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A global decline in research productivity? Evidence from China and Germany

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ABSTRACT

In a recent paper, Bloom et al. (2020) find evidence for a substantial decline in research productivity in the U.S. economy during the last 40 years. In this paper, we replicate their findings for China and Germany, using detailed firm-level data spanning three decades. Our results indicate that diminishing returns in idea production are a global phenomenon, not just confined to the U.S.

1. Introduction

Economists have proposed that continual decline in research productivity at the technology frontier potentially drives the observed stagnating or slowing growth rates in advanced economies over time (Gordon, 2016; Cowen, 2011). Bloom et al. (2020) present extensive empirical evidence in support of this hypothesis, and discuss implications for technological change and economic growth theories. The authors employ the following idea production function, one that is at the heart of many endogenous growth models (Romer, 1990; Aghion and Howitt, 1992), as a starting point for their analysis:

$$\dot{A}_t/A_t = \alpha \cdot S_t. \tag{1}$$

S_t measures inputs to idea production, such as the number of scientists working in a specific sector, and $\dot{A}_t/A_t$ measures total factor productivity (TFP) growth. The productivity of the research process, α, is usually assumed to be constant over time, which implies exponential growth in TFP, as well as final output, for a constant level of inputs. Bloom et al. present case study evidence from various industries, products and firms that cast doubt on this assumption though. They find input levels to be steadily increasing, while output growth remains constant, at best, implying that research productivity is actually declining over time (Bloom et al., 2020).

While the analysis of Bloom et al. focuses on the U.S., if replicable, their findings would have important policy implications elsewhere too. However, U.S. productivity trends might not necessarily be representative for developments in other jurisdictions. The U.S. economy has consistently been the global technology leader since WWII (Comin and Hobijn, 2010; Boeing and Mueller, 2016), with exceptionally high growth rates in GDP during the postwar period (Gordon, 2016). Thus, perhaps a noticeable decline in research productivity is simply a reflection of a 'regression to the mean' phenomenon (Pritchett and Summers, 2014).

Our goal in this paper is to replicate the analysis in Bloom et al. for other countries. We thereby focus on comparative analysis at the firm-level given that it is more generalizable than case

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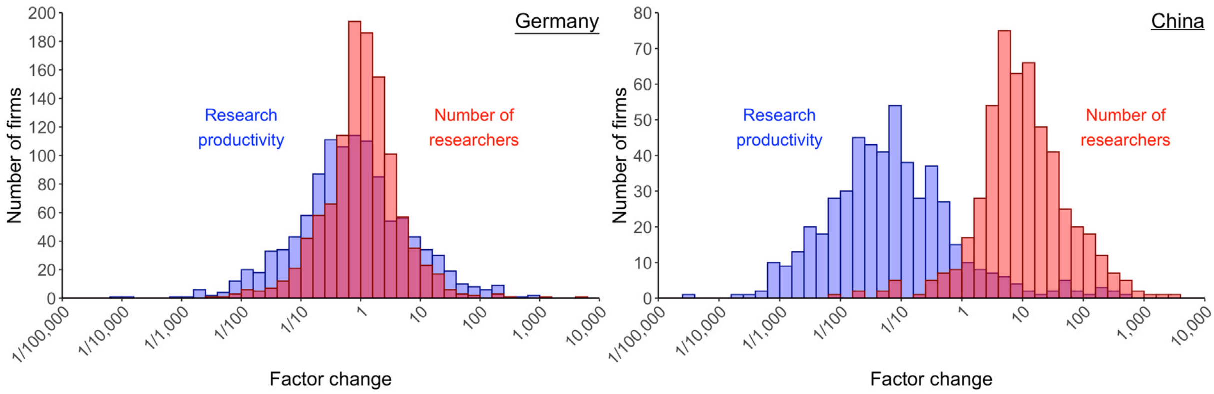

Fig. 1. Distributions of factor changes (sales revenue)

studies.[1] Since the methodology requires panel data for R&D-active firms over a long period, few data sources are suitable for this purpose. In the following, we present replication results for Germany, based on the Community Innovation Survey (CIS), and China, using data for publicly listed firms from the Chinese databases CSMAR, WIND and CNINFO. According to the OECD, China was the second largest, global R&D spender in 2017 (after the U.S.), and, analogously, Germany was the largest R&D spender in the E.U.

2. Data and methodology

The CIS is conducted on behalf of Eurostat as part of the official E.U. science and innovation statistics (OECD/Eurostat, 2018) to document the innovation activities of European firms. While cross-sectional and biennial in most countries, the CIS in Germany is organized as an annual panel survey (see Peters and Rammer, 2013). It covers the entire manufacturing sector, as well as large parts of the agrarian and service sectors. The data is representative of the overall structure of the German business enterprise sector and contains many small and medium-sized enterprises (avg. firm size = 468 employees, median = 31). We collect data for a sample of 64,902 firms across the period 1992–2017. Voluntary participation, however, reduces the number of firms that can be analyzed in the long run.

