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# The new wealth of nations: How STEM fields generate the prosperity and inequality of individuals, companies, and countries

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ABSTRACT

Fundamental research in physics has long been a prerequisite for computer scientists and engineers to design innovative products, such as laptops and cell phones. Technological innovations and fundamental research are both part of the so-called STEM fields (Science, Technology, Engineering, and Mathematics), which are known to substantially contribute to economic growth. However, the questions still remain: how much contribution do these fields make to both wealth accumulation and inequality at different levels of analysis? First, analyzing the lists of world's wealthiest individuals, the Zipf plot analysis demonstrates that STEM billionaires contribute more to wealth inequality than their non-STEM counterparts. Analyzing the companies in the S&P500, we find that STEM firms contribute more to wealth inequality and have larger growth rates on average than the non-STEM firms. Finally, we show that the more STEM graduates in a country, the larger its GDP growth rate. In combination, we demonstrate that STEM is a fractal mechanism that drives wealth accumulation—and the wealth inequality— at different scales of economy—from individual wealth to firm valuation to country GDP.



How innovations contribute to wealth and income inequality are questions that have long been studied by economists, sociologists, and management scholars [1–9]. These studies indicate how technology innovations lead to fast-growth entrepreneurial companies [8,9] and are drivers of long-term economic growth [10]. Technological innovations attributed to STEM disciplines (science, technology, engineering, and mathematics) [11,12] have produced such advances as driverless cars, remote disease diagnoses [13], and the simulation of complex financial markets associated with risk management and portfolio optimization [14], all of which constantly push the evolution of skills required for the workforce to keep pace [15]. The prominence of STEM is evident at the national level as well. World Economic Forum [16] and National Academies (https://www.nap.edu/read/11463/chapter/1) studies indicate that STEM fields are key in economic development.

However, there can be a dark side to this prosperity: increased inequality. As Stiglitz noticed in his 2019 book [17], the small percentage of superstar corporations that dominate entire sectors of the economy (e.g., Apple, Amazon, Google) are the primary drivers of wealth disparity. Indeed, these are outliers, driven by STEM. We still do not adequately understand how much STEM fields contribute to economic growth and to wealth inequality across scales of the economy.

In the present paper we hypothesize that wealth accumulation and wealth inequality are based on a STEM-driving mechanism of income aggregation that favors the world's wealthiest individuals, the largest companies in the US, and the largest national GDPs. We find a persistent increase in the fraction of STEM billionaires among the wealthiest billionaires, and that the distribution of these STEM billionaires exhibit fatter tails than the non-STEM, indicating that the former contribute more to wealth inequality than the latter. At the firm level, STEM firms generate fatter tails than non-STEM firms, and the speed of firm wealth increase is larger for STEM than for non-STEM firms. At the country level,

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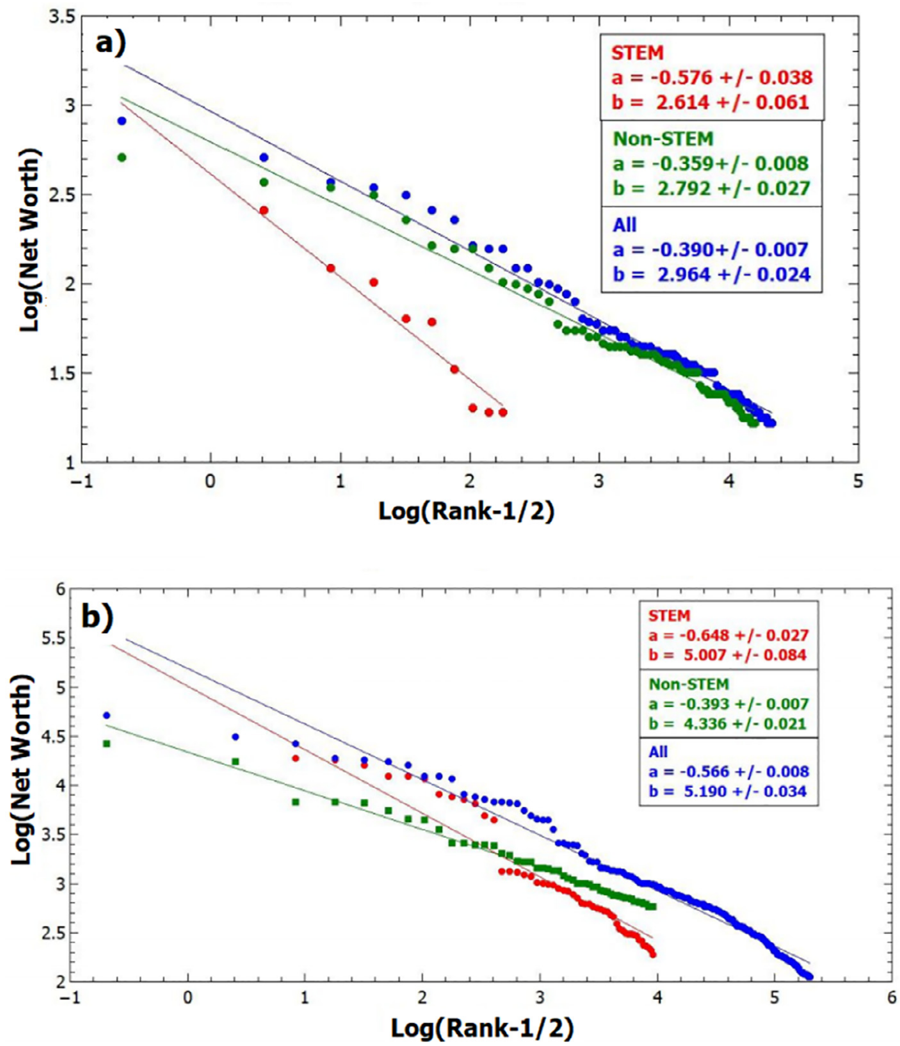


