Peer Effects in Science

Evidence from the Dismissal of Scientists in Nazi Germany

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Abstract

I investigate whether faculty quality and department size affect the productivity of scientists. The endogeneity problems related to estimating these effects are addressed by using the dismissal of science professors by the Nazi government as a source of exogenous variation. While local faculty quality is very important for PhD student outcomes it does not affect the productivity of professors. Local department attributes are thus much more important for young researchers who do not yet belong to a professional network outside their university. While not affected by the local department, professors' productivity is strongly affected by a high quality co-author network.

1 Introduction

This paper analyzes the effect of faculty quality and department size on the productivity of scientists. First I analyze whether these factors affect the outcomes of PhD students. In a second part of the analysis, I investigate whether they affect the productivity of professors. The effect of faculty quality on the productivity of professors can be characterized as peer effects in the classical sense. The relationship between professors and PhD students, however, is more asymmetric. The effect of professors on PhD student outcomes corresponds to peer effects in a loose sense only. It is widely believed that faculty quality is important for the productivity of both PhD students and professors. Professors may not necessarily consider their full impact on PhD students or colleagues when deciding where to locate. This may result in a misallocation of talent and underinvestment in academic research. Having a good understanding of the impact of faculty quality is therefore crucial for researchers and policy makers alike. Despite the widespread belief in the presence of these effects there is only limited empirical evidence for them.

This is due to the fact that obtaining causal estimates is very challenging in this setup. An important problem for any estimation of faculty quality and size effects is caused by sorting of individuals.

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Talented PhD students often attend universities with the largest and best faculty. Highly productive professors also like to locate near good colleagues. It is therefore not clear whether successful scientists are more productive because they are studying or working in a university with highly productive professors or because their productivity is higher per se. Another problem complicating the estimation of these effects is the presence of unobservable factors which affect a researcher's productivity but also the productivity of professors in the same department. The construction of a new laboratory may be a factor which can be hard to observe for the econometrician. Furthermore, estimates of peer effects may be distorted because of measurement problems. In this context the main problem is the correct measurement of faculty quality. A promising strategy to obtain unbiased estimates of these effects is therefore to analyze a researcher's productivity if the faculty changes due to reasons which are unrelated to her own productivity.

This paper proposes the dismissal of science professors by the Nazi government as an exogenous and dramatic change in department size and faculty quality for researchers in Germany. Almost immediately after Hitler's National Socialist party secured power in 1933 the Nazi government dismissed all Jewish and so called "politically unreliable" professors from German universities. Around 13 to 18 percent of all science professors were dismissed between 1933 and 1934 (13.1 of chemists, 13.6 percent of physicists, and 18.3 percent of mathematicians). Many of the dismissed scholars were outstanding members of their profession, among them the famous physicist and Nobel Laureate Albert Einstein, the chemist Georg von Hevesy who received the Nobel Prize in 1943, and the Hungarian mathematician Johann von Neumann. PhD students and professors at the affected departments were thus exposed to a dramatic change in department size and faculty quality. This shock persisted until the end of my sample period because the majority of the open positions could not be filled immediately. Researchers in departments without Jewish or "politically unreliable" professors did not experience any dismissals and thus no change in faculty quality or size.

In this paper I use the dismissal to identify faculty effects among physicists, chemists, and mathematicians. I focus on these subjects because advancements in these fields are widely believed to be important drivers of technological progress and important for economic growth in a knowledge based society. Furthermore, the productivity of scientists can be well approximated by analyzing publications in academic journals. Scientists published their results in refereed scientific journals already in the 1920s and 1930s, the time period studied in this paper. A further reason for studying scientists is Germany's leading position in those fields in the early 20th century. Of the Nobel prizes awarded between 1910 and 1940, 27 percent of the prizes in physics and 42 percent of the chemistry prizes were granted to scientists affiliated with a German university. This is a much larger fraction than that of any other country at the time. If faculty quality and peer effects are important determinants of a researcher's productivity they are likely to be especially important in a flourishing research environment such as Germany in the early 20th century.[1]

I use a large number of historical sources to construct two datasets for my analysis. The first dataset includes all individuals who obtain their PhD in mathematics from any German university between 1923 and 1938. The second dataset contains the universe of physics, chemistry, and mathematics

[1] A further reason for concentrating on the sciences is the attempt of the Nazi regime to ideologize all parts of society after 1933. These policies also affected university research. The impact on different subjects, however, varied a lot. Subjects such as economics, psychology, history, or sociology were affected much more than the sciences. The sciences were not completely unaffected by the Nazi regime. The most famous example is the "German Physics" movement by a small group of physicists trying to ideologize physical research. The consensus among historians of science, however, is that the movement never mangaged to have a strong impact on the physics community. See Beyerchen (1977) for details.

professors teaching at all 33 universities in Germany from 1925 until 1938.[2] I do not consider the years after 1938 because of the start of World War II in 1939. The data on all dismissed professors comes from a number of different archival sources. Finally, I obtain data on publications and citations of these researchers in the leading academic journals of the time. More details on the data sources are given in the data section below.

I use this data to investigate the effect of faculty quality and department size using the dismissal of professors as an exogenous source of variation. The first part of the analysis focuses on outcomes of mathematics PhD students. I find that faculty quality has a strong and significantly positive effect on the probability of publishing the dissertation in a top academic journal. The magnitude of the faculty quality effect can be evaluated by considering an average department which hires a top 20 mathematics professor.[3] The corresponding increase in faculty quality increases the PhD students' probability of publishing their dissertation by about 12 percentage points. I also consider the long-term outcomes of an increase in faculty quality. Faculty quality has a strong positive effect on the probability that the former PhD student becomes full professor later in life. This probability increases by about 8.4 percentage points for an increase in faculty quality corresponding to the arrival of a top 20 mathematician in the average department. Department size does not seem to affect the outcomes of PhD students. These results are very robust to a large number of specification checks.

In a second part of the analysis I investigate the effects of faculty quality and department size on the productivity of professors in physics, chemistry, and mathematics. These effects correspond to classical localized peer effects in other setups. Surprisingly, and contrary to the belief of most researchers, I do not find any evidence for peer effects within a researcher's department. I find that these result is very robust for all subjects, different definitions of peer groups, and allowing for nonlinearities in peer effects. I further investigate professor level peer effects among *coauthoring* professors for physics and chemistry.[4] These coauthors can be, and were indeed, often located in different departments. I find that losing a coauthor of average quality reduces the average researcher's productivity by about 13 percent in physics and 16.5 percent in chemistry. Losing coauthors of higher than average quality leads to an even larger productivity loss. Furthermore, I show that the effect is solely driven by recent collaborations. The productivity of scientists who lose a colleague with whom they did not coauthor in the last four years before the dismissal does not fall after the dismissal. It is not entirely clear whether one would like to characterize the joint publication of papers a real spill-over effect. I investigate this issue and find evidence for genuine evidence for peer effects among coauthors.

Overall, I find that *localized* effects of department quality are confined to PhD students. Professors who are already more established do not benefit from the quality of their colleagues in their local department. They do, however, benefit strongly from collaborating with high quality coauthors who often work in different departments. It is quite intuitive that the PhD students are much more dependent on the quality of their local department as they have few possibilities to interact with faculty from other departments. Established professors, however, have many professional contacts outside their department. Conferences, for example, were very common and widely attended at that time. Professors are thus much less dependent on the quality of the local faculty than PhD students.

There is of course a worry that the dismissals affected the productivity of researchers through

[2]For mathematics I observe the professors from 1923 onwards as well.

[3]A top 20 mathematics professor is a mathematician who was ranked among the 20 most cited mathematics professors between 1925 and 1932.

[4]Due to the very low level of coauthorship in mathematics I cannot analyze spill-over effects for coauthors in mathematics.

other channels than peer effects. I discuss these threats to the identification strategy below and show evidence that the dismissals are uncorrelated with changing incentives in the affected departments, or the number of ardent Nazi supporters in the department. I also show that changes to the funding of professors are unlikely to explain my findings. Furthermore, I show that different productivity trends of researchers in affected and unaffected departments are not important in this setup.

Understanding the effects of the dismissal of a large number of scientists during the Nazi period is interesting in its own right.[5] The findings of my paper may also lead to a better understanding of similar events occurring in other countries. One example is the purge of thousands of scientists who did not adhere to the communist ideology in the Soviet Union under Stalin. The scope of this paper, however, goes beyond the understanding of historical events, because it allows a clean identification of faculty quality and peer effects. To my knowledge, it is the first to analyze *localized* peer effects among scientists using credibly exogenous variation in peer quality.

The question remains whether evidence on peer effects in Germany in the 1920s and 1930s can be used to understand peer interactions today. A number of reasons suggest that the findings of this study may be relevant for understanding spill-overs among present-day researchers. The three subjects studied in this paper were already well established at that time; especially in Germany. Scientific research followed practices and conventions which were very similar to current research methods. Researchers were publishing their results in refereed academic journals, conferences were common, and researchers were surprisingly mobile within the German speaking scientific community. Unlike today, they could not communicate via E-mail. They did, however, vividly discuss their research in very frequent mail correspondence with their colleagues in other universities. While it is difficult to assess the external validity of my study it is reassuring that my findings for coauthors of professors are very comparable to the findings of a recent paper by Azoulay, Zivin, and Wang (2008). They investigate peer effects among present-day coauthors in the life sciences. Using the death of a prolific researcher as an exogenous source of variation in a scientist's peer group they find that deaths of coauthors lead to a 5 to 10 percent decline in a researcher's productivity. They find stronger effects for more prolific coauthors.[6] Their setup does not allow them to directly analyze *localized* peer effects as they only observe the coauthors of dying researchers and not all peers in their department. The big advantage of my data is that I observe the universe of all university researchers in physics, chemistry, and mathematics. I can thus directly analyze localized peer effects using the dismissal as an exogenous variation in the peer group of staying scientists. Given that many decisions of scientists and policy makers affect certain universities and departments it is especially important to have a better understanding of localized spill-overs.

Few papers have analyzed localized spill-overs among university scientists. One exception is a recent paper by Weinberg (2007). He analyzes localized peer effects among Nobel Prize winners in physics and finds evidence for mild positive effects. Using the timing of starting Nobel Prize winning work he tries to establish causality. It is likely, however, that this does not fully address the endogeneity problem which may affect his results on spill-overs. Kim, Morse, and Zingales (2006) investigate peer effects in economics and finance faculties. Their strategy, however, does not address the endogenous selection of peers into certain departments. They find positive peer effects for the

[5] Recently other economists have analyzed aspects of the Nazi rise to power. Ferguson and Voth (2008), for example, show that firms supporting the Nazi movement experienced unusually high stock-market returns in the first months of the Nazi regime.

[6] Oettl (2008) extends the analysis of Azoulay et al. and shows that coauthor peer effects are large not only if the dying coauthor was very productive but also when he was considered very helpful by his surviving coauthors.

1970s, and 1980s, but negative peer effects for the 1990s suggesting that falling communication costs may explain the declining importance of localized peers groups. While not studying localized peer effects other researchers have also emphasized the role of falling communication costs for increasing long distance collaborations between professors.[7] While these recent papers suggest a fading role of geographic distance due to falling communication costs I do not find any evidence for localized peer effects among professors for the 1920s and 1930s. This casts doubt on the explanation that falling communication costs can indeed explain the increase in long-distance collaborations among professors.[8]

My findings also speak to the growing literature on the impact of university quality on student outcomes. To my knowledge this paper is the first to investigate the impact of university quality on the outcomes of *PhD* students using exogenous variation in faculty quality. Other researchers, however, have investigated the effects of university quality on the outcomes of undergraduate students. Usually these studies have looked at the impact of college quality on wages. Dale and Krueger (2002) investigate the effect of attending a more selective college on earnings later in life. They find that students who attend more selective colleges earn about the same as students who attend less selective colleges. Children from low-income families, however, earn more if they attend more selective colleges. Behrman, Rosenzweig and Taubman (1996) investigate the effect of college characteristics on wages later in life. They find that attending private colleges or colleges which also grant PhDs increase earnings later in life. Also average salary of the faculty seems to have a positive impact on students' earnings. Brewer, Eide and Ehrenberg (1999) use a structural model to model the decision of attending a college of a particular quality and find that undergraduate college quality has a significant impact on wages.[9]

Many popular accounts of the loss of scientific leadership in Germany following WWII emphasize the role of the dismissals in Nazi Germany.[10] It is important to emphasize that the absence of localized peer effects at the professorial level does not indicate that the German science community did not suffer because of the dismissals. First of all, I show below that the dismissed were often the best researchers in their fields and that the quality of many German science faculties fell because of these dismissals. In addition to that, the negative impact on staying coauthors will have had a negative impact on the productivity of the remaining professors. The large negative effects on PhD students furthermore suggest that the effects of a reduction in faculty quality are very long lived as it affects an entire generation of young researchers even in the long run.

The remainder of the paper is organized as follows: the next section gives a brief description of historical details. A particular focus lies on the description of the quantitative and qualitative loss to German science. Section 3 gives a more detailed description of the data sources used in the

[7] See for example Adams et al. (2005), Agrawal and Goldfarb (2008) and Rosenblat and Mobius (2004).

[8] Another related strand of the literature focuses on regional spill-over effects of patent citations. Jaffe, Trajtenberg, and Henderson (1993) use an ingenious method to control for pre-existing regional concentration of patent citations. They find that citations of patents are more geographically clustered than one would expect if there were no regional spill-over effects. Thompson and Fox-Keane (2005) challenge those findings in a later paper.

[9] A more recent strand of the literature has tried to disentangle the impact of different professor attributes on academic achievement of undergraduate students within a university. Hoffmann and Oreopoulos (2009) find that subjective teacher evaluations have an important impact on academic achievement. Objective characteristics such as rank and salary of professors does not seem to affect achievement of students. Carell and West (2008) find that academic rank and teaching experience is negatively related to contemporaneous student achievement but positively to the achievement in follow-on courses in mathematics and science. For humanities they find almost no relationship between professor attributes and student achievement.

[10] Careful quantitative studies, however, show that the dismissal only contributed mildly to the shift of scientific lead from Germany to the US. See for example Weinberg (2008).

analysis. Section 4 describes the identification strategy. The effect of faculty quality and department size on PhD student outcomes is analyzed in section 5. In section 6 I then evaluate the effect on the productivity of professors. Section 7 concludes.

2 The Expulsion of Jewish and 'Politically Unreliable' Scholars from German Universities

Just over two months after the National Socialist Party seized power in 1933 the Nazi government passed the "Law for the Restoration of the Professional Civil Service" on the 7th of April of 1933. Despite this misleading name the law was used to expel all Jewish and "politically unreliable" persons from civil service in Germany. At that time most German university professors were civil servants. Therefore the law was directly applicable to them. Via additional ordinances the law was also applied to other university employees who were not civil servants. The main parts of the law read:

> *Paragraph 3:* Civil servants who are not of Aryan descent are to be placed in retirement... (this) does not apply to officials who had already been in the service since the 1st of August, 1914, or who had fought in the World War at the front for the German Reich or for its allies, or whose fathers or sons had been casualties in the World War.
>
> *Paragraph 4:* Civil servants who, based on their previous political activities, cannot guarantee that they have always unreservedly supported the national state, can be dismissed from service.
>
> ["Law for the Restoration of the Professional Civil Service", quoted after Hentschel (1996)]

In a further implementation decree it was specified that all members of the Communist Party were to be expelled. The decree also specified "Aryan decent" as: "Anyone descended from Non-Aryan, and in particular Jewish, parents or grandparents, is considered non-Aryan. It is sufficient that one parent or one grandparent be non-Aryan." Thus Christian scientists were dismissed if they had a least one Jewish grandparent. In many cases scientists would not have known that their colleague had Jewish grandparents. It is therefore quite unlikely that the majority of the dismissed had been treated differently by their colleagues before the rise of the Nazi party. The law was immediately implemented and resulted in a wave of dismissals and early retirement from the German universities. A careful early study by Harthorne published in 1937 counts 1111 dismissals from the German universities and technical universities between 1933 and 1934.[11] This amounts to about 15 percent of the 7266 university researchers present at the beginning of 1933. Most dismissals occurred in 1933 immediately after the law was implemented. Not everybody was dismissed as soon as 1933 because the law allowed Jewish scholars to remain in office if they had been in office since 1914, if they had fought in the First World War, or had lost a father or son in the war. Nonetheless, many of the scholars who could stay according to this exception decided to leave voluntarily; for example the Nobel laureates James

[11] The German university system had a number of different university types. The main ones were the traditional universities and the technical universities. The traditional universities usually covered the full spectrum of subjects whereas the technical universities focused on technical subjects.

Franck and Fritz Haber. They were just anticipating a later dismissal as the Reich citizenship laws (*Reichsbürgergesetz*) of 1935 revoked the exception clause.

Table 1 reports the number of dismissals in the three subjects studied in this paper: physics, chemistry, and mathematics. Similarly to Harthorne, I focus my analysis on researchers who had the Right to Teach (*venia legendi*) at a German university. According to my calculations about 13.6 percent of the physicists, 13.1 of the chemists, and 18.3 percent of the mathematicians were dismissed between 1933 and 1934.[12] It is interesting to note that the percentage of dismissals in these three subjects and at the German universities overall was much higher than the fraction of Jews living in Germany. It is estimated that about 0.7 percent of the total population in Germany was Jewish at the beginning of 1933.

My data does not allow me to identify whether the researchers were dismissed because they were Jewish or because of their political orientation. Other researchers, however, have investigated this issue and have shown that the vast majority of the dismissed were either Jewish or of Jewish decent. Deichmann (2001) studies chemists in German and Austrian universities (after the German annexation of Austria in 1938 the Nazi government extended the aforementioned laws to researchers at Austrian universities). She finds that about 87 percent of the dismissed chemists were Jewish or of Jewish decent. The remaining 13 percent were dismissed for political reasons. Siegmund-Schultze (1998) estimates that about 79 percent of the dismissed scholars in mathematics were Jewish.

Before giving further details on the distribution of dismissals across different universities I am going to provide a brief overview over the fate of the dismissed researchers. Immediately after the first wave of dismissals in 1933, foreign émigré aid organizations were founded to assist the dismissed scholars with obtaining positions in foreign universities. The first organization to be founded was the English "Academic Assistance Council" (later renamed into "Society for the Protection of Science and Learning"). It was established as early as April 1933 by the director of the London School of Economics Sir William Beveridge. In the US the "Emergency Committee in Aid of Displaced Scholars" was founded in 1933. Another important aid organization, founded in 1935 by some of the dismissed scholars themselves, was the Emergency Alliance of German Scholars Abroad ("Notgemeinschaft Deutscher Wissenschaftler im Ausland"). The main purpose of these and other, albeit smaller, organizations were to assist the dismissed scholars in finding positions abroad. In addition to that prominent individuals like Eugen Wigner, Albert Einstein or Hermann Weyl tried to use their extensive network of personal contacts to find employment for less well-known scientists. Due to the very high international reputation of German scientists many of them could find positions without the help of the aid organizations. Less renowned and older scientists had more problems in finding adequate positions abroad. Initially many dismissed scholars fled to European countries. Many of these countries were only temporary refuges because the dismissed researchers often obtained temporary positions, only. The expanding territory of Nazi Germany in the early stages of World War II led to a second wave of emigration from the countries which were invaded by the German army. The main destinations of dismissed physicists, chemists, and mathematicians were the United States, England, Turkey, and Palestine. The biggest proportion of dismissed scholars in all three subjects eventually moved to the

[12] This number is consistent with the numbers obtained by historians of science who studied the dismissal of scientists in Nazi Germany. Fischer (1991) reports that 15.5 percent of physicists were dismissed between 1933 and 1940. Deichmann (2001), who studied chemists in the Third Reich, calculates a loss of about 24 percent from 1933 to 1939. The difference between my figure and hers can be explained by the fact that she includes all dismissals from 1933 to 1939. Furthermore, my sample includes 5 more universities which all have below average dismissals. Unfortunately there are no comparable numbers for mathematics by other researchers.

