate fractal nature in the wealth data, taking into account both individual and firm levels.

Insert Fig 4 about here

FIG. 4. Firm Level. (a) The Zipf plot of MCAP of the members of the S&P500 index. (b) The Zipf plot of the world's 100 largest companies in 2020.

To establish whether or not similar results on non-STEM and STEM firms acquired for the U.S. stock market can be found for the E.U. stock markets as well, thus potentially confirming the universality of STEM dominance, we analyse the French CAC index constituents. For each of the 40 companies in the CAC40 index, Figure 5(a) shows the growth rate calculated as the log difference over a three-year period between 01/01/2016 and 01/01/2019. Separately, for STEM companies, we obtain an average growth rate equal to 0.166. For non-STEM companies, the average growth rate equals 0.062. Applying the Mann-Whitney test for the right tail test, where H_0*: STEM = non-STEM* and *H1: STEM > non-STEM*, at the 5% confidence level, Table 5 gives a *p*-value equal to 0.0374. This reveals that, on average, even for the French market, STEM firms perform better than non-STEM firms. In order to confirm the previous findings, in Figure 5(b) we also perform a test for the five-year period between 01/01/2014 and 01/01/2019, validating the STEM supremacy among French firms at the 5% confidence level (p = 0.0258, see Table 5). The results are not surprising: both STEM and non-STEM firms are reliant on innovations, but it is plausible that, on average, STEM firms apply STEM innovations to a larger extent than non-STEM firms.

It is reasonable to expect that innovative firms perform better during economic downturns in comparison to their less innovative counterparts. However, it is surprising that the calculations for the most recent pandemic year – 2020 – reveal results that oppose the U.S. market's insignificant performance differences between French non-STEM and STEM firms. This intriguing result reveals that the most recent pandemic was detrimental to all sectors of French industry. However, an alternative interpretation is that French STEM firms are not as innovative as U.S. STEM firms.

Insert Table 5 about here

Insert Table 6 about here

We further perform STEM vs. non-STEM analysis for constituents of the German DAX index. As with the previous two markets, Figures 6(a) and (b) show the growth rate calculated as the log difference for each of the 30 companies trading on the Frankfurt Stock Exchange within the DAX index. Again, we begin by analysing the three-year time span between 01/01/2016 and 01/01/2019, applying the Mann-Whitney test for the right tail test where, again, H_0*: STEM = non-STEM* and H_1*: STEM > non-STEM*. In contrast to the U.S. and French markets, Table 6 reveals a surprising *p*-value of 0.44, implying that there is no significant difference in performance between non-

STEM and STEM firms at the 5% confidence level. Repeating the test, firstly over the five-year period between 01/01/2014 and 01/01/2019 and then over the 2020 pandemic year, we again confirm that there is no significant difference between STEM and non-STEM German firms (p = 0.863). When comparing the French and German indexes, it was surprising to find that, over the years of expansion, non-STEM and STEM firms significantly varied in the French market in favor of STEM firms. However, we found no significant difference in the German market. However, for both the French and German financial markets, in contrast to the U.S. market, we surprisingly find no significant differences between STEM and non-STEM firms during the pandemic year over the time span between 01/01/2020 and 01/01/2021.

Insert Figure 5 about here

FIG. 5. Firm Level. Constituents of the French financial index, CAC40. The growth rates are calculated over (a) a three-year period and (b) a five-year period.

Insert Figure 6 about here

Fig. 6. Firm Level. Constituents of the German financial index, DAX. The growth rates are calculated over (a) a three-year period and (b) a five-year period.

V. WEALTH INEQUALITY AT A COUNTRY LEVEL

Generally, in contrast to individuals and firms, it is less clear how countries should be divided with regards to STEM and non-STEM. However, it is reasonable to assume that countries with a large number of STEM firms and STEM graduates attract foreign STEM students and reign supreme with regards to STEM startups and numbers of patents. An important factor in the overall graduate demographics is the fraction of STEM graduates because, according to the World Economic Forum (WEF), STEM has become the most important fraction for graduates (HRC, 2016). For 2016, the World Economic Forum (World bank, 2021) *revealed that India had 2.6 million*, *while the U.S. had 568,000 STEM graduates*. Pure numbers say nothing about the quality of graduates.

Here, we assume that there is a functional dependence between a country's number of patents and the number of STEM students, since one would expect that patents are mainly based on STEM innovations. In Figure 7, for OECD countries over a nine-year period (2000-2009), we show how the average number of STEM students in a given country is associated with the number of patent grants over not the same period, but rather during the subsequent nine-year period (2010-2019). Figure 7 reveals the significant functional dependence between a country's number of patents and its number of STEM graduates.

