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BOMBS, BRAINS, AND SCIENCE: THE ROLE OF HUMAN AND PHYSICAL CAPITAL FOR THE CREATION OF SCIENTIFIC KNOWLEDGE

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Abstract—I examine the role of human and physical capital for the creation of scientific knowledge. I address the endogeneity of human and physical capital with two exogenous shocks: the dismissal of scientists in Nazi Germany and World War II bombings. A 10% shock to human capital reduced output by 0.2 SD in the short run, and the reduction persisted in the long run. A 10% shock to physical capital reduced output by 0.05 SD in the short run, and the reduction did not persist. The dismissal of star scientists caused much larger reductions in output because they are key for attracting other successful scientists.

I. Introduction

WHICH inputs create successful research universities? Anecdotal observation suggests that human and physical capital are important inputs in the production of scientific knowledge (Machlup, 1962). Understanding the causal effect of these inputs and their relative role for the creation of scientific output is important for policymakers, university administrators, and researchers alike, especially in times of substantial changes in government funding for the higher education sector.

Despite the significance of these issues, we know little about the effects of different inputs in the production of scientific knowledge. As highlighted by a large literature in industrial economics about firms, the estimation of production functions is difficult because managers adjust inputs after unobservable productivity shocks (e.g., Ackerberg et al., 2007). Estimating knowledge production functions is similarly challenging. Star scientists select into more productive departments and increase these departments' productivity. Similarly, high-quality labs are often built in more productive departments and further enhance productivity. Because star scientists often attract funding for labs, complementarities between human and physical capital complicate the estimation of knowledge production functions.

To overcome these challenges, I use two extensive, but temporary, shocks that affected German and Austrian science departments. First, I use the dismissal of mostly Jewish scientists in Nazi Germany between 1933 and 1940 as a large shock to human capital. Second, I use the destruction of science facilities during the Allied bombing campaign of World War II (WWII) as a large shock to physical capital. The two shocks create ample variation across departments. Some departments lost more than 60% of their faculty, while others did not lose anyone. Similarly, some departments were completely destroyed by Allied bombings, while others remained fully intact. The department-level variation allows me to isolate the effects of the human and physical capital shocks from other shocks that may have affected German and Austrian science departments during and after the war.

To investigate the long- and short-run effects of the two shocks, I construct a data set of all scientists in German and Austrian physics, chemistry, and mathematics departments at seven points in time between 1926 and 1980. The microdata contain more than 10,000 scientist-year observations with detailed publication records for each scientist. These data allow me to construct output measures for all science departments between 1926 and 1980. I add information on the two shocks from detailed historical records of dismissals in Nazi Germany and from archival material on bombing destruction during WWII.

Results show that both human and physical capital shocks had a negative effect on scientific output in the short run. A 10% shock to human capital lowered department output by 0.2 standard deviations. A 10% shock to physical capital lowered output by 0.05 standard deviations. The short-run results offer insights into the underlying importance of human and physical capital for the creation of scientific knowledge because departments took time to hire new scientists and reconstruct buildings in the immediate aftermath of the shocks.

I also investigate the long-run persistence of the two shocks. The human capital shock persisted in the long run and continued to have a negative impact on scientific output until 1980, almost fifty years after the dismissals. The physical capital shock, however, did not persist. Scientific output of departments that were bombed during WWII

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recovered by 1961. By 1970, bombed departments even had slightly higher output than other departments, suggesting that bombed departments benefited from upgrading during postwar reconstruction.

My empirical strategy relies on department-level variation in the two shocks. Thus, I can control for other changes that affected German and Austrian science departments in a similar way by including year fixed effects or even subject-times-year fixed effects. My results are robust when I control for a variety of changes stemming from the war and from postwar events at regional, city, and university levels. In particular, the results are robust to controlling for postwar occupation zones, for the creation of federal states after WWII, for city-level bombing destruction, for changes in the fraction of Jews, for investment in armament-related industries, for distance to the iron curtain after the division of Germany, for changes in university age, for competition from newly founded universities, for mean reversion, and for other university-wide changes after 1945. The results are also robust to excluding East German or Austrian universities from the sample, using Swiss universities as an alternative control group, measuring the two shocks in alternative ways, and addressing measurement error of bombing destruction.

Recent work has highlighted the importance of star scientists for the creation of scientific knowledge (Azoulay, Zivin, & Wang, 2010; Moser, Voena, & Waldinger, 2014). Many of the dismissed scholars were among the leaders of their profession; my data include eleven dismissed Nobel laureates such as physicists Albert Einstein and Max Born and chemists Fritz Haber and Otto Meyerhof. I can therefore investigate how losing high-quality scientists affected department output. The loss of a scientist in the top 5th percentile, for example, reduced output by between 0.7 and 1.6 standard deviations, compared to the 0.2 standard deviation reduction in output associated with the loss of any scientist. These results indicate that star scientists are indeed the main drivers of knowledge production.

I then evaluate potential mechanisms that could explain the persistence of the human capital shock. A reduction in department size after the dismissals explains only some of the decline in output. I show that a key mechanism for the persistence of the human capital shock was a permanent fall in the quality of hires, in particular, after losing high-quality scientists.

Recent work on the short-run effects of the dismissal of scientists in Nazi Germany has documented that the quality of Ph.D. students declined in affected departments, while the productivity of established scientists was unaffected by the dismissal of their colleagues (Waldinger, 2010, 2012).[1] This earlier research indicates that the productivity of individual faculty peers was not affected by the dismissal of high-quality colleagues, but the results in this paper show that total department quality declined in the short run because departments lost some of their best researchers and that this decline persisted in the long run because departments could not hire adequate replacements. These new results show that despite the absence of localized productivity spillovers, the loss of human capital can have persistent and large negative effects on output because departments do not manage to hire appropriate replacements for lost professors, especially star scientists.

To my knowledge, no previous research has examined the roles that human capital and physical capital play in the creation of scientific knowledge. My research uses exogenous variation to compare and contrast the influence of both. Existing empirical evidence has shown that scientific output of university departments is correlated with department size and research expenditure (Johnes, Taylor, & Francis, 1993). At the country level, patenting is significantly related to R&D manpower and spending (Furman, Porter, & Stern, 2002).[2] In a recent paper, Agrawal, McHale, and Oettl (2014) show that the hiring of a star scientist leads current evolutionary biology departments to increase output through the subsequent hiring of other good scientists but not through positive spillovers on existing members of the department. While Agrawal et al. (2014) cannot rely on exogenous variation for the hiring of star scientists, their results suggest that my findings for the human capital shock may also apply more broadly and beyond the historical context.

My findings also relate to several papers investigating the persistence of large economic shocks. Physical capital shocks, such as those from extensive bombings, usually dissipate relatively quickly (Davis & Weinstein, 2002; Brackman, Garretsen, & Schramm, 2004; Miguel & Roland, 2011). Most human capital shocks, however, seem to persist in the long run. The extinction of the Jewish population in the Soviet Union by the German Army during WWII still affects city growth, per capita income, wages, and political outcomes today (Acemoglu, Hassan, & Robinson, 2011) and reduces entrepreneurship and support for markets and democracy (Grosfeld, Rodnyansky, & Zhuravskaya, 2013). In Germany, the decline of the Jewish population during the Nazi era had persistent negative effects on education levels (Akbulut-Yuksel & Yuksel, 2015). In this paper I analyze the persistence of human and physical capital shocks within the same framework for the first time. My results corroborate the findings of earlier papers that have separately analyzed human and physical capital shocks.

This paper also improves our understanding of Germany's decline as a scientific superpower after WWII. At the beginning of the 20th century, German scientists were

[1] Similarly, Borjas and Doran (2012) document that the migration of highly qualified Soviet mathematicians to the United States did not lead to a productivity increase of incumbent U.S. mathematicians but rather to a decrease in publication output.

[2] A number of papers investigate other drivers of university output. University governance significantly affects how changes in funding affect research performance (Aghion et al., 2010). An increase of university funding increases the number of published papers but not their quality (Payne & Siow, 2003; Whalley & Hicks, 2014). At the level of individual scientists, National Institutes of Health funding has only a limited impact on the research of marginal grant recipients (Jacob & Lefgren, 2011). However, Howard Hughes Medical Institute grants, which tolerate early failure and reward long-run success, increase the probability of publishing high-impact papers (Azoulay, Graff Zivin, & Manso, 2011).

at the pinnacle of their professions. The leading German universities, especially Göttingen and Berlin, attracted large numbers of foreign scholars. In the 1920s, Göttingen offered permanent and visiting positions that attracted some of the world's most prominent physicists, including Arthur Compton (Nobel Prize, 1927) and Robert Oppenheimer from the United States, Leo Szilard and Eugene Wigner (Nobel Prize, 1961) from Hungary, Enrico Fermi (Nobel Prize, 1938) from Italy, and many Germans such as Werner Heisenberg (Nobel Prize, 1932), Max Born (Nobel Prize, 1954), and James Frank (Nobel Prize, 1925) (Dardo, 2004, 171). Many of these illustrious scientists were later dismissed by the Nazi regime. After WWII, the importance of German science plummeted, and the United States rose to become the world's scientific leader. This development is reflected in data on Nobel Prizes as shown in figure A1 in the online appendix. Germany's decline may have been caused by a number of factors. The dismissal of some of the most prominent scientists and bombing destruction during WWII are obvious factors that I consider in this paper.

My estimates indicate that the dismissals of scientists reduced output in affected German and Austrian science departments between 1933 and 1980 by 9,576 top journal publications, a reduction of about 33.5%. Output as measured by citation-weighted publications declined by 191,920 (34.6%) citations as a result of the dismissals. In the same time period, dismissed scientists produced 1,181 top journal publications receiving 32,369 citations. These results indicate that German science lost much more than the publications of the dismissed scientists because the reduction in output in departments with dismissals persisted at least until 1980. WWII bombings of German and Austrian science departments reduced output of affected departments between 1944 and 1980 by 1,028 top journal publications, a fall of about 5.7%; citation-weighted publications declined by 22,194 (6.4%).[3] These calculations suggest that the dismissal of scientists in Nazi Germany contributed about nine times more to the decline of German science than physical destruction during WWII.[4]

II. Human and Physical Capital Shocks

Scientific knowledge is produced by human and physical capital (Machlup, 1962). University governance determines how these inputs are combined in knowledge production. Recent research has shown that more autonomous universities and those operating in a more competitive environment are better at converting funding increases into research output (Aghion et al., 2010).

[3] The time periods for these calculations differ for dismissals and bombings because dismissals started in 1933 and bombings intensified in 1943.

[4] For subject-level results and details on these calculations, see appendix section 8.3.

Estimating knowledge production functions is challenging because managers adjust inputs after unobservable productivity shocks (Ackerberg et al., 2007) and because star scientists select, and are selected, to work in more productive universities. Establishing causality is therefore difficult in this context. Even without these endogeneity concerns, it is challenging to directly estimate the production function of universities because it is difficult to measure physical capital of science departments over reasonably long time periods. To overcome these challenges, I analyze the importance of human and physical capital by investigating the effect of large and exogenous shocks to the human and physical capital of German and Austrian science departments. I estimate how these shocks affected department output in the short and long run as follows:

$$\begin{aligned} Output_{dt} = \beta_1 &+ \sum_{t\neq 1931}^{t} \beta_{2t} HCShock(1933\text{-}40)_d \times Year_t \\ &+ \sum_{t\neq 1940}^{t} \beta_{3t} PCShock(1942\text{-}45)_d \times Year_t \\ &+ \beta_4 DepartmentFE_d + \beta_5 YearFE_t \\ &+ \beta_6 X_{dt} + \varepsilon_{dt}. \end{aligned} \tag{1}$$

$Output_{dt}$ is a measure of department d's research output in year t, measured by publications or citation-weighted publications. $HCShock(1933\text{-}40)_d$ measures the shock caused by the dismissal of scientists by the Nazi government between 1933 and 1940. *PCShock(1942-45)* measures the shock caused by Allied bombings between 1942 and 1945. I describe both shocks in more detail below. The interactions of the shocks with year dummies (one for each of the seven years between 1926 and 1980 for which I observe department output; one of those seven interactions will be excluded as the omitted category) allow me to investigate the short- and long-run effects of the two shocks.[5] The short-run results offer insights into the underlying importance of human and physical capital for the creation of scientific knowledge because departments needed time to hire new scientists and reconstruct buildings in the immediate aftermath of the shocks. The long-run persistence of the two shocks indicates how quickly departments recovered from sharp losses to human and physical capital.

