

# Supplemental Appendix for: Does Ideology Influence Hiring in China? Evidence from Two Randomized Experiments\*

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## Abstract

China after Mao is typically characterized as a country where economic opportunities are based on merit instead of ideological conformity. However, the salience of ideology has grown under the rule of Xi Jinping. Using a large-scale resume audit experiment and a conjoint survey experiment of hiring managers in China, we find that firms in China do not reward job candidates for expressing conformity to the ideology of the regime, but job candidates who express support for Western democracy are less employable. Results suggest that firms in innovative industries designated as strategically important by the Chinese regime (e.g. artificial intelligence) penalize support for Western democracy by the largest magnitude while the remaining firms in innovative industries do not penalize political non-conformity.

**Keywords:** labor market, firms, China, ideology, democracy, experiment

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# Online Supplementary Appendix

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# 1 Appendix: Resume Design Process

We identified features common to Chinese resumes through large-scale analysis of job postings and actual resumes, and incorporated relevant features in our fictitious resumes. We thoroughly pretested our proxy for political orientation using methods ranging from interviews to conjoint survey experiments.

## 1.1 Features of Chinese Resumes

We collected a random sample of 30,409 job postings made in 2015 (the year prior to our experiment) on the national website where we conducted our experiment, and we collected nearly 100 actual resumes of students applying for jobs on the website through snowball sampling. From this process, we identified the features our resumes should include to be realistic. These include name, gender, university, major, cohort GPA ranking (how one’s GPA compares to others in the same year and major), CCP membership, internship experience, extracurricular activities, certificates, level of English proficiency, computer skills, and hobbies.

For each feature, we created a pool of elements from which we could randomly select. We created a pool of 20 gender-neutral names so we could randomly assign male or female gender to the resume. We created a pool of 24 Chinese universities. Twelve universities are ranked within the top 50 (“higher tier”), and twelve are ranked between 51 and 100 (“lower tier”) based on the “2015 Zhong Guo Da Xue Pai Hang Bang [2015 Ranking of Chinese Universities]”.<sup>1</sup> The 24 universities in our pool also cover different levels of prestige using the Chinese government’s classification, including “985” and “211” categories.<sup>2</sup>

We developed a pool of five blocks of majors—economics and business, computer science, mechanical engineering, humanities and social sciences, and medical science—with two to five majors and six internships associated with each block.<sup>3</sup> In our interviews with

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<sup>1</sup>See <http://bit.ly/2cM5i0S>.

<sup>2</sup>12 of the 24 universities are “211” universities and the remaining 12 universities are not. Seven of the 24 universities are “985” universities and the remaining 17 are not.

<sup>3</sup>These five blocks represent the five industries that posted jobs most frequently on the job posting website we used, based on the 30,409 job postings we collected there in 2015.

employers and student job seekers before the experiment, we showed these prepared majors and internships to interviewees in each corresponding industry/major, and we confirm that within each block, all majors and internships we prepared are realistic and signal the merit and productivity characteristics that are often required of student job-seekers in the corresponding industry. In addition, we created a pool of six politically and academically neutral extracurricular activities, such as hip hop dance and roller-skating. We created a pool of six sports certificates, a pool of six computer skills, a pool of six hobbies, and a pool of three slightly different resume formats.

Since we submitted three resumes, each with a different political orientation, to each job vacancy, we ensured the three resumes had different names, different universities, different internship experiences, different extracurricular activities, different certificates, and different formats by randomly selecting elements from their respective pools without replacement.<sup>4</sup> For each resume, we compiled all selected elements into one document, which was in Chinese followed by an English translation, as was the norm among the resumes we analyzed. We submitted the three resumes (in randomized order) to the job posting on different days of the week.<sup>5</sup>

The constructed resumes maximized the pool of jobs we could apply to in three ways. First, the fictitious resumes describe an applicant who has completed a bachelor's degree and is currently working on a master's degree, because most job postings we analyzed on the national website required an advanced degree. Second, certain skills often required in the job postings were included on all resumes. These include CET-6 as the level of English proficiency, a certificate in Mandarin Proficiency, and computer skills in Adobe Photoshop and Microsoft Office.

Third, we matched the applicant's major and internship experiences as closely as possible to the requirements of the job posting. We block-randomized majors and internships

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<sup>4</sup>For the remaining components on the resume (e.g. gender and CCP membership), we selected an element from the corresponding pool with replacement.

<sup>5</sup>Out of 19,221 applications and over 3,500 responses, in only two instances did we receive questions from the employer about why certain resumes were so similar—one employer asked if the applicants were friends, and the other employer asked if this was a research project. This gives us confidence that our resumes were realistic to employers and the risk that one of the three resumes submitted to the employer would affect the employer's evaluation of the other resumes is minimal.

by job vacancy. For each job vacancy we applied for in the audit experiment, we identified the most relevant block of majors and randomly chose one major and two internships from that block to include on the resume. This means for the three resumes—politically conformist, politically non-conformist, and non-political—submitted to each job vacancy, each resume’s major and two internships always matched the requirement of the job vacancy. We randomly selected internships without replacement so that no resumes submitted to the same vacancy had the same internships.