Insert Figure 7 about here

FIG. 7. Country level. WIPO patents. The more STEM graduates in a country, the larger the number of patents. For both patents and STEM graduates, the average is calculated as a logarithm of these variables.

Next, we apply our Zipf analysis at a macro (country) level. Because countries are more complex economic systems than firms, one can see how the Zipf exponent calculated for countries differs from those calculated for firms and individuals. Few studies focus on Zipf analyses, reporting a power law on world wealth or GDP per capita (Di Guilmi et al., 2003). Next for 2019, Figure 8(a) shows the Zipf plots with corresponding exponents calculated for both GDP at PPP (purchasing power parity) and GDP in constant dollars. We find that the Zipf exponents, ξ = 1.32 calculated for GDP at PPP and ξ = 1.2 calculated for GDP in constant dollars, are both significantly larger than the one calculated for firms. This suggests that wealth inequality at a country level is generally larger than wealth inequality at a firm level. It is intriguing that these exponents, obtained for GDP data, are similar to the information obtained when applying the Zipf analysis to the MCAP data in Figure 8(b) where, for the largest 60 countries, for 2019 we find the Zipf exponent ξ = 1.24. In agreement with individual and firm levels, if we were able to divide countries on STEM and non-STEM, we can only assume that the Zipf exponent for more STEM-orientated countries would be larger than the Zipf exponent for less STEM-orientated countries.

Insert Figure 8 about here

FIG. 8. Country Level. The Zipf plot. GDP in constant dollars and at PPP. The Zipf exponent $\xi = 1.32$ is approximately two times larger than those calculated at individual and firm levels. b) Zipf of MCAP of countries, $\xi = 1.24$, in 2019.

Insert Figure 9 about here

FIG. 9. Venture Capital Data per capita for OECD countries.

VI. Model for the fractal growth of individuals, firms, and countries

For international business, it is intriguing that the E.U. and the U.S. are similar in GDP and are military and economic allies. However, E.U. counterparts of U.S. high-tech companies, such as Google, Amazon, and Apple, are hard to find. The economic deterioration of the E.U. was accentuated during the pandemic, when the E.U. was forced to buy COVID vaccines from the U.K. and the U.S. as not a single "pure" E.U. company manufactured vaccines. Figure 9 speaks for itself. It shows, for 2019, how V.C. funding was distributed across different OECD countries (per capita). Ranking V.C. investments from largest to lowest, thus using international data, we obtained the Zipf exponent $\xi = 2.2$. The difference between the U.S. and the E.U. is astonishing, and this perhaps explains why it is the largest attractor for new technological companies. Here, we propose a simple model encompassing the following assumptions:

a) The U.S. attracts more global high-tech companies than the E.U. due to its larger Venture Capital;

b) In the U.S., STEM-orientated companies are better performers than non- STEM.

c) The Zipf exponent of wealth consistently increases with the advancing scale of a system, from individuals and firms to countries.

To reproduce the growth rates between non-STEM and STEM or U.S. and E.U. firms, and in full awareness that the STEM firms generally generate heavier tails in wealth distribution than non-STEM, we propose an extension of Simon's rich-gets-richer model (Simon, 1955). Simon's rich-gets-richer model is commonly applied in economic theory for firm growth. For the sake of simplicity, we presume that the world economy is comprised of only two countries (or groups of countries) - the U.S. and the E.U., for instance. According to a), the model assumes that these two countries vary in attracting STEM-risky entrepreneurship, wherein V.C. mainly finances these firms. Here, the larger the V.C. (see Figure 9), the larger the probability q of attracting new superstar STEM firms. Of course, not all V.C.-financed companies are STEM, but we have sought to make the model as simple as possible. We assume that V.C. is generally intended for STEM firms.

Each Simon model is developed in line with the evolution of either non-STEM or STEM firms. Inspired by the preferential attachment (PA*I*) growth mechanism (Barabasi & Reka, 1999), for non-STEM firms, we firstly assume that, at the start of the country's economy, thus at initial time $t = 1$, there were a few non-STEM firms. The number of these is deliberately chosen. Then, to follow a *P.A.* formalism, at any other time t_i, a fixed probability p_N a unit of wealth (Barabasi & Reka 1999) is given to the country's economy, representing a new firm. With the rest of the probability $1 - p_N$, this new unit of wealth can be taken over by one of the country's existing firms. In the P.A. mechanism, the larger an existing firm j, the more likely its probability of absorbing the unit of wealth (38,39). This probability equals $(1 - p_N)A(j)/\Sigma_A(k)$, and $A(j)$ denotes the firm size, as measured by the number of units previously attracted.

