Political Pressure and the Direction of Research: Evidence from China's Academia

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January 24, 2021

— PRELIMINARY DRAFT —

Abstract

Freedom of inquiry is often considered as the foundation of innovation. Does political pressure impact the direction and quality of innovation in general, and academic research in particular? To answer this question, we collect comprehensive data on the scientific publications of researchers in the leading 109 Chinese universities and the leadership changes in these universities. We use NLP methods to estimate the similarity between faculty members' and their leaders' research portfolios. We find that immediately after — and not before — the leaders take office, faculty members begin to shift their research direction towards that of their leaders. Such shifts are stronger in departments that have no external review of promotion decisions and when the academic leader has lower research output. We also estimate larger effects when career concerns for future promotion are stronger. Finally, leaders tend to hire new faculty closer to their research style. Taken together, our results suggest that political pressure impacts the direction of academic research and that this also creates a type of race to the bottom in research quality because of the stronger responses to lower-productivity leaders.

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1 Introduction

The freedom to experiment and pursue new and sometimes unconventional ideas is often viewed as fundamental to innovation (Hayek, 1978; Ridley, 2020). Conversely, there are ample examples of political interference from rulers or other powerful actors blocking innovations: ranging from the possibly apocryphal story of the Roman Emperor Tiberius killing an inventor who had come up with unbreakable glass and suppressing his innovation, to Queen Elizabeth I of England blocking William Lee's "stocking frame" knitting machine (Acemoglu and Robinson, 2012). Political inference in innovation does not typically take the form of explicitly blocking (let alone execution of innovators); but rather, political influence could often work by discouraging certain lines of inquiry and elevating political or other non-economic considerations ahead of innovation potential. This is no less true when it comes to academic research and innovation. Nevertheless, there is little direct evidence on whether political considerations impact the direction of innovation in general, and academic research in particular.

Academia in Mainland China provides an ideal setting for such an inquiry. Fostering innovation has been a central aim of the Chinese Communist Party, which recognizes the importance of technological progress for continued economic growth and has substantially increased funding for academic research during the past decades. This desire notwithstanding, Chinese universities have enjoyed only limited autonomy, as exemplified by the fact that each faculty in every university has a centrally-appointed Communist Party representative in charge.[1] The juxtaposition of emphasis on innovation and the lack of academic freedom provides a unique opportunity to understand whether political pressures curtailing academic autonomy and freedom impact the direction and quality of innovation. Moreover, because China now accounts for a significant fraction of global research and innovation output, the potential distortion in Chinese academia is likely to have significant consequences for global innovation.

In this paper, we investigate this question by estimating the effects of new academic "leaders" (e.g., deans or department heads) on the type of research conducted by impacted faculty members across a large number of disciplines and Chinese universities. We are particularly interested in whether the politically-driven career concerns of faculty make them change their research so as to be more similar to their academic leaders' work and whether this impacts the quality of their research. To explore the role of polit-

[1] Academic freedom has further declined since President Xi Jinping's accession to power in November 2012. This is best illustrated by the decisions of many leading universities to remove clauses related to the "freedom of thought" from their charters; source: `https://reut.rs/39RVCNx`.

ical pressures in this process, we pursue three strategies. First, we compare the extent of these effects across more or less meritocratic departments. Second, we look at heterogeneous effects for faculty with more or less career concerns. Finally, we plan to investigate whether these considerations have become more important for faculty after President Xi Jinping's clampdown on (already limited) academic autonomy, particularly after 2015.[2] We also estimate the effects of leadership changes on research quality.

Our exploration of the linkages between political pressure and academic research is built on two new datasets. First, we collect information on the departmental organization across the social science disciplines in Chinese universities, as well as the departmental leadership transitions since 1990.[3] Second, we collect (close to) the universe of research publications by the faculty members and the department leaders during this period. We use natural language processing (NLP) methods to construct measures of research similarity between faculty members and their (department) leaders. We then investigate whether faculty members change their research style to make it more similar to that of their leaders.

Our baseline empirical strategy compares the similarity in research output between faculty members and their respective leaders, before and after the leaders take on the leadership position. Identification with this strategy relies on researcher-leader level variations over time, exploiting the fact that each researcher is observed under multiple leaders over the course of her academic career, and the leadership transitions take place at different times and with different frequencies across departments. This setup allows us to include a full set of researcher-leader pair fixed effects as well as calendar year fixed effects. In other words, we can account for other time-invariant factors that drive the similarity in research portfolios between researchers and their departmental leaders and changes thereof, and focus solely on changes in research similarity between faculty members and leaders driven by the appointment of the leaders.

We find that on average, the similarity in research output between faculty members and their respective leaders significantly and substantially increase after new leaders take office. Such changes indicate that the direction of research is shifted towards the portfolio of the current leader. The increase in research similarity between researchers and leaders emerge almost immediately after the leadership transition, and it persists for at least four years into the new leaders' tenure. Bolstering confidence in our identification strategy, we do not find analogous changes in similarity *before* a leader takes up her position.

[2]President Xi called for Chinese authorities to exert greater control over the universities in 2016; source: `https://bit.ly/36aoXSf`.

[3]We focus on social sciences for now, and we will expand to science and engineer disciplines subsequently.

We document that leaders' influence on researchers' output concentrates on the faculty members under their direct jurisdiction. The appointment of new leaders may also signal a change in national research direction, which might impact faculty members' research through political pressure or other channels. To distinguish the impact of leaders on the research style of faculty under their direct supervision, we estimate the effects of new leader appointments in the same discipline but other institutions, and also separately for new leaders in the same discipline but only in other top institutions where such signaling may be particularly salient. In both cases we do not find significant effects from these external leaders. Also reassuringly, we do not find any increase in research similarity between academic research in other disciplines and faculty members. These results thus increase our confidence that we are estimating the causal effect of new academic leaders on the research direction of faculty under their direct supervision.

Shifts in research activities after leadership transition could be driven by standard career incentives, which may not be directly related to political pressures. To clarify the role of political factors, we show that the convergence of researchers' output towards the areas of their leaders is stronger when political interference is more powerful and more likely. First, we show that the effects of leaders on research similarity are greater in lower-ranked departments and universities and those that have not adopted reforms mimicking a tenure-track system with external reviews. Second, compared to department chairs, the department's Communist Party secretaries exert stronger influence on the faculty members' research direction. These party secretaries are directly appointed by the Communist Party, and they represent closer alignment of the intention and direction of the Chinese Communist Party and the Chinese authority. Third, we find that the effects of leadership transition are substantially stronger among faculty members who have greater (political) career concerns, and driven by leaders who are themselves not productive and more devoted to non-academic activities. These results suggest that the baseline career incentives are significantly amplified in the presence of greater and more consequential political interference.

Finally, we develop several strategies to estimate the effects of political pressure on the quality of innovation. First, we find that the increase in research similarity is significantly greater when new leaders have lower academic productivity, and stronger among department party secretaries who are relatively distant from the frontier academic research. This suggests that Chinese researchers are making their research more similar to precisely less productive and prolific leaders. Second, we explore the effects on citation-weighted productivity of researchers. Last, we also document that departments begin to hire new faculty that are more similar to new leaders, suggesting a shift in the composition of the department.

Taken together, these results suggest political factors shape the direction and quality of academic research in China. Political pressure induces Chinese scholars to make their research more similar to their academic leaders and that this is driven by the influence of leaders who have direct supervisory power over them. Because the effects are stronger in lower-ranked institutions and in departments without external review, we interpret these findings as going beyond the normal career concerns and academic collaboration that might exist in any academic environment. We provide evidence that they are particularly pronounced for faculty members who have greater (political) career concerns themselves. Our results also indicate that quality of research suffers because of this political pressure — in other words, researchers under political influence may not have realized their full potential had they align their research efforts with their comparative advantage.

Our paper is most closely related to the branch of the political economy literature investigating linkages between political factors and innovation. Much of the emphasis in this research has been on the risk of expropriation or political interference on entrepreneurship, investment and innovation, for example, as in (North et al., 2009; Acemoglu and Robinson, 2012). Potential future political threats from successful entrepreneurs may also encourage elites to block innovation to preserve their political power and rents (Acemoglu and Robinson, 2006).[4] Our mechanism is rather different as it shows the effects of local political pressure in academia — though the origin of this pinnacle pressure likely comes from national institutions. Our focus on academic research and innovation also connects our work to the growing literature on innovation economics, specifically, the various incentives that affect research production (e.g., Azoulay et al., 2011; Manso, 2011; Akcigit et al., 2018).

Our work also contributes to the literature on innovation in China. A large literature studies the Chinese economy and its growth in the past four decades. Recent works have carefully described the innovation landscape in China (e.g., Wei et al., 2017; Bombardini et al., 2018) and its potential implications for academic research (e.g., Freeman and Huang, 2015). More closely related to our paper is Jia et al. (2018), who document that academic leaders in economics departments in China's top universities tend to become more productive through co-authorship after they become leaders. This pattern — political power is used by academic leaders for their own benefit — suggests a different type of political

[4] A nascent literature documents the alignment between the autocratic institutions and private innovation, particularly in the context of China. For example, Bai et al. (2020) examine how crony capitalism combined with local governments' competition can foster growth; Beraja et al. (2021) study how provision of government data and surveillance state's demand for AI can promote private innovation in the AI sector, due to the economies of scope arising from government data.

distortion and is thus complementary to our research. We contribute to the understanding of how politics interact with innovation by providing, to the best of our knowledge, the first systematic analysis on the effects of political pressure on the direction and quality of academic research.

2 Data

Our empirical analysis combines two primary datasets that we collect from scratch: *(i)* the structure of Chinese higher education institutions and the leadership information in the university departments; and *(ii)* the scientific publications of all affiliates in these institutions. We now describe each of these datasets in turn.