United States. For the purposes of this paper it is important to note that the vast majority of the emigrations took place immediately after the researchers were dismissed from their university positions. Further collaborations with researchers staying in Germany were thus extremely difficult and did hardly occur. A very small minority of the dismissed did not leave Germany and most of them died in concentration camps or committed suicide. Extremely few, managed to stay in Germany and survive the Nazi regime. Even these scientists who stayed in Germany were no longer allowed to use university laboratories and other resources. The possibility of ongoing collaboration of the dismissed scientists with researchers staying at the German universities was thus extremely limited.

The aggregate numbers of dismissals hide the fact that the German universities were affected very differently by the dismissals. Even within a university there was a lot of variation across different departments. Whereas some departments did not experience any dismissals others lost more than 50 percent of their personnel. The vast majority of dismissals occurred in 1933 and 1934. Only a small number of scientists was dismissed after these years. The few dismissals occurring after 1933 affected researchers who had been exempted under the clause for war veterans or for having obtained their position before 1914. In addition to that, some political dismissals occurred during the later years. In order to have a sharp dismissal measure I focus on the dismissals in 1933 and 1934. Table 2 reports the number of dismissals in the different universities and departments. An example for the huge variation in dismissals is the university of Göttingen, one of the leading universities at the time. The university lost 40 percent of its researchers in physics and almost 60 percent in mathematics. In chemistry, however, not a single scholar was dismissed between 1933 to 1934.

Table 3 gives a more detailed picture of the quantitative and qualitative loss in the three subjects. The dismissed physicists were younger than the average but made above average scientific contributions; they received more Nobel Prizes (either before or after the dismissal), published more papers in top journals, and received more citations for their publications.[13] The scientific excellence of the dismissed physicists has already been noticed by Fischer (1991). In chemistry the dismissed were more similar to the researchers staying in Germany. The dismissed mathematicians were of even higher excellence compared to the average researcher than the physicists.

About 33 percent of the publications in top journals were co-written papers in physics. About 11 percent of all papers were co-published with a coauthor holding a faculty position at a German university. This fraction is much lower than the overall level of co-publishing because of two reasons. A large fraction of coauthors were assistants or Ph.D. students. Secondly, some coauthors were teaching at a foreign university or were employed by a research institute. The last line of Table 3 shows the low level of cooperation within a department; only about 4 percent of all publications were coauthored with a member of staff from the same university. In chemistry 76 percent of papers were coauthored, 12 percent were coauthored with a coauthor holding a faculty position at a German university and only 5 percent of publications were coauthored with a faculty member from the same university. In mathematics these numbers were 11 percent, 6 percent, and 3 percent, respectively.

[13] For a more detailed description of the publications data see the Data section.

3 Data

3.1 Data on Dismissed Scholars

The data on dismissed scholars is obtained from a number of different sources. The main source is the "List of Displaced German Scholars". This list was compiled by the relief organization "Emergency Alliance of German Scholars Abroad" and was published in 1936. The purpose of publishing the list was to facilitate the finding of positions for the dismissed researchers in countries outside Germany. Overall, the list contained about 1650 names of researchers from all university subjects. In the introductory part of the list the editors explain that they have made the list as complete as possible. Most historians of science working on the dismissal of researchers in Nazi Germany have used this list as the basis for their research. I extracted all dismissed physicists, chemists, and mathematicians from the list. In the appendix I show a sample page from the physics section of the list. Interestingly, four physicists who had already received the Nobel Prize or were to receive it in later years appear on that page. Out of various reasons, for example if the dismissed died before the list was compiled, a small number of dismissed scholars did not appear in the list. To get a more precise measure of all dismissals I complement the information in the "List of Displaced German Scholars" with information from other sources.[14]

The main additional source is the "Biographisches Handbuch der deutschsprachigen Emigration nach 1933 - Vol. II : The arts, sciences, and literature". The compilation of the handbook was initiated by the "Institut für Zeitgeschichte München" and the "Research Foundation for Jewish Immigration New York". Published in 1983 it contained short biographies of artists and university researchers who emigrated from Nazi Germany.[15]

In addition to these two main data sources, I rely on data compiled by historians who studied individual academic subjects during the Nazi era. Beyerchen (1977) included a list of dismissed physicists in his book about the physics community in Nazi Germany. I use the information included in that list to amend my list of dismissed scholars. Furthermore, I use data from an extensive list of dismissed chemists which was compiled by Deichmann (2001). Similarly, I complement my list with the information listed in Siegmund-Schultze's (1998) book on dismissed mathematicians.

My list of dismissals also contains the few researchers who were initially exempted from being dismissed but resigned voluntarily. The vast majority of them would have been dismissed due to the racial laws of 1935 anyway and were thus only anticipating their dismissal. All of these voluntary resignations were directly caused by the discriminatory policies of the Nazi regime.

3.2 Data on all Scientists at German Universities between 1925 and 1938

To investigate the impact of the dismissals on the researchers who stayed at the German universities I construct a full list of all scientists at the German universities from 1925 to 1938. Using the semi-official University Calendar[16] I compile an annual roster of the universe of physicists, chemists, and

[14] Slightly less than 20 percent of 1933 to 1934 dismissals do only appear in those additional sources.

[15] Kröner (1983) extracted a list of all dismissed university researchers from the handbook. I use Kröner's list to append my list of all dismissed scholars.

[16] The University Calender was published by J.A. Barth. He collected the official university calenders from all German universities and compiled them into one volume. Originally named "Deutscher Universitätskalender". It was renamed "Kalender der deutschen Universitäten und technischen Hochschulen" in 1927/1928. From 1929/1930 it was renamed "Kalender der Deutschen Universitäten und Hochschulen". In 1933 it was again renamed into "Kalender der reichsdeutschen Universitäten und Hochschulen".

mathematicians from the winter semester 1924/1925 (lasting from November 1924 until April 1925) until the winter semester 1937/1938. The data for the technical universities starts in 1927/1928, because the University Calendar included the technical universities only after that date. The University Calendar is a compilation of all individual university calenders listing the lectures held by each scholar in a given department. If a researcher was not lecturing in a given semester he was still listed under the heading "not lecturing". From this list of lectures I infer the subject of each researcher to construct yearly faculty lists of all physics, chemistry, and mathematics departments.[17,18]

To assess a researcher's specialization I consult seven volumes of "Kürschners deutscher Gelehrten-Kalender". These books are listings of German researchers compiled at irregular intervals since 1925.[19] The editors of the book obtained their data by sending out questionnaires to researchers asking them to provide information on their scientific career. I use this information to ascertain a scientist's specialization. Because of the blurred boundaries of the specializations in mathematics a lot of mathematicians did not specify their specialization. In those cases I infer the specialization from the main publications they list in the "Gelehrtenkalender". As the participation of the researchers in the compilation was voluntary not all of them provided their personal information to the editor. If I cannot find a scientist's specialization in any of the volumes of the "Gelehrtenkalender", which occurs for about 10 percent of scientists, I conduct an internet-search for the scientist to obtain his specialization. Overall I obtain the scientist's specialization for about 98 percent of all researchers.[20] Table A1 in the appendix gives an overview of all specializations and the fraction of scientists in each of them.

3.3 Publication Data

To measure the professors's productivity I construct a dataset containing the publications of each researcher in the top academic journals of the time. At that time most German researchers published in German journals. The quality of these German journals was usually very high because many of the German physicists, chemists, and mathematicians were among the leaders in their field. This is especially true for the time before the dismissal as is exemplified by the following quote; "Before the advent of the Nazis the German physics journals (*Zeitschrift für Physik, Annalen der Physik, Physikalische Zeitschrift*) had always served as the central organs of world science in this domain [...] In 1930 approximately 700 scientific papers were printed in its (the Zeitschrift für Physik´s) seven volumes of which 280 were by foreign scientists." (American Association for the Advancement

[17] At that time a researcher could hold a number of different university positions. Ordinary Professors held a chair for a certain subfield and were all civil servants. Furthermore there were different types of Extraordinary Professors. First, they could be either civil servants (*beamteter Extraordinarus*) or not have the status of a civil servant *(nichtbeamteter Extraordinarius).* Universities also distinguished between extraordinary extraordinary professors *(ausserplanmäßiger Extraordinarus)* and planned extraordinary professors *(planmäßiger Extraordinarius).* Then as the lowest level of university teachers there were the *Privatdozenten* who were never civil servants. Privatdozent is the first university position a researcher could obtain after the 'venia legendi'.

[18] The dismissed researchers who were not civil servants (Privatdozenten and some Extraordinary Professors) all disappear from the University Calendar between the winter semester 1932/1933 to the winter semester 1933/1934. Some of the dismissed researchers who were civil servants (Ordinary Professors and some Extraordinary Professors), however, were still listed even after they were dismissed. The original law forced Jewish civil servants into early retirement. As they were still on the states' payroll some universities still listed them in the University Calendar even though they were not allowed to teach or do research anymore. My list of dismissals includes the exact year after which somebody was barred from teaching and researching at a German university. I thus use the dismissal data to determine the actual dismissal date and not the date a dismissed scholar disappears from the University Calendars.

[19] The first volume was compiled in 1925. The other volumes I have used were published for the years 1926, 1928/29, 1931, 1935, 1940/41, and 1950.

[20] Some researchers cite more than one specialization. Therefore, physicists and chemists have up to two specializations and mathematicians up to four.

of Science (1941)). Simonsohn (2007) shows that neither the volume nor the content of the "Zeitschrift für Physik" changed dramatically in the post dismissal years until 1938. Not surprisingly, however, he finds that the dismissed physicists published less and less in the German journals after the dismissal. It is important to note, that the identification strategy outlined below relies on changes in publications of researchers in different German departments which were differentially affected by the dismissal. A decline in the quality of the considered journals would therefore not affect my results as all regressions are estimated including year fixed effects.

The top publications measure is based on articles contained in the online database "ISI Web of Science".[21] I extract all German speaking general science, physics, chemistry, and mathematics journals that are included in the database for the time period 1925 to 1938. Furthermore, I add the leading general journals which were not published in Germany, namely Nature, Science, and the Proceedings of the Royal Society of London. I also include four non-German top specialized journals which were suggested by historians of science as journals of some importance for the German scientific community.[22]

Table A2 lists all journals used in my analysis. For each of these journals I obtain all articles published between 1925 and 1938. A very small number of the contributions in the top journals were letters to the editor or comments. I restrict my analysis to contributions classified as "articles" as they provide a cleaner measure for a researcher's productivity. The database includes the names of the authors of each article and statistics on the number of subsequent citations of each of these articles. For each researcher I then calculate two different yearly productivity measures. The first measure is equal to the sum of publications in top journals in a given year. In order to quantify an article's quality I construct a second measure which accounts for the number of times the article was cited in *any* journal included in the Web of Science in the first 50 years after its publication. This includes citations in journals which are not in my list of journals but which appear in the Web of Science. The measure therefore includes citations from the entire international scientific community. It is therefore less heavily based on German science. I call this measure citation weighted publications and it is defined as the sum of citations (in the first 50 years after publication) of all articles published in a certain year. The following simple example illustrates the construction of the citation weighted publications measure. Suppose a researcher published two top journal articles in 1932. One is cited 5 times the other 7 times in any journal covered by the Web of Science in the 50 years after its publication. The researcher's citation weighed publications measure for 1932 is then 5+7=12.

Table A3 lists the top researchers for each subject according to the citation weighted publications measure. The researchers in this table are the 20 researchers with the highest yearly averages of citation weighted publications between 1925 and 1932. It is reassuring to realize that the vast majority of these top 20 researchers are well known in the scientific community. Economists will find it interesting that Johann von Neumann is the most cited mathematician. The large number of Nobel laureates among the top 20 researchers indicates that citation weighted publications are a good measure of a scholar's

[21] In 2004 the database was extended to include publications between 1900 and 1945. The journals included in that extension were all the journals which had published the most relevant articles in the years 1900 to 1945. For that extension Thomson Scientific judged the importance of a journal by later citations (cited between 1945 and 2004) in the Web of Science of articles published between 1900 and 1945. (For more details on the process see www.thomsonscientific.com/media/presentrep/facts/centuryofscience.pdf). My publication measure therefore includes all relevant top journals for German scientists of the time.

[22] The relevant journals for chemists were suggested by Ute Deichmann and John Andraos who both work on chemistry in the early 20th century. Additional journals for mathematics were suggested by Reinhard Siegmund-Schultze and David Wilkins; both are specialists in the history of mathematics.

productivity. Nevertheless, the measure is not perfect. As the "Web of Science" only reports last names and the initial of the first name for each author there are some cases where I cannot unambiguously match researchers and publications. In these cases I assign the publication to the researcher whose field is most closely related to the field of the journal in which the article was published. In the very few cases where this assignment rule is still ambiguous between two researchers I assign each researcher half of the (citation weighted) publications. Another problem is the relatively large number of misspellings of authors' names. All articles published between 1925 and 1938 were of course published on paper. In order to include these articles into the electronic database Thomson Scientific employees scanned all articles published in the historically most relevant journals. The scanning was error prone and thus lead to misspellings of some names. As far as I discovered these misspellings I manually corrected them.

I merged the publications data to the roster of all German physicists, chemists, and mathematicians. From the list of dismissed scholars I can identify the researchers who were dismissed and those who stayed at the German universities. The end result is a panel dataset of the universe of physics, chemistry, and mathematics professors in all German universities from 1925 until 1938 with detailed information on their publications in the top academic journals and their dismissal status.

3.4 Data on PhD Students

In order to assess the effect of the dismissals on the outcomes of PhD students I obtain a dataset containing the *universe* of students who received their PhD in mathematics from a German university between 1923 to 1938.[23] The data were originally compiled by Renate Tobies for the German Mathematical Association (Deutsche Mathematiker Vereinigung). She consulted all university archives of the former PhD students and combined that information with data from additional sources.[24] The dataset includes short biographies of the PhD students including information on the universities the PhD students attended, whether and where they published their dissertation, and their professional career after obtaining their PhD. I define two outcome variables for PhD students. The first, a short term outcome, is a dummy variable indicating whether the student publishes her dissertation in a top journal. The second outcome looks at the long run career of the PhD students. It is a dummy variable which takes the value of 1 if the former student ever becomes full professor in his career.

Table 4 summarizes some of the characteristics of the PhD students in my sample. The mathematicians are on average 27 years old when they obtain their PhD. About 9 percent are female and 8 percent foreigners, respectively. Around 24 percent of them publish their dissertation in a top academic journal. Later in their career about 19 percent become Chaired Professor. Table 4 also demonstrates that students who obtained their PhD from a top 10 university (measured by the average quality of the faculty) have better outcomes. They are more likely to publish their dissertation in a top journal and more likely to become university professor. This, of course, does not indicate that university quality has a causal impact on PhD student outcomes because of the endogenous sorting of good students into high quality universities.

Combining the data from all sources I obtain two datasets for my analysis. The first dataset is a student level dataset containing all PhD students in mathematics from 1923 to 1938, including information on the quality and size of the faculty of the university where they obtained their PhD.

[23] Unfortunately there is no comparable data on PhD students in chemistry or physics.

[24] For a more detailed description of the data collection process see Tobies (2006).

The second dataset is a faculty level panel dataset containing yearly information on all faculty level scientists in physics, chemistry, and mathematics from 1925 to 1938.

4 Identification

Using these dataset I investigate the effect of faculty quality and department size. In the first part of the analysis I estimate the effect of faculty quality and department size on PhD students' outcomes. In the second part I evaluate the effect of faculty quality and department size on the productivity of professors.

To estimate the effect of faculty quality on PhD student outcomes I propose to estimate the following regression model.

$$\text{Outcome}_{idt} = \beta_1 + \beta_2(\text{Avg. Faculty Quality})_{dt-1} + \beta_3(\text{Department Size})_{dt-1} + \beta_4\text{Female}_{idt} + \beta_5\text{Foreigner}_{idt} + \beta_6\text{CohortFE}_t + \beta_7\text{DepartmentFE}_d + \varepsilon_{idt} \quad (1)$$

I regress the outcome of student i from department d who obtains her PhD in year t on a measure of university quality, department size and other controls. Average faculty quality is calculated as the mean of the average productivity of all professors.[25,26] In the following I use the term professors for all faculty level researchers (at least Privatdozenten). Over time changes of the average faculty quality measure will only occur if the composition of the department changes. Yearly fluctuations in publications of the same set of professors will leave the faculty quality measure unaffected. The underlying assumption is therefore that Richard Courant always has the same effect on his PhD students independent of how much he publishes in a given year.

I further include dummy variables indicating whether the PhD student is female or foreigner. To control for factors affecting a whole PhD cohort I also include a full set of yearly cohort dummies. I also control for department level factors which are constant over time and affect all PhD students in the same way by including department fixed effects.

The main coefficients of interest are β_2 and β_3 indicating how faculty quality and department size affect PhD students' outcomes. Estimating this equation using OLS will, however, lead to biased results, as university quality and department size are likely to be endogenous. Inherently better students usually do their PhD in better universities. OLS would therefore overestimate the effect of university quality on PhD student outcomes. Another problem is caused by omitted variables, such as student motivation. If these omitted variables are correlated with university quality and affect the outcomes OLS estimates will be biased. A further problem is caused by mismeasurement of faculty quality. Even though the publications data is of very high quality there may still be some misspellings in names introducing measurement error. Further measurement error is introduced by the fact that average citation weighted publications are a noisy measure of those aspects of faculty quality which matter for PhD students. Measurement error would lead to a downward bias of the OLS estimates.

[25] Say a department has 3 professors in 1930. One published on average 10 (citation weighted) publications between 1925 and 1938. The other two have 20 and 15 citation weighted publications respectively. Then the average faculty quality for 1930 is 15.

[26] I use the department mean of average faculty quality between 1925 and 1938. An alternative way of calculating the average peer productivity uses only the pre-dismissal years 1925 to 1932. This measure is, however, not defined for researchers who join after 1933. I therefore present the results using the first measure. Using the alternative measure does not affect my findings.

Similar concerns also apply to the coefficient on department size. For example because inherently better PhD students may choose to study in bigger departments.

In order to estimate the effect of faculty quality and department size on the productivity of professors I propose the following equation which is very similar to the PhD student regression:

$$(2) \quad \#\ \text{Publications}_{idt} = \beta_1 + \beta_2(\text{Avg. Peer Quality})_{idt-1} + \beta_3(\text{Department Size})_{dt-1} + \beta_4\text{Age Dummies}_{idt} + \beta_5\text{YearFE}_t + \beta_6\text{DepartmentFE}_d + \beta_7\text{IndividualFE}_i + \varepsilon_{idt}$$

In this regression the number of publications of researcher i in department d and year t is regressed on measures of faculty (peer) quality, department size, and other controls. In the professor level regressions I calculate the average peer quality as the department average of citation weighted publications not including professor i.[27] I therefore call this variable average *peer* quality instead of average *faculty* quality. Other than that the measures are exactly the same as before.

