Adverse Experience and Occupational Outcomes: Evidence from Children of the Cultural Revolution

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Abstract

This paper studies the long-term occupational effects of China's Cultural Revolution (1966–76, CR), which involved a strong sense of dislike towards professionals. Using a difference-in-differences design, I find that individuals whose fathers experienced higher levels of violence during the CR are less inclined to pursue professional occupations. However, I do not observe a significant impact of mothers' exposure. Furthermore, there is limited evidence that the CR led to constraints hindering access to professional jobs in terms of human capital, family environment, and local economic conditions. I find patterns consistent with a model of preference transmission within families. Additionally, I provide evidence indicating that the dislike towards professional occupations may persist in the third generation, especially in the patriarchal line.

Keywords: Cultural Revolution, Occupational Choice, Culture Transmission, China

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1 Introduction

Growing up in an adverse environment can leave a significant imprint on one's life trajectory. For instance, an extensive literature in economics has documented the impacts of violence, one of the most extreme forms of adversity, on those directly exposed to it (e.g., Michaelsen and Salardi, 2020; Koppensteiner and Menezes, 2021; Ang, 2021). By contrast, less is known about whether and how adverse experiences may exert long-term influences across generations and thus affect those with little direct exposure.

In this paper, I investigate this issue using the lens of children of China's Cultural Revolution (1966–76; CR hereafter), namely, the individuals whose parents experienced the CR. The CR featured intensive civilian violence against a group of "counter-revolutionaries" deemed incompatible with the socialist system, many of whom were professionals, e.g., teachers, scientists, and intellectuals (Wang, 2001; Booth et al., 2022; Bai and Wu, forthcoming; Zhou and Hou, 1999). As such, a stigma may become attached to being professionals and be passed on intergenerationally.

I estimate the effect of parents' CR experience on children's entry into professional occupations.[1] To estimate this effect, I employ a difference-in-differences (DiD) design, leveraging a combination of prefecture-level variation in CR violence intensities and cohort-level variation in parents' exposure to violence during their impressionable years (Krosnick and Alwin, 1989; Alwin and Krosnick, 1991; Sears, 1971). The specification includes granular province-by-child-cohort-by-calendar-year fixed effects. That said, I compare individuals within the same province, cohort, and calendar year, who differ in parents' CR experience but are otherwise subject to similar local conditions. Using data from the Chinese censuses of 2000 and 2005, I find that when individuals have *fathers* exposed to the CR during impressionable years, a one standard deviation increase in CR

[1] Throughout this paper, I refer to "occupational effect of parents' CR experience" or similar phrasing to denote "the impact of parents' CR experience on children's entry into professional occupations".

intensity, roughly equivalent to the gap between Beijing and the average prefecture, leads to a 0.43 percentage point decrease in the likelihood of entering professional occupations.[2] This effect corresponds to approximately 6.5 percent of the sample mean. However, I do not find a significant effect of *mothers'* CR experience. Additionally, I find that children of the CR era are more likely to pursue careers as state employees as opposed to professional occupations.

One potential concern with my identification strategy is the possible correlation between CR violence intensities and local dynamics in occupational choices. To address this, I estimate an event-study model to zoom in on the occupational effects of fathers' CR experience. There are no differential pre-trends in entering professional occupations among individuals whose fathers were old and experienced CR violence *after* impressionable years; the negative effects occur only if the experience was *during* impressionable years; and no differential post-trends are detected if fathers experienced violence *before* impressionable years or had no experience at all. These patterns strengthen the plausibility of the identification strategy. In addition to the event-study check, I show that my findings do not markedly change when flexibly controlling for variables that may relate to CR violence and long-run local development, including the severity of the Great Chinese Famine (1959–61), urbanization, industrialization, demographics, and political control.

I perform several robustness checks to address additional concerns regarding my findings, including sample selection, regional heterogeneity, and statistical inferences. Moreover, I take into account recent advancements in the econometric literature on DiD designs with continuous treatment (Callaway et al., 2021; de Chaisemartin et al., 2022); I show that my results are not due to insensible aggregation of heterogeneous treatment effects.

[2] As I will define subsequently, professionals encompass engineers, technicians, teachers, doctors, and other skilled occupations.

Having observed the negative effect of fathers' CR experience on children's entry into professional occupations, I delve into exploring the underlying mechanisms. I begin by examining whether the CR resulted in barriers to accessing professional job opportunities. I explore several possibilities to shed light on this matter. In a nutshell, the results suggest that constraints on opportunities may not be the primary explanation.

First, as professional occupations typically require high levels of human capital, it is plausible that the CR had a negative impact on educational attainment across generations, leading to a reduction in entry into professional occupations. However, I find no evidence that fathers' CR experience had a salient impact on children's high school completion rates. Furthermore, even when focusing exclusively on high school graduates, I observe that fathers' CR experience still exhibits a negative effect on children's entry into professional occupations, and the effect size is even greater than those who did not complete high school. There is also no strong evidence that fathers' CR experience is associated with the worse health of their children.

Second, apart from educational attainment and health, it is possible that the CR affected human capital across generations in other intangible ways, such as skills transmitted from parents to children. To explore this, I test whether experiencing the CR affected high school completion and entry into professional jobs in the parent generation. No significant impacts are detected, indicating that skill transmission likely plays a minor role in explaining the observed effects. Additionally, there is no strong evidence that women's experience of the CR influences fertility, suggesting that a quantity-quality tradeoff in allocating resources to children may not be at play (Becker and Lewis, 1973).

Lastly, one potential explanation for my findings could be that the CR caused lasting damage to the local economy, thereby reducing the availability of professional jobs. However, this explanation does not align with the observed effects: within the same province, birth cohort, and calendar year, individuals with fathers exposed to the CR are still less likely to be professionals compared to those without such exposure. Furthermore, I show that CR intensities are not strongly associated with contemporary measures of economic development, in line with Bai and Wu (forthcoming)'s findings that the CR's negative economic impacts diminished after the late 1980s.

Given that the material constraints alone do not explain much of my findings, I investigate whether the findings can, at least partially, be attributed to preferences shaped by the CR and transmitted across generations. In light of the CR's ideology and violence against professionals, I posit that a stigma may become associated with professional occupations, which could have been transmitted intergenerationally. This hypothesis aligns with previous research in economics and political science that has demonstrated the significant impact of socio-political shocks in shaping the attitudes of immediately affected generations (e.g., Malmendier and Nagel, 2011) and their descendants (e.g., Lupu and Peisakhin, 2017).

However, it is challenging to test the preference-transmission channel due to the lack of detailed information on the transmission process and preferences toward professional jobs across generations. I provide two pieces of indirect evidence. First, I test the comparative statics of a within-family preference transmission model in the spirit of Bisin and Verdier (2001). The model predicts that if fathers associate a stigma with professional occupations due to the CR and attempt to align children's occupational choices with their own preferences, they would exert greater influences to discourage entry into professional occupations when (i) social factors tend to attract children into "undesirable" professional occupations, and (ii) they prioritize the alignment of children's choices to a greater degree. Regarding (i), I show that fathers' CR experience has a more pronounced effect in the presence of strong pull factors toward professional jobs, proxied by a higher share of professional workers and a higher wage rate for professionals. Regarding (ii), I build upon China's son preferences, under which parents tend to more actively influence sons' choices than daughters' (Edlund, 1999; Knight et al., 2010). Tellingly, I find that fathers'

CR experience is more impactful on sons than on daughters, corroborating the model's predictions. Taken together, these patterns suggest that a preference-transmission channel may be at play.

The second piece of evidence speaks to the CR's impacts on parenting attitudes toward the third generation. Specifically, I focus on a "father-individual-child" chain. I find that having fathers exposed to the CR makes individuals less likely to desire their own children to pursue professional occupations in the future. Importantly, this effect is only present in the patriarchal line, namely, in the "father-man-son" chain. This echoes the earlier finding that preference transmission may concentrate on sons. Additionally, I find that the CR does not influence willingness to invest in the next generation, as represented by expectations for the next generation to attend college. This accentuates the dislike towards professional occupations.

This paper relates to several strands of literature. First and foremost, it adds to the literature on the long-term impact of large socio-political events (Alesina and Fuchs-Schündeln, 2007; Kaplan et al., forthcoming; Michaelsen and Salardi, 2020; Padilla-Romo and Peluffo, 2023). I contribute to this literature by studying the occupational effects of CR experience during impressionable years in an intergenerational setting. By doing so, I also add to the burgeoning economic literature on the impressionable years hypothesis, which highlights the long-run impacts on behaviors and preferences of late-adolescence or early-adulthood experiences (Cotofan et al., 2020; Magistretti and Tabellini, 2022; Carreri and Teso, 2021).

Second, this paper contributes to the literature on parents' influences on their children. Parents can shape children's outcomes through various channels (see Doepke et al., 2019 for a review), including the transmission of their worldviews (Bisin and Verdier, 2001; Doepke and Zilibotti, 2008, 2017; Dohmen et al., 2012). While most existing studies in this area are theoretical, this paper joins recent empirical work (Campante and Yanagizawa-Drott, 2015; Alesina et al., 2021; Lupu and Peisakhin, 2017; Li and Goetz, 2019).

Lastly, the paper relates to studies on China's Cultural Revolution. Existing literature has examined the CR's impacts on various aspects, such as human capital, industrialization, political trust, and social mobility (Li and Meng, 2022; Bai and Wu, forthcoming, 2020; Ou and Xiong, 2021; Wang, 2021; Alesina et al., 2021; Zhang et al., 2023; Chen et al., 2020). The current paper complements to findings by investigating occupational effects across generations.[3] Considering the profound implications of the occupational distribution for development, it is useful to understand how the CR influences occupational choices intergenerationally (Banerjee and Newman, 1993; Baumol, 1990; Eeckhout and Jovanovic, 2012). In this respect, this paper also relates to recent papers about the political and institutional factors of occupational choices in contemporary China (Lai and Li, 2023; Jia et al., 2021; Bai et al., 2021).

The rest of this paper proceeds as follows. Section 2 presents the historical background. Section 3 introduces the data. Section 4 discusses the empirical strategy. Section 5 reports the CR's occupational effects. Section 6 investigates the underlying mechanisms. Section 7 concludes. Supplementary information can be found in the Online Appendix.

2 Background and Hypothesis

2.1 Cultural Revolution

The Cultural Revolution (CR) holds great importance in China's modern history. It was launched by Chairman Mao in 1966 and concluded in 1976 following Mao's death.

[3] Bai and Wu (forthcoming) find that counties with greater CR violence intensities exhibited worse development up until the early 1980s. They suggest reduced entry into professional occupations as one potential mechanism, but they do not systematically analyze this issue. I provide a more in-depth treatment of how the CR intervened in occupational choices.

There has been extensive and growing literature on the events during the CR and their consequences (e.g., MacFarquhar, 1974; MacFarquhar and Schoenhals, 2009; Su, 2011; Zhou and Hou, 1999). It is out of the scope of this paper to provide a comprehensive account of the CR in this section. Rather, I provide details about the CR pertinent to the subsequent analysis.

Officially labeled as a "soul-touching revolution," the CR placed a strong emphasis on ideology and culture from its inception. Mao proclaimed that bourgeois elements had infiltrated the government and society, necessitating a cultural revolution to preserve the socialist system.[4] Consequently, the CR revolved around salient anti-bourgeois ideology. As stated by People's Daily (1966), the CR aimed to "suppress bourgeois leaders, academics, and ideology", "reform education, literature, art, and all other superstructure", and "consolidate and develop the socialist system".

The CR featured mass mobilization, with nearly everyone involved. People were encouraged to participate in revolutionary activities, despite the interruption of education or production. State propaganda also actively promoted Mao's directions and ideology, which heightened revolutionary fervor (Ou and Xiong, 2021). During the CR, "class struggle" became the guiding principle of social life. It targeted people suspected incompatible with or disloyal to the socialist system, including ex-landlords, capitalists, and in particular, intellectuals (Bai and Wu, 2020; Su, 2011; Zhou and Hou, 1999; Ou and Xiong, 2021). The "class enemies" were subject to public denunciations, forced self-criticisms, and beatings if not outright death. Many victims were distributed in professional occupations. For instance, the struggle against educators was well known. Wang (2001) even called the CR "student attacks on teachers". The 1966 official directive also explicitly mentioned targeting

[4]There is debate around whether Mao genuinely believed bourgeois elements posed a threat to Chinese socialism. Some argued that Mao might have used the revolution as a means to restore his authority, which had been undermined by the failure of the Great Leap Forward (MacFarquhar and Schoenhals, 2009). These origins may not be mutually exclusive. It is beyond the scope of this paper to identify the true origins of the CR. Nonetheless, regardless of the true origins, the CR did feature material anti-bourgeois ideology and violence (introduced in detail later), which I take as given and explore the impacts on occupational outcomes.

scientists and technicians. One high-profile anecdote was that even scientists working for China's nuclear project, who presumably should have been respected and protected, suffered brutal struggles and violence; some were killed.