## **1.2 Selecting an Attribute to Proxy Political Orientation**

We interviewed 40 undergraduate and master’s degree students to better understand the recruiting process and what they included in their resumes. We also interviewed 12 employers in public institutions, state-owned enterprises, private Chinese firms, and foreign/joint venture firms operating in China to understand how they evaluated various components of the resumes, and how they would interpret potential proxies for political orientation. From this process, we generated three potential ways to realistically signal high (**H**) and low (**L**) political conformity as shown in Table A1: a person’s major, the courses highlighted in the resume, and extracurricular activities (study group). High levels of political conformity are proxied by support for the ruling ideology of the CCP, in particular Socialism with Chinese Characteristics. Low levels of political conformity refers to support for Western values, political philosophy, and institutions, which have been deemed by the CCP to be antithetical to its ruling ideology.

We then used the Chinese version of Mechanical Turk to conduct a conjoint survey experiment to select one attribute out of the three options. Respondents were those currently living in mainland China and at least 25 years of age. The survey experiment also included an attention filter and respondents who failed that were screened out. We asked online respondents to assume the role of HR manager and to compare two job candidate profiles side by side and rate each candidate’s political conformity, academic merit, and political connections on a scale of 1-10, and to choose the candidate they would advance to the next stage of the recruitment process. Each candidate profile included the three attributes for political orientation listed in Table A1, two attributes for academic merit

Table A1: Pretested Attributes for Political Orientation

Attribute	Level of Political Conformity
Master’s major	<b>L:</b> International politics <b>H:</b> Scientific socialist and communist movements
Highlighted courses	<b>L:</b> Western Political Philosophy, History of Western Political Philosophy, Political Regimes in Western Capitalist States <b>H:</b> Socialism with Chinese Characteristics, Transnational Socialism, Mao Zedong Thought and Socialism with Chinese Characteristics
Extracurricular activities	<b>L:</b> Western Political Philosophy Study Group. From this experience, I realize that “human rights take precedence over sovereignty and the Chinese government should keep increasing the freedom of speech and the dissemination of information” <b>H:</b> Socialism with Chinese Characteristics Study Group. From this experience, I realize that “sovereignty takes precedence over human rights and the Chinese government should keep controlling public discourse and information dissemination”

(GPA cohort ranking and English proficiency score), the name of a Chinese university (six possible values), and CCP membership (yes or no). The level of each attribute was randomly assigned. A total of 1,210 profiles were rated by 121 validated respondents.

We select the attribute of political conformity that maximizes the following objective function:

$$D = \hat{\tau}_{conformity} - (|\hat{\tau}_{connections}| + |\hat{\tau}_{merit}|)$$

where  $\hat{\tau}_{conformity}$ ,  $\hat{\tau}_{merit}$  and  $\hat{\tau}_{connections}$  are the effects of each attribute on respondents’ ratings of political conformity, academic merit, and political connections, respectively.

Table A2 presents the results of the conjoint experiment for the proxies of political orientation. Specifically, it shows estimates of the effects of each attribute on the rating of political conformity, academic merit, and political connections. All dependent variables are on the scale of 1-10, and  $D = \hat{\tau}_{conformity} - (|\hat{\tau}_{connections}| + |\hat{\tau}_{merit}|)$ . Standard errors are clustered at the respondent level.

Extracurricular study group maximizes the objective function  $D$  described above.

Table A2: Comparison of Political Orientation Proxies

Attribute	$\hat{\tau}_{conformity}$	$\hat{\tau}_{merit}$	$\hat{\tau}_{connection}$	D
Master's major	-0.00 (0.12)	-0.03 (0.08)	0.05 (0.10)	-0.10
Highlighted courses	0.19 (0.13)	-0.15** (0.07)	0.07 (0.12)	-0.02
Extracurricular study group	0.49*** (0.15)	-0.02 (0.09)	0.10 (0.11)	0.37

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Compared to a study group on Western political philosophy, participation in a study group focused on Socialism with Chinese Characteristics has a strong, significant, and positive impact on respondents' rating of political conformity but does not influence ratings of academic merit or political connections. We also examine the effects of each attribute by CCP membership, by the prestige of the school, and by ordering of comparison task pairs. The results are similar across these sub-groups and extracurricular study group consistently outperforms other attributes for signaling political orientation.

## 2 Appendix: Audit Experiment Implementation

We applied to 6,407 job vacancies posted on a national-level job posting site in China. This website contains a nearly comprehensive database of job advertisements from all 31 of China's provinces aimed at recent college graduates. Using vacancies on this website allowed us to apply to a large number of jobs that were unlikely to be biased toward particular sectors, industries, or regions.<sup>6</sup> We applied only to jobs that allowed application via email and did not require additional materials beyond a resume.

