The Impact of Automation on the Future of Work and Higher Education

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Higher education takes the inputs of faculty and students and produces the outputs of education credentials and scientific discovery. Until the turn of the 21st century, higher education was impervious to technological change. Faculty would lecture to students in person, assign readings, and conduct assessments designed to result in credentials that would be used in the labor market. The rise of the internet and related technologies has transformed higher education and the labor market in new and interesting ways. The COVID-19 pandemic required higher education to move online and teach remotely. Technology enabled these rapid changes and will have long-lasting effects on higher education and the type of work that our students will do in the future. In this essay, we consider the demographic challenges facing higher education, the role of robots, automation, and artificial intelligence (AI) in the labor market, and the downstream effects of AI on the student test score gap. We will conclude with a set of social science research recommendations that respond to the creative destruction of technological change.

Depressing Demographics

Kansas had below-average population growth of only 3% between 2010 and 2020, less than half the rate of U.S. growth of 7.4%. There were 35,000 fewer children in the state of Kansas in 2020 than there were in 2010. If matriculation patterns do not change, this means there will be fewer students attending universities in Kansas in the next decade. The Kansas Board of Regents estimated the number of high school graduating seniors by race for the next decade. Because there are meaningful correlations between race and higher education enrollment, we applied enrollment rates by race from 2019 to these projections in Figure 1 (on page 58). This figure shows that, at best, enrollment rates will remain flat in the next decade.

This likely reflects two factors: first we are in the echo of the "Baby Bust." The "Baby Bust" generation was much smaller than the preceding "Baby Boom," and their numbers of children are also lower. Total enrollments peaked in 2011 with 20.6 million students enrolled in higher education institutions. These were the children of the "Baby Boom." Since then, enrollments have dropped as the much smaller cohort of children of the "Baby Bust" went to college. In the fall of 2019, there were 18.2 million students, a drop of enrollments of 12%. COVID-19 made things worse and, as of the spring of 2021, only 16.9 million students were enrolled nationwide (National Clearinghouse, 2022).

The second factor pertains to race and higher education enrollment. U.S. enrollment in higher education tends to be highest for white students and lower for students of color who most often are first-generation college students. In Kansas and across the nation, there are proportionally fewer white children. These students historically have been more