According to Walder (2014)'s estimate, 1.1–1.6 million were killed during the CR. Most deaths can be linked to persecutions during 1966–71 associated with the "Cleansing the Class Ranks Campaign" starting in 1968 (see Figure A1). The violence started to fade after 1969 when Mao ordered the military to re-establish order and mobilized young revolutionaries to go to remote rural areas (Wang, 2021).

2.2 Hypothesis: Children of the Cultural Revolution

The ideology and violence against professionals during the CR could have resulted in the stigmatization of professional occupations. Thus, it raises the question of how such stigmatization influenced occupational choices. As the memories about the CR can be enduring across generations,[5] I hypothesize that children with parents exposed to the CR may be less inclined to pursue professional occupations, even if they themselves have little direct exposure to the CR ideology.

This paper concentrates on the children of the Cultural Revolution for several reasons. First, understanding the long-term, intergenerational impacts could be more pertinent to contemporary China. Second, the child generation may provide a better testing ground to identify the CR's occupational effects via molding ideology. The parent generation additionally experienced economic turmoil due to the CR, making it hard to isolate the ideological impacts. By contrast, the child generation mostly entered the labor market in China's reform era, when the economy had recovered (Bai and Wu, forthcoming). However, the CR ideology may not have faded away and so exert influences across generations. Relatedly, some recent studies exploit Maoist policies as "natural experiments"

[5] According to the nationally representative survey of the China Family Panel Study in 2010, 98.23% of respondents knew the class label assigned to their family during the CR.

in conjunction with intergenerational settings to demonstrate the importance of cultural traits in economic outcomes (Li and Goetz, 2019; Alesina et al., 2021).

3 Data

This section introduces the data used in this study. Section 3.1 discusses the measurement of local CR intensities. Section 3.2 defines exposure to the CR. Section 3.3 reports the construction of the main sample in subsequent analysis.

3.1 Measuring CR Intensities

The CR intensity in a prefecture p is measured as follows (Wang, 2021; Bai and Wu, 2020, forthcoming):

$$CR_p = \ln(1 + \text{deaths per million in the CR})\,. \tag{1}$$

In my sample, the average prefecture in my sample had 428 deaths per million population during the CR. CR_p is in the log form to reduce skewness (see Figure A2 for the distribution). One standard deviation of CR_p reflects the difference in intensities between Beijing and the average prefecture.

To calculate CR_p, I employ a dataset on death rates obtained from Walder (2014). The death rates are estimated based on county gazetteers published by local governments after the CR.[6] I aggregate the death rates at the prefecture level,[7] using the administrative divisions in 2000–05, which aligns with the timeframe of the main sample I analyze (see Section 3.3).[8]

[6] According to Walder (2014), more than 90 percent of gazetteers he used were published by 2001.
[7] The prefecture is the second-level administrative division in China. It is between province and county.
[8] In cases where a county is split and incorporated by different prefectures in 2000–05, I evenly distribute the county's deaths and population during the CR among all receiving prefectures.

The variable CR_p may have two potential measurement errors. First, the local government may have incentives to underreport deaths resulting from violence during the CR. If the extent of underreporting is correlated with local dynamics of occupational outcomes, it could introduce bias into the subsequent DiD estimates. Second, aside from underreporting due to political incentives, the accuracy of death rates can (inevitably) be affected by the resources a local government devoted to compiling the gazetteer. In particular, the compilation of gazetteers is coordinated at the province level, so wealthier provinces may be able to provide more precise data on deaths during the CR. If this discrepancy in data quality across provinces is associated with differential trends in occupational outcomes, the estimate could also be biased.

To address these measurement errors, I will account for variations in reporting efforts (due to political pressures or resources) in all regressions. First, I control for the detailedness of gazetteers, measured by (i) the number of words in the section dedicated to the CR and (ii) the number of words in the section discussing major events in a county's modern history. Tellingly, more detailed gazetteers tend to have higher reported death rates during the CR. Second, as the compilation of gazetteers is coordinated at the provincial level, province fixed effects are included to leverage only *within-province* variations.

3.2 Measuring Exposure to the CR

Next, I define exposure to the CR, which aims to capture the group most vulnerable to the CR's ideological influences. To operationalize this idea, I draw upon the impressionable years hypothesis (IYH) from political psychology (Krosnick and Alwin, 1989; Alwin and Krosnick, 1991; Sears, 1971). The IYH suggests that certain preferences and beliefs are durably molded during ages 18–25, referred to as "impressionable years" or "formative years". It is during this period that people are particularly receptive to socio-political changes, which can significantly impact their attitudes; after this period, people's preferences and beliefs tend to stabilize and change less substantially. A range of studies in economics has provided support for the IYH (Cotofan et al., 2020; Akbulut-Yuksel et al., 2020; Eichengreen et al., 2021; Carreri and Teso, 2021; Magistretti and Tabellini, 2022).

Building upon the IYH, I create a dummy variable, Exp_t, to measure cohort t's exposure to the CR. Exp_t is equal to one if cohort t reached ages 19–24 during 1966–71, the most violent episode of the CR. This definition ensures that the exposed individuals have at least one full year of exposure to the CR violence during their impressionable years. Figure 1 depicts Exp_t as a function of birth cohort t. It shows that individuals born between 1942–52 are exposed, while individuals born earlier or later are considered unexposed.

Besides being motivated by the IYH, this definition of exposure also aligns with historical facts. During the CR, many young students were mobilized to form radical revolutionary groups, known as the Red Guards. That said, people who were in their impressionable years during the CR could even be at the forefront of violence against professionals.

3.3 Main Sample

Sample Construction. The main sample used in this study is constructed based on the Chinese censuses of 2000 (Minnesota Population Center, 2020) and 2005. It comprises 370,677 individuals from 332 Chinese prefectures (out of 340).

The sample is restricted to individuals born after 1960 and at least 25 years old. These individuals were old enough to be in the labor market at the time of censuses. However, they were still young or even not yet born during the CR, and therefore were not exposed to the CR based on their own cohorts (cf. Figure 1). However, their parents, who were born between 1900 and 1961, may have been exposed to the CR.

The parent-child link is identified based on a variable coding an individual's relationship to the household head. Consequently, individuals who did not live with their parents are excluded from the sample because of the absence of information about their parents. It is important to note that this sample restriction raises a potential selection issue: if the decision to coreside with parents is correlated with the CR and occupational choices, the estimates can be biased due to endogenous entry into the sample. I address this issue in Section 5.2 and find that the results are unlikely to be driven by selection on coresidence.

The main outcome of interest is a dummy variable of professional occupations. Professional occupations are broadly defined, including engineers, technicians, teachers, doctors, and other skilled occupations.[9] This definition follows Bai and Wu (forthcoming) and skilled occupations outlined in the classical International Standard Classifications of Occupations (ISCO).

Summary Statistics. Table 1 presents summary statistics of the main variables. I divide the sample into high-intensity versus low-intensity groups (above versus below the sample median CR intensity). Within each group, in the first two columns, I present summary statistics separately for individuals whose fathers were exposed to the CR or not; the gaps in means are reported in the third column. Column (7) presents the difference-in-differences (DiD) statistics, reflecting the differential gaps that can be attributed to the CR.

The first line of Table 1 shows that in the high-intensity group, individuals with exposed fathers (Column (1)) are 0.4-percentage-point *less* likely to be professionals than those with unexposed fathers (Column (2)). When it comes to the low-intensity group, individuals with exposed fathers (Column (4)) are in fact *more* likely to become professionals than those with unexposed fathers (Column (5)). This distinction between high- versus low-intensity groups indicates that fathers' CR may have reduced children's entry into occupational occupations. This pattern is also visualized by Figure 2, which depicts the relationship between individuals' likelihood of being professionals and their fathers' birth cohorts. Notably, there is a noticeable drop in the likelihood of individuals being professionals if their fathers were born between 1942 and 1952 and thus experienced the CR during

[9] Table A1 provides a full list of 14 professional occupations (out of 64 in total) in Chinese censuses.

impressionable years. Such a drop is more pronounced in high-intensity prefectures. In fact, individuals in these prefectures had a higher probability of being professionals if their fathers were born before 1942 than in low-intensity prefectures; the probability dropped significantly for individuals whose fathers were born during 1942–52 but rebounded for those with fathers born after 1952.[10]

Table 1 also shows that there are some differences in several other characteristics by exposure or CR intensity, which will be taken into account in subsequent regression analyses.

4 Empirical Strategy

Estimating Equation. To estimate the effect of parents' CR experience on children's entry into professional occupations, I adopt a difference-in-differences (DiD) model specified as follows:

$$Y_{ijbtp} = \beta\left(CR_p \times Exp_t\right) + X_i'\zeta + \left(X_i' \times Exp_t\right)\phi + \lambda_p + \mu_t + \gamma_{r(p)} \times \delta_b + \varepsilon_{ijbtp}. \tag{2}$$

In this regression, i indexes individual. j indexes individual i's parent (father or mother). b and t index individual i's and parent j's birth cohorts, respectively. p indexes prefecture. $r(p)$ indexes the province that prefecture p locates.

The dependent variable, Y_{ijbtpr}, is a dummy variable indicating whether individual i is in a professional occupation. CR_p is the CR intensity in prefecture p as defined in Section 3.1. Exp_t is a dummy variable that equals one if parent j of cohort t experienced the violent episode of the CR (1966–71) during the impressionable years (see Section 3.2). X_i is a set of

[10]Table A2 and Figure A3 conduct these exercises based on mothers' exposure. Within both high- and low-intensity groups, individuals with exposed mothers are more likely to be professionals than those with unexposed mothers; however, the gap does not vary significantly with CR intensities.

covariates, including gender, ethnicity, and urban residency (shown in Table 1).[11] I also include the interaction term, $X_i \times Exp_t$, to allow for more flexible controls. λ_p and μ_t absorb prefecture and parent j's birth cohort fixed effects. $\gamma_{r(p)}$ and μ_b are province and individual i's birth cohort fixed effects. All fixed effects and covariates are interacted with calendar year fixed effects (2000 or 2005). ε_{ijbtp} is the error term. Standard errors are clustered at the prefecture level, the same level as the identifying variation in CR intensity, CR_p.

Identification. β is the coefficient of interest. It captures how parents' CR experience influences an individual's entry into professional occupations. I expect it to be negative, given the CR's stigmatization of being professionals. Throughout this paper, all estimated β are scaled to reflect the effect of one standard deviation (SD) change in CR intensity CR_p. Recall that one SD of CR_p is roughly equivalent to the gap between Beijing and the sample average.

Identification of β follows from the common trends assumption: in the absence of parents' exposure to the CR, the individuals' occupational outcomes would evolve similarly between high- and low-intensity prefectures, conditional on the controls included. Equation 2 is a relatively stringent specification to purge potential differential trends. With the inclusion of province-by-cohort(-by-calendar-year) fixed effects, $\gamma_{r(p)} \times \delta_b$, the coefficient of interest β is estimated off variations in CR intensities (CR_p) and parents' exposure (Exp_t) among individuals in the same province, birth cohort, and calendar year. This helps control for a range of spatial and cohort heterogeneity, for instance, policies featuring provincial-level variations in rollout or implementation (Wang and Yang, 2021).[12] I also estimate an event-study model to conduct usual pretrends checks, which lends support to the common trends assumption (see Section 5.1).

[11] I include a minimum set of covariates here to avoid possible bad control problem (Angrist and Pischke, 2009). In Section 6, I explore several factors that are likely the outcomes of the CR and influence occupation outcomes.

[12] See Ebenstein (2010), Tang et al. (2020), and Chen and Kesten (2017) for examples in this regard. They, respectively, study provincial variations in the one-child policy, compulsory education law, and college admission reforms.