### 2.1 Ethical Considerations

Similar to other resume audit studies (Bertrand and Mullainathan, 2004; Deming et al., 2016; Gift and Gift, 2015; Kroft et al., 2013; Riach and Rich, 2002), the audit experiment in this study utilized deception and waived informed consent. The decision to conduct such an experiment was not made lightly. We used an audit experiment because other

<sup>6</sup>To keep the names of firms we applied to confidential, we do not disclose the name of this website.

methods such as firm-level survey data of non-conformity or linking survey and behavioral data are infeasible and would produce externally invalid and/or unreliable results.<sup>7</sup> We took numerous steps to minimize risks and costs to firms as well as to actual job applicants. We did not record personally identifying information about the individuals who made callbacks, and will not make public the names of firms. We strove to minimize burdens on the firms' time by limiting our interactions with them in four ways. First, unlike previous resume audit studies that submitted two resumes for each treatment to each firm (Bertrand and Mullainathan, 2004; Deming et al., 2016), we only submitted one resume for each treatment for each firm. Second, we limited our study to the first phase of the recruitment process. Third, for employers who called back offering to move the applicant to the next stage of the interview process, we called each employer back within 24 hours to inform them that the candidate was no longer interested or available. This prevented employers from continuing to spend time on our fictitious applicant, and increased the chances of employers moving to other, real applicants for the position. Finally, we did not debrief employers to protect future job applicants. We secured approval from our university IRB for all elements of this research. Before conducting any experiments, we consulted with legal scholars and lawyers in China to ensure that our study did not violate any local laws or regulations. We also conducted extensive training to protect the safety of the research team (Pan, 2021).

## **2.2 Characteristics of Job Vacancies**

Table A3 displays the characteristics of all jobs on the national college-graduate job website (column 1), the characteristics of the jobs we applied for (column 2), and whether there are statistically significant differences between all job vacancies and job vacancies we applied for (column 3). Overall, the jobs we applied for have similar distributions by ownership sector, industry, region of position, and type of position as all jobs posted

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<sup>7</sup>Hypothetically, we could study the response of firms to political non-conformity by gathering hiring and/or promotion data from firms and using surveys to measure employee non-conformity. In an authoritarian context, survey-based measures of dissent are often biased (our conjoint survey experiment of hiring managers reveals these biases; see Appendix Section 5.3) and might expose survey respondents to risks. Behavioral measures such as expression of non-conformity on social media or participation in protest are extremely difficult to obtain (Zhang and Pan, 2019). Even when this data can be found, linking online behavior to employment is often impossible and poses risks for human subjects.



Table A3: Job Characteristics in the Audit Experiment

	All jobs	Applied jobs	p-value
<b>By ownership sector</b>			
Public institution	13.7%	6.3%	<0.001
State-owned enterprise	11.1%	16.1%	0.01
Private	52.5%	56.3%	0.17
Foreign/JV	22.8%	21.4%	0.54
<b>By industry</b>			
Non-profit	5.2%	1.5%	<0.001
Media & education	16.3%	13.8%	0.20
Energy & resource	3.0%	3.8%	0.49
Real estate	5.1%	5.5%	0.71
Technology	22.3%	25.1%	0.23
Finance	12.9%	14.1%	0.53
Automotive & manufacturing	9.5%	11.6%	0.25
Health	5.7%	7.5%	0.21
Consumer	6.2%	4.5%	0.17
Agriculture	1.3%	2.5%	0.14
Other (service)	12.2%	10.1%	0.21
<b>By region of position</b>			
East	81.5%	81.2%	0.87
Middle	9.1%	9.3%	0.88
West	7.5%	5.8%	0.19
Cross-regional	1.7%	3.5%	0.07
<b>By type of position</b>			
Technical job	13.4%	19.8%	<0.01
Professional	62.3%	65.3%	0.26
Teacher	6.5%	4.5%	0.11
Secretarial	12.7%	8.0%	<0.01
Blue collar service	2.6%	1.5%	0.13
Blue collar worker	0.5%	0.8%	0.66

*Notes:* Entries of “All jobs” are calculated using all posts from the national job website on three random days during implementation, which are 11/25/16 (Friday) , 01/09/17 (Monday) and 02/09/17 (Thursday). Eastern provinces include Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan, Liaoning, Jilin, and Heilongjiang. Middle provinces include Shanxi, Anhui, Jiangxi, Henan, Hubei, and Hunan. Western provinces include Neimenggu, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang. This categorization comes from <http://bit.ly/2pS0ygQ>.

on the website. The share of public institution jobs is much smaller among the jobs we applied to than among all jobs because public institution jobs often require in-person application or additional materials beyond a resume. As a result, public institutions in the experiment are limited to public schools and hospitals, which represent 94% of jobs in this ownership sector in our sample. The remaining public institution openings are internships and part-time jobs at government agencies. We also applied to relatively fewer non-profit organization jobs and secretarial jobs, and relatively more state-owned enterprise (SOE) jobs and more technical positions compared to all jobs posted.