Proposition 1. *At each step ti, the PAI mechanism is applied for STEM firms and STEM entrepreneurs (potential billionaires), wherein a new unit of wealth is entered in the economy. To account for the faster growth of STEM firms, in contrast with the non-STEM sector, a STEM unit is created in the world's pool and, with the probability of q, the unit is assigned to the U.S. and* $1 - q$ *is assigned to the E.U. Here, in the model, we assume that q linearly depends on the size of* *the V.C. market and, accordingly, we approximately establish that $q = 19/20$, in agreement with Figure 9, where V.C. is shown to be much larger in the U.S. than in the E.U. Consequently, at each step, the STEM firm's sector and STEM entrepreneur's growth equals $1 + q$ in the U.S. and $2 - q$ in the E.U. With a probability pS, the new units are given to the country's economy as the initial wealth of a new independently growing firm and also the wealth of its founder. With a probability of $1 - p_S$, based on PA mechanisms, the new units of wealth created within a country are taken over by a pre-existing STEM firm and are independently assumed by an existing entrepreneur. For STEM firms only, we assume that, at each time, with probability p',a fixed number of boxes m' is transferred from the bulk to the tail part of the probability distribution, contributing to the growth of firms. The tail part for STEM firms' scales, with exponent $\alpha = 1/(1 - p_S + p'm'/(1 + q))$, while the tail part for STEM billionaires (richest entrepreneurs) scales is $\alpha = 1/(1 - p_S)$. We approximate that the non-STEM firms (entrepreneurs) in both countries grow equally (not tested in the data) for one unit at each step.*

Proof: Applying the preferential attachment used in Simon (1955), we first analysed the U.S. STEM sector and gradually developed a model. In agreement with Simon (1955), the rate at which a firm i (and its founder, potential billionaire) grows is $\partial k_i/\partial t = (1 + q)(1 - p_S)k_i/(1 + q)t$, which yields $k_i(t) = (1 + q)(t/t_i)^{(1-p_S)}$. Note that, besides regular growth (unit box), we add an additional growth q due to STEM V.C.s, which serve to attract the world's innovative individuals. Secondly, for firms only, we divide STEM firms in the distribution on the tail and the bulk part, assuming that firms in the tail part are generally more successful and therefore attract resources and humans from the bulk part, making the growth of the tail part even higher. Alongside Simon's standard rich-gets-richer model for STEM firms, we introduce additional rich-gets-richer competition mechanisms between the rich and the poor. Hence, we assume that, with a probability *p', m'* boxes are taken over from the bulk part, correcting the rate at which firm i in the tail part grows as

$$\partial k_i/\partial t = ((1 + q)(1 - p_S) + m'p')k_i/((1 + q)t) = (1 - p'_S)k_i/t, \qquad (2)$$

where $1 - p'_S = 1 - p_S + m'p'/(1+q)$. For the bulk part of the probability distribution, $m'p'$ is replaced by $-m'p$. However, here we are predominantly interested in the tail part. Then, following Barabasi and Reka (1999), the probability that firm i is smaller than k, $P(k_i(t) < k)$ alternatively equals $P(t_i > ((1+q)/k)^{1/(1-p'_S)}t)$. Assuming that new boxes are entered into the economy homogeneously in time (Barabasi & Reka, 1999), it is easy to obtain $= P(t_i > ((1+q)/k)^{1/(1-p'_S)}t) = 1 - P(t_i \leq ((1+q)/k)^{1/(1-p'_S)}t) = 1 - ((1+q)/k)^{1/(1-p'_S)}\, t/((1+q)t+m_0)$. Finally, following Barabasi and Reka (1999), the probability density $P(k)$ derives from the cumulative distribution $P(k) = \partial P(k_i(t) < k)/\partial k$, which asymptotically leads to a stationary solution that, in the tail part, resembles the form $P(k) \propto k^{-1/(1-p'_S)-1}$ with power-law exponent $\alpha = 1/(1 - p_S + p'm'/(1+q))$ and (see Eq. (1))

$$\xi = 1 - p_S + p'm'/(1+q). \quad (3)$$

Here, the model parameters can be set to mimic the empirical findings in Figure 4, where the larger p_S value follows the smaller ξ value (and the larger α value). Similarly, the larger the rich-gets-richer competition mechanism ($p'm'/(1+q)$), the larger the ξ value. For STEM billionaires, there are no additional competition mechanisms, and the tail part has an exponent