5 Occupational Effects

5.1 Main Results

5.1.1 Baseline Effects

Table 2 reports the estimates of Equation 2 with several variants. The coefficients are scaled to reflect the effect of one standard deviation (SD) change in CR intensity CR_p. Recall that one SD of CR_p is roughly equivalent to the gap between Beijing and the sample average.

Columns (1)–(3) first investigate the impact of having a father exposed to the CR. Column (1) is a minimum specification, only including prefecture and father's birth cohort fixed effects that are necessary for the DiD design. Column (2) controls for province-by-cohort heterogeneity. Column (3) further incorporates variables likely related to occupational outcomes (X_i and $X_i \times Exp_t$). All estimates are negative. The estimate with all controls in Column (3) suggests that if having a father exposed to the CR, a one SD higher CR intensity would reduce an individual's likelihood of being a professional by $0.0043 \times 100 = 0.43$ percentage points. In other words, Beijing's children of the CR are 0.43-percentage-point less likely to be professionals, *ceteris paribus*; this effect amounts to $\frac{0.43}{6.61} \times 100 = 6.5$ percent of the sample mean.

Columns (4)–(6) examine the role of mothers' exposure to the CR. The results indicate that mothers' CR experience does not have a discernible effect on their children's entry into professional occupations. In Column (7), a horse race model compares the effect of fathers' and mothers' exposure to the CR, reinforcing the finding that fathers' exposure plays a more influential role in shaping children's occupations. Furthermore, Column (8) shows the robustness of results if considering having *at least* one parent exposed to the CR. One possible explanation for fathers' and mothers' distinct roles is the patriarchal culture in China, where fathers hold a stronger position within the family and have a greater influence on their children. Based on these results, in the subsequent analysis, I focus on the impact of fathers' exposure to the CR.

Given the decrease in entry into professional occupations, which occupations do people with exposed fathers pursue instead? Figure 4 speaks to this question. I estimate Equation 2 using dummies for alternative occupations as dependent variables; I also estimate a multinomial logit model. Figure 4 shows that there is a general shift away from agriculture. With a lower likelihood of entering professional occupations, people with fathers exposed to the CR tend to be state employees. The increase in state employment is remarkable. State jobs require a comparable level of human capital in terms of educational attainment as professional jobs; however, they are more widely perceived as prestigious in China (Baumol, 1990; Lai and Li, 2023). It may suggest that people, especially the skilled ones, are prompted to pursue prestigious jobs due to the CR-induced stigmatization of professional jobs. In Section 6, I present an analysis that sheds light on underlying mechanisms.

5.1.2 Dynamic Effects

My identification strategy draws upon cohort-based variation in fathers' exposure to CR during their impressionable years. To gain more insights, I estimate an event-study model to examine the occupational effects separately by fathers' birth cohorts. The model is specified as follows:

$$Y_{ijbtp} = \sum_{\tau} \beta_\tau \left(CR_p \times T_{t\tau}\right) + X_i'\zeta + \left(X_i' \times Exp_t\right)\phi + \lambda_p + \mu_t + \gamma_{r(p)} \times \delta_b + \varepsilon_{ijbtp}. \tag{3}$$

$T_{t\tau}$ is a dummy variable equal to one if i's father j was born in cohort τ; other variables are defined the same as in Equation 2. Thus, coefficients β_τ's capture the effects of having a father experiencing the CR (or not) at different life stages.

Figures 3a and 3b plot the estimated coefficients β_τ's by birth cohorts and by birth cohort bins. β_{1941} and $\beta_{1939-41}$ are the omitted reference groups, respectively. Both figures show similar patterns. If fathers were born before 1941 and thus had already passed the impressionable years during 1966–71, the CR had no significant effects on their children's entry into professional occupations. If fathers were born between 1942 and 1952 and thus experienced violent times during impressionable years, their children were less likely to be professionals. These negative effects on professional entry dissipate among people whose fathers were born after 1952 and thus had not yet reached impressionable years during 1966–71.[13]

Two remarks are in order regarding these patterns. First, the patterns shed light on the validity of the DiD design. There are no differential (both pre- and post-) trends in occupational outcomes among people whose fathers were not exposed to the CR during their impressionable years. Second, the patterns echo the impressionable years hypothesis. The negative occupational effects occur *only* among people whose fathers experienced the CR violence during impressionable years, motivating further in-depth investigations of preferences shaped by the CR and transmitted intergenerationally.

5.2 Robustness Checks

In this subsection, I provide a battery of checks for to address several concerns regarding my findings. I show that my findings are not due to selection on coresidence, regional heterogeneity, and migration. I also domonstrate the robusteness to variants of statistical inferneces, alternative measurements, and the estimation approach.

[13]The dynamic effects of a mother's exposure is overall flat, consistent with the previous finding that the mother's exposure is not influential (see Figure A4).

5.2.1 Coresidence

One limitation of the main sample is that censuses only allow for the identification of parent-child relationships when parents and children live together in the same household. This limitation may introduce bias if people's CR experience was systematically correlated with coresidence with their children and children's occupational outcomes. I address this concern in various ways.

First, I examine whether people exposed to the CR are more or less likely to live with their children. Column (1) in Table 3 examines all people born before 1961 (same as parents in the main sample) in the censuses of 2000 and 2005; Figure 5a presents the event-study plot.[14] There is no strong evidence that exposure to the CR affected the likelihood of parent-child coresidence. Columns (2) and (3) in Table 3 look at men and women separately, confirming the CR did not have a pronounced effect on living arrangements between parents and children.

Second, I redo the analysis in Table 2 using a sample not conditioned on coresidence. The origin of selection on coresidence is that, for people who do not live with their fathers ("independent individuals"), fathers' exposure to the CR, Exp_t, cannot be measured due to the lack of information on t. To get around this issue, I impute exposure of independent individuals' fathers using information from the main sample. Specifically, the imputed exposure, denoted by $\widehat{Exp_t}(b)$, is given by the formula

$$\widehat{Exp_t}(b) = \Pr\{t \in [1942, 1952] \mid b\}, \tag{4}$$

where $\Pr\{t \in [1942, 1952] \mid b\}$ is the probability of having a father born during 1942–52 given that an independent individual was born in b. $\Pr\{t \in [1942, 1952] \mid b\}$ is estimated

[14] As the census only reports childbearing history for women between 15 and 50, one cannot know if couples have children at all. Therefore, estimates would capture a combination of the CR's extensive-margin effect on fertility *and* effect on coresidence. I specifically examine the CR's effect on fertility in Section 5.2.

using province-specific distributions in the main sample. With this imputation, the analysis can include *all* individuals born after 1960 regardless of their coresidence status with parents. I estimate Equation 2 with Exp_t replaced by $\widehat{Exp}_t(b)$ for independent individuals.[15] Standard errors are clustered (i) by prefecture level, as before, to account for common shocks on people within the same prefecture and (ii) by province-by-cohort level to account for correlations between observations due to imputation. Column (4) in Table 3 displays the result of this exercise. The sample size significantly increases (N = 4,198,123). As expected, the imputation estimate is imprecise but remains sizeable compared to the baseline estimate (-0.0036 versus -0.0043 in Column (2) in Table 2). Furthermore, I estimate the event-study model (Equation 3) using imputed exposure in the larger sample. Figure 5b shows a pattern similar to Figure 3b; in fact, the CR's negative impact on entry into professional occupations is more accentuated in Figure 5b. These results imply that my findings still hold when not conditioning on coresidence.

Third, as a complement to the second approach, I estimate Equation 2 using the China Family Panel Study (CFPS) survey of 2018. In the CFPS, respondents directly report birth cohorts of their parents, so Exp_t can be measured for everyone regardless of coresidence status. Reassuringly, Column (5) in Table 3 confirms that fathers' CR experience significantly reduces children's probability of entering professional occupations.[16] It also accentuates my finding — even in 2018, four decades after the CR concluded, fathers' CR experience still discourages children's entry into professional occupations.

Taken together, my findings should not have been driven by sample selection on coresidence.

[15]One issue in this estimation is that fathers' birth cohort fixed effects, μ_t, cannot be defined for independent individuals. So for them, I alternatively control for a set of probabilities for fathers' birth cohorts, namely, $\Pr(t \in T \mid b)$, where T is an interval of birth cohorts.

[16]Appendix II reports construction of the CFPS sample. Table A8 replicates the specifications in Table 2 using the CFPS sample, which delivers similar implications.

5.2.2 Regional Heterogeneity

The DiD design compares the evolution of occupational outcomes across prefectures with varying CR intensities. One concern is that the results may be confounded by differential trends due to regional heterogeneity associated with CR intensities. Some earlier results have alleviated this concern. For instance, the event-study plot (see Figure 3) exhibits patterns consistent with the IYH. Nonetheless, I provide additional robustness checks to ascertain that my findings are not driven by regional heterogeneity.

First, I control for several pre-CR local characteristics that may relate to violence but also long-term development. They include: (i) population loss index in the Great Chinese Famine (1959–61), (ii) share of the urban population, (iii) share of workers in population, (iv) share of cadres in population, (v) share of party members in population, (vi) distance to Beijing, (vii) distance to provincial capital, and (viii) sex ratio.[17] The variables may proxy for factors likely associated with both CR intensities and long-term local dynamics.[18] I flexibly control these variables by including their interactions with fathers' birth cohort fixed effects in Equation 2. Figure 7 displays the results, showing that the inclusion of these variables does not markedly change the baseline result.

Second, I examine the robustness of the results by excluding some potentially distinctive regions. Table A4 displays these exercises. In Column (1), I drop prefectures with a CR intensity of top or bottom 5th percentiles. In Column (2), I exclude four direct-controlled

[17]Appendix III reports the construction of the population loss index in the Great Chinese Famine, following Meng et al. (2015) and Chen and Yang (2015). (ii)–(v) are from Walder (2014). (vi) and (vii) are calculated by the author. (viii) is from Wang (2021).

[18]Regarding (i), the catastrophic Great Chinese Famine killed over 30 million people (Meng et al., 2015); Chen and Zhou (2007) find that the famine leads to serious health and economic consequences for the survivors, especially for those in early childhood during the famine. I control for famine severity to address concerns that the CR intensity may pick up the Famine's adverse, persistent impacts. Regarding (ii), MacFarquhar and Schoenhals (2009) document that insurgencies occurred mostly in urban areas; urbanization also relates to long-run development. For (iii), workers were mobilized to engage in revolutionary activities. (iv)–(vii) capture political alignment and control, which can be associated with insurgencies as well as development. For (viii), the sex ratio can be related to insurgencies (MacFarquhar and Schoenhals, 2009; Wen, 2020) and economic outcomes (Wei and Zhang, 2011).

municipals (Beijing, Tianjin, Shanghai, and Chongqing; DCMs), which may have unique political and economic conditions. In Column (3), I exclude four DCMs and all provincial capitals. In Column (4), I restrict the sample to provinces in "China proper", excluding border and minority provinces.[19] All results remain robust throughout.

5.2.3 Migration

There may be a measurement error in the CR intensity CR_p as the prefecture of residence at census time (in 2000 or 2005) is used as a proxy for the prefecture (during 1966–71) where one experienced the CR. If fathers' CR experiences were systematically related to migration and children's entry into professional occupations, this measurement error could introduce bias into the estimate.

However, migration might not be a primary concern in the sample. Rural-urban migration didn't significantly increase until 1997 (Frijters et al., 2015), and the central government only began easing institutional restrictions on internal migration around 2000 (Tian, 2022). The 2000 census provides information on birthplace (unlike the 2005 census). In 2000, approximately 85% of people lived in their birth counties, and 94% lived in their birth provinces. Given that prefecture is the administrative division between county and province, these facts suggest that migration is unlikely to have a major impact on the main results. Nevertheless, in Columns (1)–(3) of Table A3, I conduct robustness checks on my findings by (i) excluding the most recent 2005 census, (ii) excluding those who do not live in their birth provinces, and (iii) excluding those who do not live in their birth counties. All results remain robust throughout. Additionally, in Columns (4) and (5) of Table A3, I demonstrate that the CR experience does not have a significant impact on migration to other provinces or counties.

[19]These provinces include: Gansu, Qinghai, Ningxia, Tibet, and Xinjiang, Hainan, Sichuan, Yunnan, Inner Mongolia, Heilongjiang, and Jilin.

