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ABSTRACT

The Wage Premium of Communist Party Membership: Evidence from China*

Social status and political connections may confer large economic benefits on an individual. Previous studies focused on China have examined the relationship between Communist Party membership and earnings and found a positive correlation. However, the correlation could be partly or totally spurious. Using data from three surveys spanning three decades, we estimate the causal effect of Chinese Communist Party membership on monthly earnings in China. We find that, on average, membership in the Communist Party of China increases monthly earnings and the wage premium has grown in recent years. We explore potential causes and discover evidence that improvements in social networks and social rank, acquisition of job-related qualifications, and greater life satisfaction likely play important roles in increased earnings.

JEL Classification: D31, J31, P2

Keywords: wage premium, political status, China, Communist Party

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I. Introduction

A number of economic studies have examined the ways in which political and social status influence individual economic outcomes. Recent empirical research in developing countries has documented the causal impact of political status on investments (Fishman, 2001), firm value (Erkal and Kali, 2012), and wages (Li et al., 2007). China's rapid economic development and its one-party government provide an ideal context to examine the interplay between political status and economic outcomes. Previous studies demonstrate that political status in China could result in a number of economic benefits (Morduch and Sicular, 2000; Li et al., 2007; Appleton et al., 2003; Wu, Wu, and Rui, 2010). Party membership provides access to social networks that impact employment outcomes. Previous studies have also identified how a social network or improved social status could shape an individual's economic outcomes.[1]

In this study, we estimate the wage premium associated with membership in the Chinese Communist Party over the span of three decades. We use data from the China Household Income Project (CHIP), the China Housing Survey (CHS), and the Chinese General Social Survey (CGSS). The Communist Party of China currently boasts over 80 million members with an annual average growth of approximately 1 million members per year. The party is—and will likely remain—the largest party in the world (Yuen, 2013).[2] Previous estimates of the effect of political status on economic outcomes in China relied on ordinary least squares (OLS) estimations, using observational data. Since such study designs could not separate the possible influence of party membership from that of other background characteristics on employment outcomes, they could not identify the true causal effects of party membership on wages. To estimate the effect of Communist Party membership on monthly earnings, we use a propensity score matching method (Rosenbaum and Rubin, 1983, 1984; Imbens, 2004; Imbens and Wooldridge, 2009; Imbens and Rubin, 2014; Abadie et al., 2003; Angrist and Krueger, 2000; Angrist and Pischke, 2009). We also perform a variety of robustness checks to bolster the credibility of our results. Although the

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[1] Montgomery (1991) models the role of social networks in employee referrals for better employment prospects and shows how networks could improve the employer-employee match. Other studies have documented the effect of various types of social networks on employment outcomes—e.g., fraternity and sorority membership at an American university (Marmaros and Sacerdote, 2001), ethnic networks (Patacchini and Zenou, 2012), and "*guanxi*" networks in China (Bian, 1994).

[2] In the past, more than 80% of the upperclassmen at Chinese universities applied for Communist party membership (The Economist, 2014). Rather than it being an ideological choice, many people have decided to join because of a belief that party membership would provide better job market prospects; party membership increasingly has been viewed a means to boost a resume (Yuen, 2013).

matching method offers several important advantages over the OLS method, it is also prone to bias in the presence of selection on observables. To gauge the presence of potential bias based on selection on unobservable characteristics, we bound the magnitude of the potential bias with Rosenbaum bounds.

We report three main findings. First, the propensity score matching technique serves to identify that Communist Party members earn approximately 20% more than non-members do. Our estimated effect sizes complemented those presented in the literature that used data from developing countries and that demonstrated substantial wage benefits associated with political status and social connections (Siddique, 2010; Madheswaram and Attewell, 2007; Das and Dutta, 2007). We further bolster the credibility of the estimated effect sizes with several robustness checks; we examine the sensitivity of our results with the matching algorithm method and the estimation technique. Finally, by using a Rosenbaum bounds method, we gauge the potential selection bias due to potential selection on unobservable variables.

Second, the evidence from three major surveys suggests that the wage premium has grown modestly over the past three decades. The OLS and propensity score matching results demonstrate that the wage premium associated with party membership has increased.

Third, we explore various mechanisms that could explain why party membership could lead to higher wages. Party membership could translate into better employment outcomes due to several distinct mechanisms. Members could obtain a greater number of job referrals as well as access to better types of jobs (Morduch and Sicular, 2000) from the wider social network of local party members. These job referrals could serve to improve employer-employee matches over time. Finally, some employment opportunities in provincial and local governments are available only to party members (The Economist, 2014). Based on the available longitudinal data from one of the data surveys, we examine four main channels: the strength of the individual's social network, the acquisition of human capital as a party member, the improvement in social rank, and overall life satisfaction. We provide suggestive evidence of at least three factors that positively impact the wages of party members: the opportunity to secure a government job, better positioning within the job hierarchy, and improvement in overall social rank. We also detect some evidence (although not statistically significant) that members report being happier than non-members. In summary, all of the findings provide evidence on the important economic role that political connections could play in the world's most populous economy.

This study contributes to the empirical literature on the economic benefits of political affiliation in at least four ways.[3] First, we examine the progression of the earnings premium associated with party membership over a period of three decades. Previous studies on the topic rely exclusively on single datasets and therefore could only calculate the wage premium for a single year or a much narrower period. We analyse data from three major Chinese surveys—the China Household Income Project (CHIP), the China Housing Survey (CHS), and the Chinese General Social Survey (CGSS)—which included questions about party membership, earnings, and information on various labour market factors. The datasets cover a period of three decades. Second, we provide empirical evidence that the earnings premium associated with party membership has either remained constant or increased. Third, we show that the estimated earnings premium based on the propensity matching method[4] differs from the one based on the OLS method: the matching estimates are typically lower than the estimated effect size using the OLS method. This finding is consistent with evidence of self-selection (Roy, 1951) into party membership.[5] Finally, perhaps the most novel aspect of this study is that we shed light on important channels that mediate the relationship between party affiliation and earnings. We find suggestive evidence that party membership results in a growing social network, perceived improvements in social and job status, and access to better jobs.

The remainder of this paper is structured as follows. Section II provides background on the party membership process, presents the various channels that mediate the relationship between party affiliation and higher earnings, and provides an overview of previous empirical studies.

[3] Extensive research on the caste system in India as status differentiation has documented persistent economic impacts (Singh, 2010; Das, and Dutta, 2007; Attewell and Madheswaran, 2007; Siddique, 2010; Eswaran et al., 2013). Siddique (2010) notes that, on average, low-caste applicants had to send 20% more resumes to get the same number of callbacks as other applicants. Madheswaram and Attewell (2007) and Das and Dutta (2007) document differences between low-caste and high-caste workers that ranged from 15% to 30% more resumes. Previous studies also examine the effect of status in the context of organizations and social networks (Patacchini and Zenou, 2012; Marmaros and Sacerdote, 2001). Patacchini and Zenou (2012) find that living in an area with a high concentration of those with the same ethnic status increased the probability of finding a job through social contacts. Marmaros and Sacerdote (2001) discover that social networks played an important role in job searches for students at Dartmouth College. The concept of social networks has been closely linked to that of social capital, defined by the density and diversity of an individual's social networks (Growiec and Growiec, 2015). Zhang and Anderson (2014) note that "bridging" social capital yielded positive economic returns, while "bonding" social capital did not. Growiec and Growiec (2015) argue that the returns from "bridging" social capital could best be represented as a U-shaped curve.

[4] We estimate the causal effect of Communist Party membership on wages by using a propensity score matching technique (Rosenbaum and Rubin, 1983, 1984; Imbens, 2004; Imbens and Wooldridge, 2009; Imbens and Rubin, 2014; Abadie et al., 2003; Angrist and Krueger, 2000; Angrist and Pischke, 2009).

[5] Positive selection implies that workers who are party members generally have better unobservable characteristics that both drive selection into party membership and determine higher earnings.

Section III provides a description of the data. Section IV outlines our identification strategy. Section V discusses the results. Section VI summarizes the robustness checks. Section VII concludes.

II. Background

A. The Communist Party of China

The Communist Party of China is the largest political party in the world, with a membership of nearly 88 million in 2015, a number greater than the population of Germany. However, party membership accounted for only 7% of the total Chinese population of 1.37 billion (South China Morning Post, 2015). Recently, the party has been trending towards a more youthful and better-educated member base. In 2014, 2.1 million new members were accepted. About 81% of the new members were under 35 years of age. The percentage of members with university degrees rose from 36.4% to 39% between 2013 and 2017. The Communist Party of China has been overwhelmingly male, with only 21.7 million female members (25%). In 2015, the party had 26 million (30%) agricultural workers, 7.3 million (8%) non-agricultural workers, 12.5 million (14%) professionals, 9 million (10%) administrative personnel, and 7.4 million (8%) government workers. The remaining 25.8 million members (29%) did not identify with any of the employment categories (South China Morning Post, 2015).

The party initiation process involves several steps. The first step for a party hopeful is to compose a letter to the party organization affiliated with his school or workplace, making the case for membership. Successful letters include descriptions of academic success, positions held, and involvement in party-related activities, as well as evidence of loyalty to the Communist Party and knowledge of party history. Individuals chosen by the party organization to become an applicant—or "activist" according to party rhetoric—begin training (McMorrow, 2015). Successful activists frequently participate in political activities, such as community service and attendance at lectures given by the local branch secretary. Activists are required to submit regular "self-assessments" (Bian et al., 2001). Liaisons assigned by the party organization conduct evaluations based on the activist's political loyalty, work or academic performance, social activities, and personal relationships (Li et al., 2007). Additionally, activists must attend a party class led by a professor of political ideology, studying the party's history, structure, and political purpose (McMorrow, 2015). This process lasts for approximately two to three years (Li et al., 2007).

Once the party determines that a final decision should be made about an activist's transition to full membership, a final assessment takes place. The activist must take a two-hour written examination on Marxism and Chinese communist ideology, including the works of Mao Zedong and Deng Xiaoping. In addition, the local party organization interviews the activist's peers and superiors to gain more insight into the activist's personal qualities and political character (McMorrow, 2015). A panel of party members also interviews the activist directly, inquiring about his political activities and quizzing him on knowledge of recent party statements and events (McMorrow, 2015). This final decision-making process culminates in a closed-door meeting in which the local party organization tasks its members with judging the activist's political performance, personal history, and family background (Bian et al., 2001). This meeting ends in a vote on admission into the party. If the party organization votes in favour of the activist's membership, the activist is registered as a tentative party member, with full membership granted after a probationary period of one year (Bian et al., 2001).[6]

Membership in the Communist Party of China acts as an initial step toward becoming one of China's administrative elite. Positions in government and state-run organizations with political or managerial authority are only open to party members. Within the party hierarchy, access to positions at a certain level is controlled by authorities at the next highest level. Personnel offices of local party committees keep dossiers on all of the party members under their jurisdiction, record successes and failures, and use these documents to assess a candidate who has applied for a position (Bian et al., 2001).

B. Conceptual Framework

Several factors could account for a relationship between party membership and greater wage premiums. First, it could be that individuals who become party members learn useful skills through their exposure to or directly from other party members.[7] This channel is similar to the way that formal education represents a form of human capital. The only difference would be that

[6] During the probationary period, members participate in all of the party meetings and activities but cannot vote on party initiatives or be considered for party positions (Bian et al., 2001). These party activities include meetings to study party documents or discuss national policies (McMorrow, 2015). During the probationary period, members are closely monitored by the party organization. Applicants become full members if they do not break any party rules or engage in subversive activities during the probationary period (Li et al., 2007).