2.1 University structure and departmental leadership

We first construct a dataset that describe the organizational structure and leadership of universities in Mainland China. We begin by examining all the social sciences departments among the top universities in China. We focus on the 109 universities that belong to the "Project 985" and "Project 211," two higher education ranking schemes that unambiguously list the top academic institutions in China.[5] Out of a total of 2,914 universities in Mainland China, these 109 top universities capture 70% of all research funding, and more than 50% of major scientific publications (Zhu, 2009; Zong and Zhang, 2019).

For each university, we collect the departmental organization structure for social sciences disciplines. We focus on "school" level bureaucratic structure, the organizational unit one level beneath the university in most Chinese universities, hence the leadership at the school level has most direct control over the personnel decisions of the faculty members. We standardize the organizational structure to make the school level definition comparable across universities.

We focus on schools and departments that are continuously active between 1990 and 2019, which is also the time window during which we collect publication records. For the schools and departments that cease to exist either due to splits or mergers, we track these changes and link schools and departments together. This ensures that we don't have leader switches that only caused by changes in school structure. Overall, during the period of 1990 and 2019, there are on average 7.75 schools in a given university.

[5]"Project 985" and "Project 211" are two major projects undertook by the Chinese government to promote the development and reputation of the Chinese higher education system by founding world-class universities. The universities included in these projects are top ranked in China, and many of them have since then ranked among the top 500 universities globally; source: `https://bit.ly/3ibF8Uo`.

Broadly speaking, we group various schools and departments into a total of 11 disciplines: economics, management, business, finance; political science and public management; law; education; literature and media; history; psychology; philosophy, anthropology, ethnology, sociology; regional studies; foreign language; and Marxism. For the schools and departments that are interdisciplinary in nature, we classified them into the 11 disciplines by taking the disciplines within a school as children and the school as their parent. Then we group the parents into one classification if they have connected components. The details are described in Appendix A.

Finally, for each school, we identify its leaders during the 1990 to 2019 period from a variety of sources: university official websites, university yearbooks, *Baidu Baike* (a Chinese-language collaborative online encyclopedia), and various online reports that mention school leadership. We manually extract the department chairs and party secretaries for each school. For the years that we cannot locate precise leadership information, we employ several interpolation methods. [6] On average, each school experiences 2.8 leadership transitions during the three decades between 1990 and 2019. The average tenure of a given school chair is 5.8, though this varies fairly substantially across disciplines: ranging from 4.8 years in the discipline of Marxism, to 6.3 in the discipline of foreign language.

Note that similar to the bureaucratic structure in many organizations in China, universities and the schools within them have two parallel leadership posts: school chair in the academic track, and Chinese Communist Party secretary in the political track. We primarily focus on the leadership in the academic track since those individuals are scholars and have records of academic publications, making it relevant to study the potential re-pivoting of research effort by faculty members. In contrast, party secretaries often have no academic background and are rotated in from other Communist Party organs. We are able to identify a subset of school party secretaries who have academic track records, and we will compare their influences to the faculty members relative to that of the department chairs.

[6] Normally, if we find a faculty member showed up as a leader in the news in Year_1 and Year_2, we assume that this leader was holding this position from Year_1 to Year_2 if years in between are missing. When it is different leaders before and after the missing cell, if the missing years are no more than three, we conjecture that one of the leaders before and after the missing cell was still leader, and we interpolate by assigning the past leader to the missing cell. This is assuming that there may be less information about leaders that are about to step down, but for the new leader who just get on the position, it is more likely to have info about him/her. 16% of the missing department chairs are be solved under this assumption.

2.2 Research publications

We next construct a dataset of all scientific publications by scholars in the corresponding institutions during the three decades spanning 1990 and 2019. The scientific publication dataset serves two primary purposes: it provides the description of research output by researchers which we rely on to construct our primarily outcomes of interest (describe in detail in Section 3.1). Moreover, the publication dataset allows us to retrospectively construct a roster of scholars affiliated with each institutions and the schools, since administrative records of complete school faculty roster are absent for most school and most years during the previous decades.

We rely on two major sources. First, *China National Knowledge Infrastructure (CNKI)*, a full-text database covering 90% of all official published Chinese journals. Second, *Wanfang Data*, which is a comprehensive database of Chinese journals, dissertations, and academic conferences. It provides access to 8,183 journals published in China and over 43.17 million articles, including 42.89 million full-text records (as of May 2019). To the extent that the coverage of these two databases do not fully overlap, they complement each other and when combined together, provide us with close to full coverage of scientific publications in Chinese journals.

For each researcher affiliated with the universities of interests described in Section 2.1, we collect all the papers she publishes during 1990 to 2019. We exclude publications on non-academic outlets such as newspaper opinion pieces. We also exclude publications as dissertation (e.g., part of the graduate studies) and other school internal journals. For each paper in the collection $\mathcal{D}$, we collect information about title, authors, publication year, abstract, and citations. This amounts to a total of 5,290,503 papers.

We then use the publication dataset to extract rosters of faculty members (and those who were or will become school and department leaders) in each academic unit. In a nutshell, we assign the academic affiliation to each author of a paper based on the publication information. Not all papers indicate affiliations at the school level; we thus assign the school level affiliation from any publication of a given author to all her papers. In order to rule out individuals who are affiliated with the school as student (and hence publishing sparsely) rather than faculty members, we use the dissertation database to locate the graduation year of a given researcher and count the post-graduation period as faculty affiliation. We also restrict the faculty members to those who publish more than 5 papers under a given affiliation and has publication records for more than 3 years, further excluding the ones that may publish with a temporary position such as visiting scholar. Our faculty roster extraction procedure performs well when we validate it with a set of contemporaneous school faculty list that we can obtain from the school's official website (see Appendix B for details).

This procedure provides us a list of faculty members affiliated with a particular school s, at a university u, in year t. Overall, we identify 42,395 active faculty members in social sciences disciplines in top universities during 1990 and 2019. On average, there are 62.2 faculty members in each school, ranging from 15.3 in the discipline of regional studies, to 103.0 in the discipline (category) of management, economics, finance, business. Each faculty member publishes on average 1.3 papers in a given year, ranging from 0.8 paper per year in the discipline of foreign language, to 2.4 papers per year in the discipline of psychology.

We notice a general trend of increased publication by scholars across all disciplines over the sampling period: the research productivity grows from 102 papers per year in 1991 to about 32,428 papers per year in 2018, reflecting the overall growth of Chinese academic institutions and research capacity over this period. We include year fixed effects in all baseline specifications to account for the secular trend in research activities.

3 Similarity measures and empirical strategy

In this section, we describe the empirical strategy, first on our core measurement of research similarity in Section 3.1, then on our baseline empirical specifications in Section 3.2.

3.1 Measurement of research similarity

3.1.1 Similarity of paper pairs

The building block of our measures of similarity in research outputs rests on constructing similarity scores over pairs of scientific publications. For each pair of papers in the paper collection $\mathcal{D}$, we construct a variety of measures of similarity $s : \mathcal{D} \times \mathcal{D} \mapsto \mathbb{R}^+$.

There are two broad classes of similarity measures: *(i)* non-parametric methods; and *(ii)* methods based on machine learning. Our baseline estimation uses the term frequency–inverse document frequency (TF-IDF), a non-parametric method, to measure similarity. We also use several alternative text-similarity measures, which we will describe in turn.[7]

Term frequency–inverse document frequency (TF-IDF) TF-IDF is statistical measure commonly used to evaluate how important a word is to a document in the context of a

[7]In this preliminary draft, we focus on results based on TF-IDF. We will introduce results using other similarity measures in subsequent draft.

given corpus of documents. The importance increases proportionally to the number of times a word appears in the document but is offset by the frequency of the word in the corpus. Mathematically, for a word i, its TF-IDF score will be expressed as:

$$\text{TF-IDF}(i, d, \mathcal{D}) = \text{tf}(t, d) \times \text{idf}(t, \mathcal{D}), \tag{1}$$

where $\text{tf}(i, d)$ is the frequency of word i in document d, and $\text{idf}(i, \mathcal{D})$ is the log of one over the share of documents containing j in the corpus $\mathcal{D}$.

The collection of publications forms the text corpus $\mathcal{D}$ in which every individual document d is an abstract of a paper. By adopting the bag-of-words model, each document d can be represented as a vector $\mathbf{v}^d$ based on its words, discarding specific grammar and word order. The length of $\mathbf{v}^d$ is equal to the number of words in the vocabulary of the corpus $\mathcal{D}$[8].

Intuitively, we can let each element v_i^d be the number of times word i occurs in document d. Simply calculating the distance between the vectors of word frequencies to measure the similarity is problematic, however, because words that are common in every document (often called "stop words") will introduce bias in the similarity score.

With TF-IDF, we are able to map a document d to a vector $\mathbf{v}^d$ in which each element $v_i^d = \text{tf-idf}(i, d, \mathcal{D})$. Then for two document $f, l \in \mathcal{D}$, the similarity measure is defined as:

$$s(f, l) = \mathbf{v}^f \cdot \mathbf{v}^l. \tag{2}$$

Co-citation and bibliographic coupling Instead of using text data, we also utilize citations of each paper to construct the similarity score. For each paper d, we collect its reference and denote it as a set $\mathcal{R}^d$, in which each element r is an *author*[9] cited by d.

For two document $f, l \in \mathcal{D}$, we calculate the average of match ratios in two publications on the level of reference authors:

$$s(f, l) = \frac{M(f, l) + M(l, f)}{2}, \quad M(f, l) = \sum_{r \in \mathcal{R}^f} \mathbb{1}_{r \in \mathcal{R}^l}. \tag{3}$$

Thus, this measure captures the intuition that two papers that have highly overlapping citations and references are more likely to be treating a related subject matter.

Latent Dirichlet Allocation (LDA) LDA (Blei et al., 2003) is a generative probabilistic model for topic modeling. The model will give statistical inference for topics in each

[8]Here is an abuse of the notation $\mathcal{D}$. In previous context, $\mathcal{D}$ servers as the population of papers. But here we use it to refer a structured set of texts. Each text in this set is the abstract of a paper.