### **2.3 Protocol for Recording Callbacks**

All requests from employers for participation in the company's written assessments or in interviews, as well as contact seeking more information or clarification, or providing the applicant with referrals are counted as callbacks. When referrals and/or clarification calls are excluded, all treatment effects remain substantively unchanged.

To receive callbacks, we used unique email addresses from Chinese email providers and unique phone numbers with a Beijing area code for the three treatments (political conformity, political non-conformity, and apolitical conditions), two levels of cohort GPA ranking, and four ownership sectors (public, SOE, private, and foreign). Our protocol was to not answer the call immediately, but to call back within 24 hours and ask for the name of the employer. Doing this allowed us to match the callback with the exact resume submitted. Also, it allowed us to identify rejection calls and to remove spam calls. All outgoing phone calls and emails we used to communicate with employers were made from inside mainland China. We analyzed all results using the cleaned callback rates (after removing spam calls and rejection calls) for each unique mobile number/email address as well as the raw callback rates, and all treatment effects remain the same.

### 3 Appendix: Audit Experiment Overall Effect Details

#### 3.1 Covariate Balance

Table A4 shows that resume covariates are balanced across the three treatment groups of political orientation.<sup>8</sup>

Table A4: Covariate Balance across Treatment Groups

	Obs.	Apolitical	Conformity	Non-conformity	p-value
High GPA ranking	19,221	0.496	0.495	0.504	0.494
Male	19,221	0.510	0.497	0.500	0.322
CCP member	19,221	0.505	0.493	0.504	0.334
Higher-tier university	19,221	0.497	0.495	0.510	0.181

*Notes:* Group means for non-political (Comic Book Club), signal of conformity (Socialism with Chinese Characteristics Study Group), and signal of non-conformity (Western Political Philosophy Study Group) as well as p-values corresponding to F tests of the conformity and non-conformity treatment indicators.

#### 3.2 Callback Rates by Group

Table A5 shows the callback rates at the resume level for different resume characteristics.

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<sup>8</sup>Other characteristics of job vacancy, such as ownership sector and required major, are perfectly balanced and not shown because we submitted three resumes, one for each political orientation, to each job vacancy.

Table A5: Summary Statistics of Callbacks in Audit Experiment

	Callback rate	Number of resumes
Overall	0.191	19,221
<b>By political orientation</b>		
Apolitical (Comic Book Club)	0.197	6,407
Conformity (Socialism with Chinese Characteristics Study Group)	0.195	6,407
Non-conformity (Western Political Philosophy Study Group)	0.180	6,407
<b>By academic merit</b>		
High merit (top 5% of cohort)	0.193	9,580
Average merit (top 45% of cohort)	0.188	9,641
<b>By prestige of university</b>		
Higher-tier university	0.207	9,622
Lower-tier university	0.175	9,599
<b>By gender</b>		
Male	0.197	9,658
Female	0.184	9,563
<b>By CCP membership</b>		
CCP member	0.189	9,619
Non-CCP member	0.192	9,602
<b>By ownership sector</b>		
Public institution	0.179	1,740
State-owned enterprise	0.152	2,784
Private firm	0.212	10,635
Foreign/Joint venture	0.167	4,062

### 3.3 Alternative Parametric Models

Table A6 presents the overall treatment effects using linear regressions.

Table A6: Effect of Conformity and Non-conformity on Callback Rates

	(1)	(2)	(3)
Conformity	-0.002 (0.005)	-0.002 (0.005)	-0.002 (0.005)
Non-conformity	-0.017*** (0.005)	-0.017*** (0.005)	-0.018*** (0.005)
Observations	19,221	19,221	19,221
Vacancy fixed effects	No	Yes	No
Controls	No	No	Yes

*Notes:* The dependent variable is a dummy for whether the employer called back. All columns use OLS regression. Robust standard errors are clustered on the vacancy level.  
\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

## 4 Appendix: Audit Experiment Heterogeneous Effect Details

### 4.1 Heterogeneous Effects by Ownership Sector

Table A7 presents the heterogeneous effects of non-conformity vs. apolitical and conformity by ownership sector. For each ownership sector (each column), the comparison group is all other ownership sectors.

Table A7: Heterogeneous Effects of Non-conformity by Ownership Sector

	OLS				Logit			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Non-conformity * Public	-0.004 (0.014)				-0.005 (0.021)			
Non-conformity * SOE		0.009 (0.012)				0.007 (0.019)		
Non-conformity * Private			-0.009 (0.008)				-0.007 (0.012)	
Non-conformity * Foreign				0.010 (0.010)				0.009 (0.016)
Non-conformity	-0.016*** (0.004)	-0.017*** (0.005)	-0.011* (0.006)	-0.018*** (0.005)	-0.016** (0.006)	-0.017*** (0.006)	-0.012 (0.009)	-0.018*** (0.007)
Public	-0.012 (0.015)				-0.012 (0.012)			
SOE		-0.048*** (0.011)				-0.047*** (0.009)		
Private			0.050*** (0.009)				0.049*** (0.007)	
Foreign				-0.033*** (0.010)				-0.032*** (0.008)
Apolitical and conformity callback rate in all other ownership sectors	0.197	0.203	0.168	0.203	0.197	0.203	0.168	0.203
Observations	19,221	19,221	19,221	19,221	19,221	19,221	19,221	19,221

