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Peer Effects in Science

Evidence from the Dismissal of Scientists in Nazi Germany

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Abstract

This paper analyzes peer effects among university scientists. Specifically, it investigates whether the quality and the number of peers affect the productivity of researchers in physics, chemistry, and mathematics. The usual endogeneity problems related to estimating peer effects are addressed by using the dismissal of scientists by the Nazi government in 1933 as a source of exogenous variation in the peer group of scientists staying in Germany. To investigate localized peer effectes, I construct a new panel dataset covering the universe of scientists at the German universities from 1925 to 1938 from historical sources. I find no evidence for peer effects at the local level. Even very high quality scientists do not affect the productivity of their local peers.

1 Introduction

It is widely believed that localized peer effects are important among academic researchers. Individual researchers do not necessarily take these effects into account when they decide where to locate. This may result in misallocation of talent and underinvestment in academic research. Having a good understanding of peer effects is therefore crucial for researchers and policy makers alike. In this paper I analyse localized peer effects among scientists whose research is often believed to be an important driver of technological progress. Understanding these effects may therefore be particularly important for science policy-makers in a knowledge based society.

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Despite the widespread belief in the presence of peer effects in academia, there is very little empirical evidence for these effects. Obtaining causal estimates of peer effects is challenging because of a number of problems. An important issue complicating the estimation of peer effects is the sorting of individuals. Highly productive scientists often choose to locate in the same universities. Sorting may therefore introduce a positive correlation of scientists' productivities within universities which has not been caused by peer effects. Another problem complicating the estimation of peer effects is the presence of unobservable factors which affect a researcher's productivity but also the productivity of his peers. Measurement problems further increase the difficulty of obtaining unbiased estimates for peer effects. A promising empirical strategy would therefore be a setup where a scientist's peer group changes due to reasons which are unrelated to his own productivity.

In this paper I propose the dismissal of scientists by the Nazi government in 1933 as an exogenous change in the peer group of researchers in Germany. Only 66 days after Hitler's National Socialist party secured power the Nazi government dismissed all Jewish and so called "politically unreliable" scholars from German universities. Around 13 to 18 percent of university scientists were dismissed between 1933 and 1934 (13.6 percent of physicists, 13.1 of chemists, 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. Scientists in affected departments were therefore exposed to a dramatic change in their peer group. Researchers in departments which had not employed Jewish or "politically unreliable" scholars did not experience any dismissals and therefore no changes to their peer groups.

I use a large number of historical sources to construct the dataset for my analysis. From historical university calendars I assemble a panel of the universe of physicists, chemists, and mathematicians working at German universities between 1925 and 1938. I combine this data with a complete list of all dismissals and with publication data to measure productivity.

This allows me to obtain the first clean estimate of localized peer effects among scientists using exogenous variation in the quality and quantity of peers in a researcher's department. Contrary to conventional wisdom, I do not find any evidence for peer effects within a scientist's department. This finding is robust to narrowing the peer group to peers from the same specialization only; i.e. by considering only theoretical physicists when constructing the peer group for theoretical physicists. Recent work on life scientists suggests that "star scientists" have a particularly large effect on their colleagues' productivity (Azoulay, Zivin, and Wang, 2010 and Oettl 2009). As the dismissals include some of the most prominent scientists of their time, I can investigate how the loss of top quality peers affects the productivity of scientists staying in Germany. The results indicate that even the loss of very high quality peers does not have a negative impact on the productivity of stayers.

One may be concerned that the dismissals affected the productivity of stayers through other channels than peer effects. Most of these expected biases, such as an increased teaching load or an increase in administrative duties, would lead me to overestimate the effect of peers. There are, however, other potential biases that could lead to an underestimation of peer effects. I discuss these threats to the identification strategy below and show evidence that the dismissals are uncorrelated with changing incentives, changes is funding, and the number of ardent Nazi supporters in the affected departments. Furthermore, I show that different productivity trends in affected and unaffected departments cannot explain my findings.

Few papers have empirically analysed localized spillovers among university scientists. One example is Weinberg (2007) who analyses peer effects among Nobel Prize winners in physics. He finds that physicists arriving in a city where other Nobel Laureates are working are more likely to start Nobel Prize winning work. It is, however, not clear how much of this effect is driven by sorting of scientists. Dubois, Rochet, and Schlenker (2010) investigate externalities among mathematicians in the United States. Similarly to the findings in this paper they do not find evidence for peer effects at the local level. While they have an extensive dataset of mathematicians all over the world, they cannot rely on exogenous variation to identify peer effects. Similarly, Kim, Morse, and Zingales (2009) investigate peer effects in economics and finance and find evidence for positive peer effects in the 1970s and 1980s, but negative peer effects in the 1990s. While they consider selection of researchers into particular universities in other specifications, they do not address the selection of researchers in the specification that directly tests localized peer effects.[1]

Recently a number of studies have suggested that falling communication costs reduced the importance of location in academic research (Kim, Morse, and Zingales, 2009, Adams et al. 2005, Agrawal and Goldfarb 2008, Rosenblat and Mobius, 2004). The findings of this paper, however, suggest that location was already "history" in the 1920s and 1930s - at least in Germany.[2]

The remainder of the paper is organized as follows: the next section gives a brief description of historical details. Section 3 describes the construction of the dataset. Section 4 outlines the identification strategy. The effect of the dismissals on the productivity of scientists remaining in Germany is analysed in section 5. I then use the dismissals as an exogenous source to identify localized peer effects in section 6. Section 7 discusses the findings and 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,

[1] In addition to papers analysing peer effects among university researchers there is a growing literature examining peer effects in other, mostly low skill, work environments (e.g. Mas and Moretti, 2008 and Bandiera, Barankay, and Rasul, 2010).

[2] Similarly, Dubois, Rochet, and Schlenker (2010) who analyse mathematicians do not find evidence that the importance of location decreased between 1984 and 2006.

1933. The law served as the legal basis to expel all Jewish and "politically unreliable" persons from the German civil service.[3] The relevant paragraphs 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, "Aryan descent" was specified as follows: "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." Christian scientists were therefore 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 unlikely that the majority of the dismissed had been treated differently by their colleagues before the rise of the Nazi party. The decree also specified that all members of the Communist Party were to be expelled under paragraph 4. The law was immediately implemented and resulted in a wave of dismissals and early retirements from German universities. More than 1,000 academics were dismissed between 1933 and 1934 (Hartshorne, 1937). This amounts to about 15 percent of all 7,266 university researchers. Most dismissals occurred in 1933 immediately after the law was implemented.

The law allowed exceptions for scholars of Jewish origin who had been in office since 1914, or who had lost a close family member in the First World War. Nonetheless, many of these scholars decided to leave voluntarily; for example the Nobel Laureate James Franck, who resigned from his professorship at the physics department in Göttingen, and Fritz Haber, a Nobel Laureate in chemistry who resigned from the University of Berlin. These resignations merely anticipated a later dismissal, as the Reich citizenship laws (Reichsbürgergesetz) of 1935 revoked all exception clauses.