**Fig. 1.** Individual level. Forbes list. The top wealth distribution follows a power law. The top world billionaires' wealth versus rank for the richest 400 billionaires in (a) 1996, and (b) 2018, representing first and last year of the time span. Fat tails exist for each year but the exponent varies. The average exponent value is specific for Levy regime, characterized by infinite variance. We show also STEM and non-STEM billionaires.

as more STEM graduates are produced, the larger the GDP growth rate.

## Wealth inequality at the individual level: empirical evidences. STEM vs. non-STEM

Here we use the international standard definition for STEM education that follows the International Standard Classification of Education (ISCED) (UNESCO-UIS, 2012) (https://www.oecd.org/publications/). To be part of the STEM educated population, an individual must have an academic qualification at an ISCED level of education that is in one of the three STEM fields: (i) natural sciences, mathematics, and statistics, (ii) information and communication technologies, or (iii) engineering, manufacturing and construction. We here also include "superstar dropouts" as STEM graduates, e.g., Bill Gates and Mark Zuckerberg who are demonstrably STEM-educated without a formal degree.

To test our hypothesis that the STEM fields are a fractal mechanism that drive wealth at varying levels of economy, our first analysis is at the level of individual wealth. From the work of Pareto we know that the tail of an income distribution follows a power law [1–3,5–9]. The American business magazine *Forbes* annually publishes a list of the world's wealthiest people. The list includes the net worth of each individual and a short summary of the primary businesses that produce their wealth. The list of richest people includes individuals from varying sectors of economy, ranging from "old money" firms in finance, retail, and fashion industry, to fast-growth companies in communication, computer software, to firms embracing newly-emerging technologies.

In the *Forbes* list of the 400 richest Americans, the tail of the US wealth distribution follows a power-law (Pareto) distribution $P(X)\ X^{-1-\alpha}$ [19]. We extend this analysis to include the world's richest billionaires, again with a focus on how STEM billionaires emerge over time. As above, we base our STEM definition on the formal and informal educational levels indicated by *Forbes* and Bloomberg. To avoid a variation in the number of billionaires from year to year, we include the 300 richest billionaires for each year of our analysis. To map the distribution, we order their wealth—defined as net worth—from largest to smallest.

Fig. 1 shows the log-log Zip plots of wealth versus rank [20–22], which is an alternative representation of the Pareto distribution [20–22]. When a probability distribution is asymptotically represented by a Pareto distribution, then a Zipf plot of size $s$ versus rank $R$ asymptotically also follows a power law in which exponent $\xi$ relates the Pareto exponent $\alpha$ to be [23]

