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

Daron Acemoglu
David Y. Yang
Jie Zhou*

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Abstract

Can China stimulate and sustain innovation with its juxtaposition of top-down emphasis on innovation and the presence of powerful leaders within academic institutions? In this paper, we investigate whether powerful actors curtail academic autonomy and freedom, and impact the direction and quality of innovation. 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 measure 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 cannot be explained by the signaling of star researchers' activities, but can be attributed to leaders' political power over faculty members' career trajectories. Leaders appointed by the Communist Party exert greater influence on faculty members' research directions, and leaders' influence is stronger among disciplines and institutions that have historically or recently experienced academic persecution. We also document significant costs of leaders' influence on research quality. Below-median productivity leaders lead to even greater increases in similarity, and switches from above-median to below-median leaders is associated with sizable declines in citations. Such decline is driven by citations to papers that are most similar to new leaders.

*Acemoglu: Massachusetts Institute of Technology and NBER; email: `daron@mit.edu`. Yang: Harvard University and NBER; email: `davidyang@fas.harvard.edu`. Zhou: Massachusetts Institute of Technology; email: `jiezhou@mit.edu`. Leo Dai, Minsoo Kang, Junxi Liu, Michelle Han, Tiffany Qiu, Saier Wu, Peilin Yang, Andy Zhao, Hanyao Zhang, Xiaoyang Zhang, and Xinrui Zhou provided excellent research assistance.

1 Introduction

Fostering innovation has been a central aim of the modern Chinese regime, which has substantially increased funding for academic research during the past decades. China's basic research spending rose from 25.8 billion RMB in 2013 to 42.3 billion RMB in 2018, and the country now devotes more resources to research than other industrialized nations, such as Japan, Germany, and France.[1] Chinese universities have also benefited from increased spending, and many metrics of academic performance, including the number of publications and patents, have risen rapidly as well (Marginson, 2022). At the same time, however, there is growing concern that the *quality* of research has not improved as much. Average citation per paper from China is about half of the citation rate for papers from the US, the UK, Germany, or France (Jia, 2017), and Chinese universities are still ranked low relative to their international peers.[2] Even in fields such as artificial intelligence, which is a main area of focus for the Chinese government, few breakthroughs are coming from Chinese academia or companies, Chinese patents are often of low quality (China Power Team, 2021), and the vast majority of Chinese AI patent applications have been rejected (Zhang et al., 2022).

One feature that distinguishes Chinese academia from its Western counterparts is a greater degree of bureaucratic, top-down control (Kirby, 2022). Chinese university leaders, such as heads of departments, deans and provosts, are appointed centrally and have much greater powers than those in the West. These leaders decide the allocation of resources within their units, are directly responsible of faculty promotions, and can terminate members of their unit without meritocratic review. In addition, each Chinese department has party-appointed leaders, who have various administrative roles, including in promotions and hiring. This structure may appear inimical to the freedom to experiment and pursue new and sometimes unconventional ideas, which is considered fundamental to innovation in general (Hayek, 1978; Ridley, 2020; Huang, 2023) and academic research in particular (Cole, 2010). Could it be that Chinese research and academia are held back by top-down, bureaucratic decision-making and limited autonomy? Can China stimulate and sustain innovation despite this top-down structure and powerful academic leaders?

In this paper, we aim to answer these questions and examine whether the bureaucratic power of academic leaders is an important factor holding back Chinese academic research. Specifically, we investigate the effects of new academic leaders on the type and

[1] See Appendix Figure A.1. Source: `http://www.stats.gov.cn/tjsj/ndsj/2019/indexeh.htm`.

[2] As ranked by Academic Ranking of World Universities (ARWU), none of the world's top 20 universities are Chinese, and only 2 make to the top 50; source: `https://www.shanghairanking.com/rankings/arwu/2021`.

quality of research conducted by faculty members across a large number of disciplines in Chinese universities. We also explore whether these impacts are driven by bureaucratic career concerns — meaning the incentives created by the bureaucratic structure of Chinese universities and the career concerns that they induce.

Our exploration of the linkages between bureaucratic career concerns and academic research is built on three new datasets. First, we collect information on organizational structures and leadership transitions in the social science departments of Chinese universities since 1990. Second, we collect (close to) the universe of research publications — in both Chinese and English language journals — by faculty members and 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. Third, we collect citation information for this sample of research publications. Using these measures of research similarity and quality, we investigate the impact on the direction and quality of faculty members' research in the event of leadership shifts.

Our baseline empirical strategy compares the (topical and textual) similarity in research output between faculty members and their respective leaders, before and after leadership switches. Identification with this strategy relies on faculty-leader pair level variations over time, exploiting the fact that each researcher is observed under multiple leaders over the course of her academic career, and leadership transitions take place at different times and with different frequencies across departments. This setup — by including a full set of faculty-leader pair fixed effects as well as calendar year fixed effects — allows as to account for other factors that might impact research similarity between a faculty-leader pair and isolate sharp changes in faculty research direction driven by the appointment of specific leaders.

We find that faculty members' direction of research shifts towards the portfolio of a new leader. The change takes place almost immediately after a leadership transition and persists for at least four years (the average tenure of an academic leader is 5.8 years). Moreover, this impact is quantitatively large. The increase in research similarity between a new leader and a faculty member corresponds to 81% of the existing level of similarity between two random, non-coauthoring faculty members in the same departments. Academic leaders have analogously large effect on the type of faculty that are hired, again favoring those with research portfolios more similar to theirs.

This shift in research direction after a leadership transition is robust to a range of alternative empirical specifications, including different measures of research similarity and different controls. Reassuringly, we do not find any increase in research similarity between faculty members and new leaders in *other* disciplines in the same university. Bolstering confidence in our identification strategy, we also do not find analogous changes in similarity *before* a leader takes up her position. We additionally confirm that the results are not driven by differential publication strategies in Chinese and English language journals: we find very similar results when analyzing English publications alone, or when we combine English and Chinese publications together.

Shifts in research activities after a leadership transition could be driven by two related but distinct channels. The first is bureaucratic career concerns: researchers may be pandering to the new leader who has direct control over them — for example, who will decide their promotion, termination and the amount of resources they have available. The second is also potentially related to bureaucratic career concerns, but works through signaling: researchers may follow the signals embedded in the appointment of a new leader with a certain research emphasis and track record. If the second channel is the main one, then we should expect a powerful response to the appointment of new leaders in other departments as well. However, further exploration shows that same-discipline leaders from other universities do not have any impact on faculty members' research direction, suggesting that the first, direct channel is the one that is responsible for our results. Similarly, we do not find that public recognition of colleagues' research has a discernible impact on one's research direction, providing further evidence against the signaling channel.

We also provide more direct evidence supporting the direct channel. First, compared to department chairs, we find that the department's Communist Party representatives exert stronger influence on faculty's research. Tellingly, this is despite the fact that party representatives are rarely leading academics; they are directly appointed by the Chinese Communist Party and represent closer alignment to the intention and direction of the party. Since Communist Party representatives are unlikely to impact research direction via their academic achievements, this provides further evidence that the direct channel is operative, and also suggests that the bureaucratic channel is entangled with political power.

Second, we explore the consequences of a tenure and promotion reform introduced in some elite universities. Although this new structure could have in principle encouraged meritocratic review, in practice it further empowered department leaders in the promotion and termination of faculty in their unit, and as such could be expected to increase bureaucratic career concerns. Consistent with this expectation, we find that the similarity effects are significantly amplified after this reform.

Third, we explore whether academic persecution in the past has persistently shaped the present-day academic environment and influenced the extent to which leaders are able to influence research directions. Following Wang and Kung (2021), we measure each academic discipline's likelihood of facing persecution during the Cultural Revolution. We find that disciplines that suffered worse persecution four decades ago exhibit greater impacts on research direction from leadership switches. This finding thus suggests that bureaucratic career concerns matter more in disciplines that suffered greater (political) persecution in the past and, once again, bureaucratic and political considerations are intermingled.

Fourth, and relatedly, we examine whether the leadership effects become stronger after major incidences of researchers removed explicitly due to their political stances.[3] We find that after the occurrence of these incidents in a given university, leadership transitions in the same institution (across all disciplines) exhibits substantially stronger effects on researchers' output.

Fifth, we decompose the sources of convergence in research output into political and scientific language. We do so by separately training text similarity models using word embeddings from the Chinese Wikipedia (scientific semantics) and the *People's Daily*, the Communist Party's official newspaper (political semantics). We observe that, controlling for the research similarity as measured using scientific language, leaders' and faculty members' research portfolio converge in terms of political language as well. This suggests a political source of leadership transmission on researchers' activities.

Finally, we investigate the implications of the bureaucratic power of academic leaders on research quality. This is, in principle, challenging, because any change in metrics of research quality following the appointment of a new leader is *relative* to the impact of the previous leader. To overcome this challenge, we develop a number of strategies. First, we compare the effects of above-average and below-average leaders (defined in terms of research productivity) on the citations of researchers after leadership switches. Our results show significant deterioration in citations after switching from an above-average to a below-average leader and significant improvements after switching from a below-average to an above-average leader. Switches between leaders of the same quality have no impact on citations. Second, we explore the sources of changes in citations after leader switches. Here, we find that the change in citations received by a researcher after a leadership switch is driven entirely by their papers that have the greatest similarity to their new leaders' research, and that there is no change in citations received by papers that are minimally related to a new leader's agenda. Given that leaders of lower productivity exert

[3]These incidents occur after 2013, reflecting the further decline of academic freedom 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`.

greater influence on faculty members' research portfolios, together these results indicate that the change in research direction induced by political pressures in China have significant costs in terms of research quality. Third, we estimate that the negative effects of leadership switches on research quality are cumulative and become larger after a faculty member experiences several leadership switches.

Taken together, these results suggest that bureaucratic decision-making and the career concerns that it imposes has a major impact on the direction and quality of academic research in China. Bureaucratic career concerns induce Chinese scholars to align their personal research agenda more closely to that of their leaders, resulting in lower-quality research output.

One naturally wonders whether bureaucratic career concerns are uniquely present in Chinese universities. To shed light on this question, we replicate our baseline exercise among the major universities in Singapore, which are situated in a cultural environment similar to that of China but have drastically different academic institutions closely modeled after their counterparts in the UK and the US. We find that leadership transitions in Singaporean universities do not affect faculty members' research directions. This result — though not a comprehensive investigation of universities around the world — suggests that the bureaucratic incentives we identify in Chinese universities could indeed be closely tied with political considerations and the political power that academic leaders command. As China is coming to account for a growing fraction of the world's research and innovation output, potential distortions in Chinese academia are likely to have significant consequences for global innovation as well.

Our paper is most closely related to the branch of existing literature on political economy investigating linkages between political factors and innovation. Much of the emphasis in this literature has been on the risk of expropriation or political interference on entrepreneurship, investment and innovation (e.g., 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 political pressure likely comes from national institutions. In so doing, our work also joins the recent studies that examines the impact of academic persecutions, ranging from the Nazi Germany's per-

[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 the state's demand for AI for surveillance purposes can promote private innovation in the AI sector, due to the shareability of government data across multiple purposes.

secution of Jewish researchers (e.g., Waldinger, 2012; Becker et al., 2021), to persecution of scholars during China's Cultural Revolution (Wang and Kung, 2021). 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; Hill and Stein, 2021).

Our work further contributes to the literature on innovation in China. A large literature studies the organization of the Chinese economy and the factors that drive its economic growth over the past four decades. Recent works have carefully described the innovation landscape in China (e.g., Wei et al., 2017; Bombardini et al., 2018), its potential implications for academic research (e.g., Freeman and Huang, 2015), as well as the political and historical roots (e.g., Huang (2023)). More closely related to our paper is the innovative paper by Jia et al. (2019), 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 being used by academic leaders for their own benefit — suggests a different type of political 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 of the effects of powerful, political actors on the direction and quality of academic research.

The rest of the paper is organized as follows. Section 2 describes the data sources used for this project. Section 3 describes the key measure of research similarity and the empirical strategy; Section 4 presents the results of leadership transition on career incentives. Section 5 presents evidence of that the research similarity effects we estimate are a consequence of politically-motivated career concerns. Section 6 assesses the costs on research quality associated with politically-charged career incentives. Section 7 concludes, while the Appendix contains additional results and more information on data construction.

2 Data

Our empirical analysis combines three primary datasets that we collect from scratch: *(i)* the structure of Chinese universities and the leadership information in the university departments; *(ii)* the scientific publications of all affiliates in these institutions; and *(iii)* the number of citations for each of the publications. We now describe each of these datasets in turn. Figure 1 plots the overview of the data construction procedures. In a parallel analysis, we also replicate this procedure for universities and scholars in Singapore.

2.1 University structure and department leadership

We first construct a dataset tracking the organizational structure and leadership changes in Mainland China's universities. We study all social science departments among the top universities in China. Specifically, we focus on the 109 universities that belong to "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 data on organizational structure for departments within social science disciplines, based on universities' websites, catalogs, and archival yearbooks. We focus on the organization structure one level beneath the university's top administrative hierarchy, which corresponds to "departments" in some universities and "schools" in a few others. We will refer to them interchangeably for the rest of the paper for brevity. This is the level at which leadership has the most direct control over resources, promotions and hiring decisions. We standardize the diverse organizational structures across the 109 universities to make the department level definition comparable throughout.

We focus on schools and departments that are continuously active between 1990 and 2019, which is also the time window for which we collect faculty members' publication records. For the schools and departments that cease to exist either due to splits or mergers, we track these administrative changes and link schools and departments to their contemporary organizational structure. This enables us to appropriately attribute past research activities in previous academic units to the corresponding units today, and ensures that we don't have changes in leadership that are caused mechanically by changes in organizational structure. Overall, there are on average 7.8 departments in a given university in the period between 1990 and 2019, and they can be categorized into 11 disciplines.[6]

Finally, we identify school or department leaders during our sample period (1990 to 2019) from a variety of sources: official websites of universities, university yearbooks, *Baidu Baike* (a Chinese-language collaborative online encyclopedia), and various news re-

[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`.

[6] These disciplines are: economics, management, business, and finance; political science and public management; law; education; literature and media; history; psychology; philosophy, anthropology, ethnology, and sociology; regional studies; foreign language; and Marxism. For the schools and departments that are interdisciplinary in nature, we categorize disciplines based on the shared components among sub-divisions within the schools. The details are described in Appendix A.

ports that mention department leadership. We manually extract the department chairs and the Communist Party secretaries for each department. For the years that we cannot locate precise leadership information, we employ several interpolation methods. If we find a faculty member appeared as a leader in Year_1 and Year_2, we assume that this individual held the leadership position throughout Year_1 to Year_2. If two different individuals were located as leaders with intermediate years with missing information, we interpolate by assigning the past leader to the missing cell, assuming that there may be less information about leaders that are about to step down, but for the new leader who just began a position, it is more likely to obtain information about her.[7] The average tenure of a department chair is 5.8 years, though this varies considerably across disciplines: ranging from 4.8 years in the discipline of Marxism, to 6.3 years in the discipline of foreign language. On average, each faculty member in our sampling period (between 1990 and 2019) experiences 1.82 leadership transitions.

Similar to the bureaucratic structure in many organizations in China, universities and the schools/departments within them have two parallel leadership posts: school chair in the academic track and Chinese Communist Party secretary in the political track. These dual leaders hold comparable powers within the academic units, though the Party secretary often has veto rights in personnel decisions. 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. Nevertheless, we are able to identify a subset of department Party secretaries who are previously scholars and have academic track records. We will compare their influences on faculty members to the influences of the school chairs in the academic track.

2.2 Research publications

We construct a dataset of all scientific publications by scholars in the corresponding institutions during the three decades between 1990 and 2019. The scientific publication dataset serves two primary purposes: firstly, it provides a description of research output of researchers, which we rely on to construct our primary outcomes of interest (described in detail in Section 3.1). Moreover, this publication dataset allows us to retrospectively construct a roster of scholars affiliated with each institution and department, since administrative records of faculty rosters are incomplete or absent for most schools in most

[7] About 16% of the missing department leadership (by year) information is resolved under this assumption. Our baseline results are robust to alternative interpolation strategies.

years during the previous decades.

To construct this dataset, we rely on two major sources. The first is *China National Knowledge Infrastructure (CNKI)*, a full-text database covering 90% of all official published Chinese journals. The second is *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.

In addition to Chinese-language publications, we also collect information on scholars' publications in English-language journals. For each scholar we already collected Chinese-language publications, we searched her publications, compiled in the CNKI, from 1990 and 2019 and restrict the language of publications to be English. We verify and consolidate authors' information and consolidate duplicate English spellings of different Chinese names. In total, we found 14,105 scholars (31%) with 97,031 English papers. Appendix C.1 provides details on cross-checks of data completeness based on information collected in Google Scholar.

For each researcher affiliated with the 109 universities of interests, we collect all the papers she publishes between 1990 and 2019. We exclude publications in non-academic outlets such as newspaper opinion pieces. We also exclude dissertation archives and other internal school journals. This amounts to a total of 5,290,503 academic publications. For each paper, we collect information on its title, authors, publication year, abstract, and citation counts.

We then use the publication database to extract rosters of faculty members (and those who ever served as school or department leaders) affiliated with each academic unit. In a nutshell, we assign an academic affiliation to each author of a paper based on publication information. Because not all papers have information on affiliations at the school level, we assign the school level affiliation from any publication of a given author to all of her papers. In order to rule out individuals who are affiliated with a school as a student (and hence publishing sparsely) rather than a faculty member, we use the dissertation database to locate the graduation year of a given researcher and consider the post-graduation period as their faculty affiliation. We also restrict 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 ones that may publish during a temporary affiliation such as visiting scholar. Our faculty roster extraction procedure performs well when we validate it with a set of contemporaneous faculty lists that we can obtain from the school's official website (see Appendix B for details).