The vast majority of dismissed scientists emigrated and most of them obtained positions in foreign universities. The most important emigration destinations were the United States, the United Kingdom, Switzerland, Turkey, and the British Mandate of Palestine (later Israel). For the purposes of this paper it is important to note that most emigrations took place immediately after the researchers were dismissed from their university positions. Further collaborations with

[3] Most German university professors at the time were civil servants. Therefore the law was directly applicable to them. Via additional ordinances the law was also applied to other university researchers who were not civil servants.

researchers staying in Germany were therefore extremely difficult. A very small minority of the dismissed did not leave Germany. Most of them died in concentration camps or committed suicide. Extremely few managed to stay in Germany and survive the Nazi regime. Even scientists staying in Germany were no longer allowed to use university laboratories and other resources. The possibility of ongoing collaboration of the dismissed with scientists staying in Germany was therefore extremely limited.

According to my calculations, 13.6 percent of physicists, 13.1 of chemists, and 18.3 percent of mathematicians were dismissed between 1933 and 1934 (Table 1).[4] The vast majority of dismissals occurred between 1933 and 1934. Later dismissals affected researchers who could initially stay under the exception clause or if political reasons for a dismissal were discovered later on. In order to have a sharp dismissal measure I therefore focus on the dismissals in 1933 and 1934.

My data does not allow me to identify whether the researchers were dismissed because they were Jewish or for political reasons. Previous historical work indicates that the vast majority of the dismissed were either Jewish or of Jewish descent. Deichmann (2001), for example, finds that about 87 percent of dismissed chemists were of Jewish origin. Siegmund-Schultze (1998) estimates that about 79 percent of dismissed mathematicians were of Jewish descent.

The aggregate number of dismissals hides the fact that German science departments were affected very differently. Some departments lost more than half of their personnel while others did not experience any dismissals. Even within a university there was a lot of variation across different departments (Table 2). Whilst 40 percent of physicists and almost 60 percent of mathematicians were dismissed from the renowned University of Göttingen there were no dismissals in chemistry.

The top panel of Table 3 gives a more detailed picture of the quantitative and qualitative loss in the three subjects. As has already been documented (Fischer, 1991) dismissed physicists were younger than the average age but made above average scientific contributions, received more Nobel Prizes (either before or after 1933), published more papers in top journals, and received more citations.[5] In chemistry, the dismissed were also of higher than average quality but the difference to the stayers was less pronounced. In mathematics many of the dismissed were truly outstanding members of their profession and of much higher quality than the average mathematician.

Table 3 also reports collaboration patterns before and after the dismissals. In physics, about 32 percent of the publications in top journals were coauthored. About 11 percent of all publications were coauthored with another scientist holding a faculty position at a German university. This percentage is lower than the overall level of coauthoring because physicists coauthored extensively with assistants, Ph.D. students, and senior colleagues at research institutes or foreign

[4]These numbers are consistent with the numbers obtained by historians who have 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) calculates a loss of about 24 percent of chemists between 1933 and 1939. Her figure is higher than mine because she considers all dismissals between 1933 and 1939 (while I focus on the 1933 to 1934 dismissals) and because my sample includes 5 additional universities with below average dismissals.

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

universities. The table also shows a low level of cooperation within departments; only 4 percent of all publications were coauthored with faculty from the same university. In chemistry, 75 percent of papers were coauthored, 12 percent were coauthored with a colleague holding a faculty position, and only 4 percent were coauthored with a faculty member from the same department. In mathematics these numbers were 17 percent, 10 percent, and 3 percent, respectively.

The table also shows that before 1933, the fraction of stayers' publications that were coauthored with scientists who were later dismissed was always higher than the fraction of the dismissed in the population. While 13.6 percent of physicists were dismissed, 19 percent (= (2.0/10.3)*100) of stayers' coauthoring activity could be accounted by collaboration with scientists who were later dismissed. In chemistry, 15 percent of stayers' coauthoring activity involved chemists who were later dismissed, and in mathematics 39 percent of stayers' coauthoring activity involved mathematicians who were later dismissed.

The bottom part of table 3 shows publication and collaboration patterns for the post dismissal period. It shows that the productivity of the dismissed dropped substantially because they were first relocating and then restarting their career abroad. The panel also shows that collaborations of stayers with dismissed scientists became very rare. Only 0.6 percent of papers published by staying physicists were coauthored with the dismissed scientists. For chemistry (0.4 percent) and mathematics (0 percent) these numbers were even lower. Figure A1 in the online appendix shows collaboration patterns between stayers and dismissed scientists by year. Not surprisingly, stayers and dismissed still coauthored in 1933 and 1934 (as the dismissals did not occur until April 1933 and I also consider dismissals in 1934). After that, collaborations fell sharply and even disappeared completely in many of the later years.

For comparison reasons, I report current collaboration patterns for the top 10 science and economics departments in Germany and the United States focusing on tenured faculty (Table A1 in the online appendix). Current collaboration patterns for German and U.S. science departments look relatively similar.[6] There is little coauthoring with researchers from the same department. The big exception is physics with a high level of collaboration within departments. This is mostly driven, however, by physicists conducting research involving particle accelerators; a technology that was invented by E. Lawrence in Berkeley in 1930 and became first available in Germany in 1944, and thus after the time period analysed in this paper. The publications involving results from particle accelerators usually list hundreds of authors (often more than 500, one article in the Physical Review Letters even has 744 authors). For physicists working with particle accelerators, coauthoring does therefore not seem a very good measure for close collaboration. If one excludes these physicists from the analysis (about 15 percent of physicists overall), current collaboration patterns are more similar to the historical data for physicists as well.

[6]See the data appendix for more details on the data of current science and economics departments. As collaborations are measured with publications in top journals the data on within department level collaborations is not very informative for current economics departments in Germany because only 33 of the 218 German economists have published in a top 5 journal since 2000.

3 Construction of a Panel Dataset of German Scientists

3.1 Data on Dismissed Scholars

I obtain data on dismissals from a number of historical sources. The main source is the List of Displaced German Scholars (1937) from which I extract all dismissed physicists, chemists, and mathematicians. The list was compiled by the relief organization "Emergency Alliance of German Scholars Abroad", which supported dismissed scholars in finding positions in foreign universities. It contains about 1650 names of dismissed university researchers from all subjects. Online appendix 2 shows a sample page from the physics section of the list. The page shows four physicists who had already received the Nobel Prize or were to receive it in later years (Figure A6).

For various reasons, for example if the dismissed died before the List of Displaced German Scholars was compiled, a small number of dismissed researchers did not appear in the list. To get a more complete measure of all dismissals I complement the data on dismissals with information from secondary sources (Biographisches Handbuch, 1983, Beyerchen, 1977, Deichmann, 2001, Siegmund-Schulze, 1998).[7] Online appendix 2 contains more detail on data construction and the secondary sources.

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

To investigate the impact of the dismissals on scientists who stayed in Germany, I obtain data on all scientists in German universities from 1925 to 1938. The data originate from historical University Calendars (see online appendix 2 for details) from which I compile an annual roster of scientists in all physics, chemistry, and mathematics departments from winter semester 1924/1925 (lasting from November 1924 until April 1925) to winter semester 1937/1938.[8] The data contain all scientists who were at least "Privatdozent". That is the first university position a researcher could obtain after the "venia legendi" and would allow the researcher to give lectures at German universities.