For China, we observe 3947 firms listed on the Chinese A-share market, between 2001 and 2019.[2] Listed firms provide the only Chinese firm-level data that span almost two decades and cover R&D expenditures. These firms are large- and medium-sized enterprises (LMEs) (avg. firm size = 5701 employees, median = 1775), which contributed 78.6% of the total R&D expenditures of industrial LMEs in 2018. Approximately two thirds of listed firms are in the manufacturing sector and the coastal region is represented proportionately more than inland regions. Such a composition closely resembles the sectoral and regional contribution of Chinese economic growth of the last two decades.

Following Bloom et al. we calculate the research productivity parameter, α, in Eq. (1), by taking the average of output growth per firm and decade (1990s, 2000s, and 2010s), and dividing by average input levels. As measures for output we use sales revenue, employment, revenue labor productivity, and market capitalization (monetary units deflated by the GDP implicit price deflator).[3] Market capitalization is not available for Germany's predominantly privately owned companies and we substitute it with sales revenue from innovative products and services. Regarding inputs, Bloom et al. (2020) show theoretically that research inputs in (1) can be measured by $\tilde{S}_t$, the "effective number of researchers", by deflating a firm's R&D expenditures, S_t, with the nominal wage rate for high-skilled workers in the economy.[4] In line with the original methodology, we make the following sample restrictions:

(i) firms need to be observed at least three times per decade;
(ii) decades in which a firm experiences negative average output growth (which is assumed attributed to reasons other than innovation) are not considered; and
(iii) the years 2008 and 2009 are dropped due to the financial crisis.

We then compute growth in research productivity over two consecutive decades[5] and calculate an average across firms, weighted by the median number of effective researchers employed during the observation period, as well as the corresponding factor changes (over ten years).

3. Results and conclusion

Table 1 depicts our results. In Germany, the effective number of researchers grows at an annual rate of 1.5% to 4.9%. Like Bloom et al.'s findings for the U.S., however, such input growth is not

[1] Bloom et al. use data from Compustat, which covers publicly listed firms, and the U.S. Census of Manufacturing. Because economy-wide productivity growth could be predominantly driven by firm entry and adding new product lines, they also present macro-level indicators. However, their main focus is on the micro-level for two reasons. Firstly, aggregate evidence clearly points toward rising R&D expenditures while growth rates are stagnating or decreasing, consistent with a decline in research productivity (Jones, 1995). This is similar in China and Germany. Secondly, aggregate indicators can be deceiving if achieving productivity growth in new product lines requires rising levels of aggregate R&D although R&D productivity within each product variety remains constant. We therefore concur with Bloom et al. that micro-level evidence is the more interesting case to consider.

[2] Chinese A-shares represent the second largest domestic equity market in the world with a total market capitalization of 8.5 trillion USD in 2019.

[3] Although the literature has related firm innovation to stock market capitalization, employment, sales, and revenue labor productivity to fundamental productivity, these variables can change for reasons other than the discovery of new ideas (see discussion in Bloom et al., 2020, p.1129). We refrain from the estimation of revenue total factor productivity, another typical performance measure, due to data concerns — including insufficient price information, reporting nuisances and the inclusion of the service sector firms in our sample.

[4] This result is based on a "lab equipment" model, in which both capital and labor are used as inputs in the idea production function (Romer, 1987). For Germany, we use gross wages in *performance group 2* (according to Destatis definition) to deflate R&D spending. For China, we take wages in the science sector. When instead using the average of wages in the Chinese urban, ICT and science sectors, our results remain virtually unchanged.

[5] For China, the first decade refers to the 2001–2010 period and the second decade to the 2011–2019 period. Bloom et al. also look at changes across three and four decades, which is, unfortunately, infeasible with our data.

Table 1
Research productivity in Germany and China.

	Effective research		Research productivity	
	Factor increase	Avg. growth (%)	Factor decrease	Avg. growth (%)
Germany:				
Revenue labor productivity (966 firms)	1.2	1.5	1.3	−2.4
Sales revenue (1121 firms)	1.4	3.8	2.3	−7.8
Employment (1317 firms)	1.3	2.8	2.1	−7.0
Sales with new products (230 firms)	1.6	4.9	1.5	−3.7
China:				
Revenue labor productivity (480 firms)	6.7	21.0	13.9	−23.1
Sales revenue (516 firms)	7.0	21.4	24.1	−27.3
Employment (332 firms)	8.6	24.0	5.3	−15.4
Market capitalization (601 firms)	6.9	21.2	32.2	−29.3