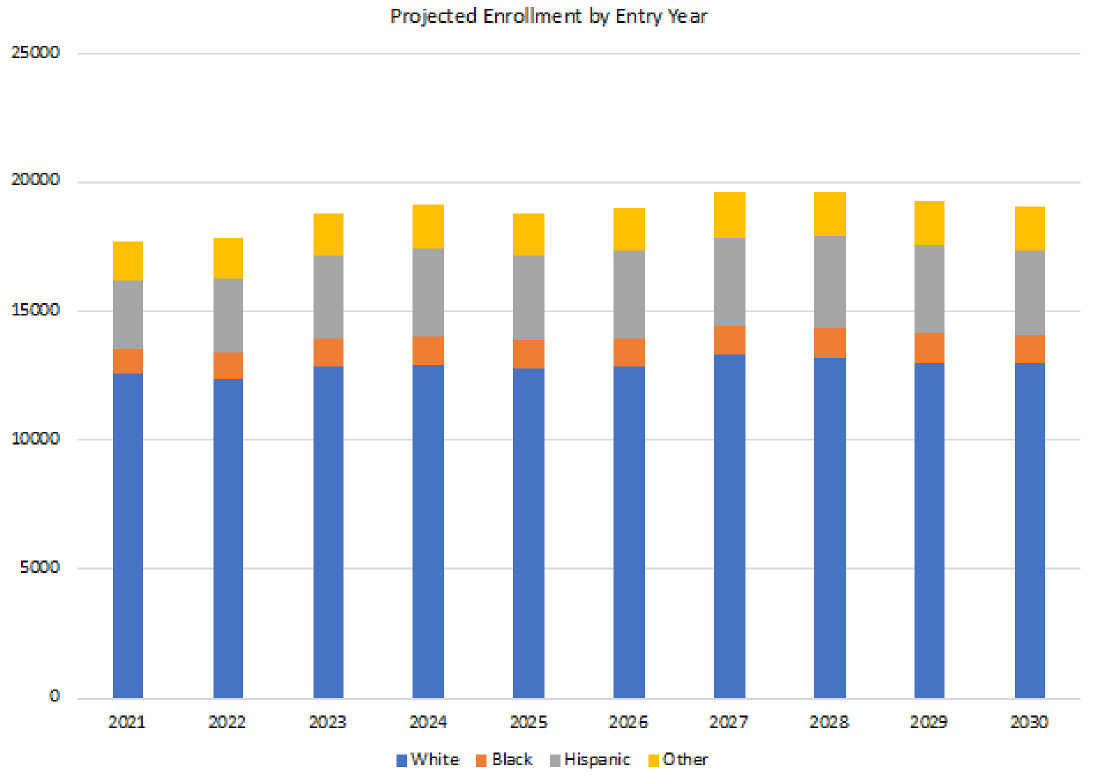

Figure 1: Projected Enrollment in Higher Education Institutions. Source: Kansas Board of Regents.

likely to attend college. Figure 2 (on page 59) shows the share of the Kansas population under the age of 18. Kansas has a higher share of the population under the age of 18 (24%) than the U.S. as a whole (22%). Color saturation for a geographic area in Figure 2 indicates a higher concentration of children in the population. Southwestern Kansas counties have higher concentrations of children. These counties also have higher numbers of immigrants. Because immigrants are more likely to be children of color, this suggests that the future students in Kansas will be more likely to be children of color. In the past decade, over 2,600 more Hispanic students graduated from Kansas high schools while 1,900 fewer white students graduated. Again, students of color have been less likely to enroll in higher education than white students. These depressing demographics suggest that fewer students will be enrolling in Kansas universities for the foreseeable future.

Creative Destruction and the Future of Work

With the backdrop of these depressing demographics, technology is changing work as we know it. In *Capitalism, Socialism & Democracy*, Joseph Schumpeter discussed how the dynamic economy evolves (p. 83):

> The opening up of new markets, foreign or domestic, and the organizational development from the craft shop to such concerns as U.S. Steel illustrate the same process of industrial mutation—if I may use that biological term—that incessantly revolutionizes the economic structure from within, incessantly destroying the old one, incessantly creating a new one. This process of Creative Destruction is the essential fact about capitalism.

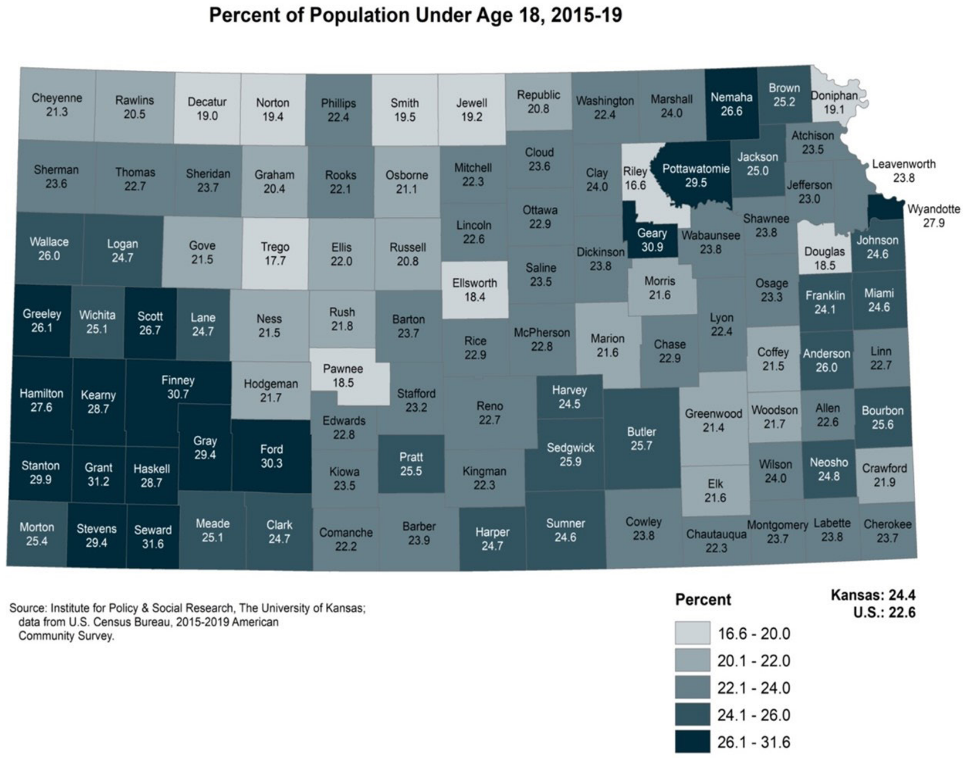

Figure 2: Percent of Population under the Age of 18. Source: Estimates from the American Community Survey 2015-2019.