[9]The most straightforward way to construct $\mathcal{R}^d$ is to directly use paper titles rather than author names. However, in our setting, since most papers have little overlap in their citations, the similarity score is close to zero if we use paper titles. To generate enough variation in the similarity score, we use authors instead.

document so that we can compute similarity by comparing generated topics.

Doc2Vec Doc2Vec is a neural network approach that is based on training a neural network to predict a word vector from a context (neighboring words) or vice versa (predict the context from the word).

3.1.2 Similarity score for a faculty-leader pair

Based on the similarity score between paper pairs, we can then construct measures of similarity in research portfolio for each pair of faculty member and her corresponding departmental leader.

Let $\mathcal{F}$ be the population of faculty and $\mathcal{L}$ be the set of all the leaders. For each faculty-leader pair $(F, L) \in \mathcal{F} \times \mathcal{L}$, we denote the set of papers published by the faculty member F in year t as $\mathcal{D}^F(t) = \{f_{t1}, f_{t2}, ..., f_{tn}\}$; the set of papers published by the leader L in year t as $\mathcal{D}^L(t) = \{l_{t1}, l_{t2}, ..., l_{tn}\}$; and the similarity score of a pair of papers (f, l) as $s(f, l)$.

Then for the faculty-leader pair, we construct the research similarity score at time t based on pairs of papers belonging in the following set: $\mathcal{P}^{(F,L)} = \{(f, l) | f \in \mathcal{D}^F(t), l \in \cup_{k \leq t} \mathcal{D}^L(k)\}$. Namely, we compare all the papers published by the faculty in year t with all the papers that the leader has been published up until (and including) year t.

In order to capture the (potentially strategically) targeted pivoting of research activities specifically on a subset of salient papers, we define the similarity score between faculty-leader pair $i = (F, L)$ in year t as the maximum of the similarity among all pairs of papers published by these two researchers during the corresponding period: $y_{i,t} = \max\{s(f, l) | (f, l) \in \mathcal{P}^{(F,L)}\}$.[10]

3.2 Empirical specification

Our baseline empirical strategy follows a modified event-study design. We compare the research similarity between pairs of faculty-leader, before and after the leaders take office, controlling for faculty-leader pair fixed effects and calendar time fixed effects. In other words, the shifts in faculty members' research portfolio is identified out of within faculty-leader pair variation over time. The baseline specification is:

$$Y_{i,t} = \sum_{l \neq -1; l=-3}^{4} \psi_l D^l_{i,t} + \alpha_i + \lambda_t + v_{i,t}, \quad (4)$$

[10] To capture the average shifts in research portfolio, we also define a specification of the research similarity based on the average similarity scores across all pairs of papers: $y_{i,t} = \frac{1}{|\mathcal{P}^{(F,L)}|} \sum_{(f,l) \in \mathcal{P}^{(F,L)}} s(f, l)$.

where $Y_{i,t}$ is the similarity score for the faculty-leader pair i at time t; $D^l_{i,t}$ is an indicator for faculty-leader pair i being l periods away from initial treatment at calendar year t; α_i is a full set of the faculty-leader pair fixed effects; and λ_t is a full set of calendar time fixed effects. For each faculty-leader pair, we focus on the period of three years before and four years after the leadership transition. Our baseline results are robust to alternative choices of time window.

By conducting the analyses at faculty-leader pair level, we take advantage the fact that academic leadership transitions are not synchronized across universities. and departments. Such empirical strategy can account for any general shifts in research trends that could change researchers' effort and attention at a given time across all universities, as well as alleviating the typical concerns of selection into treatment. Moreover, to the extent that within a given discipline, departments across universities are not led by researchers working on similar topics and share particular research agendas, research direction shifts within faculty-leader pairs allow us to isolate department and leadership term specific effects that need not be identical throughout the departments within the discipline.

3.3 Threats to identification

The key identification assumption is that the only leader-faculty-pair-by-year level shocks that affect the similarity in research portfolio between the corresponding faculty member and her leader is the leadership transition that takes place in a particular year. We can examine the pre-trend leading up to the leadership transition to rule out any pending up effects leading to the leadership transition. We will also discuss a variety of placebo exercises that help rule out other leader-faculty-pair-by-year level shocks that could be correlated with the leadership transition.

One may be worried that leadership transition induces changes in faculty members' research productivity and research output quantity, thus changing the denominators of the research portfolio similarity between faculty and leaders. We examine faculty members' productivity changes leading up to and after leadership transition in the corresponding academic unit. Specifically, we regress the total number of academic publications per year on the time relative to leadership transition, controlling for faculty member fixed effects and calendar year fixed effects. This allows us to isolate the differential effects of productivity changes due to leadership transition, holding fixed the overall level of productivity of a particular faculty member and any time-specific general shock that affects researchers' productivity. In Figure 1, we present the results. One can see that leadership transition does *not* induce changes in faculty members' research productivity (in terms of publication count), and there is no changes in productivity leading up to the leadership transition either.

4 Results

In this section, we present our main results.

4.1 Leadership transition and direction of research

We first examine the average effects of leadership transition on faculty members' research direction across all disciplines, all institutions, and over the past three decades. We pool all the sample together and estimate the baseline specification as described in Section 3.2. Our results are presented in Figure 2, where we plot the non-parametrically estimated ψ_l coefficients along with the corresponding 95% confidence intervals. The research portfolio similarity score between leaders and faculty members' publication at the year *prior to* leaders take office is normalized to zero, and the timing of leadership transition is marked by the vertical red line.

The estimates plotted in Figure 2 show a significant increase in research similarity between faculty members and their leaders. There is no increase in similarity before the leader takes office, and the similarity index takes off immediately after leader turnover and persist for at least four years into the new leader's tenure. This timing, with no pre-trends, is reassuring concerning the validity of our identification strategy. The absence of pre-trends also suggests that there are no anticipation effects before new leaders take office, or that researchers are selected to lead departments based on the similarity of the research portfolios with the rest of the faculty members.

Recall that our analysis analysis is conducted at the faculty-leader pair level. To the extent that faculty members' research activities and output within a department are diverse, the patterns depicted in Figure 2 suggest that, after the appointment of a new leader, faculty members pivot their heterogeneous research activities towards the same direction, getting closer to that of their leader's research portfolio. By the same token, the estimates also indicate that, after the appointment of a new leader, researchers pivot away from the research of past leaders.

Interestingly, the magnitude of the influence of leadership transition and the resulting shifts in political pressure on researchers' outputs differ noticeably across disciplines. We re-estimate the baseline specification separately by discipline and plot the similarity measure between leaders and faculty members at the five-year horizon in Figure 3. The largest effects are in education, Marxism, management, economics, finance, business, law, media, philosophy, anthropology, ethnology, and sociology, while the effects are muted in political science, public management, and foreign language, and even negative, though imprecise, in history and psychology. We also find pre-trends in history and psychology, suggesting that these estimates are less reliable, perhaps because there are anticipatory changes in research styles and faculty members preemptively shift their research activities towards that of the incoming leaders. This would also be bolstered by the fact that leaders in these disciplines tend to have long tenure and potentially overlap in leadership during the formal leadership transition periods.

4.2 Effects of leaders from other departments and disciplines

As mentioned in the Introduction, leaders may affect the research trajectories of faculty through two distinct but related channels: the local career concerns of faculty members under their direct jurisdiction, and the signals that all faculty in the discipline receive from the appointment of a leader with a particular research style and portfolio (which may also be related to career concerns since those heeding the signals may be more successful).

To isolate the effect working through the local career concerns, we estimate the baseline specification (4), including new leaders in the same discipline but other universities. Because signals from lower-ranked schools may not be very influential, we also separate leaders in the same discipline in other, higher-ranked As an additional placebo check, we also include leader switches in other disciplines, which should have no impact on the similarity between these new leaders in other disciplines and the faculty in question.

More specifically, to construct placebo leaders from the same disciplines but from other, higher-ranked departments ($\mathcal{L}2$), and from other, lower-ranked departments ($\mathcal{L}3$), we follow these steps.[11] First, for each $(F, L1, T1)$ in $\mathcal{L}1$, we filter all the leaders in our sample with the following criteria: *(i)* in other schools; *(ii)* in the same discipline; *(iii)* from departments that are top ranked (for $\mathcal{L}2$) or lower ranked ($\mathcal{L}3$);[12] and *(iv)* for whom the leader switch happens in the range $[T1 - 3, T1 + 3]$. Second, in this filtered pool, we randomly select a leader $\mathcal{L}2$ (or $\mathcal{L}3$) and match her with the faculty member F. If there is no leader left after filtering, we skip the faculty-leader pair. Third, we put the leader back to the sample when we do the random matching for other observations in $\mathcal{L}1$. After

[11] We denote the actual leaders as Type I leaders, $\mathcal{L}1$.

[12] The ranking is based on the evaluation contacted by the Ministry of Education in 2019. The evaluation has 9 categories: A+: top 2%; A: 2%-5% (2% is not included); A-: 5%-10%; B+: 10%-20%; B: 20%-30%; B-: 30%-40; C+: 40%-50%; C: 50%-60%; C-: 60%-70%.

matching each observation in $\mathcal{L}1$ with a new leader $\mathcal{L}2$ (or $\mathcal{L}3$), we can get the new sample $\mathcal{L}2$ (or $\mathcal{L}3$) in which each observation is $(F, L2, T2)$ (or $(F, L3, T3)$), where $T2$ (or $T3$) is the calendar year when $\mathcal{L}2$ (or $\mathcal{L}3$) becomes the leader of her own school.

We present the results for leaders in the same discipline but other departments in Figure 4, Panel A. The results indicate that there is no effect from these leaders, regardless of whether they come from lower-ranked or higher-ranked departments where potential signaling may be more salient. In other words, our main estimates are driven by *local* career concerns — the political power of leaders controlling the department.