It is quite likely that the effect of peers is only measurable after a certain time lag. Peers influence the creation of new ideas and papers before the actual date of publication. Another delay is caused by the publication lag (the time it takes for a paper to appear in a journal after the paper was submitted by the author). Science research, however, is published faster than research in other subjects like economics. Anecdotal evidence suggests that the effect of peers should be measured with a lag of about one year. An illustrative example for the timing of peer interactions in science at the time period studied in this paper is the postulation of the "uncertainty principle" by Heisenberg in 1927. In 1926 Heisenberg was working with Niels Bohr in Copenhagen. It is reported that during that time Heisenberg and Bohr spent days and nights trying to refine the concepts of quantum mechanics. Early in 1927, Niels Bohr went on a holiday and it was during that time that Heisenberg discovered and formulated his famous "uncertainty principle". He published this discovery in the "Zeitschrift für Physik" in 1927.[28] Other time lags do not affect my findings.

As further controls I include a full set of 5-year age group dummies to control for life-cycle changes in productivity.[29] Furthermore, I control for yearly fluctuations in publications which affect all professors by including year fixed effects. To control for individual differences in a researcher's talent I also add individual fixed effects to all specifications. Furthermore, I add department fixed effects to control for university specific factors affecting a researcher's productivity. These can be separately identified because some scientists change universities. I show below that the results are hardly affected by including university fixed effects in addition to individual fixed effects.

Similar problems as discussed for the PhD student regression affect the OLS estimates of β_2 and β_3 in equation (2). An important problem is caused by selection effects because better scientists usually work alongside better peers. Furthermore, larger departments tend to hire researchers with above average qualities. The inclusion of university fixed effects would in principle address this problem. Differential time trends, however, would make selection issues an important concern even in models which include university fixed effects.

Another problem may be caused by omitted variables, such as the construction of a new laboratory which may not be observed by the econometrician. This would lead to further biases of the OLS

[27] Average peer quality is calculated as follows: Say a department has 3 professors in 1930. One published on average 10 (citation weighted) publications between 1925 and 1938. The other two have 20 and 15 citation weighted publications respectively. Then the average peer quality variable for researcher 1 in 1930 will be (20+15)/2 = 17.5. Average peer quality for researcher 2 will be (10+15)/2 = 12.5 and so on.

[28] For a detailed historic description of the discovery of the uncertainty principle see Lindley (2007).

[29] Levin and Stephan (1991) show that age is an important determinant of scientists' productivity.

estimates. Furthermore, measurement error could bias the estimates of regression (2). An important problem is the measurement of peer quality. As even good measures of peer quality, such as the average number of citation weighted publications are by no means perfect. Even if one were to believe that this measure could perfectly quantify peer quality, misspellings of names in the publication data would introduce measurement error.

The professor level regressions are also affected by the fact that a researcher's productivity is affected by his peers but at the same time the researcher affects the productivity of his peers. Manski (1993) refers to this problem as the reflection problem. It is therefore important to keep in mind that the estimated effects will be total effects after all productivity adjustments have taken place.[30]

In order to address the concerns affecting the OLS estimates of equations (1) and (2) I propose the dismissal of professors by the Nazi government as an exogenous source of variation in the number and quality of science professors. Figure 1 shows the effect of the dismissal on department size and faculty quality in mathematics departments.

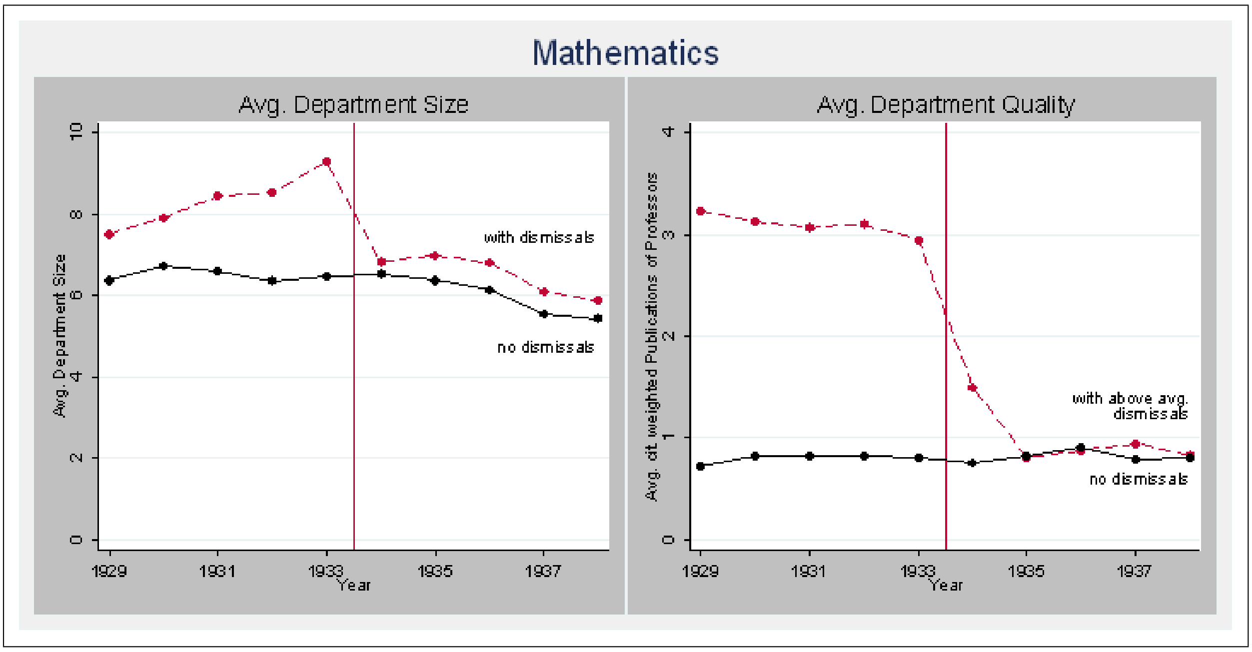

Figure 1: First Stages Mathematics

The dashed line shows mathematicians in departments with dismissals in 1933 or 1934. The solid line shows mathematics professors in departments without dismissals. Figure 1 shows that the affected departments were of above average size. The dismissal caused a strong reduction in the number of mathematics professors in the affected departments. The size of departments without dismissals, on the other hand, did hardly change. The dismissed were not immediately replaced because of a lack of suitable researchers without a position and the slow appointment procedures. Successors for dismissed chaired professors, for example, could only be appointed if the dismissed scholars gave up all their pension rights because the dismissed professors were originally placed into early retirement. The states did not want to pay the salary for the replacement and the pension for the dismissed professor at the same time. It thus took years to fill open positions in most cases. Highlighting this problem Max

[30]The reflection problem may also affect the PhD level estimates if PhD students affect the quality of their supervisors. Also the PhD level results will therefore estimate total effects after all adjustments.

Wien, a physicist in Jena, sent a letter to Bernhard Rust the Minister of Education in late November 1934. Describing the situation for chaired professorships he wrote that "out of the 100 existing [chaired professor] teaching positions, 17 are not filled at present, while under natural retirements maybe two or three would be vacant. This state of affairs gives cause for the gravest concern..." (cited after Hentschel, 1996).

The second panel of Figure 1 shows the evolution of average peer quality in the two types of departments. Obviously, one would expect a change in average peer quality only if the quality of the dismissed was either above or below the pre-dismissal department average. The right panel of Figure 1 demonstrates two interesting points: the dismissals mostly occurred at departments of above average quality and within many departments the dismissed were on average more productive than the mathematicians who were not dismissed. As a result average professor quality in affected departments fell after 1933. It is important to note that the graph only shows averages for the two groups of departments. It therefore understates the department level variation I am using in the regression analysis. As can be seen from Table 2 some departments with dismissals also lost below average peers. Average department quality increased in those departments. Overall, however, the dismissal reduced average department quality in mathematics. Figures A2 and A3 in the appendix show the effect of the dismissal on the peer groups of physicists and chemists. In physics the affected departments were also better than departments without dismissals. In chemistry the affected department were of above average quality as well but the difference was less pronounced than in the other two subjects.

It is important to note that the effect that most of the dismissals occurred in bigger and better departments does not invalidate the identification strategy as level effects will be taken out by including department and individual fixed effects. The crucial assumption for this difference-in-differences type strategy is that the trends in affected versus unaffected departments were the same prior to the dismissal. I show below various ways that this is indeed the case.[31]

The figures suggest that the dismissal had a strong effect on average department quality and department size. It is therefore possible to use the dismissal as an instrument for the endogenous faculty quality and department size variables. This gives rise to two first stage equations:

$$\text{(3)} \quad \text{Avg. Faculty Quality}_{dt} = \gamma_1 + \gamma_2(\text{Dismissal induced Reduction in Faculty Quality})_{dt} + \gamma_3(\#\text{ Dismissed})_{dt} + \\ + \gamma_4\text{Female}_{idt} + \gamma_5\text{Foreigner}_{idt} + \gamma_6\text{Cohort}_t + \gamma_7\text{DepartmentFE}_d + \varepsilon_{idt}$$

$$\text{(4)} \quad \text{Department Size}_{dt} = \delta_1 + \delta_2(\text{Dismissal induced Reduction in Faculty Quality})_{dt} + \delta_3(\#\text{ Dismissed})_{dt} + \\ + \delta_4\text{Female}_{idt} + \delta_5\text{Foreigner}_{idt} + \delta_6\text{Cohort}_t + \delta_7\text{DepartmentFE}_d + \varepsilon_{idt}$$ [32]

Equation (3) is the first stage regression for average faculty quality. The main instrument for average peer quality is the "dismissal induced reduction in faculty quality". It is measured as the pre-dismissal average quality of all researchers in the department minus the average quality of the researchers who were not dismissed. The variable is 0 until 1933 for all departments. In departments

[31] The fact that mostly bigger and better departments were affected does, however, affect the interpretation of the IV estimates. According to the LATE interpretation pioneered by Imbens and Angrist (1994) the estimated IV effects will correspond to a change in peer quality and number of peers in bigger and better departments. As nowadays most science departments are bigger than in the average in the early 20th century this LATE effect is arguably more interesting than the corresponding ATE.

[32] The corresponding first stage regressions for the professor level analysis are:

$$\text{(3a)} \quad \text{Avg. Peer Quality}_{dt} = \gamma_1 + \gamma_2(\text{Dismissal induced Reduction in Peer Quality})_{dt} + \gamma_3(\#\text{ Dismissed})_{dt} \\ + \gamma_4\text{Age Dummies}_{idt} + \gamma_5\text{YearFE}_t + \gamma_6\text{DepartmentFE}_d + \gamma_7\text{IndividualFE}_i + \varepsilon_{idt}$$

$$\text{(4a)} \quad \text{Department Size}_{dt} = \delta_1 + \delta_2(\text{Dismissal induced Reduction in Peer Quality})_{dt} + \delta_3(\#\text{ Dismissed})_{dt} \\ + \gamma_4\text{Age Dummies}_{idt} + \gamma_5\text{YearFE}_t + \gamma_6\text{DepartmentFE}_d + \gamma_7\text{IndividualFE}_i + \varepsilon_{idt}$$

with *above* average quality dismissals (relative to the department average) it will be *positive* after 1933. The variable will remain 0 for the other departments. The implicit assumption is therefore that below average dismissals did not affect the productivity of scientists.[33] The second instrument is the number of dismissals in a given department. This will mostly affect department size. The number of dismissals variable is 0 until 1933 and equal to the number of dismissals thereafter.[34]

The dismissals between 1933 and 1934 may have caused some PhD students or professors to change university after 1933. This switching behavior, however, will be endogenous. To circumvent this problem I assign each researcher the relevant dismissal variables for the department he attended at the beginning of 1933.

The effect of the dismissal is likely to be correlated within a department. I therefore account for any dependence between observations within a department by clustering all results at the department level. This not only allows the error to be arbitrarily correlated for all researchers in one department at a given point in time but it also allows for serial correlation of these error terms.

Using the dismissal as an instrumental variable relies on the assumption that the dismissal had no other effect on researchers' outcomes than through its effect on faculty quality and department size. It is important to note that any factor affecting all German researchers in the same way, such a possible decline of journal quality, will be captured by the year fixed effects (or PhD cohort effects) and would thus not invalidate the identification strategy. As the unaffected departments act as a control group, only factors changing at the same time as the dismissal and exclusively affecting the departments with dismissals (or only at those without dismissals) may be potential threats to the identification strategy. In the following I discuss some potential worries which may affect the validity of the identification strategy.

The dismissals may have changed the incentive structure for professors in the affected departments. Professors in departments with many dismissals may have an incentive to work more to obtain one of the free chairs within the department. Their incentives could also be affected in the opposite direction if they lost an important advocate who was fostering their career. These effects may also affect the attention they give to PhD students. In order to investigate this concern I regress a dummy variable of ever being promoted on the dismissal variables and the same controls as in the regressions proposed before.[35] The results from this regression are presented in the first panel of Table A4. The coefficients on the dismissal variables are all very small and none of them is significantly different from 0. This suggests that the results of this paper are probably not contaminated by changes in the incentive structures in the affected departments.

Another worry is that departments with more ardent Nazi supporters would increase their productivity because they received more research funding or by receiving other privileges. This would threaten the identification strategy if the number of Nazi supporters was correlated with dismissals.

[33] An alternative way of defining the dismissal induced change in peer quality would be to allow the dismissal of *below* average peers to have a *positive* impact on the productivity of scientists. In specifications not reported in this paper I have explored this. The results do not change.

[34] This variable is 0 until 1933 for all departments (As I use a one year lag in the peer group variables it is 0 for 1933 inclusive). In 1934 it is equal to the number of researchers who were dismissed in 1933 in a given department. From 1935 onwards it is equal to the number of dismissals in 1933 and 1934. The following example illustrates this. In Göttingen there were 10 dismissals in mathematics in 1933 and one dismissal in 1934. The # dismissed variable for mathematicians in Göttingen will therefore take the value 0 until 1933. It will be 10 in 1934 and 11 from 1935 onwards. The dismissal induced reducution in peer quality is defined accordingly.

[35] The estimated regression is:

$(\text{Ever Promoted})_{idt} = \beta_1 + \beta_3(\textit{Dismissal inducedin Fall in Peer Quality})_{dt} + \beta_3(\#\ \text{Dismissed})_{dt} + \beta_4\text{Age Dummies}_{idt} + \beta_5\text{YearFE}_t + \beta_6\text{DepartmentFE}_d + \beta_7\text{IndividualFE}_i + \varepsilon_{idt}$

Looking at the number of party members to investigate this issue would not be very helpful because most university researchers eventually joined the Nazi party. In November 1933, however, 839 university professors (out of more than 10,000 professors in Germany) signed the "Commitment of Professors at the German Universities (...) to Adolf Hitler and the National Socialist State..." This list should signal the professors' support of the new Nazi government and was widely publicized in newspapers. Most people signing the list were strong supporters of the Nazi regime and would have benefited from any differential treatment. To test this hypothesis I regress a dummy for signing the support list on the dismissal variables and other controls. The results are reported in the middle panel of Table A4. The coefficients on the dismissal variables are all small and none of them is significantly different from 0, indicating that strong support of the Nazi party was not different in departments with dismissals.[36]

Another worry is that scientists in departments with many dismissals took over laboratories from the dismissed and thus increased their productivity. This may have also affected the quality of PhD student supervision. I show below that the results are very similar for mathematicians and theoretical physicists. This is reassuring because the two groups of scientists usually carry out their research outside the laboratory.

The identification strategy may also be invalidated if the Nazi government did increase the funding of affected departments in order to counterbalance possible negative dismissal effects. Salaries for university employees were paid by the states and were directly linked to the position of the researcher. They hardly changed over the time period and not differentially across different departments. Scientists could also apply for funding of individual research projects. The main provider of research grants in the 1920s and 1930s was the "Emergency Association of German Science" (Notgemeinschaft der Deutschen Wissenschaft) which was jointly funded by the state and donations from companies.[37] The grants were approved by a panel of specialists based on the quality of the grant proposal and covered costs for experiments, such as materials or expensive equipment. Unfortunately, there is no readily available consistent yearly data on supported scientists. Nonetheless, I managed to obtain comparable data on scientists who received funding for two years: the academic year 1928/1929 before the dismissal and for 1937/1938 after the dismissal. The data are relatively coarse as the reports only state whether a scientist received funding from the Notgemeinschaft but not how much he received. To check whether funding patterns changed after the dismissal, I regress an indicator of receiving funding on the dismissal variables on the sample of stayers in the two years.[38] The results are reported in the last panel of Table A4. All but one of the coefficients are very small and not significantly different from 0 indicating that changes in funding are not related to the dismissal. The coefficient on the fall in peer quality for physics is negative, indicating that stayers in departments with high quality dismissals received less funding after the dismissal. There is therefore no worry that compensatory funding can explain my results. Any bias due to changing funding patterns would go against my finding that department level peer effects in physics are not important.

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[36] As there is no time variation in the dependent variable I estimate the regression including all scientists who were present in November 1933. The estimated regression is:

$(\text{Signed Support List})_{id} = \beta_1 + \beta_2(\textit{Dismissal induced}\ \text{Fall}\ \ \textit{in Peer Quality})_d + \beta_3(\#\ \text{Dismissed})_d + \beta_4\text{Age Dummies}_{id} + \beta_5\text{DepartmentFE}_d + \varepsilon_{id}$

Alternatively, one could estimate this regression without University FEs. This does not change the results.

[37] The Notgemeinschaft was renamed in "Deutsche Gemeinschaft zur Erhaltung und Förderung der Forschung" in 1937 and is still the main funding source for individual researchers in Germany under the name "Deutsche Forschungsgemeinschaft".

[38] I regress the following regression for one pre-dismissal and one post-dismissal year:

$(\textit{Received Notgemeinschaft Funding})_{idt} = \beta_1 + \beta_2(\textit{Dismissal induced Fall in Peer Quality})_{dt} + \beta_3(\#\ \textit{Dismissed})_{dt} + \beta_4\textit{Age Dummies}_{idt} + \beta_5\textit{Year Dummy}_t\ \beta_6\textit{DepartmentFE}_d + \beta_7\textit{IndividualFE}_i + \varepsilon_{idt}$.

Any difference-in-differences type strategy relies on the assumption that treatment and control groups did not follow differential trends over time. I address this concern in two ways. First, I show that the results presented below are not affected by including linear department specific time trends in the regressions. This approach would not address the problem if differential trends were nonlinear. I therefore estimate a so-called placebo experiment only using the pre-dismissal period and moving the dismissal from 1933 to 1930. Columns (1) and (2) of Table A5 report the results for the PhD student sample. Columns (3) to (5) show the results for the professor sample. The coefficients are all close to 0 and none of the coefficients is significant. These results indicate that departments with dismissals do not have different productivity trends compared to the unaffected departments in the pre-dismissal period.

Below I furthermore show that disruption effects cannot explain my findings. These additional checks on the identification assumption indicate that the dismissal can indeed be used as a valid instrument for faculty quality and department size.

5 PhD Student Results

5.1 Effect of Dismissal on PhD Student Outcomes

In the first part of the empirical investigation I evaluate the effect of faculty quality on PhD student outcomes. An interesting starting point is to investigate the outcomes of PhD students in departments with dismissals versus students in departments without dismissals. Figure 2 shows the probability of publishing the dissertation in a top journal for different PhD cohorts in departments with dismissals (dashed line) and departments without dismissals. It is again important to note that this figure heavily understates the variation I am using in the econometric analysis. In the regression analysis I use department level variation in dismissals. Before 1933 the probability of publishing the dissertation in a top journal is always above 0.4 in departments which later on experience dismissals of professors. Students graduating from those departments in the years after 1933, however, have a much lower probability of publishing their dissertation in a top journal. The probability of publishing the dissertation varies from year to year in departments which do not experience any dismissals but it does not change substantially after 1933. This indicates that faculty quality, which fell massively in the universities with high quality dismissals, does indeed affect PhD student outcomes.