In some specifications I use the scientists' specialization to identify their relevant peer group. The data on specialisations come from seven volumes of "Kürschners deutscher Gelehrten-Kalender". The books are listings of German researchers compiled at irregular intervals since 1925. The Gelehrtenkalender contains about 90 percent of scientists in my sample. For the remaining 10 percent I conduct an internet search to find the scientists' specialization. Overall, I obtain information on the specialization for 98 percent of the scientists.[9] Table A2 in online appendix 1 gives an overview of all specialisations and the fraction of scientists in each of them.

[7] Slightly less than 20 percent of 1933 to 1934 dismissals only appear in the additional sources but not in the "List of Displaced German Scholars".

[8] Data for the technical universities were only published from winter semester 1927/1928 onwards.

[9] Some researchers name more than one specialization. Physicists and chemists therefore have up to two specialisations and mathematicians up to four.

3.3 Publication Data

To measure the productivity of scientists I construct a dataset containing the publications of each researcher in the top academic journals of the time. In the period under consideration, most German scientists published in German journals. German journals were of very high quality because many of the German physicists, chemists, and mathematicians were among the leaders in their profession. This is especially true for the time before the dismissals, 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 of Science, 1941). Historical research indicates that the journals considered in the analysis did not change substantially between 1933 and 1938 (Simonsohn, 2007). It is important to note, that the identification strategy outlined below relies on changes in publications of researchers in German departments that were differentially affected by the dismissals. 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”. The database is provided by Thomson Scientific and contains all contributions in a large number of science journals. In 2004, the database was extended to include articles in journals published between 1900 and 1945. The journals included in this backward extension were all journals that had published the most relevant articles in the years 1900 to 1945. The publication measure used in this paper therefore measures publications in the top journals of the time.

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 science journals that 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 that were suggested by historians of science as journals of some importance for the German scientific community (see online appendix 2 for details). Online appendix Table A3 lists all journals used in the analysis.

For each researcher I calculate two 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 also 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 that are not in my list of journals but that appear in the Web of Science. As a result, this measure 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 to all articles published in a certain year.

Online appendix Table A4 lists the top 20 researchers for each subject according to the citation weighted publications measure. It is reassuring to realize that the vast majority of these top 20 researchers are very well known in the scientific community. Economists will find it interesting that Johann von Neumann who emigrated to the Institute of Advanced Studies in Princeton was 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 productivity.

4 Identification

4.1 Estimating Peer Effects

Using this panel dataset I estimate peer effects among scientists. The collaboration of researchers can take different levels of intensity. A very direct way of peer interaction is the collaboration on joint research projects involving joint publication of results. In many cases, however, peer interactions are more subtle. Scientists discuss research ideas and comment on each other's work without copublishing. Yet another way in which peers may affect a researcher's productivity is through peer pressure. Furthermore, peers may attract more research funding to the department, or have better contacts to influential members of the profession. In this paper I estimate the sum of all aforementioned peer effects.

The standard approach when estimating peer effects consists of regressing an individual's productivity on the average productivity of his peers. The productivity of academic researchers, however, is not only affected by the average quality of peers but also by the number of peers they can interact with.

As university departments differ substantially in quality and size, it is important to distinguish these two dimensions of peer effects among scientists. I therefore propose the following regression which will be estimated for all scientists staying in Germany (in the following I will refer to as "stayers"):

$$\begin{aligned}(1)\qquad \#\text{ Publications}_{iut} &= \beta_1 + \beta_2(\text{Peer Quality})_{ut} + \beta_3(\#\text{ of Peers})_{ut} \\ &+ \beta_4\text{Age Dummies}_{iut} + \beta_5\text{YearFE}_t + \beta_6\text{IndividualFE}_i + \varepsilon_{iut}\end{aligned}$$

I regress the number of publications of scientist i in university u and year t on measures of his peer group and other controls. The regressions are estimated separately for physics, chemistry, and mathematics because the subjects under consideration have different publication and collaboration patterns. Peer quality is calculated as the mean of the average productivity of a researcher's peers.[10] Over time changes in average peer quality only occur if the composition of the department changes. Yearly fluctuations in publications of the same set of peers do

[10] To measure average peer quality I use the department mean of individual productivities calculated between 1925 and 1938. An alternative way of measuring average peer quality uses only pre-dismissal years. This measure, however, is not defined for researchers coming into the sample after 1933. I therefore present results using the first measure. Using the alternative measure does not affect my findings.

therefore not affect peer quality. The underlying assumption is that Albert Einstein always had the same effect on his peers independently of how much he published in a given year.

It is 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 publication lags. Science research is published much 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. Coauthoring of scientists staying in Germany with colleagues who were dismissed in 1933 and 1934 allow the investigation of likely lags of peer interactions. Figure A1 in online appendix 1 reports the fraction of papers that stayers coauthored with dismissed scientists. As chemists not only copublished a larger amount of their papers but also published more papers on average, the data for chemistry is the least noisy. The number of stayers' publications with the dismissed scientists plummeted in 1935, exactly the year after the dismissals considered in this paper. I therefore use a one year lag for the peer group variables when estimating equation (1). Using different lags does not affect the results.

The regression also includes a full set of 5-year age-group dummies to control for life-cycle changes in productivity. Year fixed effects control for yearly fluctuations in publications which affect all researchers in the same way. To control for differences in a researcher's talent I add individual fixed effects to all specifications. In some robustness checks I also add university fixed effects to control for university specific factors affecting a researcher's productivity. These can be separately identified because some scientists change universities.

4.2 Using the Dismissals as Instruments for the Number and Quality of Peers

Estimating equation (1) using OLS would lead to biased estimates of β_2 and β_3. An important problem is caused by selection. Selection not only occurs because scientists self-select into departments with peers of similar quality but also because departments appoint professors of similar productivity. Omitted variables, such as the (unobserved) construction of a new laboratory, may further complicate the estimation of peer effects. Furthermore, measuring peer quality with error could bias the regression estimates.[11]

To address these problems I propose the dismissal of scientists by the Nazi government as an instrument for the peer group of scientists. Figure 1 shows the effect of the dismissal on the peer group of physicists.

[11] Even good measures of peer quality, such as the average number of citation weighted publications, are by no means perfect measures of peer influence.