This procedure provides us with 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 science disciplines in top universities between 1990 and 2019. On average, there are 62.2 faculty members in each school/department, ranging from 15.3 in the discipline of regional studies, to 103.0 in the discipline category of management, economics, finance, and business (e.g., business schools). Each faculty member publishes on average 1.5 papers in any given year (in either Chinese or English language journals), ranging from 0.9 paper per year in the discipline of foreign language, to 2.7 papers per year in the discipline of psychology.[8]

2.3 Citation counts

In order to measure research quality, we also collect data on the citation counts for all research publications in our sample.

Data on citation counts are constructed separately from the publication dataset previously described. From the same CNKI and Wanfang databases, citation counts data is collected and matched back to each paper in the publication dataset based on the paper's title and publication year. When CNKI and Wanfang databases report different citation counts, we take the higher count of the two as the paper's overall citation counts. This process yields citation counts for 95.6% of the papers included in analysis. We exclude the papers with missing citation records from the baseline analysis; the results are robust if we instead assume that papers with missing citation records have zero citation.

On average, each paper has a mean of 13.9 citations, with leaders averaging slightly more at 18.2 citations per paper, and faculty averaging slightly less at 13.7 per paper (see Appendix Table A.1 for summary statistics). Faculty at higher-ranked universities publish papers with substantially higher citation counts: for example, among faculty members at the top-ranked Peking University, mean citation counts are almost doubled (24.0 citations per paper).

[8]There is a general trend of increased publication by scholars across all disciplines over the sampling period: the research productivity in a university grows from 158 papers on average in 1991 to about 50,279 papers in 2018, reflecting the overall growth of Chinese academic institutions and research capacity over this period (see, among others, Xie et al. (2014)). We include year fixed effects in all baseline specifications to account for the secular trend in research activities and other changes in the overall research environment.

2.4 Leadership transition and research output in Singapore

Aimed at examining whether the effects we identify in China would be present in academic institutions elsewhere, we replicate the data construction procedure described above to universities and scholars in Singapore, albeit the data is drawn from different sources than the ones that we use for China. Overall, we identify 58 leadership transitions from 17 social sciences departments, potentially affecting 1,470 faculty members who have published a total of 121,365 papers during the time period of 2000 to 2020. Appendix D provides details on the data collection process.

3 Empirical strategy

In this section, we present our empirical strategy. The first step is the construction of research similarity measures, described in the Section 3.1. We discuss our identification strategy in Section 3.2.

3.1 Measurement of research similarity

3.1.1 Similarity of paper pairs

To measure similarity between any given two research papers, we construct similarity scores between pairs of scientific publications. For each pair of papers in the paper collection $\mathcal{D}$, we construct a variety of measures of similarity, each of which can be viewed as a mapping from pairs of research papers into a similarity score — $s : \mathcal{D} \times \mathcal{D} \mapsto \mathbb{R}^+$.

We use a non-parametric method — term frequency inverse document frequency (TF-IDF) — as a baseline measure for textual similarity. We also use an alternative class of text-similarity measure based on machine learning — Doc2Vec — to demonstrate that our baseline results are not driven by specific choice of such measures.

Term frequency inverse document frequency (TF-IDF) TF-IDF is a statistical measure commonly used to evaluate how important a word is to a document in the context of a given corpus of documents (Biasi and Ma, 2020; Kelly et al., 2018). The importance score 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 is:

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

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 i in the corpus $\mathcal{D}$.

The collection of publications forms our text corpus $\mathcal{D}$, elements of which are individual papers represented by their abstracts. 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 $\mathcal{D}$.[9]

We let each element v_i^d be the number of times word i occurs in document d. 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 documents $f, l \in \mathcal{D}$, the similarity measure is defined as:

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

When the pairs of publications involve English-language articles, we first translate the articles into Chinese and then construct the similarity measures within the Chinese textual space. Appendix C.2 provides more details on the procedure, and demonstrates that the similarity measures are not sensitive to alternative translation procedures such as translating Chinese articles into English instead.

Doc2Vec TF-IDF is a conservative measure in textual similarity as it may underestimate the similarity between two documents. This potential underestimation is rooted in two assumptions: *(i)* the meaning of the words are orthogonal to each other, and *(ii)* the word order is not taken into account when measuring the similarity between two texts.

To relax the two assumptions, we in addition calculate a vector $\mathbf{v}^d$ for each document d by training a Doc2Vec model (Dai et al., 2015). Doc2Vec is an unsupervised neural network algorithm that learns the fixed-length feature vectors from variable-length documents. Doc2Vec predicts each word in document d by utilizing the current document and a sliding window around the target word.

We train a Doc2Vec model by using titles and abstracts of papers in paper collection $\mathcal{D}$ as the training set. We start with the pre-trained models and further fine-tune them to fit our paper collection $\mathcal{D}$. Specifically, we use two pre-trained Chinese word embeddings provided by Li et al. (2018): *(i)* Word2Vec trained with People's Daily News (the official newspaper of the Chinese Communist Party and the largest newspaper group in China); and *(ii)* Word2Vec trained with Chinese Wikipedia. More details about the training process are in Appendix E.

[9] With a slight abuse of notation, here $\mathcal{D}$ refers to a structured set of texts. Each text in this set is the abstract of a paper.

After the training stage, each document $d \in \mathcal{D}$ is mapped to a document-unique feature vector $\mathbf{v}^d$, which represents the " concept" of the document. With the vector representation of each document, we take the cosine distance to measure the similarity between two documents $f, l \in \mathcal{D}$: $s(f,l) = \mathbf{v}^f \cdot \mathbf{v}^l$.

3.1.2 Similarity score for a faculty-leader pair

Based on the similarity score between pairs of papers, we then construct measures of similarity in research portfolio for each pair of faculty member and department leader.

Specifically, let $\mathcal{F}$ be the population of faculty members and $\mathcal{L}$ be the set of all 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 $\mathcal{L}$ in year t is denoted by $\mathcal{D}^L(t) = \{l_{t1}, l_{t2}, ..., l_{tn}\}$. Finally, the similarity score of a pair of papers (f,l) is designated as $s(f,l)$.

Next, for the faculty-leader pair, we construct pairwise similarity scores by comparing all papers published by the faculty member in year t with all the papers that the leader has published up until (and including) year t. This holds the existing research portfolio of department leader as benchmark, and allow us to capture year-to-year changes in faculty members research activities due to their new research output. Specifically, the research similarity score at time t is based on pairs of papers belonging in the following set:

$$\mathcal{P}^{(F,L)}(t) = \{(f,l) | f \in \mathcal{D}^F(t), l \in \cup_{k \leq t} \mathcal{D}^L(k)\}.$$

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

3.2 Empirical specification

Our baseline empirical strategy follows a modified event-study design. We compare research similarity between faculty-leader pairs, measured as described in Section 3.1, before and after the leader takes office. Importantly, we control for faculty-leader pair fixed effects as well as calendar time fixed effects. Thus, changes in research similarity are identified entirely from *within* faculty-leader pair variation over time. This strategy controls for any general shifts in a discipline's research priorities over time and also filters out any differences in research similarity resulting from the fact that leaders work in different areas and have different productivity levels generically.

Specifically, we estimate the following baseline specification:

$$Y_{i,t} = \sum_{l \neq -1; l=-3}^{4} \psi_l D_{i,t}^{l} + \alpha_i + \lambda_t + v_{i,t}, \tag{3}$$

where $Y_{i,t}$ is the similarity score for the faculty-leader pair i at time t; $D_{i,t}^{l}$ 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 faculty-leader pair fixed effects; and λ_t denotes a full set of calendar time fixed effects. For each faculty-leader pair, we focus on the time window comprising of three years before and four years after the leadership transition. Our baseline results are robust to alternative choices of time window. We use the TF-IDF based research similarity measures in the baseline specification, and we introduce alternative measures in the robustness exercise.

By conducting the analyses at the faculty-leader pair level, we take advantage of the fact that academic leadership transitions are not synchronized across universities and across departments. Our key identifying assumption is that variation in the similarity between a faculty member and a leader is orthogonal to other changes that happen at the same time as the leadership transition. Potential threats to the validity of this assumption include changes in (national) research priorities that take place at the same time as the appointment of a new leader and various types of selection determining which leaders are appointed to which departments. Our extensive fixed effects (most importantly at the faculty-leader pair level) should account for these selection-related concerns.

Additionally, we bolster the plausibility of this identifying assumption in two ways. First, we examine the pre-trends in research similarity between a researcher and a leader in the years leading up to the appointment of the leader. Second, we conduct a range of placebo exercises, such as estimating the effects of leadership transition occurred in universities other than faculty members' own institution. These placebo exercises allow us to assess whether our results are not driven by spurious correlation between faculty and leader research styles and also enable us to distinguish the effects of new leadership appointments working via signals to all faculty within a discipline about which areas are prioritized by the Communist Party or other higher authorities.

One may also be concerned that a leadership transition induces changes in faculty members' research productivity and research output quantity, thus changing the denominators of the research portfolio similarity between faculty members and leaders. We examine faculty members' productivity changes leading up to and after leadership transitions in the corresponding academic unit. Specifically, we regress the total number of academic publications per year on time relative to the date of 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 transitions. We show that leadership transitions does *not* induce changes in researcher productivity (see Appendix Figure A.2. This pattern makes research similarity between faculty and leaders (and later citation counts) more straightforward to interpret.

4 Leadership transition and direction of research

4.1 Baseline results

We first examine the average effects of leadership transitions on faculty members' research direction across all disciplines and all institutions over the past three decades. We pool our entire sample together and estimate the baseline specification in (3).

We present the estimated coefficients graphically in Figure 2, which plots the non-parametrically estimated ψ_l coefficients along with the corresponding 95% confidence intervals. The research portfolio similarity score between leaders and faculty members in the year prior to the leader taking office is normalized to zero and the timing of the leadership transition is marked by the vertical red line. Table 1, column 1, presents the results in regression form.

We observe a significant increase — by approximately 7% — in research similarity between faculty members and their leaders due to leadership transition. This effect is quantitatively large: the increase in research similarity between a new leader and a faculty member corresponds to 81% of the existing level of similarity between two random, non-coauthoring faculty members in the same departments.

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

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.

Robustness of baseline results

Our baseline results are robust to a range of alternative specifications. First, when we measure research similarity using the two types of Doc2Vec similarity scores described in Section 3.1, one pre-trained with People's Daily and the other with Chinese Wikipedia, we find consistent patterns as the baseline results (see Table 1, columns 2-3, and Appendix Figure A.3). Before the new leader takes office, there is no rise in research similarity, but once the new leader is in charge, the similarity index increases significantly and we see this effect lasting for at least four years.

Second, the results are robust to alternative choices when constructing the sample and the research similarity measures. Specifically, the results are robust if we measure similarity against department leaders' past 5 years of research output rather than entire portfolio up to year t (see Table 1, column 4).

Third, the rise in research similarity is robust to including faculty members' and leaders' publications in English language journals. We construct TF-IDF similarity score between Chinese and English publications following the methods illustrated in Appendix C and re-estimate the baseline specification. Table 1, column 5 presents the estimated coefficients, which are nearly identical to the baseline estimates (see, also, Appendix Figure A.4). This indicates that while the faculty members pivot their research activities towards the new leaders, English language journals, which may be considered as less politically salient, are not utilized as alternative outlets for researchers to retain their previous research direction.

Finally, our results are robust to including just leader and faculty fixed effects (rather than leader-faculty pair fixed effects in the baseline specification), as shown in Table 1, column 6. We find qualitatively similar effects. This is a useful specification to benchmark since our analysis of political career concerns on research quality (shown in Section 6) will not include leader-faculty pair fixed effects.

Placebo: effects of leadership transition from other disciplines

We carry out a placebo exercise where we re-estimate our baseline specification (3), but for leadership transition in different disciplines but from the same academic institution. Such leadership transition should have little effect on faculty members' research activities and direction.

We focus on leaders that are appointed within a seven year window around an actual leadership switch and randomly allocate them to a faculty member experiencing a leadership switch as a placebo leader. The results of this exercise are presented in Figure 3, which includes our baseline estimates for reference. This placebo exercise shows no significant increase in similarity in research portfolios between faculty members and placebo leaders, and the point estimates are quantitatively much smaller than our baseline estimates. Overall, this placebo exercise bolsters our interpretation that the increase in research similarity detected in Figure 2 is not driven by spurious factors and reflects the causal effect of a leader switch.

4.2 Bureaucratic career concerns vs. signals on overall research direction

Leadership transition may affect the research trajectories of faculty members through two distinct but related channels: *(i)* the bureaucratic career concerns of faculty members under their direct jurisdiction — through control over promotion, termination, or the amount of resources that faculty members have available; and *(ii)* the signals that all faculty in the discipline receive from the appointment of a leader with a particular research style and portfolio. The latter channel of influence may also be related to career concerns since those heeding such signals may be more successful. To isolate the effects working through the local career concerns, we conduct a number of exercises.

Effects of leadership transition from other universities

First, we re-estimate the baseline specification (3), examining the leadership transition effects of new leaders in the same discipline but from other universities. Such leadership transition may carry signal values of successful or promising research directions, but should not impose direct career concerns on specific faculty members outside of the leaders' own institutions.

Specifically, to construct pairs of faculty members and leaders within the same discipline from other universities, we locate all leaders within the same discipline at different universities, appointed within a seven year window around the leadership switch of interest, and we then randomly allocate a same-discipline leader to the faculty members in question.

The results are presented in Figure 4, Panel A. The black circle dots replicate the baseline results of effects of researchers' own leaders, and the orange square dots indicate the effects of new leaders in the same discipline from other universities. The patterns depicted in this figure indicate that there is no increase in research similarity after a leadership switch between researchers and same-discipline leaders from other universities. These findings suggest that only a minimum component of the effects presented so far could be driven by signaling of prioritized research directions. Rather, it seems that most of our estimates reflect the political power of leaders that control resources and promotions in the focal faculty members' own institution.

Effects of recognition of star researchers

Second, we examine the impact of public recognition of star researchers on faculty members in the respective disciplines' research trajectories. We focus on researchers awarded the Cheung Kong Scholar during 1999 to 2018, the highest academic award issued to an individual researcher recognizing her academic achievements in higher education by China's Ministry of Education. These star researchers and their recognition signals the promising direction for future research, but most of these researchers are not in academic leadership positions to exert direct career influences on faculty members.

We re-estimate the baseline specification (3), investigating the effects of Cheung Kong Scholar award on the research direction of faculty members in corresponding disciplines. We use the year when specific Cheung Kong Scholar is awarded as the time of treatment, and we follow the same procedure to calculate the time-varying research portfolio similarities between star researchers and faculty members.

The results are presented in Figure 4, Panel A, marked in green diamond dots. We do not observe the same pattern of convergence in research directions toward these star researchers once they are publicly recognized. In fact, if anything, faculty members' research similarities with the star researchers decrease about three years after their recognition, suggesting that rather than an overwhelming effects of public signal on promising research directions, they may represent previously successful research trajectories that are currently on decline.

Leaders with high vs. low academic achievement

Finally, we investigate the heterogeneous effects of leadership transition (of one's own department) with respect to the new leaders' academic achievement.

We begin by re-estimating the baseline specification (3), but allow the leadership transition effects to differ across three sub-samples divided according to the department's research output relative to other departments in the same discipline. We separate departments into those in the top 10% of this relative ranking, those in the range 10%-40%, and finally those in 40-70%, according to their rankings by China's Ministry of Education.

Note that even the relatively lowered-ranked departments in our sample are among the top academic institutions in China, since we are focusing on the top 109 universities in the country; the bottom 30% of the departments are no in our sample to begin with. Figure 4, Panel B, represents the results. While we observe greater research similarity between faculty members and leaders after the leadership transition across all ranking groups, the effects are noticeably larger for schools ranked below the 50th percentile and smallest for the top 10th percentile ones. Reassuringly, there are no statistically significant pre-trends for any of the three groups. That our effects should be stronger in lower-ranked departments is plausible: reflecting the top-down nature of Chinese academic institutions, leaders tend to have substantial power over promotion and dismissal decisions, and this power is even greater in lower-ranked departments.

Next, we categorize leaders' own productivity based on their publication records prior to taking the leadership posts. We then separately estimate the leadership transition effects among new leaders who are above-median productive and those who are below-median productive. Figure 4, Panel C. We observe that the impact of leadership transition on faculty members' research direction is substantially larger among leaders who are below-median in terms of their own productivity, and the effects are minimum among above-median productive leaders. In other words, the re-pivoting of research directions occur primarily when a less productive scholars take on academic leadership position, again demonstrating that the baseline leadership transition effects are unlikely driven by signals on research directions alone.

Taken together, these results — consistent with the little effects of star researchers presented above — show that rather than leaders from higher ranked institutions or highly productive themselves imposing stronger effects on faculty members' research directions, we observe consistent evidence that those from lower ranked institutions and with lower productivity who drive the baseline leadership transition effects. Moreover, these patterns anticipate a potential decrease in research quality and greater distortions among faculty members, which we will explore more systematically in Section 6.

4.3 Faculty hiring decisions

Having documented that political interference shifts the research direction of faculty members towards their leaders' style and research portfolio, we next examine whether leadership transition could in addition changes the composition of faculty members. Note that since our baseline specification includes faculty-leader pair fixed effects, such composition changes do not directly contribute to the baseline effects of leadership transition that we identify.