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

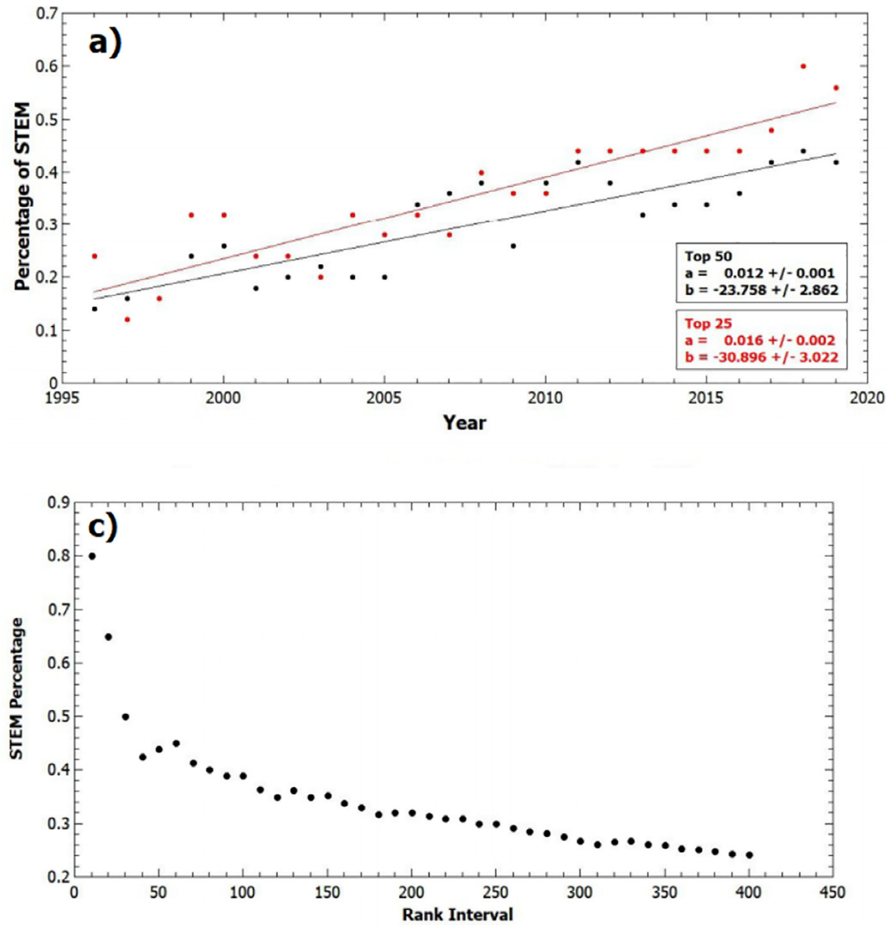


**Fig. 2.** Individual level. Forbes list. STEM billionaires significantly start to dominate over the old money with a constant rate. (a) Obvious non-stationarity. Over years the fraction of STEM billionaires among the 25 (50) richest billionaires constantly increases. (b) For 2018 we show the fraction of STEM billionaires for different number of top richest billionaires. The fraction of non-STEM billionaires increases with moving away from the very top.

We use the Gabaix-Ibragimov $R-1/2$ method of fitting Zipf plots [21]. For the year 1996, we apply a Zipf plot to both STEM and non-STEM billionaires and find a Zipf exponent $\xi = 0.39 \pm 0.007$ corresponding to $\alpha = 2.56$. For the year 2018, $\xi = 0.57 \pm 0.008$ corresponding to $\alpha = 1.75$. Note that in this result the $\alpha$ value is within a range $\alpha \in (0,\ 2)$ and is specific for Levy distributions [23], which have an infinite variance for which *the Central Limit Theorem* does not hold. We perform the same procedure for every year from 1996 to 2018 We find that in most years the $\alpha$ value corresponds to the Levy regime ($\xi \geq 0.5$). Our results reinforce literature in management, finance, and economics which suggest that most performance-based outcomes are dominated by a small percentage of outliers [22–24], which highly skew the distribution to the right and violate literally all Gaussian assumptions. Explaining the emergence of these power law distributions requires a scale-free theory, where an explanation at one level applies to all preceding and subsequent levels [18,24,25].

In economics, the exponent $\alpha$ quantifies societal economic inequality. The smaller the $\alpha$ value, the fatter the tail of the Pareto distribution, and the larger the income gap between the rich and the poor. Thus we extend our search for a mechanism of wealth inequality, perform a separate analysis for STEM and non-STEM billionaires, and focus on the industry sector from which billionaires derive their fortune. Fig. 1 shows a significant difference between the slopes of the Zipf plot of STEM billionaires and non-STEM billionaires, and that STEM billionaires generate a fatter tails than non-STEM billionaires, implying that in each year STEM billionaires contribute more to wealth inequality than non-STEM (see Eq. (1)).

We use a longitudinal analysis to further explore this issue. How does STEM entrepreneurship evolve over time compared to other entrepreneurships? Does the fraction of STEM entrepreneurships increase, decrease, or remain steady over time? For example, James Watt and Henry Ford were widely known engineers—STEM entrepreneurs in modern terms—who built large companies. Is their STEM-based wealth in its time equivalent to the STEM-based wealth of today? By limiting our analysis to the top 25 and 50 wealthiest billionaires each year, we determine how the population of STEM billionaires has emerged over the last two decades. Fig. 2(a) shows a rapid increase in STEM billionaires, quantified by a steady increase in the fraction of STEM billionaires among the 25 and 50 wealthiest world-wide. Fig. 2(b) shows the increase in total wealth of 25 and 50 STEM billionaires year-by-year, with the dot-com bubble preceded its crash in 2000.