While Schumpeter was not discussing technological change per se, technology "incessantly revolutionizes the economic structure from within." Technology eliminates jobs and industries. Desktop publishing eliminated the job of typesetter, and those who worked for printing companies left to find new work. Resources shift from declining industries to new industries so that former typesetters now become web designers. However, in the United States, where the social safety net is often an afterthought, individual workers bear the costs of creative destruction in the form of job loss and lower wages.

A seminal paper by David Autor, Frank Levy, and Richard Murnane (2003) developed a taxonomy of tasks that were subject to automation (job destruction). Tasks were divided into a quadrant of routine, non-routine, cognitive, and non-cognitive. Computers and robots displace workers in routine cognitive and non-cognitive tasks. For example, computers and robots replaced workers on assembly lines (routine, non-cognitive) and in bookkeeping (routine, cognitive). However, Autor, Levy, and Murnane (2003) also argued that non-routine tasks, both cognitive and non-cognitive, would be less likely to be displaced. Truck driving, the largest occupation of men in the United States, is an example of a non-routine, non-cognitive occupation. Legal work would be an example of non-routine, cognitive work.

The long-term effects of the creative destruction of technology can be observed in the agriculture industry. As agriculture became increasingly automated, farm labor declined significantly. Figure 3 (on page 60) shows the number of farmers and farm laborers in the U.S. from 1850 to 2015. The number of farmers peaked at 6.5 million in 1920. Automation decreased the number of farmers and

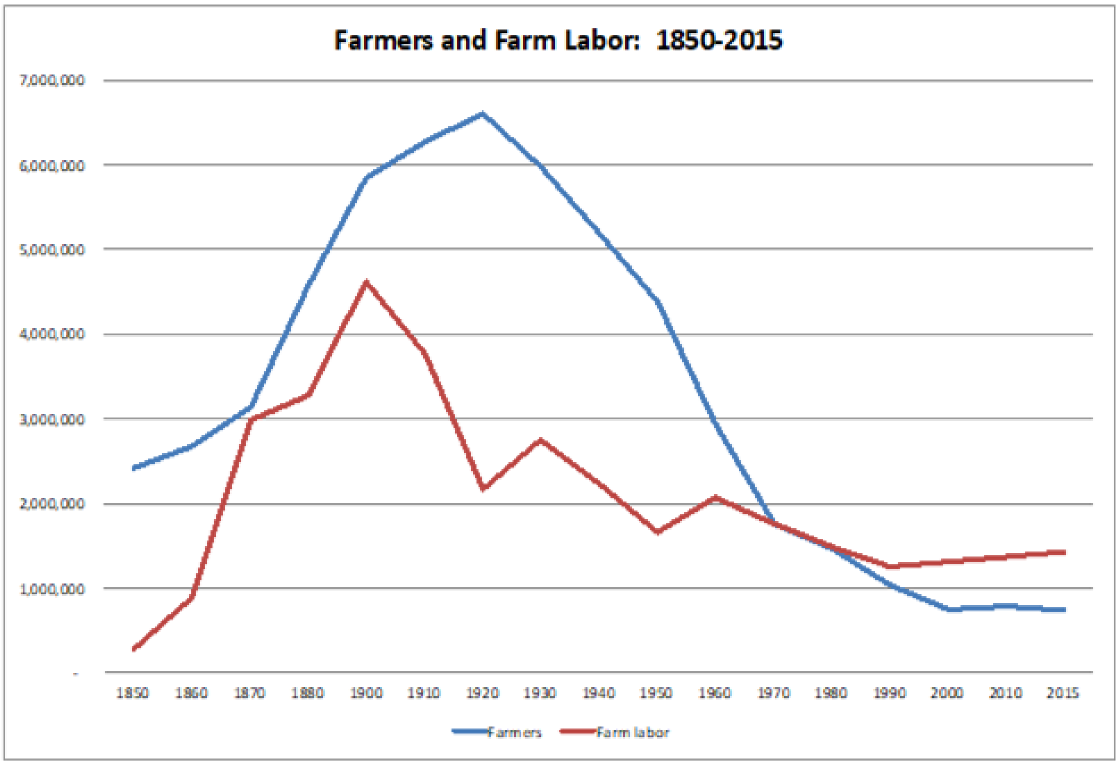

Figure 3: Farmers and Farm Laborers in the United States, 1850-2015.

farm laborers. Farms grew in size over time, so that the number of farm laborers now exceeds the number of farmers. Automation, coupled with economies of scale reduced total employment in agriculture. This trend continues with the introduction this year of the John Deere Fully Autonomous Tractor. The tractor uses a GPS guidance system and can be controlled by a mobile phone app. Now a farmer can plow a field from the comfort of his living room. In the next two or three decades, the production of wheat in Kansas may no longer require labor.