[7] The rigorous process of applying to and joining the party confers valuable transferrable skills in the Chinese labour market (Pan, 2010).

skill acquisition occurs through other party members, as opposed to the formal schooling cited in human capital theory (Mincer, 1974; Willis, 1986).[8]

Second, party membership increases social capital by providing access to a social network that could yield valuable connections. These connections could consequently lead to referrals for jobs. The connections obtained through party membership have been mentioned as a type of "bridging" social capital that results in economic returns (Zhang and Anderson, 2014). Bian (1994) discovers that party members are more likely to use social connections to find jobs than non-members are. Additionally, party membership results in connections with higher-status individuals than those found outside the party; these connections provide referrals for high-status jobs (Bian, 1994). Social networks have proven to be a pervasive and well documented factor in labour markets. In a survey of residents of a Massachusetts town, Granovetter (1973, 1995) finds that over 50% of the available jobs are obtained through social contacts. Early work by Rees (1966), also in the context of the U.S., finds that figure reached over 60%.

Third, party membership may translate into higher wages because of the fixed cost associated with securing certain jobs—some high-paying jobs are available only to party members. Many employment opportunities in provincial and local governments also have been open only to party members (The Economist, 2014). Moreover, manager-level or higher-level jobs in state-run organizations only have been open to party members (Bian, 1994). Although the data utilized in this study did not permit the measure of each of these channels' individual importance, all of them contributed to better employment prospects for party members because of the extensive margin or likelihood of landing a job, a better job match that resulted in higher wages, or in higher wages. We provide suggestive evidence for the importance of each of these channels below.

C. Towards More Causal Estimates of the Wage Premium of Party Membership

Our paper builds on the empirical literature that attempts to measure the effect of party membership

[8] Membership in the Communist Party may also serve as a signal and a proxy of one's unobserved ability (Spence, 1974). Signals can serve an important purpose during the hiring process as employers have a hard time observing true ability and the hiring process is hindered by imperfect information (Yashiv, 2007). Further, it may be challenging for employers to assess how good a match might turn out to be because, in addition to ability, job-specific productivity can be driven by other factors: personalities, fit with job culture, and other employee-specific preferences (Velasco, 2011). Signals, such as party membership, can help employers make hiring decisions because party membership can serve as a good proxy for unobserved ability. The Communist Party attempts to attract the best and brightest members of Chinese society; employers can take party membership as a signal for better ability, which can lead to higher paying jobs. However, our survey sources do not provide direct information on cognitive abilities so we cannot directly assess the extent to which Communist Party membership captures variation in cognitive abilities.

on earnings. One early study in this literature is Morduch and Sicular (2000), which attempts to estimate the effect of being a Communist Party member on household income in rural China using an OLS approach.[9] That study finds that households with a cadre member had earnings approximately 20% higher than those that did not. However, the study fails to detect differences in household income between households with just one party member and those with no party members. These results seem to suggest that the monetary benefit of party membership are conferred and mediated only through higher levels of Communist Party involvement. Due to the study's OLS-based research design, it also cannot claim estimation of true causal effects of party membership.[10]

Li et al. (2007) use data from the Chinese Twins Survey, conducted in five Chinese cities. The study examines the effect of party membership on income within pairs of twins where one is a member and the other is not a member. It uses twins to account for observable and unobservable differences that result in omitted variable bias in OLS-based observational data estimation. The study estimates that the income of party members is 10% higher than the income of non-party members. However, after accounting for within-twin-pair fixed effects to control for differences in ability and family background, the study detected no difference in income between party members and non-party members.

Although twin study designs present some advantages (as highlighted above), they also have some important limitations (Griliches, 1979; Neumark, 1999). For example, Neumark (1999) extends the analysis found in Griliches (1979) to show that the within-twin instrumental variable (IV) estimator amplifies the bias from any omitted-ability differences between twins, as compared to the standard within-twin estimator. Moreover, the paper clearly demonstrates that if omitted ability upwardly biases cross-section estimates of the return to schooling, and is not fully removed

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[9] The study measured involvement in the CPC on two levels: 1) The household includes a party member and 2) the household includes a party cadre. A party cadre is someone who "holds an official position of political or administrative leadership" (Morduch and Sicular, 2000). Morduch and Sicular (2000) argue that in a socialist country like China in order for transition to succeed, rank-and-file officials (in the case of China, party cadres) need to have some incentive to administer the changes of the transition even if it could have a negative effect on their political and economic status. Subsequently, one should expect to see positive household income effects on a household with a cadre member.

[10] Morduch and Sicular (2000) only examine rural China, where the networks and credentials that Communist party membership confers may have very little benefit because of a lack of employment opportunities. In addition, because they rely on OLS design, their estimation is likely plagued by omitted variable bias due to party membership being related to ability or other time-variant individual specific characteristics that influence earnings. In contrast, in this paper we examine the effect of party membership in two of China's major cities, Tianjin and Shanghai, where the benefits conferred by social and party networks and credentials are substantially higher. Nikolov, Jimi and Chang (2020) examine the important role of ability on determining earnings in the context of developing countries. The study demonstrates the importance of general ability measures and specific cognitive domains for earnings in the classical Mincer equation.

by differencing within twin pairs, the within-twin IV estimator would be upward biased (possibly substantially) relative to the standard within-twin estimator, and possibly relative to the cross-section estimator as well. This point proves relevant for any application in which instrumental variable estimation is used for differenced data, when the differencing may not fully eliminate the omitted variable. Neumark (1999) notes that the rationale for within-twin estimation of the return to schooling is the assumption that identical twins would possess equal abilities, which drops out of the within-twin difference. However, this does not explain the source of schooling differences within twin pairs.

The notion that within-twin estimates provide a natural experiment for estimating the return to schooling is based on the assumption that schooling differences within twin pairs represent “as if” random variation. Using data from 17 million births in 72 countries, Bhalotra and Clarke (2020) show that twin births are not random. Numrous maternal factors are associated with the occurrence of the twin birth. Furtheremore, once alternative reasons for schooling differences among twins are considered, the conditions that could confirm the experiment might be violated and, in some circumstances, the bias in within-twin estimates is greater than that in cross-sectional estimates.

The second important limitation of twin studies rests on an important assumption that some empirical papers have recently challenged: within-pair variation in schooling is explained by factors unrelated to wage-earning ability. Sandewall, Cesarini, and Johanneson (2014) develop a framework for testing this assumption. Using a large sample of monozygotic twins, they show that the twins-based estimated return to schooling falls if adolescent IQ test scores are included in the wage equation. Using birth weight as an alternative proxy for ability yields qualitatively similar results. The results of Sandewall, Cesarini, and Johanneson (2014) cast strong doubts on the validity of twins-based estimates.[11] In this study, the effect of Communist Party membership on earnings hinges critically on a similar assumption that within-pair variation in party membership could be explained by factors unrelated to earning ability. Twin studies used to examine the effect of party membership on earnings could be flawed because there would likely exist non-random variation in party membership that correlated with any differences in the twins’ abilities.

[11] With respect to educational attainment and estimating the return to schooling, twin study designs have two important disadvantages: (1) they can exacerbate measurement error (Light and Flores-Lagunes, 2006; Ashenfelter and Krueger, 1994; Behrman et al., 1994; Miller et al., 1995), and (2) non-random variation in schooling correlated with ability differences of the twins; see Sandewall, Cesarini and Johannesson (2014). Both of these issues potentially represent threats to the validity of empirical estimates of party membership on earnings based on twin study designs.

III. Data and Survey Sources

A. Survey Data

We draw on data from three major Chinese surveys that included information on party membership, earnings, and a variety of labour market factors: the China Housing Survey, the Chinese Household and Income Project Survey, and the Chinese General Social Survey.

The China Housing Survey (CHS). First, we use data from the China Housing Survey (CHS). The survey was conducted in 1993 in Tianjin and Shanghai. Cross-sectional data were collected at the household level. A total of 2,096 households participated. The addresses of the participating households and neighbourhoods were randomly selected. Additionally, each respondent was selected at random from each household. The surveys were nearly identical in each city and were simultaneously conducted. The government authorized the surveys in both of the cities. The response rates were close to 100%. However, the sampling methods differed slightly for Tianjin and Shanghai (Bian et al., 1999).[12,13] This study drew heavily from demographic information, including data on ethnicity, gender, marital status, education, and neighbourhood.[14]

The Chinese Household and Income Project Survey (CHIP). The second source is the Chinese Household Income Project (CHIP), a survey conducted between 1988 and 2013 of about 8,000 rural households (representing some 35,000 individuals) and almost 7,000 urban households (approximately 22,000 members). To track the dynamics of income distribution in China, the CHIP conducted household surveys on income and expenditures in 1989, 1996, 2003, 2008, and

[12] The Tianjin Academy of Social Sciences coordinated the data collection in Tianjin. Households from a randomly selected set of 125 neighborhoods were interviewed. One neighborhood was chosen from each sub-district of the city. The addresses for the households chosen were randomly selected from the Tianjin household registration system. The Tianjin surveys were incorporated into an annual Tianjin municipal government survey called the "One Thousand Household Survey." In total, 1,042 households were surveyed in Tianjin. The sample from Tianjin was slightly biased towards male heads of households. However, distributions on other characteristics proved comparable to those for the general population in Tianjin, as reported in the census (Bian et al., 1998).

[13] In Shanghai, data collection was coordinated by the Shanghai Academy of Social Sciences. One neighborhood from every sub-district was randomly selected. There was a total of 110 neighborhoods. The households interviewed were drawn from these neighborhoods, and their addresses were randomly selected from the Shanghai census. A total of 1,054 households were surveyed in Shanghai. The distributions of the sample's characteristics were comparable to those of Shanghai's general population (Bian et al., 1998).

[14] Intended primarily as a housing survey, CHS elicited information on length of stay and frequency of moves, physical style of housing and organization of housing space, accessibility of utilities, amount of rent/payment and work unit subsidies, strategies for obtaining better housing, and neighborhood support networks. Other items included employment opportunities, collective welfare programs, employee training programs, and relationships with others in the work unit and with the work unit leader. Information was collected on up to nine of the respondent's household members, as well as the respondent's spouse, parents, and in-laws, regardless of whether they lived in the household.

2013.[15] In this study, we used data from the 1988 and 2002 waves. These surveys were carried out as part of a collaborative research project on income and inequality in China. The survey was organized by Chinese and international researchers, with assistance from the National Bureau of Statistics (NBS).

The urban survey covered 10,000 households. A total of 29,262 individuals were selected from 302 cities in 16 provinces. The rural survey covered 13,000 households, with 51,847 individuals selected from 287 counties in 16 provinces. The migrant survey covered nearly 5,000 households. A total of 8,404 individuals were selected from 15 cities in nine provinces. In order to obtain a nationally representative sample that would reflect variations in economic development and geography, the provinces were selected from four distinct regions.[16,17]

A considerable amount of time was devoted to verifying the accuracy of the data. Data were cleaned to reduce measurement error; a careful examination of income for each year and each individual was performed to identify unexpected or odd values. In some cases, individuals with unusual corresponding data were removed from the sample. In other cases, it proved reasonable to alter the recorded income. For example, zeros would be added if they were missing (but other parts of the survey implied zeros) for a given year.

The two main advantages of the survey for this study are the quality of the data on income, earnings, and expenditures (i.e., earnings as the outcome variable) and the wealth of information it provided on educational background, job networking, social network features, management responsibilities, and leadership roles. Data from these domains are useful in examining the variety of mechanisms underpinning the relationship between party membership and wages.