Finally, we consider yet another type of placebo leaders — those from different disciplines ($\mathcal{L}4$). To construct placebo leaders $\mathcal{L}4$, the procedure is the same as that for $\mathcal{L}2$ and $\mathcal{L}3$, except for the conditions used for filtering leaders in the first step. Since and not being in the same discipline is the sufficient condition for being in different schools by construction, we only use one criterion to select the placebo leader $\mathcal{L}4$ here: $\mathcal{L}4$ is not in the same discipline as F. After matching each observation in $\mathcal{L}1$ with a new leader $\mathcal{L}4$ we can get the new sample $\mathcal{L}4$ in which each observation is $(F, L4, T4)$, where $T4$ is the calendar year when $\mathcal{L}4$ becomes the leader of her own school.

Figure 4, Panel B, turn to the results on the influence of academic leaders from other disciplines. Reassuringly, there is no effect in this case either.

4.3 Politically-charged career incentives

There is politics and career concerns in every academic institution. Is academia in China different? In this section, we undertake four complementary exercises to show that the answer is likely yes.

First, we show that the effects concentrate in departments that are lower-ranked and are not subject to any type of external review. In these departments, academic leaders have huge power over promotion and dismissal decisions, which is a reflection of the top-down nature of Chinese academic institutions and is potentially also related to the fact that many of the academic leaders are appointed explicitly or implicitly by the various administrative and bureaucratic units controlled by the Communist Party.

Namely, we re-estimate our baseline specification on sub-samples of the schools and departments, dividing them into three groups based on their ranking in the respective disciplines and information on whether there are any external review criteria: top 10%, top 10%-40% and 40-70%. Figure 5 presents the results. One can see that, indeed, while we observe increase in research similarity between faculty members and leaders after the leadership transition across all ranking groups, the effects are noticeably larger among the schools ranked below the 50th percentile and smallest for the top 10% group. Reassuringly, there are no statistically significant pre-trends for any of the three groups.

Second, we examine whether the Communist Party secretaries of the departments exert stronger influence on the faculty members' direction of research. Similar to the bureaucratic structure of many organizations in China, two parallel leadership posts exist in universities and in each departments: chairs (or deans) and the Chinese Communist Party secretary. The party secretaries often have no academic background, and are directly appointed within the party organization and are rotated in from other Communist Party organs. We focus on a subset of school party secretaries who have academic track records — they are inactive scholars who embark on the political track within the academic leadership. We re-estimate our baseline specification, investigating the effects of leadership transition of the party secretaries on the research similarity between the faculty members within the department and the corresponding party secretaries. Figure 6 presents the estimates. There are no statistically significant pre-trends prior to the party secretaries take office, and the research similarity between faculty members and their party secretaries begin to increase right afterwards. Albeit noisy estimated, we observe that the faculty members' research direction is, on average, three times more affected by the party secretaries, compared to that of the department chairs.

Third, we examine whether the faculty members who have stronger (political) career concerns shift their research more towards those of new leaders. Specifically, we look at faculty members who eventually become department or school leaders. This type of promotion is likely to be more responsive to currying favor with political powerful superiors, and our results back this expectation up. Figure 7 plots the distribution of *changes* in research similarity between faculty members and leaders. This enables us to compare the extent of the response between faculty members would never become leaders in our sample and those who are later promoted to leadership positions. As expected, we find greater increases in research similarity with newly-appointed leaders among the group with stronger career concerns.

Finally, as mentioned in the Introduction, political pressure in Chinese academia intensified in the early years of President Xi. To see if this change in Communist Party policy towards academic freedom has an impact, we estimate our models separately before and after 2015 The results, plotted in Figure 8, indicate that the increase in similarity with newly-appointed leaders is greater after 2015, suggesting that in an environment with weaker protection for academic freedom, political factors and career concerns have become more important.

Taken together, these results suggest that the baseline career incentives are substantially exaggerated when they interact with forces of political interference and/or when there are no other guarantees of meritocratic promotion or advancement.

4.4 Political influence and hiring decisions

Having documented that political interference shifts the research direction of the faculty members towards their leaders', we next examine whether such influence extends beyond the existing faculty members. Since, as we have already noted, leaders are often very powerful, they can also shape the hiring direction of their department.

To shed light on this question, we first examine whether leaders tend to hire faculty members whose research portfolio is closer to themselves. We focus on all faculty members who begin affiliation with a particular department or school during the 1990 to 2019 sampling period. We construct average research similarity scores between these faculty members and all leaders in the corresponding departments. The leaders who are in leadership position at the time faculty members' affiliation begins are the "hiring leader," under whose leadership (or potentially direct influence) the specific hiring decision is made. We investigate whether the research similarity between new hires and department leaders are particularly high if the leader is the hiring leader as well.

Table 1 presents results of the regression estimates of the faculty-hiring-leader pair's research similarity, relative of other faculty-leader pairs. We include a full set of faculty member fixed effects, which means that we are only exploiting variation across leaders. Our results indicate that the research similarity between faculty members and the hiring leaders are higher than that with other leaders in the same department. This indicate that leaders are more likely to hire new faculty members whose research portfolios are similar to the leaders themselves. Combined with the results presented so far, this pattern suggests that new leaders may be able to have very large impact on the research direction of the department by also influencing the identity of researchers.

The final question we investigate is whether, conditional on starting off as relatively closer to the hiring leader in terms of research direction, newly-hired faculty further shift the research portfolio to be closer to that of their leader. To examine this question, we re-estimate our baseline specification on sub-samples of the faculty-leader pairs of those who are existing faculty members, and of those who are new hires and their corresponding hiring leaders. Figure 9 presents the estimated results. While, as in our results so far, we can see the entire department shifting towards their leader's research portfolio, there is even a larger pivoting towards the leader's style among the newly-hired faculty. This pattern is consistent with politically-powerful leaders exerting a substantial effect on faculty who start their employment under their rule.

This impact on new hires and their research direction also suggests that there could be significant misallocation costs resulting from political pressure in Chinese academia.

4.5 Misallocation costs

Do these politically-charged incentives also impact research quality? We deploy two strategies to answer this question.

First, we investigate whether the role of academic leaders' on faculty members' direction of research are stronger among leaders who are less academically oriented. To operationalize this, we re-estimate the baseline specifications on sub-samples of faculty-leader pairs divided based on the leaders' relative productivity within the profession. The academically less productive leaders are further from the academic track, and closer to the political track in terms of aiming for administrative and political leadership within the academic institutions. Specifically, in Figure 10, the yellow (grey) dots represent results estimated from faculty-leader pairs of whom the leaders publish more (less) papers prior to them becoming leaders than the median faculty members in the discipline. We observe that the influence that leaders exert on the faculty members under their jurisdiction is substantially stronger among less productive, less academically oriented leaders (though the more productive leaders also exhibit positive effects). At face value, this finding suggests that misallocation costs could be significant, since the increase in similarity is driven by academics trying to adopt the styles of academically less inclined and successful leaders. This pattern is also corroborated with the result that researchers are differentially more affected by the party secretaries, who are leaders less likely to be on the academic track and hence further away on the research frontier.

Second, in ongoing work, we are looking at the effects of leader transitions on citation-weighted research output of academics.

5 Conclusion

Throughout history, many authoritarian regimes have been suspicious of innovation, research and new technologies, and have often discouraged or even sometimes blocked them (Mokyr, 1992; Acemoglu and Robinson, 2012). Even Soviet Russia, which poured huge resources into military and nuclear technologies and cultivated top-quality research in chemistry, physics and mathematics, was opposed to new technologies that were deemed to be destabilizing (Fitzpatrick, 1999). Modern-day China may thus be viewed as an almost unique case of an authoritarian regime deeply committed to innovation. But do the authoritarian political system and its reverberations throughout Chinese bureaucracy and society still distort the direction of research and suppress its quality? This question is central not just for the future of China's growth, but also for global innovation, especially given China's growing role therein. Nevertheless, we are not aware of any systematic investigation of the impact of political factors in the direction and quality of research and innovation.

In this paper, we undertake such a study, focusing on the top 109 Chinese universities. We exploit the appointment of new departmental leaders, who typically have extensive powers, partly as a reflection of the Chinese authoritarian system and how Chinese academia has been organized. The main question we explore is whether the appointment of new leaders leads to a change in the research portfolio and style of faculty members under their jurisdiction. We build a data set comprising the academic publications of all leaders and faculty members in these universities, and using NLP methods we construct measures of similarity between leaders' and faculty members' research output.

Our main finding is a strong increase in research similarity between a leader and the faculty under her jurisdiction. Reassuringly, there is no pre-trend — the increase in similarity starts after the new leader takes up office. We also show that leaders in the same discipline but in other universities as well as leaders in other disciplines do not have similar effects. We interpret these results as being due to politically-charged career concerns in Chinese academia that primarily impact faculty via local pressures exerted by (or implicitly felt from) the leaders under whose jurisdiction they are.

Career concerns are not confined to Chinese academia or authoritarian settings, however. It is plausible to presume that analogous changes in research strategy may happen in academic systems with greater autonomy. To build the case that the patterns we describe go beyond what would happen in situations where there is greater autonomy, less political interference and better institutional safeguards for meritocratic promotions and external review, we adopt a number of complementary strategies. First, the effects of new leaders on their faculty is more pronounced in lower-ranked departments, which typically lack procedures for external review. Second, we document that they have grown in importance after 2015, when academic autonomy started declining further under President Xi. Third, we show that they are significantly larger for faculty who themselves have political career concerns — in particular, those who later become leaders themselves.

Do political pressures affect the quality as well as the direction of research? We provide, albeit indirect, evidence that the answer is likely yes. First, the increase in research similarity between leaders and faculty under their jurisdiction is much higher for leaders who themselves have lower academic productivity, which suggests that faculty are emulating the research agenda of low-productivity leaders. Second, we show that leaders hire new faculty that have a similar research portfolio to theirs, and these newly-hired faculty further change their research trajectory to make their output even more similar to that of the leader. Finally, even though we find no impact on the total number of papers, we are currently exploring whether citation-weighted output of faculty is impacted while they are trying to make their output more similar to their leaders'.