Clearly, agriculture was a victim of its own success in terms of employment, and former farm workers moved into other sectors such as trucking or transportation. Twenty years ago, the non-routine, non-cognitive work of driving a truck could not be automated. Now as many as 18 companies are developing autonomous trucks (Ribiero, 2021). Autonomous vehicles may soon replace truck drivers—again, the largest occupation for men. As technology makes rapid improvements, jobs that are non-routine and non-cognitive tasks may soon be eliminated by artificial intelligence.

This is also happening for highly skilled workers. For example, attorneys are being displaced by artificial intelligence systems. Electronic discovery products reduce the demand for attorneys and paralegals. Today, non-routine, cognitive and non-cognitive jobs are increasingly subject to automation and creative destruction.

Consider the following projections. Any task that can be broken into codifiable steps, regardless of complexity is increasingly prone to AI-driven automation. This leaves humans the inherently non-routine tasks that involve higher order capabilities (Jaimovich et al., 2021). Other researchers have predicted that AI will replace between 20% and 47% of all occupations in the U.S. economy by 2035 (Frey and Osborne, 2017, Felten, Raj, and Seamans, 2018; Nedelkoska and Quintini,

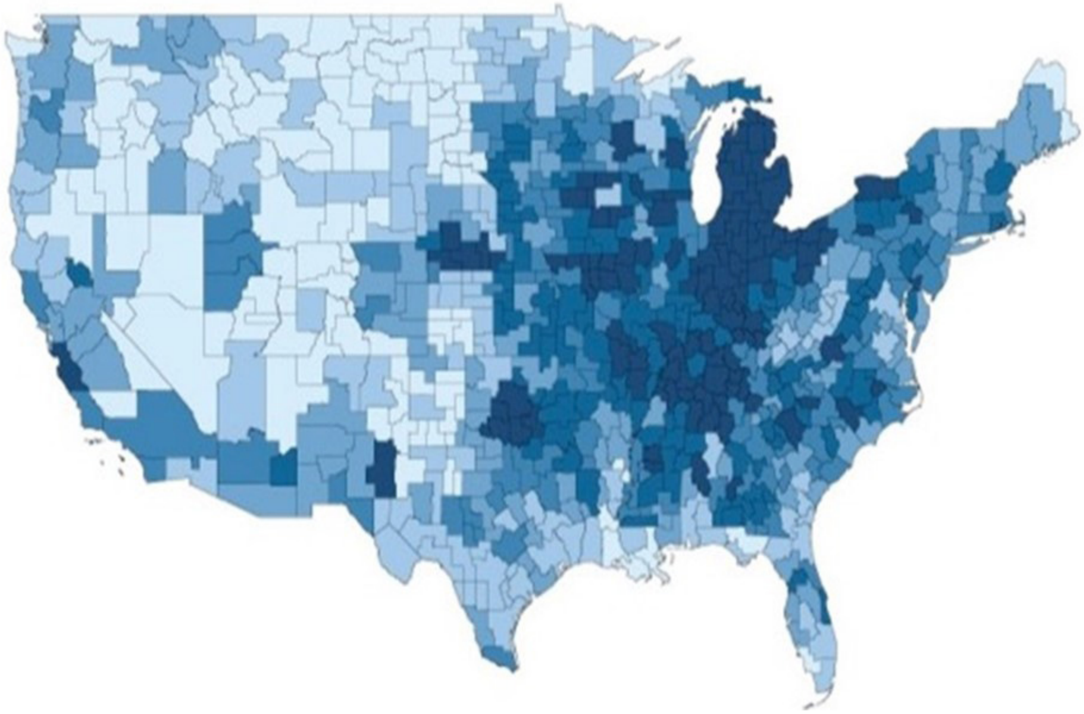

Figure 4: Occupation Automation Risk (OAR) by Commuting Zone.

2018). According to Manykia et al. (2017) about 60% of occupations will have at least a third of tasks that can be fully automated within a decade. This translates into 51% of the U.S. economy accounting for $2.7 trillion in wages. We now consider the impact of artificial intelligence in the labor market on the children of these workers.