The Chinese General Social Survey (CGSS). Our third data source is the Chinese General Social Survey (CGSS). The CGSS's main objective was to systematically monitor the changing relationship between social structure and quality of life in urban and rural China. The survey

[15] The CHIP survey was conducted in 1988, 1995, 2002, 2007, and 2013: CHIP1988, CHIP1995, CHIP2002, CHIP2007, and CHIP2013.
[16] Beijing and Shanghai were selected to represent China's large metropolitan cities; Liaoning, Jiangsu, Zhejiang, Fujian, and Guangdong to represent the eastern region; Shanxi, Anhui, Hebei, Henan, Hubei, and Hunan to represent the central region; and Chongqing, Sichuan, Yunnan, and Gansu to represent the western region. The provinces covered in the urban and rural surveys are almost identical, with the exception that Shanghai was only included in the urban survey and Hebei was only included in the rural survey.
[17] The data are derived from larger samples designed by China's State Statistics Bureau (SSB), but the questions about income were different from the SSB's surveys. Non-responses were rare. However, the survey excluded responses from participants who lacked a formal certificate of residence (*hukou*)—an increasingly serious omission over time as the size of the population grew. Individuals were asked to keep a record of their income and expenditures and to consult their records before providing information on income from previous years.

includes urban households and 4,100 rural households in the 2003–6 Phase; the post-2006 design was slightly modified to recognize the changes in community development in rural and urban areas. The large sample size was required to reach each of the five strata relevant to regional and geo-administrative variations in China, and to allow for an attrition and replacement rate of 15% between adjacent years of the surveys.[18]

We use data from two CGSS waves: 2003 and 2013. The surveys from these years were conducted following the CHIP survey. Moreover, they provided additional labour market information that made it possible to gauge the channels between party membership and earnings.

The CGSS survey offers two main advantages to this study. First, the survey included very recent data on party membership and earnings. Additionally, it allows for an examination of the questions posed in the CHS and the CHIP surveys, but with more recent data. Second, the CGSS survey collected data on parental party membership and thereby provided an opportunity to apply an instrumental variable methodology using parental information as a potential instrument.

B. Descriptive Statistics

[Figure 1 about here] [Table 1-A, 1-B, 1-C, 1-D, 1-E about here]

Figure 1 reports data on the earnings distribution for the three surveys. Panel A reports the earnings distribution by party membership for CHIP 1988. Panel B reports the earnings distribution by party membership for CHS 1992. Panel C reports the earnings distribution by party membership for CHIP 2002. The final two panels show the earnings distributions for CGSS 2003 and 2013.

Table 1 reports summarized earnings statistics by party affiliation. The table also illustrates the breakdown of various socio-economic factors by party affiliation. In the five survey samples, Communist Party members accounted for a range from nearly 10% to slightly more than 20%. Communist Party members tended to be slightly older than the general sample; the average age

[18] The distribution of sampling units was designed as follows: (1) a total of 125 primary sampling units (PSU) were selected for the national sample; (2) four secondary sampling units (SSU) were selected from each selected PSU; (3) two third-level sampling units (TSU) were selected from each selected SSU; and (4) 10 households were selected from each selected TSU. One eligible person 18 years of age or older (18 to 69 for the 2003 CGSS) was randomly selected from each sampled household to serve as the survey respondent. PSUs were county-level units. In official statistics, this refers to (a) counties (*xian*), (b) county-level cities (*xian ji shi*), and (c) city districts (*qu*) in cities with administrative levels of prefecture or higher. Limited to the fifth population census, there were 2,801 PSUs from which 125 PSUs were selected by the following procedures: within each stratum, all of the PSUs were ranked according to the percentage of eligible respondents with a middle or higher educational level and a given number of PSUs were selected by using a method of "proportionate to population size." In this procedure, population refers to the civilian population ages 18 to 69.

for members is in the mid-50s compared to the high 40s of the general population. Communist Party members are more likely to be male, married, and to have attained some level of higher education (i.e., college or above). Finally, the average monthly earnings of non-members are lower than those of party members. Table 1 shows the positive relationship between party membership and earnings.

IV. Estimation Strategy

A. Econometric Benchmark 1: Ordinary Least Squares

In general, the goal of this paper is to estimate an equation of the form:

$$(1) \qquad \ln(Earn_i) = \beta_0 + \beta_1 C_i + \sum_{j=2}^{n} \beta_j X_{ji} + \theta_i + \delta_{ki} + \epsilon_i \, ,$$

where $(Earn)_i$ represents monthly earnings, and C_i denotes whether or not an individual is a member of the Communist Party. $\sum_{j=2}^{n} \beta_j X_{ji}$ is a set of demographic variables: educational level,[19] gender (whether a respondent is male), ethnicity (whether a respondent is of the Han majority), age (continuous variable), marital status (whether the respondent is married), religion (whether the respondent is religious), health (whether a respondent reports to be in poor health), and educational level attained. θ_i and δ_{ki} in (1) respectively capture the individual-specific and the district-fixed effects for individual *i* living in district *k*.[20] Empirically, θ_i cannot be identified with a cross-sectional dataset (i.e., all three surveys) that has only a single observation per person.

Our estimate of β_1 in (1) captures the differences in earnings between a party member and non-party member, assuming that party membership, $C_{i,}$, is uncorrelated with other factors not taken into account that determine earnings.

[19] The CHS dataset does not collect schooling information measured continuously as years of schooling. Rather, the survey instructed each respondent to report one of the following categories: "No formal schooling," "Elementary," "Junior high school," "Senior high school," "Technical school," "Vocational school," "Three-year college," "Formal college," and "Graduate school."

[20] For the CHS survey, the districts in the city of Tianjin included in the dataset are Hepin, Nankai, Hexi, Hedong, Hongxiang, Hebei, Tanggu, Hanggu, and Dagang. The districts in the city of Shanghai included in the dataset are Huangpu, Nanshi, Luwan, Xuhui, Changning, Jingan, Putou, Zhabei, Hongkou, Yangpu, Minhang, and Baoshan.

B. Econometric Benchmark 2: Propensity Score Matching

We augment the approach above with a propensity score matching method (Rosenbaum and Rubin, 1983, 1984; Imbens, 2004; Imbens and Wooldridge, 2009; Imbens and Rubin, 2014; Abadie et al., 2003; Angrist and Krueger, 2000; Angrist and Pischke, 2009).

First, we estimate a propensity score for each observation of the likelihood of Communist Party membership:

$$(2) \qquad C_i = \alpha_0 + \sum_{j=1}^{n} \gamma_j \chi_{ji} + \epsilon_i \,,$$

where $\sum_{j=1}^{n} \chi_{ji}$ is a vector of time-invariant variables: gender, ethnicity, marital status, religion, and level of education attained.[21] The vector $\sum_{j=1}^{n} \chi_{ji}$ does not include variables that may have been affected by the treatment of interest (Rosenbaum, 1984; Frangakis and Rubin, 2002; Greenland, 2003).[22] Based on the propensity score, we then match individuals who are party members with counterfactual units of non-party members. Specifically, we use a 1:1 matching with replacement. For robustness, we report results based on other matching methods. In its simplest form, 1:1 nearest neighbour matching selects for each treated individual *i* and the control individual with the smallest distance from individual *i*. In the final step, we estimate the effect of Communist Party membership on wages using:

$$(3) \qquad Ln(Earn_i) = \beta_0 + \beta_1 \hat{C}_i + \sum_{j=2}^{n} \beta_j X_{ji} + \delta_{ki} + \epsilon_i.$$

For the estimation of (2), we use only observations on the common support.[23] In the estimation procedure, party members are matched with statistically similar (i.e., counterfactual) non-party members.

Subclassifying or matching on the propensity score made it possible to estimate treatment effects, controlling for covariates. Within subclasses that are homogeneous in the propensity score,

[21] Because educational levels are highly correlated with age, we do not include respondent's age though we estimate specifications with the age variable and the size of the key coefficient remains stable.
[22] This is especially important when the covariates, treatment indicator, and outcomes are all collected at the same point in time, as is the case here.
[23] The common support ensures that persons with the same X values have a positive probability of being both participants and non-participants (Heckman, LaLonde, and Smith, 1999).

the distributions of the covariates are the same for treated and control units (e.g., are "balanced"). For a specific value of the propensity score, the difference between the treated and control means for all of the units with that value is an unbiased estimate of the average treatment effect, assuming the conditional independence between treatment assignment and potential outcomes for the observed covariates ("strongly ignorable treatment assignment" assumption) based on Rosenbaum and Rubin (1983).

β_1 in specification (3) yields the average treatment effect (ATE) of being a party member on one's monthly earnings. This assumption implies that the treated and non-treated are similar in their observable characteristics. The matching approach and the various matching algorithms capture all of the relevant observable differences between members and non-members of the Communist Party. We address the identifying assumption in the two sections that follow.

V. Results: The Wage Premium of Party Membership

A. OLS Results

[Table 2 about here]

Table 2 reports the results from the OLS-based specification (1). The estimated coefficient is based on a regression with a full set of controls including regional fixed effects. The estimated earnings return associated with party membership ranged from 7.5% to almost 25%. Two facts merit attention. First, all of the estimated effect sizes on the Communist Party variable are statistically significant (at the 1% level). Second, the effect size based on these three survey sources seems to increase over the span of three decades. In analyses not reported in the tables, we find that the differences between the estimated coefficients are statistically significant. The estimated coefficient based on the CHIP 1988 survey is 7.5%, implying that, all else equal, party membership increases earnings by 7.5%. The associated effect size based on the CGSS 2013 sample is almost triple in size or 25% (statistically significant at the 1% level).[24] However, this empirical estimation is likely plagued by omitted variable bias, a concern we attempt to address below.

[24] We examine some of the potential mechanisms underlying the increase of the wage premium in the next section.

B. Propensity Score Matching Results

To the extent selection into party membership occurs (an issue we address below) on observable characteristics, the wage premium associated with being a Communist Party member can be estimated by using the propensity score approach. Before we present the results based on this econometric approach, we provide analyses on the identifying assumptions.

Common Support Assumption and Post-Matching Balancing. First, we test whether or not the common support assumption is fulfilled (Kahn and Tamer, 2010).[25] The substance of the common support assumption implies that there must be both treated and untreated observations for each value of X.[26] The assumption essentially ensures that individuals with the same X-values have a positive probability of being both participants and non-participants (Heckman, LaLonde, and Smith, 1999). We present a graphical examination of the common support assumption for the five samples. Figure 2 (and Online Appendix A, Figure A.1) reports the results.

[Figure 2 about here]

It is easy to discern, based on Figure 2, that for each class of the "propensity score," a certain number of "non-treated" individuals also exist. Figure 3 displays the estimated density of the predicted probabilities that a Communist Party member is a non-member.[27] Based on Busso, DiNardo, and McCrary (2014), neither plot indicates much probability mass near 0 or 1; the two estimated densities reveal substantial overlap in their respective masses. Therefore, we detect no evidence that the overlap assumption is violated. Nor is there any visual evidence that the common support assumption is violated in the five data samples. To confirm the graphical test, we perform a Kolmogorov-Smirnov (K-S) test to test the equality of two distributions. The K-S test does not reject the null hypothesis of equality of distributions between groups after matching.

Next, we examine the balancing of covariates based on the propensity score matching exercise. Before we explore the effect of party membership on earnings, we analyse balancing after the propensity score matching has been executed.