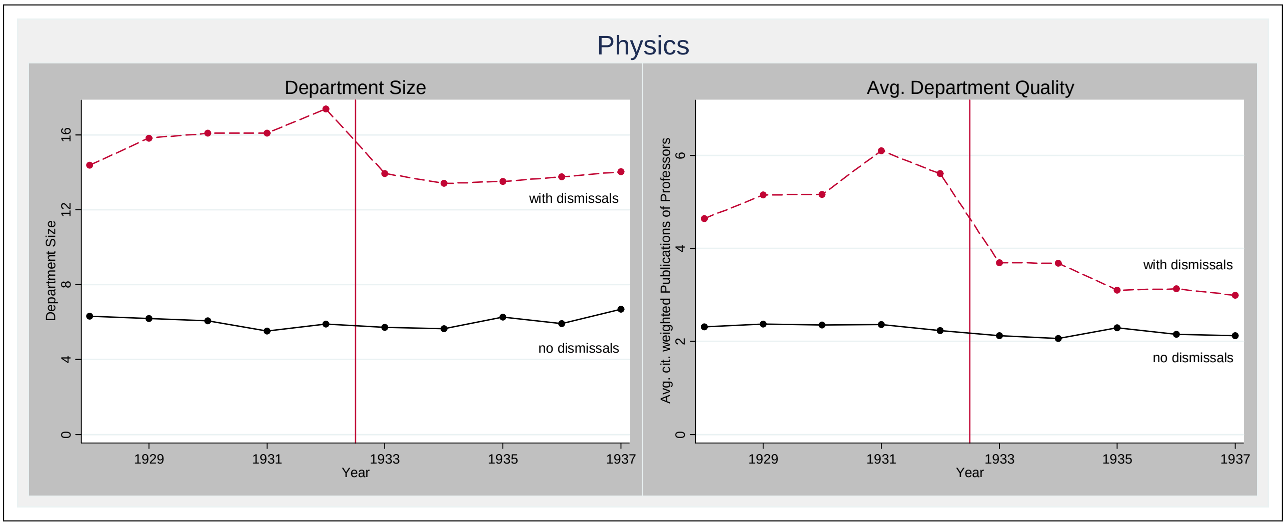

Figure 1: Effect of Dismissals on Department Size and Peer Quality

Note: The left hand panel reports average department size in departments with (dashed line) and without (solid line) dismissals respectively. The right hand panel reports average department quality in the two sets of departments. Department quality is measured by the department mean of average citation weighted publications in top journals between 1925-1938. See section 4.1. for details.

The left-hand panel shows average department size for two groups of physicists: physicists in departments with dismissals in 1933 or 1934 and physicists in departments without dismissals. The figure shows that affected departments were of above average size and that the dismissals led to a strong and permanent reduction in department size. The dismissed were not immediately replaced because of a lack of suitable researchers without a position and slow appointment procedures.[12] The right-hand panel of Figure 1 shows the evolution of average peer quality in departments with dismissals and in departments without dismissals. The dismissed were on average more productive than physicists who were not dismissed. As a result, average peer quality in affected departments fell after 1933. The graph only shows averages for the two groups of departments and therefore understates the variation I am using in the regression analysis. As can be seen from Table 2, some departments with dismissals also lost below average quality peers. Average department quality increased in those departments. Overall, however, the dismissal reduced average department quality in physics. Online appendix figures A2 and A3 show the evolution of department size and quality for chemistry and mathematics. In chemistry, affected departments were of above-average quality but the difference was less pronounced than in physics. Despite the fact that the dismissals did not have a large effect on peer quality for the average across all departments it strongly affected average quality in many

[12] Successors for dismissed chaired professors of Jewish origin, for example, could only be appointed if the dismissed scholars ceded all pension rights because they were originally placed into early retirement. The employers 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 Wien a physicist in Jena, wrote a letter to Bernhard Rust the Minister of Education in late November 1934. Describing the situation for chaired professorships at the German universities 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).

departments as can be seen from Table 2. The effects in departments with reductions in average peer quality and in departments with improvements in peer quality, however, almost cancel out in the aggregate. In mathematics, departments with dismissals were on average larger and of higher quality. After 1933, department size and peer quality fell sharply in affected departments.

The fact 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 individual fixed effects. The crucial assumption for the difference-in-differences type strategy is that trends in affected versus unaffected departments were the same prior to the dismissal. Below, I show in various ways that this was indeed the case.[13]

I use the dismissals to instrument for average peer quality and the number of peers. The two first stage regressions are:

$$\text{(2)} \quad \text{Avg. Peer Quality}_{ut} = \gamma_1 + \gamma_2(\text{Dismissal induced Fall in Peer Quality})_{ut} + \gamma_3(\#\ \text{Dismissed})_{ut} + \gamma_4\text{Age Dummies}_{iut} + \gamma_5\text{YearFE}_t + \gamma_6\text{IndividualFE}_i + \varepsilon_{iut}$$

$$\text{(3)} \quad \#\ \text{of Peers}_{ut} = \delta_1 + \delta_2(\text{Dismissal induced Fall in Peer Quality})_{ut} + \delta_3(\#\ \text{Dismissed})_{ut} + \delta_4\text{Age Dummies}_{iut} + \delta_5\text{YearFE}_t + \delta_6\text{IndividualFE}_i + \varepsilon_{iut}$$

Equation (2) is the first stage regression for average peer quality. The crucial instrument for average peer quality is called "dismissal induced fall in average peer quality". It measures how much peer quality fell because of the dismissals. The variable is 0 until 1933 in all departments. After 1933 it is defined as follows:

Dismissal induced Fall in Peer Quality = (Avg. Peer Quality before 1933) – (Avg. Peer Quality before 1933|Stayer)

After 1933, "dismissal induced fall in peer quality" is positive for scientists in departments with dismissals of above average department quality. The variable remains 0 for researchers in departments without dismissals or for scientists who lost peers whose quality was below the department average.[14] The instrument is based on changes in peer quality measured by 1925-1932 productivity measures. Using quality measures after 1933 in the construction of the instrumental variable would be problematic because post 1933 productivity may be affected by the dismissals.

The second instrument is the number of dismissals in a given department. The variable is 0 until 1933 and equal to the number of dismissals thereafter.[15]

[13] The fact that mostly bigger and better departments were affected by the dismissals affects the interpretation of the IV estimates. According to the LATE interpretation of IV (Imbens and Angrist, 1994), IV estimates the effect of changes in size and quality for large and high quality departments. As nowadays most science departments are bigger than in the average in the early 20th century this LATE effect is potentially more interesting than the corresponding ATE.

[14] The implicit assumption is that below average dismissals did not affect the productivity of scientists. An alternative way of defining "dismissal induced fall 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.

[15] The 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

The dismissals may have caused some scientists to change university after 1933. The change is likely to be endogenous and thus have a direct effect on researchers' productivity. I therefore assign each scientist the dismissal variables for the department he attended at the beginning of 1933. As the dismissal effect is likely to be correlated for all stayers in a department I cluster standard errors at the university level.

5 The Effect of Dismissals on Scientists who remained in Germany

As a starting point of the empirical analysis I show how the dismissals affected the productivity of scientists who stayed at the German universities. Figure 2 plots yearly publications of stayers in physics departments with and without dismissals. While yearly fluctuations in top journal publications are relatively large, the dismissal does not seem to have an obvious effect on publications of stayers. Equivalent figures for chemistry and mathematics show similar patterns (Figures A4 and A5 in the online appendix).