The estimating equation also includes 105 department fixed effects. They control for factors that did not change over time and affected scientific output, such as persistent quality differences across departments. Year fixed effects

[5] One may be concerned that bombings also affected human capital if scientists were killed during the bombing campaign. I find no evidence that the number of scientists who disappear from the sample between 1940 and 1950 (for nonretirement reasons) is correlated with bombing destruction. In a regression of the number of scientists who disappear between 1940 and 1950 on bombing destruction, the coefficient on department-level destruction interacted with the 1950 dummy is –0.006 with a p-value of 0.43. This evidence is consistent with historical accounts that document relatively low casualty rates of the Allied bombing campaign.

control for factors that had the same effect on output in all German and Austrian science departments in a given year, such as the general disruption of scientific activity during WWII. The short- and long-run effects of the human and physical capital shocks are identified from department-level variation of the two shocks.

A. *Human Capital Shock: Dismissal of Scientists in Nazi Germany*

The dismissal of Jewish and "politically unreliable" scientists by the Nazi government was a large shock to the human capital of German and Austrian science departments. On April 7, 1933, just over two months after the National Socialist party seized power, the new government passed the Law for the Restoration of the Professional Civil Service. Jewish and "politically unreliable" persons were dismissed from civil service positions all over Germany.

Anybody with at least one Jewish grandparent was considered Jewish and summarily dismissed. Scientists of Jewish origin who had been civil servants since 1914, or had fought in WWI, or had lost a close family member during the war, were exempted initially. In 1935 the Reich Citizenship Law (Reichsbürgergesetz) revoked the exemptions, and remaining scientists of Jewish origin were ultimately dismissed. The 1933 law also served to dismiss civil servants with opposing political views, such as members of the Communist party. The law was immediately implemented and resulted in a wave of dismissals and early retirements from German universities. After the annexation of Austria on March 12, 1938, the law was extended to Austrian universities.

Overall, more than 1,000 academics were dismissed from German universities. This included 15.0% of physicists, 14.1% of chemists, and 18.7% of mathematicians (table 1). Most dismissals occurred in 1933, immediately after the law had been passed.[6]

Many dismissed scientists were outstanding members of their profession. They published more top journal papers and received more citations than average scientists. While 15.0% of physicists were dismissed, they published 23.8% of top journal papers before 1933, and received 64% of the citations to papers published before 1933. In chemistry, 14.1% were dismissed but wrote 22.0% of top journal articles and received 23.4% of citations. In mathematics, 18.7% were dismissed but wrote 31.0% of top journal papers and received 61.3% of citations (table 1).

Most of the dismissed scientists emigrated, and the majority of them obtained positions in foreign universities. The main emigration destinations were the United States, the United Kingdom, Turkey, the British Mandate of Palestine (later Israel), and Switzerland. In the United States, the

[6] I cannot identify whether researchers were dismissed because of their Jewish origin or their political orientation. Historical studies have shown that about 87% of dismissals in chemistry (Deichmann, 2001) and 79% of dismissals in mathematics (Siegmund-Schultze, 1998) affected scientists of Jewish origin.

Table 1.—Number and Quality of Dismissed Scientists

	Physics				Chemistry				Mathematics			
Year of Dismissal	Number of Dismissals	Percentage of All Scientists in 1931	Percentage of Publications Published by Dismissed	Percentage of Citation-Weighted Publications Published by Dismissed	Number of Dismissals	Percentage of All Scientists in 1931	Percentage of Publications Published by Dismissed	Percentage of Citation-Weighted Publications Published by Dismissed	Number of Dismissals	Percentage of All Scientists in 1931	Percentage of Publications Published by Dismissed	Percentage of Citation-Weighted Publications Published by Dismissed
1933	32	9.4	13.6	59.3	38	7.8	11.2	11.2	27	11.7	23.6	51.3
1934	6	1.8	6.8	1.4	8	1.6	1.0	1.3	4	1.7	0.8	0.0
1935	6	1.8	1.6	1.5	6	1.2	2.7	1.5	5	2.2	3.5	0.8
1936	0	0.0	0.0	0.0	1	0.2	0.4	0.8	0	0.0	0	0.0
1937	1	0.3	0.3	0.0	3	0.6	0.3	0.5	2	0.9	1.7	5.7
1938	3	0.9	0.6	0.1	9	1.8	5.5	7.3	3	1.3	0.9	3.3
1939	2	0.6	0.6	0.0	3	0.6	0.8	0.7	1	0.4	0.3	0.0
1940	1	0.3	0.2	1.6	1	0.2	0.1	0.1	1	0.4	0.3	0.2
1933–1940	51	15.0	23.8	64.0	69	14.1	22.0	23.4	43	18.7	31.0	61.3

Number of Dismissals is the total number of dismissals in a subject (physics, chemistry, or mathematics) in a given year. Percent of All Scientists in 1931 reports dismissals as a percentage of total faculty in 1931. Percentage of publications published by dismissed reports the percentage of publications that were published by the dismissed between 1928 and 1932. Pecentage of Citation-Weighted Publications Published by Dismissed reports the percentage of citation-weighted publications that were published by the dismissed between 1928 and 1932.

arrival of émigrés from Nazi Germany led to large increases in the number of patents granted to U.S. chemists (Moser et al., 2014).

The dismissals affected departments to a varying degree, even within universities. Some departments lost more than 60% of their faculty, while others did not lose anyone (table 2).

There may be a concern that the number of dismissals was correlated with other factors that may have had a direct effect on scientific output in affected departments. Prior work has shown that the dismissal of scientists was uncorrelated with many potential confounders (Waldinger, 2012). In particular, the dismissals were uncorrelated with the number of ardent Nazis in a department, because anybody with a Jewish grandparent was dismissed independently of scientific merits.[7] Furthermore, the dismissals did not differentially alter promotion prospects in affected departments, presumably because academic labor markets operate at the national or international level. The dismissals were also uncorrelated with the probability that nondismissed scientists retired or left for foreign universities or for industry jobs. The dismissals were also uncorrelated with changes to funding as measured by individual research grants from the Notgemeinschaft der Deutschen Wissenschaft.

B. *Physical Capital Shock: Allied Bombings during WWII*

Allied bombings during WWII were a large shock to physical capital. At the beginning of the war in 1939, the United Kingdom's Royal Air Force (RAF) concentrated bombings on military targets such as the German fleet. After the German invasion of the Low Countries and the bombing of Rotterdam by the Luftwaffe in May 1940, the RAF started bombing other targets, such as oil reservoirs, railway lines in the Ruhr area, aircraft factories, aerodromes, U-boat shipyards, and ports. To avoid the German antiaircraft defense, the majority of raids were flown under the cover of darkness, which made targeting extremely difficult.

At the end of 1940, the RAF flew the first area attacks on German cities to "affect the morale of the German people" (Webster & Frankland, 1961, p. 156) and to "concentrate the maximum amount of damage in the centre of town" (Peirse, 1940). In 1941 the RAF increased the number of small-scale area attacks on German cities. Most of these attacks, however, did not cause large destruction. Only about 20% of bombers managed to navigate within five miles of their destination, and even fewer managed to hit the target. As a result, the smallest potential targets were entire towns (Frankland, 2005; Webster & Frankland, 1961). Even these were often missed. A bombing raid of Karlsruhe and Stuttgart on October 1, 1941, for example, hit not only the two target cities but also 25 other cities, some of them several hundred kilometers away (Webster & Frankland, 1961).

The appointment of Sir Arthur Harris as head of Bomber Command on February 23, 1942, and the area bombing directive issued during the preceding week caused an intensification of the bombing campaign. On May 30, 1942, the RAF flew the first 1,000-bomber attack against Cologne, a city that had been bombed with, at most, forty planes in each of the 107 preceding attacks. The raid damaged about a third of Cologne's surface area (Hohn, 1991; Webster & Frankland, 1961). To maximize destruction of inner cities, the RAF used incendiary bombs that started fires in bombed cities. The introduction of heavy bombers (in particular, the Lancaster bomber that was gradually introduced after March 1942), the use of radar and radar-like devices (introduced in March 1942), and the deployment of Pathfinder target-marking planes (first used in January 1943) increased the precision and efficiency of bombings.

In January 1943, the U.S. Army Air Force (USAAF) entered the bombing campaign against Germany. While the British continued to fly nighttime raids and, in particular, area attacks against inner cities, the USAAF largely attacked during the day and bombed strategically important targets such as the German aircraft and ball-bearing industries.

The bombing of targets in Germany intensified in 1944 with the introduction of the "double-blow" tactic, in which two or later three attacks were conducted over short time periods to increase the efficacy of incendiary bombs. The increased air supremacy of the Allied forces further facilitated the bombings. Toward the end of the war, the bombardments were extended to smaller cities that had been spared in previous attacks.

Overall, about 1.35 million tons of bombs were dropped over German territory. Data on monthly bomb loads show an almost continuous increase between 1940 and 1945, with particularly large increases in the last years of the war (figure A2).

Allied bombings completely destroyed about 18.5% of homes in what later became the Federal Republic of Germany (Hohn, 1991). Because area bombings targeted the inner cities of all larger cities, destruction in larger cities was usually higher.

Universities were never listed as targets in any of the Allied bombing directives or similar documents. Nonetheless, many university facilities were destroyed because of targeting problems that persisted until the end of the war. Because of these problems, bombs fell relatively randomly within cities, and there was large variation in destruction across different university departments (table 2). Targeting buildings of particular departments would have been impossible. Because many bombing raids involved the use of incendiary bombs, fires in affected buildings destroyed most of the scientific equipment and important manuscripts that had not been relocated to safer locations. At the University

[7] As outlined above, the majority of dismissals affected scientists of Jewish origin. The remaining dismissals occurred for political reasons. While clear rules guided many political dismissals (such as a rule that all members of the Communist Party were to be dismissed), departments may have found ways to affect a small number of political dismissals. These additional political dismissals mostly occurred in later years. Results are robust to measuring the dismissal shock with 1933 and 1934 dismissals only.

TABLE 2.—DISMISSAL AND BOMBING SHOCKS ACROSS SCIENCE DEPARTMENTS

	Physics				Chemistry				Mathematics					
	Dismissal Shock			Bombing Shock	Dismissal Shock			Bombing Shock	Dismissal Shock			Bombing Shock	Total Destruction	
	Number of Scientists	Dismissed 1933–1940		Destruction 1940–1945	Number of Scientists	Dismissed 1933–1940		Destruction 1940–1945	Number of Scientists	Dismissed 1933–1940		Destruction 1940–1945	University Destruction	City Destruction
University	(1931)	Number	Percentage	in Percentage	(1931)	Number	Percentage	in Percentage	(1931)	Number	Percentage	in Percentage	in Percentage	in Percentage
Aachen TU	5	1	20.0	20.4	11	1	9.1	52.4	6	2	33.3	25.0	70	49
Berlin	41	10	24.4	10.0	47	16	34.0	65.0	14	5	35.7	10.0	45.8	37
Berlin TU	30	9	30.0	25.0	41	11	26.8	11.1	17	5	29.4	48.0	48	37
Bonn	10	1	10.0	50.0	14	2	14.3	20.6	8	1	12.5	20.6	40	24
Braunschweig TU	5	0	0	90.0	11	0	0	47.0	2	0	0	25	70	26
Darmstadt TU	10	3	30.0	m	12	4	33.3	m	5	1	20.0	m	75	46
Dresden TU	11	1	9.1	100.0	17	1	5.9	5.0	8	0	0	100.0	65	39
Erlangen	5	0	0	0	9	1	11.1	0	3	0	0	0	0	4.8
Frankfurt	13	2	15.4	37.0	18	5	27.8	57.0	8	4	50.0	27.0	60	32
Freiburg	5	1	20.0	100.0	11	2	18.2	60.0	5	1	20.0	85.0	72.5	28
Giessen	6	1	16.7	50.0	9	0	0	100.0	4	0	0	50.0	67.5	53
Göttingen	20	8	40.0	0	17	3	17.6	0	16	10	62.5	0	1.7	2.1
Graz	7	1	14.3	10.0	8	0	0	0	6	0	0	0	5	33
Graz TU	1	0	0	0	7	0	0	0	5	0	0	50.0	20	33
Greifswald	7	0	0	0	4	0	0	0	4	0	0	0	0	0
Halle	4	0	0	0	7	1	14.3	0	5	1	20.0	0	5	5
Hamburg	15	2	13.3	30.0	12	2	16.7	30.0	8	1	12.5	15.0	50	54
Hannover TU	4	0	0	22.2	10	0	0	37.5	4	0	0	22.2	41.3	47
Heidelberg	6	0	0	0	19	2	10.5	0	5	3	60.0	0	0	1
Innsbruck	6	0	0	0	8	0	0	50.0	5	0	0	0	m	60
Jena	14	1	7.1	0	10	0	0	62.5	5	0	0	50.0	87.3	20
Karlsruhe TU	5	1	20.0	75.0	16	5	31.3	100.0	5	1	20.0	75.0	70	26
Kiel	7	1	14.3	62.5	8	0	0	50.0	5	2	40.0	75.0	60	41
Köln	6	1	16.7	66.7	6	0	0	50.0	5	1	20.0	0	20	44
Leipzig	12	2	16.7	41.0	21	2	9.5	100.0	8	2	25.0	0	70	19
Marburg	5	0	0	0	8	0	0	50.0	6	0	0	0	16.3	4
München	11	2	18.2	42.0	19	3	15.8	95.0	8	1	12.5	70.0	70	32