Notes: The dependent variable is a dummy variable for whether the employer called back. Coefficients are marginal effects on callback probability. \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

## 4.2 Heterogeneous Effects by Industry Sector

**Effects by State Specialized Permission** Table A8 presents the heterogeneous effects of non-conformity vs. apolitical and conformity by whether an industry requires specialized license and permit from the Chinese government. The comparison group is firms that do not need specialized license or permit. Based on prior literature, we identify three industries in the pool of jobs we applied to that require specialized permit from the government: banking, natural resource extraction, and real estate development (Brehm, 2008; Shih, 2004). We code firms that fall into any of these three industries as firms that required specialized state permit.

Table A8: Heterogeneous Effects of Non-conformity by Specialized Permission

	OLS	Logit
Non-conformity * Specialized permit	0.006 (0.023)	0.003 (0.047)
Non-conformity	-0.016*** (0.004)	-0.016*** (0.006)
Specialized permit	-0.061** (0.024)	-0.059*** (0.020)
Apolitical and conformity callback rate in all other firms	0.197	0.197
Observations	19,221	19,221

*Notes:* The dependent variable is a dummy for whether the employer called back. Coefficients are marginal effects on callback probability. \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

**Structural Topic Model** The intuition behind a structural topic model is that it clusters a corpus of texts into topics based on the frequency of word co-occurrence (e.g. how frequently word A is used right before/after word B). Table A9 displays the top keywords (in English and Chinese) associated with each topic (industry grouping) identified by the structural topic model.

Table A9: Top Words by Topic

Topic	Top words (English)	Top words (Chinese)
Intelligent software	Highest prob: tech, software, create, easy, cloud FREX: tech, cloud, online, software, intelligent	Highest prob: 科技, 软件, 创, 易, 云 FREX: 科技, 云, 在线, 软件, 智慧
Biotech, education	Highest prob: edu, Guangzhou, develop, Nanjing, biology FREX: edu, biology, Guangzhou, Nanjing, Zhengzhou	Highest prob: 教育, 广州, 发展, 南京, 生物 FREX: 教育, 生物, 广州, 南京, 郑州
Media, culture, sports	Highest prob: Beijing, culture, media, east, comm FREX: Beijing, comm, sports, culture, insurance	Highest prob: 北京, 文化, 传媒, 东方, 传播 FREX: 北京, 传播, 体育, 文化, 人寿
Financial service outsourcing	Highest prob: Shanghai, China, info, finance, service FREX: finance, ship, branch, resource, service	Highest prob: 上海, 中国, 信息, 金融, 服务 FREX: 金融, 船舶, 分行, 资源, 服务
IT and electronics R&D	Highest prob: electronic, college, and, reach, R&D FREX: health, automation, reach, excellent, branch	Highest prob: 电子, 学院, 和, 达, 研发 FREX: 健康, 自动化, 达, 卓越, 行
Real estate	Highest prob: global, Xiamen, trade, real estate, Ningbo FREX: chemical, machine, web, food, export & import	Highest prob: 国际, 厦门, 贸易, 房地产, 宁波 FREX: 化工, 器械, 网, 食品, 进出口
Materials, metallurgical	Highest prob: new, Zhejiang, energy, material, ten thousands FREX: material, new, invest, digital, Yantai	Highest prob: 新, 浙江, 能源, 材料, 万 FREX: 材料, 新, 投, 数码, 烟台
Construction	Highest prob: project, Guangdong, design, construct, re- search institute FREX: plan, design, China construct, construct, bureau	Highest prob: 工程, 广东, 设计, 建设, 研究院 FREX: 规划, 设计, 中建, 建设, 局
University research lab	Highest prob: center, university, training, research, science FREX: research, center, medical school, nation, public	Highest prob: 中心, 大学, 培训, 研究, 科学 FREX: 研究, 中心, 医学院, 国家, 公共
Investment management	Highest prob: manage, consult, invest, asset, fund FREX: asset, manage, invest, consult, wealth	Highest prob: 管理, 咨询, 投资, 资产, 基金 FREX: 资产, 管理, 投资, 咨询, 财富
Pharmaceutical, hospital	Highest prob: Shandong, Jiangsu, hospital, Qingdao, pharma FREX: knowledge, property right, intern, agent, pharma	Highest prob: 山东, 江苏, 医院, 青岛, 医药 FREX: 知识, 产权, 实习生, 代理, 药业
Securities	Highest prob: securities, insurance, business, section, data FREX: search, fixed, revenue, accountant, mark	Highest prob: 证券, 保险, 商务, 部, 数据 FREX: 搜索, 固定, 收益, 会计师, 注明

*Notes:* Highest prob includes the top five words that appear most frequently in each topic. FREX includes the top five words that are both frequent and exclusive; namely, words that distinguish topics.