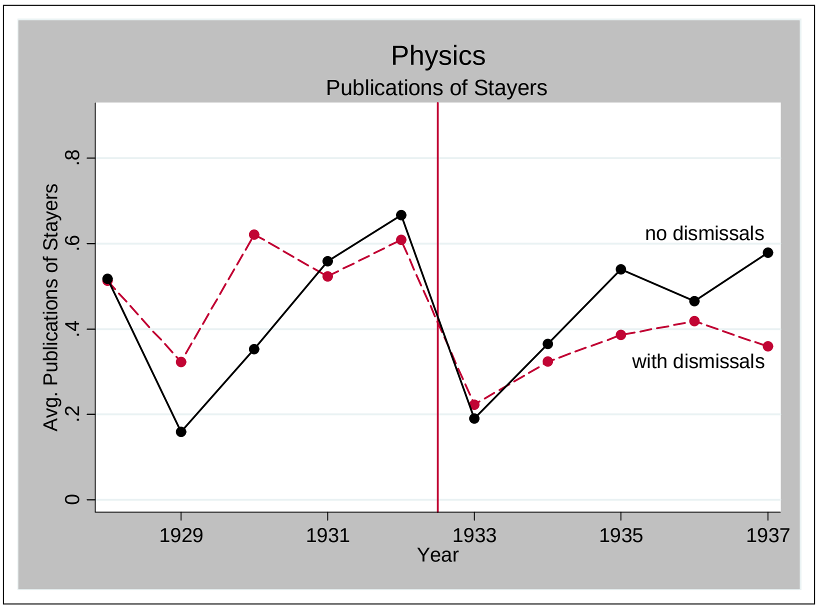

Figure 2: Effect of Dismissals on Stayers

Note: The Figure reports average yearly publications in top journals of stayers in affected (dashed line) and unaffected (solid line) departments respectively.

To obtain a quantitative estimate of the dismissal I estimate the reduced form equation.

$$(4) \qquad \text{\# Publications}_{iut} = \theta_1 + \theta_2(\text{Dismissal induced Fall in Peer Quality})_{ut} + \theta_3(\text{\# Dismissed})_{ut}$$

department. From 1935 onwards it is equal to the number of dismissals in 1933 and 1934. I use the example of Göttingen to illustrate the definition of the IV. Göttingen experienced 10 dismissals in mathematics in 1933 and one dismissal in 1934. The # dismissed variable for mathematicians in Göttingen is therefore 0 until 1933. It is equal to 10 in 1934 and equal to 11 from 1935 onwards. Dismissal induced reduction in peer quality is defined accordingly.

$$+ \theta_4 \text{Age Dummies}_{iut} + \theta_5 \text{YearFE}_t + \theta_6 \text{IndividualFE}_i + \varepsilon_{iut}$$

I regress a researcher's (citation-weighted) publications in each year on the instruments proposed above. This regression is essentially a difference-in-differences estimate of the dismissal effect. It compares changes 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. If the dismissals had a negative effect on the productivity of stayers, one would expect negative coefficients on the dismissal variables.

Estimated coefficients are all very close to 0 and only one coefficient on the number of dismissals is significantly negative (Table 4). Coefficients are larger for regressions using citation-weighted publications as dependent variable because the mean of citation weighted publications is much larger. Most of the coefficients on the dismissal induced fall in peer quality have a positive sign. This is particularly surprising as peer quality is usually believed to be the main driver of peer effects.

It is interesting to investigate which effect sizes can be ruled out given the 95 percent confidence intervals of my results. For the number of dismissals one can rule out a reduction in publications of more than 0.06 after losing one peer in physics (the mean of publications in the pre-dismissal period is 0.47). For chemistry and mathematics one can rule out effects larger (in absolute magnitude) than 0.036 (mean of publications is 1.69) and 0.050 (mean of publications is 0.33).

To evaluate which effect size can be ruled out at 95 percent confidence for the reduction in peer quality, I use 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 stayers' publications can I rule out with 95 percent confidence? This is an appealing question as this may be related to a top department today that loses a Nobel Laureate to another university. The results indicate that the effect of losing a Nobel Laureate would reduce yearly publications of stayers in physics by at most 0.0019 publications (the mean of publications is 0.47).[16] In chemistry the quality loss associated with losing a Nobel Laureate would not reduce publications by more than 0.031 (the mean of publications is 1.69). In mathematics one can rule out a fall in publications of 0.048 for losing a top 20 mathematician, as there is no Nobel prize in mathematics (the mean of publications is 0.33.

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 that specifically addresses the nature of the data. Table A5 in the online appendix reports Poisson regressions of the reduced form. The results are very similar.[17]

[16] This is calculated as follows. Average department quality in 1933 was 5.35. Average department size in 1933 was 13.18. The average Nobel Laureate's quality was 17.22. Department quality after the dismissal falls by 0.97 to 4.38. The estimated reduced form coefficient is 0.03 with a 95 percent confidence interval of [-0.0020 0.061]. The reduction in peer quality therefore has at most an effect of -0.0020*0.97 = 0.0019.

[17] As Santos Silva and Tenreyro (2010) describe, including a fixed effect for a scientist who never publishes

An important assumption for using the dismissals to identify peer effects is that publication trends of stayers in affected and unaffected departments would have followed the same trend in the absence of the dismissals. To investigate this identification assumption I therefore estimate a placebo experiment using the pre-dismissal period, only, and moving the dismissal from 1933 to 1930. The results reported in online appendix Table A6 indicate that stayers in departments with dismissals did not follow different productivity trends before 1933.

6 Using the Dismissals to Identify Localized Peer Effects in Science

6.1 Department Level Peer Effects

In this section, I use the dismissals to provide exogenous variation in an empirical model that explicitly estimates localized peer effects. I first estimate the two first stage equations; one for average peer quality and the other one for the number of peers.

"Dismissal induced fall in peer quality" has a very strong and significant effect on average peer quality in all three subjects (Table 5, columns 1, 3, and 5). The number of dismissals does not significantly affect average peer quality in physics and chemistry but is significant for mathematics.

First stage regressions for the number of peers are reported in columns 2, 4, and 6 of Table 5. "Dismissal induced fall in peer quality" does not affect the number of peers, but the number of dismissals has a strong and significant effect on the number of peers. This pattern is reassuring as it indicates that the dismissals indeed provide two orthogonal instruments: one for average peer quality and one for department size.[18]

Table 6 reports results from estimating the peer effects model according to equation 1. The OLS results are not very informative due to the problems illustrated in the identification section. I therefore turn immediately to discussing IV results where I use the dismissals to instrument for the peer group variables. While columns 2, 6, and 10 report results for publications as dependent variable, columns 4, 8 and 12 report results for citation weighted publications. Coefficients on the peer group variables are very small and none is significantly different from 0. The coefficient on average peer quality even has a negative sign in most specifications. The results indicate that the number, and in particular the quality of peers is unlikely to affect

leads to convergence problems 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 therefore use the ppml command as suggested by Santos Silva and Tenreyro (2011).

[18]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 Jogo (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. For two endogenous regressors and two instruments the critical value is 7.03 and thus always below the Cragg-Donald EV statistics reported in Table 5.

the productivity of scientists. The result holds for the two different productivity measures. This indicates that differences in citations for articles from scientists in departments with or without dismissals cannot explain the findings. Furthermore, the result is robust across the three different subjects.

6.2 Robustness of Department Level IV Results

Surprisingly, I do not find evidence for peer effects at the local level. I therefore estimate a number of robustness checks to analyse the sensitivity of this result. All regressions results discussed in this section are reported in the online appendix. To investigate whether the results are driven by disruption affecting the whole academic system during the early dismissal years I estimate the IV results dropping 1933 and 1934 from the regression. Omitting those turbulent years does not affect my findings (Table A7, column 1).