[25] The standard common support assumption is: $0 < Pr(D=1|X) < 1$. The strict common support assumption is $0 < c < Pr(D=1|X) < 1-c < 1$.
[26] When estimating the ATET, all that is required is untreated units for each value of *X* to correspond to at least one treated unit.
[27] Online Appendix A Figure A.1 reports the proportion of propensity scores by treatment status and it clearly shows an overlap of the distribution of propensity scores for treated and untreated units.

[Figure 3 about here]

Related to the conditional independence assumption, we also assess the quality of matching to determine whether or not the propensity score matching adequately balances characteristics for the treatment and comparison groups. The objective of these tests is to verify that treatment is independent of unit characteristics after conditioning on observed characteristics (as estimated in the propensity score model).[28] It is important to note that only "after-matching" tests provide a comparison of differences between the means of time-invariant covariates (that are unaffected by treatment) for the resulting matched sample.

Figure 3 and Online Appendix A Table A.1 report the results of after-matching balancing. Figure 3 displays the overall balancing for treated and untreated units, based on the propensity score. We examine them graphically and through a comparison of means to ensure that any differences in the covariate means between the two groups in the matched sample have been eliminated; this would improve the likelihood of unbiased treatment effects. Online Appendix A Table A.1 reports the balancing post-matching for the five datasets: CHIP 1988 is reported in Online Appendix A Table A.1-1, CHS 1993 is reported in Online Appendix A Table A.1-2, CHIP 2002 is reported in Online Appendix A Table A.1-3, CGSS 2003 is reported in Online Appendix A Table A.1-4, and CGSS 2013 is reported in Online Appendix A Table A.1-5. The tables also display the results of a formal test to determine if the matching is fulfilled, obtained through a formula applied to the post-matching sample that compared the means between treated (i.e., party members) and non-treated (non-party members). The formal tests reveal successful matching based on the chosen covariates. Furthermore, we follow Imai and Ratkovic (2014), and conduct a test to compare the covariate means between treatment and control units (reported in Online Appendix A Table A.2).[29] The test fails to reject the null hypothesis that the propensity score model is balanced based on the chosen covariate to predict party membership.

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[28] Formally, this assumption entails $T \perp X \mid p(X)$, where X is the set of characteristics that are believed to satisfy the conditional independence assumption. In other words, after conditioning on p(X), there should be no other variable that could be added to the conditioning set of the propensity score models that would improve the estimation. Following the application of matching, there should be no statistically significant differences between covariate means of the treatment and comparison units.

[29] Imai and Ratkovic (2014) developed a test to determine whether or not the estimated propensity score balanced the covariates. The score equations for parameters of the propensity-score model defined a precisely identified and generalized method of moments (GMM) estimator. Imai and Ratkovic (2014) used the conditions imposed by mean balance as over-identifying conditions. A standard GMM test for the validity of the over-identifying conditions is then a test for covariate balance.

Average Treatment Effects. We estimate the average treatment effect (ATE) by propensity-score matching (PSM) based on a nearest neighbour 2:1 matching with replacement. PSM estimators impute the missing potential outcome for each subject by using an average of the outcomes for similar subjects that receive the other treatment level. Matching with replacement can often decrease bias because controls that look similar to many treated individuals can be used multiple times. This has proven particularly helpful in settings where there have been few control individuals comparable to the treated individuals (e.g., Dehejia and Wahba, 1999). Additionally, the order in which the treated individuals are matched does not matter when matching with replacement. The next section addresses the algorithm matching procedure and the robustness of the estimated effect size.

[Table 3 about here]

Table 3 reports the results from the propensity score-matching method based on specification (3).[30] There are several points worth mentioning with regard to the estimated effect sizes. First, the estimated effect sizes range from approximately 18% percent from the 1988 sample to 21% from the CGSS sample. The CHS effect size is noticeably smaller. However, this could be expected as the CHS samples include observations from only two specific urban areas (i.e., Tianjin and Shanghai), whereas the CHIP and CGSS samples include both urban and rural observations.[31] Second, the estimated effect sizes based on the matching procedure are generally lower compared to the effect sizes based on the OLS estimation. The decrease (increase) in the estimated effect sizes based on matching suggests that the matching procedure likely addresses additional positive (negative) selection that took place during the party initiation process. Section 6 includes a greater discussion of effect size estimates' sensitivity to the chosen matching algorithm used and potential additional bias due to unobservable characteristics. Third, the reported effect size estimates reveal some evidence of an increase in the estimated wage premium associated with party membership.

C. Heterogeneous Treatment Analysis

Using the propensity score-based estimation, we examine how the treatment effect of party

[30] The PSM estimation was obtained using the effects in Stata 15.

[31] In an analysis not reported here, we compared estimates from the same two regions in CGSS. The benchmark analysis showed extremely similar results.

membership on earnings differs by important individual covariates. In particular, we focus on gender, education, ethnicity, and whether or not a parent is a member of the Communist Party. We augment specification (3) to estimate the heterogeneous impact with the following specification:

$$(4) \qquad Ln(Earn_i) = \beta_0 + \beta_1 \hat{C}_i + \sum_{j=2}^{n} \beta_j \hat{C}_i \times X_{ji} + \delta_{ki} + \epsilon_i.$$

X_i captures covariates that we test for treatment effect heterogeneity. Table 4 presents the combined effects (on the binary variable and the interaction).[32] We detect statistically significant differences for the Han ethnicity population. In terms of gender, we detect slightly larger effect sizes for women throughout the years for which the data permitted analysis. These results imply that party membership has a larger wage effect for females and Han Chinese. These differences are consistent with a theoretical model in which women likely face more binding (social) constraints to accessing certain types of jobs or qualifications, both of which are factors that we examine in our next section.

[Table 4 about here]

D. Mechanisms

Next, we assess the relative importance of various channels in explaining the linkage between party membership and better wage outcomes. Party membership could change several aspects of daily life that could potentially contribute to the observed wage effects. In particular, it could improve the strength or quality of an individual's social network. Enhanced social networks could produce various labour market benefits, such as reduced time devoted to job searches, information about available job opportunities, and information on better-paying jobs. Party membership also could encourage individuals to pursue better job qualifications or certifications. People with better qualifications would enjoy greater knowledge or better wages. Third, party membership could grant access to jobs that offer higher pay. Fourth, party membership or better social capital could represent an important determinant of an individual's overall well-being (Yip et al., 2007).

[32] Conceptually, the main difference between subgroup analysis and interaction terms is that stratified regressions allow all regression coefficients to vary across subgroups; the difference between subgroup analysis and interaction term-based regressions—in practice—will depend on the number of control variables, and the assumption that control variables are orthogonal to the treatment.

Therefore, it seems likely that behavioural adjustments are, at least in part, responsible for the positive wage effects reported in the previous section. We study these mechanisms further with additional data.

We use the panel feature of the 2002 CHIP survey, which provides additional information on annual earnings and on potentially mediating variables that could shed light on the mechanisms underlying the relationship between party affiliation and wages. Based on the available data from the two survey samples, we explore four main channels: strength of social networks, human capital acquisition that resulted from party membership, improvement in social rank, and overall life satisfaction. Specifically, the 2002 CHIP (the urban questionnaire) provides information on government employment, the number of friends available to help find a job, professional titles, months spent in the search for a new job, happiness level, and self-perceived social rank. Table 5 reports the results.

[Table 5 about here]

Column 1 reports the main results from Table 3. The remaining columns add the specific channel variables one at a time. The final column (in Table 5) controls for all channel variables in the regression. Only the statistically significant individual variable specifications with no missing observations are in the final row. The final regression in Table 5 (for CHIP 2002) demonstrates compelling evidence that the strongest impact on wages resulted from an increased likelihood of a government job, a higher job position, and improvement in overall social rank. Although we observe a positive effect size on the happiness variable, it is statistically significant. Of course, the evidence presented in Table 5 is only suggestive and relies on the assumption that the changes in the channel variables presented increase wages. Methodological problems and data limitations in the three survey sources make it challenging to conduct a formal mediation analysis. Nevertheless, there is suggestive evidence that wage increases accompanied changes in three important channels: access to a subset of government jobs, the acquisition of additional job-related qualifications, and an overall improvement in social rank.

VI. Robustness Checks

A. Matching Algorithm Method

We first examine the robustness of the estimated effect sizes for the five data samples with respect to the matching algorithm method. In addition to the main matching results (which are based on the nearest neighbour 2:1 matching with replacement method), we further re-estimate the effect sizes using the nearest neighbour matching (NN), the caliper method, the kernel method, and the IPW matching method. The most straightforward matching estimator is nearest-neighbour (NN) matching. The individual from the comparison group is chosen as a matching partner for a treated individual that is closest in terms of the propensity score. Several variants of NN matching are possible. For example, there is NN matching "with replacement" and "without replacement." In the former case, an untreated individual can be used more than once as a match, whereas in the latter case it is considered only once. Matching with replacement involves a trade-off between bias and variance. NN matching runs the risk of poor matches if the closest neighbour is distant. This may be avoided by imposing a tolerance level on the maximum propensity score distance (i.e., caliper matching). Imposing a caliper works in the same direction as allowing for replacement. Poor matches are avoided and the matching quality consequently improves. The idea of stratification matching is to partition the common support of the propensity score into a set of intervals (strata) and to calculate the impact within each interval by taking the mean difference in outcomes between treated and control observations (Rosenbaum and Rubin, 1983). We use five subclasses to remove 90% of the bias due to measured confounders, as has been done in the majority of propensity score studies (Thoemmes and Kim, 2010; Cochran, 1968; Rosenbaum and Rubin, 1984).

Kernel matching (KM) and local linear matching (LLM) are non-parametric matching estimators that use weighted averages of all of the individuals in the control group to construct the counterfactual outcome. Thus, one major advantage of these approaches is the lower variance achieved through the use of more information. Imbens (2004) noted that propensity scores also could be used as weights to obtain a balanced sample of treated and untreated individuals (IPW method). If the propensity score is known, the estimator may be directly implemented as the weighted average of the differences between the treated and untreated individuals.

Online Appendix B Table B.2 displays estimates from the algorithm matching techniques outlined above. The results in the table show that the effect size estimates are fairly robust to the choice of algorithm matching technique: estimates range from 8.25% to 9.24% higher wage premiums for members of the Communist Party. Only the radius caliper (0.2) matching for CGSS 2013 yields a slightly lower premium.[33,34]

B. Two-Stage Least Squares Method

We also augment our matching procedure results with a two-stage least squares estimation (2SLS), in which we instrument the individual's party affiliation with parental party affiliation. Parental party membership could represent a valid instrumental variable for the individual's party affiliation if party affiliation influences monthly earnings only by a switch in own party affiliation. Although the 2SLS approach represents a promising alternative and has several advantages over the matching procedure, only a small subset of the datasets we use have data on parental party affiliation. Even for these datasets, information on parental affiliation is missing for a very large number of observations. Based on two datasets (CHIP 2002 and CGSS 2013), we re-estimate the wage premium associated with party membership with the limited data we have on parental party affiliation.