Fig. 3 (a) and (b) shows the dominance of STEM billionaires among the richest individuals and shows the annualized growth rate of billionaire wealth for both STEM and non-STEM billionaires. We show data for the top 50 and top 300 billionaires. For each billionaire in 2018 we determine how early they appeared in previous lists—noting the initial and final wealth levels and the year span $T$—and we calculate the annualized growth rate $ln(W_2/W_1)/T$. The difference between STEM and non-STEM billionaires decreases when we increase the size of the list. To test whether STEM and non-STEM billionaires comprise two sub-groups, we apply the

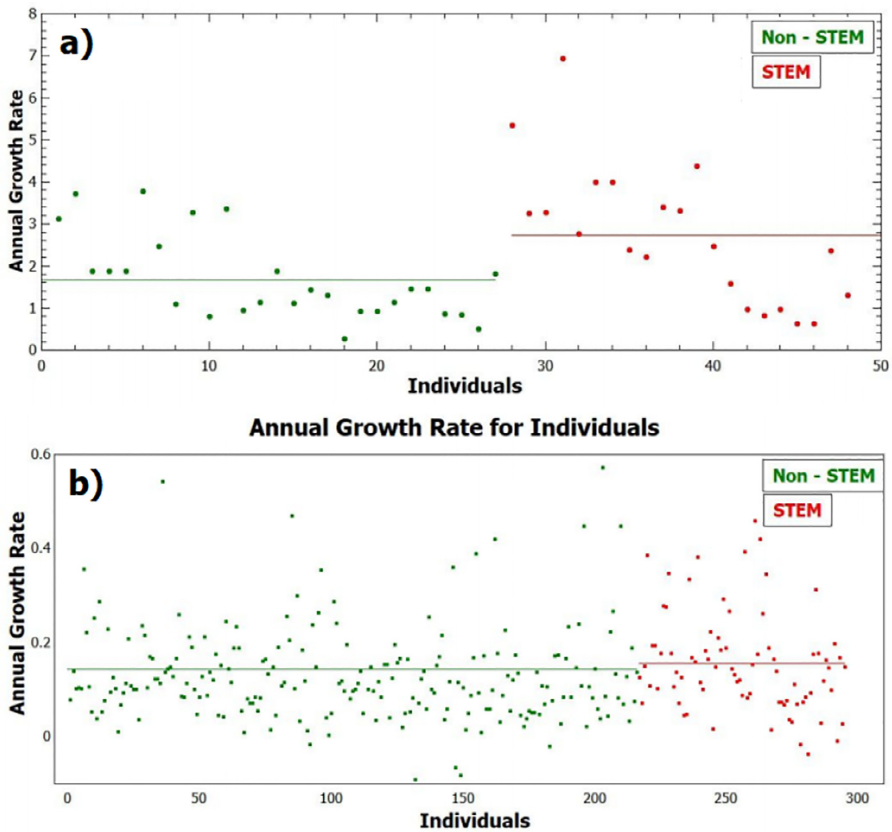


**Fig. 3.** Individual level. Forbes list. Annualised growth rate of individual wealth increase, for STEM and non-STEM billionaires vs. the number of the first wealthiest 50 and 300 billionaires, respectively. STEM billionaires are characterized by the larger average speed of wealth increase.

Mann-Whitney $U$ test that quantifies the difference between two populations based on the difference between the ranks of their growth rate. Here the null hypothesis is that the distributions of the two subgroups are the same. We find that for the set of the 50 wealthiest individuals, the test statistics produce $z$ score $= -2.17$. We thus reject the null hypothesis and confirm that at a 5% confidence level STEM billionaire wealth increases much faster than non-STEM billionaires.

## Wealth inequality at the firm level: empirical evidences. STEM vs. non-STEM

We now test our hypothesis that the STEM fields are a driving mechanism responsible for wealth at the firm level. We examine the largest firms included in the S&P500 index. In addition to the education and training of the founding entrepreneurs of these companies, all STEM firms embrace innovation, which introduces novelty into the system. On the individual level it is clear who is a STEM graduate and who is not, but on the firm level that distinction is less clear. For example many banks, which are non-STEM, may use STEM technologies, especially when carrying out high frequency trading or working with derivatives, but often their profits do not depend on these STEM innovations. In contrast, some new financial providers are providing cloud computing options in their financial services, and thus can be classified as STEM. A contrasting example is the Ford Motor Company, which was a breakthrough STEM company at its founding but now is considered an old STEM industry.

To determine whether a company is STEM, we use the Global Industry Classification Standard (GICS), which consists of 11 sectors, 24 industry groups, 69 industries and 158 sub-industries. Fig. 4(a) shows a Zipf plot of all firms and of STEM vs. non-STEM companies. There is a significant difference between the Zipf plot slopes of STEM and non-STEM firms. The tails of STEM firms are fatter than those of non-STEM firms. This indicates that STEM firms contribute more to wealth increase than the non-STEM firms and also more strongly contribute to economic inequality than non-STEM firms. Comparing billionaires and firms in Figs. 1 and 4(a), we find similar Zipf exponents. This may be because many large companies, especially those that are STEM-based, were created by "superstar" high-tech entrepreneurs [25].

Fig. 4 (b) shows the growth rate over the last 3 years for 100 fastest growing STEM and non-STEM firms in the S&P500 index. We examine the growth rate $\Delta S/S_i$, where $S_i$ is the stock price at 1 June 2016, with a focus on the fastest growing companies. To test whether STEM and non-STEM firms are two distinct sub-groups within the S&P500 index, we again use the Mann-Whitney U test that measures the difference between the ranked growth rates of the two groups. We find the statistical value $z = -2.88$ and thus reject the null hypothesis and confirm at a 5% confidence level that STEM and non-STEM firms grow at different speeds (for details see the SI). We apply the same test to the top 500 companies and get $z = -4.46$, which again confirms that STEM and non-STEM firms comprise two different groups.