5.2.4 Alternative Statistical Inference

I show that my results are robust to alternative statistical inferences. I conduct a permutation test. I permute the CR intensities across prefectures and re-estimate Equation 2 to derive a counterfactual occupational effect. Figure 6 displays the distribution of the counterfactual effects derived from 1,000 permutations. The dashed vertical line is the actual effect, and it lies at the tail of the distribution, yielding a p-value = 0.048.

In Table A5, I show the robustness of my findings by using alternative standard errors. I implement two-way clustering by prefecture and birth cohort to take into account common shocks on individuals in the same prefecture and cohort. There are likely spatially correlated factors influencing both CR intensities and occupational outcomes. To address this issue, I use standard errors clustered at the provincial level and Conley standard errors (Conley, 1999).

5.2.5 Alternative Measurement of Exposure

Table A6 demonstrates the robustness of my findings when measuring exposure to the CR (Exp_t) in different ways. In the baseline specification, Exp_t is represented as a *binary* variable indicating whether the impressionable years overlap with 1966–71, which corresponds to the most violent period of the CR (refer to Figure 1). One concern is that this simple construction does not adequately measures exposure to the CR. Therefore, I use an *alternative continuous* measure that captures the proportion of impressionable years overlapping with 1966–71. Additionally, I develop other measures by extending the time frame to include the entire period of the CR (1966–76). Nevertheless, all alternative measures yield results that align with the baseline findings.

5.2.6 Alernative Estimator

My DiD design exploits variation in continuous CR intensity, CR_p. Recent econometric literature on DiD designs with continuous treatment suggests that the fixed effects estimator may not correctly aggregate treatment effects when the effects are highly heterogeneous (Callaway et al., 2021; de Chaisemartin et al., 2022).[20] This can lead to misleading interpretations: the fixed effects estimate may have a sign opposite to the causal parameter of interest (e.g., average treatment effect).

To address the concern about incorrect aggregation, I first implement de Chaisemartin et al. (2022)'s heterogeneity robust estimator. Figure A5 presents the event-study plot using the robust estimator, showing a pattern similar to Figure 3a that uses fixed effects estimator. In sum, my finding of the CR's negative effect on entry into professional occupations should not be due to incorrect aggregation.

6 Mechanisms

Thus far, I have found evidence that people with fathers exposed to the CR during impressionable years are less inclined to pursue professional occupations. This section delves into the underlying mechanisms.

There are several mechanisms through which fathers' CR experience can influence children's entry into professional occupations. I will broadly explore two sets of mechanisms (Fehr and Hoff, 2011). The first set revolves around the constraints faced by people. For instance, fathers' exposure to the CR may hinder their children's ability to pursue professional careers due to a lack of skills or a disadvantaged background. The second mechanism involves individuals' preferences. The CR may instill a dislike for professional

[20]This occurs even if there is no variation in treatment timing (as in my application). In DiD designs with binary treatment, the aggregation problem arises only when there is timing variation in adoption (Goodman-Bacon, 2021).

occupations, which can be passed down across generations. Consequently, individuals may choose not to enter professional occupations even if they possess the necessary qualifications. It is important to note that these two mechanisms may not be mutually exclusive. For example, it is plausible that fathers' distaste for professional occupations leads to underinvestment in their children's human capital, making children less likely to pursue professional occupations. I will further discuss this issue below.

6.1 Constraints

I examine several sources of constraints that individuals may encounter when attempting to pursue professional occupations.

Human Capital. Professional occupations typically demand a high level of human capital. As depicted in Figure 8, based on the 2000 census, professionals exhibit the highest high school completion rate at 85 percent, surpassing other occupations. Consequently, individuals may encounter difficulties in entering professional occupations if their fathers' CR experience has a negative impact on their educational attainment. Table 4 investigates this hypothesis.

In Column (1), I do not detect a significant impact on high school completion of fathers' CR experience. Column (2) controls for high school completion when studying the occupational effect of fathers' CR experience, and the coefficient on the interaction term changes little than the baseline (0.0037 vs. 0.0043), indicating that educational attainment mediates does not mediate much of the occupational effect (Baron and Kenny, 1986). Furthermore, when considering only high school graduates (Column (3)), a substantial decrease in the likelihood of entering professional occupations is still observed among individuals whose fathers were exposed to the CR. Notably, this effect is even more pronounced among individuals who did not complete high school. These findings suggest that educational attainment alone cannot fully explain the occupational effects of the CR.

Additionally, in Table A9, using the CFPS data, I show that fathers' CR experience has no discernible effect on children's health. This indicates that children do not fail to pursue professional occupations because of undermined health.

Family Environment. Apart from educational attainment and health, the CR may have influenced human capital across generations in various intangible ways. I explore several possibilities in Table 5.

Panel A investigates whether the CR affects the entry of the parent generation into professional occupations, as this can be associated with occupation-specific traits and subsequently influence the likelihood of the child generation becoming professionals. However, there is no strong support for this hypothesis. Using data from the 1982, 1990, and 2000 censuses and focusing on individuals born before 1961 (the same as the parents in the main sample), I find no evidence that the parent generation's CR experience has a discernible effect on their own likelihood of pursuing professional careers. That said, the CR only appears to affect the indirectly exposed child generation and not the directly exposed parent generation. One possible explanation for this interesting discrepancy is that the parent generation encountered obstacles in job selection during the planned economy era.

Panel B in Table 5 examines parents' educational attainment, which may relate to household well-being and so children's human capital. However, I do not find that the CR has a significant influence on high school completion.

Panel C explores fertility rates. According to the quantity-quality tradeoff (Becker and Lewis, 1973), a smaller family size may lead to better-educated individuals and a higher likelihood of becoming professionals. However, Panel C shows that there is no strong relationship between CR experience and fertility. If anything, there is a negative relationship in the 1982 census, but it is not economically salient and would, in theory, work against finding a negative occupational effect.

Macroeconomic Conditions. Another potential explanation is that the CR has a long-term negative impact on local development, resulting in a reduced availability of professional job opportunities. Figure 6 investigates this aspect by correlating CR intensities with various indicators of development. However, no significant associations are detected. This finding aligns with the results of Bai and Wu (forthcoming), who reported that the CR's most significant adverse effects were concentrated in the early 1980s, with subsequent economic recovery in local economies.

Taken together, the constraints faced by people may not play a major role in explaining my findings.

6.2 Preferences

This section aims to explore the possibility that the CR creates a long-lasting stigma associated with professional occupations, thereby reducing the likelihood of individuals entering such occupations. One empirical challenge in investigating this hypothesis is the unobservable nature of preference transmission from parents to children. However, the decision of preference transmission is made by parents and can be influenced by various factors, resulting in some heterogeneous effects on children's outcomes that allow for testing the existence of the preference transmission channel. To guide empirical investigations, I present a simple model that provides testable predictions.

A Stylized Model. I develop a simple model of preference transmission within families, following Bisin and Verdier (2001). The details and proofs can be found in Appendix I; here, I outline the key features and intuitions of the model. In this model, parents altruistically evaluate their children's occupational choices based on their own preferences. Consequently, while being altruistic, parents prefer children to behave in alignment with their preferences, and they would attempt to transmit preferences to influence children's choices. This implies that a higher intensity of CR experienced by parents would result in a greater reduction in their children's likelihood of entering professional occupations, as a stronger stigma of being professionals is forged and passed on. This prediction is consistent with previous findings. More importantly, the model predicts that parents would transmit their preferences to varying degrees, implying heterogeneous impacts of parents' CR experience on children's entry into professional occupations.

Prediction 1. *Parents' CR experience is more impactful on children if the social factors tend to attract entry into professional occupations.*

Prediction 2. *Parents' CR experience is more impactful on children if they internalize children's choices to a greater degree.*

These two predictions inform heterogeneous effects of parents' CR experience. Prediction 1 follows from the idea that parents exposed to the CR would want to counteract the social factors that may encourage their children to be professionals, which are at odds with their preferences. Prediction 2 is intuitive: parents are more incentivized to pass on preferences if they place greater weight on children's choices (that align with their preferences).

Evidence for Model Predictions. Columns (1)–(4) in Table 7 provide evidence supporting Prediction 1. I consider two factors that can capture the attractiveness of professional occupations: the proportion of professionals and the professional wage rate. If professional occupations are locally popular or they offer better payments, an individual could be more inclined to pursue professional jobs, prompting their parents (particularly fathers) who experienced the CR to interfere more in these circumstances. The results show that fathers' CR experience is indeed more impactful in prefectures with more professionals and higher professional wages. These patterns hold even within high school graduates, for whom educational attainment is not a major obstacle in pursuing professional occupations, which substantiates the role of preferences.

Columns (5)–(6) turn to test Prediction 2. Motivated by China's son preferences, under which parents may place a greater weight on sons' choices (e.g., Edlund, 1999; Knight et al., 2010), I compare the effect of fathers' CR experience on sons with that on daughters. Tellingly, the effect is larger on sons than on daughters, suggesting that sons are subject to stronger preference transmission within the family.

On the Preferences Transmitted. I provide further evidence that parents' CR experience influences their children's preferences toward professional occupations. My test here hinges on the following three-generation chain:

$$\text{fathers} \underset{(1)}{\Rightarrow} \text{individuals} \underset{(2)}{\Rightarrow} \text{children.}$$

If individuals receive a stigma associated with professional occupations from their fathers (linkage 1), they are likely to project such a preference on their own children (linkage 2). I test this hypothesis using the CFPS survey of 2018. In the CFPS survey, individuals with young children are asked about their hopes regarding their children's future occupations. As each generation's occupational preferences are not elicited, this setting provides a testing ground for preference changes. It also relates to the persistence of the CR's occupational effects in the third generation.

I estimate the following DiD model:

$$P_{hijtp} = \beta \left(CR_p \times Exp_t \right) + W'_{hijtp}\gamma + \lambda_p + \mu_t + \nu_{hijtp}. \tag{5}$$

h indexes children. i indexes individuals. j indexes fathers. t indexes father j's birth cohort. p indexes prefecture. λ_p and μ_t are prefecture and father birth cohort fixed effects. W_{hijtp} is a set of control variables, including individuals' and fathers' demographics. P_{hijtp} is a dummy variable that equals one if individual i reports that they want child h to pursue professional occupations. Therefore, coefficient β captures how a father's CR experience influences child i's occupational expectations for grandchild h.

Panel A in Table 8 presents the results. First of all, professionals appear to be a popular occupational choice. In the full sample, 61.43 percent of respondents report that they want their children to pursue professional occupations in the future. However, Column (1) shows that having fathers exposed to the CR makes individuals less likely to want their children to pursue professional occupations. Specifically, a one SD higher CR intensity reduces the likelihood of expecting children to pursue professional occupations by 4.30 percentage points, or 7.0 percent of the sample mean.

Columns (2)–(5) explores the gender heterogeneity of this effect on occupational expectations. Columns (2)–(3) focus on respondents' gender. They show that the effect is primarily driven by male respondents. In Columns (4)–(5), I turn to examine the role of children's gender. I find that it is sons, rather than daughters, that are discouraged from entering professional occupations due to the CR.

Taken together, I find that men tend to inherit a dislike of professional occupations from their fathers and then transmit it to their sons. These patterns echo the previous finding that fathers are more prone to influence sons' preferences (cf. Table 7). Moreover, they suggest that the CR-induced changes in occupational preferences may persist in the *patriarchal* line.

Panel B in Table 8 studies whether fathers' CR experience affects individuals' expectations for their children to attend college, and there is no significant impact. This finding suggests that the observed occupational effect may not be attributed to a lack of willingness to invest in the next generation's human capital. On the contrary, despite a pessimistic view of professional occupations, people still recognize the value of education.

7 Conclusions

Using the lens of China's Cultural Revolution, this paper studies the impact of violence on occupational outcomes across generations. The results show that having a father exposed to anti-professional violence during the CR makes an individual less likely to pursue professional occupations, though the individual themselves has little direct exposure to the CR. I explore the mechanisms underlying the occupational effects. There is limited evidence that the CR results in barriers to entry into professional occupations in terms of educational attainment, health, family background, and macroeconomic conditions. By contrast, preference transmission emerges as a potential explanatory factor. I find patterns consistent with a within-family preference transmission model; I also find that fathers' CR experience makes people less inclined to want their children to pursue professional occupations. These findings suggest that the CR may have generated a lasting distaste towards professional occupations.