$$\xi = 1 - p_S \quad (4).$$

In short, for STEM firms, while we introduce q to take into account that the richer market as a whole attracts experts and resources from the outside, the last term $p'm'$ in Eq. (3) is added to explain a similar flow inside the market, from the poor to the rich. For STEM firms, we expand Simon's rich-gets-richer model through additional rich-gets-richer competition mechanisms, accounting for the larger levels of inequality existing among STEM firms relative to STEM billionaires. Thus, the growing ξ exponent, moving from individual to firm level (see Figs. 2 and 4), is modelled by the competition mechanism, where the larger the difference between their ξ exponents in Eq. (3) and (4), the larger the competition mechanism. For the E.U. STEM market, q in the above formulas should be replaced with $(1 - q)$. For non-STEM firms, the formulas are similar, where p_S is replaced by p_N . In our model, for non-STEM sectors, p_N is generally larger than p_S, and the competition mechanism is generally weaker for non-STEM than for the STEM sector, enabling larger inequalities in the STEM sector relative to the non-STEM. Q.E.D.

Proposition 2. *To include a variety of countries in the growth of STEM economy, we assume that each country is labelled by index n. We change Proposition 1 only by assuming that m new boxes are added internationally, where the probability that they will be taken by country n equals* $P(n) = (\gamma - 1)/n^{\gamma}$, *where* $\gamma > 1$, *represents the fractal wealth transfer at a country level. Unlike in Proposition 1, there is no unit of wealth generated for each country. The total wealth of country n evolves as* $W(n) = mt(\gamma - 1)/n^{\gamma}$.

Proof: The rate at which firm i in country n will add new boxes is $\partial k_{n,i}/\partial t = ((1 - p_S)mP(n) + m'p')/(mP(n)t)\, k_{n,i}$, which yields $k_{n,i}(t) = mP(n)(t/t_i)^{1-p_S + m'p'/(mP(n))}$. Again, $m'p'$ is introduced to account for the transfer of capital and experts within a country; i.e., the term represents the wealth transfer at a firm level. We could even have entered the transfer of capital and experts between countries to account for the competition at a country level. Finally, the stationary solution of the probability density at country n tends to $P(k) \propto k^{-\alpha_n^{-1}}$ with exponent $\xi_n \equiv 1/\alpha_n = 1 - p_S + m'p'/(mP(n))$. In this model, the aggregated firm wealth serves as a proxy for the market capitalization of country n, which evolves as $MCAP(n) = mt(\gamma - 1)/n^{\gamma}$. Taking logarithm, we obtain

$$\ln(MCAP) = \ln(mt(\gamma - 1)) - \gamma \ln(n) \tag{4}$$

where, to mimic the results in Figure 8(b), we can approximately set $\gamma = 4/3$.

VII Discussion and Conclusion

Only a few years ago, the Japanese government suggested that its universities close or substantially reduce their social sciences and humanities departments in size to *"serve areas that* *better meet society's needs*" (The Diplomat, 2015). This demonstrates the ways in which STEM has become increasingly important in the battle for world dominance.

Thus, in this study, motivated by Stieglitz (2019) who stated that a small fraction of companies in the U.S. economy control the entire industrial sectors and contribute to increasing inequality, we extand this Stieglitz's notion to varying scales of economy and demonstrate that wealth and inequality at varying levels of economy, ranging from individuals and firms to countries, roughly exhibit fractal natures, in which STEM disciplines play a crucial role. This fractal nature is approximate because the Zipf exponent, set to quantify the wealth inequality, persistently increases as the scale of a system grows, from individuals to firms and countries. Applying the Zipf methodology, we reveal how inequality grows, moving from a smaller to a larger scale, from individual and firm to country level. At an individual level, the Zipf plot of the wealth of the world's richest STEM individuals exhibits a steady increase in wealth inequality, where the Zipf exponent for STEM billionaires increases faster than the Zipf exponent for non-STEM billionaires.

At a firm level, analysing the constituents of the S&P500 index, the French CAC40 index, and the German DAX index for the S&P500 index and the CAC40 index, we obtain that STEM firms are better performers than non-STEM firms during good years or economic expansion. Surprisingly, for the DAX index, we find no significant difference between non-STEM and STEM firms during years of economic expansion. However, as the main difference relative to the E.U. market, only for the S&P500 index, STEM firms performed better during the 2020 pandemic year than non-STEM. With these results in mind, we can only speculate that better STEM performance over non-STEM in the U.S. is, on the one hand, due to much larger Venture Capital market in the U.S. compared to the E.U., and on the other hand because the U.S. attracts more international students than the E.U. does.