**Effects by CCP Priority and Innovation** Table A10 shows the heterogeneous effects of non-conformity vs. apolitical and conformity by whether an industry is prioritized by the CCP as strategically important and whether the industry is innovative. For each group (each column), the comparison group is all other firms that do not have the characteristic of that group. In Figure 5 of the main paper, estimates are the absolute value of the coefficients on interaction terms between non-conformity and each group in Table A10.

Table A10: Heterogeneous Effects of Non-conformity by CCP Priority and Innovation

	OLS				Logit			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Non-conformity * CCP priority and innovative	-0.027*** (0.009)				-0.028** (0.012)			
Non-conformity * Not priority and innovative		0.024** (0.012)				0.026 (0.020)		
Non-conformity * CCP priority and not innovative			-0.004 (0.015)				0.002 (0.017)	
Non-conformity * Not priority and not innovative				0.012 (0.008)				0.012 (0.013)
Non-conformity	-0.008* (0.005)	-0.019*** (0.005)	-0.016*** (0.004)	-0.022*** (0.006)	-0.008 (0.007)	-0.019*** (0.006)	-0.016** (0.006)	-0.021*** (0.008)
CCP priority and innovative	-0.002 (0.009)				-0.002 (0.008)			
Not priority and innovative		-0.046*** (0.012)				-0.045*** (0.009)		
CCP priority and not innovative			0.115*** (0.016)				0.112*** (0.013)	
Not priority and not innovative				-0.022** (0.009)				-0.022*** (0.007)
Apolitical and conformity callback rate in all other industry sectors	0.196	0.202	0.183	0.206	0.196	0.202	0.183	0.206
Observations	19,221	19,221	19,221	19,221	19,221	19,221	19,221	19,221

Notes: The dependent variable is a dummy variable for whether the employer called back. Coefficients are marginal effects on callback probability. \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table A11 shows the effect of non-conformity vs. apolitical and conformity in each group.

Table A11: Effects of Non-conformity by Subgroup

	OLS	Logit
<b>CCP priority, innovative</b>		
Non-conformity	-0.035*** (0.008)	-0.035*** (0.011)
Callback in apolitical and conformity	0.195	0.195
Observations	5,610	5,610
<b>Not CCP priority, innovative</b>		
Non-conformity	0.005 (0.011)	0.005 (0.015)
Callback in apolitical and conformity	0.156	0.156
Observations	2,595	2,595
<b>CCP priority, not innovative</b>		
Non-conformity	-0.019 (0.015)	-0.019 (0.021)
Callback in apolitical and conformity	0.298	0.298
Observations	2,109	2,109
<b>Not CCP priority, not innovative</b>		
Non-conformity	-0.009 (0.006)	-0.009 (0.009)
Callback in apolitical and conformity	0.184	0.184
Observations	8,907	8,907

*Notes:* The dependent variable is a dummy for whether the employer called back. Coefficients are marginal effects on callback probability. \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

### 4.3 Effects of Other Resume Characteristics

Table A12 presents difference in callback rates by tier of schools, gender, and geographic proximity between job location and university location.

Table A12: Effects of tier of University, Gender, and Geographic Proximity on Callbacks

	(1)	(2)	(3)
Higher-tier	0.209*** (0.037)		
Male		0.086** (0.037)	
Geographic proximity			0.24*** (0.066)
Observations	19,221	19,221	19,221

*Notes:* The dependent variable is an dummy variable for callback from the firms. All columns use logistic regression. The lower tier of schools is the comparison school tier. Female is the comparison gender category. Not the same province between the job and the candidate's university is the comparison geographic proximity category. Robust standard errors are clustered at the vacancy level.  
\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

### 4.4 Additional Analyses from Pre-analysis Plan

We present analysis of other hypotheses we included in our pre-analysis plan. All of these hypotheses are sub-group analyses of the effect of political conformity. We do not include them in the main text because the conformity treatment did not have a significant effect on callbacks.

**By Ownership Sector Estimates at Each Level of Academic Merit:** Table A13 presents the effects of conformity and non-conformity on callback rates by ownership sector among resumes with a top 5% GPA ranking. Table A14 presents the effects of conformity and non-conformity on callback rates by ownership sector among resumes with a top 45% GPA ranking in the candidate's cohort.

Table A13: Effects of Conformity and Non-conformity at High Academic Merit

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<b>Public</b>								
Conformity	-0.039 (0.030)	-0.026 (0.032)						
Non-conformity	-0.038 (0.027)	-0.017 (0.025)						
<b>SOE</b>								
Conformity			-0.010 (0.022)	0.009 (0.022)				
Non-conformity			-0.028 (0.021)	-0.020 (0.023)				
<b>Private</b>								
Conformity					-0.002 (0.012)	-0.015 (0.012)		
Non-conformity					-0.033*** (0.012)	-0.031*** (0.012)		
<b>Foreign</b>								
Conformity							0.024 (0.018)	0.015 (0.018)
Non-conformity							0.010 (0.016)	0.006 (0.015)
Apolitical callback	0.224	0.224	0.170	0.170	0.225	0.225	0.152	0.152
Observations	850	850	1,380	1,380	5,321	5,321	2,029	2,029
Vacancy fixed effects	No	Yes	No	Yes	No	Yes	No	Yes

*Notes:* The dependent variable is a dummy variable for any callback from the potential employer. All regressions use OLS. Columns (2), (4), (6), and (8) include vacancy fixed effects. Robust standard errors are clustered at the vacancy level. Under a Bonferroni correction, the results remain the same in all sectors.