Peer effects may be especially important in either the early or the later stages of a scientist's career. I investigate this hypothesis by splitting the sample into two groups: scientists younger that fifty years of age and scientists fifty or older. There is no indication that peer effects are especially important for certain age groups as none of the coefficients is significantly different from 0 (columns 2 and 3).

I furthermore investigate the importance of peer effects in large versus small departments (columns 4 and 5) and high quality versus low quality departments (columns 6 and 7). Cutting the sample along these potentially important dimensions for peer effects gives very similar results.

The regressions reported above include year fixed effects and individual effects. As scientists move universities one can separately identify individual and university fixed effects. Column 8 reports results from specifications that include university fixed effects in addition to individual fixed effects. The results are very similar and in fact all results reported in this paper are almost identical when I include university and individual fixed effects at the same time.

To rule out differential productivity trends in affected departments I include university specific time trends in the regressions. The inclusion of university specific time trends hardly affects the results (column 9). This provides further reassurance that differential time trends cannot explain the absence of peer effects.

A further worry is that stayers may have taken over laboratories or experiments from the dismissed in affected departments. This may have had a positive effect on their productivity counteracting any possible negative effects from the loss of peers. The mathematics results should not be contaminated by such behaviour and are indeed very similar to the results for the other two subjects. An additional way of exploring whether taking over laboratories may be driving the results is to estimate the regression for theoretical physicists only. Even though the results are less precisely estimated, the findings show no evidence for peer effects in theoretical physics (column 10).

Using the dismissals as instrumental variables relies on the assumption that the dismissals only affected scientists' productivity through its effect on the researchers' peer groups. It is important to note that any factor affecting all researchers in Germany in a similar way, such as a possible decline of journal quality, will be captured by the year fixed effects and would thus not invalidate the identification strategy. Because unaffected departments act as a control group, only factors changing at the same time as the dismissal and exclusively affecting departments with dismissals (or only those without dismissals) may be potential threats to the identification strategy. Most of the potentially worrying biases, such as disruption effects or increased teaching loads, would bias the IV estimates in favour of finding peer effects. As I do not find evidence for localized peer effects, one has to worry less about these biases. Some violations of the exclusion restriction, however, would lead me to underestimate peer effects. In results discussed in more detail in the online appendix (Appendix 1 and Table A8) I show that the dismissals were unrelated to changes in promotion incentives. Furthermore, the dismissals were not related to the probability that stayers left the sample for retirement or other reasons. I also show that the number of ardent Nazi supporters, who could have benefited from preferential treatment by the Nazi government, was not related to the dismissals. Finally, I show that changes in funding are unlikely to drive my results.

6.3 Specialization Level Peer Effects

The definition of the peer group in the previous regressions was based on all peers in a scientist's department. It is, however, possible that the productivity of scientists is only affected by peers who work in very similar fields. To investigate this hypothesis I use the scientists specialization to define their peer group. According to this definition of the peer group, the relevant peers of an experimental physicist are only the other experimentalists in his department, not theoretical physicists, technical physicists or astrophysicists.

Similarly to the department level results, the coefficients on the peer group variables are very small and none of them is significantly different from 0 (Table 7).[19] Furthermore, the coefficients on peer quality mostly have the wrong sign if one were expecting positive peer effects. The results for mathematics are less precisely estimated because most mathematicians did not confine their research to only one or two specialisations. Many of them were working on very different topics that even today cannot be precisely assigned to particular specialisations. Nonetheless, there is no evidence for any significant peer effects in mathematics. It may be possible that localized peer effects occur in even more specialized subfields. As the mean number of researchers in the specialisations I consider here is about 3.5 these even smaller subfields would have to be extremely specialized.

[19] First stage regressions for the specialization level results are reported in Table A9 in the online appendix.

6.4 Peer Effects from High Quality Peers

Recent research on life scientists in the United States has indicated that star scientists have a particularly large impact on coauthors (Azoulay, Zivin, and Wang, 2010). In the previous regressions I have investigated how average peer quality affects productivity. It may well be the case that only colleagues of very high quality affect the productivity of scientists.

To investigate this hypothesis I start by regressing yearly productivity on the number of peers (instrumenting with the number of dismissals). I then investigate how the number of peers of above median quality (now instrumenting with the number of above median quality colleagues who were dismissed) affect productivity; continuing with the number of peers in the top quartile, in the top 10 percentile, and the top 5 percentile always instrumenting with the number of dismissed peers in the relevant quality group. Since many of the dismissed scientists were of very high quality I have enough variation in peer quality even at very high quality levels.

First stage regressions are reported in online appendix Table A10 and are highly significant (with first stage F-statistics between 8.2 and 488.6; only one of the 15 first stage regressions have a F-statistic below 10 and many have F-statistics above 100). Instrumental variable regressions are reported in Table 8. Unlike previous tables, Table 8 reports different regressions for 5 different definitions of the relevant peers (number of peers, number of above median quality peers, number of peers in top quartile, and so on). Strikingly, 28 of the estimated IV coefficients are not significantly different from 0 and many of them even have a negative sign. 2 coefficients are significantly different from 0 at the 5 percent level but have the wrong sign if one expected that high quality peers have a positive effect on their colleagues' productivity. These results provide further evidence that peers, even very high quality ones, do not seem to have a positive effect on the productivity of scientists.

7 Discussion and Conclusion

I have used the dismissal of scientists as exogenous variation in the quality and quantity of peers and have shown that peers do not seem to affect the productivity of scientists. The finding is robust to analysing different subjects and across many different specifications. This is a surprising result given that many researchers believe that local peer effects are important.

While only suggestive, there are a number of possible explanations for the lack of localized peer effects. First, I do not investigate long-run run effects as my data ends 5 years after the 1933 dismissals. A second explanation may be that I analyse relatively established researchers. It is quite likely that peer interactions become less important once one has established a scientific career. In fact, the dismissal of high quality mathematics professors had strong negative effects on Ph.D. student outcomes (Waldinger, 2010). A further possible explanation for the absence of localized peer effects is that the scientific community in Germany before the Second World War was very integrated. Conferences were common and scientists were very mobile within

Germany. Geographic location of researchers may therefore not have been very important for more established researchers. A further reason for the absence of localized peer effects may be that science is much more specialized than other subjects such as economics.

An important question is whether evidence on peer effects in the 1920s and 1930s can help us understand peer interactions today. A number of reasons suggest that the findings of this study may be relevant for understanding spillovers among present-day researchers. The three subjects studied in this paper were already well established at that time, especially in Germany. In fact, Germany was the leading country for scientific research in the first decades of the 20th century. If peer effects are an important determinant of scientific productivity they are likely to be especially important in a flourishing research environment such as Germany in the early 20th century. Scientific research at the time followed practices and conventions which were very similar to current research methods. Scientists 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.

Recent research on today's scientists also seems to suggest that localized spillovers are unlikely to be important. Dubois, Rochet, and Schlenker (2010) show that localized spillovers do not affect the productivity of mathematicians between 1984 and 2006. Furthermore, Azoulay, Zivin, and Wang (2010) find that the loss of a local coauthor does not have a larger impact on the productivity of life scientists than losing a coauthor who was located in a different university.