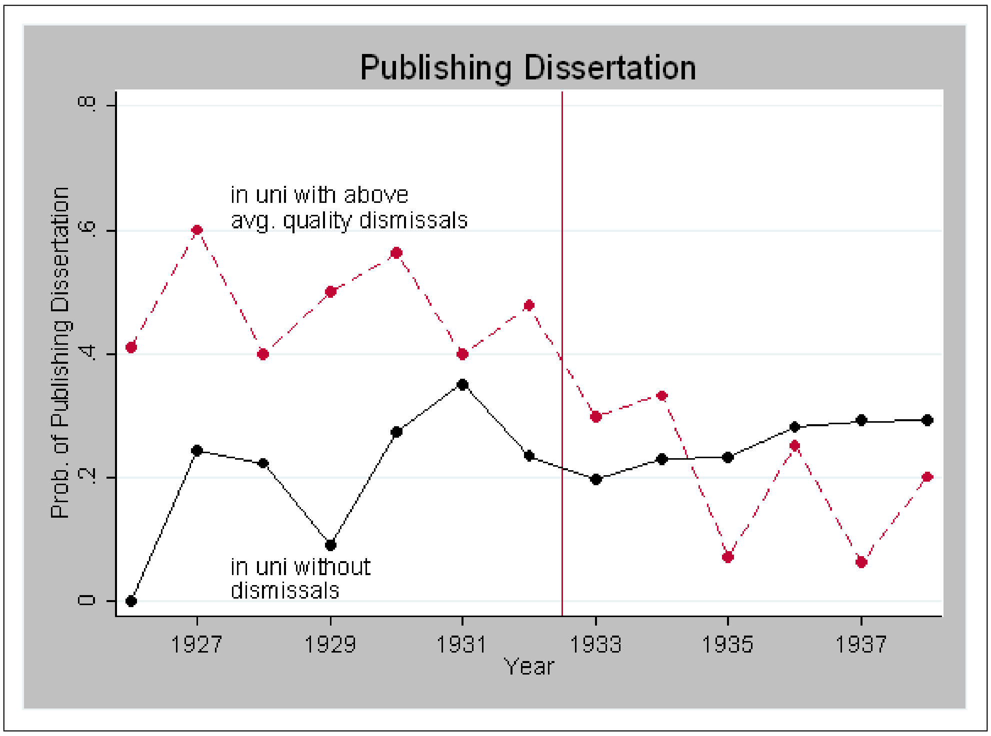

Figure 2: Reduced Form PhD Students

In the following I estimate the effect of the dismissal on PhD students' outcomes using the following reduced form model.

$$\text{(5)} \quad \text{Outcome}_{idt} = \beta_1 + \beta_2(\text{Dismissal induced Reduction in Faculty Quality})_{dt} + \beta_3(\#\ \text{Dismissed})_{dt} + \beta_4\text{Female}_{idt} + \beta_5\text{Foreigner}_{idt} + \beta_6\text{CohortFE}_t + \beta_7\text{DepartmentFE}_d + \varepsilon_{idt}$$

The first column of Table 5 reports results for the probability of publishing the dissertation in a top journal.[39] The dismissal induced reduction in faculty quality has a strong negative effect on publishing the dissertation in a top journal. The number of dismissed professors in a student's department does not seem to affect the publication of the dissertation. Column (2) shows that the probability of becoming a full professor later in life is strongly affected by the dismissal induced fall in faculty quality. As before, the number of dismissals in a department does not affect the students' outcomes.

5.2 The Effect of Faculty Quality and Department Size on PhD Student Outcomes

In the following I investigate the effect of faculty quality and department size on PhD student outcomes. As discussed before, both faculty quality and department size are endogenous. Using the dismissal as an instrument can overcome these endogeneity problems. Table 6 reports the two first stage regressions equivalent to equations (3) and (4) presented before. Some of the students may have reacted to the dismissal of professors by changing departments after 1933. I address this problem by assigning the

[39] The PhD student data only includes students who have finished their PhD. The dismissal induced reduction in faculty quality may have caused some post 1933 PhD students in the affected departments to quit the PhD altogether. It would be more difficult to detect an effect of the dismissals if the quitting students had been the weakest ones.

department fixed effect for all post 1933 years according to department which a student attended at the beginning of 1933.[40]

Column (1) reports the first stage regression for faculty quality. As expected the dismissal induced reduction in faculty quality has a strong and highly significant effect on average faculty quality. The number of dismissals does not affect faculty quality. The second first stage regression for department size is reported in Column (2). In this case the dismissal induced reduction in faculty quality has no significant effect. The number of dismissals, however, is a strong and highly significant predictor of department size. This pattern is very reassuring as it indicates that the dismissal indeed provides two orthogonal instruments: one for average faculty quality and one for department size.[41]

Table 7 reports the OLS and IV results. Columns (1) and (2) show the effect of faculty quality and department size on the probability of publishing the dissertation in a top journal. Faculty quality has a strong positive and significant effect on the probability of publishing the dissertation. Department size, however, does not affect the probability of publishing the dissertation in a top journal. The IV estimate of faculty quality is not only highly significant but it is also relevant in economic terms. Suppose a department of average size and quality hires a top 20 mathematician (as shown in Table A2). In this case the resulting increase in faculty quality would increase the student's probability of publishing her dissertation in a top journal by about 12 percentage points.

Column (4) reports the IV results for becoming full professor later in life. Again the IV coefficient on faculty quality is positive and significant. Using the same thought experiment as before the arrival of a top 20 mathematician would increase a graduate's student probability of later becoming full professor by 8.4 percentage points.[42]

In the following, I report a large number of checks indicating that these findings are very robust. First, I add a set of 26 dummies controlling for father's occupation.[43] The results are reported in columns (3) and (4) of Table 8. It is reassuring that the inclusion of powerful individual controls hardly affects the results.

One may worry that the results are mostly driven by Jewish students. They may have been the best students studying in the best universities with more dismissals. Jewish students faced substantial difficulties after 1933. One would therefore find a drop in the probability of publishing the dissertation or becoming full professor for students in the affected departments which is not caused by a fall in faculty quality. I investigate this issue by reestimating the regressions for non-Jewish students only, as reported in columns (5) and (6).[44] The fact that the coefficients do hardly change indicates that

[40] Therefore only students who finished their PhD before 1933 or who had at least started their undergraduate studies at the beginning of 1933 are included in my sample.

[41] In this setup the instruments are strong predictors of the peer group variables. Furthermore, the model is just identified as the number of instruments is equal to the number of endogenous variables. Therefore one has to worry less about bias due to weak instruments. Stock and Yogo (2005) characterize instruments to be weak not only if they lead to biased IV results but also if hypothesis tests of IV parameters suffer from severe size distortions. They propose values of the Cragg-Donald (1993) minimum eigenvalue statistic for which a Wald test at the 5 percent level will have an actual rejection rate of no more than 10 percent. In this case the critical value is 7.03 and thus way below the Cragg-Donald statistic for the first stages which is reported at the bottom of Table 7.

[42] Interestingly, some of the IV standard errors are slightly smaller than the corresponding OLS ones. This only occurs when I cluster the standard errors at the department level. As the IV residuals are different from the OLS residuals the intra-department correlations of these residuals may be smaller in the IV case. If I do not cluster, all results remain very similar and highly significant.

[43] The data does include very detailed information on father's occupation. Unfortunately the information is missing for about 30 percent of the data. I include an additional dummy for all those who do not have any information on their father's occupation.

[44] The data does not include the students' religion. It does, however, include a lot of biographical information. Most Jewish students managed to emigrate from Germany. This is indicated in the biographical information of the data. I classify any student who emigrates between 1933 and 1945 as Jewish.

the results are not driven by Jewish students.

Another worry is that student life in the dismissal years may have been disrupted. To address this concern I reestimate the regressions omitting the years 1933 and 1934 in which most of the dismissals took place. Interestingly, the point estimates reported in columns (7) and (8) are now larger. This indicates that students who finished their PhD in the early years after the dismissal actually suffered less than students who finished later and were thus exposed to the fall in faculty quality for a longer time period. It is thus relatively unlikely that acute disruption effects can explain my findings.

A related concern is that students' outcomes may have worsened because of the disruption caused by the loss of their advisor not necessarily because of a fall in faculty quality. I investigate this concern by reestimating the regressions focusing on students who were still doing coursework at the beginning of 1933 and who had thus not yet started working on their dissertation with a specified advisor.[45] Reassuringly the results are unchanged and the point estimates are again higher as columns (9) and (10) demonstrate. This indicates that students who had not yet started their dissertation were in fact harmed even more by the fall in faculty quality than those who lost their advisor just before submitting their PhD.

Finally, I investigate whether differential time trends across departments can explain my findings by including linear department specific trends. While the point estimates reported in columns (11) and (12) are now slightly lower they are still positive and significant suggesting that faculty quality is an important predictor of PhD student outcomes.

One defining feature of these results is that the IV point estimates are higher than the corresponding OLS estimates. One important reason for this finding is measurement error of faculty quality. It attenuates the OLS estimates because average citation weighted publications are not perfectly measuring those aspects of faculty quality which are important for PhD students. Another important reason for obtaining higher IV estimates is the fact that these estimates can be interpreted as a Local Average Treatment Effect (LATE) as pioneered by Imbens and Angrist (1994). The dismissals mostly affected high quality departments. It is quite likely that the compliers in this setup have indeed very high returns to changes in faculty quality as students in those department are much more research oriented and may thus respond more strongly to changes in faculty quality. Table 9 shows OLS and IV results for students in top 10 departments (ranked by average faculty quality) and students in lower ranked departments. It is obvious that both the OLS and the IV returns to faculty quality are higher for students in top departments. Furthermore, the low Cragg-Donald EV statistic for the lower ranked department indicates that the instruments do not affect faculty quality and department size in lower ranked departments.

6 Professor Results

6.1 The Effect of the Dismissal of Peers on the Productivity of Professors

The PhD student results indicate that faculty quality in their local department is an important determinant of their future outcomes. I now turn to investigate the effects of faculty quality and department size on professors' productivity. I first investigate whether professors' productivity declined because they had fewer and less productive peers after the dismissal. The following figure tries to give a

[45] For the pre-1933 cohorts I of course include all students as they by definition were not doing coursework anymore.

graphical answer to this question. Figure 3 plots the publications for stayers in two sets of mathematics departments: those with dismissals and those without dismissals. The yearly fluctuation in top journal publications of professors is relatively large. Despite this fluctuation, the figure suggests that the dismissal did not have an obvious effect on the publications of the staying professors.

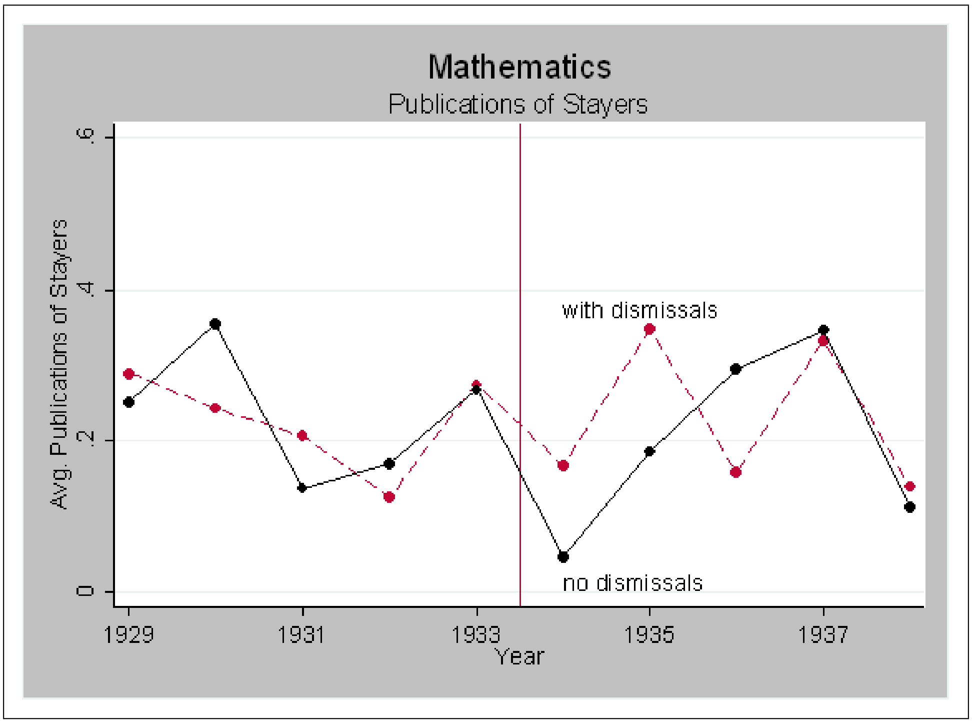

Figure 3: Reduced Form Mathematics Professors

Figures A4 and A5 shows the evolution of the stayers' publications in physics and chemistry departments. Again there seems to be no evidence that the dismissal reduced the productivity of stayers in the affected departments. In order to verify this finding and to quantify the effect of the dismissal on the stayers I estimate the following reduced form equation.

$$\text{(6)} \quad \#\ \text{Publications}_{idt} = \beta_1 + \beta_2(\text{Dismissal induced Fall in Peer Quality})_{dt} + \beta_3(\#\ \text{Dismissed})_{dt} + \beta_4\text{Age Dummies}_{idt} + \beta_5\text{YearFE}_t + \beta_6\text{DepartmentFE}_d + \beta_7\text{IndividualFE}_i + \varepsilon_{idt}$$

All professors level regressions are estimated for science professors who were present at the beginning of 1933 and were not dismissed (the so called stayers). I estimate all professor regressions separately for the three subjects because they have very different collaboration patterns. One example for the different intensity of collaboration is the fact that the rate of coauthoring papers is very different in the three subjects (see Table 3). Using all scientists below 70 years of age, I regress the researchers' (citation weighted) publications in each year on the instruments proposed above.[46] This regression is essentially a difference-in-differences estimate of the dismissal effect. It compares the change in publications from the pre to the post dismissal period for researchers in affected departments to the change between the two periods for unaffected researchers.

[46] I focus on stayers below 70 which was the usual age of retirement for university professors in the early years of my sample period. Older scientists, who were still teaching at a very high age are thus not very representative. Including those older scientists hardly affects the results.

Table 10 reports the reduced form results using the peers in a researcher's department as the relevant peer group. If the dismissal had a negative effect on the number of publications one would expect negative coefficients on the dismissal variables. The estimated coefficients are all very close to 0 and only the coefficient on the number of dismissals in chemistry when I do not include department fixed effects is significantly negative. Not surprisingly, the coefficients in specifications with citation weighted publications as the dependent variable are larger because the mean of citation weighted publications is much larger than the one for publications. It is widely believed that the quality of peers is the main driver of potential peer effects. The coefficients on the dismissal induced fall in peer quality are, however, not only insignificant but most of them have the wrong sign if one expected that a fall in peer quality would reduce the stayers' productivity.

Publications and citation weighted publications are count data with a relatively large proportion of zeros and can never be negative. Instead of OLS one may therefore prefer to estimate the reduced form using a model specifically modelling the nature of the data. I therefore reestimate the reduced form using a Poisson model including the same fixed effects as before and clustering at the university level.[47] The results are reported in Table A6 where I report the coefficients as incidence ratios. A coefficient of 1 would indicate no effect of the dismissal on the productivity of scientists. The majority of the coefficients is very close to 1. Once more the coefficients on the fall in peer quality would indicate a very small positive and not significant effect of the dismissal on the productivity of the stayers. Both OLS and Poisson models suggest that the dismissal did hardly affect the productivity of the stayers and especially the fall in peer quality did not negatively affect the stayer's productivity.

6.2 Using the Dismissal to Identify Localized Peer Effects among Science Professors

In the following I use the dismissal as an exogenous source of variation in a science professor's peer group to identify localized peer effects. As before I estimate two first stage equations: one for the average quality of peers number of peers and one for the number of peers in a researcher's department. I estimate The first stage results separately for the three subjects are presented in Table 11. As in the PhD student sample each instrument strongly and highly significantly affects one of the endogenous variables. Dismissal induced reduction in peer quality is a very good predictor for peer quality and the number of dismissals is a strong predictor for department size.

Table 12 reports results from estimating the peer effects model as proposed in equation (2).[48] The first columns of Table 12 show the results for physicists. The OLS results are not very informative due to the problems illustrated in the identification section. I therefore turn immediately to discussing the IV results where I use the dismissal to instrument for the peer group variables. Column (2) reports the results for publications as the dependent variable. The coefficients on the peer group variables are very small and never significantly different from 0. The coefficient on average peer quality even has

[47] As Santos Silva and Tenreyro (2009) point out including a fixed effect for a scientist who never publishes is leads to convergence problem as the (pseudo) maximum likelihood does not exist in this case. Standard regression packages do not address this problem and will therefore lead to non-convergence of the estimator. I use the simple procedure suggested by Santos Silva and Tenreyro, which essentially drops all problematic fixed effects, to estimate the Poisson model.

[48] While very few stayers changed their department until 1938 one may be worried that endogenous switching behaviour due to the dismissals may affect the estimates including department fixed effects. I therefore reestimate all professor level regressions without department fixed effects. The results are unaffected and available upon request.

the wrong sign if one were expecting positive peer effects from interactions with high quality peers. The standard error implies that one can rule out positive effects greater than 0.03 with 95 percent confidence. These are small effects given that the mean of the dependent variable is about 0.5. Also the coefficient on the number of peers is small and not significantly different from 0.

The chemistry and mathematics results are reported in the next few columns of Table 12 and are very similar. The coefficients on average peer quality and department size are all very close to 0 and insignificant. Especially for average peer quality one can indeed rule out small positive effects. For chemistry one can rule out positive effects of average peer quality larger than 0.017 (mean of publication variable is 1.7). For mathematics one can rule out positive peer quality effects larger than 0.035 (mean of publications is 0.33). The point estimates for department size are also never significantly different from 0 and small.

The results presented in Table 12 show no evidence for department level peer effects in any of the three subjects. The fact that the results are very similar for all three subjects can be seen as a first confirmation that there are indeed no department level peer effects among professors in this setting. Also the fact that I find very similar results for publications and citation weighted publications is reassuring. This indicates that differences in citation behavior of articles from scientists in departments with or without dismissals cannot explain these findings. In the following I investigate whether the absence of localized spillovers is a robust result with a large number of alternative specifications.

It is quite surprising that I do not find evidence for peer effects at the local level. A potential reason may be that the effect the dismissals caused some disruption to the whole system during the first years. I therefore reestimate the IV results dropping 1933 and 1934 from the regression. Omitting those turbulent years does not affect my findings as shown in columns (3) and (4) of Tables 13 to 15.

Peer effects may be especially important in the early or the late stages of a professorial career. Regressions which are run for the whole department may therefore not be able to detect significant peer effects. To investigate this hypothesis I therefore split the sample into two groups: scientists below 50 and scientists 50 or older. The results are reported in columns (5) to (8). There is no indication that peer effects are especially important for certain age groups as none of the coefficients is significantly different from 0 in any of the subjects.

An important check to rule out differential productivity trends in affected and unaffected departments is to include university specific time trends in the regressions. The results for those specifications are reported in columns (9) and (10). Reassuringly, the inclusion of university specific time trends hardly affects the results.