To shed light on this question, we examine whether leaders tend to hire faculty members whose research portfolio is closer to their own. Focusing on all faculty members who begin affiliation with a particular department or school between 1990 and 2019, we construct average research similarity scores between these faculty members and all leaders in the corresponding departments. The leaders who are in a leadership position at the time a faculty members' affiliation begins are the "hiring leader," under whose leadership (or potentially direct influence) the specific hiring decision is made. We investigate whether research similarity between new hires and department leaders are particularly high when the leader in question is also the hiring leader. Appendix Table A.2 presents results of the regression estimates of the research similarity between new faculty members and the leaders who hired them, relative to that between new faculty members and non-hiring leaders. We include a full set of faculty member fixed effects, exploiting only variation across leaders. We find that the research similarity between faculty members and hiring leaders are higher than with other leaders in the same department. This indicates that leaders tend to hire new faculty members whose research portfolios are similar to theirs.

Conditional on already having a similar research portfolio with their hiring leaders, do newly hired faculty members further shift their research direction towards their leader after being hired? To examine this question, we re-estimate our baseline specification on the sub-samples of existing faculty members and newly-hired members around a leadership switch. The results, which are presented in Appendix Figure A.5, show a pronounced impact on newly-hired faculty members. As in our results so far, the entire department shifts towards the new leader's research portfolio, but in particular, the pivot of newly-hired faculty in this direction is even larger. This pattern is consistent with politically-powerful leaders having an even more defining influence on researchers who start their employment under their rule.

Combined with the results presented so far, this pattern suggests that new leaders tend to have a substantial impact on the research direction of the departments they control, both by changing the research direction of existing faculty and by hiring new researchers more aligned with their research style or priorities. This hiring channel also highlights the potentially persistent effects of leaders on the research trajectory of the departments under their control.

5 Politically-charged career incentives

How much of the leadership influence on research direction can be attributed to career concerns arisen from political pressures? There is politics and career concerns in every academic institution — is academia in China different? In this section, we undertake several complementary exercises to show that much of the effects that we identify could be related to the political pressure and top-down controls that characterize the Chinese academic environment.

Academic leadership from the Communist Party

First, we examine whether the Communist Party representatives in academic departments exert as strong, or even stronger, influence on the faculty members' direction of research as academic leaders. Similar to the bureaucratic structure of many organizations in China, two parallel leadership posts co-exist in each department: academic leaders (who are department heads or deans) and the Communist Party representative or secretary. Party secretaries often have little academic background and are directly appointed within the party organization. Typically they are rotated from other Communist Party organs. For this exercise, we focus on the subset of party secretaries who have academic track records but have embarked on a political track within academic leadership.

We re-estimate our baseline specification (3) to explore the effects of Party secretaries on the research direction of faculty members in their departments. Figure 5, Panel A, presents the estimates. Reassuringly, there are no significant pre-trends prior to the Party secretary taking office, but the research similarity between faculty members and their Party secretaries starts increasing immediately thereafter. Although the estimates are noisy (which is inevitable given the smaller sample size of academically-active party secretaries), their magnitude is, on average, about three times the magnitude of the effect for academic leaders. This pattern confirms the political nature of the career concerns we have documented in the previous section, and is also consistent with the pattern that leaders with lower academic credentials tend to exhibit stronger influence on the faculty members' research activities.

Tenure and promotion reform that increased leadership power

Second, we examine whether the leadership transition effects become amplified when leadership power increases. As Chinese universities gradually introduce tenure track appointment and promotion system, the power of the department leaders increase since the system enables the leaders to review, promote, and terminate faculty appointment.[10] Although these promotions are in principle based on "merit," there is typically no external review and little views of objective criteria, amplifying the bureaucratic power of departmental leaders.[11]

For 20 social science departments at Peking University, we collect the starting date of the tenure track system. As tenure track appointment and promotion system changes the nature of academic appointment, faculty members hired by the university prior to the introduction of tenure track system are unaffected by its promotion rules. Among 5,770 faculty-leader pairs at Peking University, we classify 911 pairs as falling under the new tenure track system if the faculty member in question was hired after the tenure track reform. We then jointly estimate the effect of a leader switch on similarity scores for faculty-leader pairs that are either unaffected or affected by the tenure track system.

The results, presented in Appendix Figure A.8, show that there is a larger impact of leaders on research direction among faculty members hired after the introduction of tenure track system. Such amplified effect is consistent with the interpretation that the routine review and promotion of faculty members as part of the tenure track system increases the power of the (already powerful) academic leaders, allowing them to make explicit decisions concerning the careers of the faculty under them as they often retain veto rights on faculty members' tenure promotion case.[12]

Legacy of historical academic persecutions

Third, we explore whether academic persecution in the more distant past may have persistently shaped the present-day academic environment and influenced the extent to which leaders are able to influence research directions. The ability of academic leaders to exert control over faculty members under their jurisdiction may have its roots in the broader institutional structure of modern China. If so, we may also expect that these roots are persistent and may be linked to prior episodes of top-down actions to control

[10] Faculty members hired prior to the tenure track reform remain as national civil servants, whose appointment was determined by the central government rather than the university. As a result, firing of faculty members is rare as it requires multi-level approvals beyond university leadership.

[11] While a robust, independent tenure track system is one of the quintessential institutional features that ensures academic freedom in American and European universities, academic freedom and autonomy is *not* a primary objective of China's introduction of tenure track system. Several departments (such as the Department of Physics at Tsinghua University) introduced tenure track appointment and promotion system in the early 2000s, the vast majority of departments in the universities that we examine formally began tenure track reform on or after 2013.

[12] Albeit an extreme example, a recent murder case of a department Party Secretary in Fudan University due to his denial of tenure to a faculty member demonstrates the controls leaders can exert during the tenure promotion process (see `https://bit.ly/3qq3hKG` for more details).

academia by the Chinese Communist Party.

For this purpose, we follow Wang and Kung (2021) and measure the academic disciplines' likelihood of facing top-down persecution during the Cultural Revolution (1966-1976). Wang and Kung (2021) show that academics in disciplines with higher ideological dissension, particularly those in humanities and social sciences, faced disproportionately higher rates of intellectual persecution during the Cultural Revolution than their peers in sciences, applied sciences and engineering. We follow Wang and Kung (2021) in using the Discipline Classification and Code (*xueke fenlei yu daima*) developed by the National Standardization Management Committee (*guojia biaozhunhua guanli weiyuanhui*) to construct a measure of ideological dissent for each academic discipline.[13] Based on the ranking of second-level classification codes, we construct a normalized index which assigns a value of zero to the discipline with the lowest level of ideological dissent and one to the discipline with the highest dissent.

We then re-estimate the baseline specification in (3) separately by discipline. We plot, in Figure 6, the estimated leadership transition effects against the ideological dissent rank.[14] We observe a positive association between the severity of persecution during the Cultural Revolution and the impact of leaders on the research direction of the faculty under their control (*p-value* = 0.0966). This suggests that more severely-persecuted disciplines (during the Cultural Revolution) exhibit greater responsiveness to leader switches today. We interpret this finding as showing a persistent legacy of political pressure and deprivation of academic freedom that originated during the Cultural Revolution. It also raises the intriguing possibility that lack of academic freedom can have persistent effects holding back independent research initiatives in present day, potentially resulting in substantial long-term cost to research quality (as we explore next).

[13] Under this classification scheme, each academic discipline is ranked based on the level of "consensus" and "paradigmatic development" in the discipline. The classification scheme assigns a unique code that identifies up to three levels of classification for each academic discipline: 62 first-level discipline groups (e.g., economics) are divided into 676 second-level disciplines (e.g., labor economics), and then further subdivided into 2,382 third-level disciplines (e.g., labor economic history). As in Wang and Kung (2021), we use the second-level classification code for analysis. A faculty member in the discipline of economics, for example, is assigned a unique second-level classification code based on whether they specialized in political economy, labor economics, development economics, business economics, economic history, etc. Consensus within a discipline around general accepted theories, laws, frameworks, methods and beliefs serves as a proxy for how much ideological dissent vs. general academic co-optation there is within that discipline. Disciplines that exhibit lower consensus (and thus higher ideological dissent) are those in humanities and social sciences, while natural sciences show higher consensus and thus lower ideological dissent.

[14] Appendix Figure A.7 presents the estimated baseline effects of leadership transition, discipline by discipline. In this exercise, 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.

Influence of contemporary academic persecutions

Fourth, we examine whether the leadership effects become stronger after major incidences of researchers removed explicitly due to their political stances. Experience of academic persecution in close proximity may indicate more powerful top-down academic control in the institutions, or may induce strong reaction among faculty members in order to submit to academic authorities and leadership.

We gather a record of academic persecution throughout China after 2013, which includes 38 cases at the department level.[15] These cases of academic persecution typically involve faculty members publicly publishing articles or expressing opinions criticizing the government's political agenda, resulting in the subsequent firing of these faculty members from their academic positions. We create a university-year-specific shock, and we investigate whether the main leadership transition effects we identify intensify after the shock.

We re-estimate the baseline specification separately for leadership transitions that occur before and after the occurrence of academic persecution in the corresponding universities. Figure 5, Panel B presents the results. We observe that after the occurrence of these incidents in a given university, leadership transitions in the same institution (across all disciplines) exhibits substantially stronger effects on researchers' output.

Political vs. scientific semantics

Fifth, we decompose whether convergence in research output is driven by scientific language used in the publication or political language. Since word embeddings in NLP methods reflect different political sentiments (Yang and Roberts, 2021),[16] we evaluate research convergence measuring textual similarity based on different semantics.

Specifically, we construct two separate textual similarity scores using two sets of word embeddings from Word2Vec models: one is pre-trained with (and hence load more weights on) *People's Daily* newspaper, the official newspaper of the Chinese Communist Party and hence capturing political semantics; the other is pre-trained with *Chinese Wikipedia*, capturing scientific semantics. If two research papers are similar primarily because they use similar political language, then the similarity measures trained on the *People's Daily* would score high relative to the measure trained on the Chinese Wikipedia. In contrast, if two

[15] Faculty members in social sciences are more vulnerable to academic persecution. Only 3 of the 38 events happen to professors in the natural science departments.

[16] Yang and Roberts (2021) show that, compared with Chinese language Wikipedia which is free of censorship, word embeddings trained on corpora that are monitored by the Chinese government can have very different semantic meaning for a variety of concepts such as democracy, freedom, collective action, and equality.

papers are similar primarily because they use similar scientific language, then the similarity measures trained on the Chinese Wikipedia would score relatively high. Appendix Table A.3 illustrates this with several examples.

Using these two similarity measures using political and scientific semantics, we examine, conditioning on the convergence in scientific content in research, whether leadership transition induces a residual convergence in content that aligns the political authority more generally. We estimate the leadership transition effect on research similarity in political semantics, following the baseline specification (3) but in addition controlling for research similarity in scientific semantics. The results are shown in Appendix Figure A.6. We observe significant increase in the similarity in political semantics after leadership transmission controlling for research similarity measured using scientific semantics, suggesting that political incentives is an important mechanism through which leaders can influence faculty's research direction.

Comparison with Singaporean universities

Finally, we replicate our baseline exercise among universities in Singapore in order to shed light on whether bureaucratic career concerns are uniquely present in Chinese universities. Singaporean universities are good case for such test as they are situated in a cultural environment similar to that of China but have drastically different academic institutions closely modeled after their counterparts in the UK and the US.

Figure 7 presents the results following the baseline specification (3) but examining the effect of leadership transition of department chairs in Singaporean universities. One observes that leadership transitions in Singaporean universities do *not* affect faculty members' research directions. Not only is the magnitude of the estimated effects substantially smaller than that we observe in Chinese universities, the point estimates are in fact negative — opposite of convergence in research activities due to leadership transition. While not intended to be a comprehensive investigation of universities around the world, this result suggests that the bureaucratic incentives we identify in Chinese universities could indeed be closely tied with political considerations and the political power that academic leaders command.

6 Implications for research quality

Do leadership transition and politically-charged incentives among faculty members impact research quality? We already saw that leadership transition induces stronger effects on faculty members' research portfolio in lower-ranked universities and for leaders who are themselves below-average in terms of research output, suggesting that the overall research quality may be compromised. We now directly look at whether attempts to carry favor with leaders results in lower-quality research. We do so using several empirical strategies.

First, we examine whether changes in the quality of academic leaders due to leadership transition affect the citation counts received by the papers published by the faculty members under different leadership.[17] Specifically, we define high (low) productivity leaders as those who have produced above (below) median numbers of research publications prior to their leadership appointment, relative to other leaders in the same discipline in similarly-ranked universities. We estimate the effects on citation counts of future research papers following leader switches from below-average to above-average leaders, and vice versa. For comparison, we show the effects of leadership transitions with no change in leader quality as well. In all specifications, we control for a full set of faculty member fixed effects and year fixed effects.

The results are presented in the top panel of Figure 8, as well as Appendix Table A.4, columns 1-4. We find that a switch from a below-median to an above-median leader is associated with greater citation counts (on average a 7.6% increase) and a switch from an above-average leader to a below-average leader is associated with significantly fewer citation counts (on average a 19.7% decrease). There are no effects from switches that involve leaders in the same quality category. These results are robust if we instead assume that papers with missing citation information receives no citation (see Appendix Table A.4, columns 5-8).

We further separately examine the impact of leadership transition on citations to papers that are most similar to the new leaders (defined as the paper with the highest similarity score with the current leader for each researcher) and citations to papers least similar to leaders (defined as as the paper with the lowest similarity score with the current leader for each researcher). These results are presented in the middle and bottom panels of Figure 8. Notably, we observe that the baseline effect on faculty members' average publication citation counts is entirely driven by citation counts of papers that are most similar to the leaders' research. When we look at papers that have little similarity to leaders, there are precise zeros, which suggests that our estimates are not driven by spurious

[17]Since the faculty members are always exposed to academic leaders, we cannot identify the main effect of political influence by leaders on research quality — for example, if the political career concerns caused by leaders in Chinese academia leads to, say, a 10% lower citation counts per paper, this will be the same both before and after a leader switch. Indeed, Appendix Figure 9, discussed below, shows that a first leadership transition has no impact on research quality. This motivates our empirical design where we look at the differential effects of below-average leaders.

factors. In addition, in none of these cases do we see any effect before the relevant switch, which is comforting regarding the validity of this empirical design.

Second, we investigate whether the impact on faculty members' research quality intensifies after the second or third leadership transition that faculty members experience since joining their current department. Multiple re-pivoting of research directions may become increasing costly. The results are presented in Appendix Figure 9. We find that when experiencing repeated transitions to low quality leaders, the negative impact on faculty member's research quality increase. When experiencing repeated transitions to high quality leaders, the positive effect of the first transition diminishes and turns negative after the 2nd such transition. These patterns suggest that there may be a cumulative negative impact of leadership transitions on research quality — perhaps because several changes in research direction intended to carry favor with department leaders start to have considerable compounded costs.

Third, we examine whether leadership transition's impact on faculty members' research quality increases after occurrence of academic persecution cases in the specific universities. We follow the identification of academic persecution cases in Section 5, and we separately estimate the effect of leadership transition on research quality before and after occurrence of academic persecution in a given university. Since the leader switch effects on citation are in different directions for transitions to low and high-quality leaders, we switch sign of the outcome of interest to negative if leadership transitions to high-quality leaders. Appendix Figure A.9 presents the results. We find that the negative effect of leadership transition on faculty members' citation counts increases after universities experience academic persecution.

Taken together, the evidence presented above indicates that the pivot of research direction towards a new leader's style tends to move faculty members away from their academic strength and comes at the cost of producing lower quality research. Combined with our earlier results that showed an oversized influence of below-average leaders and Communist Party representatives, these results suggest that Chinese researchers are often incentivized to change their research style to suit the preferences of academically-undistinguished leaders, and indeed, this is often associated with low-citation research papers. Such re-pivot resulted from local political concerns and political pressure in the academic environment impose meaningful costs on research quality.

7 Conclusion

Throughout history, most 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). In this light, modern-day China may be viewed as an almost unique case of an authoritarian regime deeply committed to innovation. But is this enough for producing high quality research? Or do the authoritarian political system and its reverberations throughout Chinese bureaucracy and society still distort the direction of research and suppress its quality? These questions are 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. We exploit the appointment of new department leaders in the 109 top Chinese universities, who typically have extensive powers for resource allocation, promotion and termination. These leaders and their powers at least partly reflect the authoritarian nature of Chinese political system and the organizational structure of Chinese academia. 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, and whether this comes at a significant cost in terms of research quality. We build a data set comprising the academic publications of all leaders and faculty members in these universities. Using NLP methods, we construct measures of similarity between leaders' and faculty members' research output. We combine these data together with data on changes in leadership switches (where leaders comprise of department heads, deans and Chinese Communist Party representatives and departments) and data on citation counts.

Our main finding is 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 after a leadership transition, 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. Environment of greater autonomy, less political interference and better institutional safeguards for meritocratic promotions and external review are designed to minimize such interference on academic inquiry. While we find that the the effects of new leaders on their faculty is more pronounced in lower-ranked departments, which typically lack procedures for external review and robust tenure track system, such effects has grown in importance after tenure track appointment and promotion system was introduced. Intriguingly, this suggests that tenure track reform may be context dependent, and its introduction in environment with top-down political and academic control may in fact increase the *de-facto* power of academic leaders over the careers of faculty under their rule.