We next determine which STEM subgroups contribute most to overall growth. We use the Mann-Whitney test and compare software, semiconductors, and electronic manufacturing and equipment with the entire non-STEM group (where the higher the $z$ value, the greater the difference between the two populations). When we compare each STEM subgroup with each non-STEM subgroup we find a significant difference between the growth rates ranks, with values of $z = -4.25$, $z = -3.71$, $z = -2.93$, respectively.

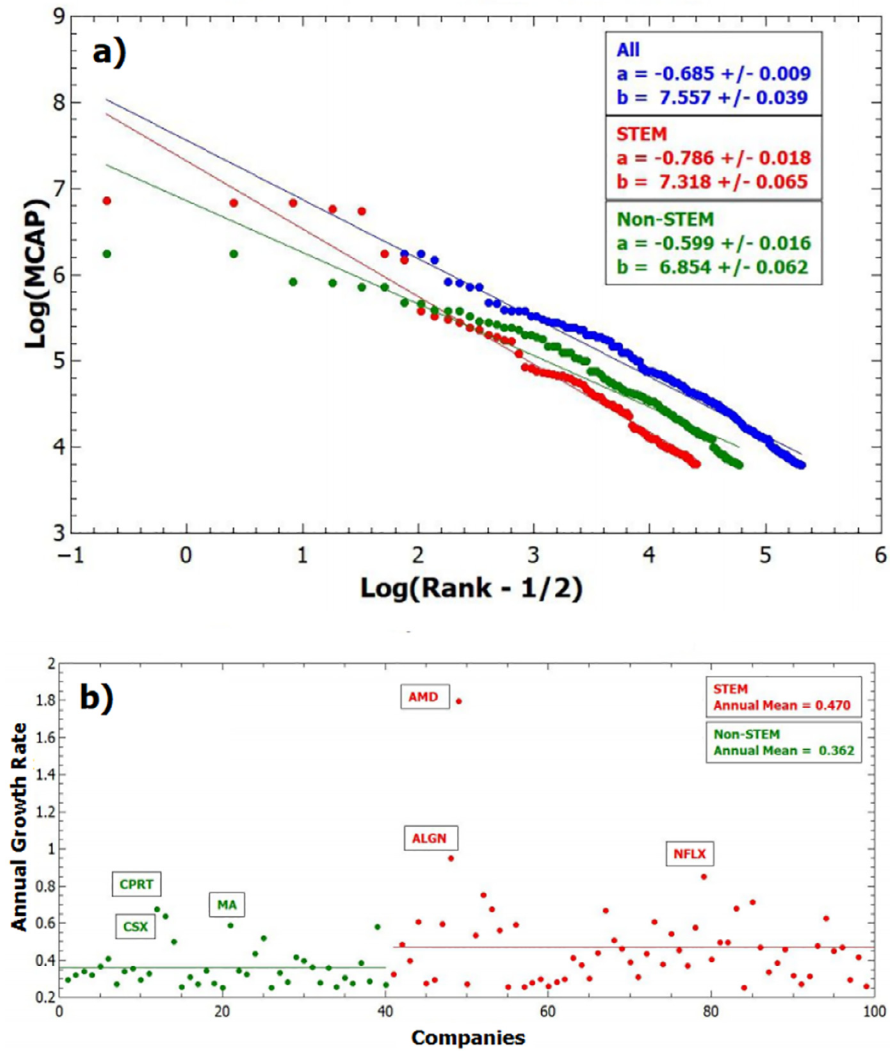


**Fig. 4.** Firm level. SP500 list. Analysed. (a) The Zipf plot of STEM-based US firms. (b) For 100 fastest growing companies, randomly presented, shown are growth rates $\Delta S/S_i$, for STEM and non-STEM companies. Regarding growth performance, STEM dominates over non-STEM.

For other industries, such as aerospace and defense, biotechnology, automobile, there are no significant differences in the $z$ value. We here suggest that when comparing them to non-STEM fields the new STEM fields in the first micro-test perform better than the more common STEM fields. Technology is changing rapidly in the automobile sector, and even more rapidly in the pharmaceutical, but not rapidly enough to beat the performance of non-STEM firms.

## Wealth inequality at country level: empirical evidences. STEM vs. Non-STEM

A US National Academies study of global competitiveness stress the importance of the STEM disciplines reporting that 40 percent of Chinese graduates majored in STEM fields in 2013—over twice the US percentage. Similarly, the WEF reported that in 2016, China had 4.7 million STEM graduates, that India had 2.6 million, and that the US had only 568,000. Using data from SCImago Journal & Country Rank (SCImago) database, in Fig. 5 for a set of countries we show how the number of publications since 1996 change over time in (a) Computer Science, (b) all STEM fields, (c) Economics, Business and Social Sciences, and (d) Arts&Humanities. Fully aware that here we compare countries with significantly different population and GDP, we first note how China and India dramatically ramp up its research output in Computer Science and entire STEM, where China even managed to surpass the US in the number of publications in this field. In contrast to STEM, and Computer Science, China and India put less focus in Social Science and A&H. How does this dramatic increase in Chinese STEM graduates and publications affect its levels of innovation and global competitiveness?