A further worry is that stayers may have taken over laboratories or experiments from the dismissed in the affected departments. The positive effects from additional laboratories may have neutralized negative effects from a fall in peer quality or the number of peers. The mathematics results should not be contaminated by such behavior and are indeed very similar to the results for the other two subjects. An additional way of exploring whether taking over laboratories may have affected my results is to estimate the regression for theoretical physicists, only. Theoretical physicists do not need laboratories for their research. Even though the coefficients are less precisely estimated the results presented in Columns (11) and (12) of Table 13 show no evidence for peer effects for theoretical physicists. This suggests that the takeover of laboratories or experiments is not likely to explain my results.

In the previous regressions I used the department as the relevant peer group for science professors. It is possible that professors affect each other within much smaller groups, only. In order to investigate this hypothesis I use the professors' *specialization* to define his peer group. The peers of an experimental physicist are now only the other experimentalists in his department; not theoretical physicists, technical physicists or astrophysicists.

Table 16 reports the results from estimating equation (2) with specialization level peer variables. Similarly to before, all coefficients on the dismissal variables are very small and none of them is significantly different from 0. Furthermore, the coefficients on peer quality mostly have the wrong sign if one expected positive peer effects. In physics, the standard errors imply than one can rule out positive effects for average peer quality larger than 0.03 (the mean of publications for physicists is 0.5). In chemistry, one can rule out any positive effects of peer quality greater than 0.007 with 95 percent confidence (mean of publications for chemistry is 1.7). Again very small positive effects can be ruled out for the effect of peer quality on scientists productivity. The results for mathematics are much less precise than for physics and chemistry because most mathematicians did not confine their work to only a few specializations. Mathematicians were working on different topics which even today can not be precisely assigned to certain specializations. Nonetheless, there is no evidence for any significant peer effects in mathematics.[49]

The results on specialization level peers support the evidence that localized peer effects were indeed not present among the science professors. It has to be pointed out, that localized peer effects may occur at even more specialized subfields. As the mean number of researchers in the specializations I consider here is 3.5 these even smaller subfields would indeed have to be extremely specialized.

Researchers investigating peer effects often investigate non-linear peer effects. Scientists of different abilities may benefit very differently from their peers. It may be impossible to detect effects of peer quality because only certain quality groups are affected by their peers. In order to investigate this hypothesis I split the researchers into three quality groups according to their pre 1933 citation weighted publication averages. I then interact the department level peer group variables with dummies indicating the scientist's *own* quality tercile. The IV results are reported in Table A7. Of course some of the peer group times own quality cells are relatively small and the results are therefore not precisely estimated for these cells. There were for example relatively few stayers in the top tercile (given that many dismissed were among the best researchers). Therefore the estimates for the interactions with the top tercile are much less precise. Despite this caveat there is no evidence for non linear peer effects especially for peer group quality. The majority of the peer quality estimates again have the wrong sign and the more precisely estimated coefficients are also very close to 0.

Of course it could also be the case that there are nonlinearities going in the other direction: Only peers of a certain quality may actually affect their colleagues. To investigate this issue I split the peer group according to their quality tercile and then include the average quality and number of each tercile in each department separately in the regressions. The results are reported in Table A8. There is no indication that top quality peers positively affect their colleagues. Similarly, middle quality peers do not seem to have a positive effect on their peers. These regressions do not include the coefficients for the lowest tercile peers because there were too few dismissals among those really bad researchers. The dismissal can therefore not be used as a valid instrument for lowest quality peers. The robustness of the professor level results indicate that nonlinearities in localized peer effects are not important for science professors.

[49] All robustness checks presented for department level peers have been estimated for specialization level peers as well. None of the coefficients is significantly different from 0. The results are available upon request.

6.3 Effect of Dismissal on Coauthors of Dismissed Professors

After showing conclusively that there is no evidence for *localized* peer effects at the professorial level I now investigate peer effects among coauthors. It is important to emphasize that the majority of coauthorships that I analyze took place across departments. Many scientists coauthored with PhD students and other assistants in their own department but my data does not include these younger researchers for chemistry and physics. Very few mathematicians coauthored papers at the time. For example only one mathematics professor staying in Germany lost a coauthor. For mathematics I can therefore neither investigate coauthor effects among professors nor between professors and PhD students.

I analyze peer interactions among coauthors by investigating the change in productivity of science professors who lose a coauthor due to the dismissal. Figure 4 illustrates the impact of losing a coauthor for physics professors. The figure plots average yearly publications for two groups of professors; researchers who lost a high quality coauthor due to the dismissal and researchers without dismissed coauthors. Figure 4 suggests that physicists who lost a prolific coauthor experienced a drop in their research productivity but managed to recover after some years. The relevant figure for chemistry presented in the abstract also shows a drop in publications after the dismissal and a recovery towards the end of the period even though chemists who lose a coauthor seem to have slightly declining publications in the few years before the dismissal. It is important to note again, that these figures vastly understate the variation I am using in the following regressions as the quality of dismissed coauthors was very different and I use the additional variation in the regressions reported below.

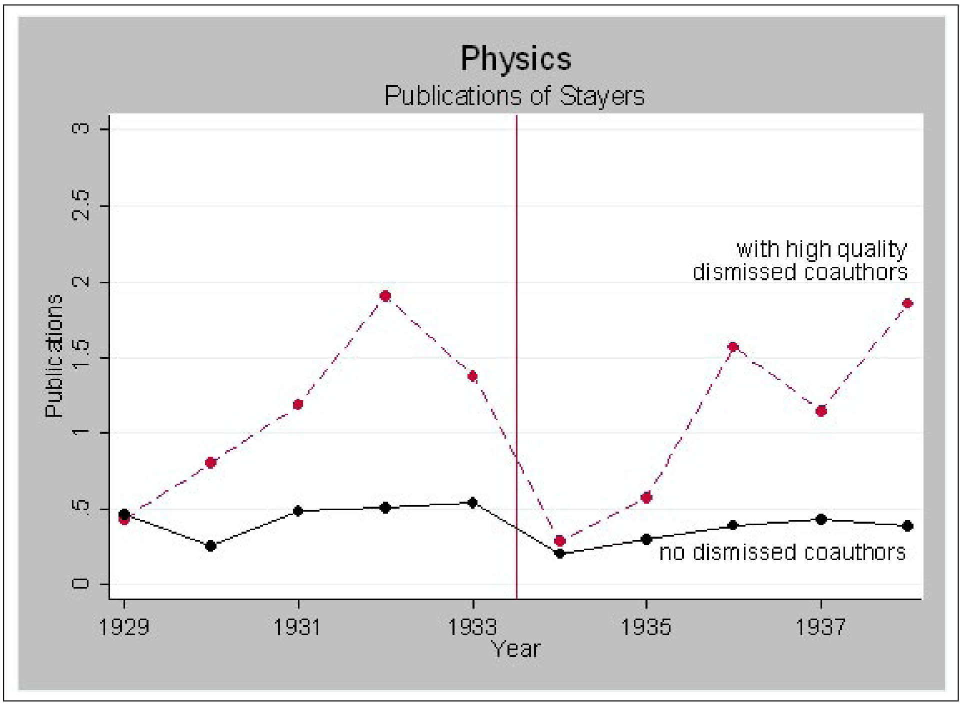

Figure 4: Effect of Dismissal of Coauthors Physics

I estimate the following reduced form equation:

$$(7)\quad \#\ \text{Publications}_{idt} = \beta_1 + \beta_2(\text{Avg. Quality of Dismissed Coauthors})_{idt} + \beta_2(\#\ \text{Dismissed Coauthors})_{idt} + \beta_4\text{Age Dummies}_{idt} + \beta_5\text{YearFE}_t + \beta_6\text{DepartmentFE}_d + \beta_7\text{IndividualFE}_i + \varepsilon_{idt}$$

I regress the number of publications of researcher i in period t and department d on the number of dismissed coauthors, the average quality of the dismissed coauthors, and the same controls as in the regressions reported above. For the basic regression a scientist's coauthors are defined as all colleagues who have coauthored a paper with the scientist in the last five years before the dismissal; i.e. from 1928 to 1932. As before I estimate this regression for professors staying in Germany, only. This regression corresponds to the reduced form regressions reported for the department level peers reported before. An equivalent instrumental variable approach is not feasible for coauthors because the timing of the peer interactions cannot be well defined for coauthors. It is neither clear when peer interactions among coauthors start nor when these interactions terminate because they are likely to interact also before and after they have coauthored papers. I therefore focus on the reduced form results for coauthors because the dismissal provides a sudden breakup of the coauthor tie. Investigating how this sudden end of the coauthor collaboration affects the productivity of stayers can shed light on peer effects among coauthors.

The regression estimates of equation (7) are reported in Table 17.[50] Columns (1) and (2) show the results for physics. The coefficient on average quality of the dismissed coauthor is significantly negative indicating that losing a coauthor of higher quality reduces the productivity of the physicist staying in Germany. The point estimate presented in column (2) indicates that losing a coauthor of average quality reduces the productivity of a physicist of average quality by about 13 percent. The coefficient on the number of dismissed coauthors is never significantly different from 0. The results for chemists are reported in columns (3) and (4). The average quality of the dismissed coauthors is again highly significant. The estimated coefficient for citation weighted publications indicates that losing a coauthor of average quality reduces the productivity of an average chemist by about 16.5 percent. The number of dismissed coauthors does not seem to play an important role for the productivity of chemists.

The regressions reported in Table 17 use the total number of publications and citations weighted publications as dependent variable. A coauthored publication is counted as a full publication for both coauthors. Another approach is to normalize joint publications by dividing each publication and the citations of each publication by the number of coauthors. Table 18 shows the results obtained when using normalized (citation weighted) publications as the dependent variable. The results are very similar to before.

These results show that scientists who lost high quality coauthors suffered more than scientists who lost less prolific coauthors. The fact that I do not find a significant effect on the number of dismissed coauthors suggests that this effect is not driven by the fact that researchers who lost a coauthor published less because they were lamenting the loss of a coauthor.

The effect of losing a coauthor may depend on the time span which elapsed since the last collaboration. The regressions reported in Table 19 explore this hypothesis. I split the dismissed coauthors into two groups: recent coauthors who had collaborated with a stayer between 1929 and 1932, and former coauthors who had co-written papers with the stayer between 1924 and 1928 but not thereafter. As expected, the estimates indicate that only the dismissal of recent coauthors matters for a stayer's

[50] I am estimating these regressions on the same sample as the department level regressions reported before. The number of observations differs slightly from the number of observations in the department level specification because the department level specifications include a researcher twice if he has a joint appointment at two universities (This occurs very rarely. Estimating the department level regressions with weights to account for the few researchers who are appointed at two departments does not alter those results). The total number of researchers in the two sets of regressions, however, is exactly the same.

productivity.

As mentioned above, it is not clear whether the joint publication of papers can be classified as a genuine peer effect as opposed to joint production of knowledge. There are, however, interactions among coauthors corresponding to peer effects. Coauthors discuss research projects which they are not planning to publish together. They may also indirectly affect each other's productivity by being very productive or very lazy. This more subtle effect of peer pressure could be classified as a peer effect. In order to investigate genuine peer effects among coauthors I analyze how the dismissal affected the number of publications excluding joint publications with the dismissed coauthors. Finding a negative effect of the dismissal on the publications without the dismissed coauthors would suggest the presence of peer effects among coauthors which are more subtle than coauthoring. This is a powerful test for spill-over effects because one would expect that researchers who lose a coauthor substitute towards single-authored publications and publications with other coauthors. Any such substitution should reduce the estimated dismissal effect. The results on publications without the dismissed coauthors are reported in Table 20. As before the dismissal of a high quality coauthor has a negative and significant effect on the productivity of the coauthor staying in Germany. The number of dismissed coauthors does not affect the productivity of scientists. These results suggest the presence of effects between coauthoring professors which go beyond joint production effects.

7 Conclusion

This paper uses the dismissal of science professors by the Nazi government to identify the effects of department size and faculty quality on the productivity of scientists. I show that the dismissal was not correlated with a number of factors which might affect researchers productivity through other channels.

In a first part of the analysis I show that faculty quality has a strong effect on the outcomes of PhD students. The size of the effect can be assessed by considering a department of average size and quality. If this department were to hire a top 20 mathematician the resulting increase in faculty quality would increase the students' probability of publishing their dissertation in a top journal by about 12 percentage points. I furthermore show that these effects persist into the long run. The students' probability of becoming full professor during their career would increase by 8.4 percentage points.

In a second part I show that the quality of the local department (i.e. the quality of the local peers) does not affect the productivity of science professors. This result holds for mathematics, physics, and chemistry professors. Almost all estimated effects are very close to 0 and often have the 'wrong' sign if one were expecting positive peer effects from having better quality peers. In this context it is interesting to investigate which effect sizes can be ruled out given the 95 percent confidence intervals of my results. I do this with the following thought experiment: Suppose a department of average quality and average size loses one Nobel Laureate (of average Nobel Laureate Quality) due to the dismissal. How much of a drop in the publications of the stayers can I rule out with 95 percent confidence? This is an appealing question as this may be related to a top department today which loses one Nobel Laureate to another university. The reduced form results indicate that the effect of losing a Nobel Laureate would reduce the yearly publications of the stayers in physics by at most 0.0017 publications (the mean of publications for physicists is about 0.5.)[51] The point estimate of course would predict that publications do actually go up in the affected departments (see the reduced form results). In chemistry one could rule out a drop in yearly publications larger than 0.05 in absolute value (the mean of publications is 1.69). In mathematics one can rule out a fall in publications of 0.054 for losing a top 20 mathematics professor (as there is no Nobel prize in mathematics). The mean of publications in mathematics is 0.33. One can therefore rule out very small positive peer effects, especially for physics and chemistry. Of course, other estimates presented before are less precise but the overall picture seems quite striking in that there is no evidence for positive peer effects for professors. It is important to note that these results do not imply that being at a good university does not have a positive effect on a researcher's productivity. The regressions reported above include university fixed effects which control for unobserved differences in the quality of laboratories, research seminars, research students, and the like. My results show that university quality matters because the null hypothesis that the university fixed effects are all zero can easily be rejected. There is, however, no evidence for peer effects at the local level.

These results suggest that the local department is very important for young researchers who do not yet have a network of colleagues in other departments. More established researchers, however, are much less dependent on the quality of their local department. Professors, however, benefit a lot from a network of high quality coauthors. Already in the 1920s and 1930s many of these coauthors were not located in the same department. The absence of localized peer effects for professors is striking given that many researchers believe that local peer effects are important. While only suggestive an important explanation for this finding is the fact that the scientific community in Germany was extremely integrated before the Second World War. Conferences were common and the scientists were very mobile within Germany. One famous example are the famous summer lectures of theoretical physics in Göttingen. In the summer of 1922 Niels Bohr from Copenhagen, held a two week lecture series on theoretical physics and many experts in quantum theory from all over Europe and especially Germany gathered in Göttingen. (amongst them: Sommerfeld (University of München), Ehrenfest (Leiden, Netherlands), Lande (Frankfurt), Pauli (Copenhagen), Heisenberg (Göttingen), and many others).[52] Also the annual conference of German scientists was attended by a very large proportion of researchers. The geographic location of researchers was therefore not very important for more established researchers.

Even though the local department does not seem to affect the productivity of established professors they still benefit a lot from being in a network with other high quality researchers. These coauthors, however, do not need to be in the same location. I find that an average professor's productivity falls by 13 percent in physics and by 16.5 percent in chemistry if he loses a coauthor of average quality. The loss of a higher quality coauthor has even more negative effects. As mentioned before, my coauthor results are remarkably similar to the results obtained by Azoulay et. al (2008). They cannot test for localized peer effect in their setup as they do not observe the universe of researchers at a dying scientist's university. They can show, however, that the coauthor effect is not different for coauthors who are co-located compared to coauthors who are located at another university. This is present-day evidence that co-location does not intensify the collaboration among professors.

[51] This is calculated as follows. Average department quality in 1933 was 5.06. Average department size in 1933 was 13.20. The average Nobel Laureate's quality was 17.22. Therefore department quality changes by 1.00 due to the dismissal of a Nobel Laureate. The estimated reduced form coefficient is 0.03 with a 95 percent confidence interval of -0.0017 to 0.062. Therefore the reduction in peer quality has an effect of -0.0017*1.00.

[52] See Hund, Maier-Leibnitz, and Mollwo (1988).

These results are interesting from a policy perspective as well. It seems that the efficient way of training PhD students is to have large PhD programs in a few very high quality departments. Interestingly this is a pattern than can be observed for a large number of subjects and universities today. A minority of very high quality departments produce a large fraction of all PhD students.

On the other hand it seems to be much less important for established researchers to have very high quality local peers. For them it is important to be part of a network of high quality coauthors. Falling communication and transportation costs have probably further reduced the importance of location for collaborations of established researchers. In addition to that the increasing specialization of researchers may have increased the need and potential for collaborations of researchers in different locations.[53] This suggests that bringing together a number of high quality researchers in one place may not be a very successful tool to increase scientific innovation among established researchers. It is probably more important to increase the possibility for collaborations across departments by fostering the mobility of researchers and their exposure to researchers with similar research interests. The funding of conferences and active support of collaborations among researchers through travel grants or other policies may therefore be a very effective tool to increase total research output of established researchers.

[53] See Wuchty et al. (2007) for a description of the increased importance of teams in scientific research.