Online Appendix A.3 reports the results for the estimated wage premium. Online Appendix A.3, Column (1) includes the estimated effect size for the CHIP 2002 dataset. The estimated effect size shows a 17% increase (imprecisely estimated) in monthly earnings associated with Communist Party membership. Online Appendix A.3, Column (2) illustrates the estimated effect size for the CGSS 2002 dataset; there is a 27% increase in monthly earnings (imprecisely estimated) associated with Communist Party membership. Although both estimates of the wage premium coefficient are not statistically significant, they are comparable to the results from the matching procedure. The CGSS 2013 based on the 2SLS is slightly higher than the effect size

[33] We also explore the stability of the results for the NN matching technique by the number of propensity-influencing variables (not reported but available upon request). To satisfy the assumption of ignorable treatment assignment, it proved important to all variables known to be related to both treatment assignment and the outcome in the matching procedure (Rubin and Thomas, 1996; Heckman et al., 1998; Glazerman et al., 2003; Hill et al., 2004). We add 5–15 additional variables and we examine how the treatment effects change. The results are stable with the inclusion of additional matching variables.

[34] Online Appendix Tables B.1-1 through B.1-5 illustrate how treatment varies according to the probability of selection into treatment, as suggested by Xie, Brand, and Jann (2012). Online Appendix Tables B.1-1 to B-1.5 display our examination of the variation in the effect size by the treatment probability. We detect very small differences by propensity score strata. The results regarding the relationship between party membership and monthly earnings are stable and most differences are statistically insignificant.

based on the matching procedure. This could be because the instrument reduces the measurement error in the outcome variable. The difference could also be due to the fact that the 2SLS is based on a different subset (compared to the estimation sample in matching procedure) of the study sample: the so-called group of compliers (Angrist and Krueger, 1999). The complier population could be the subset of individuals who have higher marginal return to party membership to begin with.

C. Quantile Regressions

We also estimate (reported in Online Appendix B Tables B.3) the effect of party membership by estimating an equation that expresses each quantile of the conditional distribution. In this type of estimation, we allow for the effects of the independent variables to differ across the quantiles. We estimate the propensity score for each quantile as 0.25, 0.50, and 0.75. Using these specifications, we find that for individuals who earn less (those represented in the 0.25 quantile), the effect of party membership on earnings is particularly pronounced. We cannot detect strong effects for individuals in the 0.50 and 0.75 quantiles. We also graph (Online Appendix A Figure A.2) the estimated coefficients for the effects of Communist Party membership on wages for each quantile regression in quantile increments of 0.05, as done by Koenker and Basset (1978).

D. Rosenbaum Bounds

The estimation of treatment effects that relies on the matching estimators is based on the conditional independence assumption (CIA); a selection based on observable characteristics. If there are unobserved variables that affect assignment into treatment and the outcome variable simultaneously, a hidden bias could arise. In this section, we explore the sensitivity of the treatment effect if inference about treatment effects is altered by unobserved factors. We examine how strongly an unmeasured variable must influence the selection process in order to undermine the implications of the matching analysis presented. Rosenbaum (2002) developed a method of sensitivity analysis to assess if the estimation based on matching is robust with the possible presence of an unobserved confounder. This sensitivity analysis for matched data provides a specific understanding about the magnitude of hidden bias that would need to be present to explain the associations actually observed (Rosenbaum, 2002).

We estimate the Rosenbaum bounds based on the main estimation matching technique. The results are reported in Online Appendix B Tables B.4-1 through B.4-5. Γ (gamma) is a measure of the degree of departure from a study that is free of bias. Overall, the lowest critical value for Γ ranges from 1 to 10 and varies between the Hodges-Lehmann point estimate and the 95% confidence interval.[35] Gamma captures the log odds of differential assignment due to unobserved factors. In other words, gamma permitted an examination of any changes in treatment effect if differential likelihood for assignment into the treatment group is introduced. We find the lowest critical value that includes zero ranges from 2.00 to 5.00 (Hodges-Lehmann point estimate). Such a high H-L critical value constitutes strong evidence that our estimated positive effects of Communist Party membership on wages are robust for even a small amount of bias based on self-selection based on unobservable characteristics.

VII. Conclusions

One million Chinese citizens join the Chinese Communist Party every year, and over 80% of graduating college students apply. Membership in the party is perceived as an investment in political capital that may help secure a good job and a high salary. In this paper, we estimate the wage premium of membership in the Chinese Communist Party using data that spans three decades.

We report three main findings. First, using a propensity score-matching method, we find that Communist Party members earn an average of a little over 20% more in monthly earnings than non-members do. This estimated effect is larger than previous estimates summarized in Li et al. (2007). Our estimates are based on samples from both rural and urban areas in China, whereas previous studies rely on data predominantly from urban areas. This finding adds to previous research that uses data from developing countries and provides evidence on substantial monetary benefits associated with political status and social connections (Siddique, 2010; Madheswaram and Attewell, 2007; Das and Dutta, 2007). To bolster the credibility of our estimates, we examine the robustness of the results with respect to various factors: the matching algorithm method, the estimation technique, and potential selection bias due to unobservable characteristics. Second, because we rely on data that spans three decades, there is evidence that this wage premium has

[35] See Hollander and Wolfe (2013) for more details on the Hodges-Lehmman point estimate for the sign rank test.

grown modestly over that time. In both the OLS and propensity score matching results, we detect evidence that the wage premium has increased. Finally, we explore the relative importance of various channels that could explain the linkage between party membership and better wage outcomes. Based on the available data from the two data samples, we explore four main channels: the strength of the social network, human capital acquisition from party membership, improvement in social rank, and overall life satisfaction. We provide suggestive evidence that at least three important channels likely exert a strong positive impact on wages for Communist Party members: improved access to government jobs, higher-ranking positions within a job hierarchy, and an overall improvement in social rank.

All of the findings provide robust evidence that political connections may play an important economic role in the world's most populous economy. These results also shed new light on the reasons why Communist Party membership has more than doubled since the early 1980s and is likely to continue to do so in the future.

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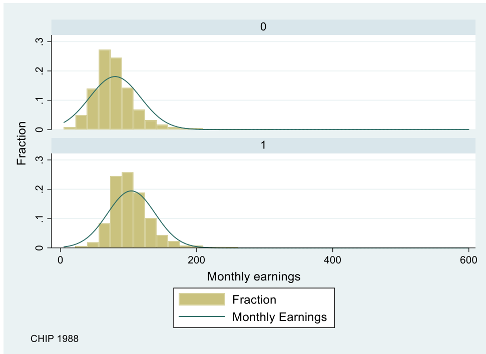
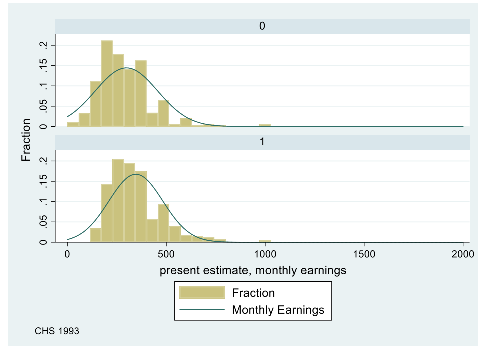
Figures

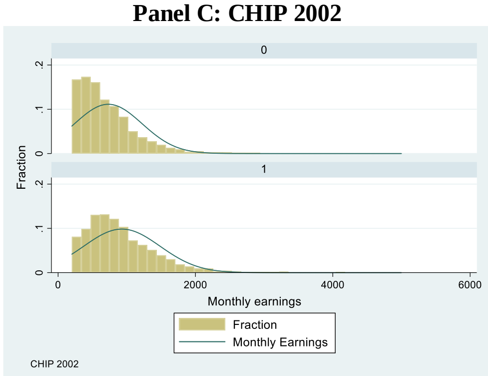
Panel A: CHIP 1988



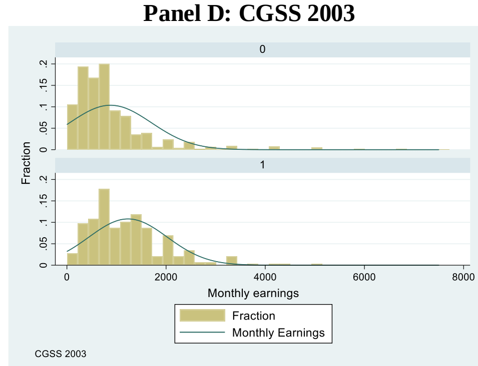
Panel B: CHS 1993



Panel C: CHIP 2002



Panel D: CGSS 2003



Panel E: CGSS 2013

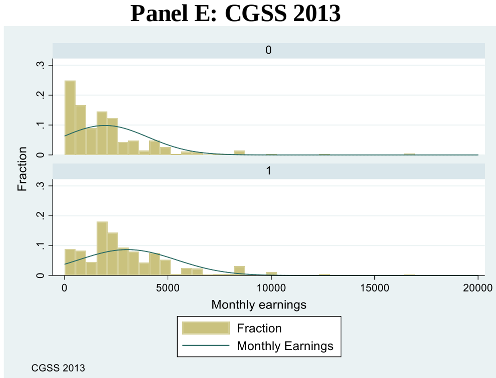


FIGURE 1 Distribution of Logged Monthly Earnings (in RMB), By Survey Source
Note: Distribution for each value of the party membership variable (1=Communist party member; 0=non-member)

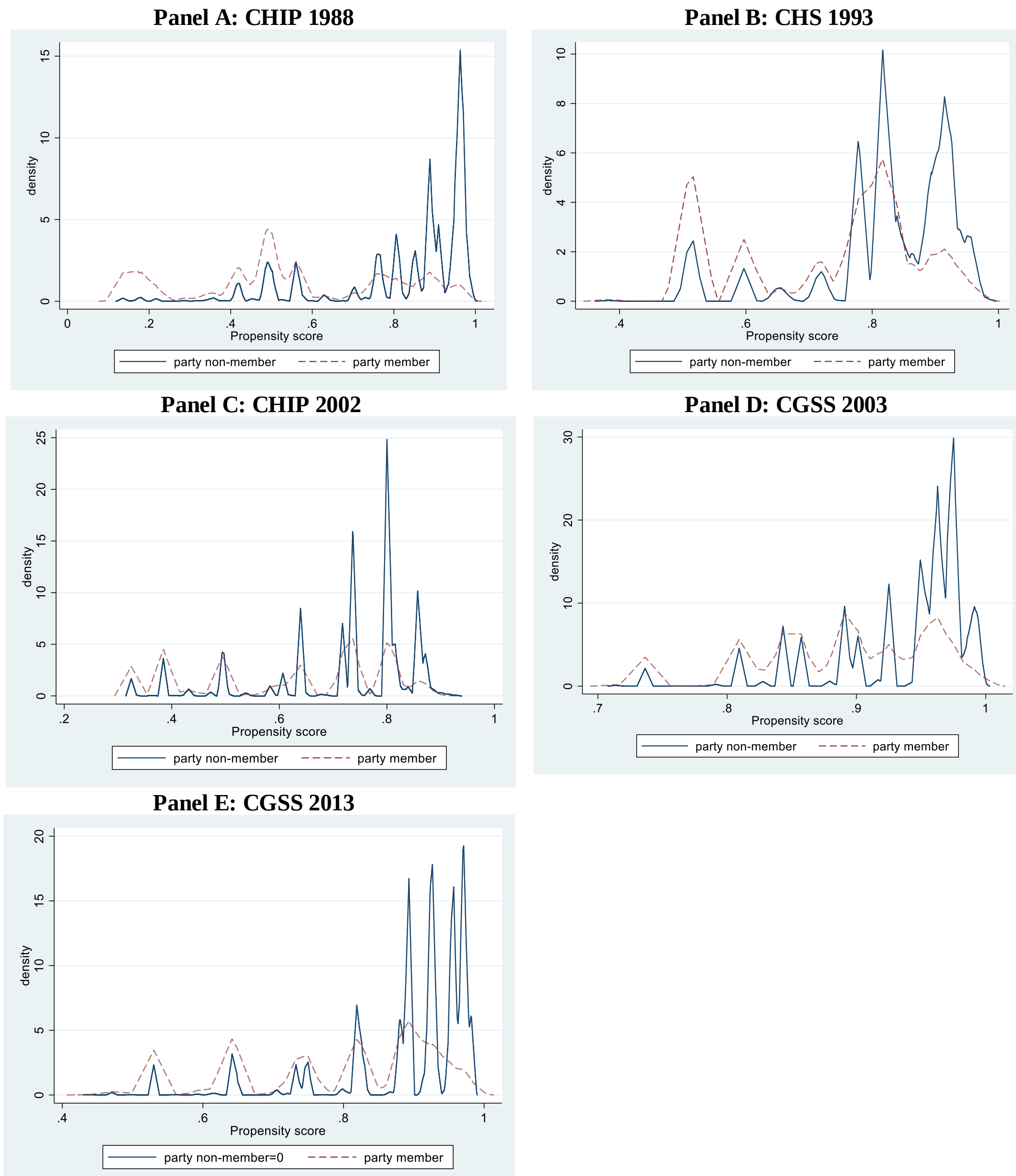
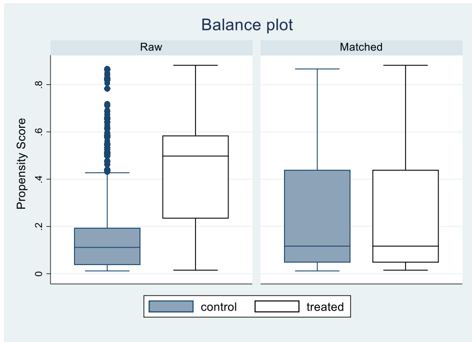