At a country level, for OECD countries, we find a significant relationship between the number of patents and the number of STEM students. It is likely that the patents are predominantly based on STEM innovations.

To validate our finding that wealth inequality rises with the scale of the economy, we propose a variant of the Simon model alongside additional competition mechanisms. This reveals that, at any moment, the richer can take wealth from the poorer. We involve the competition mechanism in the model because it is plausible that this mechanism increases, moving from individuals to firms and countries. After all, firms have more recourses than individuals, and countries have more resources than individuals and firms. Unlike individuals and firms, countries are entitled to impose sanctions against opponents. In our model, the larger the competition mechanism on a given scale, the larger the ξ exponent or, the larger the degree of wealth inequality.

In the Western world, particularly in the U.S. and in Europe, due to weak interest in STEM disciplines among domestic students, international students are attracted. In 2018, in contrast to the interest of U.S. students, 62% of international students in U.S. colleges and universities studied STEM disciplines, such as science and engineering. International students made up 81% of all graduate students in petroleum and electrical engineering, 69% of students in statistics, 75% in industrial engineering, 59% in civil engineering, 63% in mechanical engineering and economics, and 57% in chemical engineering (NFAP, 2017). In computer science (C.S.), where students study cyber security and A.I. – both topics of huge interest for a nation's security – U.S. students made up only 21% of the cohort (NFAP, 2017). 69% of U.S. public school teachers teaching students from fifth through to eighth grade lack a degree in mathematics. This may be contributing to a weak interest in STEM disciplines among young Americans. Even more disturbing is that 93% of U.S. public school students have teachers with no degree in physics teaching physics (National Center for Education Statistics, Qualifications of the Public School Teacher Workforce, 2003). U.S. officials are particularly worried, because the U.S. higher education system relies on international students. Of these, 69% are from the most competitive Asian nations (National

Science Board, 2018). These percentages reveal that, if STEM departments in leading U.S. higher education institutions relied on U.S. students alone, they would probably not survive.

While most international students achieving U.S. STEM Ph.D. degrees would like to stay in the U.S., the number of STEM Ph.D. recipients from China and India who wish to stay in the U.S. has decreased (AIP, 2018). Once these students receive their Ph.D., most return to their own countries, helping them compete against the U.S. in research, leading to high-tech supremacy. This ongoing competition for high-tech supremacy reminds us to a high degree of a similar competition between the Americans and the Russians seven decades ago. Namely, when the Russians launched Sputnik into space in the 1960s, ensuring their initial dominance in the airspace program. This event propelled the U.S. into action, resulting in a rapid increase in expenditure for aeronautical disciplines, reshaping educational programs to take the lead in space disciplines.

Nowadays, a similar threat from the Far East Asian countries with regard to A.I. and STEM disciplines will most likely make Americans focus on these disciplines to maintain their leading position in advanced technologies. The U.S. will enter into a new educational transition phase (National Science Board, National Science Foundation, 2020) where, firstly, departments in higher education will have to collaborate more with other departments, especially STEM and non-STEM, and secondly, the focus will most likely be shifted from a predominance of undergraduate studies, based on pure Social Science, Arts, and Humanities, to studies based more on STEM-orientated disciplines.

The National Science Foundation of the USA defines interdisciplinary research as*: a mode of research, conducted by teams or individuals, by integrating different methodological perspectives (e.g., information, data, techniques and tools), concepts and/or theories from two or more disciplines to solve problems* (National Science Foundation, 2020). The best universities worldwide are shifting towards a joint interdisciplinary program, with STEM on the one hand and the Social Sciences, Arts, and Humanities on the other. A good example of this would be Aalto in

Finland, which aims to improve students' "soft" skills, combined with data literacy and textual and math literacy, closely linked to STEM and non-STEM education. The high school educational system is also challenged by a growing number of individuals without formal education who can accomplish respectable careers if trained in Data Science.