We view our paper as a first step in a research agenda that explores the relationship between the direction and quality of innovation and political factors, originating both from national institutions and local organizations. This agenda appears important for several reasons. As new technologies such as AI, nanotechnology and new materials become increasingly important, the role of research and innovation for global prosperity is likely to grow. However, how different political systems and local and global incentives, coming from political or other considerations, impact the direction of this research is unclear. This is critical for the future of Chinese growth, which can be seen as a unique historical experiment in combining an authoritarian political system with a relentless focus on innovation. It is also central for understanding the forces impacting the nature of academic research anywhere and designing better academic institutions under democratic institutions as well as contributing to academic freedom and autonomy in less democratic environments.

In this light, there are several interesting research areas that can be further explored. First, it is important to conduct similar studies in other contexts, to benefit from a comparative perspective — in particular to see whether similar politically-charged career concerns are present in the academia of less authoritarian countries. Second, in other, more data-rich environments, it may be possible to look at other characteristics of leaders, for example, where they have obtained their degree and how they have risen in the academic hierarchy. Last but not least, a similar analysis in the context of corporate innovation, for example, linking the nature of patents to the priorities and organizational structure of the firms under which the research is being conducted, would be a very fruitful area.

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Figures and Tables

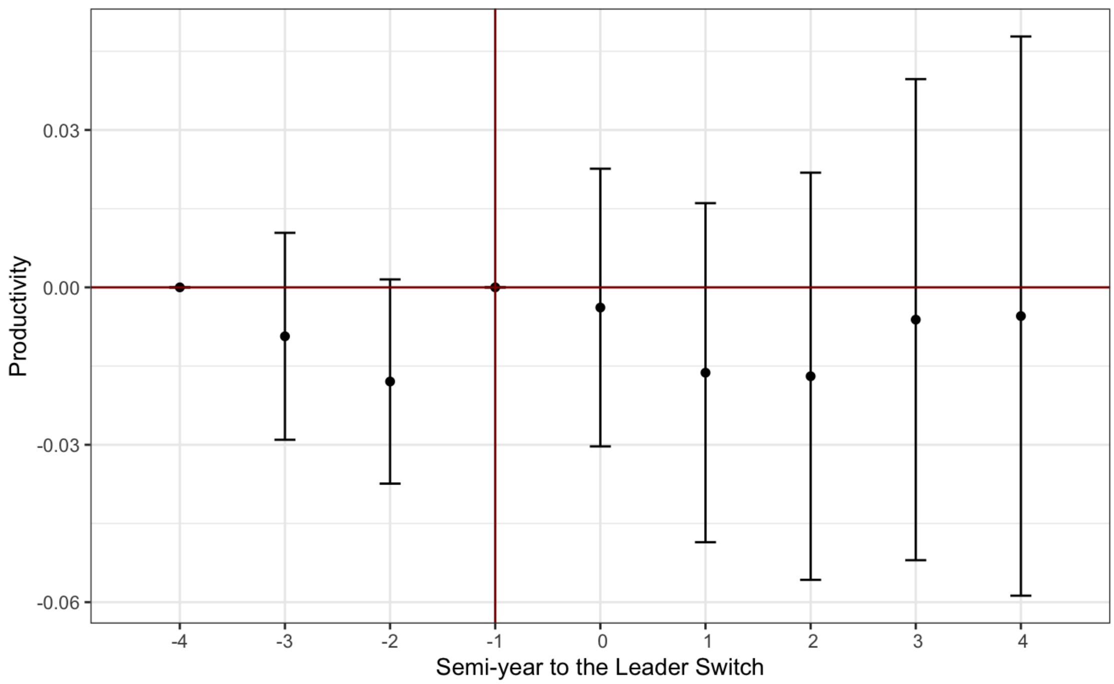


Figure 1: Impact of leader switch on the productivity of faculty. Using the number of publications per year as the outcome variable, we re-estimate the baseline specification (equation 4) restricting the sample to a balanced panel of faculty-leader pairs.

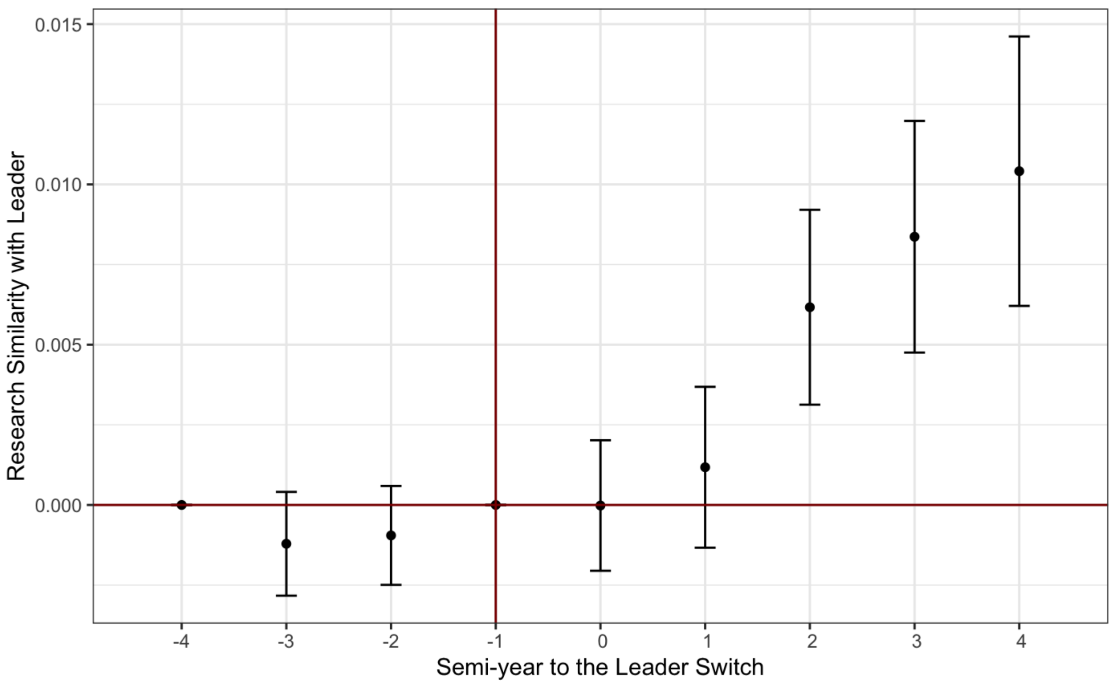


Figure 2: Impact of leader switch on the faculty-leader similarity score. The points in the figure represent the estimated effects of event time (i.e., the ψ_l from the nonparametric event study in equation 4). The error bars represent the 95% confidence intervals.