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table A14: Effects of Conformity and Non-conformity at Average Academic Merit

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<b>Public</b>								
Conformity	-0.007 (0.025)	-0.005 (0.025)						
Non-conformity	-0.026 (0.028)	0.003 (0.030)						
<b>SOE</b>								
Conformity			0.034* (0.020)	0.008 (0.021)				
Non-conformity			0.023 (0.020)	0.007 (0.022)				
<b>Private</b>								
Conformity					-0.010 (0.012)	-0.005 (0.013)		
Non-conformity					-0.014 (0.012)	-0.018 (0.012)		
<b>Foreign</b>								
Conformity							-0.005 (0.018)	0.015 (0.019)
Non-conformity							-0.017 (0.019)	-0.017 (0.021)
Apolitical callback	0.172	0.172	0.129	0.129	0.218	0.218	0.180	0.180
Observations	890	890	1,404	1,404	5,314	5,314	2,033	2,033
Vacancy fixed effects	No	Yes	No	Yes	No	Yes	No	Yes

*Notes:* The dependent variable is a dummy variable for any callback from the potential employer. All regressions use OLS. Columns (2), (4), (6), and (8) include vacancy fixed effects. Robust standard errors are clustered at the vacancy level. Under a Bonferroni correction, the results remain the same in all sectors except that we do not find a significant effect of conformity signal on callbacks among SOE jobs.

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

**Relative Strength of Treatment Effects:** Table A15 presents the relative strength of the effect of signaling conformity on callbacks with the effect of academic merit within

Table A15: Relative Strength of Effects of Conformity and Merit by Ownership Sector

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<b>Public</b>								
Conformity	-0.023 (0.015)	-0.023 (0.015)						
Non-conformity	-0.032** (0.016)	-0.032** (0.016)						
High merit (top 5% cohort)	0.037** (0.019)	0.028* (0.015)						
<b>SOE</b>								
Conformity			0.013 (0.012)	0.013 (0.012)				
Non-conformity			-0.003 (0.012)	-0.002 (0.012)				
High merit (top 5% cohort)			0.009 (0.014)	0.008 (0.012)				
<b>Private</b>								
Conformity					-0.006 (0.007)	-0.006 (0.007)		
Non-conformity					-0.023*** (0.007)	-0.023*** (0.007)		
High merit (top 5% cohort)					0.004 (0.008)	0.000 (0.007)		
<b>Foreign</b>								
Conformity							0.009 (0.011)	0.010 (0.011)
Non-conformity							-0.004 (0.010)	-0.004 (0.010)
High merit (top 5% cohort)							-0.009 (0.012)	0.000 (0.011)
Apolitical average merit callback	0.179	0.179	0.144	0.144	0.220	0.220	0.170	0.170
p-value for $\beta_{conformity} - \beta_{merit} = 0$	0.017	0.019	0.820	0.754	0.335	0.496	0.234	0.518
Observations	1,740	1,740	2,784	2,784	10,635	10,635	4,062	4,062
Vacancy fixed effects	No	Yes	No	Yes	No	Yes	No	Yes

*Notes:* The dependent variable is a dummy variable for any callback from the potential employer. All regressions use OLS. Columns (2), (4), (6), and (8) include vacancy fixed effects. Robust standard errors are clustered at the vacancy level. The last but two row presents the p-value from a t-test between the coefficient on conformity and that on high merit in each regression.

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

each ownership sector. Table A16 presents the relative strength of the effect of signaling conformity on callbacks with the effect of gender in each ownership sector.

Table A16: Relative Strength of Effects of Conformity and Gender by Ownership Sector

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<b>Public</b>								
Conformity	-0.022 (0.015)	-0.021 (0.015)						
Non-conformity	-0.030* (0.016)	-0.029* (0.016)						
Male	0.028 (0.018)	0.053*** (0.016)						
<b>SOE</b>								
Conformity			0.011 (0.012)	0.011 (0.012)				
Non-conformity			-0.003 (0.012)	-0.003 (0.012)				
Male			0.046*** (0.014)	0.047*** (0.013)				
<b>Private</b>								
Conformity					-0.006 (0.007)	-0.006 (0.007)		
Non-conformity					-0.023*** (0.007)	-0.023*** (0.007)		
Male					0.002 (0.008)	0.016** (0.007)		
<b>Foreign</b>								
Conformity							0.010 (0.011)	0.011 (0.011)
Non-conformity							-0.003 (0.010)	-0.003 (0.010)
Male							0.011 (0.012)	0.019* (0.011)
Apolitical female callback	0.182	0.182	0.127	0.127	0.220	0.220	0.160	0.160
P-value for $\beta_{conformity} - \beta_{male} = 0$	0.029	0.001	0.064	0.024	0.443	0.027	0.941	0.557
Observations	1,740	1,740	2,784	2,784	10,635	10,635	4,062	4,062
Vacancy fixed effects	No	Yes	No	Yes	No	Yes	No	Yes