I close the paper with two remarks. First, I rely on observational data to *infer* preference transmission. Future studies may exploit experimental methods to trigger relevant memories and directly test for preference changes, which can complement the findings here. Second, given the CR's negative impact on the uptake of professional occupations, it raises intriguing questions about its potential influence on other economic outcomes, such as entrepreneurship, inequality, and innovations, which merits further, rigorous investigations.

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Figures

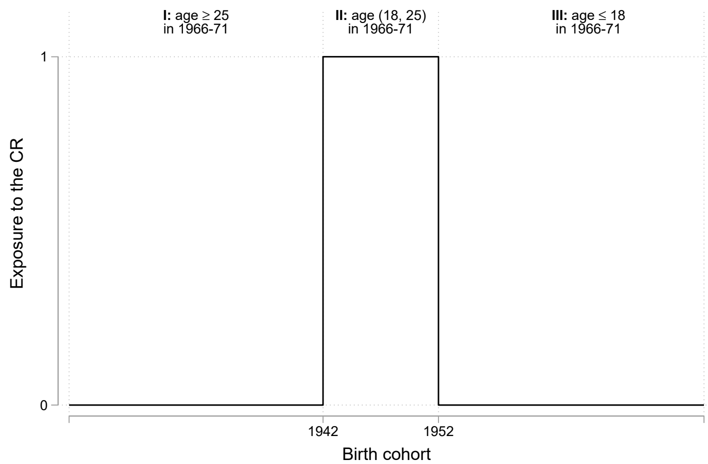


Figure 1. Exposure to the CR

Notes: This figure depicts exposure to the CR, Exp_t, as a function of one's birth cohort t. Based on the impressionable years hypothesis, Exp_t equals one if one was between ages 18 and 25 during 1966–71, the most violent episode of the CR. Equivalently, Exp_t equals one if birth cohort t is between 1942 and 1952.

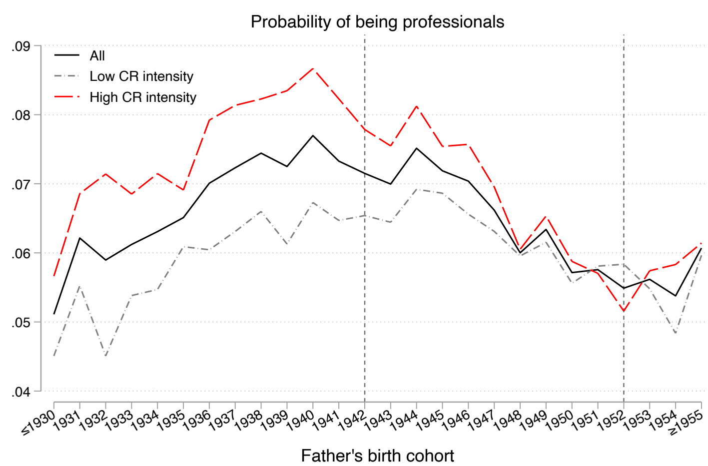
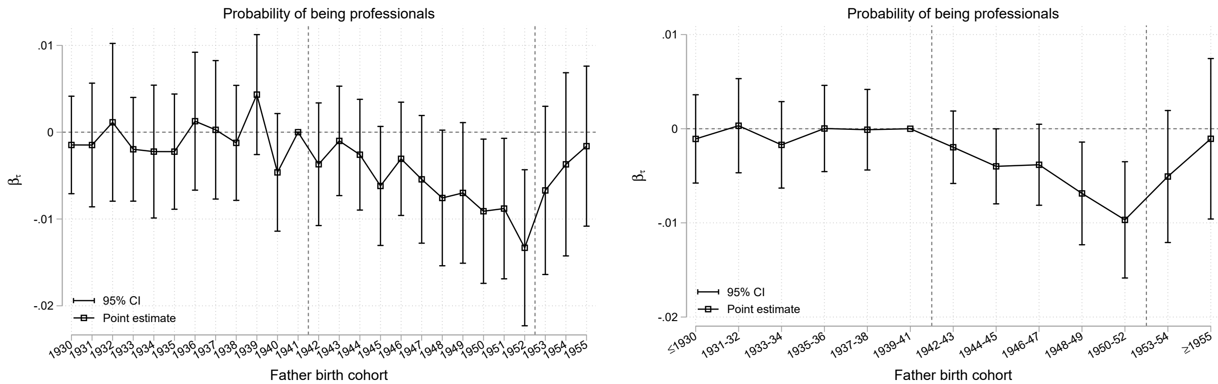


Figure 2. Individuals' Probability of Being Professionals and Their Fathers' Birth Cohorts

Notes: This figure depicts the relationship between individuals' probability of being professionals and their fathers' birth cohorts. The relationship is depicted separately for all individuals, individuals in low CR intensity prefectures, and individuals in high CR intensity prefectures.



a. By Cohorts

b. By Cohort Bins

Figure 3. Dynamic Effects of Fathers' CR Experience on Entry into Professional Occupations

Notes: This figure depicts the dynamic effects of fathers' CR experience on children's probability of being professionals, based on Equation 3. Figures 3a and 3b plot dynamic effects by cohorts and cohort bins, respectively. The dots are point estimates. The caps are 95% confidence intervals.

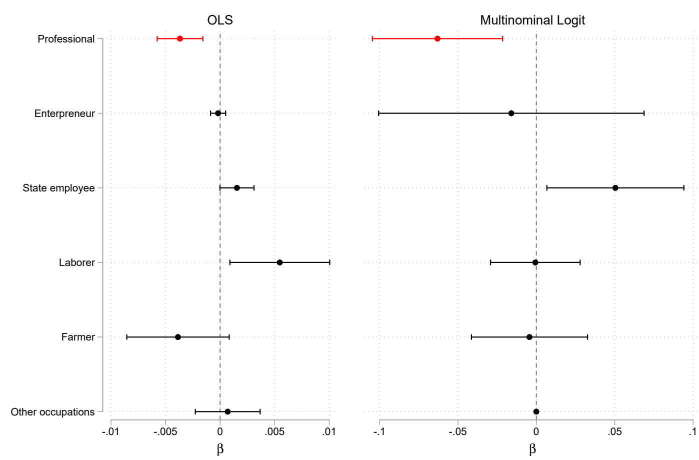
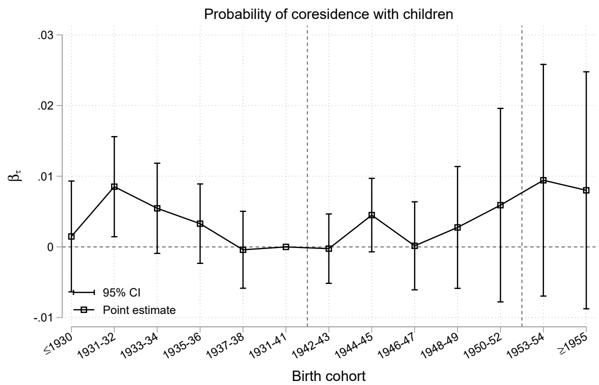
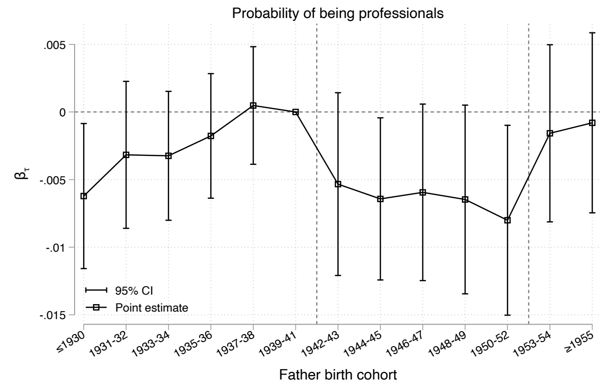


Figure 4. Occupational Effects of the CR

Notes: This figure studies the effects of fathers' CR experience on different occupational outcomes, including professionals, entrepreneurs, state employees, laborers, farmers, and other occupations (unemployment included). The left column presents OLS estimates of Equation 2. The right column uses a multinomial logit model (using other occupations as the base group). The dots are point estimates. The caps are 95% confidence intervals.



a. Coresidence



b. Professional Occupaitons

Figure 5. Robustness: Selection on Coresidence

Notes: Event-study plots reported in this figure investigate the robustness of my findings to selection on coresidence. Figure 5a studies the effects of the CR experience on coresidence with children. Figure 5b uses the full census sample in conjunction with imputed exposure to the CR to re-study the effects of fathers' CR experience on children's uptake of professional occupations. The dots are point estimates. The caps are 95% confidence intervals.

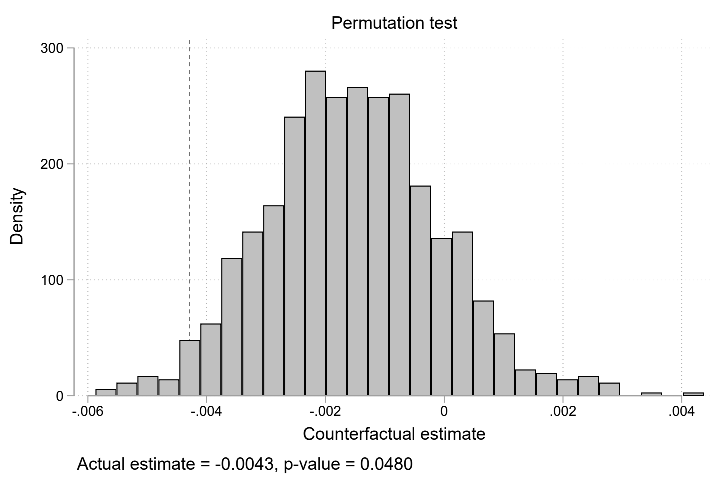


Figure 6. Robustness: Permutation Test

Notes: This figure reports the permutation test. Specifically, I permute the CR intensities across prefectures and then re-estimate Equation 2 to obtain a counterfactual estimate. This is repeated 1000 times. The histogram depicts the distribution of these 1,000 counterfactual estimates. The dashed line depicts the actual estimate.

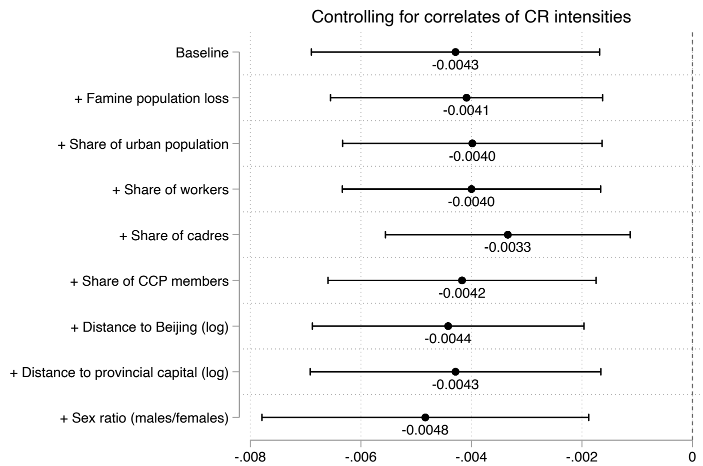


Figure 7. Robustness: Controlling for Correlates of the CR Intensities

Notes: The figure shows the robustness of my findings after including potential correlates of CR intensities. Specifically, I re-estimate Equation 2 with including the interaction of each correlate and father's birth cohort fixed effects. The dots are point estimates. The caps are 95% confidence intervals.

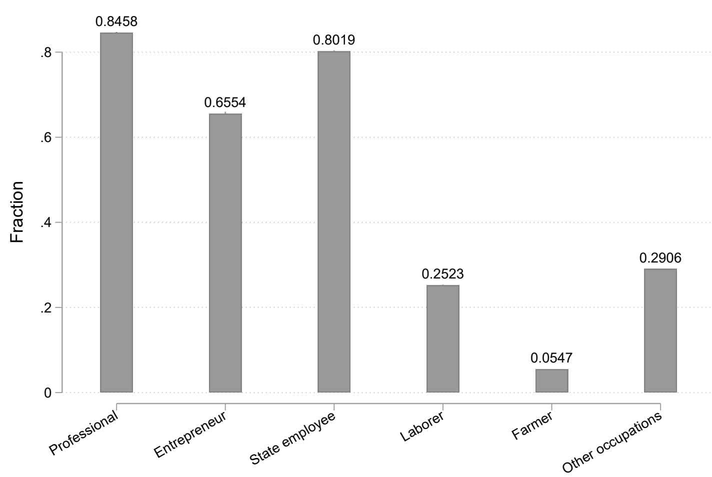


Figure 8. Share of High School Graduates by Occupation

Notes: This figure displays the share of high school graduates by occupation. Data sources: Chinese censuses of 2000 and 2005.