TABLE 2.—(CONTINUED)

University	Physics: Dismissal Shock: Number of Scientists (1931)	Physics: Dismissed 1933–1940: Number	Physics: Dismissed 1933–1940: Percentage	Physics: Bombing Shock: Destruction 1940–1945 in Percentage	Chemistry: Dismissal Shock: Number of Scientists (1931)	Chemistry: Dismissed 1933–1940: Number	Chemistry: Dismissed 1933–1940: Percentage	Chemistry: Bombing Shock: Destruction 1940–1945 in Percentage	Mathematics: Dismissal Shock: Number of Scientists (1931)	Mathematics: Dismissed 1933–1940: Number	Mathematics: Dismissed 1933–1940: Percentage	Mathematics: Bombing Shock: Destruction 1940–1945 in Percentage	Total Destruction: University Destruction in Percentage	Total Destruction: City Destruction in Percentage
München TU	15	1	6.7	36.7	17	1	5.9	30.0	5	0	0	50.0	80	32
Münster	4	0	0	100.0	7	0	0.0	100.0	6	0	0	75.0	75.3	49
Rostock	4	0	0	0	6	0	0.0	0	1	0	0	0	0	40
Stuttgart TU	7	1	14.3	76.7	10	1	10.0	66.7	9	0	0	40	80	35
Tübingen	3	0	0	0	9	0	0.0	0	4	0	0	0	0	5
Wien	4	0	0	25.0	30	5	16.7	37.5	9	2	22.2	25.0	30	28
Wien TU	8	0	0	0	19	1	5.3	40.0	13	0	0	0	13.3	28
Würzburg	29	3	10.3	90.0	12	1	8.3	90.0	3	0	0	90.0	82.5	75

Number of Scientists (1931) reports the number of scientists in a department in 1931 (before the dismissal shock). Dismissed 1933–1940 reports the number of dismissals in a department between 1933 and 1940. The total number of dismissals is slightly higher than in table 1 because professors with appointments in two universities are reported twice in this table. Destruction 1940–1945 reports percentage destruction of department facilities due to Allied bombings between 1940 and 1945. University Destruction reports the percentage of university facilities that were destroyed by Allied bombings between 1940 and 1945. City Destruction reports city level percentages of buildings that were destroyed by Allied bombings. The letter *m* indicates missing data. See online appendix for data sources.

of Cologne, for example, the bombing raids of the chemical institute destroyed scientific materials such as chemicals, glass storage bottles, and other valuable equipment with a total value of about 50,000 RM (about $300,000 in today's U.S. dollars). At the Institute of Applied Physics, bombings destroyed X-ray valve tubes, capacitors, electrical instruments, and other apparatuses with a total value of about 127,000 RM (about $813,000 in today's U.S. dollars) (table A1). At the time, Cologne had small science departments that were not particularly productive. In larger departments, the loss of valuable scientific material was probably much larger. The fires also destroyed many of the valuable private libraries that professors had assembled during their careers.

Most science departments were hit in 1944 or 1945 when Allied bombings intensified. Data I obtained from university archives indicate the exact dates for the first and last bombing raids that destroyed university buildings at some universities. According to these data, the first raid occurred in June 1941 and destroyed buildings at the Technical University of Aachen. Bombing raids that hit other universities continued and intensified until the end of WWII.

After the end of the war on May 8, 1945, reconstruction of university buildings was hampered by a lack of funds and skilled craftsmen, insufficient construction supplies, and the overall devastation of many German cities. Most universities enlisted students to clear away rubble and help with reconstruction. The universities of Bonn, Karlsruhe, and Hannover, for example, required up to 1,000 reconstruction service hours from its students until 1949 (van Rey, 1995; Hoepke, 2007; Wolters, 1950). In June 1951, James M. Read, the chief of the education and cultural relations division of the High Commission for Occupied Germany, reported that there remained a "need for new buildings and libraries and classrooms and scientific apparatus, many of which, destroyed by the war, are still not replaced" (Read, 1951). By the end of the 1950s, most universities had completed reconstruction, but some continued reconstruction until the 1960s (Hoepke, 2007; Technische Universität Dresden 1996).

III. Panel Data Set of Science Departments

A. Scientists in German and Austrian Universities, 1926–1980

To evaluate the effect of the two shocks, I construct a new panel data set of physicists, chemists, and mathematicians at German and Austrian universities. I obtain these data from Kürschners Deutscher Gelehrtenkalender, a register of all German university professors, that has been published since the 1920s in five- to ten-year intervals. For this paper, I use data from volumes published in 1926, 1931, 1940/41, 1950, 1961, 1970, and 1980 to construct complete faculty rosters for science departments at these seven points in time spanning 54 years.

I extract all scientists who were chaired professors, extraordinary professors, or *Privatdozenten* (the first position in the German university system with the right to give lectures) from each volume.[8] I include scientists from all 35 German or Austrian universities that existed in 1926 and remained on German (both FRG and GDR) or Austrian territory after 1945 (see table 2 for a listing of the universities in my sample).[9] For each university I obtain data on physics, chemistry, and mathematics departments—105 science departments overall.[10] The online data appendix provides additional details and references. The microdata include 5,716 scientists (2,456 chemists, 2,000 physicists, and 1,260 mathematicians) with 10,387 person-year observations (4,605 in chemistry, 3,594 in physics, and 2,188 in mathematics). The number of scientists in German and Austrian universities increased massively after 1926, with the exception of 1941 (and 1950 in chemistry), the first time periods after the dismissals (figure A3).

B. *Output of German and Austrian Science Departments*

To measure department output, I first obtain publications and citation-weighted publications for each scientist from the ISI Web of Science. The publication and citation data include both historical and current top journals for German and Austrian scientists. Top journals from the historical period include all science journals that were published in Germany and are covered by the Web of Science.[11] Furthermore, I consider the most important international journals that were outlets for German scientists in the historical period, including general science journals (e.g., *Nature* and *Science*) and international field journals (e.g., *Acta Mathematica*). Current top journals include those that are in lead positions of contemporary rankings. Table A2 includes the full list of top journals, and appendix 8.4 provides additional information on data construction and sources.

I first download all articles published between 1920 and 1985 in any top journal as defined above.[12] I then calculate the number of top journal publications and citation-weighted publications for each scientist and year. The Web of Science data include only the last name and the initials of the first names for each author. Most German scientists have distinct last names that are also different from most foreign names. In the rare cases that a last name–first initial combination does not uniquely identify a scientist in my data, I split (citation-weighted) publications according to the number of scientists with the same last name and first initial combination. Table A3 shows the most cited scientists in my data. Most of them are very well known in the scientific community, indicating that the output measures carry meaningful information. Interestingly, Johann von Neumann, who later emigrated to the United States, is the most-cited mathematician.

To measure department output for each of the seven points in time, I add individual output measures within departments. Individual output is measured using a five-year window around the relevant year. Albert Einstein's individual output measure for 1926, for example, is the sum of his publications between 1923 and 1927.[13] I then add up the individual output measures within departments. Say a department had three scientists with individual output equal to 1, 2, and 3; total department output would be $1+2+3=6$. The Web of Science data also include information on the number of times each article was subsequently cited in any journal covered by the Web of Science. This allows me to construct an analogous output measure based on citation-weighted publications.[14]

Publication and citation patterns are different across the three subjects. To ensure comparability across subjects, I normalize total department output to have zero mean and unit variance in each subject. This also allows for easy interpretation of the estimated regression coefficients.

C. *Data on Dismissals*

I obtain data on dismissed scientists from a number of sources. The main source is the List of Displaced German Scholars, compiled by a relief organization, Emergency Alliance of German Scholars Abroad, which was founded by some dismissed scientists to support other dismissed scholars seeking positions in foreign universities (Notgemeinschaft Deutscher Wissenschaftler im Ausland, 1936). The list contained about 1,650 names. I extract all dismissed physicists, chemists, and mathematicians from the list.

As this list was published before 1938, it did not include dismissals from Austrian universities. I consult the *Biographisches Handbuch der deutschsprachigen Emigration nach 1933: Vol. 2: The Arts, Sciences, and Literature* (1983) to obtain dismissals from Austria. This source also contains a few additional dismissals from German universities, because some dismissed scientists passed away before the List of Displaced German Scholars was compiled, for example. Together, the two sources cover about 90% of all dismissals. I augment this information with data on a few

[8] *Privatdozenten* are comparable to junior faculty at U.S. universities. Extraordinary professors are comparable to associate professors, and chaired professors are comparable to full professors.

[9] The sample excludes three universities (the University and Technical University of Breslau, now Wroclaw, and the University of Königsberg, now Kaliningrad) that were based in eastern territories that Germany lost after WWII. The *Gelehrtenkalender* did not list these universities after 1945.

[10] Scientists in universities located in the GDR were not listed in the *Gelehrtenkalender* in 1980.

[11] Historical journals with coverage in the Web of Science were the top journals at their time because Thomson Scientific digitized only the most cited journals for the period 1900 to 1944.

[12] A few top journals, such as *Physical Review Letters*, were founded after 1920. For these, I download all articles published after the various journals' inception. Because all regressions include year fixed effects, the changing pool of journals does not affect the results.

[13] Publications are measured using an asymmetric window around the relevant year of the *Gelehrtenkalender*; output for 1926 is measured with publications between 1923 and 1927. The asymmetry accounts for the delay in the publication of the *Gelehrtenkalender* because questionnaires for a certain volume had to be sent out and returned before publication. Using a symmetric window does not affect the results.

[14] The citation-weighted productivity measure is constructed as above by adding all citations to publications published in a five-year window around the relevant year. Citations are measured in all papers published until today.

additional dismissals from three secondary sources compiled by historians who have studied the dismissal of scientists in Nazi Germany.[15]

D. *Data on Bombings of Science Departments*

To measure department-level bombing destruction, I construct a new data set from university archives. After bombing raids, university institutes often provided detailed destruction reports to obtain funds and materials for reconstruction. I use these reports and other sources to construct a measure of destruction at the department level.

I obtained this information by asking university archivists for information on WWII destruction of buildings used by physicists, chemists, and mathematicians. In cases where university archivists could not provide adequate information, a research assistant or I personally consulted the relevant archive to obtain a measure of bombing destruction.

After each bombing raid, most universities estimated the degree of damage inflicted by bombs on each building. Damage was usually measured in percentages (e.g., 50% destroyed). Some universities provided accurate descriptions or even maps of bombing destruction (see figure A4 for a map provided by the Technical University of Berlin). Other departments did not report destruction in percentages but instead wrote verbal descriptions of bomb damage. I convert the verbal information into percentages using a fixed rule outlined in appendix section 8.4. If a department occupied various buildings, I average the percentage of destruction across all buildings used by the department.[16]

While the destruction measure captures the destruction of buildings, it also serves as a proxy for the destruction of scientific equipment and materials. As described for the case of Cologne, the bombing raids often destroyed scientific equipment and other physical inputs. Unfortunately, detailed data on the destruction of scientific equipment are not available for most universities.

To analyze the importance of measurement error, I also construct a measure of destruction from bombing campaigns at the university level. I collect data for this alternative measure from information on university websites and a number of additional sources (see online appendix 8.4 for details).

E. *Data on Control Variables*

I also collect data on control variables from a number of different sources. The control variables include university age, foundation years of new universities, the share of firms in armament-related industries in 1933, the fraction of Jews at the city level in 1933, and distance to the iron curtain. Further information and sources for these variables can be found in appendix 9.4.

The final data set contains panel data for German and Austrian science departments covering seven points in time (1926, 1931, 1940, 1950, 1961, 1970, and 1980). The data include different measures of department output, information on dismissal and bombing shocks, and time-varying control variables.

IV. The Effect of Human and Physical Capital Shocks on Department Output

A. *Main Results*

I estimate equation (1) to analyze how the human and physical capital shocks affected output in the short run (before departments fully adjusted to the shocks) and in the long run. The first specifications focus on the human capital shock that happened between 1933 and 1940. Between 1931, the omitted interaction in equation (1), and 1940, output in departments with one more dismissal fell by .17 standard deviations compared to departments without dismissals (see table 3, column 1). This short-run effect persisted in the long run. Coefficients on the interactions with subsequent years are significantly negative until 1980. Controlling for subject times year fixed effects, to allow for differential output trends in the three subjects, does not affect the results (column 2). Further controlling for occupation zone (U.S. zone, U.K. zone, French zone, Soviet zone) times post-1945 dummies has a negligible effect on estimated coefficients but lowers standard errors (column 3). Estimates imply that the dismissal of one scientist lowered department output, even in the long run, by between 0.17 and 0.28 standard deviations (column 3).