Do political pressures affect the quality as well as the direction of research? We show that the answer is likely yes. When there is a switch from a below-average leader to an above-average leader (in terms of publication output), there is an increase in the quality of research as measured by citation counts. Conversely, a switch from an above-average to a below-average leader is associated with significant costs in terms of citation counts. We document that these results are driven entirely by papers that are most similar to new leaders' research portfolio, thus bolstering the case that research is being redirected away from areas in which faculty have expertise towards less highly cited, lower-quality areas intended to curry favor with new leaders. We also present results suggesting that leadership switches have negative cumulative effects — faculty experiencing several leadership switches become less productive.

We view our paper as a first step in a research agenda that explores the relationship between political factors and the direction and quality of innovation, originating both from national institutions and local organizations. This agenda is important for several reasons. As new technologies such as artificial intelligence, nanotechnology and new materials become increasingly important, the quality and direction of research and innovation for global prosperity are 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 in many other contexts, and as input into designing better academic institutions under democratic institutions.

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, which would enable a valuable comparative perspective — in particular to see whether similar politically-charged career concerns are present in the academia of less authoritarian countries. Second, in more data-rich environments, it may be possible to look at other characteristics of leaders, such as 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

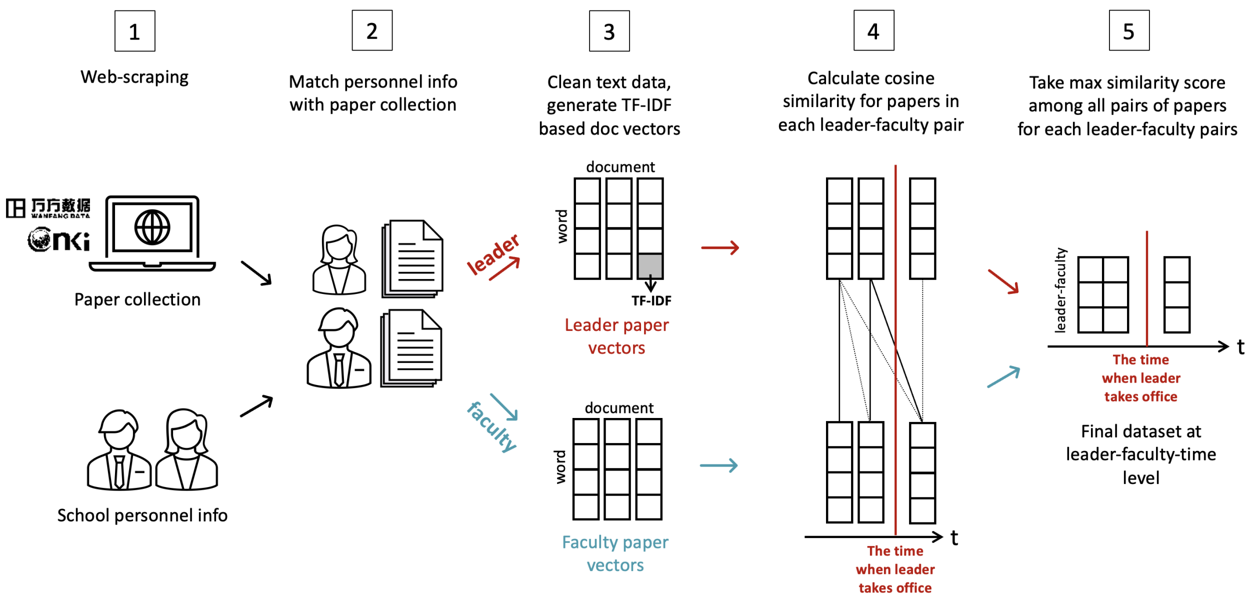


Figure 1: The data construction procedure.

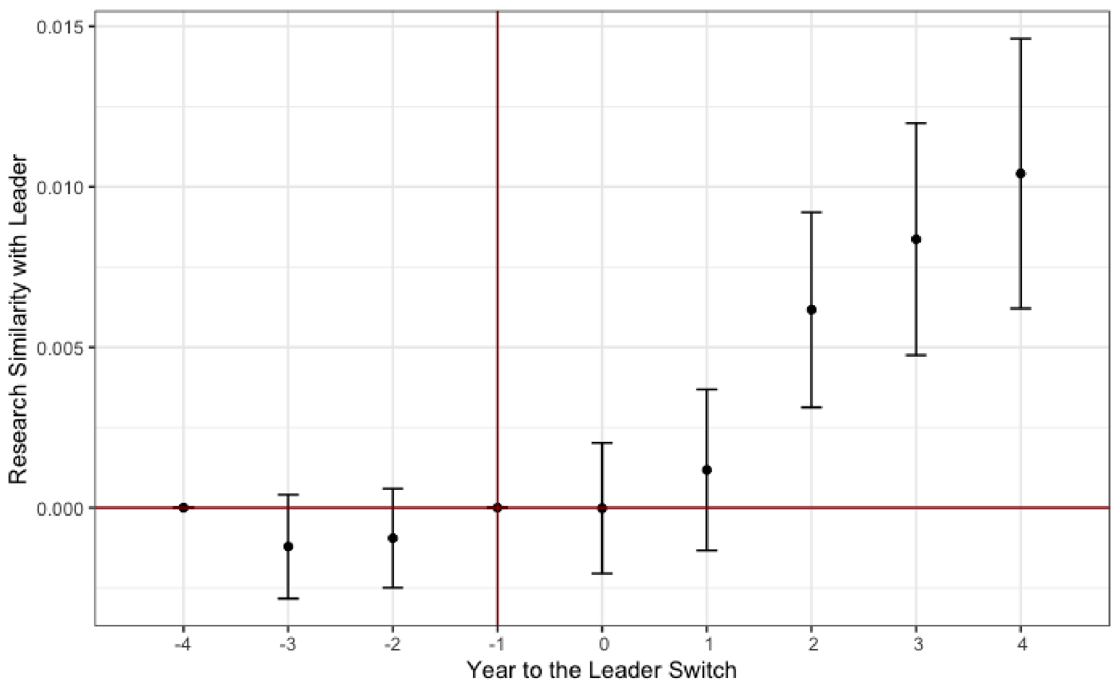


Figure 2: Impact of leader switch on the faculty-leader similarity score. The points in the figure represent the estimated effects of event time relative to leadership switch, controlling for the full sets of faculty-leader pair fixed effects and time fixed effects (i.e., the ψ_l from the nonparametric event study in equation 3, $Y_{i,t} = \sum_{l\neq-1;l=-3}^{4} \psi_l D_{i,t}^{l} + \alpha_i + \lambda_t + v_{i,t}$). The error bars represent the 95% confidence intervals.

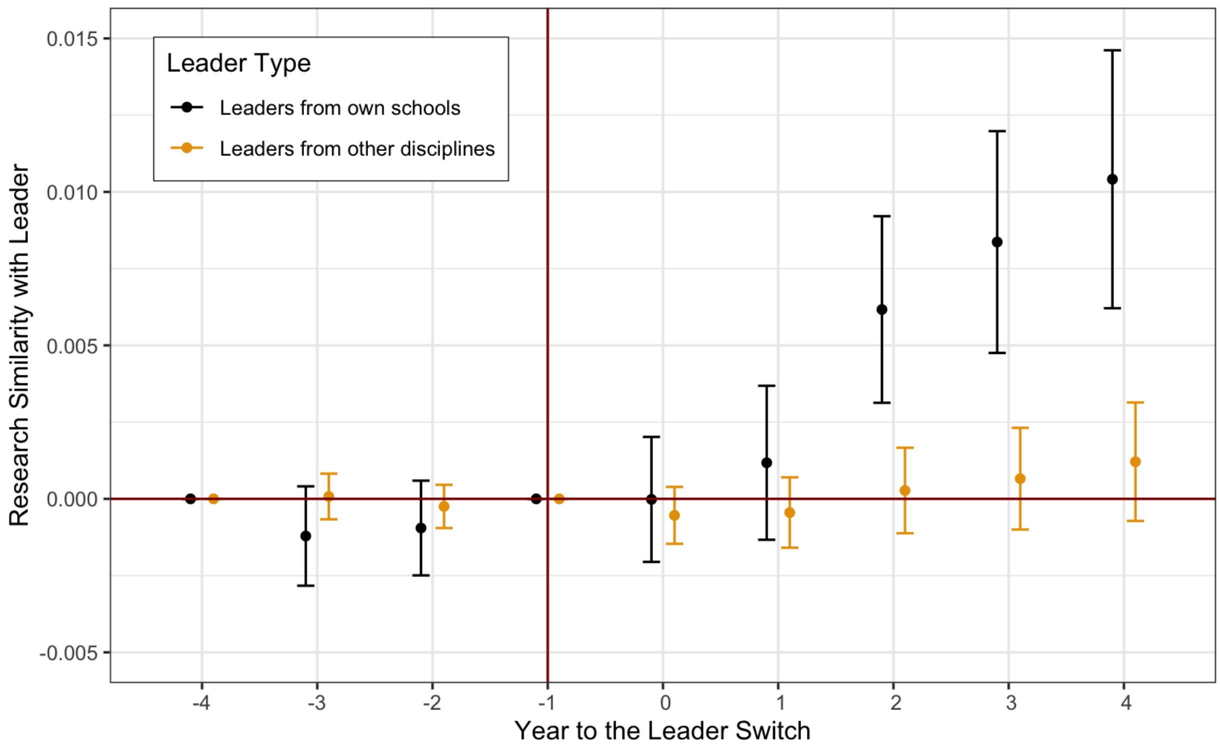
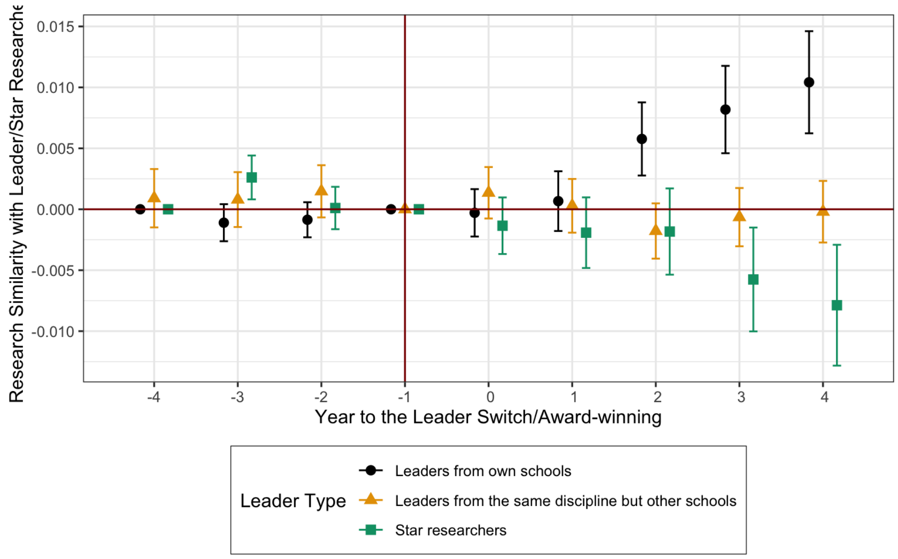
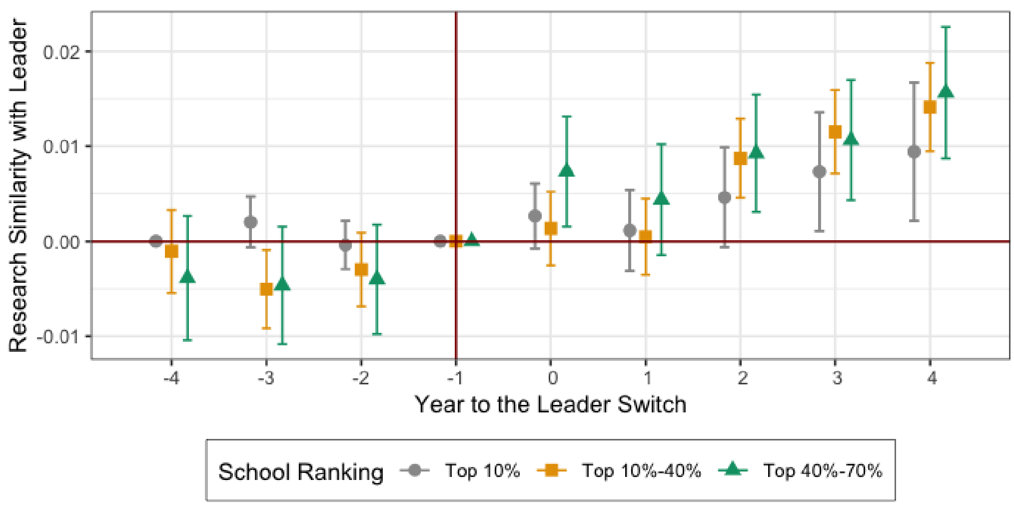


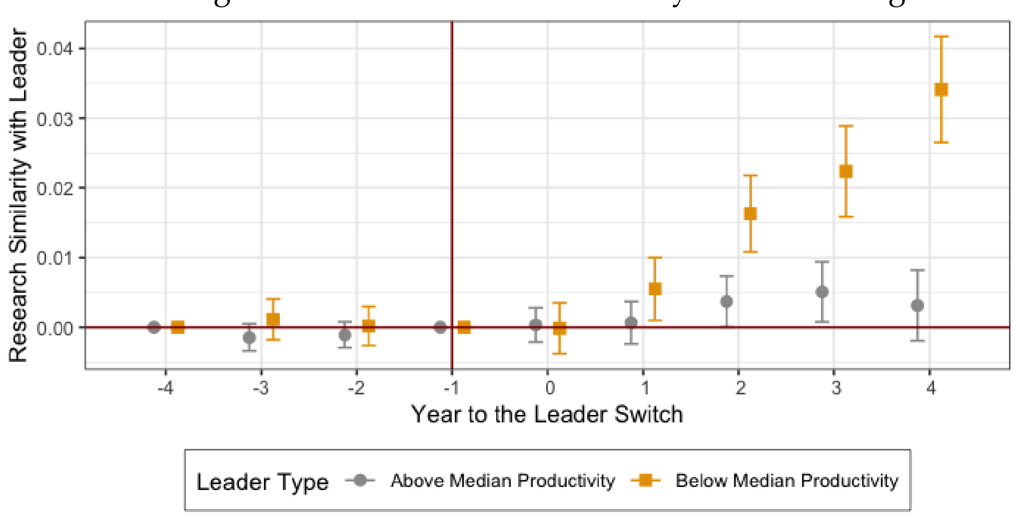
Figure 3: Impact of leaders from other disciplines on the similarity score. This panel uses the faculty-leader pairs in which leaders from other disciplines. The yellow lines/markers in the figure the estimated effects of event time relative to leadership switch, controlling for the full sets of faculty-leader pair fixed effects and time fixed effects (i.e., the ψ_l from the nonparametric event study in equation 3, $Y_{i,t} = \sum_{l \neq -1; l=-3}^{4} \psi_l D_{i,t}^l + \alpha_i + \lambda_t + v_{i,t}$). The black lines/markers replicate our baseline results in Figure 2.



Panel A: Impact of leaders from other higher ranked schools, leaders from other lower ranked schools, and star researchers on the similarity score.

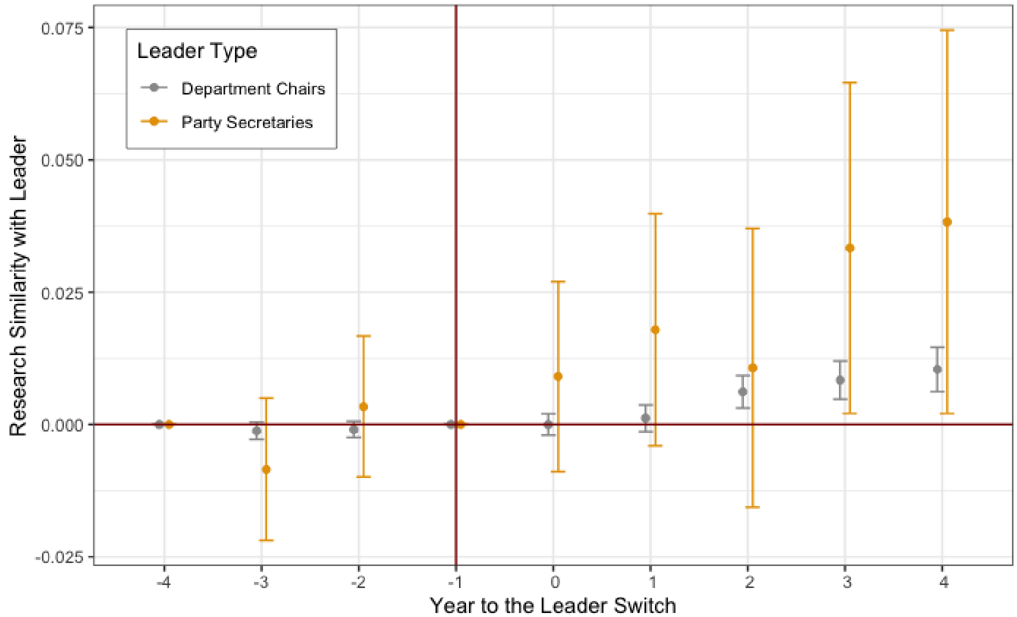


Panel B: Heterogeneous effect of leader switch by school ranking.