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8 Tables

Table 1: Number of Dismissed Scientists across different Subjects

	Physics		Chemistry		Mathematics	
Year of Dismissal	Number of Dismissals	% of all Physicists in 1933	Number of Dismissals	% of all Chemists in 1933	Number of Dismissals	% of all Mathematicians in 1933
1933	33	11.5	50	10.7	35	15.6
1934	6	2.1	11	2.4	6	2.7
1935	4	1.4	5	1.1	5	2.2
1936	1	0.3	7	1.5	1	0.4
1937	1	0.3	3	0.6	2	0.9
1938	1	0.3	4	0.9	1	0.4
1939	1	0.3	2	0.4	1	0.4
1940	1	0.3	0	0.0	1	0.4
1933 - 1934	39	13.6	61	13.1	41	18.3

Table 2: Dismissals across different Universities

University	Physics: Scientists 1933	Physics: Dismissed 1933-34 #	Physics: Dismissed 1933-34 in %	Physics: Dismissal Induced Δ to Dep. Quality	Chemistry: Scientists 1933	Chemistry: Dismissed 1933-34 #	Chemistry: Dismissed 1933-34 in %	Chemistry: Dismissal Induced Δ to Dep. Quality	Mathematics: Scientists 1933	Mathematics: Dismissed 1933-34 #	Mathematics: Dismissed 1933-34 in %	Mathematics: Dismissal Induced Δ to Dep. Quality
Aachen TU	3	0	*0*	0	12	2	*16.7*	+	7	3	*42.9*	+
Berlin	38	8	*21.1*	−−	45	15	*33.3*	−	13	5	*38.5*	−−
Berlin TU	21	6	*28.6*	−	41	13	*31.7*	−	14	2	*14.3*	+
Bonn	12	1	*8.3*	+	16	1	*6.3*	−	7	1	*14.3*	+
Braunschweig TU	4	0	*0*	0	8	0	*0*	0	3	0	*0*	0
Breslau	12	2	*16.7*	+	10	1	*10.0*	−	6	3	*50.0*	−−
Breslau TU	1	0	*0*	0	14	2	*14.3*	−	5	2	*40.0*	−−
Darmstadt TU	9	1	*11.1*	+	18	5	*27.8*	−−	9	1	*11.1*	+
Dresden TU	6	1	*16.7*	−−	17	1	*5.9*	−−	10	0	*0*	0
Erlangen	4	0	*0*	0	8	0	*0*	0	3	0	*0*	0
Frankfurt	12	1	*8.3*	−	18	5	*27.8*	+	8	1	*12.5*	+
Freiburg	8	0	*0*	0	15	3	*20.0*	+	9	1	*11.1*	−
Giessen	5	1	*20.0*	−−	10	0	*0*	0	7	1	*14.3*	+
Göttingen	21	9	*42.9*	−−	17	0	*0*	0	17	10	*58.8*	−−
Greifswald	6	0	*0*	0	5	0	*0*	0	3	0	*0*	0
Halle	4	0	*0*	0	9	1	*11.1*	+	7	1	*14.3*	+
Hamburg	11	2	*18.2*	+	11	2	*18.2*	+	8	0	*0*	0
Hannover TU	3	0	*0*	0	14	0	*0*	0	6	0	*0*	0
Heidelberg	8	0	*0*	0	18	1	*5.6*	+	5	1	*20.0*	+
Jena	13	1	*7.7*	+	10	0	*0*	0	5	0	*0*	0
Karlsruhe TU	8	0	*0*	0	14	4	*28.6*	+	6	1	*16.7*	0
Kiel	8	1	*12.5*	−	11	0	*0*	0	5	2	*40.0*	+
Köln	8	1	*12.5*	+	4	1	*25.0*	−−	6	2	*33.3*	+
Königsberg	8	0	*0*	0	11	1	*9.1*	−−	5	2	*40.0*	−
Leipzig	11	2	*18.2*	+	24	2	*8.3*	−	8	2	*25.0*	−
Marburg	6	0	*0*	0	8	0	*0*	0	8	0	*0*	0
München	12	3	*25.0*	+	18	1	*5.6*	−	9	0	*0*	0
München TU	10	1	*10*	+	15	0	*0*	+	5	0	*0*	0
Münster	5	0	*0*	0	12	0	*0*	0	5	0	*0*	0
Rostock	3	0	*0*	0	8	0	*0*	0	2	0	*0*	0
Stuttgart TU	5	0	*0*	0	9	1	*11.1*	+	6	0	*0*	0
Tübingen	2	0	*0*	0	10	0	*0*	0	6	0	*0*	0
Würzburg	3	0	*0*	0	11	0	*0*	0	4	0	*0*	0

This table reports the total number of scientists in 1933. # Dismissed indicates how many scientists were dismissed in each department. % Dismissed indicates the percentage of dismissed scientists in each department. The column "Dismissal Induced Δ to Peer Quality" indicates how the dismissal affected average department quality: −− indicates a more than 50% drop in average department quality; − a drop in average department quality between 0 and 50%; 0 indicates no change in department quality; + indicates an improvement in average department quality between 0 and 50%.

Table 3: Quality of Dismissed Professors

	Physics				Chemistry				Mathematics			
			Dismissed 33-34				Dismissed 33-34				Dismissed 33-34	
	All	Stay-ers	#	% Loss	All	Stay-ers	#	% Loss	All	Stay-ers	#	% Loss
Researchers (Beginning of 1933)	287	248	39	13.6	466	405	61	13.1	224	183	41	18.3
# of Chaired Profs.	109	97	12	11.0	156	136	20	12.8	117	99	18	15.4
Average Age (1933)	49.5	50.2	45.1	-	50.4	50.5	49.7	-	48.7	50.0	43.0	-
# of Nobel Laureates	15	9	6	40.0	14	11	3	21.4	-	-	-	-
Avg. publications (1925-1932)	0.47	0.43	0.71	20.5	1.69	1.59	2.31	17.9	0.33	0.27	0.56	31.1
Avg. publications (citation weighted)	5.10	3.53	14.79	39.4	17.25	16.07	25.05	19.0	1.45	0.93	3.71	46.8
% Publ. coauthored	33.3	33.6	31.6	-	76.0	75.8	77.1	-	11.3	9.7	14.8	-
% Publ. coauthored (Coaut. at German uni)	10.6	9.9	13.9	-	11.7	12.1	9.7	-	6.3	5.9	6.7	-
% Publ. coauthored (Coaut. same uni)	4.2	3.4	8.7	-	5.1	5.4	3.8	-	2.7	2.0	4.1	-

% Loss is calculated as the fraction of the dismissals among all researchers or as the fraction of Nobel Laureates, publications, and citation weighted publications which were contributed by the dismissed.

Table 4: Summary Statistics Mathematics PhD Students

	All	Obtaining PhD in Top 10 Department	Obtaining PhD in lower ranked Department
Average Age at PhD	27.5	26.9	28.1
Average Time to PhD in years (from beginning of studies)	7.4	7.2	7.7
% Female	8.7	8.2	9.2
% Foreign	7.5	9.7	5.3
Outcomes:			
% Published Dissertation in Top Journal	24.1	29.5	18.3
% Became Chaired Professor later in life	18.7	25.0	12.1
# of PhD students	690	352	338

Table 5: Reduced Form PhD Students

	(1)	(2)
Dependent Variable	Published Top	Full Professor
Dismissal Induced	-0.119	-0.079
Fall in Faculty Quality	(0.018)**	(0.018)**
Number Dismissed	0.020	0.011
	(0.011)	(0.008)
Female	0.004	-0.093
	(0.048)	(0.038)*
Foreigner	0.030	-0.130
	(0.049)	(0.054)*
Cohort Dummies	✓	✓
Department FE	✓	✓
Observations	690	690
R-squared	0.22	0.16

**significant at 1% level *significant at 5% level
(All standard errors clustered at department level)

Table 6: First Stages PhD Students

	(1)	(2)
Dependent Variable:	Average Quality	Department Size
Dismissal Induced	-0.859	0.313
Fall in Faculty Quality	(0.095)**	(0.156)
Number Dismissed	0.039	-0.670
	(0.036)	(0.072)**
Female	0.106	-0.158
	(0.081)	(0.177)
Foreigner	-0.078	0.066
	(0.105)	(0.105)
Cohort Dummies	✓	✓
Department FE	✓	✓
Observations	690	690
R-squared	0.77	0.82
F-Stat on Instruments	65.0	51.5

**significant at 1% level *significant at 5% level
(All standard errors clustered at department level)

Table 7: Instrumental Variables PhD Students

	(1)	(2)	(3)	(4)
Dependent Variable:	Published Top		Full Professor	
	OLS	IV	OLS	IV
Average Faculty Quality	0.049	0.105	0.030	0.074
	(0.019)*	(0.020)**	(0.022)	(0.021)**
Department Size	-0.015	-0.035	-0.005	-0.019
	(0.014)	(0.018)	(0.009)	(0.014)
Female	-0.014	-0.024	-0.098	-0.105
	(0.060)	(0.058)	(0.042)*	(0.040)*
Foreigner	0.016	0.024	-0.134	-0.128
	(0.048)	(0.050)	(0.053)*	(0.055)*
Cohort Dummies	✓	✓	✓	✓
Department FE	✓	✓	✓	✓
Observations	690	690	690	690
R-squared	0.16		0.15	
Cragg-Donald EV Statistic		72.2		72.2

**significant at 1% level *significant at 5% level
(All standard errors clustered at department level)

Table 8: Robustness Instrumental Variable Results of PhD Students

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Sample:	Full Sample		Full Sample		Non-Jewish Students		Omitting 1933 and 1934		Coursework in 1933		Full Sample	
Dependent Variable:	Published Top	Full Professor	Published Top	Full Professor	Published Top	Full Professor	Published Top	Full Professor	Published Top	Full Professor	Published Top	Full Professor
Average Faculty Quality	0.125	0.088	0.132	0.099	0.118	0.074	0.201	0.125	0.151	0.105	0.054	0.056
	(0.022)**	(0.022)**	(0.021)**	(0.025)**	(0.025)**	(0.028)*	(0.048)**	(0.039)**	(0.030)**	(0.030)**	(0.023)*	(0.023)*
Department Size	-0.024	-0.011	-0.021	-0.016	-0.022	-0.013	-0.052	-0.048	-0.029	-0.023	-0.026	0.013
	(0.015)	(0.012)	(0.015)	(0.010)	(0.014)	(0.011)	(0.044)	(0.018)*	(0.024)	(0.014)	(0.013)	(0.011)
Father's Occupation			✓	✓								
Female & Foreigner	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Cohort Dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Department FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Dep.Spec. Time Trends											✓	✓
Observations	690	690	690	690	635	635	570	570	501	501	690	690
Cragg-Donald EV Stat.	72.2	72.2	60.3	60.3	61.2	61.2	35.8	35.8	37.4	37.4	67.2	67.2

Table 9: Heterogeneity in Returns PhD Students

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Top 10 Department				Lower Ranked Department			
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Dependent Variable	Published Top	Published Top	Full Professor	Full Professor	Published Top	Published Top	Full Top	Full Professor
Average Faculty Quality	0.065	0.113	0.041	0.092	-0.044	-0.072	-0.080	0.131
	(0.009)**	(0.030)**	(0.028)	(0.031)*	(0.050)	(0.212)	(0.052)	(0.248)
Department Size	-0.022	-0.029	-0.002	-0.017	-0.012	0.054	-0.025	0.220
	(0.021)	(0.030)	(0.012)	(0.013)	(0.029)	(0.147)	(0.017)	(0.204)
Female & Foreigner	✓	✓	✓	✓	✓	✓	✓	✓
Cohort Dummies	✓	✓	✓	✓	✓	✓	✓	✓
Department FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	352	352	352	352	338	338	338	338
R-squared	0.21		0.21		0.23		0.20	
Cragg-Donald EV Statistic		46.6		46.6		1.9		1.9

**significant at 1% level *significant at 5% level (All standard errors clustered at department level)

Table 10: Reduced Form (Department Level Peers)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Physics				Chemistry				Mathematics			
Dependent Variable:	Publi-cations	Publi-cations	Citation Weighted Publ.	Citation Weighted Publ.	Publi-cations	Publi-cations	Citation Weighted Publ.	Citation Weighted Publ.	Publi-cations	Publi-cations	Citation Weighted Publ.	Citation Weighted Publ.
Dismissal Induced	0.029	0.030	0.312	0.357	0.012	0.013	0.383	0.403	0.022	0.027	-0.464	-0.304
Fall in Peer Quality	(0.015)	(0.016)	(0.235)	(0.252)	(0.015)	(0.014)	(0.303)	(0.312)	(0.031)	(0.037)	(0.337)	(0.346)
Number Dismissed	-0.021	-0.025	-0.017	-0.125	-0.018	-0.017	-0.130	-0.065	-0.018	-0.019	-0.016	-0.003
	(0.017)	(0.019)	(0.302)	(0.323)	(0.009)*	(0.009)	(0.222)	(0.217)	(0.015)	(0.016)	(0.167)	(0.143)
Age Dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year Dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Department FE		✓		✓		✓		✓		✓		✓
Observations	2261	2261	2261	2261	3584	3584	3584	3584	1538	1538	1538	1538
# of researchers									183	183	183	183
R-squared	0.39	0.40	0.25	0.27	0.67	0.68	0.54	0.55	0.32	0.34	0.20	0.20

**significant at 1% level   *significant at 5% level   (All standard errors clustered at department level)

Publications is the sum of a scientist's publications in top journals in one year.

Citation Weighted Publications are defined as the sum of subsequent citations (in the first 50 years after publication in any journal included in the "Web of Science", including international journals) of all articles published in a given year.

Dismissal induced ↓ in Peer Quality is 0 for all researchers until 1933. In 1934 it is equal to (Avg. quality of total department before dismissal) - (Avg. quality of researchers not dismissed in 1933) if this number > 0. From 1935 onwards it will be equal to (Avg. quality of total department before dismissal) - (Avg. quality of researchers not dismissed in 1933 and 1934) if this number is > 0. Scientists in departments with above average quality dismissals will have a positive value of the quality dismissal variable after 1933 and a value of 0 until 1933. The variable will always be 0 for all other scientists. Average quality is measured as the department level average of citation weighted publications between 1925 and 1932 such that any changes after the dismissal do not affect the values of the average.

Number dismissed is equal to the number of dismissed scientists in a researcher's department. The variable is 0 until 1933 for researchers in all departments. In 1934 it is equal to the number of dismissals in 1933 at a researcher's department. From 1935 onwards it is equal to the number of dismissals in 1933 and 1934 in a researcher's department.

Table 11: First Stages Professors (Department Level Peers)

	(1)	(2)	(3)	(4)	(5)	(6)
	Physics		Chemistry		Mathematics	
Dependent Variable:	Avg. Quality of Peers	Department Size	Avg. Quality of Peers	Department Size	Avg. Quality of Peers	Department Size
Dismissal Induced	-0.614	-0.112	-1.131	-0.001	-1.369	0.154
Fall in Peer Quality	(0.114)**	(0.118)	(0.197)**	(0.101)	(0.167)**	(0.193)
Number Dismissed	-0.034	-0.515	-0.024	-0.963	0.157	-0.529
	(0.110)	(0.111)**	(0.172)	(0.105)**	(0.059)*	(0.063)**
Age Dummies	✓	✓	✓	✓	✓	✓
Year Dummies	✓	✓	✓	✓	✓	✓
Department FE	✓	✓	✓	✓	✓	✓
Individual FE	✓	✓	✓	✓	✓	✓
Observations	2261	2261	3584	3584	1538	1538
# of researchers	258	258	413	413	183	183
R-squared	0.62	0.93	0.69	0.94	0.73	0.86
F - Test on Instruments	79.1	108.3	18.2	45.3	39.9	79.4

Table 12: Instrumental Variables Professors (Department Level Peers)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Physics				Chemistry				Mathematics			
Dependent Variable	Publications		Cit. Weighted Pub.		Publications		Cit. Weighted Pub.		Publications		Cit. Weighted Pub.	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Peer Quality	0.003	-0.059	-0.044	-0.633	0.005	-0.011	0.055	-0.356	0.015	-0.017	0.513	0.231
	(0.004)	(0.044)	(0.080)	(0.592)	(0.003)	(0.014)	(0.050)	(0.268)	(0.014)	(0.026)	(0.178)**	(0.262)
Department Size	-0.003	0.053	-0.196	0.286	-0.011	0.018	0.060	0.076	0.005	0.031	0.001	0.074
	(0.005)	(0.051)	(0.111)	(0.760)	(0.007)	(0.010)	(0.263)	(0.213)	(0.013)	(0.027)	(0.079)	(0.301)
Age Dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year Dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Department FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	2261	2261	2261	2261	3584	3584	3584	3584	1538	1538	1538	1538
# of researchers	258	258	258	258	413	413	413	413	183	183	183	183
R-Squared	0.40		0.27		0.68		0.55		0.34		0.21	
Cragg-Donald EV Statistic		13.38		13.38		78.29		78.29		68.81		68.81

**significant at 1% level *significant at 5% level (All standard errors clustered at the department level)

Table 13: Robustness Checks IV Physics Professors (Department Level Peers)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Baseline		omitting 33-34		younger than 50		50 or older		Dep. Time Trends		Theoretical Physics	
Dependent Variable	Publi-cations	Cit weig. Publ.	Publi-cations	Cit weig. Publ.	Publi-cations	Cit weig. Publ.	Publi-cations	Cit weig. Publ.	Publi-cations	Cit weig. Publ.	Publi-cations	Cit weig. Publ.
Peer Quality	-0.059	-0.633	-0.005	-0.394	-0.079	-1.614	-0.031	0.999	-0.104	-0.736	-0.061	-1.001
	(0.044)	(0.592)	(0.037)	(0.781)	(0.054)	(0.989)	(0.098)	(0.750)	(0.109)	(1.054)	(0.103)	(2.400)
Department Size	0.053	0.286	-0.004	-0.083	0.107	1.984	0.038	-1.275	0.110	0.517	0.023	-0.658
	(0.051)	(0.760)	(0.046)	(0.992)	(0.061)	(1.175)	(0.102)	(0.683)	(0.093)	(1.039)	(0.078)	(1.587)
Age Dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year Dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Department FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Dep. specific. Time Trends									✓	✓		
Observations	2261	2261	1866	1866	1203	1203	1058	1058	2261	2261	464	464
# of researchers	258	258	256	256	181	181	147	147	258	258	50	50
Minimum EV Statistic	13.38	13.38	6.24	6.24	5.57	5.57	3.75	3.75	6.54	6.54	4.07	4.07

Table 14: Robustness Checks IV Chemistry Professors (Department Level Peers)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Baseline		omitting 33-34		younger than 50		50 or older		Dep. Time Trends	
Dependent Variable	Publi-cations	Cit weig. Publ.	Publi-cations	Cit weig. Publ.	Publi-cations	Cit weig. Publ.	Publi-cations	Cit weig. Publ.	Publi-cations	Cit weig. Publ.
Peer Quality	-0.011	-0.356	-0.008	-0.189	-0.014	-0.520	-0.004	-0.032	0.039	-0.418
	(0.014)	(0.268)	(0.016)	(0.174)	(0.024)	(0.484)	(0.020)	(0.288)	(0.035)	(0.573)
Department Size	0.018	0.076	0.022	0.234	0.011	0.027	0.007	-0.165	0.015	-0.086
	(0.010)	(0.213)	(0.015)	(0.196)	(0.020)	(0.547)	(0.017)	(0.216)	(0.029)	(0.299)
Age Dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year Dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Department FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Dep. specific. Time Trends									✓	✓
Observations	3584	3584	2926	2926	1825	1825	1759	1759	3584	3584
# of researchers	413	413	411	411	265	265	241	241	413	413
Minimum EV Statistic	78.29	78.29	72.47	72.47	31.83	31.83	58.36	58.36	18.56	18.56

**significant at 1% level *significant at 5% level (All standard errors clustered at the department level)

Table 15: Robustness Checks IV Mathematics Professors (Department Level Peers)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Baseline		omitting 33-34		younger than 50		50 or older		Dep. Time Trends	
Dependent Variable	Publi-cations	Cit weig. Publ.	Publi-cations	Cit weig. Publ.	Publi-cations	Cit weig. Publ.	Publi-cations	Cit weig. Publ.	Publi-cations	Cit weig. Publ.
Peer Quality	-0.017	0.231	-0.025	0.257	-0.030	0.335	0.033	0.128	0.005	0.151
	(0.026)	(0.262)	(0.031)	(0.341)	(0.040)	(0.446)	(0.026)	(0.415)	(0.030)	(0.441)
Department Size	0.031	0.074	0.040	0.206	0.056	-0.126	-0.015	-0.307	0.016	-0.055
	(0.027)	(0.301)	(0.050)	(0.537)	(0.032)	(0.331)	(0.042)	(0.572)	(0.020)	(0.265)
Age Dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year Dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Department FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Dep. specific. Time Trends									✓	✓
Observations	1538	1538	1256	1256	899	899	639	639	1538	1538
# of researchers	183	183	183	183	125	125	97	97	183	183
Minimum EV Statistic	68.81	68.81	18.98	18.98	40.66	40.66	18.76	18.76	68.35	68.35