The next specifications focus on the bombing shock that was concentrated between 1942 and 1945. Between 1940 (the omitted interaction) and 1950, output in departments with 10% bombing destruction declined by .05 standard deviations, compared to departments without destruction. The effect is significant at the 5% level only if I control for subject times year fixed effects and occupation zone times post-1945 dummies (see table 3, columns 4–6). This short-run effect did not persist. As early as 1961, departments that had been bombed during WWII performed similarly to departments without bombings. By 1970, departments that had been bombed even performed slightly better than other departments. While the 1970 results are only significant at the 10% level in two of the three specifications, they suggest that upgrading during reconstruction may have had a small positive effect on output in the medium run.

When I jointly estimate effects of the bombing and dismissal shocks, the results are very similar (table 3, columns 7–9). In the next specification, I investigate whether the bombing results are caused by the destruction of department buildings or by more general destruction at the city-level. In a regression that adds interactions of city level destruction with

[15] Dismissed chemists come from Deichmann (2001), physicists from Beyerchen (1977), and mathematicians from Siegmund-Schultze (1998).

[16] I use university-level destruction data for the University of Darmstadt because I could not obtain information regarding damage at the department level.

TABLE 3.—PERSISTENCE OF DISMISSAL AND BOMBING SHOCKS: PUBLICATIONS

Dependent Variable:	(1) Publi-cations	(2) Publi-cations	(3) Publi-cations	(4) Publi-cations	(5) Publi-cations	(6) Publi-cations	(7) Publi-cations	(8) Publi-cations	(9) Publi-cations	(10) Publi-cations
Number of Dismissals × 1926	0.023	0.017	0.017				0.024	0.018	0.018	0.018
	(0.025)	(0.025)	(0.025)				(0.025)	(0.026)	(0.026)	(0.026)
Number of Dismissals × 1940	−0.173***	−0.173***	−0.173***				−0.172***	−0.171***	−0.171***	−0.170***
	(0.037)	(0.039)	(0.039)				(0.039)	(0.041)	(0.041)	(0.042)
Number of Dismissals × 1950	−0.210*	−0.222*	−0.219**				−0.210	−0.221*	−0.218**	−0.219**
	(0.121)	(0.125)	(0.099)				(0.124)	(0.128)	(0.102)	(0.102)
Number of Dismissals × 1961	−0.245**	−0.257**	−0.254***				−0.244**	−0.255**	−0.253***	−0.253***
	(0.102)	(0.105)	(0.080)				(0.105)	(0.107)	(0.083)	(0.084)
Number of Dismissals × 1970	−0.291***	−0.286**	−0.283***				−0.290**	−0.283**	−0.281***	−0.282***
	(0.104)	(0.108)	(0.084)				(0.108)	(0.111)	(0.087)	(0.088)
Number of Dismissals × 1980	−0.202**	−0.202**	−0.207***				−0.199**	−0.198**	−0.202***	−0.212***
	(0.077)	(0.079)	(0.071)				(0.077)	(0.078)	(0.070)	(0.077)
% Destruction × 1926				−0.004	−0.005*	−0.005*	−0.004*	−0.004**	−0.004**	−0.004*
				(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
% Destruction × 1931				−0.008***	−0.008***	−0.008***	−0.008***	−0.008***	−0.008***	−0.007***
				(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)
% Destruction × 1950				−0.002	−0.003*	−0.005**	−0.003	−0.003*	−0.005**	−0.004**
				(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
% Destruction × 1961				0.000	−0.001	−0.003	0.000	−0.001	−0.003	−0.002
				(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
% Destruction × 1970				0.003*	0.004*	0.002	0.003	0.004*	0.002	0.005**
				(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
% Destruction × 1980				0.001	0.001	−0.000	0.001	0.001	−0.000	0.003
				(0.003)	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)
Department FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes			Yes			Yes			
Subject × Year FE		Yes	Yes		Yes	Yes		Yes	Yes	Yes
Occupation Zones × Post1945			Yes			Yes			Yes	Yes
% City Destruction × Year FE										Yes
Observations	714	714	714	714	714	714	714	714	714	714
R^2	0.590	0.650	0.678	0.513	0.576	0.603	0.603	0.664	0.689	0.693

Significant at ***1%, **5%, *10%. All standard errors clustered at university level.

The dependent variable Publications is the sum of publications published by all scientists in department d in a five-year window around year t. The variable is normalized to have 0 mean and a standard deviation of 1 within subjects. Number of Dismissals × 1926 is equal to the number of dismissals between 1933 and 1940 interacted with an indicator for 1926. Interactions with other years are defined accordingly. The excluded interaction is the number of dismissals with an indicator for 1931; the last observation before the dismissals. % Destruction × 1926 is equal to percentage destruction caused by Allied bombings between 1940 and 1945 interacted with an indicator for 1926. Interactions with other years are defined accordingly. The excluded interaction is % destruction with an indicator for 1940, the last observation before the bombings. Department FE is a full set of 105 department fixed effects. Year FE is a set of year dummies. Subject × Year FE is the interaction of subject indicators (for physics, chemistry, and mathematics) with year dummies. Occupation Zones × Post1945 is the interaction of occupation zone indicators with a post-1945 dummy. Percentage City Destruction × Year FE is the interaction of city-level destruction with the full set of year fixed effects.

year dummies as additional controls, the 1950 coefficient on department-level destruction does not change substantially (table 3, column 10). These results indicate that the effect of physical capital destruction on department output is primarily driven by the destruction of department facilities instead of more general destruction at the city level.

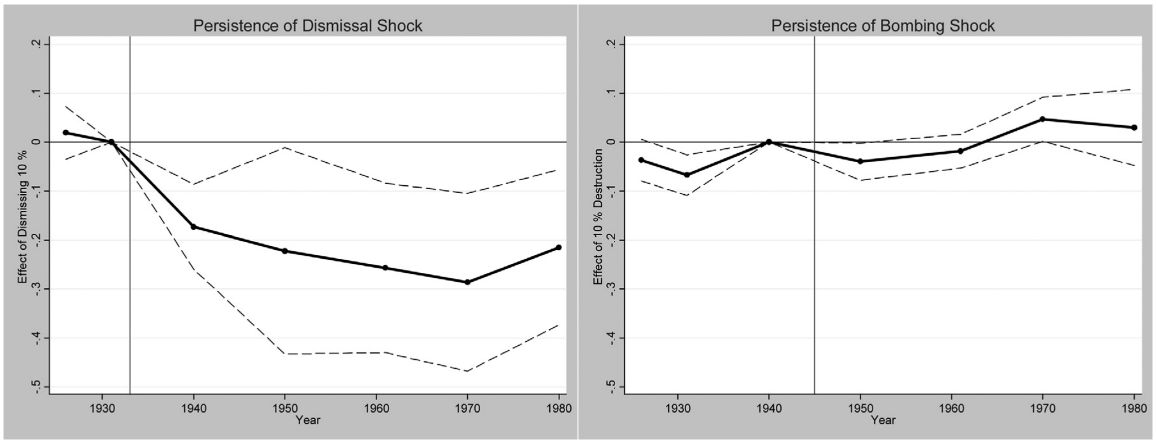
To investigate the relative magnitude of the two shocks, I plot the effect of 10% shocks to human and physical capital of a hypothetical science department.[17] In the short run, before departments could rehire faculty and reconstruct facilities, a 10% shock to human capital caused a four times stronger reduction in output than a 10% shock to physical capital (figure 1).[18] While the human capital shock persisted for almost fifty years until 1980, the physical capital shock dissipated quickly and even had a small positive effect in 1970. The figure also indicates that the human capital results are not driven by pretrends. The physical capital results, however, may be slightly underestimated because output in bombed departments increased during the pre-period relative to other departments. The 1931 interaction with WWII destruction is negative and significant, suggesting that output in departments that would be bombed during WWII rose relatively faster between 1931 and 1940 (the omitted interaction). I show below that including additional controls reduces the magnitude and significance of the pre-war bombing coefficients while leaving the postwar coefficients unchanged.

For the results reported above, I measure output as the sum of publications in top journals (normalized to have a mean of 0 and a standard deviation of 1). As an alternative output measure, I use citation-weighted publications (again normalized to have a mean of 0 and a standard deviation of 1). They quantify the quality of each published paper using valuations of the entire scientific community. The alternative measure yields similar results (table 4 and figure 2). The dismissal of one scientist reduced output, even in the long run, by between

[17] Average department size in 1931 was 10.15. A 10% shock to human capital therefore corresponds to losing 1.015 scientists. To plot figure 1, I multiply by 1.015 the dismissal coefficients and standard errors reported in column 10 of table 3. As departmental destruction is measured in percentages, I multiply by 10 the bombing coefficients and standard errors reported in column 10 of table 3.

[18] The p-value of a test of the null hypothesis: (1.015 × coefficient # dismissed × 1950) = (10 × coefficient % destruction × 1950) has a p-value of 0.097 for 1950. For all later years, the effect of a 10% shock to human capital is significantly larger than a 10% shock to physical capital (p-values between 0.001 and 0.012).

FIGURE 1.—PERSISTENCE OF 10% SHOCKS: PUBLICATIONS



The figure plots scaled regression coefficients and 95% confidence intervals obtained from the estimation of equation (1) as reported in column 10 of table 3. Point estimates and confidence intervals are scaled to reflect at a 10% shock to both human and physical capital.

0.16 and 0.22 standard deviations (column 10). Bombings had a small negative, but insignificant, effect in 1950. By 1970, bombed departments even performed slightly better (significant at the 10% level).[19]

B. *Robustness of Main Results*

Department fixed effects control for time-invariant factors that affect output at the department level. Year fixed effects control for yearly shocks that have the same effect on all science departments. Subject-times-year fixed effects control for yearly shocks that have the same effect on all physics, chemistry, or mathematics departments. For the main results, I also control for occupation zone times a post-1945 dummy and city-level destruction interacted with year fixed effects.

In the following, I show that results are robust to the inclusion of additional control variables, adjusting output for changes in a department's age structure, the use of different samples, and the use of alternative measures of the two shocks. I also address measurement error of bombing destruction with an instrumental variables strategy and control for university-wide changes after 1945 and mean reversion. Furthermore, I investigate complementarities between human and physical capital.

Additional controls and changes in departments' age structure. First, I show that results are not driven by differential postwar policies regarding universities. After WWII, federal states (*Länder*) received sole responsibility for universities in West Germany. Controlling for federal state indicators interacted with a post-1945 dummy leaves results almost unchanged (tables 5 and A4, column 1).[20]

Results are also not driven by differential trends of universities with different founding years. Controlling for university age and its square does not affect results (tables 5 and A4, column 2).

I also show that results are not driven by increased competition from newly founded universities. During the postwar period, in particular during the 1960s and 1970s, a number of new universities were founded in Germany and Austria. Including a time-varying control variable that measures the number of departments within 50 kilometers of each science department does not affect results (tables 5 and A4, column 3).

Furthermore, results are not driven by increased armaments spending by the Nazi government that may have benefited certain universities. Armament spending could be correlated with the two shocks if departments benefited from industry spillovers or if the Allied bombing campaign targeted cities with a concentration of armaments-related industry. Including controls for the share of firms in three armaments-related industries interacted with year dummies leaves results almost unchanged (tables 5 and A4, column 4).[21]

Results are also stable if I control for the fraction of Jews at the city level. The loss of the Jewish population may have had long-lasting effects (Acemoglu et al., 2011; Grosfeld et al., 2013; Akbulut-Yuksel & Yuksel, 2015) that could have been correlated with the dismissal of scientists. Adding a variable that controls for the fraction of Jews at the city level (in the pre-Nazi period) interacted with a post-1945 dummy does not affect results; if anything, the dismissal coefficients become slightly more negative (tables 5 and A4, column 5).

[19] The tests of the null hypotheses (1.015 × coefficient # dismissed × year dummy) = (10 × coefficient % destruction × year dummy) have p-values between 0.000 and 0.011.

[20] As university funding in the GDR was centralized at the federal level, I include a joint indicator for all East German universities, including the Technical University of Berlin, which was located in West Berlin. As the federal states of Hamburg and Schleswig-Holstein had only one university each, I include a joint indicator for these universities with the adjacent state of Niedersachsen. I also include a joint indicator for the five Austrian universities.