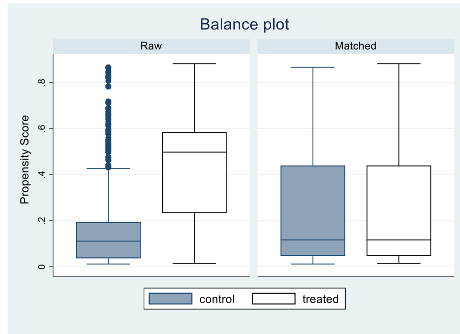
FIGURE 2 Density of the Predicted Probability

Note*:* Shows density distributions of participants and non-participants, and the region of common support; X-axis: *high* probability of participating given X

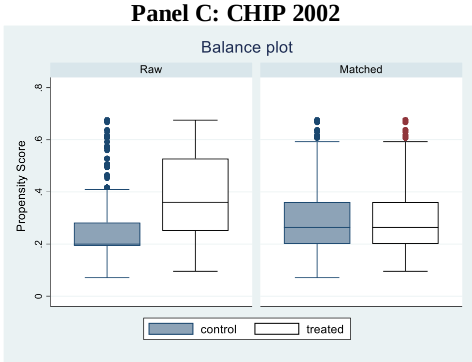
Panel A: CHIP 1988



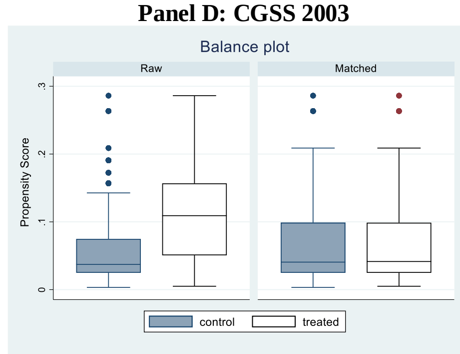
Panel B: CHS 1993



Panel C: CHIP 2002



Panel D: CGSS 2003



Panel E: CGSS 2013

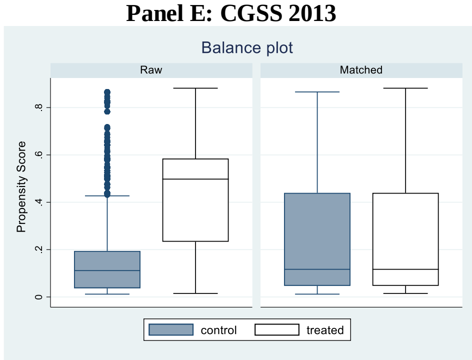


FIGURE 3 Balancing Post Propensity Score Matching
Note: Distribution for each value of the party membership variable (1=Communist party member; 0=non-member)

Tables

TABLE 1-A Descriptive Statistics (CHIP 1988)

		Sample	Non-Communist Party Members	Communist Party Members
		(1)	(2)	(3)
Monthly Earnings (in Rmbs)		87.41 (57.73)	82.01 (58.46)	105.31 (51.91)
Member in the Communist party (percent)		12.50%	0%	100%
Han (percent)		94.00%	93.87%	94.89%
Male (percent)		49.69%	46.85%	79.43%
Age		39.80 (51.71)	37.04 (37.92)	47.36 (42.19)
Education Level	Primary	5.44%	6.27%	1.79%
	Middle School	13.26%	14.54%	7.69%
	High School	35.45%	37.51%	26.41%
	Technical School	21.28%	21.81%	18.91%
	Vocational School	2.86%	3.17%	1.54%
	College[a]	7.40%	6.27%	12.31%
Occupation	Private Sector	1.00%	1.12%	0.99%
	Professional	4.89%	4.32%	15.21%
	Managerial	3.18%	1.28%	20.41%
	Office	7.03%	5.71%	25.46%
	Low-skill	18.33%	22.65%	11.80%
	Agricultural	44.14%	55.06%	17.94%
	Temporary	1.24%	1.58%	0.00%
Observations		60,897	45,338	6,476

Notes: Standard errors in parentheses. [a]College combines individuals who reported having attained college-level education and graduate school.

TABLE 1-B Descriptive Statistics (CHS 1993)

		Sample	**Non-Communist Party Members**	**Communist Party Members**
		(1)	(2)	(3)
Monthly Earnings (in Rmbs)		307.77 (155.093)	298.59 (157.93)	346.21 (136.24)
Member in the Communist party (percent)		18.61%	0%	100%
Han (percent)		98.47%	98.53%	98.21%
Male (percent)		60.31%	56.15%	78.46%
Age		47.39 (13.76)	46.50 (14.03)	51.27 (11.79)
Religious (percent)		4.3%	4.76%	2.31%
Married (percent)		86.07%	84.76%	91.79%
In Poor Health (percent)		10.16%	9.96%	11.03%
Education Level	Elementary	5.44%	6.27%	1.79%
	No schooling	13.26%	14.54%	7.69%
	Elementary	35.45%	37.51%	26.41%
	Middle School	21.28%	21.81%	18.91%
	High School	2.86%	3.17%	1.54%
	Technical School	7.40%	6.27%	12.31%
	Vocational School	8.78%	6.39%	19.23%
	Three-year College	5.34%	3.93%	11.54%
	Formal College	0.14%	0.12%	0.26%
	Graduate School	5.44%	6.27%	1.79%
Observations		2,096	1,621	390

Notes: Standard errors in parentheses

TABLE 1-C Descriptive Statistics (CHIP 2002)

		Sample	Non-Communist Party Members	Communist Party Members
		(1)	(2)	(3)
Monthly Earnings (in Rmbs)		593.98 (562.07)	525.09 (527.99)	835.22 (610.77)
Member in the Communist party (percent)		20.40%	0%	100%
Han (percent)		94.00%	93.87%	94.89%
Male (percent)		49.69%	46.85%	79.43%
Age		39.80 (51.71)	37.04 (37.92)	47.36 (42.19)
Married (percent)		76.61%	72.46%	94.50%
Education Level	Primary	18.34%	19.47%	10.17%
	Middle School	54.71%	56.12%	44.95%
	High School	14.01%	12.06%	27.92%
	Technical School	5.04%	4.49%	8.91%
	Vocational School	1.46%	1.13%	3.86%
	College[a]	0.28%	0.22%	0.71%
Occupation	Private Sector	3.83%	4.26%	2.25%
	Professional	8.45%	7.22%	13.21%
	Managerial	4.47%	1.63%	15.68%
	Office	9.91%	6.76%	22.33%
	Low-skill	8.38%	9.06%	5.93%
	Agricultural	9.45%	11.17%	3.09%
	Temporary	7.14%	8.09%	3.75%
Observations		60,897	45,338	6,476

Notes: Standard errors in parentheses. [a]College combines individuals who reported having attained college-level education and graduate school.

TABLE 1-D Descriptive Statistics (CGSS 2003)

		Sample	Non-Communist Party Members	Communist Party Members
		(1)	(2)	(3)
Monthly Earnings (in Rmbs)		941.60 (298.40)	917.31 (1,080.23)	1,294.82 (1,093.38)
Member in the Communist party (percent)		6.44%	0%	100%
Han (percent)		94.43%	94.46%	94.12%
Male (percent)		53.57%	54.07%	46.37%
Age		44.62 (12.69)	44.13 (12.62)	51.74 (11.47)
Married (percent)		84.97%	84.27%	95.16%
Education Level	Primary	12.78%	13.21%	6.57%
	Middle School	30.55%	31.75%	13.15%
	High School	18.70%	18.87%	16.26%
	Technical School	10.00%	9.54%	16.61%
	Vocational School	3.14%	3.31%	0.69%
	College	6.80%	5.93%	19.38%
	Graduate School	0.49%	0.48%	0.69%
Observations		4,491	4,202	289

Notes: Standard errors in parentheses

TABLE 1-E Descriptive Statistics (CGSS 2013)

		Sample	**Non-Communist Party Members**	**Communist Party Members**
		(1)	(2)	(3)
Monthly Earnings (in Rmbs)		2,240.94 (3,165.13)	2,082.62 (2,818.19)	3,437.46 (4,909.80)
Member in the Communist party (percent)		11.69%	0%	100%
Han (percent)		91.35%	91.25%	92.08%
Male (percent)		54.58%	51.92%	74.72%
Age		49.40 (15.72)	48.88 (15.57)	53.26 (16.29)
Married (percent)		78.82%	78.23%	83.30%
Education Level	Primary	21.63%	23.27%	9.25%
	Middle School	30.00%	31.36%	19.72%
	High School	11.52%	11.31%	13.11%
	Technical School	2.28%	2.37%	16.04%
	Vocational School	5.27%	4.81%	8.77%
	College	7.22%	5.31%	21.70%
	Graduate School	0.68%	0.46%	2.36%
Observations		9,071	8,011	1,060

Notes: Standard errors in parentheses

TABLE 2 Earnings Equation (OLS)

Dependent Variable:	**ln (Monthly Earnings), (in RMBs)**				
Survey Source /Year	CHIP 1988[a]	CHS 1993[b]	CHIP 2002[c]	CGSS 2003[d]	CGSS 2013[e]
	(1)	(2)	(3)	(4)	(5)
Communist Party	0.075***	0.134***	0.163***	0.171***	0.253***
Membership	(0.006)	(0.035)	(0.023)	(0.047)	(0.032)
District Fixed Effects	YES	YES	YES	YES	YES
R-squared	0.369	0.359	0.3244	0.3118	0.4272
Observations	19,323	1,994	11,817	4,491	9,071

Notes: Standard errors in parentheses. [a] in this specification, the control variables are educational level, ethnicity, gender, age, age-sq, urbanicity, religious status, marital status, health status;[b] in this specification, the control variables are educational level, ethnicity, gender, age, age-sq, urbanicity;[c] in this specification, the control variables are educational level, ethnicity, gender, age, age-sq, urbanicity, marital status, health status.[d] in this specification, the control variables are educational level, ethnicity, gender, age, age-sq, urbanicity, marital status, health status; [e] in this specification, the control variables are educational level, ethnicity, gender, age, age-sq, urbanicity, marital status, health status. ***, ** and * indicate significance at 1, 5 and 10%, respectively.