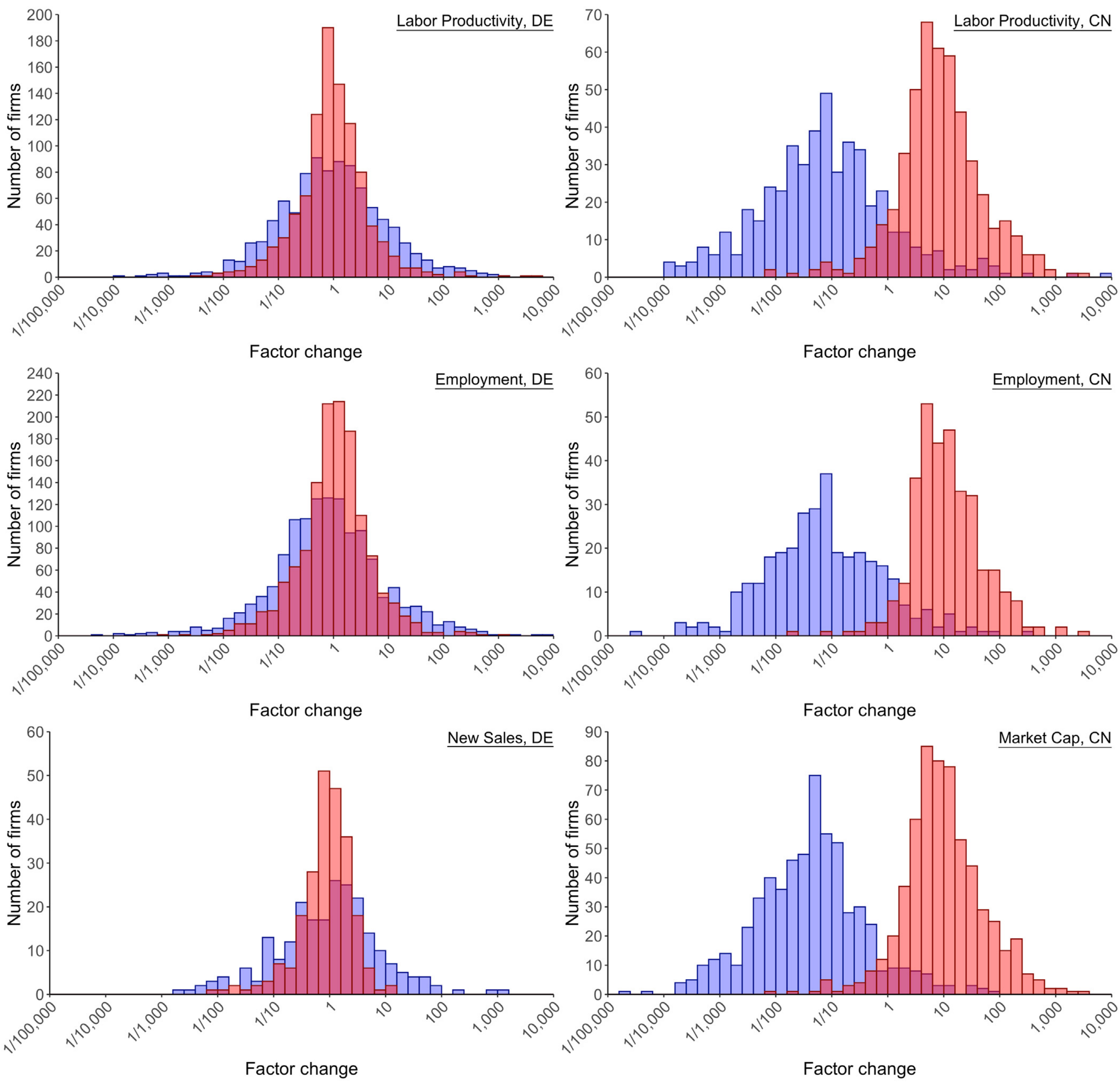

Fig. A.1. Distributions of factor changes (remaining output measures).

met with a proportional growth in output. As a result, we find declines in research productivity ranging from 3.7% to 7.8% per year. The average of the four estimates, equal to –5.225%, implies that research productivity halves every fourteen years, which is very close to the estimated half-life of thirteen years for the U.S. (Bloom et al., 2020). In China, we observe an extremely rapid expansion of research activities during the first and second decades of the 21st century, with growth rates for effective researchers ranging between 21% and 24%.[6] The resulting output growth, again, is not proportional to such inputs, which is reflected in a decrease in research productivity estimated between 15.4% and 29.3%. Averaged across estimates, this amounts to a decline of –23.775% per year, or a half-life of around 3 years.[7]

Fig. 1 depicts the distributions of factor changes, which show similar levels of heterogeneity across firms than in Bloom et al. (to allow for comparability, we depict graphs for the sales revenue data here; factor changes for the other output measures are reported in the Appendix). The null hypothesis of a constant research productivity (i.e., a factor change of one) can be rejected for the majority of firms in both countries. In Germany, with its many SMEs, the (unweighted) distributions of factor changes visually appear to be closer together than in the U.S.; while the weighted averages, calculated in Table 1, are quite similar to the magnitudes found by Bloom et al. This suggests that the average decline in research productivity in Germany is mainly driven by larger firms with generous R&D budgets. By contrast, in China, the distributions of factor changes are located much further apart, which reflects a substantial increase in research input levels coupled with a sharp decline in research productivity.