[21] The three armaments-related industries are iron and steel production, mechanical engineering and vehicle construction, and chemicals. The shares of firms in these industries are measured in 1933 (1930 for Austria).

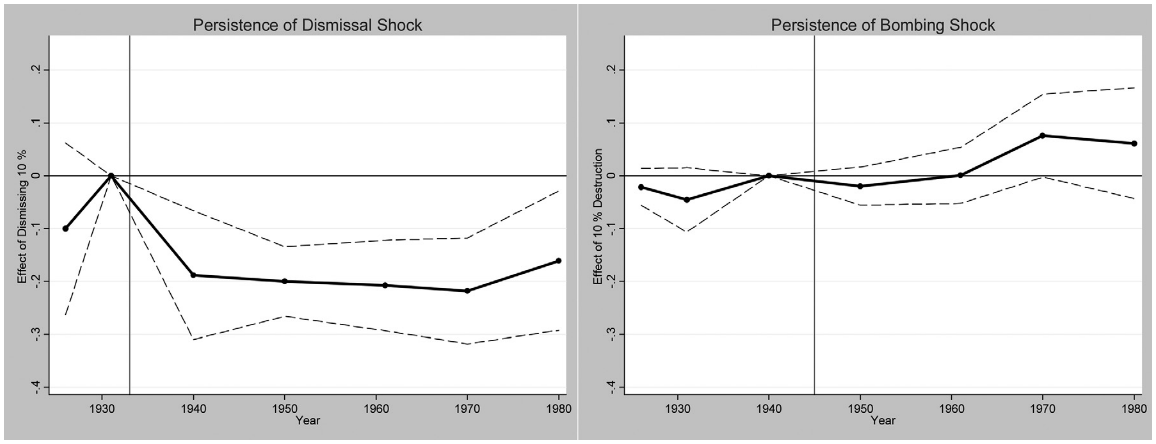
Table 4.—Persistence of Dismissal and Bombing Shocks: Citation-Weighted Publications

Dependent Variable:	(1) Citation Weight. Publications	(2) Citation Weight. Publications	(3) Citation Weight. Publications	(4) Citation Weight. Publications	(5) Citation Weight. Publications	(6) Citation Weight. Publications	(7) Citation Weight. Publications	(8) Citation Weight. Publications	(9) Citation Weight. Publications	(10) Citation Weight. Publications
Number of Dismissals × 1926	−0.093	−0.100	−0.100				−0.092	−0.099	−0.099	−0.099
	(0.076)	(0.078)	(0.078)				(0.076)	(0.078)	(0.078)	(0.079)
Number of Dismissals × 1940	−0.181***	−0.188***	−0.188***				−0.181***	−0.186***	−0.186***	−0.185***
	(0.063)	(0.062)	(0.062)				(0.060)	(0.059)	(0.059)	(0.059)
Number of Dismissals × 1950	−0.195***	−0.201***	−0.196***				−0.195***	−0.200***	−0.196***	−0.197***
	(0.030)	(0.036)	(0.031)				(0.031)	(0.036)	(0.032)	(0.032)
Number of Dismissals × 1961	−0.190***	−0.207***	−0.202***				−0.189***	−0.206***	−0.202***	−0.205***
	(0.036)	(0.041)	(0.042)				(0.034)	(0.040)	(0.042)	(0.042)
Number of Dismissals × 1970	−0.210***	−0.220***	−0.215***				−0.209***	−0.217***	−0.212***	−0.215***
	(0.047)	(0.049)	(0.053)				(0.038)	(0.042)	(0.046)	(0.049)
Number of Dismissals × 1980	−0.129*	−0.142**	−0.141**				−0.126**	−0.139**	−0.138**	−0.158**
	(0.065)	(0.059)	(0.061)				(0.059)	(0.055)	(0.057)	(0.064)
% Destruction × 1926				−0.003	−0.003	−0.003	−0.003	−0.003	−0.003	−0.002
				(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
% Destruction × 1931				−0.006**	−0.006*	−0.006*	−0.006**	−0.005**	−0.005**	−0.005
				(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)
% Destruction × 1950				−0.002	−0.002	−0.004*	−0.002	−0.002	−0.004*	−0.002
				(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
% Destruction × 1961				−0.001	−0.001	−0.003	−0.001	−0.001	−0.003	0.000
				(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
% Destruction × 1970				0.006*	0.006*	0.005	0.006*	0.006*	0.005	0.008*
				(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
% Destruction × 1980				0.001	0.001	−0.000	0.001	0.001	−0.000	0.006
				(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Department FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes			Yes			Yes			
Subject × Year FE		Yes	Yes		Yes	Yes		Yes	Yes	Yes
Occupation Zones × Post1945			Yes			Yes			Yes	Yes
% City Destruction × Year FE										Yes
Observations	714	714	714	714	714	714	714	714	714	714
R^2	0.460	0.484	0.496	0.440	0.460	0.471	0.475	0.497	0.507	0.518

Significant at ***1%, **5%, *10%. All standard errors clustered at university level.

The dependent variable Citation Weight. Publications is the sum of citation-weighted publications published by all scientists in department d in a five-year window around year t. The variable is normalized to have zero mean and a standard deviation of 1 within subjects. Number of Dismissals × 1926 is equal to the number of dismissals between 1933 and 1940 interacted with an indicator for 1926. Interactions with other years are defined accordingly. The excluded interaction is the number of dismissals with 1931, the last observation before the dismissals. % Destruction × 1926 is equal to percentage destruction caused by Allied bombings between 1940 and 1945 interacted with an indicator that is equal to 1 for observations from 1926. Interactions with other years are defined accordingly. The excluded interaction is % destruction with 1940, the last observation before the bombings. Control variables are defined as in table 3.

FIGURE 2.—PERSISTENCE OF 10% SHOCKS: CITATION-WEIGHTED PUBLICATIONS



The figure plots scaled regression coefficients and 95% confidence intervals obtained from the estimation of equation (1) as reported in column 10 of table 4. Point estimates and confidence intervals are scaled to reflect a 10% shock to both human and physical capital.

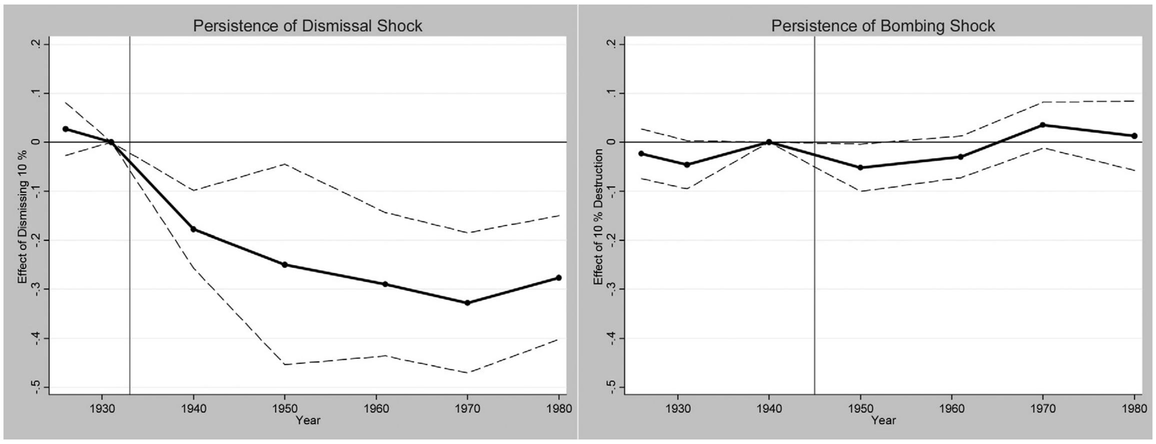
TABLE 5.—ROBUSTNESS CHECKS: PUBLICATIONS ADDING CONTROLS

Dependent Variable: Sample:	(1) Publications Full Sample	(2) Publications Full Sample	(3) Publications Full Sample	(4) Publications Full Sample	(5) Publications Full Sample	(6) Publications Full Sample	(7) Age-adjusted Publications Full Sample
# of Dismissals × 1926	0.018	0.020	0.020	0.026	0.026	0.026	0.086**
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.036)
# of Dismissals × 1940	−0.170***	−0.173***	−0.173***	−0.165***	−0.175***	−0.175***	−0.160***
	(0.042)	(0.042)	(0.042)	(0.037)	(0.038)	(0.038)	(0.053)
# of Dismissals × 1950	−0.236**	−0.244**	−0.252**	−0.236**	−0.248**	−0.246**	−0.178
	(0.102)	(0.103)	(0.108)	(0.102)	(0.103)	(0.099)	(0.122)
# of Dismissals × 1961	−0.271***	−0.282***	−0.289***	−0.276***	−0.288***	−0.286***	−0.233**
	(0.078)	(0.077)	(0.081)	(0.075)	(0.075)	(0.071)	(0.090)
# of Dismissals × 1970	−0.300***	−0.314***	−0.322***	−0.314***	−0.326***	−0.323***	−0.285***
	(0.079)	(0.078)	(0.079)	(0.074)	(0.073)	(0.069)	(0.074)
# of Dismissals × 1980	−0.234***	−0.251***	−0.261***	−0.259***	−0.272***	−0.272***	−0.287***
	(0.067)	(0.065)	(0.066)	(0.063)	(0.062)	(0.061)	(0.087)
% Destruction × 1926	−0.004*	−0.004*	−0.004*	−0.003	−0.002	−0.002	−0.004
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
% Destruction × 1931	−0.007***	−0.007***	−0.007***	−0.005**	−0.005*	−0.005*	−0.006*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
% Destruction × 1950	−0.006***	−0.005***	−0.005***	−0.005**	−0.005**	−0.005**	−0.005
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
% Destruction × 1961	−0.004**	−0.003*	−0.003*	−0.003	−0.003	−0.003	−0.004
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
% Destruction × 1970	0.003	0.003	0.003	0.004	0.004	0.003	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
% Destruction × 1980	0.001	0.002	0.002	0.001	0.001	0.001	−0.000
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Standard controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Länder Dummies × P45	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quadratic in Uni. Age		Yes	Yes	Yes	Yes	Yes	Yes
# of Deps. within 50 km			Yes	Yes	Yes	Yes	Yes
Industries (1933) × Year				Yes	Yes	Yes	Yes
Fract. Jews (1933) × P33					Yes	Yes	Yes
Dist. to Iron Curtain × P45						Yes	Yes
Observations	714	714	714	714	714	714	714
R^2	0.703	0.706	0.707	0.716	0.717	0.718	0.603

Significant at ***1%, **5%, *10%. (SE clustered at university level.)

The dependent variable Publications is the sum of publications published by all scientists in department *d* in a five-year window around year *t*. The variable is normalized to have 0 mean and a standard deviation of 1 within subjects. # of Dismissals × 1926 is equal to the number of dismissals between 1933 and 1940 interacted with an indicator for 1926. Interactions with other years are defined accordingly. The excluded interaction is the number of dismissals with 1931, the last observation before the dismissals. % Destruction × 1926 is equal to percentage destruction caused by Allied bombings between 1940 and 1945 interacted with an indicator that is equal to 1 for observations from 1926. Interactions with other years are defined accordingly. The excluded interaction is % destruction with 1940, the last observation before the bombings. Standard Controls are all controls as reported in column 10 of table 3. Länder Dummies × P45 is a set of dummy variables for each postwar German federal state (Land) interacted with a post-1945 dummy. Quadratic in Uni. Age is equal to the age of the university in each year and its square. # of Deps. within 50 km measures the number of departments in the same subject within 50 kilometers of each department in each year. Industries (1933) × Year is the fraction of firms in a city belonging to each of three armament-related universities in 1933 (1930 for Austria) interacted with a full set of year fixed effects. Fract. Jews (1933) × P33 is the fraction of Jews in each city in 1933 interacted with a post 1933 dummy. Dist. to Iron Curtain × P45 is the distance to the iron curtain from each city interacted with a post-1945 dummy.

FIGURE 3.—PERSISTENCE OF 10% SHOCKS: PUBLICATIONS WITH ALL CONTROLS



The figure plots scaled regression coefficients and 95% confidence intervals obtained from the estimation of equation (1) as reported in column 6 of table 5. Point estimates and confidence intervals are scaled to reflect a 10% shock to both human and physical capital.

Finally, I show that results are not driven by negative effects from the division of Germany. Universities that were closer to the iron curtain may have suffered after 1945 because these locations experienced a decline in population growth after the division of Germany (Redding & Sturm, 2008). Including an interaction of the distance to the iron curtain with a post-1945 dummy does not affect results (tables 5 and A4, column 6).