Our hypothesis is that STEM fields are a key factor in the economic growth of any country. As a first test we sample a small number of important STEM countries, including the US and its main economic competitors, including some that are experiencing in political conflict and economic sanctions. Fig. 6 shows the long-term growth rate of GDP at PPP between 1996 and 2016 vs. the number of STEM graduates in 2016. Due to a lack of data, this is a proxy for the average number of graduates in the period analyzed. To account for a country's economic size, we adjust the number of STEM graduates for each country for the country's GDP PPP. Because, on average, the larger the GDP value, the larger the government R&D expenditure, the variable on the horizontal axis is a proxy for the number of STEM graduates per dollar. Because GDP depends on many factors including capital and labor force, disregarding any possible causality. Fig. 6 suggests that the larger the number of STEM graduates, the larger the country's GDP growth rate in terms of dollars.

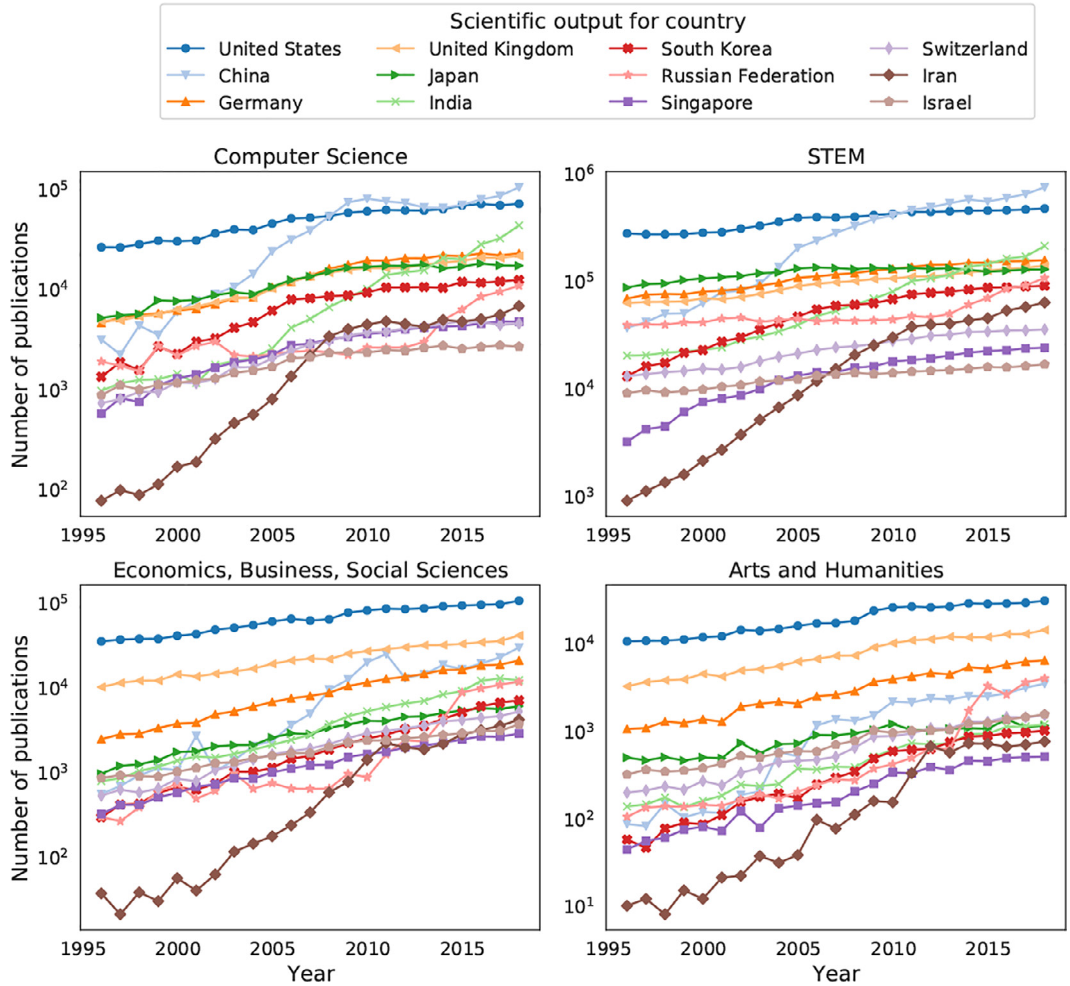


**Fig. 5.** Number of publications over 2 decades for a set of countries. Note how not only China and India but generally Asian nations put more emphasis in Computer Science and STEM fields than Western countries.