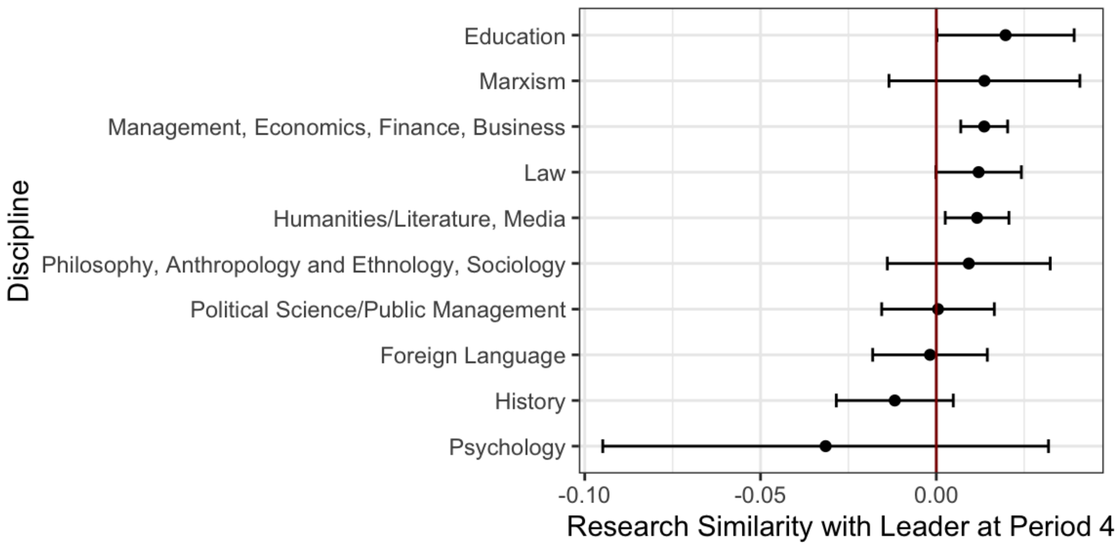
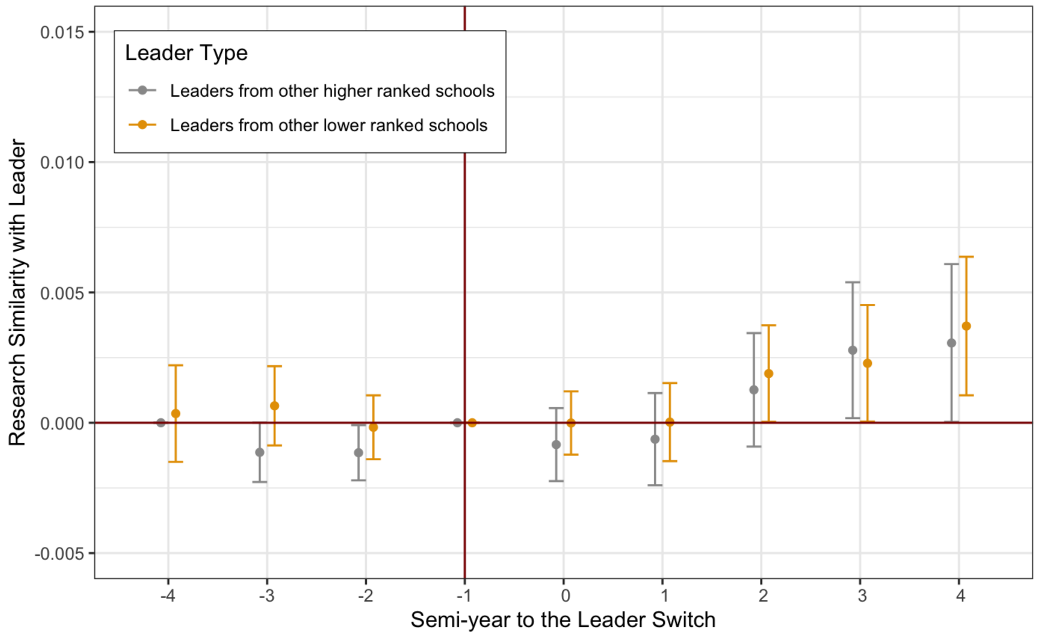
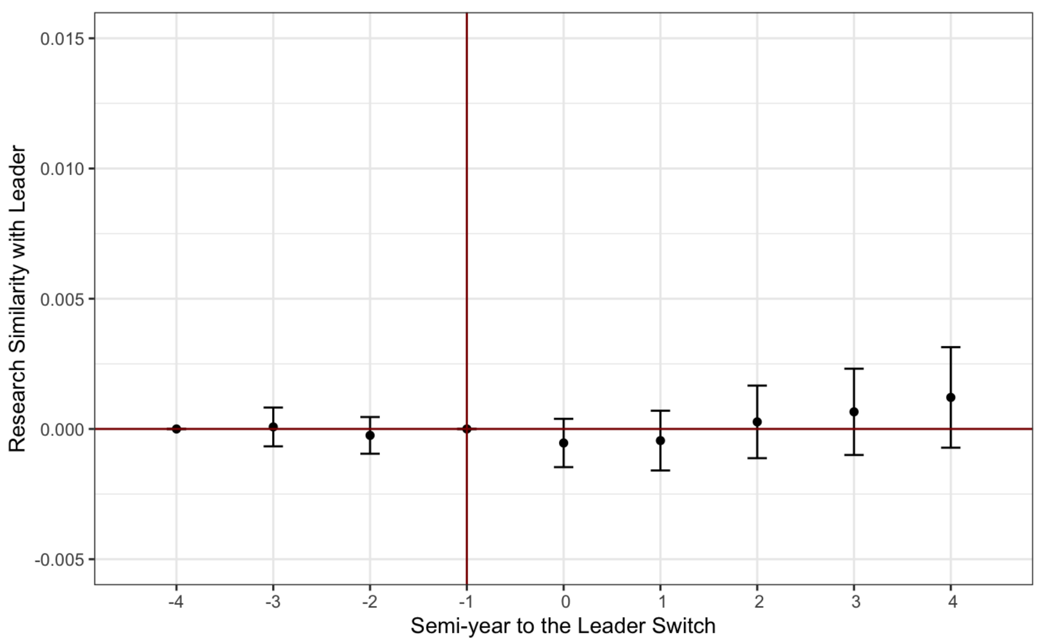


Figure 3: Heterogeneous effect of leader switch by discipline. We estimate equation 4 for each discipline. Each line/mark represent the point estimate of the 5th year for each discipline, ranked by size of the estimates. We classify schools into 10 categories by taking disciplines as the connected components of schools that share the same classification. The details are described in Appendix A.



Panel A: Impact of leaders from other higher ranked schools ($\mathcal{L}2$) vs. leaders from other lower ranked schools ($\mathcal{L}3$) on the similarity score



Panel B: Impact of leaders from other disciplines ($\mathcal{L}4$) on the similarity score

Figure 4: Impact of the switch for different types of leaders on the faculty-leader similarity score. Panel A uses the faculty-leader pairs in which leaders from other higher ranked schools ($\mathcal{L}2$) and leaders from other lower ranked schools ($\mathcal{L}3$). We estimate the effect of the two type of leaders simultaneously in regression $Y_{i,t,c} = \sum_{l\neq -1;l=-3}^{4} \mu_l^k D_{i,t,c}^l \times L_i + \sum_{t\neq -1;t=-3}^{4} \psi_l D_{i,t,c}^l + \alpha_i + \lambda_t + v_{i,t,c}$, where L_i is the indicator for whether the leader in pair i is L3 leader (=1) or not (=0). The grey lines/markers represent the estimated effects of L2 leaders (i.e., the ψ_l in the regression). The yellow lines/markers represent the estimated effects of L3 leaders (i.e., the $\mu_l + \psi_l$ in the regression). Panel B uses the faculty-leader pairs in which leaders from other disciplines ($\mathcal{L}4$). The points in the figure represent the estimated effects of event time (i.e., the ψ_l from the non-parametric event study in equation 4).

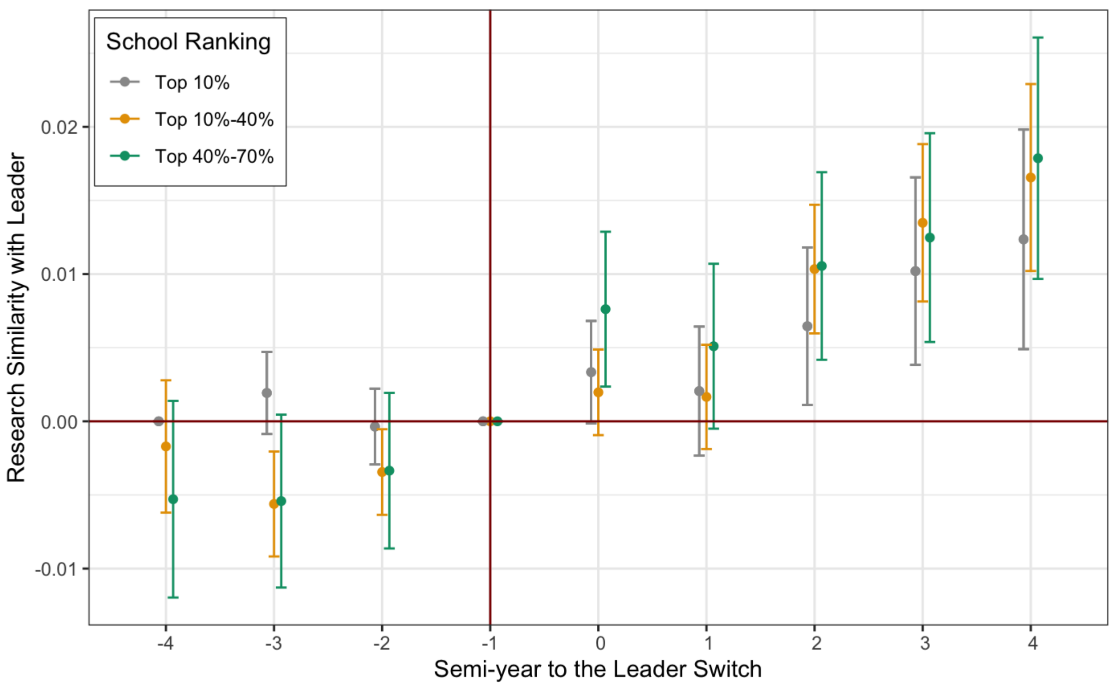


Figure 5: Heterogeneous effect of leader switch by school ranking. We estimate the effects simultaneously in regression $Y_{i,t} = \sum_k \sum_{l\neq -1;l=-3}^{4} \mu_l^k D_{i,t}^l \times R_i^k + \sum_{t\neq -1;t=-3}^{4} \psi_l D_{i,t}^l + \alpha_i + \lambda_t + v_{i,t}$, where R_i^k is the indicator for the rank of the school of pair i. The grey lines/markers represent the estimated effects of leaders from schools ranked top 10%. The yellow lines/markers represent the estimated effects of leaders from schools ranked 10%-40%. And the green lines/markers represent the estimated effects of leaders from schools ranked 40%-70%.

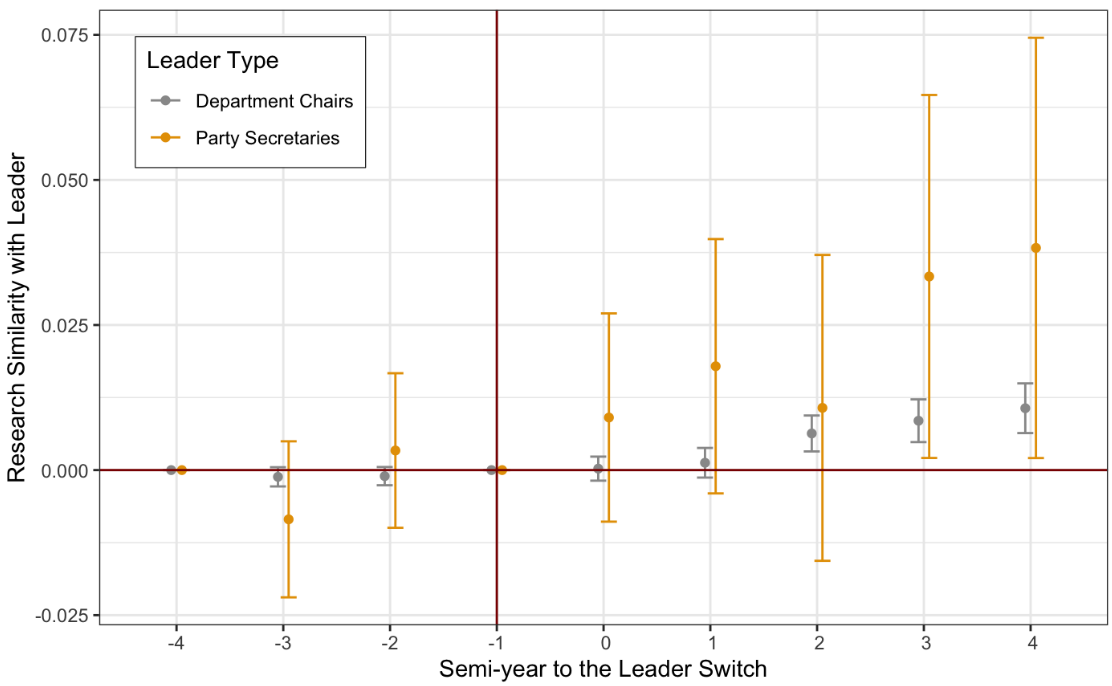


Figure 6: Heterogeneous effect of department chairs and party secretaries. The grey lines/marks represent the estimators for department chairs with the baseline regression. The yellow lines/marks represent the estimators for party secretaries, which is also based on the baseline regression. Since many party secretaries are non-academic personnel, we restrict our sample to party secretaries whose productivity is above the median of department chairs to ensure that we are focusing on academic party secretaries.