Figure 3 shows the effect of 10% shocks, including all controls. While the figure looks similar to the one that includes only a limited set of controls (figure 1), the coefficients on the human capital shock are slightly more negative than the baseline results. This suggests that results are not driven by other factors that may have affected scientific output. Furthermore, the addition of controls reduces the magnitude and significance of pretrends for the bombing shock while not affecting the 1950 coefficient (figure A5 reports equivalent results for citation-weighted publications).

In additional specifications, I show that changes in the age structure of departments with dismissals do not drive results. Prior research has shown that scientists' output declines with age (Levin & Stephan, 1991). If changes in the age structure of departments were caused by the dismissals, one would not want to control for these changes to avoid "bad control" problems. Nevertheless, I use an alternative dependent variable to investigate whether the results are affected by changes in the age structure of departments. I first regress individual output on a full set of age dummies (in five-year bins). I then sum the residuals from this regression within departments to construct department output that I normalize to have a mean of 0 and a standard deviation of 1. This alternative dependent variable yields similar results (tables 5 and A4, column 7).

Different samples. The following results show that results are robust to using different samples. Dropping Austrian universities, for example, does not affect results (tables 6 and A5, column 1). The main sample includes universities from both West (FRG) and East Germany (GDR), where reconstruction and rehiring was presumably quite different. Dropping East German universities from the sample only slightly reduces the absolute magnitude of the coefficients, suggesting that results are not driven by a differential development in the GDR (tables 6 and A5, column 2). These results also demonstrate that the development of the University of Berlin that was located in the Soviet sector does not drive results.[22] In specifications not reported in the paper, I also show that results are robust to dropping both Austria and the GDR.

In an additional test, I use Swiss universities as an alternative control group. Because many Jewish scientists were outstanding members of their profession, they concentrated in better departments. German and Austrian departments without dismissals may therefore not be an appropriate control group for the development of high-quality departments. To investigate this concern, I use four German-speaking Swiss universities as an alternative control group.[23] Some of the Swiss universities are among the top universities in the German-speaking world. I estimate results in a sample that includes only those German and Austrian departments with dismissals, and the Swiss departments as controls. Results are highly significant with point estimates that are larger in absolute magnitude (tables 6 and A5, column 3).

Alternative shock measures. The following specifications demonstrate that results are not sensitive to using alternative measures of the two shocks. In the specifications reported above, I measure the human capital shock with the number of dismissals in each department. As an alternative measure of the human capital shock, I use percentage dismissals in each department. Results with this

[22] The University of Berlin reopened in January 1946. In 1948, the Free University of Berlin was founded in the U.S. sector.

[23] Swiss universities are not in the main sample because they hired a small number of dismissed scientists.

TABLE 6.—FURTHER ROBUSTNESS CHECKS: PUBLICATIONS DIFFERENT SAMPLES, DIFFERENT SHOCK MEASURES, CONTROLLING FOR UNIVERSITY × POST1945 AND MEAN REVERSION

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent Variable:	Publications	Publications	Publications	Publications	Publications	Publications	Publications	Publications	Publications	Publications
Sample:	Dropping Austria	Dropping East Germany	Swiss Unis. as Control	Full Sample % Dismissals	Full Sample Only 33–34 Dismissals	Full Sample Same Effect on Output	Full Sample Science Dest.	Full Sample Instrument w/ Uni. Dest.	Full Sample UniFE* Post45	Full Sample Control for M. Reversion
Dismissals × 1926	0.024	0.027	0.030	−0.022	0.048	0.150	0.028	0.030	0.026	0.004
	(0.029)	(0.043)	(0.032)	(0.064)	(0.041)	(0.167)	(0.026)	(0.028)	(0.027)	(0.021)
Dismissals × 1940	−0.138***	−0.116***	−0.161***	−0.229*	−0.153***	−1.000***	−0.175***	−0.182***	−0.163***	−0.129***
	(0.041)	(0.033)	(0.029)	(0.135)	(0.040)	(0.241)	(0.036)	(0.037)	(0.039)	(0.027)
Dismissals × 1950	−0.221***	−0.080	−0.249***	−0.260	−0.209*	−1.403**	−0.242**	−0.228**	−0.148*	−0.152*
	(0.079)	(0.047)	(0.080)	(0.172)	(0.114)	(0.607)	(0.098)	(0.096)	(0.080)	(0.081)
Dismissals × 1961	−0.259***	−0.151***	−0.293***	−0.292	−0.275***	−1.630***	−0.283***	−0.268***	−0.187***	−0.143***
	(0.051)	(0.048)	(0.049)	(0.174)	(0.081)	(0.512)	(0.069)	(0.066)	(0.066)	(0.044)
Dismissals × 1970	−0.298***	−0.203***	−0.324***	−0.334*	−0.314***	−1.844***	−0.322***	−0.309***	−0.225***	−0.143***
	(0.050)	(0.069)	(0.047)	(0.177)	(0.081)	(0.531)	(0.066)	(0.068)	(0.071)	(0.038)
Dismissals × 1980	−0.271***	−0.184***	−0.321***	−0.207	−0.238***	−1.554***	−0.271***	−0.256***	−0.220***	−0.104**
	(0.053)	(0.065)	(0.076)	(0.145)	(0.059)	(0.495)	(0.061)	(0.065)	(0.079)	(0.049)
Destruction × 1926	−0.004	−0.003	−0.006**	−0.003	−0.002	−0.452	−0.003	−0.007	−0.003	−0.003
	(0.002)	(0.004)	(0.003)	(0.003)	(0.003)	(0.450)	(0.004)	(0.006)	(0.002)	(0.002)
Destruction × 1931	−0.006***	−0.005*	−0.010***	−0.005**	−0.004	−0.880**	−0.003	−0.005	−0.005**	−0.005**
	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.413)	(0.003)	(0.006)	(0.002)	(0.002)
Destruction × 1950	−0.008**	−0.007*	−0.002	−0.007**	−0.006**	−1.000*	−0.011**	−0.019***	−0.004	−0.006**
	(0.003)	(0.004)	(0.003)	(0.003)	(0.002)	(0.541)	(0.004)	(0.007)	(0.003)	(0.002)
Destruction × 1961	−0.005***	−0.002	−0.001	−0.005**	−0.004*	−0.572	−0.006*	−0.015***	−0.002	−0.003*
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.504)	(0.003)	(0.005)	(0.003)	(0.002)
Destruction × 1970	0.001	0.004	0.005	0.002	0.002	0.668	0.004	−0.003	0.005	0.003
	(0.002)	(0.004)	(0.003)	(0.002)	(0.002)	(0.554)	(0.004)	(0.006)	(0.003)	(0.002)
Destruction × 1980	−0.003	0.001	0.001	−0.001	0.001	0.249	0.001	−0.025	0.002	0.001
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.813)	(0.004)	(0.018)	(0.004)	(0.004)
Extended Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
UniFE×Post45									Yes	
Quality1926×Years										Yes
Observations	609	588	486	714	714	714	714	714	714	714
R^2	0.724	0.698	0.733	0.668	0.704	0.718	0.719	0.703	0.755	0.743

Significant at ***1%, **5%, *10%. (SE clustered at university level.)

The dependent variable Publications is the sum of publications published by all scientists in department *d* in a five-year window around year *t*. The variable is normalized to have 0 mean and a standard deviation of 1 within subjects. In columns 1–3 and 7–10 Dismissals is equal to the number of dismissals between 1933 and 1940. In column 4 Dismissals is equal to % dismissals between 1933 and 1940 (divided by 10 so that the coefficient is equivalent to a 10% change in faculty size). In column 5 Dismissals is equal to the number of dismissals between 1933 and 1934. In column 6 Dismissals is equal to the predicted change in output between 1931 and 1940, calculated as the coefficient of losing one scientist (from column 6 in table 5) multiplied by the number of dismissed scientists in each department. In columns 1–5 and 8–10, Destruction is equal to % destruction caused by Allied bombings between 1940 and 1945. In column 6 Destruction is equal to the predicted change in output between 1931 and 1940, calculated as the coefficient on percent destruction (from column 6 in table 5) multiplied by percent destruction in each department. In column 7 Destruction is equal to average destruction in the three science departments in each university. In column 8 I instrument for Destruction at the department level with percentage destruction at the university level. Extended Controls are all controls as reported in column 6 of table 5. In column 3 Extended controls do not include Armament Industries (1933) × Year FE because of missing data for Swiss cities. UniFE × Post1945 is a full set of university fixed effects interacted with a post-1945 dummy. Quality1926 × Years is the interaction of department quality in 1926, interacted with the number of years that have passed since 1926. As the regression in column 7 includes an estimated regressor, SEs are block-bootstrapped at the university level.

alternative measure are less significant, in particular for publications. The magnitude of the coefficient of a 10% decline in department size, however, is very similar to the baseline specification (tables 6 and A5, column 4). I also show that results are robust to using early dismissals (between 1933 and 1934) to measure the human capital shock, because early dismissals rarely occurred for political reasons (tables 6 and A5, column 5).

In additional specifications, I show that the stronger persistence of the human capital shock was not driven by initially larger declines in output.[24] For this test, I construct alternative shock measures that capture the initial decline in output. I measure the initial effect of the dismissal shock as $\hat{\beta}_{2-1940} \times$ # $dismissed_d$, where $\hat{\beta}_{2-1940}$ is the estimated coefficient on the number of dismissals for the year 1940 and # *dismissed* is the number of dismissals in department *d*. Similarly, I measure the initial effect of the bombing shock as $\hat{\beta}_{3-1950} \times$ % *bombing* $destruction_d$. The two measures capture the initial decline in output after the two shocks in each department. To estimate the persistence of the initial decline, I interact the two measures with year indicators and estimate the equivalent of equation (1) using the new shock measures.[25] By construction, the estimated coefficients measure the effect of a decline in output by 1 standard deviation (1 SD) in the first postshock period, which leads to a coefficient of −1 in the first period after each shock. The persistence of the shocks, however, was very different. In departments where the initial 1 SD decline in output was caused by dismissals, output remained significantly lower until 1980. In departments where the initial 1 SD decline in

[24] In departments with dismissals, the average initial decline of publication output in the first period after the shock was 0.49 standard deviations. In departments with bombings, the average decline of publication output in the first period after the shock was 0.28 standard deviations.

[25] As the regression now includes regressors that include an estimated component, I block bootstrap standard errors at the university level.

output was caused by bombings, output recovered quickly (tables 6 and A5, column 6).

The following specification explores whether a potential reallocation of buildings after the bombings affected the impact of the physical capital shock. For the main results, I measure bombing destruction at the department level. This may underestimate the bombing effect if universities reallocated buildings across departments to mitigate negative effects of bombing destruction. To investigate this possibility, I use average destruction across all science departments as an alternative measure for the physical capital shock. This measure yields a more negative coefficient on the interaction of bombing destruction with the 1950 indicator. The destruction of an additional 10% of science buildings lowered output by 0.11 instead of 0.05 standard deviations (table 6, column 7). In regressions that use citation-weighted publications as the dependent variable, the coefficient changes from −0.04 to −0.08 (table A5, column 7). These results suggest that universities could indeed mitigate some of the bombing effects by reallocating buildings across departments.[26] Using this alternative destruction measure, I also find a slightly more persistent decline in output after the bombings. The negative effect persisted until 1961 for publications (table 6, column 7, significant at the 10% level) but not for citation-weighted publications (table A5, column 7). By 1970, bombed departments had completely recovered independently of the destruction and output measures. In fact, citation-weighted publications were significantly higher in bombed departments in 1970. A similar reallocation of resources after the human capital shock was impossible because scientists usually specialize in a single field.

Measurement error in bombing destruction. My measure of physical capital destruction may contain measurement error. To investigate how measurement error attenuates the bombing results, I instrument for department-level destruction with university-level destruction.[27] Because university-level destruction is constructed from different sources (see appendix 8.4), the two measurement errors should be uncorrelated. The instrumental variable strategy therefore minimizes attenuation bias. First-stage regressions, reported in table A6, indicate that university-level destruction is a strong predictor for department-level destruction.[28] The instrumental variable results indicate that in 1950, publications fell by 0.13 standard deviations in departments with 10% more destruction. In 1961, output was still 0.11 standard deviations lower in these departments. By 1970, however, output had recovered in the bombed departments (table 6, column 8). Equivalent results for citation-weighted publications also suggest that measurement error attenuates the bombing effects for 1950 and 1961 (table A5, column 8). The finding that bombed departments had completely recovered by 1970, however, is not distorted by measurement error.