Education is generally considered important because it greatly impacts industry (Agasist et al., 2021). Developments in science and technology that occur at universities create new occupations and substantially affect labor demand (Börner et al., 2018; Frank, 2019) in the form of a feedback mechanism, wherein changes in labor demand influence what university graduates will choose to study in the future (Kutner et al., 2020). Brynjolfsson and McAfee describe how the rapid expansion of technology urges us to quickly update our skills, organizations, and institutions (Brynjolfsson & McAfee, 2014), particularly concerning two technologies—Cloud Robotics and Deep Learning. These may substantially impact the labor force and its progress (Pratt, 2015). With these technologies, every robot learns from all of the other robots. Algorithms help robots learn from common, cloud-based training sets (Pratt, 2015). *Suppose the labor force has a high proportion of highly trained workers. In that case, it assumes a large volume of skill-complementary technologies that, in turn, increase the productivity of highly skilled workers* (Acemoglu, 1998). Briefly, nations with innovation policies and economies based on innovations will rule the world (Atkinson & Ezell, 2012).

Finally, by linking innovations in science, technology, education, academia, and industry, the government could likely build a synergistic output much larger than the sum of its separate parts, eliciting a nonlinear boost to ccountries' growth (Börner et al., 2018; Park et al., 2020). This knowledge then increasingly becomes more important than the student’s place of graduation.

In summary, at multiple levels of analysis, STEM pushes the boundaries of what is possible and propels a country's growth (Bruno & Faggini, 2021). The findings of our study hold implications for monetary funds with regards to policies, particularly those evoked during a pandemic. Furthermore, our results can impact public policy as well. Economic policies can involve the results of our research when uncovering responses to questions pertaining to the direction in which education policy should evolve at national and regional levels. Future emphasis should be on STEM-related areas in interdisciplinary research preferences. To properly compete with the U.S. and Far East Asian countries, the E.U. must increase its investment in STEM education and research (Colombo & Piva, 2020). In the race for high-tech supremacy, those who are better educated in STEM topics seem to be integral to success.

References

Alderman, J., Forsyth, J., Griffy-Brown, C., & Walton, R. C. (2022). The benefits of hiring a STEM CEO: Decision making under innovation and real options. *Technology in Society*, 71, 102064.

Agasisti, T., Egorov, A., Zinchenko, D., & Leshukov, O. (2021). Efficiency of regional higher education systems and regional economic short-run growth: empirical evidence from Russia. *Industry and innovation*, *28*(4), 507-534.

Aghion, P., & Howitt, P. (1992), A Model of Growth through Creative Destruction, *Econometrica*, *60*(2) , 323-351.

Acemoglu, D. (1998). Why do new technologies complement skills? Directed technical change and wage inequality. *The Quarterly Journal of Economics*, *113*(4), 1055-1089.

AIP - American Institute of Physics, Rapid Rise of China's STEM Workforce Charted by National Science Board Report. 2018. https://www.aip.org/fyi/2018/ accessed October 1st 2021.

Atkinson, R. D., & Ezell, S. J. (2012*). Innovation Economics*, New Haven: Yale University Press, https://doi.org/10.12987/9780300189117

Autor, D., Dorn, D., Katz, L. F., Patterson, C., & Van Reenen, J. (2020). The fall of the labor share and the rise of superstar firms. *The Quarterly Journal of Economics*, *135*(2), 645-709.

Barabási, A. L., & Albert, R. (1999). Emergence of scaling in random networks. *Science*, *286*(5439), 509-512.

Börner, K., Rouse, W. B., Trunfio, P., & Stanley, H. E. (2018). Forecasting innovations in science, technology, and education. *Proceedings of the National Academy of Sciences*, *115*(50), 12573-12581.

Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. WW Norton & Company. New York.

Bruno, B., & Faggini, M. (2021). To be a STEM or not to be a STEM: Why do countries differ?. *Growth and Change*.

Brunow, S., Birkeneder, A., & Rodríguez-Pose, A. (2018). Creative and science oriented employees and firm-level innovation. *Cities*, 78, 27-38.

Bybee, R. W. (2010). What is STEM education? 329(5995), 996 https://www.science.org/doi/full/10.1126/science.1194998

Cai, Z., Winters, J. V. (2017) Self-employment differentials among foreign- born STEM and non-STEM workers, *Journal of Business Venturing*, *32*(4) 371-384, https://doi.org/10.1016/j.jbusvent.2017.03.003

Colombo, M. G., & Piva, E. (2020). Start-ups launched by recent STEM university graduates: The impact of university education on entrepreneurial entry. *Research Policy*, *49*(6), 103993.