Robots, AI, and the Test Score Gap

Economists Daron Acemoglu and Pascual Restrepo examined the impact of industrial robots on the U.S. labor market (Acemoglu & Restrepo, 2020). They estimated that each new AI-powered robot per 1,000 employees in a commuting zone eliminates 3.5 employees and reduces real wages by 0.5%. Over five years, more than 5,000 jobs would be lost, and real wages would decline by 7.5%. In our study, we investigate whether these jobs and earnings losses affect the families, communities, and student achievement. We hypothesize that AI automation coupled with import competition and offshoring has negative externalities for family structure, affected communities, and school resources. We expect that children living in commuting zones that experience increased exposure to AI-automation will experience declines in achievement in mathematics and reading.

Using the American Community Survey (ACS), we assigned an AI exposure score to each occupation. Figure 4 (above) shows the Occupation Automation Risk (OAR) by commuting zone in the U.S. The darker colors indicate higher OAR. Eastern Kansas faces a significantly higher OAR than western Kansas, but not as high as Missouri. Using two-way fixed effects estimation, we estimated the effect of commuting zone OAR on the test score gap—the gap between test scores for the economically advantaged and disadvantaged in mathematics in Figure 5 (on page 62). Economically advantaged students have higher achievement than the disadvantaged students. The gap grows with each year and is significantly different from zero. By 2018, economically advantaged students have 4% of a standard deviation in higher mathematics test scores controlling for the OAR.

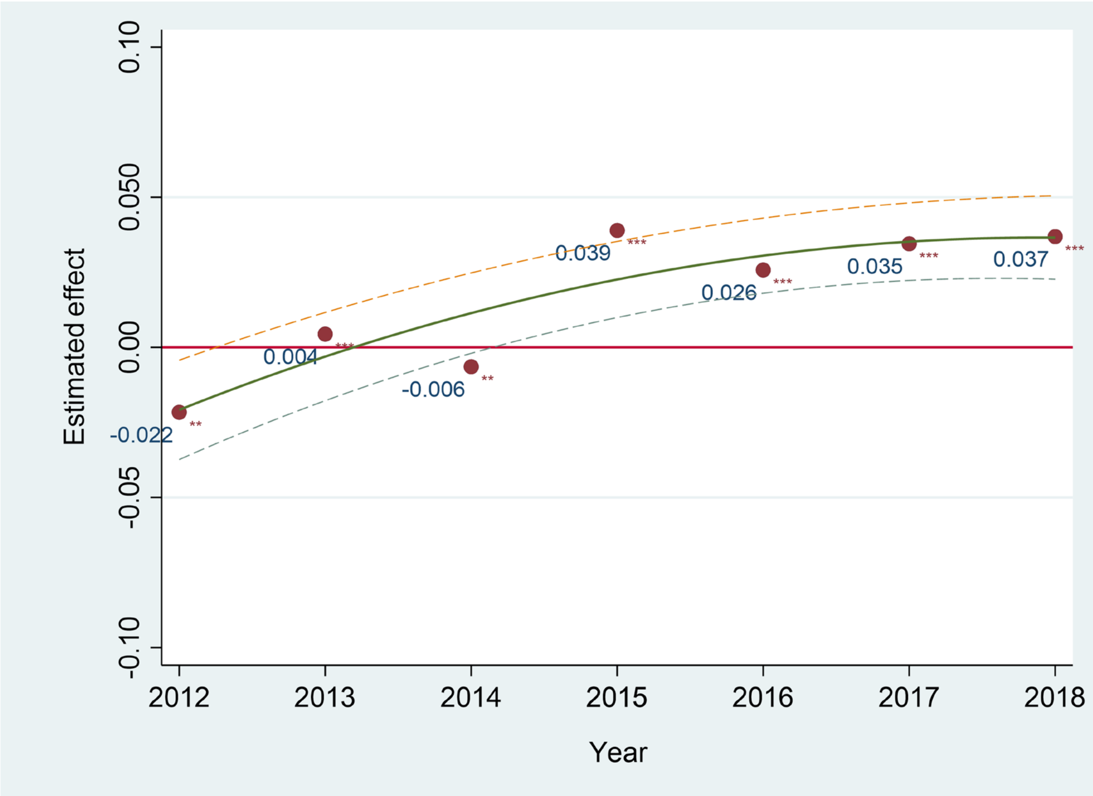

Figure 5: Estimated test score gap in mathematics between Economically Advantaged and Disadvantaged Students controlling for Occupation Automation Risk. ** p<.01, ***p<.001

This gap is troubling because students of the future are more likely to come from groups that have been historically disadvantaged. Technological change in the form of AI will increase the demand for non-routine skills. The jobs of the future will require quantitative skills and advanced degrees. This is good news for the higher education sector. However, AI and robot penetration increases the gaps between economically advantaged and disadvantaged students. Economically disadvantaged students are already less likely to matriculate in postsecondary institutions, and AI penetration appears to generate further academic and economic disadvantage.