-

TABLE 3 Earnings Equation (Propensity Score Matching Estimation)

Dependent Variable:	**ln (Monthly Earnings), (in RMBs)**				
Survey Source /Year	CHIP 1988[a]	CHS 1993[b]	CHIP 2002[c]	CGSS 2003[d]	CGSS 2013[e]
	(1)	(2)	(3)	(4)	(5)
Communist Party	0.177***	0.094***	0.188**	0.233***	0.212***
Membership	(0.010)	(0.024)	(0.022)	(0.032)	(0.052)
District Fixed Effects	YES	YES	YES	YES	YES
R-squared	0.369	0.359	0.401	0.3118	0.4272
Observations	19,323	1,994	11,817	4,491	9,071

Notes: Standard errors in parentheses. [a] in this specification, the control variables are educational level, ethnicity, gender, age, age-sq, urbanicity, religious status, marital status, health status;[b] Variables used in estimating propensity score: sex dummy (1 if respondent is male and 0 if female), ethnicity dummy (1 if respondent is of the Han majority ethnicity and 0 if of a minority ethnicity), married dummy (1 if the respondent is married and 0 if single), dummies for education (1 if the respondent achieved the specified level of education and 0 if not) and religion (1 if the respondent is religious and 0 if town). Values can be interpreted as the percent change in monthly earnings. Communist party membership in a dummy equal to 1 if the subject is a member of the Communist party and 0 if otherwise; [c] in this specification, the control variables are educational level, ethnicity, gender, age, age-sq, urbanicity, marital status, health status.[d] in this specification, the control variables are educational level, ethnicity, gender, age, age-sq, urbanicity, marital status, health status; [e] in this specification, the control variables are educational level, ethnicity, gender, age, age-sq, urbanicity, marital status, health status.

***, ** and * indicate significance at 1, 5 and 10%, respectively.

TABLE 4 Heterogeneous Treatment Analysis

Socio-economic Group		**ln (Monthly Earnings, in RMBs)**				
		CHIP 1988	CHS 1993	CHIP 2003	CGSS 2003	CGSS 2013
		(1)	(2)	(3)	(4)	(5)
Gender	Male	0.161*** (0.010)	0.124*** (0.029)	0.197*** (0.027)	0.211*** (0.035)	0.106** (0.05)
Education	College Degree	0.142*** (0.020)	-0.075 (0.078)	0.082*** (0.054)	-0.114 (0.102)	-0.025 (0.065)
Ethnicity	Han Ethnicity	0.181*** (0.011)	0.093*** (0.024)	0.184*** (0.022)	0.226*** (0.033)	0.200*** (0.055)
Parent Communist	Parental Communist Party Member Status	NA	-0.020 (0.065)	0.134*** (0.038)	NA	NA
Estimation Strategy		PSM	PSM	PSM	PSM	PSM
Observations		19,323	1,994	24,704	4,491	9,071

Notes: ***, ** and * indicate significance at 1, 5 and 10%, respectively.

TABLE 5 Mechanisms of Party Influence on Earnings (CHIP 2002[a])

Variables	**Dependent Variable: ln (Monthly Earnings), (in RMBs)**								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)[h]
CPM[a]	0.188** (0.022)	0.152 (0.120)	0.167 (0.119)	0.185 (0.119)	0.210* 0.120	0.210* 0.120	0.237*** (0.096)	0.244** (0.096))	0.079 (0.120)
Holds a government job (1=yes)		0.067*** (0.027)							0.599* (0.155)
Higher professional title (1=yes)[c]			0.471*** (0.167)						0.324* (0.170)
Friends who can help one find a job? (#)[d]				0.007 (0.023)					
Holds a management position					1.225 (0.852)				
Months to find a job? (#)[e]						0.004 (0.027)			
Happiness level[f]							0.215*** (0.049)		0.085 (0.061)
Self-perceived social rank[g]								0.490*** (0.065)	0.336*** (0.084)
Observations	5,825	4,115	4,140	4,140	4,114	222	5,768	5,811	1,961

Notes: (a) For this analysis we only use the urban sub-sample of CHIP 2002 because the survey questions on these potential mechanisms are only available in the urban survey questionnaire. (b) CPM=Communist Party Member. (c) Professional title and administrative rank of professionals and cadres of government agents, institutions and enterprises. Coded as 1 if individual reported having a senior title, being a bureau chief level and above, or division chief level and above, or section chief level and above. (d) The survey question was "If you want to change your job, how many friends and relatives can you ask to help you?" Robust standard errors in parentheses. (e) variable is not included in the final regression in column (6) because of very high number of missing observations that results in a very small sample size for that specification. (f) Happiness level is five levels and, in our regressions, the higher value indicates happier individual. The levels are: very happy, happy, so-so, not very happy, not happy at all. (g) self-perceived social rank based on living standards. Higher values indicate increase in social rank. The actual categories are: bottom quartile, second lowest quartile, second best quartile, and top quartile. (h) in this specification, we only include the variables that have do not have a considerable number of missing observations. ***, ** and * indicate significance at 1, 5 and 10%, respectively.

Online Appendix A

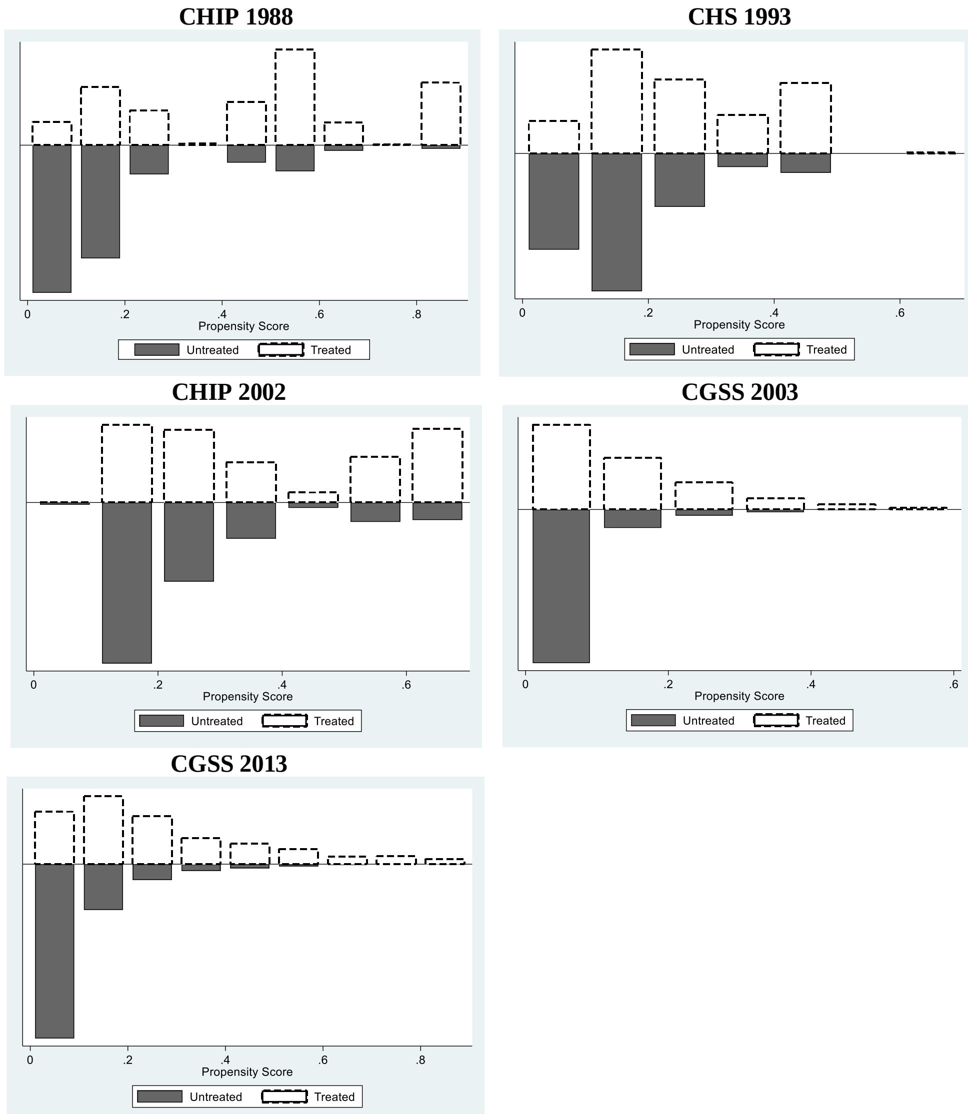


FIGURE A.1 Visual Check for Common Support Assumption

Note: Graphical check that the “common support” assumption is fulfilled. The assumption is fulfilled when there is sufficient overlap between the distributions of propensity scores across treatment and control groups. the y axis in psgraph is proportional by group – the treated and untreated are not necessarily on the same scale. Performed in Stata 15 with psgraph.

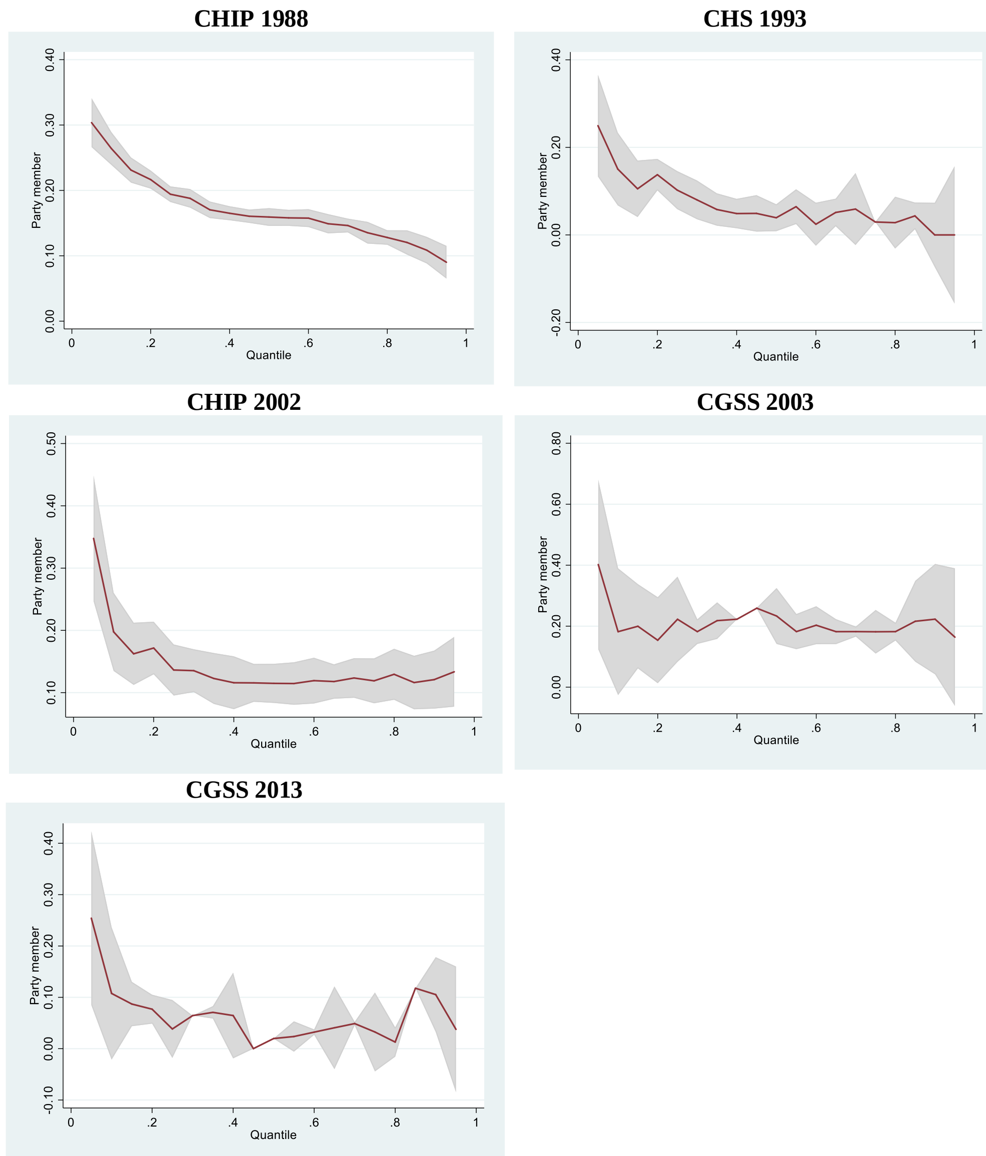


FIGURE A.2 Quantile Regression Confidence Intervals

Note: The figure displays the coefficients of a quantile regression (Koenker and Basset, 1978) and also reports the OLS confidence interval.