Table 16: Instrumental Variables Professors (Specialization Level Peers)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Physics				Chemistry				Mathematics			
Dependent Variable	Publications		Cit. Weighted Pub.		Publications		Cit. Weighted Pub.		Publications		Cit. Weighted Pub.	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Peer Quality	0.005	-0.022	-0.028	-0.401	-0.001	-0.010	-0.015	-0.005	0.007	-0.641	0.378	6.309
	(0.004)	(0.028)	(0.059)	(0.546)	(0.002)	(0.008)	(0.037)	(0.122)	(0.017)	(7.475)	(0.161)*	(69.269)
Department Size	-0.008	-0.009	-0.375	-0.621	-0.050	0.006	-0.426	-0.976	-0.003	0.728	-0.047	-6.625
	(0.017)	(0.031)	(0.263)	(0.547)	(0.028)	(0.041)	(0.381)	(0.845)	(0.017)	(8.125)	(0.132)	(75.258)
Age Dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year Dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Department FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	2257	2257	2257	2257	3567	3567	3567	3567	1538	1538	1538	1538
# of researchers	256	256	256	256	405	405	405	405	183	183	183	183
R-Squared	0.40		0.27		0.68		0.55		0.34		0.21	
Minimum Eigenvalue Statistic		87.55		87.55		79.38		79.38		0.13		0.13

**significant at 1% level *significant at 5% level (All standard errors clustered at the department level)

Table 17: Effect of Dismissal on Coauthors

	(1)	(2)	(3)	(4)
	Physics		Chemistry	
Dependent Variable	Publi-cations	Citation Weighted Pub.	Publi-cations	Citation Weighted Pub.
Avg. Quality of Dism. Coauthors	-0.007	-0.128	-0.013	-0.165
	(0.003)*	(0.047)**	(0.003)**	(0.037)**
# of Dismissed Coauthors	0.363	8.449	0.419	-0.394
	(0.574)	(8.570)	(0.349)	(5.478)
Age Dummies	✓	✓	✓	✓
Year Dummies	✓	✓	✓	✓
Department FE	✓	✓	✓	✓
Individual FE	✓	✓	✓	✓
Observations	2243	2243	3575	3575
# of researchers	258	258	413	413
R-squared	0.40	0.27	0.67	0.54

**significant at 1% level *significant at 5% level
(All standard errors are clustered at the individual level)

Table 18: Coauthors: Normalized Publications

	(1)	(2)	(3)	(4)
	Physics		Chemistry	
Dependent Variable	Publi-cations	Citation Weighted Pub.	Publi-cations	Citation Weighted Pub.
Avg. Quality of Dism. Coauthors	-0.007	-0.103	-0.008	-0.086
	(0.004)	(0.044)*	(0.002)**	(0.026)**
# of Dismissed Coauthors	0.638	9.320	0.280	-0.257
	(0.594)	(7.734)	(0.180)	(3.502)
Age Dummies	✓	✓	✓	✓
Year Dummies	✓	✓	✓	✓
Department FE	✓	✓	✓	✓
Individual FE	✓	✓	✓	✓
Observations	2243	2243	3575	3575
# of researchers	258	258	413	413
R-squared	0.39	0.26	0.68	0.49

**significant at 1% level *significant at 5% level
(All standard errors are clustered at the individual level)

Table 19: Coauthors: Timing of Coauthorship

	(1)	(2)	(3)	(4)
	Physics		Chemistry	
Dependent Variable	Publications	Citation Weighted Pub.	Publications	Citation Weighted Pub.
Coauthors 1930 - 1932				
Avg. Quality of Dism. Coauthors	-0.007	-0.126	-0.013	-0.163
	(0.003)*	(0.040)**	(0.003)**	(0.047)**
# of Dismissed Coauthors	0.359	8.944	0.114	-6.177
	(0.636)	(8.516)	(0.556)	(10.365)
Coauthors 1924 - 1929 (not later)				
Avg. Quality of Dism. Coauthors	0.007	0.118	0.004	0.069
	(0.019)	(0.440)	(0.004)	(0.068)
# of Dismissed Coauthors	-0.030	-2.725	0.008	0.231
	(0.978)	(23.682)	(0.398)	(4.556)
Age Dummies	✓	✓	✓	✓
Year Dummies	✓	✓	✓	✓
Department FE	✓	✓	✓	✓
Individual FE	✓	✓	✓	✓
Observations	2243	2243	3575	3575
# of researchers	258	258	413	413
R-squared	0.40	0.27	0.67	0.54

**significant at 1% level *significant at 5% level
(All standard errors are clustered at the individual level)

Table 20: Coauthors: Publications without dismissed Coauthors

	(1)	(2)	(3)	(4)
	Physics		Chemistry	
Dependent Variable	Publications	Citation Weighted Pub.	Publications	Citation Weighted Pub.
Coauthors 1930 - 1932				
Avg. Quality of Dism. Coauthors	-0.007	-0.144	-0.012	-0.286
	(0.003)*	(0.050)**	(0.003)**	(0.068)**
# of Dismissed Coauthors	0.510	12.814	0.311	-6.859
	(0.662)	(10.669)	(0.546)	(14.775)
Coauthors 1924 - 1929 (not later)				
Avg. Quality of Dism. Coauthors	0.028	-3.465	0.009	-1.128
	(0.970)	(26.113)	(0.394)	(5.287)
# of Dismissed Coauthors	0.007	0.142	0.003	0.065
	(0.019)	(0.490)	(0.004)	(0.070)
Age Dummies	✓	✓	✓	✓
Year Dummies	✓	✓	✓	✓
Department FE	✓	✓	✓	✓
Individual FE	✓	✓	✓	✓
Observations	2243	2243	3575	3575
# of researchers	258	258	413	413
R-squared	0.39	0.28	0.67	0.53

**significant at 1% level *significant at 5% level
(All standard errors are clustered at the individual level)

9 Appendix

Figure A1: Sample Page from List of Displaced German Scholars

Physics

BEER, Dr. Arthur P., Researcher; b. 1900., married, 1 child. (English, French, Czech.) 1928/33: Researcher Universitätssternwarte, Breslau, and Deutsche Sternwarte, Hamburg. since 1934: Researcher Solar Physics Observatory, Cambridge University. SPEC.: *Astronomy; Astro- and Geo-Physics.* Temp.

BERG, Dr. Wolfgang, F., Assistant; b. 03., married. (English, French.) 1930/33: Assistant Physikalisches Institut, Berlin University; 1934/36: Researcher Physical Lab., Manchester University; since 1936: Industrial Activity, London. SPEC.: *Experimental Physics. Fluorescence of Atoms and Molecules; Structure and Deformation of Crystals; X-Ray Methods.* Temp.

BERGSTRÄSSER, Dr. Martin, Assistant; b. 02., married. (English, French.) 1927/33: Assistant Technische Hochschule, Dresden; 1933/34: Assistant Deutsche Versuchsanstalt für Luftfahrt, Berlin. SPEC.: *Technical Physics; Testing of Materials; Solidity; Mechanics.* Unpl.

BETHE, Dr. Hans, Privatdozent; b. 06., single. (English.) Till 1933: Privatdozent Göttingen University; 1934/35: Researcher Bristol University; since 1935: Cornell University, Ithaca (N.Y.). SPEC.: *Theoretical Physics. Quantum Mechanics.* Perm.

BIEL, Dr. Erwin, Privatdozent; b. 99., married, 1 child. (English, French, Italian.) Till 1929: Assistant Geographisches Institut, Vienna University; 1929/33: Climatologist Meteorologisches Observatorium, Breslau; 1932/33: Privatdozent Breslau University. SPEC.: *Geo-Physics; Climatology.* Unpl.

BLOCH, Dr. Felix, Privatdozent; b. 05., single. (English.) Till 1933: Privatdozent and Assistant Physikalisches Institut, Leipzig University; since 1933: Prof. Stanford University, California. SPEC.: *Theoretical Physics; Atomic Physics.* Perm.

BOAS, Dr. Walter, Assistant; b. 04., single. (English, French.) 1928/32: Researcher Kaiser Wilhelm Institut für Metallforschung, Berlin; 1933/35: Assistant Fribourg University; since 1936: Researcher Physikalisches Institut, Technische Hochschule, Zürich. SPEC.: *Technical Physics; Metallography; Plasticity and Structure of Metals; X-Rays.* Unpl.

BOEHM, Dr. Gundo, Assistant. Till 1933: Assistant Physikalisches Institut, Freiburg University. SPEC.: *Micellar Structure of Muscles.* Unpl.

BORN, Dr. Max, o. Professor; b. 82., married, 3 children. (English.) 1915/19: a.o. Prof. Berlin University; 1919/21: o. Prof. Frankfurt University; 1921/33: o. Prof. Göttingen University; 1933/35: Lecturer Cambridge University; since 1936: Prof. Edinburgh University. SPEC.: *Theoretical Physics; Quantum Theory; Atomic Structure; Optics; Mathematical Physics.* Perm.

BURSTYN, Dr. Walther, a.o. Professor; b. 77., married. (English, French.) 1920/33: a.o. Prof. Technische Hochschule, Berlin. SPEC.: *Technical Physics.* Unpl.

BYK, Dr. Alfred, a.o. Professor; b. 78., married, 2 children. (English, French, Italian, Dutch.) 1905: Privatdozent Technische Hochschule, Berlin; 1909/33: Privatdozent, later a.o. Prof. Berlin University and Technische Hochschule. SPEC.: *Mathematical Physics; Theoretical Electrotechnics; Quantum Theory; Boundaries of Physics and Chemistry.* Unpl.

COHN-PETERS, Dr. H. Jürgen, Researcher; b. 07. Till 1933: Researcher Berlin University; since 1934: U.S.S.R. SPEC.: *Experimental Physics. High Tension.* Perm.

DEMBER, Dr. Alexis, Assistant; b. 12., single. (English, French.) since 1935: Assistant Physical Institute, Istanbul University. SPEC.: *Electrolytes; Photoelectricity.* Temp.

DEMBER, Dr. Harry, o. Professor; b. 82., married, 2 children. (English, French, Spanish, Turkish.) 1909/33: Privatdozent, later o. Prof. Technische Hochschule, Dresden; and Director Physikalisches Institut; since 1933; o. Prof. Istanbul University and Director Physical Institute. SPEC.: *Cathode and X-Rays; Photo-Electricity; Atmospheric Optics; Atmospheric Electricity.* Perm.

DUSCHINSKY, Dr. F., Assistant; b. 07., single. (French, Italian, Spanish, Dutch.) 1933: Assistant Kaiser Wilhelm Institut für Physik, Berlin; since 1934: Assistant Brussels University. SPEC.: *Experimental Physics; Fluorescence; Molecular Spectra; Optics; High Frequency Technics.* Temp.

EHRENBERG, Dr. Werner, Assistant; b. 01., single. (English, French.) 1924/27: Assistant Kaiser Wilhelm Institut für Faserstoffchemie, Berlin; 1928/30: Researcher Berlin University and Technische Hochschule, Stuttgart; 1930/33: Assistant Technische Hochschule, Stuttgart; since 1935: Electric and Musical Industries, Ltd., Hayes (Middlesex). SPEC.: *Experimental Physics. X-Rays; Cathode Rays; Cosmic Radiation.* Perm.

EINSTEIN, Dr. Albert, o. Professor; b. 79., married. (English.) 1913/33: o. Prof. Berlin University and Director Kaiser Wilhelm Institut für Physik; 1921 Nobel Prize; since 1934: Prof. Institute for Advanced Study, Princeton (N.J.).

EISENSCHITZ, Dr. Robert, Researcher; b. 98., married. (English, French.) 1924/27: Researcher Allgemeine Elektrizitätsgesellschaft, Berlin; 1927/33: Researcher Kaiser Wilhelm Institut für Physikalische Chemie und Elektrochemie, Berlin; since 1934: Researcher Royal Institution, London. SPEC.: *Theoretical and Experimental Physics; Spectroscopy; Viscosity; Application of Physical Theories to Chemical Problems.* Temp.

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Squares were added by the author to highlight the researchers who had already received the Noble prize or were to receive it after 1936.

Figure A2: Effect of Dismissal on Department Size and Faculty Quality in Physics

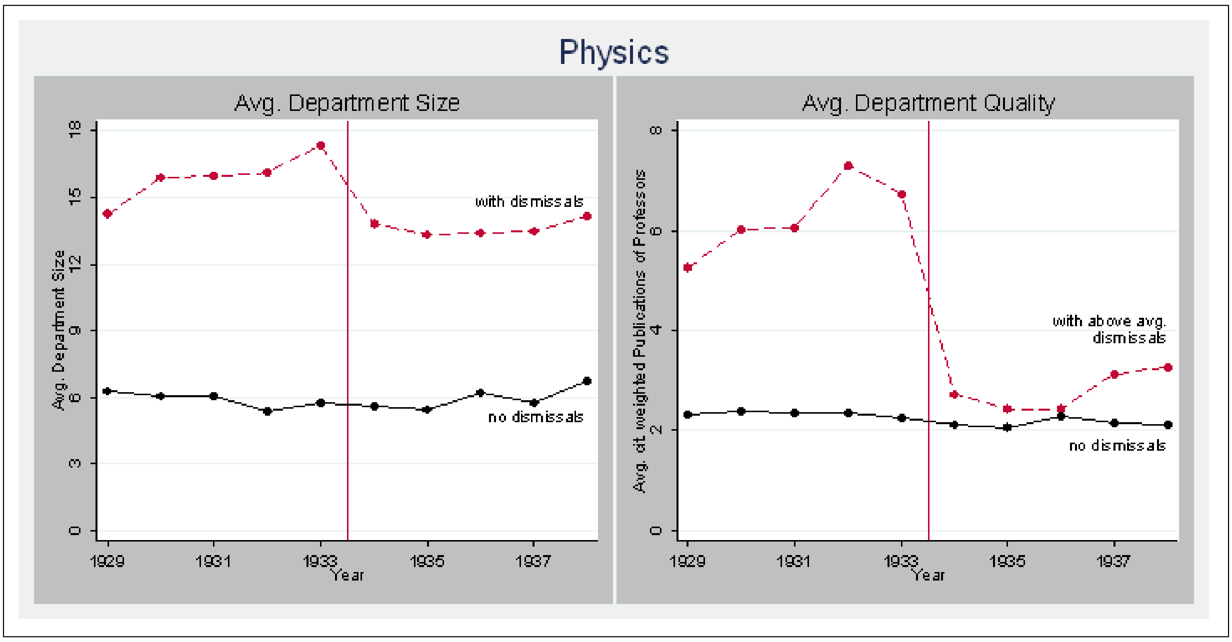

Figure A2: First Stages Physics

Figure A3: Effect of Dismissal on Department Size and Faculty Quality in Chemistry