This analysis is problematic because the growth rate of a country depends on its level of development, and least developed countries such as China are expected to have a higher growth than more developed countries. To keep the level of development constant we only analyze OECD countries, which by definition are the most developed. We analyze the GDP PPP growth rate versus the average number of STEM graduates during the 14 years of available data (1998–2012) adjusted for country size. Fig. 6(b) shows that as in the previous analysis but for a more homogeneous set of countries there is a statistically significant relationship between the number of STEM graduates and the country's growth rate. This confirms the robustness of our results, since different sets of countries (WEF and OECD) and different time spans lead to the same conclusion. Although it is widely assumed that education level affects growth, our analysis is one of the few that indicate that not every discipline makes the same contribution.

## Model

To reproduce the results in Figs. 1–6, we propose a coupled Simon model [26], an extension of the Simon model used in the theory of firm growth. Each Simon model explains the evolution of either STEM or non-STEM firms (billionaires). Figs. 1 and 4(a) show that STEM billionaires (firms) exhibit fatter tails than non-STEM billionaires (firms). Using a preferential attachment ($PA_I$) mechanism [27] for non-STEM firms, we assume that the economy begins with few non-STEM firms at initial time $t = 1$. At each step $t_i$, with a probability $p_N$ a new unit of wealth (a new firm) is added to the economy, and with a probability $1 - p_N$ the new unit of wealth is taken over by an already existing firm [26]. The probability that a new wealth unit is taken over by an existing firm $j$ is equal to $(1 - p_N)A(j)/\Sigma A(k)$, where $A(j)$ is the firm size quantified by the number of units. Thus a richer firm is more likely to acquire a new unit of wealth than a poorer firm. Simon found a stationary cumulative distribution exhibiting power-law scaling, $P(s > x) \propto s^{-\alpha}$, with exponent $\alpha = 1/(1 - p_N)$ [26]. Here the larger the $p_N$ value, the smaller the $\alpha$ value, and the larger the $\xi$ value in Eq. (1).

Fig. 4 (b) shows that STEM firms have a larger growth rate than non-STEM, and when we apply $PA_I$ in STEM firms at each step $t_i$, two new units of wealth are added to the economy. In contrast, non-STEM firms add a single new unit of wealth to the economy. The two new units of wealth are deliberately chosen, and we can slowly increase the number of new STEM units to agree with Fig. 2. With a probability $p_S$, these two units are added to the economy as a new firm. Thus according to the Simon model the STEM firms have fatter tails than the non-STEM when $p_S < p_N$ [see Eq. (1)]. Thus there is a smaller probability $p_S$ that a new STEM firm will continue as an independent company, i.e., there is a higher probability that a new firm will be taken over by an already existing firms, which is in agreement with Stiglitz, who points out that the economy is dominated by a small number of corporations [17]. Jovanovic and Rousseau analyzed how venture capitalists dispose of