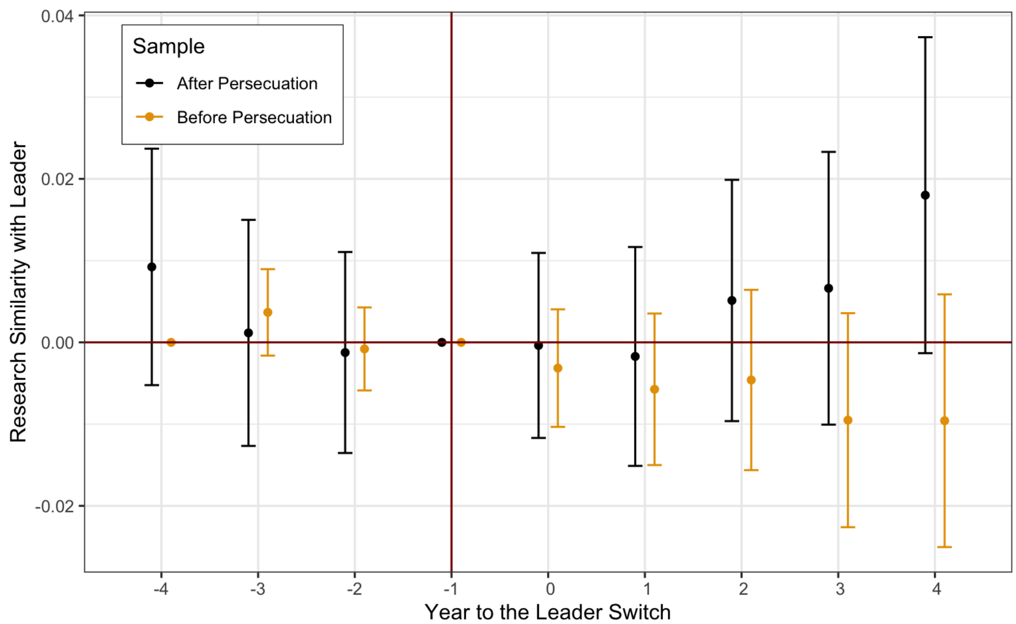


Panel C: Heterogeneous effect of leader switch by the productivity of leaders.

Figure 4: In Panel A, black, yellow and grey dots are estimated based on the faculty-leader pairs in which leaders from other higher ranked schools and leaders from other lower ranked schools. We estimate the effect of the two type of leaders simultaneously in regression $Y_{i,t,c} = \sum_{l\neq-1;l=-3}^{4} \mu_l D_{i,t,c}^{l} \times H_i + \sum_{t\neq-1;t=-3}^{4} \psi_l D_{i,t,c}^{l} + \alpha_i + \lambda_t + v_{i,t,c}$. In the equation, H_i is the indicator for whether the leader in pair i is in the same discipline as the faculty in pair i but from other schools (=1) or not (=0). The yellow lines/squares represent the estimated effects of leaders from the same discipline but other schools (i.e., the $\mu_l + \psi_l$ in the regression). The grey lines/triangles represent the estimated effects of leaders from the same discipline but other schools (i.e., the $\gamma_l + \psi_l$ in the regression). The black lines/dots replicate our baseline results in Figure 2. For the green diamonds in Panel A, they show the effect of winning the award on research similarity. Time 0 is the year when the star researchers earn the award from Changjiang Scholar Program. The grey dots/lines show our baseline result – the effect of leader switch on research similarity. Time 0 is the year when the department head starts her position. In Panel B, 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%. In Panel C, 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. The error bars represent the 95% confidence intervals.



Panel A: Heterogeneous effect of department chairs and party secretaries



Panel B: Heterogeneous effect of leader switch before and after academic persecution.

Figure 5: In Panel A, 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. The grey lines/markers represent the estimated effects of leaders department heads. In Panel B, We estimate the effects simultaneously in regression $Y_{i,t} = \sum_{l\neq -1; l=-3}^{4} \mu_l D_{i,t}^{l} \times T_i + \sum_{t\neq -1; t=-3}^{4} \psi_l D_{i,t}^{l} + \alpha_i + \lambda_t + v_{i,t}$. T_i is the indicator for whether the leader in pair i is after the university has an academic persecution event (=1) or before the event (=0). The yellow lines/markers represent the estimated effects of leaders before the persecution (i.e., the ψ_l in the regression). The black lines/markers represent the estimated effects of leaders after the persecution (i.e., the $\mu_l + \psi_l$ in the regression).

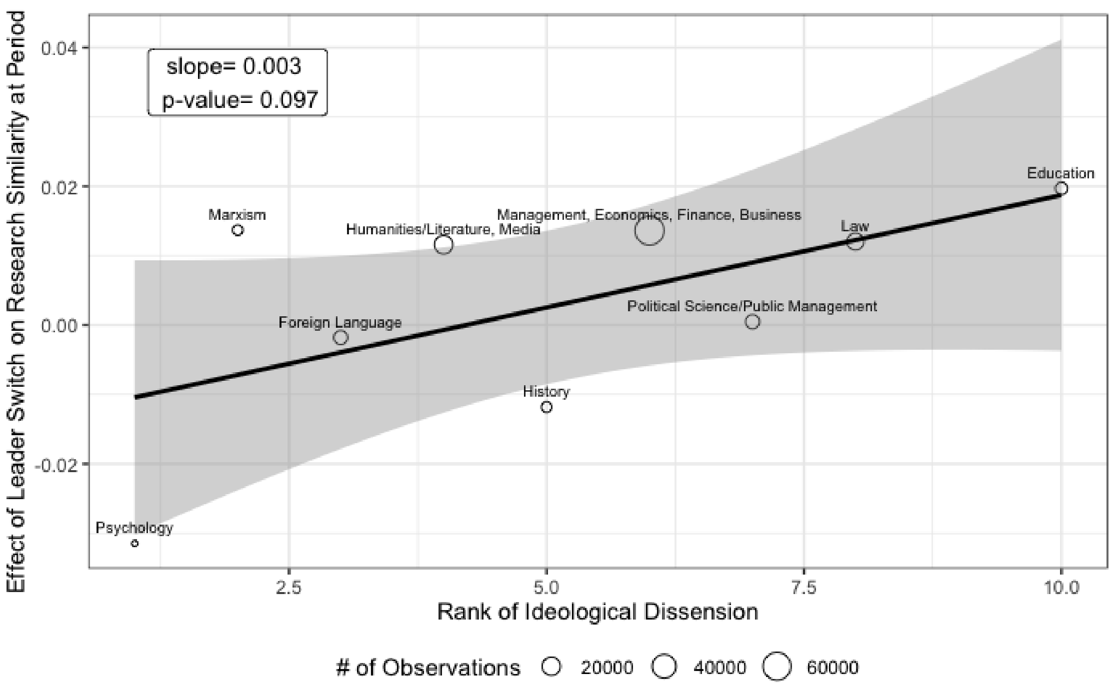


Figure 6: The correlation between the effect of leadership switch and the measure of ideological dissension. The x-axis shows the ranking of "ideological dissension." There is less ideological dissension in the discipline when the ranking is lower. The y-axis is the effect of leader switch at t=4. Each point represents a discipline.

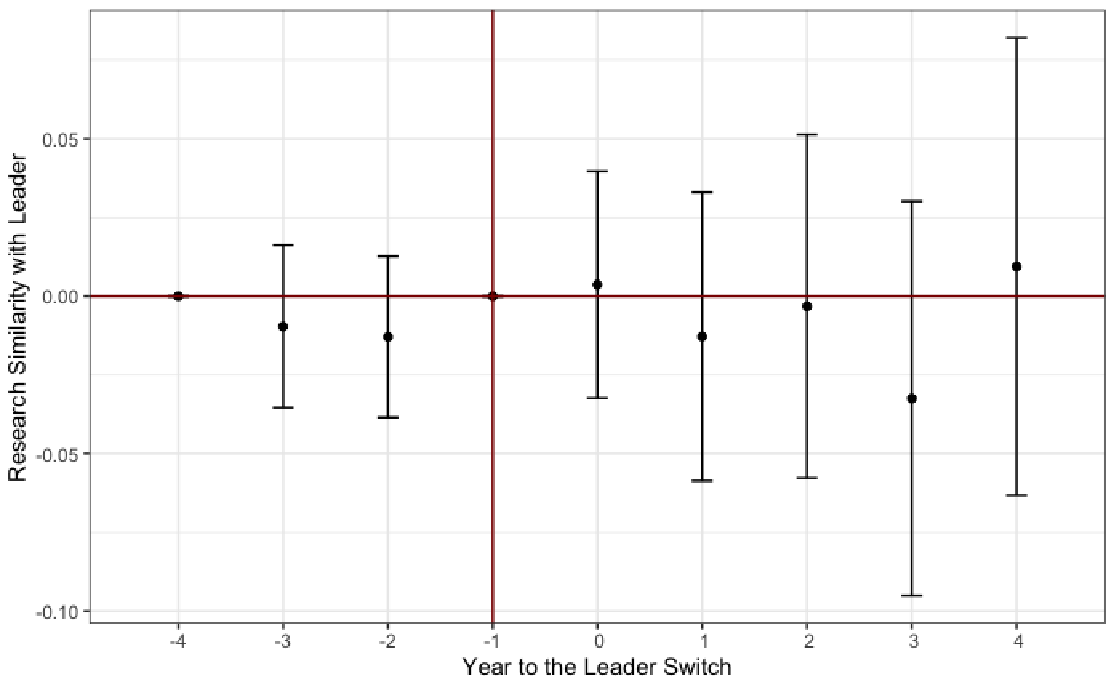


Figure 7: Impact of leader switch on the faculty-leader similarity score, among leaders and faculty members in Singaporean universities. The points in the figure represent the estimated effects of event time relative to leadership switch, controlling for the full sets of faculty-leader pair fixed effects and time fixed effects (i.e., the ψ_l from the nonparametric event study in equation 3, $Y_{i,t} = \sum_{l\neq -1; l=-3}^{4} \psi_l D_{i,t}^{l} + \alpha_i + \lambda_t + v_{i,t}$). The error bars represent the 95% confidence intervals.

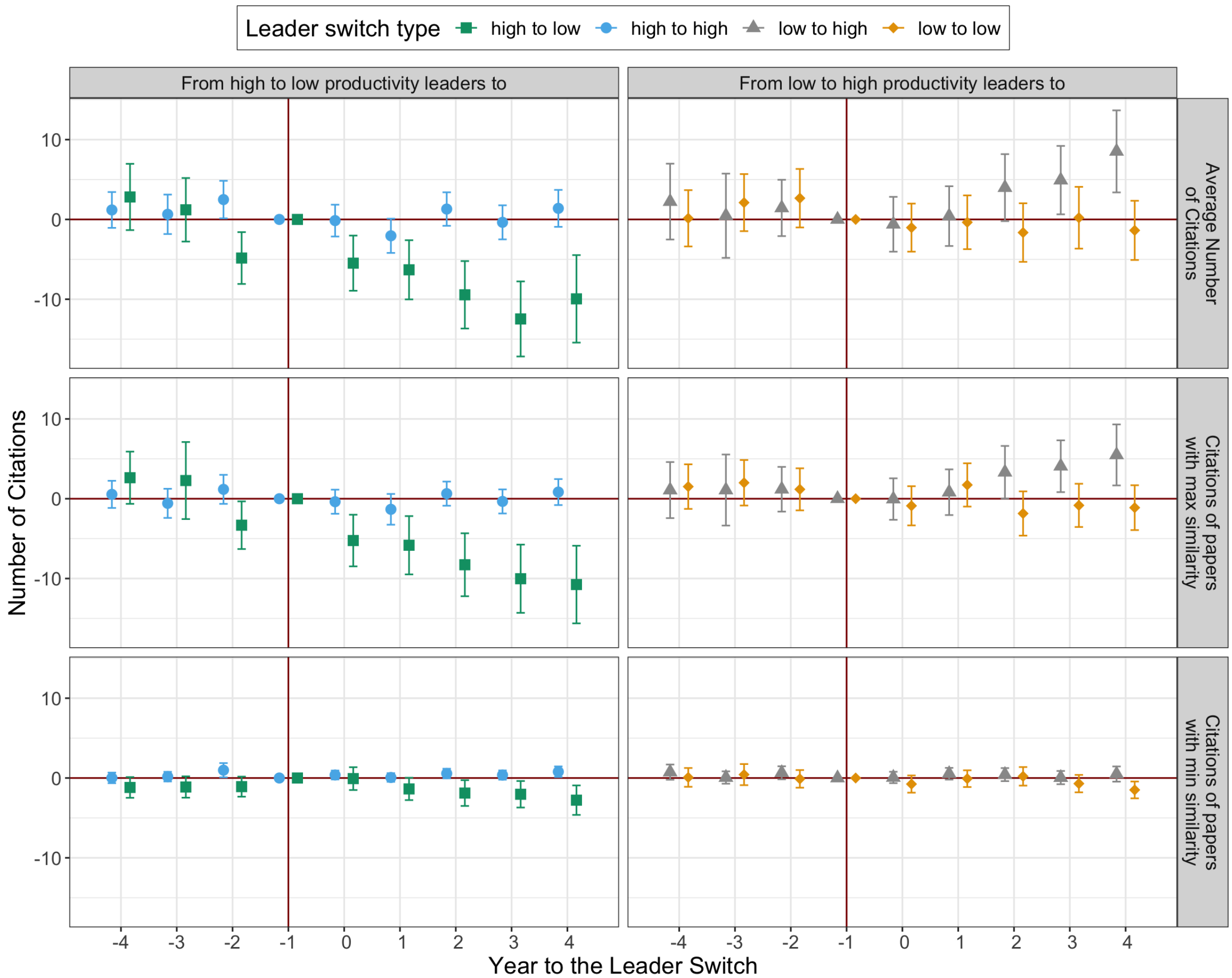
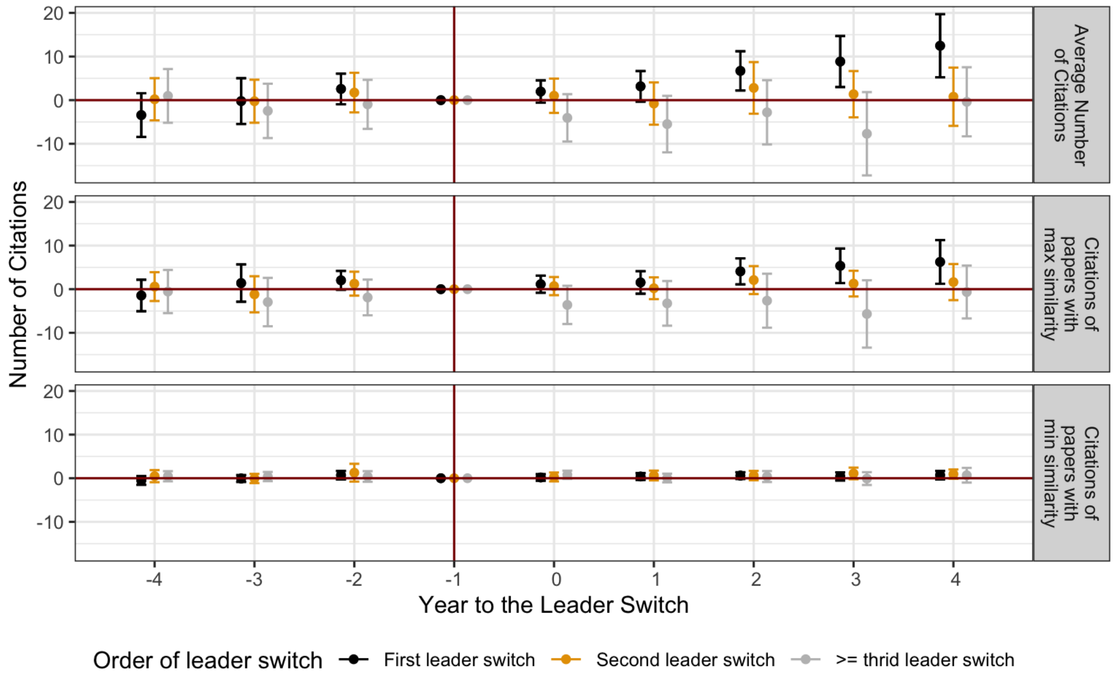
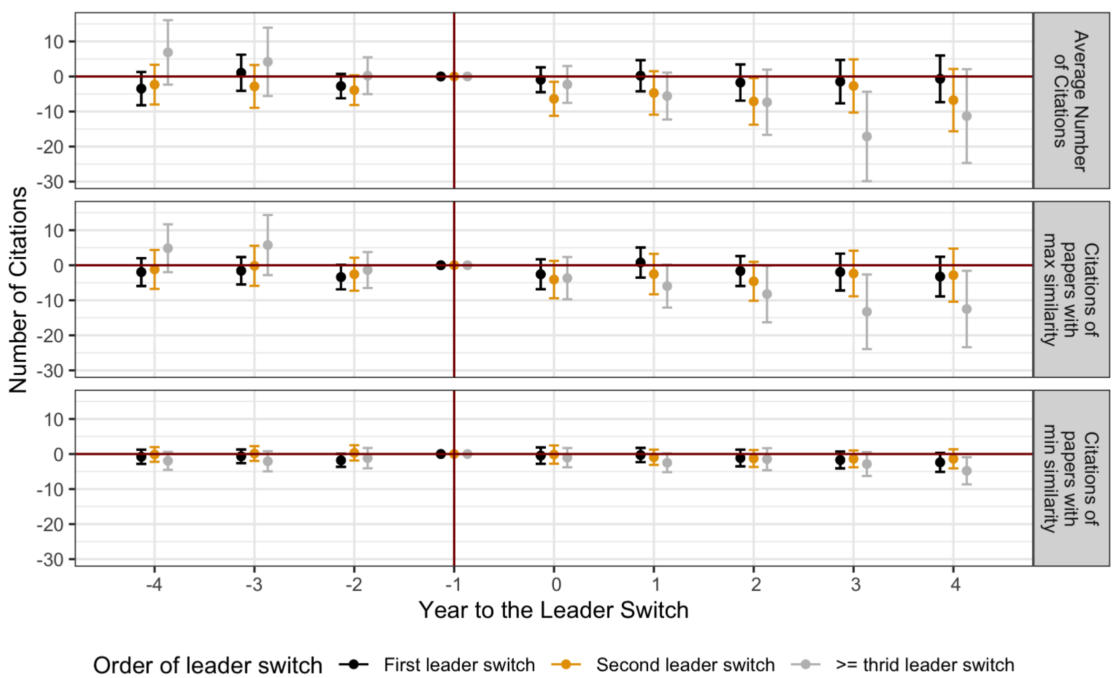


Figure 8: Impact of leaders on citation counts. The points in the figure represent the estimated effects of event time in the following regression: $Y_{i,t} = \sum_{l \neq -1; l=-4}^{4} \psi_l D_{i,t}^l + \alpha_i + \lambda_t + v_{i,t}$, where $D_{i,t}^l$ is an indicator for faculty i being l periods away from initial treatment at calendar year t; α_i is a full set of the faculty fixed effects; and λ_t is a full set of calendar time fixed effects. The error bars represent the 95% confidence intervals. The grey lines/markers represent the estimated effects using the sample of low-to-high leader switches. The yellow lines/markers represent the estimated effects using the sample of low-to-low leader switches. The green lines/markers represent the estimated effects of leaders on citation counts using the sample of high-to-low leader switches. And the blue lines/markers represent the estimated effects of leaders on citation counts using the sample of high-to-high leader switches



Panel A: Transitions to high-productivity leaders.