Tables

Table 1. Summary Statistics

	High Intensity			Low Intensity			
	(1) Exposed Father	(2) Unexposed Father	(3) Diff (1)-(2)	(4) Exposed Father	(5) Unexposed Father	(6) Diff (4)-(5)	(7) DiD (3)-(6)
Professional	0.070	0.073	-0.004	0.063	0.058	0.005	-0.009**
	(0.255)	(0.261)	(0.003)	(0.243)	(0.234)	(0.002)	(0.003)
High school graduate	0.281	0.303	-0.022	0.253	0.251	0.002	-0.023**
	(0.450)	(0.460)	(0.010)	(0.435)	(0.434)	(0.005)	(0.011)
Female	0.223	0.202	0.021	0.212	0.178	0.034	-0.014***
	(0.416)	(0.401)	(0.003)	(0.409)	(0.382)	(0.003)	(0.005)
Han ethnicity	0.889	0.886	0.003	0.950	0.945	0.005	-0.002
	(0.314)	(0.317)	(0.005)	(0.217)	(0.228)	(0.002)	(0.005)
Urban residency	0.285	0.355	-0.071	0.257	0.302	-0.045	-0.026*
	(0.451)	(0.479)	(0.013)	(0.437)	(0.459)	(0.007)	(0.015)
N	87876	95065		95440	92296		

Notes: This table presents the summary statistics. I divide the sample into high-intensity versus low-intensity groups (above or below the sample median CR intensity). Within each group, in the first two columns, I present means and standard deviations (in parentheses); the differences in means are reported in the third column with standard errors in parentheses. Column (7) presents the difference-in-differences (DiD) statistics with standard errors in parentheses. All coefficients on *CR* × *Exposed* are standardized to reflect the impacts of a one standard deviation higher CR intensity.
* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table 2. Occupational Effects of Parents' CR Experience

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CR × Exposed father	-0.0031**	-0.0058***	-0.0043***				-0.0040***	
	(0.0012)	(0.0018)	(0.0013)				(0.0014)	
CR × Exposed mother				0.0006	-0.0017	-0.0020	-0.0001	
				(0.0012)	(0.0015)	(0.0013)	(0.0013)	
CR × Exposed parents								-0.0046***
								(0.0015)
DV mean	0.0661	0.0661	0.0661	0.0661	0.0661	0.0661	0.0661	0.0661
Parent cohort FE	Y	Y	Y	Y	Y	Y	Y	Y
Prefecture FE	Y	Y	Y	Y	Y	Y	Y	Y
Province × cohort FE		Y	Y		Y	Y	Y	Y
Covariates			Y			Y	Y	Y
N	370677	370677	370677	370677	370677	370677	370677	370677
R sq.	0.0269	0.0320	0.0694	0.0270	0.0322	0.0694	0.0702	0.0702

Notes: This table presents the effects of parents' CR experience on individuals' probability of being professionals. The dependent variable is a dummy variable that equals one if the individual is in a professional occupation. The sample used here is the one described in Section 3.3. All regressions include the noted controls. Covariates include indicators for gender, ethnicity, and urban residency. All of the covariates and fixed effects are interacted with census year fixed effects (2000 or 2005). Robust standard errors clustered at the prefecture level are reported in parentheses. All coefficients on *CR* × *Exposed* are standardized to reflect the impacts of a one standard deviation higher CR intensity.
* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table 3. Robustness Check: Selection on Coresidence

	(1) Coresidence w/ Children	(2) Coresidence w/ Children	(3) Coresidence w/ Children	(4) Professional Children	(5) Professional Children
CR × Exposed	-0.0026	-0.0008	-0.0044		
	(0.0030)	(0.0026)	(0.0038)		
CR × Exposed father imputed				-0.0036	
				(0.0026)	
CR × Exposed father					-0.0137**
					(0.0062)
DV mean	0.2028	0.1915	0.2152	0.0663	0.0521
Sample	Parents	Fathers	Mothers	Children	Children (CFPS)
N	4033642	2114354	1919288	4198123	8436
R sq.	0.1678	0.1754	0.1671	0.0366	0.1130

Notes: This table shows the robustness of the results to selection on coresidence. In Columns (1)–(3), the dependent variable is a dummy variable for coresidence with children. The sample includes individuals born before 1961 (same as parents in the main sample) in censuses of 2000 and 2005; Column (1) looks at parents, while Columns (2) and (3) examine fathers and mothers, respectively. In Columns (4)–(5), the dependent variable is a dummy variable that equals one if the individual is in a professional occupation. The sample of Column (4) includes individuals born after 1960 and at least age 25 in censuses 2000 and 2005, with their fathers' exposure to the CR imputed if necessary. The sample of Column (5) includes individuals born after 1960 and at least age 25 in the CFPS survey of 2018. All regressions include the full set of covariates and fixed effects (interacted with year fixed effects), as in Equation 2. Covariates include indicators for gender, ethnicity, and urban residency. All of the covariates and fixed effects are interacted with census year fixed effects (2000 or 2005). Robust standard errors clustered at the prefecture level are reported in parentheses.

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table 4. CR, Education, and Professional Occupation

	HS Completion	Professional		
	(1) FS	(2) FS	(3) HS	(4) Non-HS
CR × Exposed father	-0.0034	-0.0037***	-0.0089**	-0.0010**
	(0.0026)	(0.0011)	(0.0036)	(0.0005)
HS completion		0.1765***		
		(0.0027)		
Equality test, p-value				
N	370677	370677	100850	269827
R sq.	0.2426	0.1451	0.0592	0.0426

Notes: This table examines the role of educational attainment in explaining the observed occupational effects of the CR. The sample used here is the main sample described in Section 3.3. Column (1) uses the full sample (FS), and the dependent variable is a dummy variable that equals one if the individual has completed high school. In Columns (2)–(4), the dependent variable is a dummy variable that equals one if the individual is in a professional occupation. Column (2) uses the full sample, Column (3) restricts to high school graduates (HS), and Column (4) restricts to those whose educational attainment is below high school (non-HS). All regressions include the full set of covariates and fixed effects. Covariates include indicators for gender, ethnicity, and urban residency. Robust standard errors clustered at the prefecture level are reported in parentheses. A test for equality of coefficients in Columns (3) and (4) is reported. All coefficients on *CR × Exposed* are standardized to reflect the impacts of a one standard deviation higher CR intensity.

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table 5. CR and Family Environment

	(1) All	(2) 1982	(3) 1990	(4) 2000
Panel A: Professional				
CR × Exposed	0.0002	0.0001	0.0005	0.0002
	(0.0006)	(0.0008)	(0.0010)	(0.0006)
D.V. mean	0.0477	0.0495	0.0529	0.0383
N	11635353	4164260	4308238	3162855
R sq.	0.0145	0.0211	0.0217	0.0127
Panel B: High school completion				
CR × Exposed	-0.0011	0.0003	-0.0020	-0.0010
	(0.0015)	(0.0012)	(0.0020)	(0.0025)
D.V. mean	0.1079	0.0732	0.1140	0.1451
N	11635353	4164260	4308238	3162855
R sq.	0.0890	0.0689	0.0975	0.0834
Panel C: Children ever born				
CR × Exposed	-0.0022	-0.0577**	-0.0038	0.0231
	(0.0135)	(0.0233)	(0.0091)	(0.0187)
D.V. mean	3.0165	4.6014	3.1145	2.0855
N	3124852	734291	1032071	1358490
R sq.	0.4877	0.2343	0.3474	0.2505

Notes: This table investigates the impacts of parents' CR experience on their own outcomes. Data used here combine censuses of 1982, 1990, and 2000. Columns (1) analyzes the full sample, and Columns (2)–(4) analyze each census separately. Panels A and B examine entry into professional occupations and high school completion. The samples are restricted to those born before 1961 and at least age 25. Panel C examines fertility rates. The sample is restricted to women between ages 35 and 50. All regressions include prefecture fixed effects and province-by-cohort fixed effects, all of which are interacted with census year fixed effects. Robust standard errors clustered at the prefecture level are reported in parentheses. All coefficients on *CR × Exposed* are standardized to reflect the impacts of a one standard deviation higher CR intensity.
* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table 6. CR and Contemporary Macroeconomic Conditions

	N	(1) Bivariate	(2) Province FE
GDP per capita (log)	283	0.0131	0.0030
		(0.0871)	(0.0792)
FDI per capita (log)	274	0.0690	0.0518
		(0.0843)	(0.0958)
Firms per capita (log)	283	-0.0759	-0.0859
		(0.0814)	(0.0701)
Elementary & middle schools per capita (log)	259	0.1710	0.1405
		(0.1038)	(0.1209)
Teacher-student ratio	259	0.0203	-0.0101
		(0.1201)	(0.1086)
Population (log)	283	0.0099	-0.0001
		(0.0930)	(0.1001)
Share of urban population	283	-0.0636	-0.0736
		(0.1044)	(0.0878)
Share of mfg. workers	283	0.0341	0.0241
		(0.0601)	(0.0566)

Notes: This table investigates the associations between CR intensities (CR_p) and contemporary measures of development (M_p, listed at the beginning of each row). Each cell in Columns (1) and (2) represents a regression. In Column (1), I estimate a bivariate regression $M_p = \alpha + \beta CR_p + \varepsilon_p$; in Column (2), province fixed effects are included in the regression. Robust standard errors clustered at the province level are reported in parentheses.
* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table 7. Comparative Statics of Culture Transmission

	By %Professionals		By professional wage premium		By Gender	
	(1)	(2)	(3)	(4)	(5)	(6)
	> Median	< Median	> Median	< Median	Son	Daughter
Panel A: Full sample						
CR × Exposed father	-0.0079***	-0.0021	-0.0061***	-0.0018	-0.0048***	-0.0013
	(0.0023)	(0.0013)	(0.0021)	(0.0013)	(0.0012)	(0.0029)
Equality test, *p*-value		0.0260		0.0812		0.2080
N	173379	174162	182421	188256	295264	75413
R sq.	0.0814	0.0484	0.0762	0.0606	0.0416	0.0984
Panel B: High school graduates						
CR × Exposed father	-0.0170***	-0.0044	-0.0097*	-0.0058	-0.0113***	-0.0037
	(0.0047)	(0.0050)	(0.0053)	(0.0046)	(0.0039)	(0.0070)
Equality test, *p*-value		0.0629		0.5794		0.2921
N	61057	35444	53772	47078	71570	29280
R sq.	0.0651	0.0630	0.0647	0.0534	0.0369	0.0677

Notes: This table examines the heterogeneity in the CR's occupational effects. The dependent variable is a dummy variable that equals one if the child is in a professional occupation for all columns. The sample used here is the main sample described in Section 3.3. Columns (1) and (2) divide the sample according to a prefecture's share of professionals in population. Columns (3) and (4) divide the sample according to a prefecture's wage rate for professionals. Columns (5) and (6) compare sons versus daughters. All regressions include the full set of covariates and fixed effects. Covariates include indicators for gender, ethnicity, and urban residency. All of the covariates and fixed effects are interacted with census year fixed effects (2000 or 2005). Robust standard errors clustered at the prefecture level are reported in parentheses. All coefficients on *CR × Exposed* are standardized to reflect the impacts of a one standard deviation higher CR intensity.
* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table 8. CR and Expectations for Children

		By individual gender		By child gender	
	(1)	(2)	(3)	(4)	(5)
	FS	Male	Female	Son	Daughter
Panel A: Expected to be a professional					
CR × Exposed Father	-0.0430*	-0.1178***	-0.0097	-0.0855**	-0.0040
	(0.0257)	(0.0346)	(0.0350)	(0.0365)	(0.0461)
DV mean	0.6143	0.5533	0.6549	0.4991	0.7430
Equality test, *p*-value			0.0184		0.1809
N	2169	857	1312	1155	1014
R sq.	0.1532	0.2950	0.2170	0.2239	0.2460
Panel B: Expected to attend college					
CR × Exposed Father	0.0060	-0.0002	-0.0091	-0.0113	0.0276
	(0.0212)	(0.0393)	(0.0237)	(0.0284)	(0.0329)
DV mean	0.8257	0.8017	0.8427	0.8151	0.8366
Equality test, *p*-value			0.8490		0.3402
N	2945	1180	1765	1553	1392
R sq.	0.1485	0.2423	0.2003	0.2037	0.2077

Notes: This table studies how the CR experience influences parenting across generations, specifically, how fathers' CR experience influences individuals' expectations for their own children. The regression is specified as Equation 5. The sample used is the CFPS survey of 2018. In Panel A, the dependent variable is a dummy for whether an individual expects their children to be professionals. In Panel B, the dependent variable is a dummy for whether an individual expects their children to attend college. Column (1) uses the full sample (FS). Columns (2) and (3) examine responses respectively from men and women. Columns (3) and (4) examine expectations for sons versus daughters. Robust standard errors clustered at the prefecture level are reported in parentheses. All coefficients on *CR × Exposed* are standardized to reflect the impacts of a one standard deviation higher CR intensity.
* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Online Appendix

(Not for Publication)

I A Simple Model of Preference Transmission

In this section, I present a model in the spirit of Bisin and Verdier (2001).