The question remains why scientists behave as if local peers are a key input in the ideas production process. One potential explanation is that being surrounded by esteemed peers is purely a private benefit, i.e. it enters a scientist's utility function but does not affect his productivity. Another explanation could be that localized spillovers are important but they are extremely localized.

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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

Note: The table reports the number of dismissals in the three subjects in each year between 1933 and 1940.

Table 2: Dismissals across different Universities

	Physics				Chemistry				Mathematics			
University	Scien-tists 1933	Dismissed 1933-34 #	Dismissed 1933-34 in %	Dismissal Induced Δ to Dep. Quality	Scien-tists 1933	Dismissed 1933-34 #	Dismissed 1933-34 in %	Dismissal Induced Δ to Dep. Quality	Scien-tists 1933	Dismissed 1933-34 #	Dismissed 1933-34 in %	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

Note: *Scientists 1933* reports the total number of scientists at the beginning of 1933. *# Dismissed* indicates how many scientists were dismissed between 1933 and 1934 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 drop in average department quality of more than 50%; − 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 Scholars

	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	43	-
# of Nobel Laureates	15	9	6	40.0	14	11	3	21.4	-	-	-	-
Publications 1925-1932												
Avg. publications	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
% coauthored	32.0	32.1	31.4	-	75.2	74.8	76.9	-	16.9	15.1	20.3	-
% coauthored with faculty	11.1	10.3	14.5	-	11.8	12.3	9.7	-	9.9	9.7	10.2	-
(with dismissed)	*(3.1)*	*(2.0)*	*(8.1)*		*(1.9)*	*(1.9)*	*(2.0)*		*(4.6)*	*(3.8)*	*(6.1)*	
% coauthored with faculty (same uni)	3.7	2.9	7.4	-	4.3	4.4	4.1	-	2.6	1.8	4.3	-
(with dismissed)	*(1.5)*	*(0.5)*	*(5.9)*		*(0.9)*	*(0.9)*	*(1.1)*		*(1.7)*	*(1.2)*	*(2.7)*	
Publications 1935-1938												
Avg. publications		0.35	0.32			1.24	0.55			0.20	0.15	
Avg. publications (citation weighted)		2.53	11.12			13.61	5.28			0.80	0.57	
% coauthored		43.0	50.0			81.0	69.6			14.9	28.0	
% coauthored with faculty		6.9	7.0			3.9	2.0			6.0	4.0	
(with dismissed)		*(0.6)*	*(4.0)*			*(0.4)*	*(2.0)*			*(0.0)*	*(4.0)*	
% coauthored with faculty (same uni)		2.6	-			0.9	-			0	-	
(with dismissed)		*(0.0)*	-			*(0.1)*	-			*(0.0)*	-	

Note: The table reports summary statistics for scientists in all German universities at the beginning of 1933. *Avg. publications* are average publications in top journals per year (see data section for list of top journals). *Avg. publications (citation weighted)* weights publications by citations in any journal covered by the Web of Science in the 50 years after publication. *% coauthored* measures the percentage of publications which were published with coauthors. *% coauthored with faculty* measures the percentage of all publications that was coauthored with other professors (at least Privatdozent) from any of the German universities. *% coauthored with faculty (same uni)* measures the percentage of all publications which were coauthored with other professors who ever worked at the same university. *% 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: Reduced Form (Department Level Peers)

	(1)	(2)	(3)	(4)	(5)	(6)
	Physics		Chemistry		Mathematics	
		Cit. weighted		Cit. weighted		Cit. weighted
Dependent Variable:	Publications	Publications	Publications	Publications	Publications	Publications
Dismissal Induced Fall	0.029	0.312	0.012	0.383	0.022	-0.464
in Peer Quality	(0.015)	(0.235)	(0.015)	(0.303)	(0.031)	(0.337)
Number Dismissed	-0.021	-0.017	-0.018	-0.130	-0.018	-0.016
	(0.017)	(0.302)	(0.009)*	(0.222)	(0.015)	(0.167)
Age Dummies	yes	yes	yes	yes	yes	yes
Year Dummies	yes	yes	yes	yes	yes	yes
Individual FE	yes	yes	yes	yes	yes	yes
Observations	*2261*	*2261*	3584	3584	1538	1538
# of researchers	*258*	*258*	413	413	183	183
R-squared	*0.39*	*0.25*	0.67	0.54	0.32	0.20

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

Note: The dependent variable *Publications* is the sum of a scientist's publications in top journals in a given year. The alternative dependent variable *Citation Weighted Publications* is the sum of subsequent citations (in the first 50 years after publication) to articles published in top journals by a scientist in a given year. Explanatory variables are defined as follows. *Dismissal induced Fall in Peer Quality* is 0 for all scientists until 1933. In 1934 it is equal to (Avg. quality of peers in department before dismissal) - (Avg. quality of peers | not dismissed in 1933) if this number > 0. From 1935 onwards it is equal to (Avg. quality of peers in department before dismissal) - (Avg. quality of peers | not dismissed between 1933 and 1934) if this number is > 0. The variable remains 0 for all other scientists. For scientists in departments with above average quality dismissals "Dismissal induced Fall in Peer Quality" is therefore positive after 1933. *Number dismissed* is equal to 0 for all scientists until 1933. In 1934 it is equal to the number of dismissals in 1933 in a scientist's department. From 1935 onwards it is equal to the number of dismissals between 1933 and 1934 in a scientist's department.

Table 5: First Stages (Department Level Peers)

	(1)	(2)	(3)	(4)	(5)	(6)
	Physics		Chemistry		Mathematics	
	Peer	Department	Peer	Department	Peer	Department
Dependent Variable:	Quality	Size	Quality	Size	Quality	Size
Dismissal Induced Fall	-0.644**	-0.147	-1.114**	0.011	-1.355**	-0.228
in Peer Quality	(0.099)	(0.130)	(0.196)	(0.110)	(0.149)	(0.174)
Number Dismissed	0.017	-0.570**	-0.047	-0.998**	0.160**	-0.470**
	(0.098)	(0.117)	(0.162)	(0.091)	(0.053)	(0.062)
Age Dummies	yes	yes	yes	yes	yes	yes
Year Dummies	yes	yes	yes	yes	yes	yes
Individual FE	yes	yes	yes	yes	yes	yes
Observations	2261	2261	3584	3584	1538	1538
# of researchers	258	258	413	413	183	183
R-squared	0.59	0.90	0.66	0.91	0.70	0.81
F - Test on Instruments	81.9	103.10	18.3	64.3	47.8	66.2
Cragg-Donald EV Statistic	12.8		89.8		46.7	

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

Note: Odd columns report the first stage regression for peer quality corresponding to equation (2) in the text. Even columns report the first stage regression for department size corresponding to equation (3) in the text. The dependent variable *Peer Quality* is measured as the mean of the average productivity of a scientist's peers present in the department in a given year. The dependent variable *Department Size* measures department size in a given year. Explanatory variables are defined as follows. *Dismissal induced Fall in Peer Quality* is 0 for all scientists until 1933. In 1934 it is equal to (Avg. quality of peers in department before dismissal) - (Avg. quality of peers | not dismissed in 1933) if this number > 0. From 1935 onwards it is equal to (Avg. quality of peers in department before dismissal) - (Avg. quality of peers | not dismissed between 1933 and 1934) if this number is > 0. The variable remains 0 for all other scientists. For scientists in departments with above average quality dismissals "Dismissal induced Fall in Peer Quality" is therefore positive after 1933. *Number dismissed* is equal to 0 for all scientists until 1933. In 1934 it is equal to the number of dismissals in 1933 at a scientist's department. From 1935 onwards it is equal to the number of dismissals between 1933 and 1934 in a scientist's department.