Notes: The dependent variable is a dummy variable for any callback from the potential employer. All regressions use OLS. Columns (2), (4), (6), and (8) include vacancy fixed effects. Robust standard errors are clustered at the vacancy level. The last but two row presents the p-value from a t-test between the coefficient on conformity and that on male in each regression.

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

## **5 Appendix: Hiring Manager Conjoint Survey Experiment Details**

We obtained informed consent from all survey participants, no deception was used, and no personally identifying information was collected.

### **5.1 Characteristics of Hiring Manager Sample**

Table A17 displays the characteristics of hiring managers who participated in our conjoint survey experiment. All 506 respondents had at least one year of experience in hiring, and we sampled respondents working in the same provinces and in the same ownership sectors as the job vacancies in our resume audit experiment.

### **5.2 Covariate Balance**

Table A18 shows that most resume covariates are balanced across the three treatment groups of political orientation.<sup>9</sup> All characteristics of hiring managers, such as age and length of working experience, are perfectly balanced and not shown because we presented three resumes, one for each political orientation, to each hiring manager respondent.

### **5.3 Callback Rates by Group**

Table A19 shows the reported “callback rates” at the resume level for the conjoint survey experiment with hiring managers. The overall reported “callback rate” was at 81.3%, substantially higher than the corresponding rate in the audit experiment, which was 19.1%.<sup>10</sup> Such differences are expected since much less is at stake for hiring managers in the conjoint experiment than in the audit experiment.

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<sup>9</sup>Resumes in the control group (non-political) have significant differences from resumes in the treatment groups on CCP membership and higher-tier university, but the two treatment groups (conformity and non-conformity) are balanced on these two covariates. Resumes in the control group have a significantly higher proportion of CCP candidates than resumes in the conformity treatment. Resumes in the control group have a significantly lower proportion of higher-tier university candidates than resumes in the conformity and non-conformity treatments respectively.

<sup>10</sup>The penalty on politically non-conformist candidates when compared to the apolitical control is also smaller in the conjoint experiment than in the audit experiment.



Table A17: Hiring Manager Characteristics in the Conjoint Survey

	Sample mean
Female	0.646
Age (years)	33.2
Ethnic minorities (non-Han)	0.040
Urban residents	0.773
CCP member	0.364
Have direct reports	0.796
<b>By work experience</b>	
1–3 years	0.162
4–7 years	0.356
8 years or above	0.482
<b>By HR experience</b>	
1–3 years	0.322
4–7 years	0.441
8 years or above	0.237
<b>By Hukou region</b>	
Eastern China	0.713
Middle China	0.166
Western China	0.121
<b>By educational level</b>	
High school and below	0.026
Bachelor	0.794
Graduate	0.180
<b>By ownership sector</b>	
Public institution	0.127
State-owned enterprise	0.138
Private firm	0.518
Foreign/Joint venture	0.217
<b>By monthly income (RMB)</b>	
Low ( $\leq 5,000$ )	0.166
Middle (5,001–8,000)	0.323
Upper middle (8,001–20,000)	0.445
High ( $\geq 20,001$ )	0.066

*Notes:* Entries in the table are proportions, except “age.”

Table A18: Covariate Balance across Treatment Groups

	Obs.	Apolitical	Conformity	Non-conformity	p-value
High merit	1,518	0.530	0.490	0.508	0.453
Male	1,518	0.504	0.496	0.510	0.907
CCP member	1,518	0.520	0.443	0.486	0.049
High-tier university	1,518	0.443	0.524	0.512	0.021
Explicit political statement	1,518	0.563	0.581	0.571	0.849
Science/Engineering major	1,518	0.407	0.425	0.377	0.299

*Notes:* Unit of analysis is resume. Group means for apolitical, signal of political conformity, and signal of political non-conformity as well as p-values corresponding to F tests of the conformity and non-conformity treatment indicators.

Table A19: Summary Statistics of Hiring Manager Survey Experiment

	Reported callback rate	No. of resume
Overall	0.813	1,518
<b>By political orientation</b>		
Apolitical (Comic Book Club)	0.792	506
Conformity (Socialism with Chinese Characteristics Study Group)	0.852	506
Non-conformity (Western Political Philosophy Study Group)	0.794	506
<b>By ownership sector</b>		
Public institution	0.818	192
State-owned enterprise	0.805	210
Private firm	0.803	786
Foreign/Joint venture	0.839	330

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