Basic Settings. For simplicity, suppose an individual can choose between two occupations: professional (indexed by 1) and non-professional (indexed by 0). Consequently, there exist two types of preferences: type-1 ("pro-professional") and type-0 ("anti-professional"). I assume that each type prefers the occupation of the same index. In other words, a type-i individual will choose occupation i ($i = 0, 1$).

Preference Formation. How do preferences form? Two forces are at play: (i) transmission and (ii) socialization.[1] *Transmission* is an action parents can take to pass on their preferences to children; specifically in this paper, the action is to make children possess a type-0, "anti-professional" preference. Parents choose an effort level for this action, $\tau \in [0, 1]$, at the cost of $c(\tau)$, where $c(\cdot)$ is a convex function. With an effort level τ, a child would become non-professional with probability τ.

In contrast, *socialization* encompasses outside-family factors that influence preferences, such as local norms and economic incentives. In the event that the transmission fails to shape an anti-professional preference, the social environment may make an individual possess a pro-professional preference with probability q.

In sum, an individual would have preferences and so occupational types according to the following rules:

$$\Pr(\text{Type-0}) = \tau + (1 - \tau)(1 - q), \tag{A1}$$

[1] In Bisin and Verdier (2001), they are referred to as "direct socialization" and "oblique socialization", respectively.

$$\Pr(\text{Type-1}) = (1-\tau)q. \tag{A2}$$

Parents' Problem. As in Bisin and Verdier (2001), parents exhibit "imperfect empathy". They internalize their children's occupational choices; however, they evaluate the choices based using their own preferences, although these evaluations may differ from children's. Let v_i denote parents' evaluation of occupation i ($i \in \{0,1\}$). Thus, the size of $d \equiv v_0 - v_1$ reflects the stigma parents attach to pursuing professional occupations, which can be influenced by the CR experience. I suppose d to be a function of the CR intensity r, namely, $d = d(r)$. $d(\cdot)$ is an increasing function, suggesting that experiencing a greater CR intensity leads to a stronger stigma.

In this model, parents' utility function is linear in the cost of transmission and the expected utility from children's occupational outcomes.[2] Parents place a relative weight, $\lambda > 0$, on the utility of children's occupational choices. Then, the parents' utility function is:

$$\begin{aligned} U(\tau;\lambda,q,r) &= \underbrace{-c(\tau)}_{\text{cost of transmission}} + \lambda \underbrace{\{[\tau + (1-\tau)(1-q)]v_0 + (1-\tau)qv_1\}}_{\text{expected utility from children's occupations}} \\ &= -c(\tau) + \lambda\left[v_0 - (1-\tau)qd(r)\right]. \end{aligned} \tag{A3}$$

Solutions and Predictions. Parents choose an effort level of transmitting preferences, τ^*, to maximize $U(\tau;\lambda,q,r)$ in Equation A3. The first-order condition yields:

$$\frac{\partial U}{\partial \tau} = -c'(\tau^*) + \lambda qd(r) = 0, \tag{A4}$$

$$c'(\tau^*) = \lambda qd(r). \tag{A5}$$

[2] Here for simplicity, I suppose parents' utility from their own consumption is constant, thus omitted.

Due to convexity of $c(\cdot)$, τ^* is increasing in $\lambda q d(r)$. Therefore, Equation A5 predicts that experiencing a greater CR intensity would make parents more likely to transmit anti-professional preferences to children. Note that

$$\text{sign}\left[\frac{\partial \tau^*}{\partial r}\right] = \text{sign}\left[\lambda q d'\right] > 0. \tag{A6}$$

Results reported in Table 2 are consistent with this prediction.

The efforts of transmitting preferences can vary with parameters q and λ. Note that

$$\text{sign}\left[\frac{\partial^2 \tau^*}{\partial r \partial q}\right] = \text{sign}\left[\lambda d'\right] > 0, \tag{A7}$$

$$\text{sign}\left[\frac{\partial^2 \tau^*}{\partial r \partial \lambda}\right] = \text{sign}\left[q d'\right] > 0. \tag{A8}$$

These prove Predictions 1 and 2.

Prediction 1. *Parents' CR experience is more impactful on children if the social factors tend to attract entry into professional occupations.*

Prediction 2. *Parents' CR experience is more impactful on children if they internalize children's choices to a greater degree.*

II China Family Panel Study

I use the 2018 survey of the China Family Panel Study survey (CFPS) to complement the analysis using census data. The CFPS is nationally representative. It covers 123 prefectures. I restrict the sample to individuals born between 1960 and 1980, the same as those in the census sample, which leaves a total of 8247 individuals. Table A7 compares the main sample and the CFPS sample. Prefectures in the CFPS had relatively greater violence intensities during the CR. The CFPS also includes more urban residents, females, and high school dropouts.

III Population Losses in the Great Chinese Famine (1959–61)

Following previous studies on the Famine (Meng et al., 2015; Kasahara and Li, 2020; Chen and Yang, 2015), I use the 1990 census to construct a measure of population losses in the Famine. Figure A6 helps illustrate the construction of the measure. It shows that there is a sharp reduction in the sizes of cohorts born between 1959 and 1961. I estimate each prefecture's reduction in 1959–61 cohorts and use it as the measure of population losses during the Famine. The construction has three steps. First, at the prefecture level, I estimate the observations in 1949–58 and 1962-66 to estimate the non-Famine-period population linear time trend. Using the estimated time trend, I can calculate the projected, counterfactual size of those born during 1959–61, denoted by $\widehat{size}_p$. Second, I calculate the actual size of those born during 1958–61, denoted by $size_p$. Lastly, a population loss index of prefecture p is given by the following formula:

$$PL_p = 1 - \frac{\widehat{size}_p}{size_p}, \tag{A9}$$

which captures the extent to which the actual size deviates from the projected size — the higher PL_p, the more severe the Famine.

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Appendix Figures

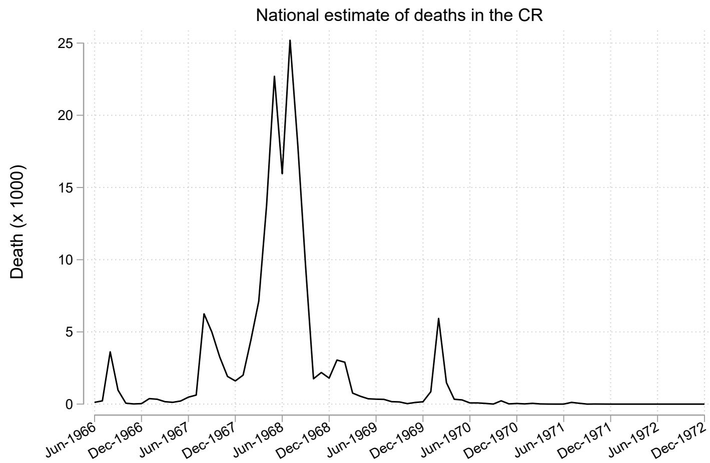
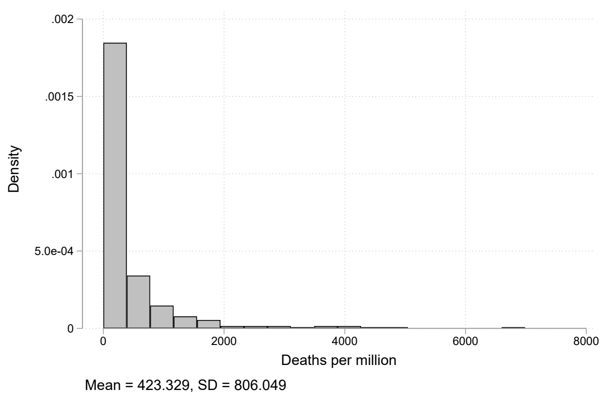
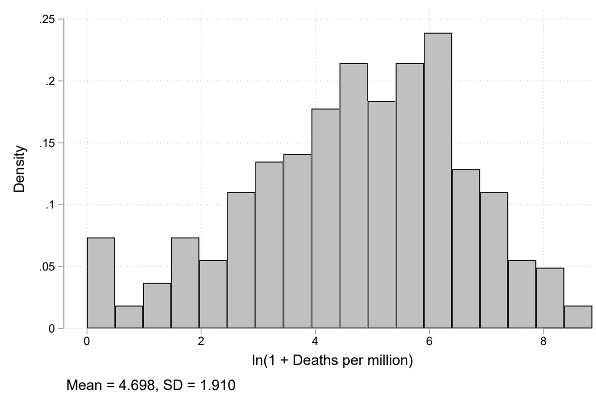


Figure A1. Temporal Distribution of Deaths in the CR

Notes: This figure displays the temporal distribution of deaths during the CR. Data sources: Walder (2014).



a. Unlogged



b. Logged

Figure A2. Distribution of CR Intensities

Notes: This figure displays the distribution of CR intensities across 332 prefectures in my sample. Figure A2a looks at deaths per million, which has a highly skewed distribution. Figure A2b looks at the log of 1 plus deaths per million, the main measure used in this study.

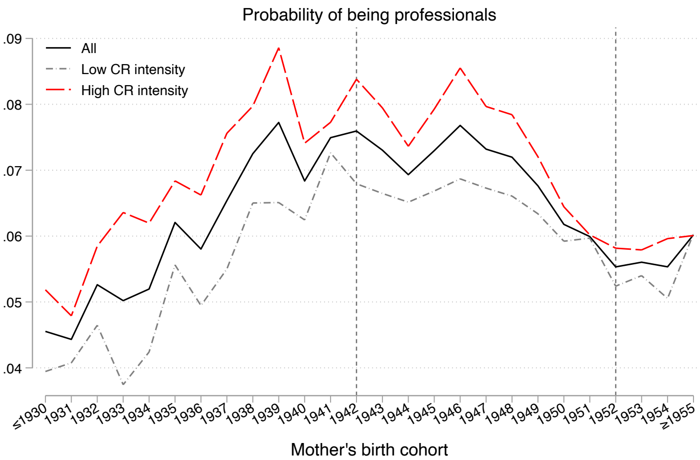
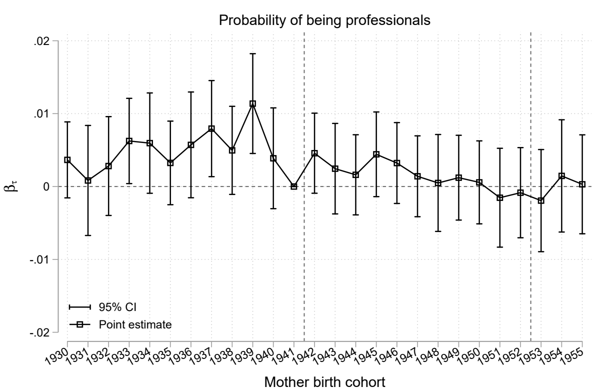
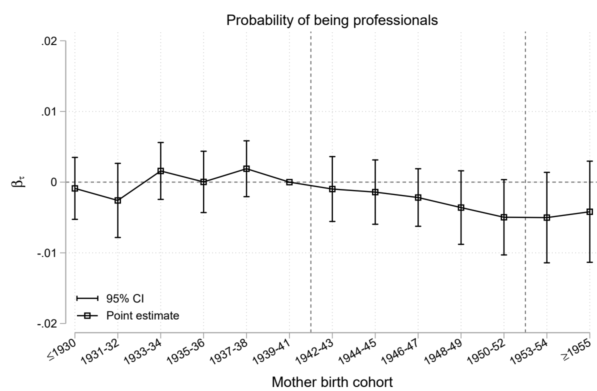


Figure A3. Individuals' Probability of Being Professionals and Their Mothers' Birth Cohorts

Notes: This figure depicts the relationship between individuals' probability of being professionals and their mothers' birth cohorts. The relationship is depicted separately for all individuals, individuals in low CR intensity prefectures, and individuals in high CR intensity prefectures.



a. By Cohorts



b. By Cohort Bins

Figure A4. Dynamic Effects of Mothers' CR Experience

Notes: This figure depicts the dynamic effects of mothers' CR experience on children's probability of being professionals, based on Equation 3. Figures A4a and A4b plot dynamic effects by cohorts and cohort bins, respectively. The dots are point estimates. The caps are 95% confidence intervals.