Panel B: Transitions to low-productivity leaders.

Figure 9: Heterogeneous effect by the order of leadership transaction. Panel A shows the effects estimated based on transitions to high-productivity leaders. Panel B is using the sample which only consists transitions to low-productivity leaders. We separately estimate the effect of leader switches on citation counts for different order of leadership transition within a faculty member. The points in the figure represent the estimated effects of event time relative to leadership switch on the faculty-leader similarity score, controlling for the full sets of faculty-leader pair fixed effects and time fixed effects (i.e., the ψ_l from the nonparametric event study in equation 3, $Y_{i,t} = \sum_{l \neq -1}^{4} \psi_l D_{i,t}^l + \alpha_i + \lambda_t + v_{i,t}$). The black markers represent the estimated effects for leader switches that are firstly experienced by faculty. The yellow lines/markers represent the estimated effects of the second leader switch experienced by faculty. And the gray lines/markers combine the effect of the rest of the switches.

Table 1: Leadership effect on research direction

	Baseline	Robustness with Different Similarity Measures			Including English publications	Different specification
	(1)	(2)	(3)	(4)	(5)	(6)
2 years before	-0.001	-0.0009	-0.0013	-0.0014	-0.0009	-0.0084
	(0.0007)	(0.0005)	(0.0005)	(0.0007)	(0.0007)	(0.0023)
4 years after	0.0104	0.0068	0.0057	0.0146	0.0103	0.0491
	(0.0021)	(0.0015)	(0.0015)	(0.0021)	(0.0021)	(0.0116)
Observations	292,968	292,968	292,968	278,381	292,968	292,968
R-square	0.0004	0.0003	0.0003	0.0006	0.0004	0.0025
Outcome variable	TF-IDF	Doc2Vec People's Daily	Doc2Vec Wikipedia	TF-IDF	TF-IDF	TF-IDF
Window of leader's publication	$[-\infty, -1]$	$[-\infty, -1]$	$[-\infty, -1]$	$[-3, -1]$	$[-\infty, -1]$	$[-\infty, -1]$
Sample of publications	Chinese	Chinese	Chinese	Chinese	Chinese+English	Chinese
Faculty-leader pair FE	✓	✓	✓	✓	✓	
Faculty FE						✓
Leader FE						✓
Year FE	✓	✓	✓	✓	✓	✓

Note: Column 1 shows the estimates of one pre-period ($t = -2$) and one post-period ($t = 4$) based on our baseline specification 3. Column 2-4 show the estimates of $t = -2$ and $t = 4$ using different versions of similarity scores. Column 2 uses the similarity score calculated based on a Doc2Vec model that is pretrained by People's Daily. Column 3 uses the similarity score calculated based on a Doc2Vec model that is pretrained by Chinese Wikipedia. Column 4 use a window of publications among leaders during the past 3 years rather than the entire portfolio to construct similarity score. Column 5 shows estimates when we extend the pool of publications by include English papers. Instead of faculty-leader fixed effects, column 6 shows estimates when we control for leader fixed effects and faculty fixed effects. Standard errors are clustered at the department level.

ONLINE 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.B1 shows the validation result.

Table A.B1: 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

C English Publications

C.1 Data Validation for English Publications

To provide a benchmark for the completeness of English publications, we use the number of papers that we previously manually collected based on the search results of Google scholar for 100 randomly selected scholars. In Figure A.C1, each dot in the figure represents a scholar. We put the number of papers collected from Google Scholar on the x-axis and the number from CNKI on the y-axis. The figure shows that our scraping results are well aligned with the 45-degree and correlation coefficient between Google Scholar and CNKI equals 0.75.

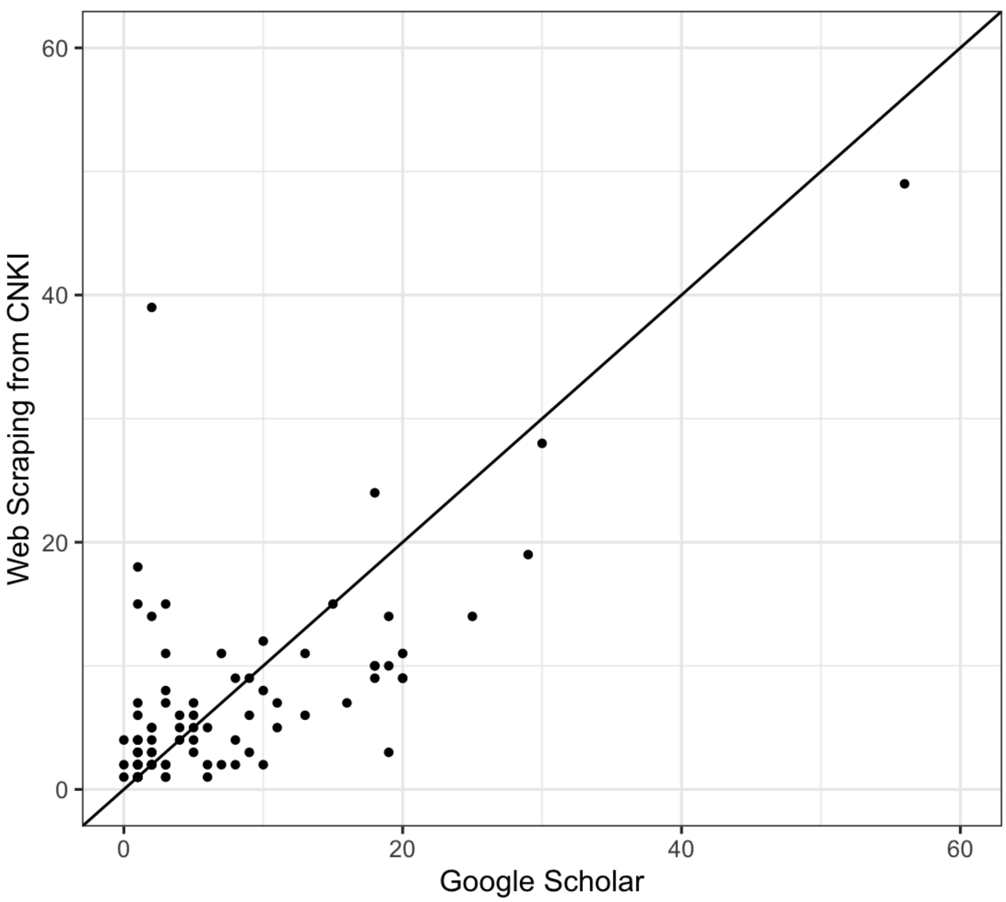


Figure A.C1: Each dot represents a scholar, for which the x-axis shows her paper number in Google scholar. The left y-axis (red) is the number of the current round, and the right (blue) is the number of our previous round. The black line is a 45-degree equivalence line.

For papers that are on Google but cannot be found through CNKI, most of the missing papers are because of CNKI's journal collection: (1) some small journals are not collected by CNK, (2) some journals on CNKI don't have author info listed. Concerns might be that these journals are censored in China and scholars will publish papers with different opinions on these journals. Based on the 10 cases we looked into, we didn't find it is the case.

Google scholar also includes papers that are (1) not published, such as NBER working paper, or (2) conference papers. These papers are not under our consideration.

C.2 NLP Analysis for English Publications

To compare the similarity between Chinese and Enlgish papers, we first translate English papers to Chinese with Azure Translator. And then, we calculate similarity scores based on the Chinese translation.

We first select 3 papers with both Chinese and English abstracts. The English abstracts are translated by the authors themselves. We select the 3 papers such that P2 is very similar to P3, and P3 is less relevant to P1. Denote the three papers as P1, P2, and P3. $P1_{eng}$ will refer to the English abstract of P1, and $P1_{zh}$ is the Chinese abstract of P1. $Sim(P1_{eng}, P1_{zh})$ then represents the similarity score between the Chinese and English abstracts of P1. Then the similarity score works well if:

1. $1 = Sim(P1_{eng}, P1_{zh})$
2. $Sim(P1_{eng}, P1_{zh}) > Sim(P2_{eng}, P1_{zh}) > Sim(P3_{eng}, P1_{zh})$

The following table shows the similarity scores calculated with the method:

$Sim(P1_{eng}, P1_{zh})$	0.988960176
$Sim(P2_{eng}, P1_{zh})$	0.980958178
$Sim(P3_{eng}, P1_{zh})$	0.971544729

D Data collection process for Singaporean universities and scholars

We first identified the most recent head of the department from department websites. To identify previous department heads, we searched google, google news and NewspaperSG with the following queries: [("NUS" OR "National University of Singapore") AND "Head" AND <department name> AND <year>] (or queries with the same search logic depending on the website). After obtaining a list of leader names from the department websites and online searches, we used personal websites, CVs, departments' information pages and other search results to identify the leaders' terms in office. We limited the list of department heads to those who held office after 2000 and identified 58 leaders from 17 departments.

Next, we gathered a list of 2,691 department staff from the NUS publication archive — NUS Scholar Bank (scholarbank.nus.edu.sg) — by recording all "researchers" associated with our short-listed departments. The website contains profiles of most researchers who worked at the time of website establishment and those who joined afterwards. Crucially, we located researcher profiles for all department leaders identified in the first step. While the exact time of website establishment is unknown, it could be inferred that the system started operation around the early to mid-2000s.

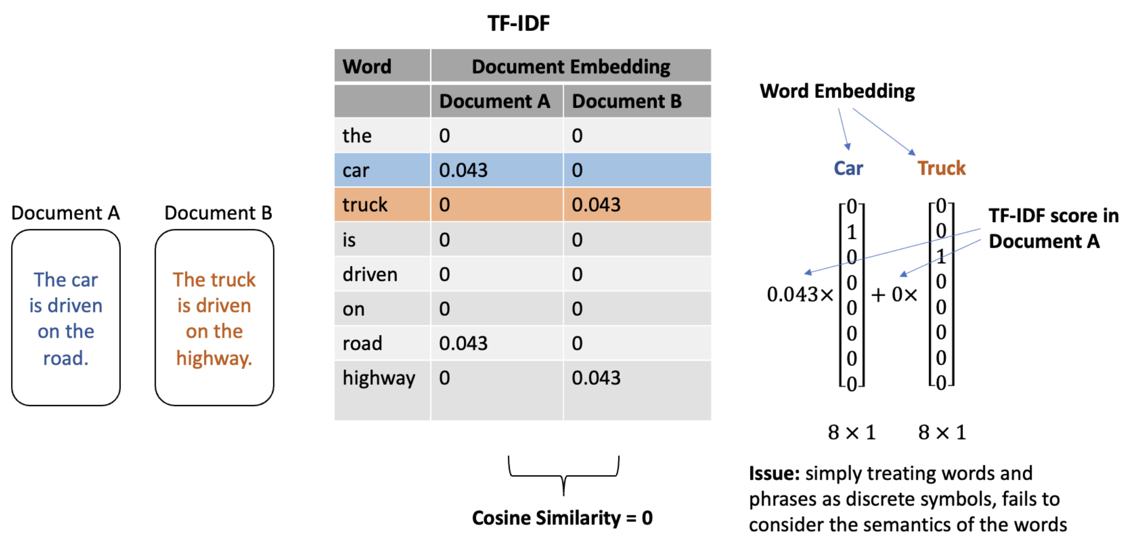
We then tried to locate researchers' profiles on Google Scholar, scinapse, and research gate. Due to inconsistent recording of names and insufficient biographical information on NUS Scholar Bank, we chose to locate profiles by manually locating the researcher's profiles on popular researcher/publication databases. Our main queries were made on Google Scholar using the phrase: [<researcher name>, <department name>, National University of Singapore] with minor modifications such as removing middle names, Chinese given names (for ethnic Chinese Singaporean researchers) or the university name. If publications topics and google scholar profiles matched with a staff's details, we saved the researcher's google scholar id (a string of characters after "user=" of the profile URL). If a researcher had not created a profile on google scholar, we would check for the presence of associated publication titles which were then used to make queries on scinapse and research gate. Similarly, we recorded profile unique identifiers on scinapse and research gates. This series of searches identified profiles for 1,470 unique researchers.

Unique identifiers from Google Scholar, scinapse and research gate allowed us to scrape relevant publication details, including titles, abstracts, and years of publication. To avoid duplicated publication records from multiple databases, we removed all subsequent publications with fuzzy-match scores above 90% by the same author. A total of 121,365 publications were identified.

E Similarity score based on Doc2Vec methods

Possible measurement error in TF-IDF The biggest issue for TF-IDF is that it can severely underestimate the similarity between two documents, which might be a major measurement error for our baseline regression. Consider comparing the similarity between the following two documents:

- Document A is "The car is driven on the road."
- Document B is "The truck is driven on the highway."



Word	Document Embedding	
	Document A	Document B
the	0	0
car	0.043	0
truck	0	0.043
is	0	0
driven	0	0
on	0	0
road	0.043	0
highway	0	0.043

Figure A.D1: A illustrative example of TF-IDF

The table in the middle shows the document embeddings (vectors) of the two documents. The document embedding is an 8x1 vector, where 8 is the size of the vocabulary. Each element in the vector is the TF-IDF score of the corresponding vector. After calculating the cosine similarity score of the two documents, we get the similarity score between the two documents equals 0. For each document embedding, we can view it as a weighted average over all of the word embeddings in the document. As shown on the right of Figure A.D1, the weights are TF-IDF scores, and the word embeddings are standard unit vectors.

Representing words as standard unit vectors treats words as discrete symbols. We assume "car" and "truck", "road" and "highway" are totally different, which leads to the result that the similarity score is 0.

Taking semantics of the words into consideration Replacing word embeddings with Word2Vec (Mikolov et al., 2013) will relax the assumption of TF-IDF that words are orthogonal.

The Word2Vec algorithm uses a neural network model to learn word associations from a large corpus of text. One of the Word2Vec structures – continuous bag of words (CBOW) – forms a sliding window around the current word and allows it to be predicted using the

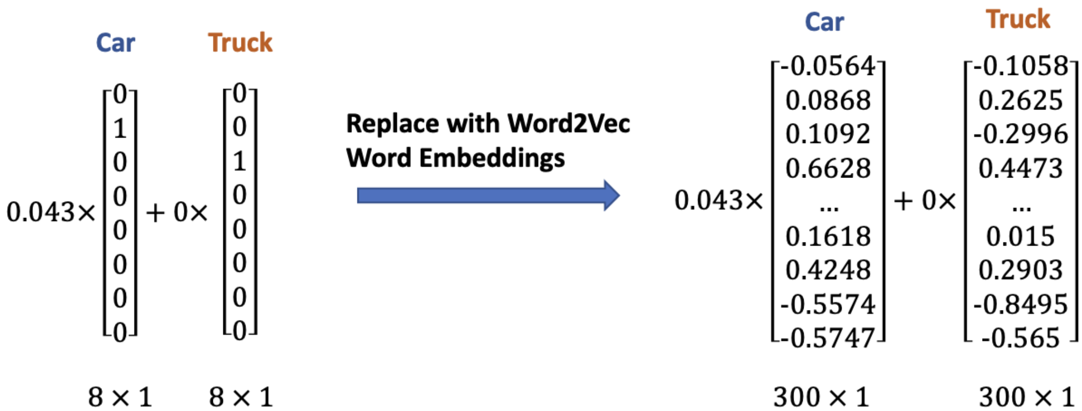


Figure A.D2: Change from TF-IDF to Weighted Word2Vec

words around it. A feature vector is used to represent each word. With this process, each word will be mapped to a $n \times 1$ vector and can represent the semantic similarity between words[1]. If we reconsider our previous example, using word embeddings from Word2Vec will increase the similarity score between Document A and B. The cosine similarity between "car" and "truck" is 0.81 rather than 0 in the TF-IDF case. With the new weighted average over all of the word embeddings in the document, the similarity score between Document A and B is 0.8442.

While training an informative Word2Vec model requires large train set and computation power, many researchers and institutions publicize their training results based on large corpus such as Wikipedia, newspapers, and twitter. One can use their results as pre-trained word embeddings and further finetune models to fit her own target corpus.

In our setting, we utilized two pre-trained Chinese word embeddings provided by Li et al. (2018): *(i)* Word2Vec trained with People's Daily News, and *(ii)* Word2Vec trained with Chinese Wikipedia.