Overall, ideas are not only getting harder to find in the U.S., but that the same holds true for the largest R&D-spending countries in Europe and Asia respectively. Although estimates are difficult to compare, due to differences between data sources, negative growth rates are, in fact, remarkably similar across Germany and the U.S. China has undergone an even larger decline in research productivity in the last two decades, which reflects its rapid transformation from principally capital-driven growth toward more innovation-led growth. More importantly, however, returns to catching-up oriented R&D that pursues the implementation of existing ideas and technologies are diminishing, as China is closing its distance to the global knowledge frontier. It remains to be seen whether China will start to follow productivity trends of advanced economies. The increasingly inward-looking and mission-driven nature of Chinese innovation policy (Chinese State Council, 2020) suggests that research productivity might continue to decline faster in China than elsewhere. Knowledge production at the technology frontier crucially relies on creative freedom, serendipitous discovery, and exchange (Stephan, 2010). If these important channels of idea creation are further curtailed, significant knowledge-based productivity growth will be harder to sustain in the future. Innovation policy, in general, may contribute to a diminishing research productivity if additional R&D has lower economic returns than privately funded projects. Explicitly mission-driven policy may be even more harmful if government-supported technologies that contribute to strategic government purposes, such as national security, turn out to be economically inferior compared to the choice of the market. While China's innovation policy often addresses cutting-edge innovation and prestige projects, the desire to leap frog and move into radically new products and technologies may come at huge opportunity costs.

Appendix

See Fig. A.1.

References

Aghion, P., Howitt, P., 1992. A model of growth through creative destruction. Econometrica 60 (2), 323–351.

Bloom, N., Jones, C.I., Van Reenen, J., Webb, M., 2020. Are ideas getting harder to find? Am. Econ. Rev. 110 (4), 1104–1144.

Boeing, P., Mueller, E., 2016. Measuring patent quality in cross-country comparison. Econom. Lett. 149, 145–147.

Comin, D.A., Hobijn, B., 2010. Technology Diffusion and Postwar Growth. NBER Working Paper 16378, National Bureau of Economic Research.

Cowen, T., 2011. The Great Stagnation: How America Ate All the Low-Hanging Fruit of Modern History, Got Sick, and Will (Eventually) Feel Better. Dutton, New York.

Gordon, R.J., 2016. The Rise and Fall of American Growth: The US Standard of Living Since the Civil War. Princeton University Press, Princeton, NJ.

Jones, C.I., 1995. R&D-based models of economic growth. J. Political Econ. 103 (4), 759–784.

OECD/Eurostat, 2018. Oslo Manual 2018: Guidelines for Collecting, Reporting and Using Data on Innovation, fourth ed. In: The Measurement of Scientific, Technological and Innovation Activities, OECD Publishing, Paris/Eurostat, Luxembourg.

Peters, B., Rammer, C., 2013. Innovation panel surveys in Germany. In: Gault, F. (Ed.), Handbook of Innovation Indicators and Measurement. Edward Elgar Publishing, Cheltenham, UK, pp. 135–177.

Pritchett, L., Summers, L.H., 2014. Asiaphoria Meets Regression to the Mean. NBER Working Paper 20573, National Bureau of Economic Research.

Romer, P.M., 1987. Growth based on increasing returns due to specialization. Am. Econ. Rev. 77 (2), 56–62.

Romer, P.M., 1990. Endogenous technological change. J. Political Econ. 98 (5), 71–102.

State Council of the Communist Party of China Central Committee, 2020. Opinions on Speeding Up the Perfection of the Socialist Market Economic System in the New Era.

Stephan, P.E., 2010. The economics of science. In: Handbook of the Economics of Innovation, vol. 1, pp. 217–273, chap. 5.

[6] This represents growth at the intensive margin, given our methodology. The sharp increase in research is also reflected by an increase in the number of firms conducting R&D activities though: from 40.3% to 90.6% in the first and second decade.

[7] We caution against a naïve extrapolation though, as the decline in research productivity amounts to only 7.3% per year in the last decade (calculated in 5-year intervals, 2010–2014 to 2015–2019), indicating that China is converging to the global research frontier.