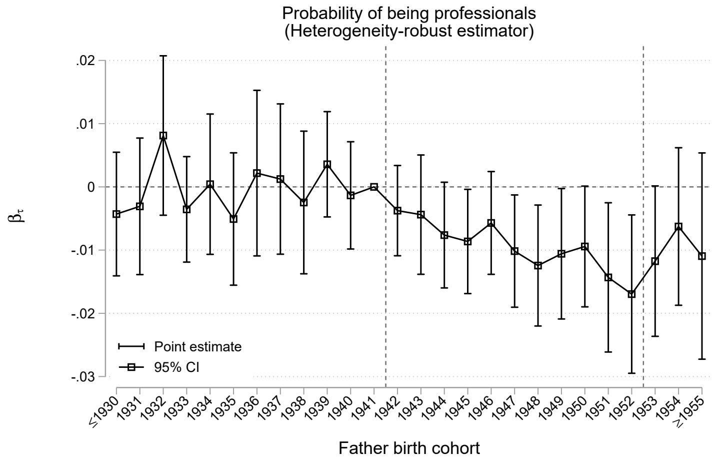


Figure A5. Heterogeneity-Robust Estimator

Notes: This figure depicts the dynamic effects of fathers' CR experience on children's probability of being professionals, based on Equation 3. The heterogeneity robust estimator proposed by de Chaisemartin et al. (2022) is implemented. The dots are point estimates. The caps are 95% confidence intervals.

Figure A6. Birth Cohort Sizes in the 1990 Census

Notes: This figure displays the cohort sizes in the 1990 census. The dashed line is fitted using observations during 1949–58 and 1962–66.

Appendix Tables

Table A1. Professional Occupations

No.	Occupation
1	Health Professionals
2	Economic Professionals
3	Teachers
4	Science Researchers
5	Engineers
6	Literary and Art Workers
7	Journalism, Publishing, and Culture Workers
8	Financial Professionals
9	Legal Professionals
10	Sports Workers
11	Religious Professionals
12	Other Professionals and Technicians
13	Ships and Aircraft Technicians
14	Agricultural Technicians

Data sources: Chinese censuses of 2000 and 2005.

Table A2. Summary Statistics: By Mother's Exposure

	High Intensity			Low Intensity			
	(1) Exposed Mother	(2) Unexposed Mother	(3) Diff (1)-(2)	(4) Exposed Mother	(5) Unexposed Mother	(6) Diff (4)-(5)	(7) DiD (3)-(6)
Professional	0.074	0.068	0.006	0.064	0.055	0.009	-0.002
	(0.262)	(0.252)	(0.003)	(0.245)	(0.229)	(0.001)	(0.003)
High school graduate	0.295	0.290	0.005	0.260	0.240	0.019	-0.015
	(0.456)	(0.454)	(0.008)	(0.438)	(0.427)	(0.004)	(0.009)
Female	0.220	0.200	0.019	0.205	0.180	0.026	-0.006
	(0.414)	(0.400)	(0.003)	(0.404)	(0.384)	(0.003)	(0.004)
Han ethnicity	0.892	0.882	0.010	0.952	0.941	0.010	-0.001
	(0.311)	(0.322)	(0.004)	(0.214)	(0.235)	(0.003)	(0.005)
Urban residency	0.313	0.334	-0.021	0.279	0.280	-0.001	-0.020
	(0.464)	(0.472)	(0.011)	(0.448)	(0.449)	(0.005)	(0.012)
N	107832	75109		114839	72897		

Notes: This table presents the summary statistics. I divide the sample into high-intensity versus low-intensity groups (above or below the sample median CR intensity). Within each group, in the first two columns, I present means and standard deviations (in parentheses); the differences in means are reported in the third column with standard errors in parentheses. Column (7) presents the difference-in-differences (DiD) statistics with standard errors in parentheses. All coefficients on *CR* × *Exposed* are standardized to reflect the impacts of a one standard deviation higher CR intensity.
* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table A3. Robustness Check: Migration

	Professional			Migration	
	(1)	(2)	(3)	(4)	(5)
	Census 2000	Stayer Same Province	Stayer Same County	Cross-Province	Cross-County
CR × Exposed father	-0.0040***	-0.0040***	-0.0035***		
	(0.0015)	(0.0012)	(0.0011)		
CR × Exposed				0.0028	0.0054
				(0.0039)	(0.0045)
N	318354	291223	259954	6305382	6305382
R sq.	0.0613	0.0482	0.0357	0.1559	0.1353

Notes: This table investigates the robustness of my findings to migration. In Columns (1)–(3), the dependent variable is a dummy variable that equals one if the individual is in a professional occupation. Column (1) uses the 2000 census subsample of the full sample described in Section 3.3. Column (2) restricts to those who stay in their birth provinces. Column (3) restricts to those who stay in their birth counties. All regressions in Columns (1)–(3) include prefecture fixed effects, fathers' birth cohort fixed effects, and province-by-cohort fixed effects. Covariates include indicators for gender, ethnicity, and urban residency. Robust standard errors clustered at the prefecture level are reported in parentheses. Columns (4) and (5) investigate whether CR experience is associated with cross-province and cross-county migration, respectively, using all individuals between ages 25 and 65 in the 2000 census. All regressions in Columns (4) and (5) include prefecture fixed effects, fathers' birth cohort fixed effects, and province-by-cohort fixed effects. In this table, all coefficients on *CR × Exposed* are standardized to reflect the impacts of a one standard deviation higher CR intensity.
* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table A4. Robustness Check: Regional Heterogeneity

	(1)	(2)	(3)	(4)
Obs. dropped:	CR intensity 5% tails	Direct-controlled municipals	Provincial capitals	Border & minority provinces
CR × Exposed father	-0.0050***	-0.0032***	-0.0024**	-0.0049***
	(0.0018)	(0.0011)	(0.0011)	(0.0015)
N	333212	344888	288146	288760
R sq.	0.0696	0.0603	0.0506	0.0701

Notes: This table investigates the robustness of my findings to regional heterogeneity. Column (1) excludes prefectures with CR intensities at the 5% tails. Column (2) excludes four direct-controlled municipals (Beijing, Tianjin, Shanghai, and Chongqing). Column (3) excludes all provincial capitals. Column (4) excludes border and minority provinces. In all regressions, the dependent variable is a dummy variable that equals one if the individual is in a professional occupation. All regressions include the full set of covariates and fixed effects. Covariates include indicators for gender, ethnicity, and urban residency. Robust standard errors are clustered at the prefecture level.
* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table A5. Robustness Check: Alternative Standard Errors

	(1) Two-way cultering	(2) Clutering by province	(3) Conely SE 200km	(4) Conely SE 500km
CR × Exposed father	-0.0043***	-0.0043***	-0.0043***	-0.0043***
	(0.0012)	(0.0016)	(0.0013)	(0.0013)
N	370677	370677	370677	370677
R sq.	0.0694	0.0694	0.0694	0.0694

Notes: This table investigates the robustness of my findings to different standard errors. Column (1) clusters standard errors at prefecture and father birth cohort levels. Column (2) clusters at the provincial level. Columns (3) and (4) use Conley standard errors, allowing for spatial autocorrelations within 200km and 500km, respectively. In all regressions, the dependent variable is a dummy variable that equals one if the individual is in a professional occupation. All regressions include the full set of covariates and fixed effects. Covariates include indicators for gender, ethnicity, and urban residency. Robust standard errors are clustered at the prefecture level.

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table A6. Robustness Check: Alternative Measurement of Exposure

Exp =	(1) Binary 1966–71	(2) Continuous 1966–71	(3) Binary 1966–76	(4) Continuous 1966–76
CR × Exposed father	-0.0043***	-0.0044***	-0.0043***	-0.0069***
	(0.0013)	(0.0016)	(0.0014)	(0.0023)
N	370677	370677	370677	370677
R sq.	0.0698	0.0698	0.0699	0.0701

Notes: This table investigates the robustness of my findings to alternative measurements of exposure to the CR. Column (1) is the baseline measurement, a binary variable indicating whether impressionable years overlap 1966–71. Column (2) adopts a continuous measure that captures the share of impressionable years overlapping 1966–71. Columns (3) and (4) define the binary and continuous measures in a similar fashion but using a different time frame, 1966–76. In all regressions, the dependent variable is a dummy variable that equals one if the individual is in a professional occupation. All regressions include the full set of covariates and fixed effects. Covariates include indicators for gender, ethnicity, and urban residency. Robust standard errors are clustered at the prefecture level.

* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table A7. Census and CFPS Samples Compared

	(1) Census 2000, 05	(2) CFPS 2018
CR	4.7779	4.8990
	(1.7709)	(1.7401)
Professional	0.0661	0.0531
	(0.2485)	(0.2243)
Birth year	1971.4761	1969.3296
	(4.0171)	(5.5307)
Father's birth year	1941.4192	1938.3603
	(7.2675)	(9.6991)
Mother's birth year	1944.3343	1941.3172
	(6.7338)	(8.9666)
Urban residency	0.3000	0.4813
	(0.4583)	(0.4997)
Female	0.2034	0.5226
	(0.4026)	(0.4995)
High school completion	0.2721	0.2092
	(0.4450)	(0.4067)
N	370677	8247

Notes: This table compares the key variables in censuses (2000 and 2005) and the CFPS (2018).
* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table A8. Results Using the CFPS Sample

	(1)	(2)	(3)
CR × Exposed father	-0.0133**		-0.0146*
	(0.0062)		(0.0074)
CR × Exposed mother		-0.0049	0.0013
		(0.0054)	(0.0064)
D.V. mean	0.0531	0.0531	0.0531
N	8247	8247	8247
R sq.	0.1242	0.1254	0.1323

Notes: This table replicates the results in Table 2 using the CFPS 2018 sample, described in Appendix II. The dependent variable is a dummy variable that equals one if the individual is in a professional occupation. All regressions include prefecture fixed effects, parent birth cohort fixed effects, province-by-cohort fixed effects, and a set of covariates. Covariates include indicators for gender, urban residency, and ethnicity. Robust standard errors are clustered at the province level.
* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$

Table A9. CR and Health

	All		Men		Women	
	(1) Height (cm)	(2) Healthy binary	(3) Height (cm)	(4) Healthy binary	(5) Height (cm)	(6) Healthy binary
CR × Exposed father	-0.2219	0.0092	-0.3179	-0.0042	-0.2162	0.0196
	(0.1557)	(0.0106)	(0.2515)	(0.0156)	(0.2038)	(0.0151)
D.V. mean	163.3354	0.2526	168.6894	0.2769	158.3829	0.2315
N	8129	8185	3900	3903	4229	4282
R sq.	0.5334	0.1196	0.3012	0.1845	0.2409	0.1753

Notes: Notes: This table examines the effects of fathers' CR on individuals' health, measured by height (cm) and self-reported health status (binary). I use the CFPS 2018 sample described in Appendix II. The dependent variable is a dummy variable that equals one if the individual is in a professional occupation. All regressions include prefecture fixed effects, parent birth cohort fixed effects, province-by-cohort fixed effects, and a set of covariates. Covariates include indicators for gender, urban residency, and ethnicity. Robust standard errors are clustered at the province level.
* $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$