Table 6: Instrumental Variables (Department Level Peers)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS	IV
	Physics				Chemistry				Mathematics			
Dependent Variable:	Publi-cations	Publi-cations	Cit. weigt. Pubs.	Cit. weigt. Pubs.	Publi-cations	Publi-cations	Cit. weigt. Pubs.	Cit. weigt. Pubs.	Publi-cations	Publi-cations	Cit. weigt. Pubs.	Cit. weigt. Pubs.
Peer Quality	0.004	-0.054	-0.048	-0.488	0.006	-0.010	0.085	-0.342	0.014	-0.022	0.517**	0.318
	(0.005)	(0.035)	(0.075)	(0.496)	(0.003)	(0.015)	(0.057)	(0.265)	(0.015)	(0.026)	(0.167)	(0.262)
Department Size	-0.007	0.035	-0.177**	0.016	-0.011	0.019	0.089	0.147	0.004	0.032	0.041	0.143
	(0.004)	(0.034)	(0.062)	(0.553)	(0.007)	(0.010)	(0.193)	(0.218)	(0.010)	(0.026)	(0.067)	(0.322)
Age Dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year Dummies	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Individual FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
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	*0.39*		*0.25*		*0.67*		*0.54*		*0.32*		*0.20*	
Cragg-Donald EV Stat.		*12.79*		*12.79*		*89.76*		*89.76*		*46.73*		*46.73*

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

Note: Odd columns report OLS results and even columns report IV results. The dependent variable *Publications* is the sum of a scientist's publications in top journals in a given year. The alternative dependent variable *Cit. weigt. Pubs* is the sum of subsequent citations (in the first 50 years after publication) to articles published in top journals by a scientist in a given year. Explanatory variables are definded as follows. *Peer Quality* is measured as the mean of the average productivity of a scientist's peers present in the department in a given year. *Department Size* measures department size in a given year. In the IV models presented in even columns I instrument for peer quality and department size with the dismissals.

Table 7: Instrumental Variables (Specialization Level Peers)

	(1)	(2)	(3)	(4)	(5)	(6)
	IV	IV	IV	IV	IV	IV
	Physics		Chemistry		Mathematics	
Dependent Variable:	Publications	Cit. weighted Publications	Publications	Cit. weighted Publications	Publications	Cit. weighted Publications
Specialization Peer Quality	-0.021	-0.410	-0.010	-0.029	-0.429	3.822
	(0.029)	(0.581)	(0.009)	(0.127)	(3.457)	(28.153)
# Specialization Peers	-0.021	-0.727	0.010	-0.725	0.465	-3.450
	(0.029)	(0.482)	(0.040)	(0.881)	(3.487)	(28.298)
Age Dummies	yes	yes	yes	yes	yes	yes
Year Dummies	yes	yes	yes	yes	yes	yes
Individual FE	yes	yes	yes	yes	yes	yes
Observations	2257	2257	3567	3567	1538	1538
# of researchers	256	256	405	405	183	183
Cragg-Donald EV Stat.	81.80	81.80	73.69	73.69	0.23	0.23

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

Note: Each column reports results from a different IV regression. The dependent variable *Publications* is the sum of a scientist's publications in top journals in a given year. The alternative dependent variable *Cit. weighted Publications* is the sum of subsequent citations (in the first 50 years after publication) to articles published in top journals by a scientist in a given year. Explanatory variables are definded as follows. *Specialization Peer Quality* is measured as the mean of the average productivity of a scientist's peers present in the department in his specialization in a given year. *# Specialization Peers* measures the number of peers in a scienstist's specialization in his departmentin a given year. I instrument for specialization peer quality and the number of specialization peers with the dismissals at the specialization level. Corresponding first stages are reported in Table A9.

Table 8: Instrumental Variables High Quality Peers

	(1)	(2)	(3)	(4)	(5)	(6)
	IV	IV	IV	IV	IV	IV
	Physics		Chemistry		Mathematics	
Dependent Variable:	Publi-cations	Cit. weigt. Pubs.	Publi-cations	Cit. weigt. Pubs.	Publi-cations	Cit. weigt. Pubs.
Number of Peers	-0.003	-0.329	0.016	0.041	0.022	0.284
	(0.013)	(0.198)	(0.010)	(0.231)	(0.017)	(0.380)
First Stage F-Statistic	*195.5*	*195.5*	*126.7*	*126.7*	*104.9*	*104.9*
Number of Top 50th Percentile Peers	-0.003	-0.221	0.027	0.174	0.019	0.219
	(0.009)	(0.142)	(0.017)	(0.364)	(0.016)	(0.335)
First Stage F-Statistic	*241.1*	*241.1*	*362.6*	*362.6*	*94.4*	*94.4*
Number of Top 25th Percentile Peers	-0.015	-0.637*	0.026	0.000	0.001	0.140
	(0.016)	(0.239)	(0.017)	(0.419)	(0.016)	(0.336)
First Stage F-Statistic	*423.7*	*423.7*	*488.6*	*488.6*	*485.8*	*485.8*
Number of Top 10th Percentile Peers	-0.011	-0.695	0.076	-0.545	0.004	0.439
	(0.032)	(0.395)	(0.048)	(1.011)	(0.030)	(0.616)
First Stage F-Statistic	*29.6*	*29.6*	*19.4*	*19.4*	39.6	39.6
Number of Top 5th Percentile Peers	-0.031	-1.336*	0.160	0.805	0.026	0.686
	(0.043)	(0.626)	(0.126)	(2.516)	(0.020)	(0.570)
First Stage F-Statistic	*201.6*	*201.6*	*8.2*	*8.2*	46.0	46.0
Age Dummies	yes	yes	yes	yes	yes	yes
Year Dummies	yes	yes	yes	yes	yes	yes
Individual FE	yes	yes	yes	yes	yes	yes

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

Note: Unlike the previous tables each column and each horizontal panel reports results from a different IV regression. The dependent variable *Publications* is the sum of a scientist's publications in top journals in a given year. The alternative dependent variable *Cit. weighted Publications* is the sum of subsequent citations (in the first 50 years after publication) to articles published in top journals by a scientist in a given year. Explanatory variables are definded as follows. *Number of Peers* measures the number of peers in a scientists department. *Number of Top 50th Percentile Peers* measures the number of peers in the top 50th percentile in a scientist's departments, and so on. Percentiles are calculated using pre-dismissal productivities. I instrument for the number of peers (or number of high quality peers) using the number of dismissals of peers in that quality group in a scientist's department. Corresponding first stages are reported in Table A10.