University-wide changes after 1945. The following specifications investigate whether university-wide changes after 1945 affect results. Universities that were heavily exposed to one of the shocks may have changed their focus away from the sciences toward other fields. To investigate this hypothesis, I include the interaction of university fixed effects with a post-1945 dummy in the regression. Results indicate that the dismissal of one scientist led publication output to fall by 0.16 to 0.23 standard deviations, with the majority of results remaining significant at the 1% level (table 6, column 9). The coefficient on bombing destruction interacted with the 1950 dummy indicates that output fell by 0.04 standard deviations in 1950, but this result is no longer significant. Equivalent results for citation-weighted publications indicate that the dismissal of one scientist led publication output to fall by 0.12 to 0.18 standard deviations, but only the 1940 coefficient remains significant at the 5% level (table A5, column 9). The coefficient on bombing destruction interacted with the 1950 dummy indicates that output fell by 0.03 SD in 1950 (not significantly different from 0).[29]

Controlling for mean reversion. In other specifications I explore whether the results are driven by mean reversion. Some of the dismissed scientists worked in the best universities at the time, such as Göttingen or Berlin. These departments may have declined regardless of the dismissals. To investigate this possibility I include the interaction of department quality in 1926 with the number of years that have passed since 1926 as an additional control.[30] Results yield smaller coefficients for the dismissals and indicate that the dismissal of one scientist lowered publication output by between 0.10 and 0.15 standard deviations. Most coefficients remain significant at the 1% level (table 6, column 10). The bombing results are almost unaffected. Equivalent results for

[26] An alternative explanation for the larger coefficient (in absolute magnitude) could be lower measurement error for science-wide destruction compared to destruction in individual science departments.

[27] Because the university-level destruction measure captures destruction of all university buildings, it is different from the average destruction in science departments that I have used above.

[28] I instrument for six interactions of department-level destruction with year dummies. As a result, the usual F-test on the excluded instruments is not appropriate in this context. Stock and Yogo (2005) propose a test for weak instruments based on the Cragg-Donald (1993) eigenvalue statistic. Stock and Yogo provide critical values only for up to two endogenous regressors. With two endogenous regressors and two instruments, the critical value is 7.03. Here, I use six instruments for six endogenous regressors. Appropriate critical values should be lower than 7.03. The Cragg-Donald EV statistic reported in table A6 is 19.6, suggesting that weak instruments do not bias the results.

[29] Alternatively, one could include the interaction of university fixed effects with a dummy for each year (i.e., adding $35 \times 6 = 210$ interactions). As the degrees of freedom become small (714 observations – 210 university FE × year – 105 department fixed effects – 18 subject × year FE – 30 time-varying controls – 1 constant) and dismissals and bombings within universities are positively correlated, the results are no longer significant.

[30] Department quality in 1926 is measured as the sum of (citation-weighted) publications for the specification with (citation-weighted) publications as the dependent variable.

citation-weighted publications indicate that the dismissal of one scientist lowered output by between 0.11 and 0.17 standard deviations with most coefficients significant at the 5% level (table A5, column 10). Bombing results indicate a small but significantly negative effect in 1950 that did not persist.

Complementarities of human and physical capital shocks. The empirical model estimated above does not allow for complementarities of human and physical capital. To investigate whether complementarities are important, I add triple interactions of number dismissed, percentage destruction, and year dummies to the regression, that is, I estimate

$$\begin{aligned} Output_{dt} = \beta_1 &+ \sum_{t \neq 1931}^{t} \beta_{2t} HCShock(1933\text{-}40)_d \times Year_t \\ &+ \sum_{t \neq 1940}^{t} \beta_{3t} PCShock(1942\text{-}45)_d \times Year_t \\ &+ \sum_{t \geq 1950}^{t} \beta_{4t} HCShock(1933\text{-}40)_d \\ &\times PCShock(1942\text{-}45)_d \times Year_t \\ &+ \beta_5 DepartmentFE_d + \beta_6 YearFE_t + \varepsilon_{dt}. \quad (2) \end{aligned}$$

The first data point that could have been affected by both shocks is 1950, and I thus include triple interactions for 1950, 1961, 1970, and 1980. The publication results show that departments with dismissals and bombings did significantly worse than other departments in 1950. The estimated coefficient indicates a reduction in publications by 0.03 standard deviations in departments that lost one scientist and 10% of department buildings. Because departments recovered quickly from the physical capital shock, triple interactions with later years are no longer significant (table A7, column 2). For the citation-weighted publications, all triple interactions are insignificant (table A7, column 4). The dismissal results are remarkably robust to the inclusion of the triple interactions. These findings suggest that complementarities between human and physical capital are relatively small. Furthermore, human capital effects are not driven by important complementarities with physical capital.

C. *Subject-Specific Results*

I also investigate whether the human and physical capital shocks had different effects across disciplines. While physical capital may be more important in chemistry and some fields of physics, it may be less important in mathematics. The estimation results, however, indicate that the decline in output after the physical capital shock barely differed across fields (table A8).

By contrast, the dismissal results reveal interesting differences across subjects, despite the fact that most results are less precisely estimated because of smaller sample sizes. For citation-weighted publications, the results are largest and most persistent in mathematics, followed by physics (even though most coefficients in physics are not significant) and then chemistry (table A8, columns 2, 4, and 6). Because dismissed scientists in mathematics and physics were of higher quality than in chemistry (table 1) the results suggest that high-quality scientists may be particularly important.

D. *The Effect of High-Quality Scientists*

To further investigate this hypothesis, I assign scientists to quality percentiles (of both dismissed and nondismissed scientists) based on their pre-dismissal citation-weighted publications. I then investigate how the dismissal of high-quality scientists affected department output. The dismissal of any scientist lowered department output by 0.18 to 0.32 standard deviations (table 7, columns 1 and 2). The dismissal of an above-median-quality scientist lowered output by between 0.24 and 0.50 standard deviations (columns 3 and 4). The dismissal of higher-quality scientists caused even larger reductions in output that persisted in the long run. The dismissal of a scientist in the top 5th percentile, for example, lowered output by 0.74 to 1.58 standard deviations (columns 9 and 10). Figure 4 summarizes these findings graphically.[31]

V. Mechanisms for the Persistence of the Human Capital Shock

The previous results indicate that the dismissal of scientists, especially high-quality ones, caused larger declines in output than the bombing of universities. Furthermore, the human capital shock was more persistent. In the following section, I investigate possible mechanisms for the long-run persistence of the human capital shock.

A. *The Effect of Dismissals on Department Size*

One possible explanation for the decline in output could be a relative fall in department size from which departments never recovered. I investigate this hypothesis by regressing department size on the dismissal and destruction variables. Departments with dismissals were significantly smaller until 1970 but completely recovered by 1980 (table A10). These results indicate that a fall in department size can explain only some of the persistence of the human capital shock.[32]

[31] To improve clarity, I do not report confidence intervals. The majority of estimated coefficients are significantly different from 0 (table 7). The coefficients reported in the figure are estimated in separate regressions for each quality group. Because dismissals in different quality groups are correlated within departments, it is difficult to jointly estimate results for five quality groups. To investigate how results are affected when I jointly investigate the effect of losing scientists of different quality, I split dismissals into three quality groups (bottom 50th percentile, between the top 50th and the top 10th percentile, and top 10th percentile and above). Results, reported in figure A6 and table A9, confirm that high-quality dismissals are particularly detrimental. In further results (available on request) I also show that results are not driven by scientists in the top 5th percentile only.

[32] It is important to note that the results for department size do not imply that departments with dismissals remained smaller in absolute terms until 1980. They remained smaller only in relative terms.

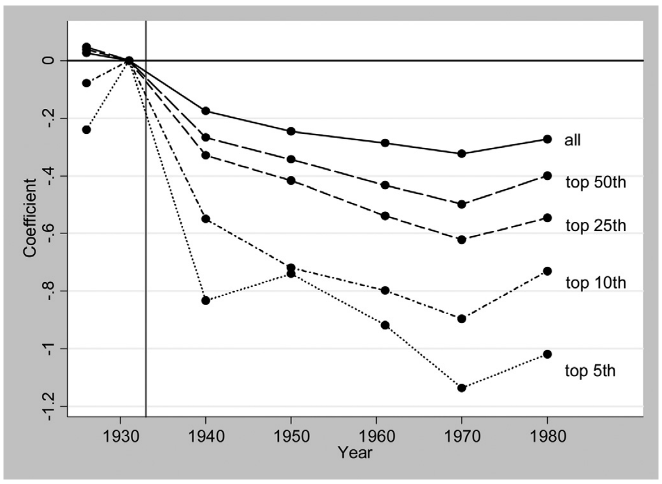
TABLE 7.—DISMISSAL OF TOP SCIENTISTS

Dependent Variable:	(1) Publications	(2) Citation-Weighted Publications	(3) Publications	(4) Citation-Weighted Publications	(5) Publications	(6) Citation-Weighted Publications	(7) Publications	(8) Citation-Weighted Publications	(9) Publications	(10) Citation-Weighted Publications
	All Dismissals		Above Median Quality		Top 25th Percentile		Top 10th Percentile		Top 5th Percentile	
Number of Dismissals × 1926	0.026	−0.087	−0.047*	−0.098	0.039	−0.161	−0.079	−0.471**	−0.241	−0.784*
	(0.026)	(0.077)	(0.028)	(0.071)	(0.057)	(0.127)	(0.067)	(0.202)	(0.237)	(0.444)
Number of Dismissals × 1940	−0.175***	−0.181***	−0.267***	−0.243***	−0.329***	−0.349***	−0.550***	−0.712***	−0.833***	−1.198***
	(0.038)	(0.064)	(0.039)	(0.085)	(0.059)	(0.111)	(0.157)	(0.153)	(0.262)	(0.298)
Number of Dismissals × 1950	−0.246**	−0.187***	−0.343**	−0.254***	−0.416*	−0.354***	−0.719**	−0.739***	−0.740	−1.078***
	(0.099)	(0.028)	(0.157)	(0.056)	(0.221)	(0.099)	(0.321)	(0.122)	(0.467)	(0.309)
Number of Dismissals × 1961	−0.286***	−0.191***	−0.433***	−0.237***	−0.539***	−0.345***	−0.798***	−0.662***	−0.918***	−1.189***
	(0.071)	(0.039)	(0.102)	(0.061)	(0.149)	(0.094)	(0.258)	(0.148)	(0.291)	(0.280)
Number of Dismissals × 1970	−0.323***	−0.215***	−0.498***	−0.278***	−0.621***	−0.428***	−0.896***	−0.845***	−1.136***	−1.441***
	(0.069)	(0.050)	(0.088)	(0.097)	(0.130)	(0.113)	(0.265)	(0.145)	(0.295)	(0.296)
Number of Dismissals × 1980	−0.272***	−0.181***	−0.399***	−0.237	−0.546***	−0.417**	−0.730***	−0.764***	−1.019***	−1.583***
	(0.061)	(0.064)	(0.104)	(0.160)	(0.125)	(0.155)	(0.259)	(0.184)	(0.270)	(0.381)
% Destruction × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Extended controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	714	714	714	714	714	714	714	714	714	714
R^2	0.718	0.552	0.726	0.548	0.720	0.555	0.708	0.572	0.683	0.584

Significant at ***1%, **5%, *10%. (SE clustered at university level.)

The dependent variable Publications reported in odd columns is the sum of publications published by all scientists in department d in a five-year window around year t. The dependent variable Citation-Weighted Publications reported in even columns is the sum of citation-weighted publications published by all scientists in department d in a five-year window around year t. Dependent variables are normalized to have 0 mean and a standard deviation of 1 within subjects. In columns 1–2, Number of Dismissals × 1926 is equal to the number of dismissals in Nazi Germany between 1933 and 1940 interacted with an indicator that is equal to 1 for observations from 1926. In columns 3–4, Number of Dismissals × 1926 is equal to the number of dismissals of above median quality interacted with an indicator that is equal to 1 for observations from 1926. The other interactions are defined accordingly. The excluded interaction is the number of dismissals with 1931, the last observation before the dismissals. % Destruction × Year FE is equal to percentage destruction caused by Allied bombings between 1940 and 1945 interacted with a set of year indicators as in the main specification. Extended Controls are all controls as reported in column 6 of table 5.

FIGURE 4.—PERSISTENCE OF HIGH-QUALITY DISMISSALS



The figure plots regression coefficients reported in table 7. The dependent variable is the total number of publications in department d and year t. The top line reports coefficients on the interaction of the number of dismissals (between 1933 and 1940) with year dummies as in column 1. The second line from the top reports coefficients on the interaction of the number of dismissals of above median quality with year dummies as in column 3, and so on.