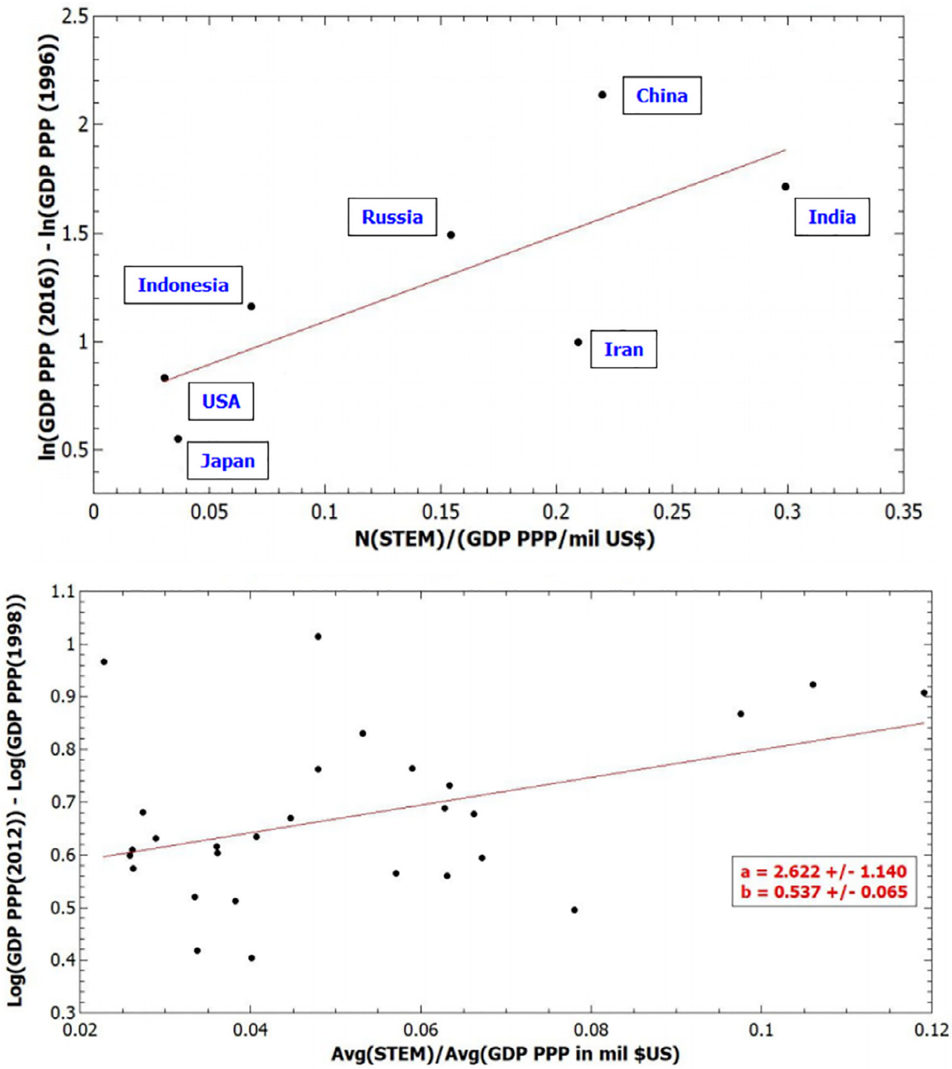


**Fig. 6.** Country level. The world economic forum: the significant dependence between economic growth and the number of STEM graduates for a small sample of countries with the largest number of STEM graduates. The number of STEM graduates is adjusted for the size of a country. Growth rate of GDP PPP during the 20 year period depending on the number of 2016 STEM graduates. (b) Not every education matters the same. STEM graduates of OECD countries.

both STEM and non-STEM companies and found a disposal probability of $p = 0.5$ [28].

To include billionaires in the model, we assume that the founder of an independent company initially owns a $q$ fraction of its total value, implying an equality in power law scaling for individuals and firms and a fractal nature in wealth inequality at the firm and individual level. Comparing Figs. 1(b) and 4(a) reveals that in 2018, the last year of our sample, the Zipf exponents of firms and individuals differ by $\approx 15\%$. We show that the average Zipf exponent for individuals calculated over the two decades is 0.56, which is close to the Zipf exponent calculated for 2018, and thus close to the Zipf exponent calculated for firms. This implies the existence of a fractal pattern in wealth inequality at the firm and individual levels. To include graduates in the model, we assume that once STEM (non-STEM) units are generated, the STEM (non-STEM) graduates immediatelu enter the economy, without stating any causal relationship.

Extending the model to the country level, we assume that with a probability $q$ at each moment two STEM units are generated, and with a probability $1 - q$ at each moment one non-STEM unit is generated. Over time the wealth of a country $G$, which is a proxy for GDP when the wealth is generated only by firms, equals $G = t[2q + (1 - q)] = t(1 + q)$. Because some countries have more STEM (non-STEM) graduates than others, we assume that $q$ will follow a homogeneous distribution. When we generate 1000 countries, the $q$ value is approximately $q = 1 - 0.001R$, where $R$ is the rank. Then $G$ for small values of $R$ decays exponentially—$ln(G) \propto -R$. If we assume that being STEM is power-law distributed—$1 + q \propto R^{\delta}$—then the Zipf plot of $G$ vs. $R$ decays as a power law.

Moving beyond individuals and firms to model the different STEM preferences of countries, we introduce a new PA mechanism ($PA_{II}$). Here at each moment two STEM units are created at the world level, and they are attracted to a country according to a PA mechanism. Thus the more STEM wealth a country has, the higher the probability they will attract new units and grow more rapidly. After a country attracts the units, we apply the previously defined $PA_I$ mechanism that holds among the firms. We similarly apply $PA_I$ and $PA_{II}$ to non-STEM units. Our mechanical model does not explain the underlying economic reasons why some countries are more STEM-alike (or non-STEM-like) but finds that STEM-like countries attract more new STEM firms, and that non-STEM-like countries attract more new non-STEM firms.

## Discussion and conclusion

We have demonstrated that there is a STEM driving mechanism for wealth accumulation at different economic scales that range from the individual to the firm to the country level. Our findings have implications in the area of public policy. Entrepreneurship and the creation of new wealth produces technologies that others can use as a platform for building complementary products. Our results suggest that public policy should increase investments in STEM research that can produce foundational technologies upon which others have the potential to build. Some examples include research in soft matter (e.g., organically growing computer chips), artificial intelligence, and virtual reality.

## Declaration of Competing Interest

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

## CRediT authorship contribution statement

**Boris Podobnik:** Conceptualization, Writing - review & editing. **G. Christopher Crawford:** Conceptualization, Writing - review & editing. **Benyamin Lichtenstein:** Conceptualization, Writing - review & editing. **Tomislav Lipic:** Conceptualization, Data curation, Formal analysis, Writing - review & editing. **Dorian Wild:** Data curation, Formal analysis, Software. **H. Eugene Stanley:** Conceptualization, Writing - review & editing.

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