Taking the ordering of the words into consideration Although weighted Word2Vec relaxes the orthogonality of semantics, another assumption is still concerning when numerically representing paragraphs – it ignores the syntax within each paragraph. Doc2Vec is developed to further tackle this issue and give paragraph embeddings.

Instead of directly using TF-IDF weights, Doc2Vec puts more structure on the relationship between words and documents to estimate the weights. Based on CBOW which utilizes words to anticipate the following word, Doc2Vec also includes a document-unique feature vector. As a result, when the word vectors are trained, the document vector is also trained which can be used as the numeric representation of the document.

[1]n will be a hyperparameter in the Word2Vec model. In the example here, we set $n = 300$.

F Additional figures and tables

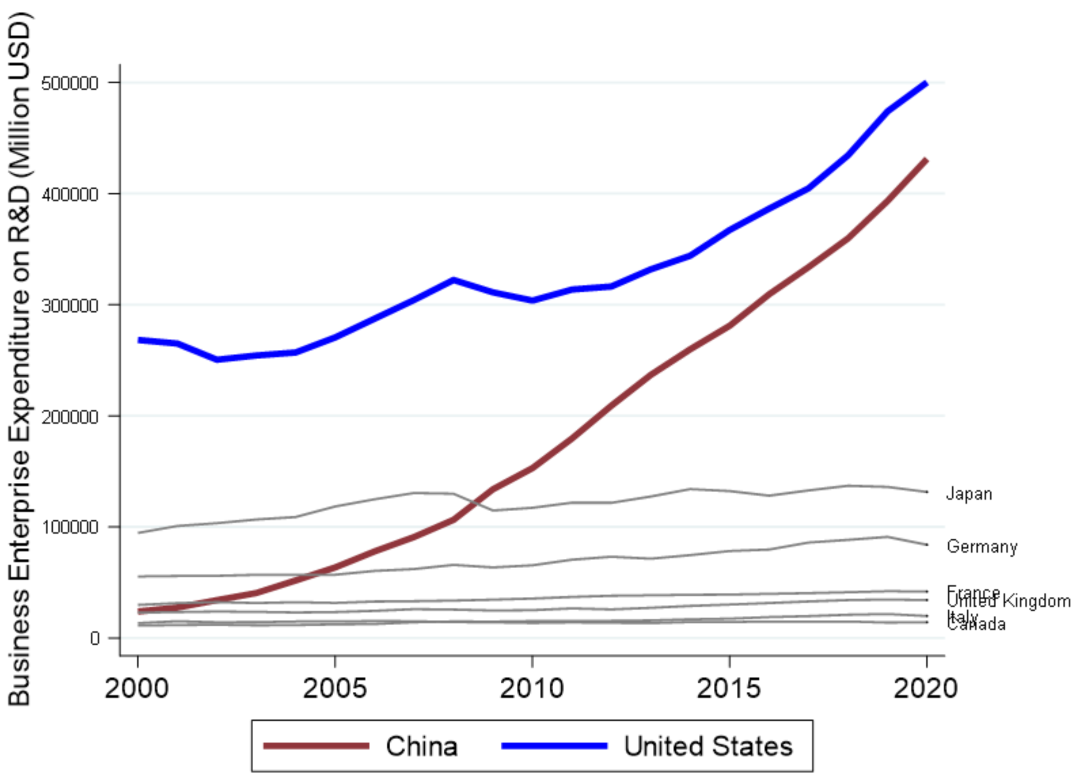


Figure A.1: Time series trend of the business enterprise expenditure on R&D for China, the U.S., Japan, Germany, France, U.K., Italy, and Canada. The figure is reported in constant price and PPP USD. Source: OECD Main Science and Technology Indicators (MSTI) database (OECD, 2022).

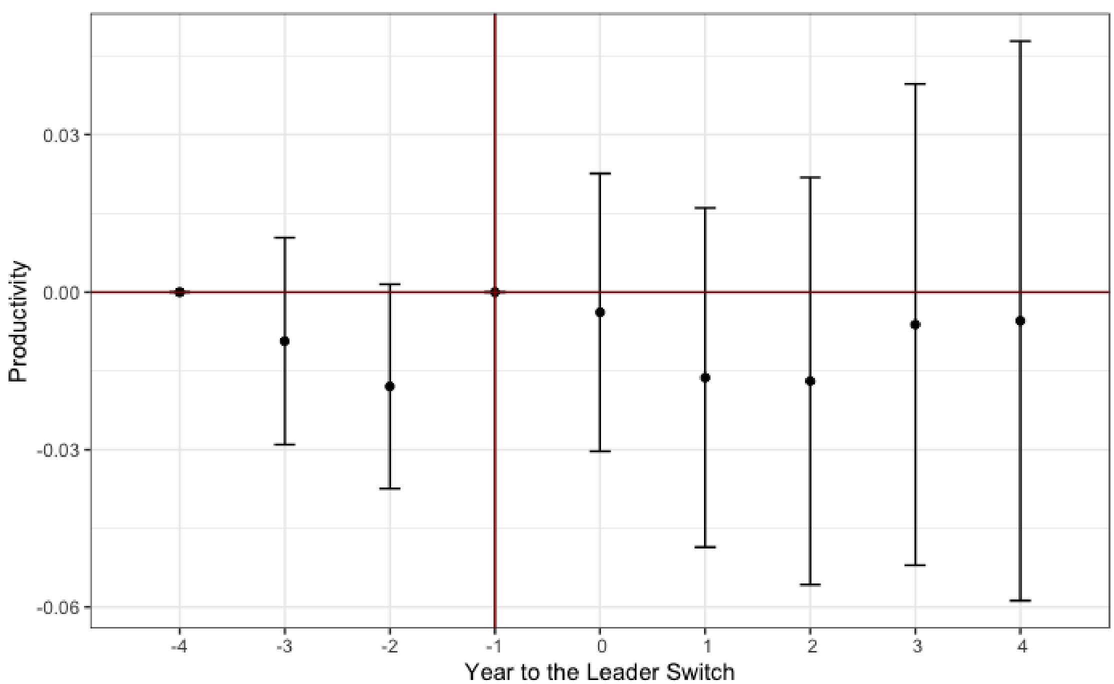


Figure A.2: Impact of leader switch on the productivity of faculty. Using the number of publications per year as the outcome variable, we re-estimate the baseline specification (equation 3) restricting the sample to a balanced panel of faculty-leader pairs.

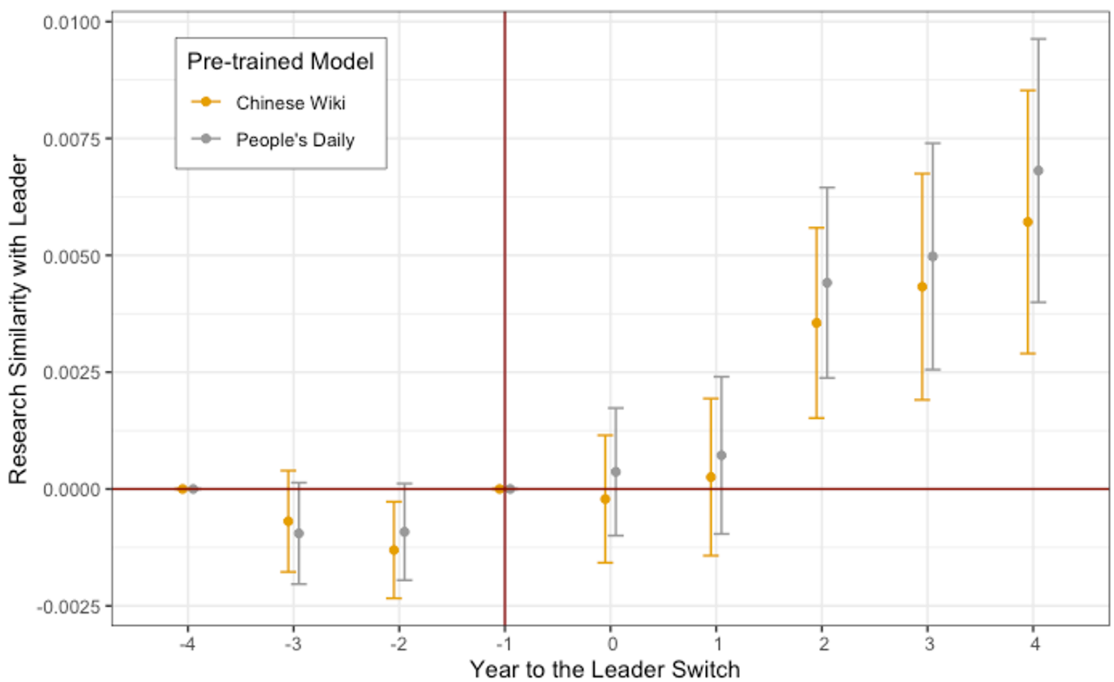


Figure A.3: Robustness check: impact of leader switch on the faculty-leader Doc2Vec similarity score. The points in the figure represent the estimated effects of event time (i.e., the ψ_l from the nonparametric event study in Equation 3). The error bars represent the 95% confidence intervals.

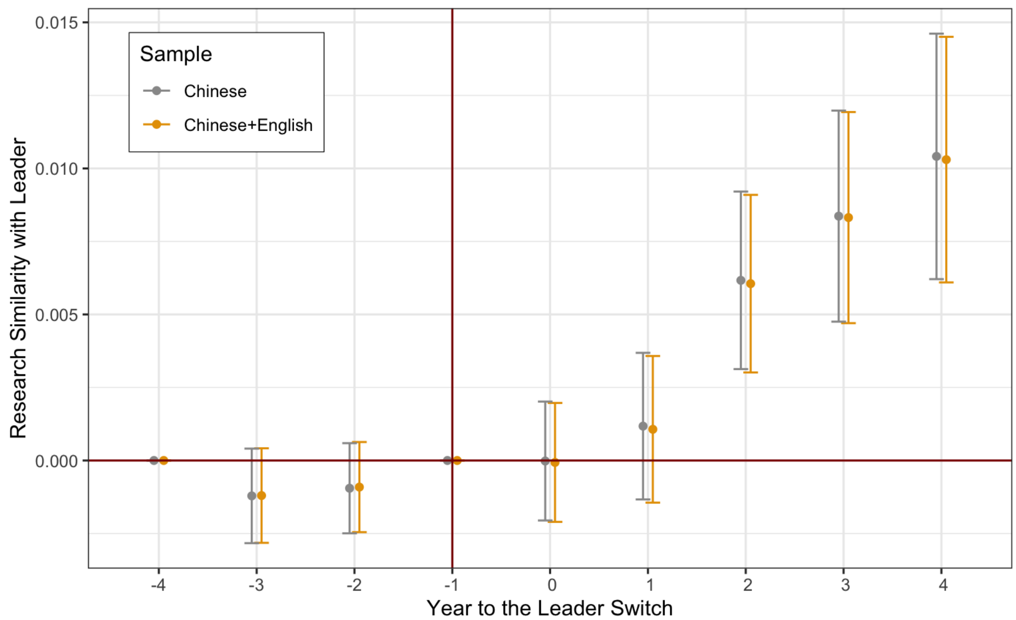


Figure A.4: Impact of leader switch on the faculty-leader similarity score, including English publications. The yellow points in the figure represent the estimated effects of event time relative to leadership switch using *both Chinese and English* publications, controlling for the full sets of faculty-leader pair fixed effects and time fixed effects. The error bars represent the 95% confidence intervals.The grey points/lines represent our baseline leader switch effects, which include Chinese publications only.

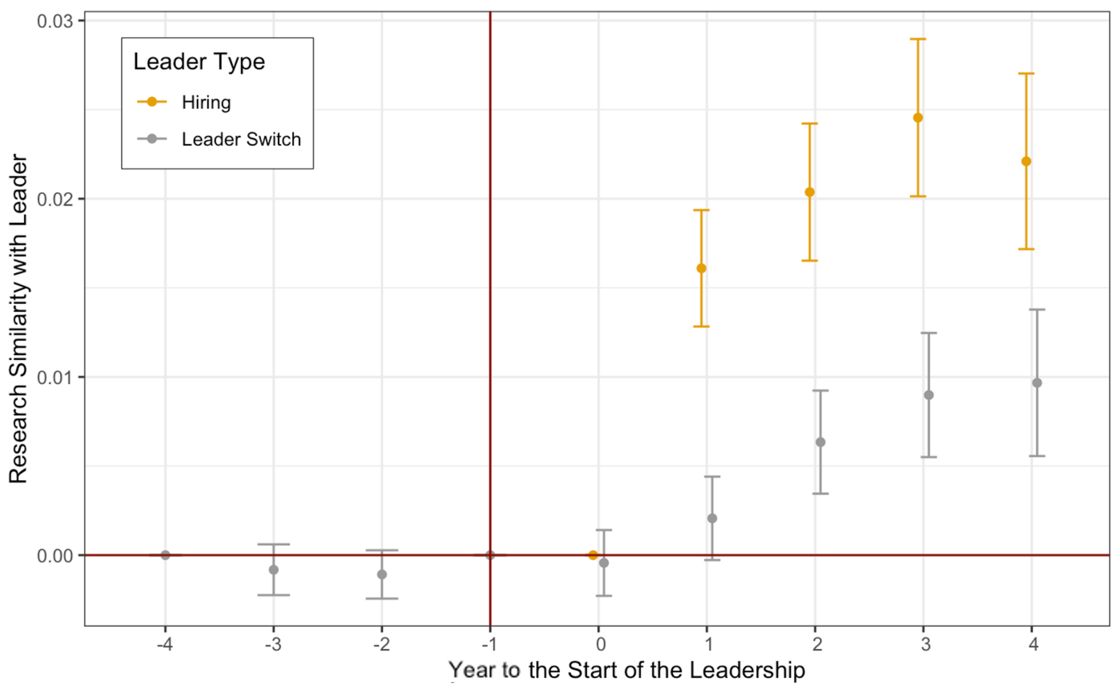


Figure A.5: Impact of leadership transition for hiring leaders versus department heads. The yellow lines/marks represent the estimators for the effect of hiring leaders. The grey lines/marks represent the effect of leader switch. We add faculty members that are newly hired to the baseline sample: (1) 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.

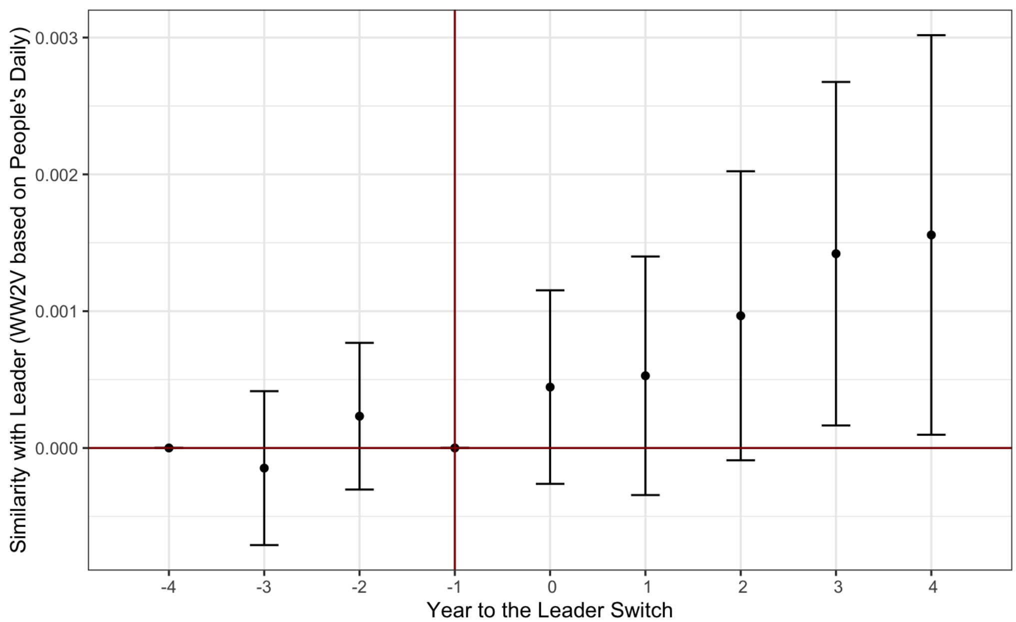


Figure A.6: Impact of department heads on faculty-leader similarity score under political semantics, while controlling scientific semantics. We estimate the leadership effect using WW2V People's Daily similarity score as outcome variable, controlling for WW2V Chinese Wiki similarity score.

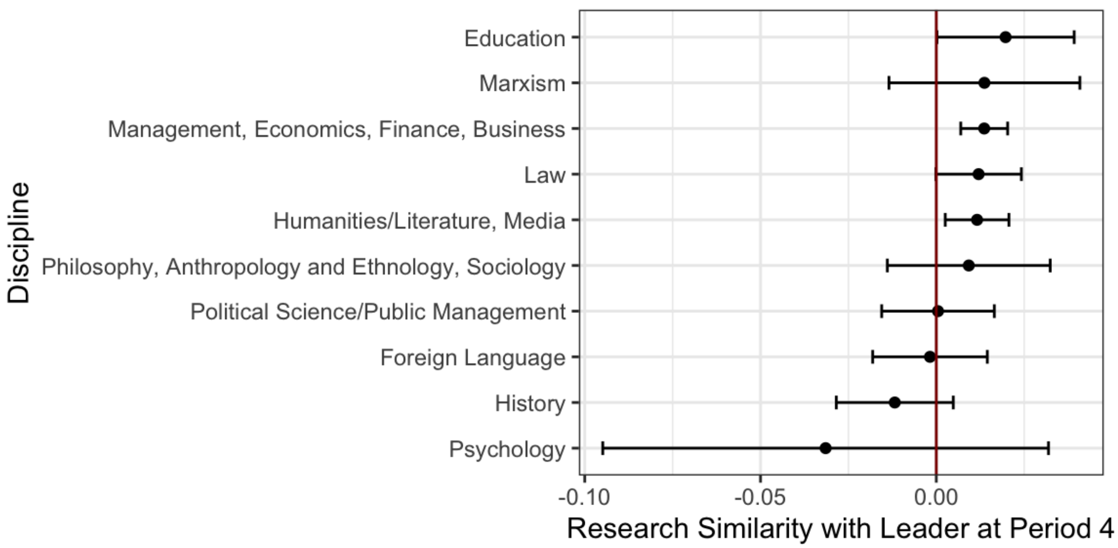


Figure A.7: Heterogeneous effect of leader switch by discipline. We estimate equation 3 for each discipline. Each line/mark represent the point estimate of the 5th year for each discipline, ranked by size of the estimates. We classify schools into 10 categories by taking disciplines as the connected components of schools that share the same classification. The details are described in Appendix A.