AI and the Future of Social Science Research

Although AI penetration has a negative impact on the educational achievement of future generations, the same forces provide significant opportunities for social science research. The availability of big data sets and causal analysis revolution have created a "Golden Age" of social science research (Buyalskaya, Gallo, & Camerer, 2021). The COVID-19 pandemic underscored the importance of social science research. Despite the significant health hazards caused by the pandemic, many people did not heed expert advice and were opposed to wearing masks and getting vaccinated. Models of the spread of COVID-19 failed to adjust for the endogeneity of behavior. These are research questions that are the purview of social scientists.

The internet, social media, mobile phone technologies, and the government have generated an ocean of data that can be used to address the fundamental questions facing society. In addition, basic research funding is increasing to address these questions. There are a series of grand challenges facing social scientists:

- Economic inequality and poverty persist by race, gender, nativity, and educational attainment.
- What is the future of work? As discussed earlier, robots and AI will destroy jobs and undermine educational attainment. How do we equip the next generation with the skills they need to live successful lives?
- Science and innovation will be needed to address social challenges. How do we convert research discovery into products and policies that improve our world?
- Political polarization, fueled by technological change, social media, misinformation, and the mistrust of experts is giving rise to authoritarianism. How do we preserve our democratic institutions?
- Climate change is upon us, and massive population displacements have begun already. Will we be able to feed 8 billion people when droughts and disasters destroy agricultural capacity?
- In the face of climate change, automation, and education inequality, how will we, as a society, address health disparities?

Social science addresses these challenges with the same data that is used to develop artificial intelligence. Evidence-based policy that uses data to inform decisions will be critical as we confront the challenges of climate change, political polarization, and the future of work. Science and social science research will provide answers to these pressing challenges, but we as academics need to do a better job of communicating our findings to a broader audience. We need to transform Big Data to Knowledge (NIH, 2021).

The future of social science research will rest upon large administrative data sets that are linked together, generating Big Data to Knowledge (BD2K). Employers are desperate for workers with data skills. According to *Fortune*, data science jobs have grown 480% since 2016. While data skills are important, AI algorithms are only as good as the data used to train the system. Social science is necessary to develop unbiased algorithms and ensure that approaches to dataset development and deployment are sound.

Social science focuses on bias and inequality in society. Data collected by surveys or algorithms reflect these biases. If data scientists adopt a naïve approach to model-building, their AI algorithms and models will reinforce the bias baked into the data. Studies have shown that racial bias in algorithms have discriminated against black patients (Obermeyer et al., 2019). Using these algorithms without understanding how bias and historical inequality influences predictions will exacerbate the bias and inequality in society. Thus, data science approaches should be informed by social science perspectives. Left to its own devices, data science focuses on data reduction and prediction. However, to draw fundamental insights from data, it is important to understand the data generating process: in other words, society. Social science builds these skills in our students while investigating pressing questions facing society.

Conclusions

In this essay we have argued that demographics and technology are reshaping higher education, employment, and educational attainment. Kansas' low population growth means that higher education enrollments will remain flat for at least the next decade. We demonstrated that artificial intelligence and robots are the driving force behind creative destruction in the economy and employment.

Artificial intelligence is skill-biased, meaning that higher education will be needed to obtain the jobs of the future. Our preliminary evidence suggests that AI is associated with an increase in the mathematics test score gap. More work remains to be done to understand the mechanisms behind the growth in the test score gap between the economically advantaged and disadvantaged. That said, it appears that AI and robots destroy jobs today and may generate additional disadvantage and inequality for the next generation.

The same factors that have created job destruction have also contributed to the "Golden Age of Social Science." The world is awash in data, and the skills taught by social scientists will prepare our students for high-demand occupations such as data scientists. Data scientists will benefit from a firm understanding of social science in order to prevent AI algorithms from reinforcing the bias and inequality that exists in society.

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