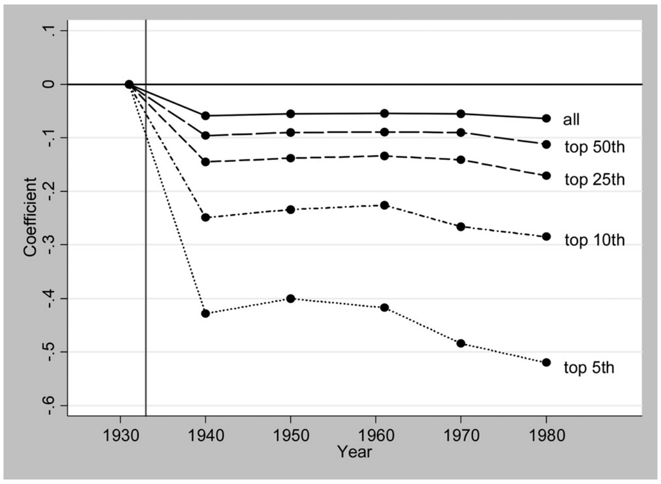
B. The Effect of Dismissals on the Quality of Hires

An alternative mechanism for the persistence of the human capital shock may be a permanent fall in the quality of hires. Star scientists are often instrumental in attracting other high-quality faculty. Before 1933, for example, the great mathematician David Hilbert helped to attract theoretical physicist Max Born (Nobel Prize, 1954) to the University of Göttingen. Born then used his influence to hire experimental physicist James Franck (Nobel Prize, 1925) (Jungk, 1963). Born and Franck were dismissed from the University of Göttingen in 1933. It is likely that these and other dismissals permanently affected the quality of subsequent hires.

To investigate changes in the quality of hires, I regress a measure of hiring quality on the dismissal variables and other controls. To identify hires, I use the faculty rosters documenting changes in the composition of departments. For 1931, for example, I classify all scientists who joined a department between 1926 and 1931 as hires. I obtain equivalent measures for subsequent years. I then construct two measures for the quality of each hire. First, I measure quality using average citation-weighted publications over the entire career of each scientist. While this measure is presumably the best summary statistic of a scientist's lifetime productivity, the measure may be endogenous to a scientist's moving decision. I therefore compute a second measure that quantifies quality by the number of pre-hire citation-weighted publications. This second measure is not affected by endogeneity concerns but is a noisier measure of quality, in particular for young scientists. I normalize both measures to have 0 mean and a standard deviation of 1 within subjects. I then construct hiring quality for each department and year by calculating the average quality of all hires.

Hiring quality fell significantly in departments with dismissals. The dismissal of one scientist lowered hiring quality by between 0.05 and 0.06 SD of lifetime citations. Estimated effects are significant for all years and persist until 1980 (table 8, panel A, column 1). Hiring quality fell even more dramatically after losing high-quality scientists, in particular after losing scientists of exceptional quality (columns 2–5). Figure 5 shows the reduction in hiring quality after the dismissal of scientists with different qualities.

FIGURE 5.—DISMISSALS AND THE QUALITY OF HIRES



The figure plots regression coefficients as reported in table 8, panel A. The dependent variable is quality of new hires in department *d* and year *t*. The top line reports coefficients on the interaction of the number of dismissals (between 1933 and 1940) with year dummies as in column 1. The second line from the top reports coefficients on the interaction of the number of dismissals of above-median quality with year dummies as in column 2, and so on. To improve clarity, 95% confidence intervals are omitted from the graph. All post-dismissal regression coefficients are significantly different from 0.

I obtain similar, but less precisely estimated, results if I use pre-hire citation-weighted publications to measure quality (table 8, panel B).

The fall in the quality of hires could have been caused by two different channels. First, the loss of high-quality scientists may have reduced a department's ability to identify promising scholars. Second, the loss of high-quality scientists may have reduced the quality of applications for open positions. My data do not allow me to distinguish these two channels because I cannot observe the pool of applicants. However, I can investigate whether the dismissal of older or younger scientists is driving the hiring results. I find that the loss of younger scientists (below median age) is particularly detrimental for the quality of new hires (table A11).[33] The scientists in my data are most productive at the beginning of their careers (figure A7). This suggests that hiring quality is driven by research-active scientists.

Some of the fall in hiring quality was likely driven by a decline in the quality of Ph.D. students in departments with dismissals after 1933 (Waldinger, 2010). As some departments hire their former Ph.D. students, the fall in Ph.D. quality may have translated into lower-quality faculty down the line.[34]

Historical data on professorial salaries suggest that the large and permanent decline in hiring quality was not driven by a compressed wage structure in German universities. While my data on all German and Austrian professors do not include information on salaries, other researchers have collected salary data. Before WWII, professorial salaries in Germany were very high, and professors belonged to the top 1% of the German wage distribution (Sohn, 2014). Even in the 1960s, professors belonged to the top 2.5% of the wage distribution. Sohn's data also indicate that the period studied in this paper was characterized by surprisingly large differences in professorial salaries both within and across universities.[35] In Sohn's random sample of 75 chemistry professors for the period 1926 to 1965, the highest-paid chemistry professor received an age-adjusted fixed salary that was 32% to 79% higher (depending on the time period) than the fixed salary of the lowest-paid chemistry professor. Professorial salaries also varied because of differences in variable pay that comprise housing allowances, add-ons for administrative positions, and lecture fees that could be negotiated by professors but were generally determined by the number of students who attended their lectures. In Sohn's sample of chemistry professors, the highest-paid chemistry professor's total earnings (including variable pay) were between 43% and 124% higher (depending on the time period) than total earnings of the lowest-paid professor. After a reform of professorial salaries in 1978, the wage structure of German professors became much more compressed. Sohn's auxiliary data suggest that in the time period studied in this paper, German universities could offer high salaries to attract highly productive scientists. Even so, departments with dismissals experienced a fall in hiring quality, presumably because they could no longer identify promising scholars or because promising scholars no longer wanted to join these departments.

C. *Localized Productivity Spillovers*

Localized productivity spillovers cannot drive persistence in this context. Prior research has shown that individual output of scientists who stayed in department with dismissals did not decline (Waldinger, 2012). If the productivity of scientists who were directly exposed to losing high-quality peers did not decline, it is unlikely that spillovers explain a large part of the persistence of the human capital shock.

VI. Conclusion

I use two WWII events—the dismissal of scientists in Nazi Germany and the Allied bombing campaigns—as exogenous and temporary shocks to the human and physical capital of science departments. In the short run, before departments

[33] Median age is 49 years for physics and chemistry and 46 years for mathematics.

[34] While German universities usually do not appoint full professors from their own staff, many researchers return to their former university in later years. Among mathematics Ph.D. students who graduated between 1912 and 1940 and obtained a university position in Germany, about 20% returned to the university that had granted their Ph.D.

[35] I thank Alexander Sohn for generously sharing his data on German professorial salaries. Before 1978, German professorial earnings were a fixed salary plus variable pay (Blomeyer, 2013). The fixed salary contained an age-related base salary (along with the option of anticipating age-related pay raises), plus fixed add-ons that universities could offer to attract highly productive professors. Professors who anticipated age-related pay increases and bargained for add-ons could increase their fixed salary by up to 50% in the postwar period (Blomeyer, 2013).

TABLE 8.—QUALITY OF NEW HIRES

Dependent Variable:	(1) Quality of Hires All Dismissals	(2) Quality of Hires Above Median Quality	(3) Quality of Hires Top 25th Percentile	(4) Quality of Hires Top 10th Percentile	(5) Quality of Hires Top 5th Percentile
A. Quality measured by lifetime citation-weighted publications					
Number of Dismissals × 1940	−0.059***	−0.096***	−0.145***	−0.249***	−0.428***
	(0.014)	(0.018)	(0.040)	(0.051)	(0.133)
Number of Dismissals × 1950	−0.055**	−0.090***	−0.138***	−0.234***	−0.400***
	(0.020)	(0.027)	(0.046)	(0.061)	(0.139)
Number of Dismissals × 1961	−0.054***	−0.089***	−0.134***	−0.226***	−0.417***
	(0.013)	(0.018)	(0.037)	(0.049)	(0.120)
Number of Dismissals × 1970	−0.055***	−0.090***	−0.141***	−0.266***	−0.484***
	(0.020)	(0.028)	(0.041)	(0.054)	(0.130)
Number of Dismissals × 1980	−0.064***	−0.112***	−0.171***	−0.285***	−0.520***
	(0.017)	(0.031)	(0.054)	(0.069)	(0.160)
B. Quality measured by prehiring citation-weighted publications					
Number of Dismissals × 1940	−0.010	−0.046*	−0.060	−0.166*	−0.174
	(0.013)	(0.024)	(0.044)	(0.094)	(0.214)
Number of Dismissals × 1950	−0.051***	−0.111***	−0.162***	−0.220***	−0.287*
	(0.010)	(0.023)	(0.046)	(0.068)	(0.156)
Number of Dismissals × 1961	−0.030**	−0.075**	−0.123*	−0.142	−0.199
	(0.014)	(0.035)	(0.061)	(0.087)	(0.181)
Number of Dismissals × 1970	−0.051***	−0.103***	−0.146***	−0.223***	−0.300*
	(0.011)	(0.024)	(0.043)	(0.072)	(0.169)
Number of Dismissals × 1980	−0.053***	−0.120***	−0.192***	−0.281***	−0.380**
	(0.016)	(0.032)	(0.049)	(0.076)	(0.172)
% Destruction × Year FE	Yes	Yes	Yes	Yes	Yes
Extended controls	Yes	Yes	Yes	Yes	Yes
Observations	602	602	602	602	602

Significant at ***1%, **5%, *10%. (SE clustered at university level.)

The dependent variable Quality of Hires measures the average quality of new hires in department d between year t and year $t-1$. In panel A, quality of hires is measured by the career average of citation-weighted publications averaged across all hires in a department. In panel B, quality of hires is measured by age-adjusted average citation-weighted publications measured before year t, averaged across all hires in a department. The average is calculated for five years at the midpoint between year t and year $t-1$. The dependent variables are normalized to have 0 mean and a standard deviation of 1 within subjects. In column 1 Number of Dismissals × 1926 is equal to the number of dismissals in Nazi Germany between 1933 and 1940 interacted with an indicator that is equal to 1 for observations from 1926. In column 2 Number of Dismissals × 1926 is equal to the number of dismissals of above-median quality interacted with an indicator that is equal to 1 for observations from 1926. The other interactions are defined accordingly. The excluded interaction is the number of dismissals with 1931, the last observation before the dismissals. % Destruction × Year FE is equal to percentage destruction caused by Allied bombings between 1940 and 1945 interacted with a set of year indicators as in the main specification. Extended Controls are all controls as reported in column 6 of table 5.

could fully respond, the human capital shock caused a four-times-larger decline in output than the physical capital shock. While the physical capital shock did not cause long-run declines in output, the human capital shock persisted in the long term, until 1980, and most likely beyond as departments with dismissals had not recaptured their former output levels until 1980. The dismissal of high-quality scientists caused particularly large declines in output. These findings suggest that human capital is more important than physical capital for the output of science departments.

The long-run results also indicate that recovering from losing professors is much more difficult than rebuilding facilities. Especially the loss of star scientists has long-lasting effects because the quality of hires falls after stars have left the department.

Of course, my findings do not indicate that physical capital is irrelevant for scientific output because postwar reconstruction targeted destroyed departments and because physical capital may have been less important than today—a time when advances in some fields (e.g., particle physics) rely on very large physical capital investments. While funding for West German universities increased substantially in the postwar period in absolute terms and in percent of GNP, the largest increases took place after 1960 when the West German economy was booming (figure A8; Pfetsch, 2010). In 1950, university funding in percent of GNP was very similar to funding in 1940, suggesting that universities did not benefit from disproportionate funding increases in the immediate postwar period. The results in this paper suggest that German universities may have spent too little of the funding increase on human capital compared to physical capital, not only in the postwar period but also in the long run.

An important question is whether evidence from historical events in Germany can help our understanding of science departments today and in other countries. As I have highlighted in this paper, recent evidence on evolutionary biology departments suggests that human capital plays a similarly important role in contemporary times and in other countries as it did in the historical German period I analyze here (Agrawal et al., 2014). Other research has shown that chemists who were dismissed from Nazi Germany and migrated to the United States increased patenting by U.S. inventors (Moser et al., 2014). The overall increase in patenting was driven by new researchers who entered the research fields of émigrés from Nazi Germany. The productivity of incumbent scientists, however, did not increase. Other research has shown that the arrival of Soviet mathematicians in the United States did not increase the productivity of incumbent U.S. mathematicians (Borjas & Doran, 2012). Furthermore, the output of mathematicians who worked in the same location but remained in the Soviet Union did not decrease after their peers left the Soviet Union (Borjas & Doran, 2015).

The findings of this paper, and other recent papers, suggest that human capital is key for the creation of scientific knowledge, especially because star scientists attract other good researchers. Spillovers on existing researchers seem much less important, and may even be absent. Attracting stars seems the most promising policy to improve the quality of academic departments.

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