Committee on Prospering in the Global Economy of the 21st Century. (2007). *Rising above the gathering storm: Energizing and employing America for a brighter economic future*. Washington, D.C.: National Academies Press. https://www.nap.edu/read/11463/chapter/1#ii

Crisp, G., Nora, A., & Taggart, A. (2009). Student characteristics, pre-college, college, and environmental factors as predictors of majoring in and earning a STEM degree: An analysis of students attending a Hispanic serving institution. *American Educational Research Journal*, 924-942 https://doi.org/10.3102/0002831209349460

da Costa, R. M., & Horn, C. H. (2021). The Co-Evolution of Technology and Employment Relations: Institutions, Innovation and Change. *Structural Change and Economic Dynamics*, 58, 313-324. https://doi.org/10.1016/j.strueco.2021.06.003

Deming, D. J., & Noray, K. (2020). Earnings dynamics, changing job skills, and STEM careers. *The Quarterly Journal of Economics*, *135*(4), 1965-2005. https://doi.org/10.1093/qje/qjaa021

Di Guilmi, C., Gaffeo, E., & Gallegati, M. (2003). Power law scaling in world income distribution. *Economics Bulletin*, *15*(6), 1−7, http://www.economicsbulletin.com/2003/volume15/EB−03O40003A.pdf

Dorn, D., Katz, L. F., Patterson, C., & Van Reenen, J. (2017). Concentrating on the Fall of the Labor Share. *American Economic Review*, *107*(5), 180-85.

Dunis, C., Middleton, P., Karathanasopolous, A., & Theofilatos, K. (2016). *Artificial intelligence in financial markets*. London: Palgrave Macmillan.

Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. *Nature*, 542(7639), 115-118.

Forbes (2018) https://www.forbes.com/billionaires/

Frank, R. H. (2012). *The Darwin Economy: Liberty, Competition, and the Common Good: With a new afterword by the author.* Economics Books. Princenton, USA

Frank, M. R., Autor, D., Bessen, J. E., Brynjolfsson, E., Cebrian, M., Deming, D. J.,.. & Rahwan, I. (2019). Toward understanding the impact of artificial intelligence on labor. *Proceedings of the National Academy of Sciences*, *116*(14), 6531-6539.

Friedman, T. L. (2005). *The world is flat: A brief history of the twenty-first century*. Macmillan.

Gabaix, X., Lasry, J. M., Lions, P. L., & Moll, B. (2016). The dynamics of inequality. *Econometrica*, *84*(6), 2071-2111.

Gabaix, X., & Ibragimov, R. (2011). Rank− 1/2: a simple way to improve the OLS estimation of tail exponents. *Journal of Business & Economic Statistics*, *29*(1), 24-39.

Geesa, R. L., Stith, K. M., & Teague, G. M. (2020). *Integrative STEM education and leadership for student success.* The Palgrave Handbook of Educational Leadership and Management Discourse, 1-20.

Greene, J. C., DeStefano, L., Burgon, H., & Hall, J. (2006). An educative, values-engaged approach to evaluating STEM educational programs. *New Directions for Evaluation*, (109), 53-71. https://doi.org/10.1002/ev.178

Jones, C. I. (2015). Pareto and Piketty: The macroeconomics of top income and wealth inequality. *Journal of Economic Perspectives*, *29*(1), 29-46.

Jones, C. I., & Kim, J. (2018). A Schumpeterian model of top income inequality. *Journal of Political Economy*, *126*(5), 1785-1826.

Lloyd, C. & Payne, J. (2019). Rethinking country effects: robotics, AI and work futures in Norway and the UK. *New Technology, Work and Employment*, *34*(3), 208–225.

Koonce, D. A., Zhou, J., Anderson, C. D., Hening, D. A., & Conley, V. M. (2011, June). What is STEM?. In 2011 ASEE Annual Conference & Exposition (pp. 22-1684).

Kutner, M., Kayumova, S., & Britton, S. (2020). STEM Education and the Theft of Futures of Our Youth: Some Questions and Challenges for Educators. In: Stewart, A. J., Mueller, M. P., Tippins, D. J. (Eds.) *Converting STEM into STEAM Programs: Methods and Examples from and for Education*, 5, 285. Springer, Cham, Switzerland

Karabarbounis, L., & Neiman, B. (2014). The global decline of the labor share. *The Quarterly journal of Economics*, *129*(1), 61-103.

Kaldor, N. (1961). Capital accumulation and economic growth. In: *The Theory of Capital* (pp. 177-222). Palgrave Macmillan, London.