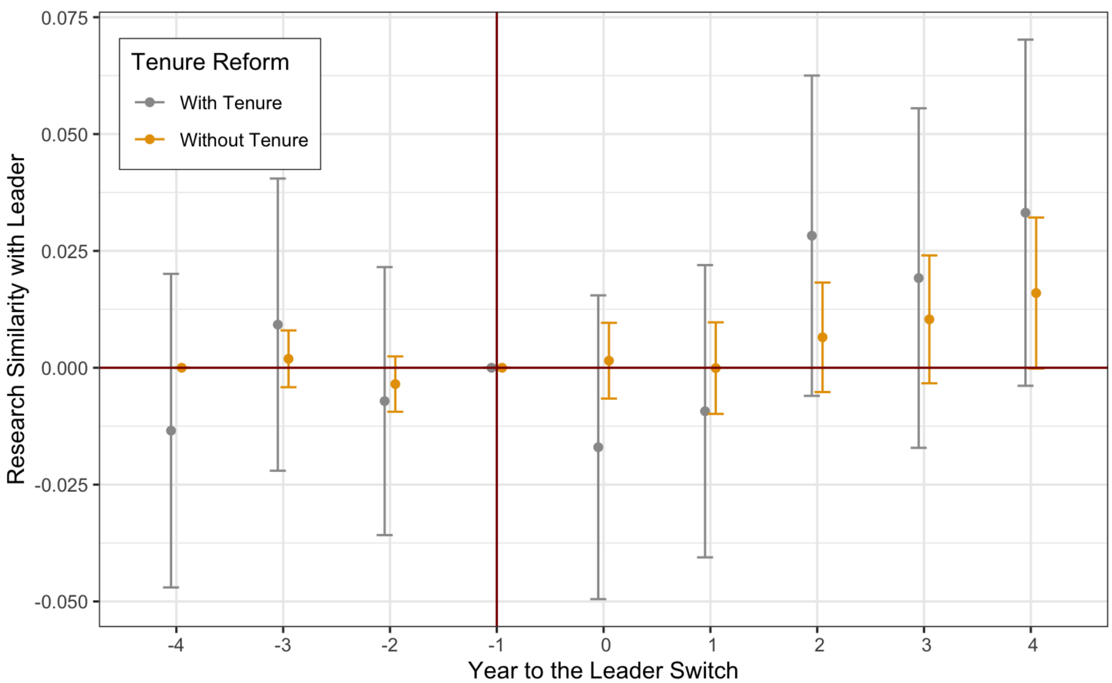


Figure A.8: Heterogeneous effect before and after tenure track reform at Peking University. The points in the figure represent the estimated effects of event time (i.e., the ψ_l from the non-parametric event study in Equation 3), using three measures of citation counts. The error bars represent the 95% confidence intervals. The grey (yellow) lines/markers represent the estimated effects for leader switches for faculty-leader pairs that are affected (unaffected) by the tenure track system reform.

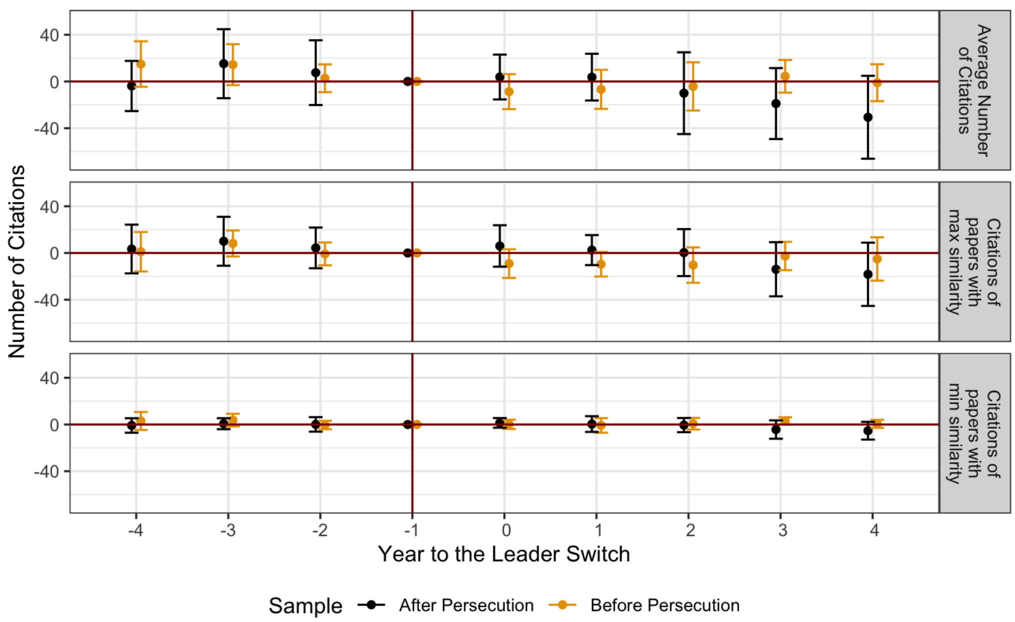


Figure A.9: Heterogeneous effect of leader switch before and after academic persecution. We estimate the effects simultaneously in regression $Y_{i,t} = \sum_{l\neq -1;l=-3}^{4} \mu_l D_{i,t}^{l} \times T_i + \sum_{t\neq -1;t=-3}^{4} \psi_l D_{i,t}^{l} + \alpha_i + \lambda_t + v_{i,t}$, where T_i is the indicator for whether the leader in pair i is after the university has an academic persecution event (=1) or before the event (=0). The yellow lines/markers represent the estimated effects of leaders before the persecution (i.e., the ψ_l in the regression). The black lines/markers represent the estimated effects of leaders after the persecution (i.e., the $\mu_l + \psi_l$ in the regression).

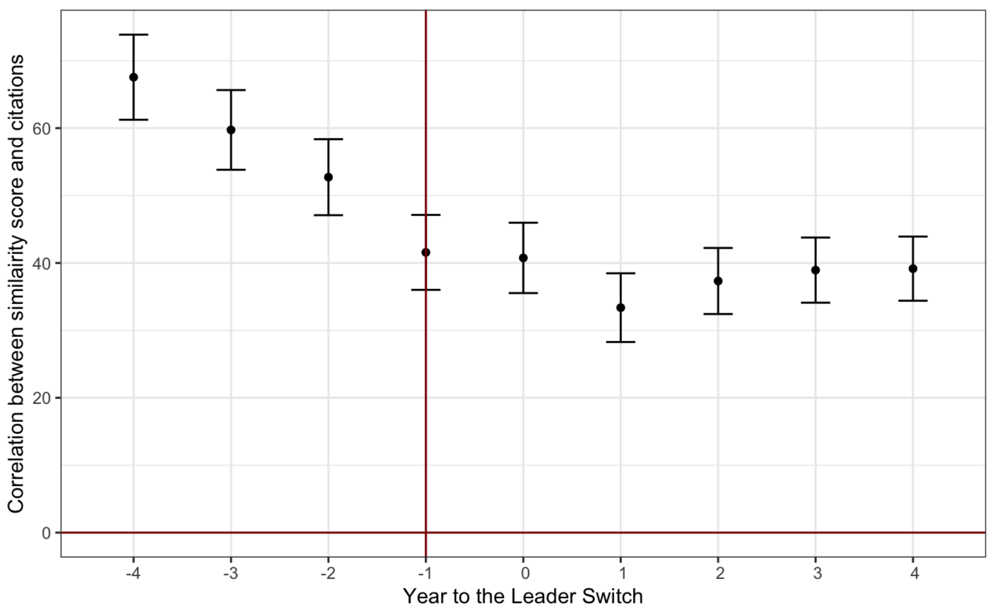


Figure A.10: Correlation between similarity score and the number of citation counts. The points in the figure represent the coefficients ψ_l in the equation $\text{Citation}_{i,t} = \sum_{l\neq-1;l=-4}^{4} \psi_l D_{i,t}^{l} \times \text{Similarity}_{i,t} + \alpha_i + v_{i,t}$, where $\text{Citation}_{i,t}$ is the average number of citations for faculty i at year t, $\text{Similarity}_{i,t}$ is the TF-IDF Max similarity score between faculty i and her leader at year t, α_i is faculty FEs.

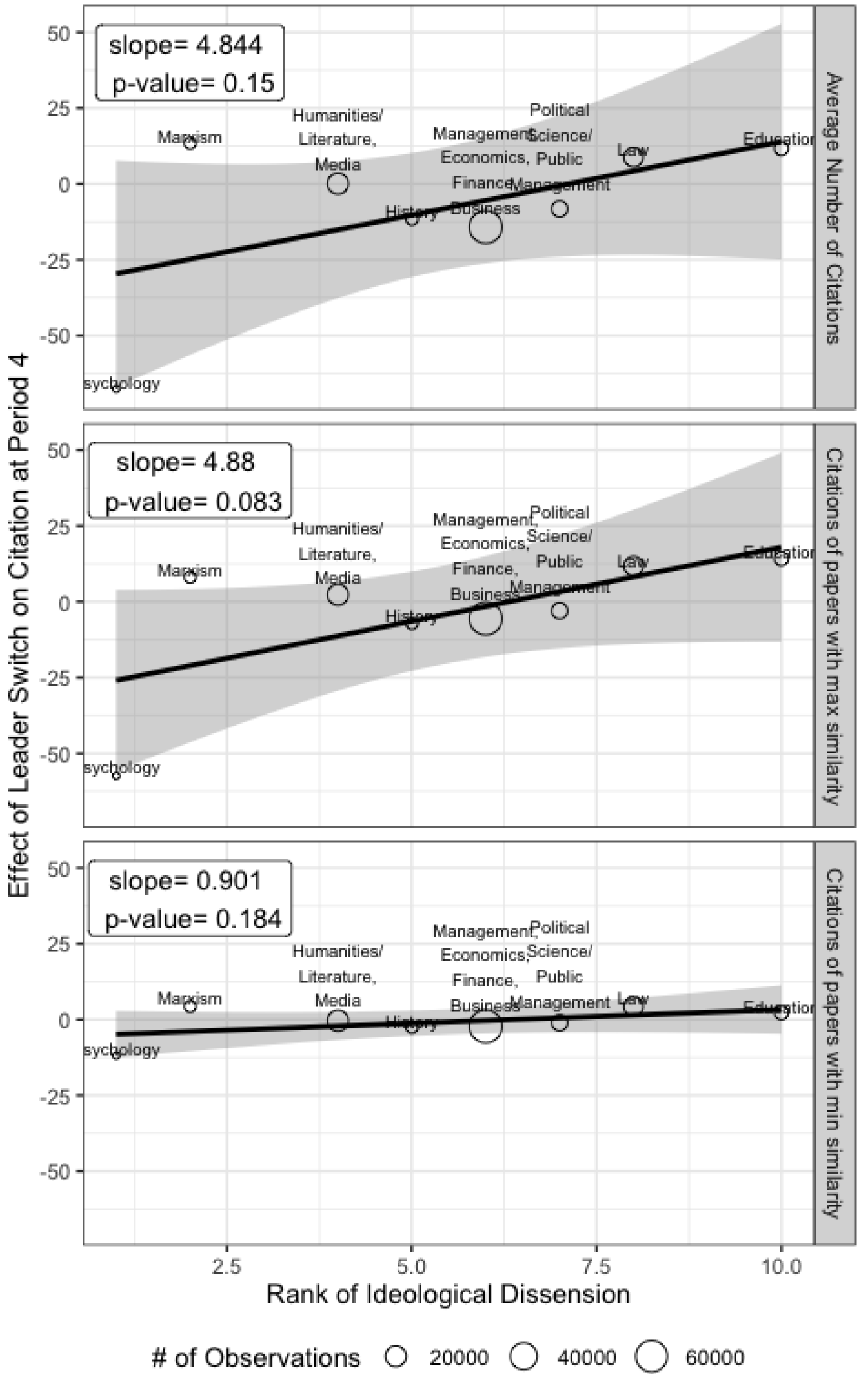


Figure A.11: The correlation between the effect of leadership switch on citation counts and the measure of ideological dissension. The sample only include high-to-low and low-to-high leader switches. We flip the sign of outcome variables for low-to-high leader switches. The panels use different measures for citation counts which are labeled on the right hand side. The x-axis shows the ranking of "ideological dissension." There is less ideological dissension in the discipline when the ranking is lower. The y-axis is the effect of leader switch at t=4. Each point represents a discipline.

Table A.1: Summary statistics on citation counts

	Citations per Paper		
	All Papers	Faculty Only	Leaders Only
Mean	13.9	13.7	18.2
25th Percentile	1.0	1.0	1.0
50th Percentile	4.0	4.0	5.0
75th Percentile	13.0	13.0	16.0
Total Papers	736,756	725,455	115,235

Table A.2: Hiring leaders vs. other leaders

	Similarity Score		
	Pooled	First year	Pooled
	(1)	(2)	(3)
Dummy for hiring leader	0.01097	-0.00226	0.00893
	(0.00137)	(0.00197)	(0.00139)
Faculty FE	✓	✓	✓
Calendar Year FE	✓	✓	✓
Control for Event Time			✓
Number of obs	207,852	61,947	207,852

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.

Table A.3: Example of similarity scores using word embeddings trained with political and scientific language

Leader's Paper	Language	Faculty's Paper	People's Daily	Chinese Wiki	Difference
Practical Issues and Policy Guidelines for Ecological Migration in Pastoral Areas of China (中国牧区生态移民实践问题与政策导向)	scientific	Analysis of Financial Structure and its Evolution in Ethnic Minority Regions of China (2001-2010) (我国民族地区金融结构演化分析（2001—2010))	0.805641	0.805479	0.000162
	scientific	The Key to Provide Farmers with More Property Rights is to Have Clear Possessory Title to Land. (明晰土地占有权是赋予农民更多财产权利的关键)	0.667511	0.821382	-0.153871
	political	Long Term Drivers of Effective Revitalization of Rural Ecology (乡村生态振兴的长效机制探析)	0.835037	0.79909	0.035947
	political	The Government's Focus on Poverty Alleviation in the Socialist New Era is Public Infrastructure Construction (政府在新时期的扶贫重点是建设公共基础设施)	0.800761	0.763097	0.037664

Table A.4: The effect of leader transition on citations

	Citation number (drop paper with missing citation)				Citation number (assume missing as zero)			
Leader transition type	low to high (1)	low to low (2)	high to low (3)	high to high (4)	low to high (5)	low to low (6)	high to low (7)	high to high (8)
Panel A: Citations of papers with max similarity								
2 years before	1.442	2.66	-4.838	2.487	0.978	0.522	-1.918	0.929
	(1.8)	(1.87)	(1.657)	(1.2)	(0.463)	(0.627)	(0.689)	(0.544)
4 years after	8.526	-1.372	-9.952	1.386	2.18	-1.651	-4.173	0.912
	(2.623)	(1.893)	(2.797)	(1.182)	(0.673)	(0.659)	(1.08)	(0.414)
Panel B: Average number of citations								
2 years before	1.189	1.175	-3.319	1.175	1.189	1.175	-3.319	1.175
	(1.429)	(1.345)	(1.523)	(0.928)	(1.429)	(1.345)	(1.523)	(0.928)
4 years after	5.488	-1.121	-10.754	0.834	5.488	-1.121	-10.754	0.834
	(1.95)	(1.433)	(2.481)	(0.83)	(1.95)	(1.433)	(2.481)	(0.83)
Panel C: Citations of papers with min similarity								
2 years before	0.654	-0.109	-1.083	0.978	0.824	0.147	-3.043	-0.093
	(0.417)	(0.564)	(0.641)	(0.455)	(0.61)	(0.834)	(1.149)	(0.721)
4 years after	0.497	-1.493	-2.776	0.787	1.901	-1.437	-6.674	0.404
	(0.485)	(0.538)	(0.942)	(0.34)	(1.016)	(0.921)	(1.593)	(0.635)
Faculty FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓

Note: Column 1-4 show the estimates of one pre-period ($t = -2$) and one post-period ($t = 4$) based on the specification $Y_{i,t} = \sum_{t \neq -1; t=-4}^{4} \psi_l D_{i,t}^l + \alpha_i + \lambda_t + v_{i,t}$, where $Y_{i,t}$ represents the statistics of faculty i's citations in year t and we drop papers with missing citations when we calculate the statistics. Column 5-8 show the estimates of one pre-period ($t = -2$) and one post-period ($t = 4$) based on the same specification. But we set the citation number as zero for missing papers when we calculate the outcome variables. Standard errors are clustered at the department level.