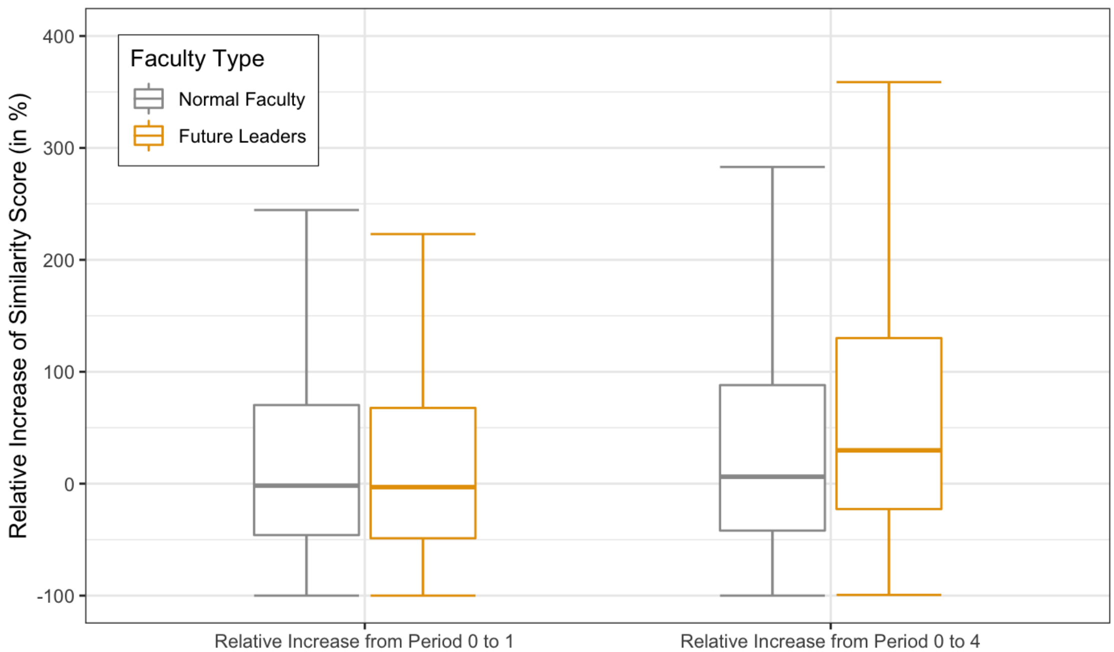


Figure 7: The distribution of changes in research similarity between normal faulty members and future leaders. Yellow (grey) boxes show the distribution of relative changes in similarity score for future leaders (normal faculty). The two boxes on the left hand sides show the relative increase of similarity score (in % term), from period 0 to 1. And the two boxes on the left hand sides show the relative increase of similarity score (in % term), from period 0 to 4.

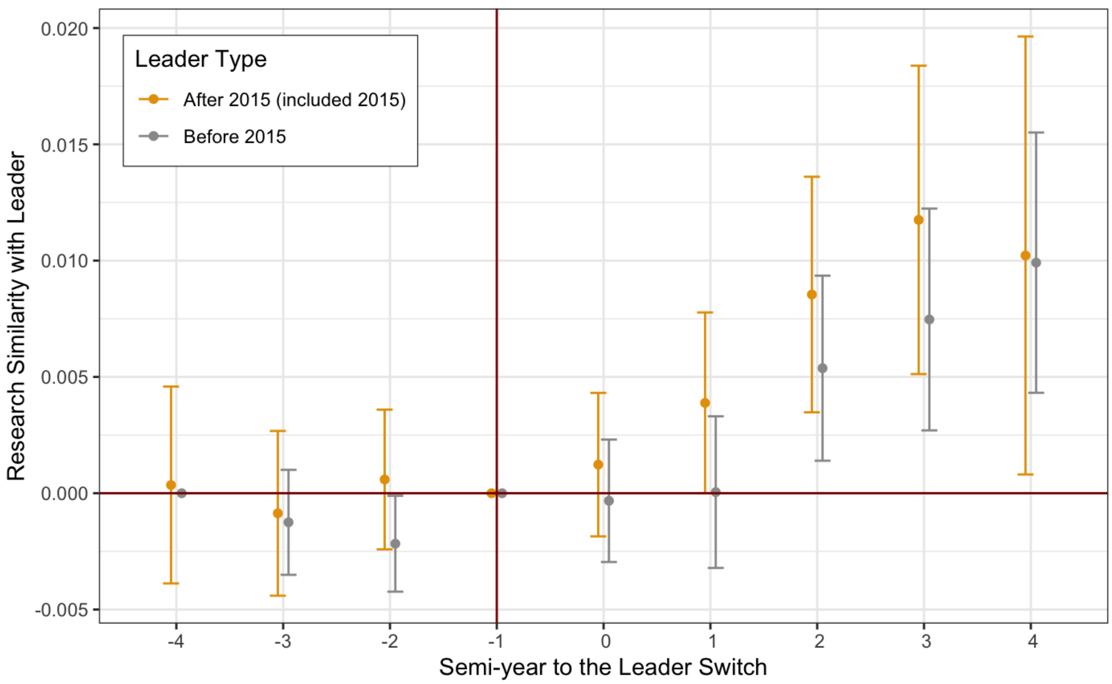


Figure 8: Heterogeneous effect of leader switch before and after 2015. We estimate the effect of leader switch before and after 2015 simultaneously in regression $Y_{i,t} = \sum_{l \neq -1; l=-3}^{4} \mu_l^k D_{i,t}^l \times \text{After}_i + \sum_{t \neq -1; t=-3}^{4} \psi_l D_{i,t}^l + \alpha_i + \lambda_t + v_{i,t}$, where After_i is the indicator for whether the leader in pair i takes office after 2015 (=1) or not (=0). The grey lines/markers represent the estimated effects of leaders before 2015 (i.e., the ψ_l in the regression). The yellow lines/markers represent the estimated effects of leaders after 2015 (2015 included) (i.e., the $\mu_l + \psi_l$ in the regression).

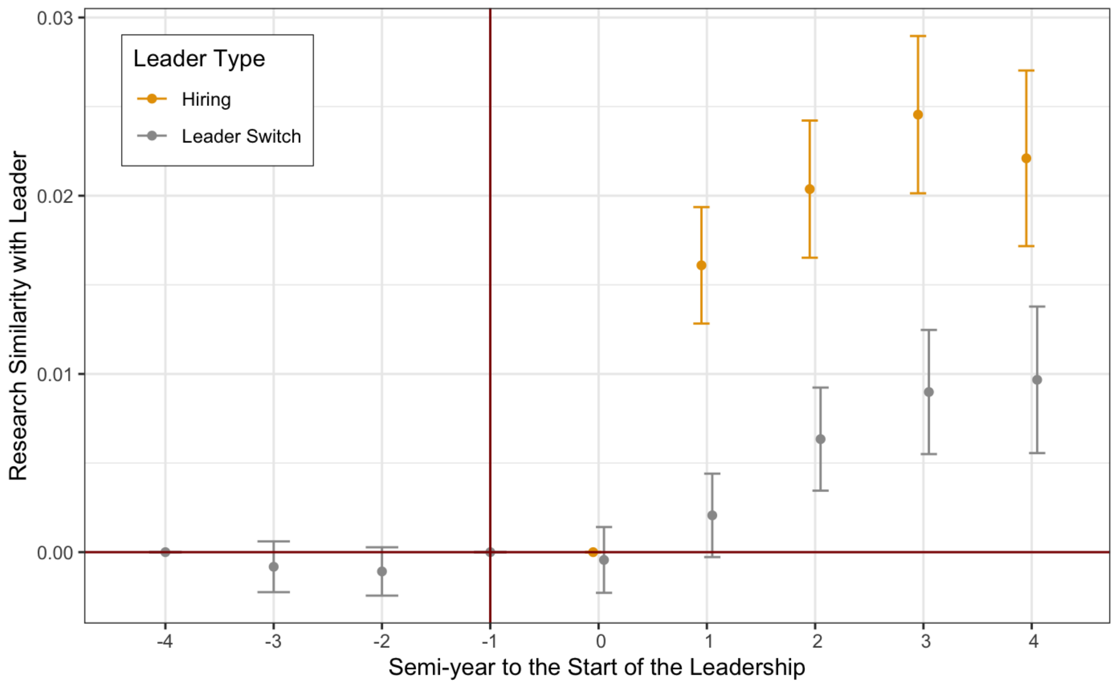


Figure 9: Impact of the leader switch vs. hiring leaders. The yellow lines/marks represent the estimators for the effect of hiring leaders. The grey lines/marks represent the effect of leader switch. We add faculty members that are newly hired to the baseline sample: (1) similarity scores will the similarity between the faculty member and the leader hired her; (2) the treatment year is the year when the faculty member is recruited by the school.