Klass, O. S., Biham, O., Levy, M., Malcai, O., & Solomon, S. (2006). The Forbes 400, the Pareto power-law and efficient markets. *The European Physical Journal* B, *55*(2), 143-147. https://doi.org/10.1016/j.econlet.2005.08.020

Manduca, R. A. (2019). The contribution of national income inequality to regional economic divergence. *Social Forces*, *98*(2), 622-648. https://doi.org/10.1093/sf/soz013

Mativo, J., Smith B., Thompson E., & Wicklein R. (2016). A formative evaluation of a Southeast High School Integrative science, technology, engineering, and mathematics (STEM) academy. *Technology in Society*, 45, 34-39. https://doi.org/10.1016/j.techsoc.2016.02.001

National Center for Education Statistics, Qualifications of the Public School Teacher Work-force: *Prevalence of Out-of-Field Teaching* 1987-1988 and 1999-2000, Washington, D.C.: U.S. Department of Education. 2003.

National Science Board (2018). *Science and Engineering Indicators 2018*. NSB-2018-1. Alexandria, VA: National Science Foundation. Available at https://nsf.gov/statistics/2018/nsb20181/report/ Accessed: August 21st 2021.

National Science Board, National Science Foundation (2020). *Science and Engineering Indicators 2020: The State of U.S. Science and Engineering*. NSB-2020-1. Alexandria, VA. Available at https://ncses.nsf.gov/pubs/nsb20201/. Accessed August 28th 2021.

Piketty, T., & Saez, E. (2003). Income inequality in the United States, 1913–1998. *The Quarterly Journal of Economics*, *118*(1), 1-41.

Pareto, V. (1964). *Cours d'économie politique* (Vol. 1). Librairie Droz. /First edition) 1896: Lausanne, Paris, Leipzig.

Park, W., Wu, J. Y., & Erduran, S. (2020). The Nature of STEM Disciplines in the Science Education Standards Documents from the USA, Korea and Taiwan. *Science & Education*, *29*(4), 899-927.

Podobnik, B., Valentinčič, A., Horvatić, D., & Stanley, H. E. (2011). Asymmetric Lévy flight in financial ratios. *Proceedings of the National Academy of Sciences*, *108*(44), 17883-17888.

Podobnik, B., Crawford, G. C., Lichtenstein, B., Lipic, T., Wild, D., Zhang, X., & Stanley, H. E. (2020). The new wealth of nations: How STEM fields generate the prosperity and inequality of individuals, companies, and countries. Chaos, Solitons, & Fractals, 141, 110323. https://doi.org/10.1016/j.chaos.2020.110323

Pratt, G. A. (2015). Is a Cambrian explosion coming for robotics?. *Journal of Economic Perspectives*, *29*(3), 51-60.

Rosen, S. (1981). The economics of superstars. *The American Economic Review*, *71*(5), 845-858.

Simon, H. A. (1955). On a class of skew distribution functions. *Biometrika*, *42*(3/4), 425-440.

Sjoquist, D. L., & Winters, J. V. (2015). The effect of Georgia's HOPE scholarship on college major: a focus on STEM. *IZA Journal of Labor Economics*, *4*(1), 1-29.

Solow, R. M. (1957). Technical change and the aggregate production function. *The Review of Economics and Statistics*, 312-320.

Stiglitz, J. E. (1969). Distribution of income and wealth among individuals. Econometrica: *Journal of the Econometric Society*, 382-397.

Stieglitz, J. E. (2019). *People, Power, and Profits.* W.W. Norton co, New York.

The Diplomat (2015) https://thediplomat.com/2015/09/the-japanese-governments-attack-on-the-humanities-and- social-sciences/ Accessed, October 10th, 2020.

The AII Report (2021) The Artificial intelligence Index Annual Report, Standford University https://aiindex.org Accessed: August 26th, 2021.

The Human Capital Report. World Economic Forum. 2016. HCR2016_Main_Report.pdf Accessed: July 31st, 2021.

The World Bank (2018) https://data.worldbank.org Accessed: September 20th 2021.

The World Bank (2021) https://data.worldbank.org Accessed: September 20th 2021.

Tsang, T. L. (2019). A quantitative analysis examining differences between US humanities and STEM students' propensity toward innovation. *Journal of Further and Higher Education*, *43*(2), 149-165.

Yildirim, B. (2016). An Analyses and Meta-Synthesis of Research on STEM Education. *Journal of Education and Practice*, *7*(34), 23-33.

Zipf, G. K. (1949) *Human Behavior and the Principle of least Effort*; Addison-Wesley Press, Cambridge, M.A.

Wang, X. (2013). Why students choose STEM majors: Motivation, high school learning, and postsecondary context of support. *American Educational Research Journal*, *50*(5), 1081-1121.

WIPO patents https://www.wipo.int/portal/en/index.html Accessed: June 1st, 2021.