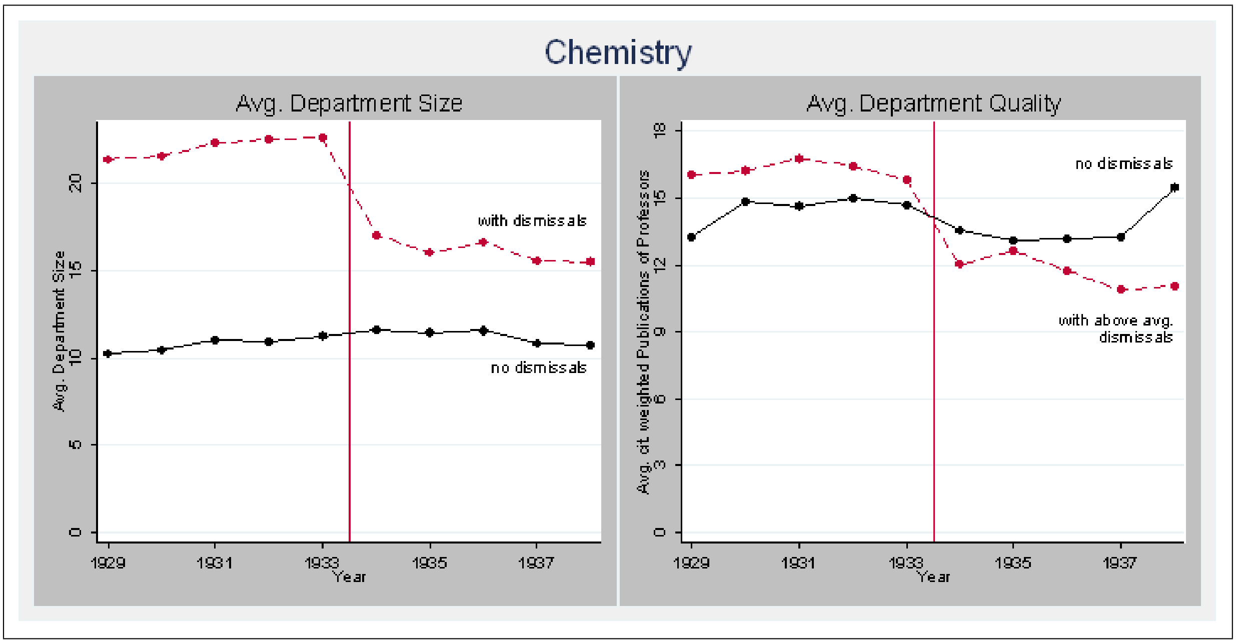

Figure A3: First Stages Chemistry

Figure A4: Effect of Dismissal on Staying Professors in Physics

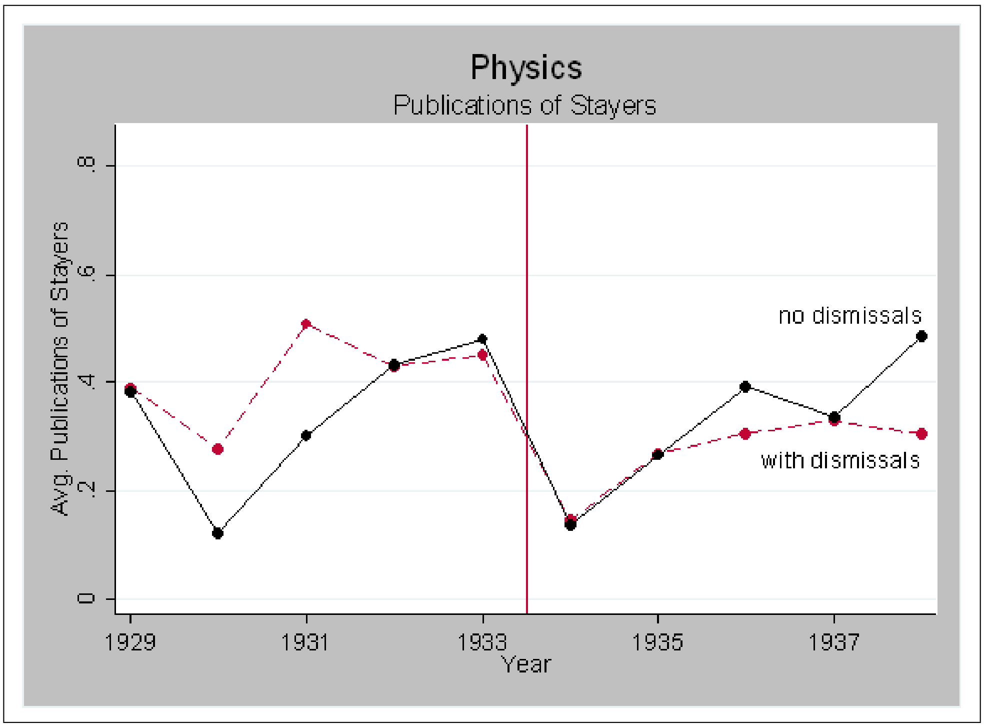

Figure A4: Reduced Form Physics Professors

Figure A5: Effect of Dismissal on Staying Professors in Chemistry

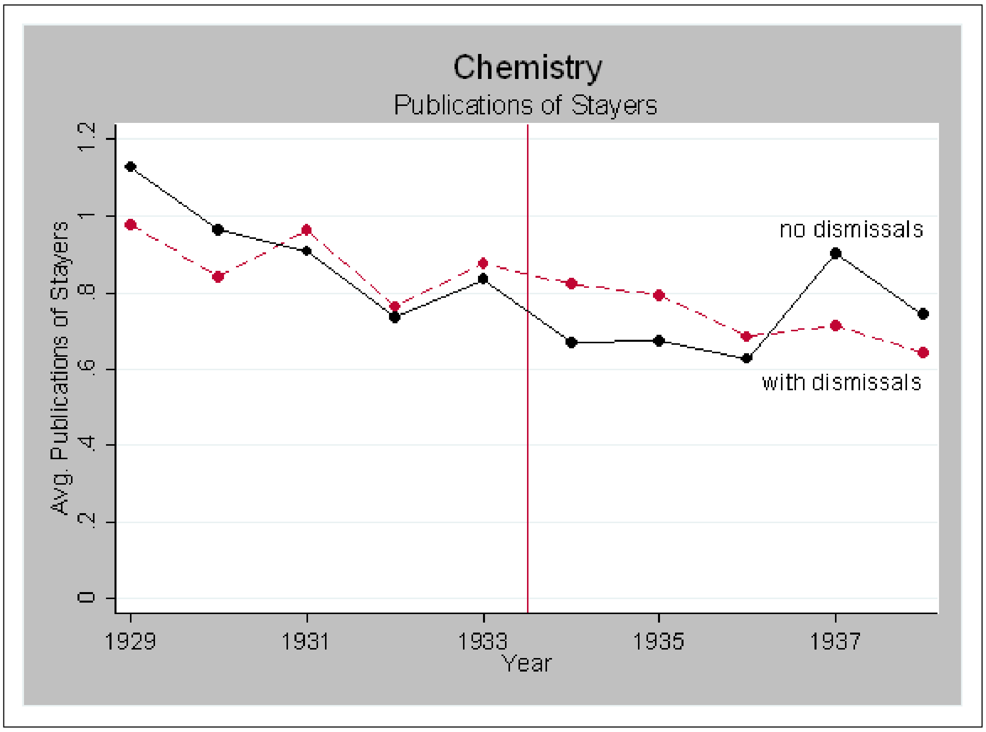

Figure A5: Reduced Form Chemistry Professors

Figure A6: Effect of Dismissal on Coauthors in Chemistry

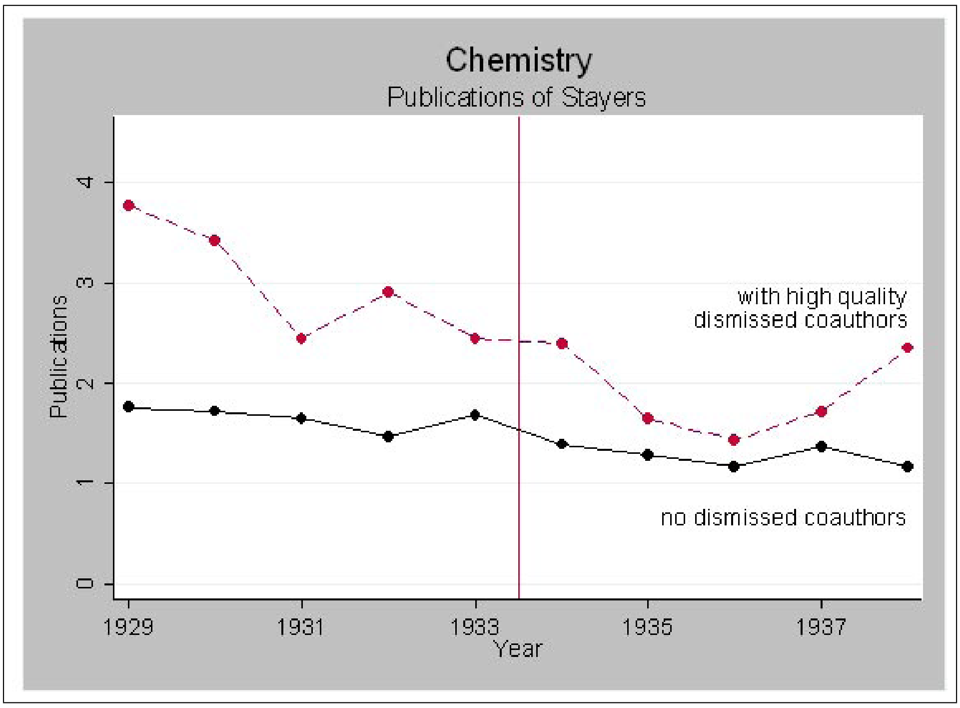

Figure A6: Effect of Dismissal of Coauthors Chemistry

Table A1: Specializations

Physics		Chemistry		Mathematics	
Specialization	% scientists in speciali-zation	Specialization	% scientists in speciali-zation	Specialization	% scientists in speciali-zation
Experimental Physics	48.5	Organic Chemistry	26.6	Analysis	45.9
Theoretical Physics	22.3	Physical Chemistry	23.8	Applied Mathematics	36.2
Technical Physics	20.6	Technical Chemistry	19.4	Algebra	19.7
Astronomy	14.7	Anorganic Chemistry	18.6	Number Theory	13.5
		Pharmacology	10.2	Metha Mathematics	5.2
		Medical Chemistry	8.0	Topology	4.8
		Biochemistry	6.7	Foundations of Math.	4.4

Percentages add to more than 100 percent because some physicists and chemists have two specializations. Mathematicians have up to four specializations.

Table A2: Top Journals

Journal Name	Published in
General Journals	
Naturwissenschaften	Germany
Sitzungsberichte der Preussischen Akademie der Wissenschaften Physikalisch Mathematische Klasse	Germany
Nature	UK
Proceedings of the Royal Society of London A (Mathematics and Physics)	UK
Science	USA
Physics	
Annalen der Physik	Germany
Physikalische Zeitschrift	Germany
Physical Review	USA
Chemistry	
Berichte der Deutschen Chemischen Gesellschaft	Germany
Biochemische Zeitschrift	Germany
Journal für Praktische Chemie	Germany
Justus Liebigs Annalen der Chemie	Germany
Kolloid Zeitschrift	Germany
Zeitschrift für Anorganische Chemie und Allgemeine Chemie	Germany
Zeitschrift für Elektrochemie und Angewandte Physikalische Chemie	Germany
Zeitschrift für Physikalische Chemie	Germany
Journal of the Chemical Society	UK
Mathematics	
Journal für die reine und angewandte Mathematik	Germany
Mathematische Annalen	Germany
Mathematische Zeitschrift	Germany
Zeitschrift für angewandte Mathematik und Mechanik	Germany
Acta Mathematica	Sweden
Journal of the London Mathematical Society	UK
Proceedings of the London Mathematical Society	UK

Table A3: Top Researchers 1925-1932 (Citation weighted Publications Measure)

Name	University beginning of 1933	First Special-ization	Second Special-ization	Third Special-ization	Avg. Cit weighted Publ.	Avg. Publ.	Nobel Prize	Dis-missed 33-34
Physics								
Fritz London	Berlin	Theo. Phy.			149.3	1.3		✓
Lother Nordheim	Göttingen	Theo. Phy.			110.0	0.7		✓
Gerhard Herzberg	Darmstadt TU	Exp. Phy.			78.0	2.0	✓	
Carl Ramsauer	Berlin TU	Exp. Phy.			75.6	3.0		
Max Born	Göttingen	Theo. Phy.			62.5	1.3	✓	✓
Hans Falkenhagen	Köln	Theo. Phy.			57.5	1.9		
Arnold Sommerfeld	München	Theo. Phy.			44.4	1.8		
Eugen Wigner	Berlin TU	Theo. Phy.			44.3	0.5	✓	✓
Heinrich Kuhn	Göttingen	Exp. Phy.	Theo. Phy.		42.0	4.0		✓
Harry Dember	Dresden TU	Exp. Phy.			40.8	1.0		✓
Karl Herzfeld		Theo. Phy.			33.7	1.3		
Richard Gans	Königsberg	Exp. Phy.			29.4	1.6		
Walter Gerlach	München	Exp. Phy.			29.1	3.1		
Wolfgang Pauli		Theo. Phy.			28.0	3.8	✓	
Max Wien	Jena	Exp. Phy.			25.4	2.0		
Werner Heisenberg	Leipzig	Theo. Phy.			25.3	1.0	✓	
Ludwig Prandtl	Göttingen	Tech. P.			23.3	1.1		
Fritz Kirchner	München	Exp. Phy.			22.5	2.5		
Johannes Malsch	Köln	Exp. Phy.			22.0	1.5		
Emil Rupp	Berlin TU	Exp. Phy.			21.4	5.2		✓
Chemistry								
Werner Kuhn	Karlsruhe TU	Physical C.			262.0	7.0		
Max Bergmann	Dresden TU	Organic C.	Biochem.		250.2	6.8		✓
Karl Lohmann	Heidelberg	Medical C.			224.0	6.0		
Ernst Bergmann	Berlin	Physical C.			223.3	17.0		✓
Carl Neuberg	Berlin	Biochem.			184.9	15.1		
Carl Wagner	Jena	Physical C.			177.5	5.0		
Otto Meyerhof	Heidelberg	Medical C.			176.3	5.8	✓	
Otto Ruff	Breslau TU	Anorganic C.			133.4	7.2		
Wolfgang Ostwald	Leipzig	Anorganic C.			127.0	8.6		
Hermann Staudinger	Freiburg	Organic C.			126.8	8.5	✓	
Gustav Tammann	Göttingen	Physical. C.			118.4	19.0		
Michael Polanyi	Berlin TU	Physical. C.			116.8	5.6		✓
Max Volmer	Berlin TU	Physical. C.			114.0	4.2		
Karl Freudenberg	Heidelberg	Organic C.			111.8	7.0		
Ulrich Hofmann	Berlin TU	Anorganic C.	Physical C.		109.0	6.0		
Richard Johann Kuhn	Heidelberg	Physical C.	Medical C.		92.1	8.0	✓	
Max Trautz	Heidelberg	Physical C.			91.9	5.3		
Wilhelm Klemm	Hannover TU	Anorganic. C.			91.4	5.2		
Mathematics								
Johann von Neumann	Berlin	Applied Math	Foundations	Analysis	36.3	1.5		✓
Richard Courant	Göttingen	Analysis	Applied Math		22.3	1.3		✓
Richard von Mises	Berlin	Applied Math	Analysis		15.6	0.9		✓
Heinz Hopf		Algebra	Topology	Geometry	13.3	1.3		
Paul Epstein	Frankfurt	Geometry	Number Th.	Algebra	11.5	0.6		
Oskar Perron	München	Algebra	Analysis		10.6	1.5		
Willy Prager	Göttingen	Applied Math			10.0	0.4		✓
Gabiel Szegö	Königsberg	Applied Math	Geometry		9.4	1.4		✓
Werner Rogosinski	Königsberg	Number Th.	Analysis		9.1	0.6		
Wolfgang Krull	Erlangen	Algebra			8.9	1.4		
Erich Rothe	Breslau TU	Analysis	Applied Math		8.0	1.0		✓
Hans Peterssonn	Hamburg	Number Th.	Analysis		8.0	2.0		
Adolf Hammerstein	Berlin	Number Th.	Analysis		8.0	0.5		
Alexander Weinstein	Breslau TU	Applied Math			6.3	0.7		✓
Erich Kamke	Tübingen	Number Th..	Foundations	Analysis	6.3	0.8		
Hellmuth Kneser	Greifswald	Applied Math	Analysis	Topology	6.3	0.6		
Bartel van der Waerden	Leipzig	Algebra	Geometry		5.8	1.8		
Max Müller	Heidelberg	Analysis			5.3	0.3		
Richard Brauer	Königsberg	Algebra			5.0	0.6		✓
Leon Lichtenstein	Leipzig	Analysis	Applied Math		4.9	1.5		✓

The university in 1933 is missing for researchers, who retire before before 1933.

Table A4: Identification Robustness Checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Probability of Ever Being Promoted			Signing Support List for Hitler			Notgemeinschaft Funding		
Dependent Variable	Promotion Dummy	Promotion Dummy	Promotion Dummy	Signing List	Signing List	Signing List	Funding Dummy	Funding Dummy	Funding Dummy
Subject	Physics	Chemistry	Mathematics	Physics	Chemistry	Mathematics	Physics	Chemistry	Mathematics
Dismissal Induced	-0.010	0.003	-0.006	0.048	0.000	0.039	-0.068	0.006	-0.005
Fall in Peer Quality	(0.008)	(0.003)	(0.032)	(0.035)	(0.001)	(0.117)	(0.016)**	(0.010)	(0.020)
Number Dismissed	0.013	-0.003	0.011	-0.019	-0.000	-0.027	0.038	-0.006	0.003
	(0.008)	(0.002)	(0.016)	(0.023)	(0.001)	(0.065)	(0.021)	(0.015)	(0.012)
Age Dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year Dummies	✓	✓	✓				✓	✓	✓
Department FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual FE	✓	✓	✓				✓	✓	✓
Observations	2261	3584	1538	202	332	144	347	567	244
# of researchers	258	413	183	202	332	144	228	367	161
R-squared	0.72	0.76	0.78	0.60	0.50	0.64	0.79	0.71	0.60

Table A5: Placebo Dismissal (Moving Dismissal to 1930)

	(1)	(2)	(3)	(4)	(5)
Dataset:	PhD students		Professors		
			Physics	Chemistry	Mathematics
Dependent Variable:	Published Top	Full Professor	Publi-cations	Publi-cations	Publi-cations
Dismissal Induced	-0.029	-0.010	-0.025	0.003	0.047
Fall in Faculty/Peer Quality	(0.100)	(0.018)	(0.031)	(0.019)	(0.060)
Number Dismissed	-0.016	0.006	0.038	-0.003	-0.013
	(0.024)	(0.014)	(0.033)	(0.023)	(0.032)
Female & Foreigner	✓	✓			
Age Dummies			✓	✓	✓
Cohort/Year Dummies	✓	✓	✓	✓	✓
Department FE	✓	✓	✓	✓	✓
Individual FE			✓	✓	✓
Observations	364	364	1314	2051	875
R-squared	0.30	0.28	0.50	0.73	0.39

**significant at 1% level *significant at 5% level (All standard errors clustered at the department level)

Table A6: Reduced Form Poisson Regression (Department Level)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Physics				Chemistry				Mathematics			
Dependent Variable:	Publi-cations	Publi-cations	Citation Weighted Publ.	Citation Weighted Publ.	Publi-cations	Publi-cations	Citation Weighted Publ.	Citation Weighted Publ.	Publi-cations	Publi-cations	Citation Weighted Publ.	Citation Weighted Publ.
Dismissal Induced	1.087	1.109	1.082	1.128	1.015	1.012	1.018	1.022	1.163	1.189	0.467	0.929
↓ in Peer Quality	(1.47)	(1.66)	(0.74)	(0.97)	(1.25)	(0.96)	(0.57)	(0.66)	(0.84)	(0.76)	(1.40)	(0.12)
Number Dismissed	0.940	0.916	1.008	0.956	0.983	0.985	0.982	0.987	0.845	0.844	0.966	0.889
	(1.01)	(1.27)	(0.06)	(0.28)	(1.36)	(1.09)	(1.01)	(0.64)	(2.45)*	(2.06)*	(0.27)	(0.71)
Age Dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year Dummies	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Individual FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Department FE		✓		✓		✓		✓		✓		✓
Observations	2261	2261	2261	2261	3584	3584	3584	3584	1538	1538	1538	1538
# of researchers	258	258	258	258	413	413	413	413	183	183	183	183
Log Quasi-Likelih.	-1380.83	-1375.73	-8503.37	-8284.26	-4242.17	-4198.09	-28389.28	-27402.24	-672.63	-654.82	-2465.51	-2227.18

**significant at 1% level   *significant at 5% level   (All standard errors clustered at the department level)

Estimates are displayed as incidence rate ratios. A coefficient of 1 would indicate no effect of the dismissal. The coefficient reported in the first line of column 1 indicates that publications increased by 8.7 percent for a one unit fall in peer quality. The effect is not significant. The absolute value of z-statistics (clustered at the department level) is reported in brackets.

Table A7: Peer Group Interacted with Own Quality Terciles (IV Estimates)

	(1)	(2)	(3)	(4)	(5)	(6)
	Physics		Chemistry		Mathematics	
Dependent Variable:	Publi-cations	Citation Weighted Pub.	Publi-cations	Citation Weighted Pub.	Publi-cations	Citation Weighted Pub.
Peer Quality*	-0.434	-4.519	0.056	0.027	0.012	0.465
Top Tercile Scientist	(0.503)	(5.210)	(0.029)	(0.824)	(0.044)	(0.547)
Peer Quality*	-0.031	-0.394	-0.012	-0.365	-0.252	-0.099
Middle Tercile Scientist	(0.117)	(1.436)	(0.026)	(0.192)	(0.221)	(0.806)
Peer Quality*	0.062	0.435	-0.061	-0.840	-0.008	-0.313
Bottom Tercile Scientist	(0.055)	(0.425)	(0.036)	(0.419)	(0.042)	(0.506)
Department Size*	0.366	3.579	0.067	1.375	0.004	0.310
Top Tercile Scientist	(0.523)	(5.534)	(0.054)	(0.927)	(0.051)	(0.756)
Department Size*	0.085	0.431	0.005	-0.473	0.062	0.116
Middle Tercile Scientist	(0.115)	(1.729)	(0.018)	(0.267)	(0.047)	(0.253)
Department Size*	0.011	0.049	-0.038	-0.695	0.015	0.012
Bottom Tercile Scientist	(0.074)	(0.836)	(0.031)	(0.475)	(0.038)	(0.610)
Age Dummies	✓	✓	✓	✓	✓	✓
Year Dummies	✓	✓	✓	✓	✓	✓
Individual FE	✓	✓	✓	✓	✓	✓
Department FE	✓	✓	✓	✓	✓	✓
Observations	2261	2261	3584	3584	1538	1538
# of researchers	258	258	413	413	183	183

**significant at 1% level *significant at 5% level (All standard errors clustered at the department level)

Table A8: Peer Group Tercile Effects Professors (IV Estimates)

	(1)	(2)	(3)	(4)	(5)	(6)
	Physics		Chemistry		Mathematics	
Dependent Variable:	Publi-cations	Citation Weighted Pub.	Publi-cations	Citation Weighted Pub.	Publi-cations	Citation Weighted Pub.
Top Tercile Peer Quality	-0.002	-0.331	-0.004	-0.053	-0.008	0.321
	(0.016)	(0.556)	(0.008)	(0.215)	(0.253)	(0.698)
Middle Tercile Peer Quality	-0.034	-14.624	0.628	20.560	11.253	9.913
	(0.518)	(26.341)	(0.890)	(37.024)	(52.342)	(129.684)
Top Tercile Number of Peers	0.013	0.827	0.025	-0.497	-0.167	-0.372
	(0.059)	(1.961)	(0.072)	(2.914)	(0.573)	(1.400)
Middle Tercile Number of Peers	-0.049	-2.234	-0.084	-2.827	-0.515	1.519
	(0.123)	(3.228)	(0.116)	(4.605)	(4.293)	(10.894)
Age Dummies	✓	✓	✓	✓	✓	✓
Year Dummies	✓	✓	✓	✓	✓	✓
Department FE	✓	✓	✓	✓	✓	✓
Individual FE	✓	✓	✓	✓	✓	✓
Observations	2261	2261	3584	3584	1538	1538
# of researchers	258	258	413	413	183	183

**significant at 1% level *significant at 5% level (All standard errors clustered at the department level)