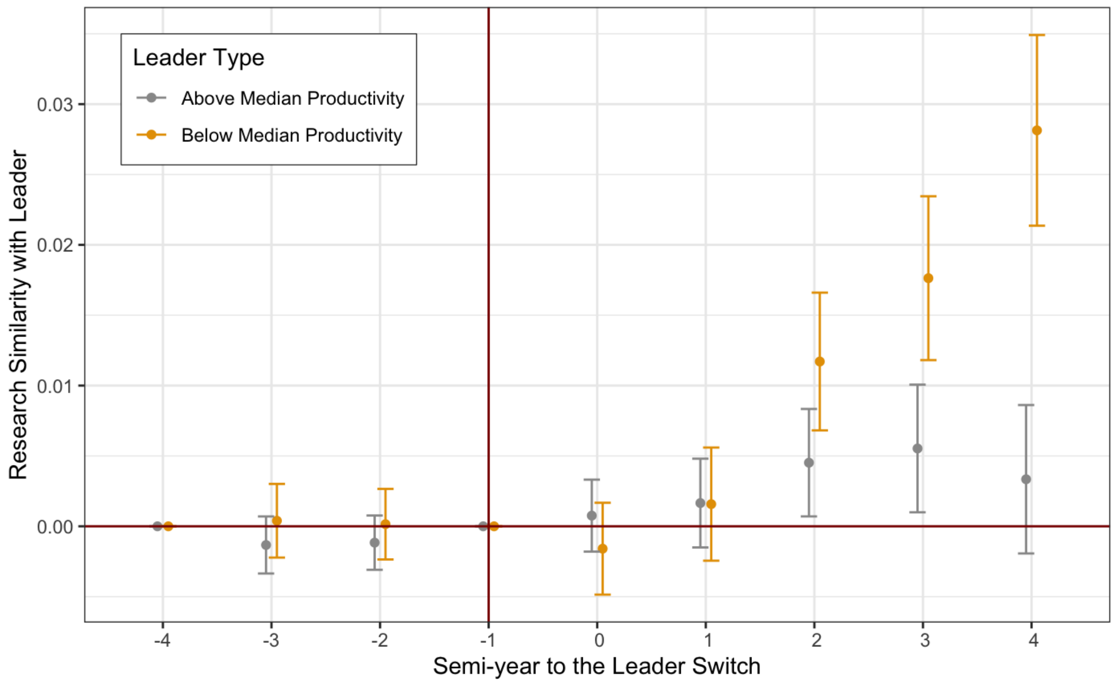


Figure 10: Heterogeneous effect of leader switch by the productivity of leaders. We define the productivity of a leader as the average number of publications of the leader in the 3 years before she is in office. Then we take the median of leaders' productivity for each discipline. A leader will be categorized as "above mean productivity" if her productivity is above the median number of her discipline. Otherwise, she will be categorized as "below median productivity". We estimate the effect of leader with different productivity level separately with our baseline regression (i.e., we assume that pairs with different leader productivity have different calendar year fixed effects). The yellow lines/marks represent the estimators for the effect of leaders that are below the median productivity. The grey lines/marks represent the estimators for those above the median productivity.

Table 1: Hiring leaders vs. other leaders

	Similarity Score		
	Pooled (1)	First year (2)	Pooled (3)
Panel A: TF-IDF Mean			
Dummy for hiring leader	0.00019	0.00015	0.00014
	(0.00021)	(0.00032)	(0.00021)
Panel B: TF-IDF Max			
Dummy for hiring leader	0.01097	-0.00226	0.00893
	(0.00137)	(0.00197)	(0.00139)
Faculty FE	Yes	Yes	Yes
Calendar Year FE	Yes	Yes	Yes
Control for Event Time	No	No	Yes
Number of obs	207852	61947	207852

Note: (1) Use the sample where the relative year is between 0 and 4. Regression here is: $Y_{ijt} = \beta H_{ijt} + \alpha_i + \gamma_t + \epsilon_{ijt}$, where Y_{ijt} is the similarity score between faculty i and leader j at calendar year t, H_{ijt} is an indicator for whether leader j is the hiring leader of faculty i at year t, α_i and γ_t control for the faculty member and year fixed effect.

(2) Only use the sample where the relative year equals to 0. Regression here is: $Y_{ijt} = \beta H_{ijt} + \alpha_i + \gamma_t + \epsilon_{ijt}$.

(3) Use the sample where the relative year is between 0 and 4. Regression here is: $Y_{ijt} = \beta H_{ijt} + \sum_l \psi_l D^l_{ijt} + \alpha_i + \gamma_t + \epsilon_{ijt}$, where D^l_{ijt} is an indicator for faculty i and leader j being l periods away from initial treatment at calendar year t.

APPENDIX

A Categorizing multidisciplinary schools

The categorization is done with the following steps:

Step 1 For each school, we extract disciplines that are (i) listed in school level code, and (ii) listed in the name of departments that are under the school. We need (ii) to improve accuracy, since some schools can cover disciplines that are not indicated by their school-level names. For example, the Guanghua School of Management of Peking University (北京大学光华管理学院) only has the discipline "management" in its name, but actually covers other disciplines including business, finance and economics.

At the end of this step, for each school, we get an array of disciplines in the school. For example, the Guanghua School of Management of Peking University has the following disciplines: (Management, Management, Management, Economics, Economics, Finance, Finance, Business).

Step 2 Within each school, we drop disciplines which only take less than 25%. The threshold is chosen ad hoc by checking if the final categorization makes sense. Notice that there are 10 out of 787 schools are dropped in this process since there is no discipline in the school is more than 25%. These schools are usually called "School of Social Science" (人文社会科学院) which are a mixture of all social sciences. If we include the 10 schools, all disciplines need to be combined into one.

After this step, one school has at most 3 kinds of disciplines. For example, the Guanghua School of Management of Peking University has 3 disciplines: Management, Economics, Finance.

Step 3 Within each school, disciplines are ranked by percentage. So the first discipline will be the major discipline of the school. Given the first discipline, we need to check what other disciplines are usually linked to it. Some links are very rare. For example, most of the Marxism schools are independent of other disciplines. But Northeastern University (东北大学) combines Marxism and Philosophy, and China Agricultural University (中国农业大学) combines Marxism and History. These links will mess up the categorization. So I dropped these rare links and categorize the schools with their first discipline. The criteria that we use is: given the first discipline, drop if this type of links only takes less than 15%.)

Step 4 Finally we group observations by the connected disciplines by using *group_twoway* by Mation and Maciente (2014). The final categorization is as follows:

- Marxism
- Political Science, Public Management
- Law

- Management, Economics, Finance, Business
- Education
- Foreign Language
- Humanities, Literature, Media
- History
- Psychology
- Philosophy, Anthropology, Ethnology, Sociology
- Regional Studies

B Identification of Faculty Members

In this section we discuss the strategy we use to identify faculty members from students or other unaffiliated researchers for a given department.

The difficulty for getting a full set of faculty from 1990 and 2019 is that most of the universities don't have good records of faculty at department level. We utilize the scientific publications of all affiliates in the 109 universities and extract faculty lists based on authors and affiliations to pin down the list of faculty and assign them to schools they are affiliated.

The general process is: *(i)* Manually find keywords for identifying department; *(ii)* Filter faculty members with certain criteria.

Manually find the "keys" for identifying department This is a key step for identifying faculty members. The affiliation entries in our publication data are typically very messy. What makes thing worse, some people don't use the full name of their departments/schools to put it in the affiliation. For example, a professor affiliated to the Department of Applied Economics of Guanghua School of Management at Peking University (北京大学光华管理学院应用经济系) could possibly put something like "Guanghua School at Peking University" (北京大学光华学院) or "DAE of Guanghua School of Management at Peking University" (北京大学光华管理学院应经系) to the affiliation of his paper. Therefore, we must manually extract some "keyword" to match the affiliation. The protocol for adding the searching keywords is:

1. University names are automatically added to the set of keywords for all the affiliated departments;
2. We make sure that each set of keywords can uniquely identify one department. One should be very careful when trying to use generic keywords to identify a department. For example, when we try to use "Fianace" (金融) to extract papers and faculty members for the Department of Finance of School of Economics at Peking University (北京大学经济学院金融系), which will be contaminated by the Department of Finance of Guanghua School of Management at Peking University (北京大学光华学院金融系) and the Department of Financial Mathematics of School of Mathematics at Peking University (北京大学数学学院金融数学系). Therefore a possible key in this case to uniquely identify the Department of Finance of School of Economics at Peking University (北京大学经济学院金融系) could be "Peking University" (北京大学), "Econ" (经), and "Finance" (金融).
3. Most affiliations in the papers are precise only to the school level (just like HBS and Harvard SEAS), not to department level (in US equivalent, Harvard Econ department and Political Science department). This is because, most Chinese "schools" are US "departments" equivalent, and Chinese "departments" are equivalent to something like the macroeconomics group at Harvard econ department, although there are typically still bureaucracy structures and CCP establishments in this very disaggregated level. We try to identify faculty members by their department (in the Chinese sense), however in many times we are not able to do that.

Filter faculty members with certain criteria After we can identify department/school from papers, we use these to identify faculty members. Our current criteria for a faculty member are: *(i)* having more than 3 years of publication span; *(ii)* having 5 or more papers. The first is to exclude PhD students who typically publish papers in 2-3 years, and the second is to guarantee enough variations for us to exploit in regressions.

Validation with one university To validate the method that we use to extract faculty members, we compare the faculty we extracted with the faculty list that we can obtain from the the official website of the School of Economics at Sun Yat-sen University. Table A.1 shows the validation result.

Table A.1: Compassion between extracted faculty and the actual personnel

Year	Actual Number of Faculty	Number of people extract from raw data	Number of Faculty after filtering
2019	44	353	23
2018	41	327	31
2017	37	305	35
2016	35	301	39
2015	33	297	39
2014	31	296	40
2013	29	337	44
2012	28	335	46
2011	24	340	52