TABLE A.1-1 Balancing Post Matching (CHIP 1988)

	Pre-matched Means (Variance)		Post-matched Means (Variance)		*t*-value for matched sample[a]
	Treatment	Control	Treatment	Control	
Han	0.954 (0.044)	0.966 (0.033)	0.954 (0.044)	0.966 (0.033)	-0.88
Male	0.775 0.174)	0.469 (0.249)	0.775 (0.174)	0.469 (0.249)	-0.05
Primary School	0.087 (0.079)	0.126 (0.110)	0.126 (0.110)	0.036 (0.035)	-0.07
Middle School	0.298 (0.209)	0.420 (0.244)	0.123 (0.108)	0.042 (0.040)	0.02
High School	0.196 (0.158)	0.256 (0.190)	0.154 (0.131)	0.088 (0.081)	-0.05
College	0.126 (0.110)	0.036 (0.035)	0.196 (0.158)	0.256 (0.190)	-0.51
Vocational School	0.123 (0.108)	0.042 (0.040)	0.298 (0.209)	0.420 (0.244)	0.55
Technical School	0.154 (0.131)	0.088 (0.081)	0.087 (0.079)	0.126 (0.110)	-0.20
Private Sector	0.010 (0.010)	0.007 (0.07)	0.010 (0.010)	0.007 (0.007)	1.12
Professional	0.215 (0.169)	0.125 (0.110)	0.215 (0.169)	0.125 (0.110)	-0.21
Director	0.249 (0.187)	0.025 (0.024)	0.249 (0.187)	0.025 (0.024)	0.00
Office	0.357 (0.230)	0.169 (0.141)	0.357 (0.230)	0.169 (0.141)	-0.00
Manual Labor	0.154 (0.130)	0.630 (0.223)	0.154 (0.130)	0.630 (0.223)	0.00
Agricultural	0.010 (0.010)	0.020 (0.019)	0.010 (0.010)	0.020 (0.019)	0.00
Temporary	0.003 (0.003)	0.018 (0.018)	0.003 (0.003)	0.018 (0.018)	-0.00
Urban Location	0.930 (0.065)	0.889 (0.099)	0.930 (0.065)	0.889 (0.099)	0.17
Observations	4,494	14,829	4,494	14,829	

Notes: Variances in parentheses. (a) t-tests for equality of means in the two samples (before and after matching if option both is specified) based on pstest in Stata 15. T-tests are based on a regression of the variable on a treatment indicator. Before matching or on raw samples this is an unweighted regression on the whole sample, after matching the regression is weighted using the matching weight variable _weight or user-given weight variable in mweight and based on the on-support sample. T-tests are based on Rosenbaum and Rubin (1985).

TABLE A.1-2 Balancing Post Matching (CHS 1993)

	Pre-matched Means (Variance)		Post-matched Means (Variance)		*t*-value for matched sample[a]
	Treatment	Control	Treatment	Control	
Han	0.982 (0.018)	0.984 (0.015)	0.982 (0.018)	0.984 (0.015)	0.00
Male	0.784 (0.0170	0.574 (0.245)	0.784 (0.170)	0.574 (0.245)	0.00
Married	0.918 (0.074)	0.859 (0.121)	0.919 (0.074)	0.859 (0.121)	0.13
Religious	0.023 (0.023)	0.043 (0.041)	0.023 (0.023)	0.043 (0.041)	0.24
Elementary	0.077 (0.068)	0.140 (0.120)	0.073 (0.068)	0.140 (0.120)	0.00
Junior High	0.264 (0.194)	0.382 (0.236)	0.262 (0.194)	0.382 (0.236)	-0.00
Senior High	0.190 (0.154)	0.222 (0.173	0.190 (0.154)	0.222 (0.173)	-0.00
Technical School	0.015 (0.015)	0.033 (0.032	0.016 (0.015)	0.033 (0.032)	-0.00
Vocational School	0.125 (0.109)	0.063 (0.060)	0.125 (0.109)	0.064 (0.060)	-0.00
Three-year College	0.192 (0.157)	0.064 (0.062)	0.195 (0.157)	0.067 (0.062)	0.00
Formal College	0.115 (0.103)	0.040 (0.038)	0.117 (0.103)	0.040 (0.038)	-0.00
Graduate	0.003 (0.001)	0.001 (0.003)	0.003 (0.03)	0.001 (0.001)	-0.00
Observations	390	1706	385	1,609	

Notes: Variances in parentheses. (a) t-tests for equality of means in the two samples (before and after matching if option both is specified) based on pstest in Stata 15. T-tests are based on a regression of the variable on a treatment indicator. Before matching or on raw samples this is an unweighted regression on the whole sample, after matching the regression is weighted using the matching weight variable _weight or user-given weight variable in mweight and based on the on-support sample. T-tests are based on Rosenbaum and Rubin (1985).

TABLE A.1-3 Balancing Post Matching (CHIP 2002)

	Pre-matched Means (Variance)		Post-matched Means (Variance)		*t*-value for matched sample[a]
	Treatment	Control	Treatment	Control	
Han	0.949 (0.048)	0.933 (0.063)	0.949 (0.048)	0.933 (0.063)	-0.18
Male	0.808 (0.155)	0.805 (0.157)	0.808 (0.155)	0.805 (0.157)	-0.11
Married	0.963 (0.036)	0.949 (0.048)	0.963 (0.036)	0.949 (0.048)	-0.13
Primary	0.061 (0.057)	0.152 (0.129)	0.061 (0.057)	0.152 (0.129)	-0.00
Middle school	0.269 (0.197)	0.430 (0.245)	0.269 (0.197)	0.430 (0.245)	-0.03
High School	0.219 (0.171)	0.217 (0.170)	0.219 (0.171)	0.217 (0.170)	-0.00
Technical School	0.124 (0.109)	0.067 (0.062)	0.124 (0.109)	0.067 (0.062)	-0.11
Vocational School	0.204 (0.162)	0.066 (0.062)	0.204 (0.162)	0.066 (0.062)	0.03
College	0.109 (0.097)	0.026 (0.025)	0.109 (0.097)	0.026 (0.025)	0.11
Urban	0.703 (0.209)	0.503 (0.250)	0.704 (0.209)	0.506 (0.250)	-0.05
Observations	3,600	8,217	3,600	8,217	

Notes: Variances in parentheses. (a) t-tests for equality of means in the two samples (before and after matching if option both is specified) based on pstest in Stata 15. T-tests are based on a regression of the variable on a treatment indicator. Before matching or on raw samples this is an unweighted regression on the whole sample, after matching the regression is weighted using the matching weight variable _weight or user-given weight variable in mweight and based on the on-support sample. Urbanicity was dropped in the matching procedure for CHIP 2002 since it was perfectly correlated with the occupational binary variables. T-tests are based on Rosenbaum and Rubin (1985).

TABLE A.1-4 Balancing Post Matching (CGSS 2003)

	Pre-matched Means (Variance)		Post-matched Means (Variance)		t-value for matched sample[a]
	Treatment	Control	Treatment	Control	
Han	0.941 (0.056)	0.945 (0.052)	0.941 (0.056)	0.945 (0.052)	-0.00
Male	0.463 (0.250)	0.541 (0.248)	0.463 (0.250)	0.541 (0.248)	-0.00
Married	0.952 (0.046)	0.843 (0.133)	0.952 (0.046)	0.843 (0.133)	-0.00
Primary	0.066 (0.062)	0.132 (0.115)	0.066 (0.062)	0.132 (0.115)	0.00
Middle school	0.131 (0.115)	0.317 (0.217)	0.131 (0.115)	0.317 (0.217)	0.00
Highschool	0.163 (0.137)	0.189 (0.153)	0.163 (0.137	0.189 (0.153)	-0.00
Vocational	0.007 (0.007)	0.033 (0.032)	0.007 (0.007)	0.033 (0.032)	0.00
Technical	0.166 (0.139)	0.095 (0.086)	0.166 (0.139)	0.095 (0.086)	0.00
Junior college	0.253 (0.189)	0.135 (0.117)	0.253 (0.189)	0.135 (0.117)	-0.00
College	0.193 (0.157)	0.059 (0.056)	0.193 (0.157)	0.059 (0.056)	-0.00
Grad	0.007 (0.007)	0.005 (0.005)	0.007 (0.007)	0.005 (0.05)	0.00
Observations	289	4,202	289	4,202	

Notes: Variances in parentheses. (a) t-tests for equality of means in the two samples (before and after matching if option both is specified) based on pstest in Stata 15. T-tests are based on a regression of the variable on a treatment indicator. Before matching or on raw samples this is an unweighted regression on the whole sample, after matching the regression is weighted using the matching weight variable _weight or user-given weight variable in mweight and based on the on-support sample. T-tests are based on Rosenbaum and Rubin (1985).

TABLE A.1-5 Balancing Post Matching (CGSS 2013)

	Pre-matched Means (Variance)		Post-matched Means (Variance)		t-value for matched sample[a]
	Treatment	Control	Treatment	Control	
Han	0.921 (0.073)	0.912 (0.080)	0.921 (0.073)	0.912 (0.080)	-0.08
Male	0.747 (0.189)	0.519 (0.250)	0.747 (0.189)	0.519 (0.250)	-0.05
Married	0.833 (0.139)	0.782 (0.170)	0.833 (0.139)	0.782 (0.170)	-0.00
Primary	0.092 (0.084)	0.233 (0.179)	0.092 (0.084)	0.233 (0.179)	0.00
Middle school	0.197 (0.158)	0.314 (0.215)	0.197 (0.158)	0.314 (0.215)	0.00
High School	0.131 (0.114)	0.113 (0.100)	0.131 (0.114)	0.113 (0.100)	0.00
Vocational School	0.088 (0.080)	0.048 (0.046)	0.088 (0.080)	0.048 (0.046)	0.00
Technical School	0.016 (0.016)	0.024 (0.023)	0.016 (0.016)	0.024 (0.023)	-0.00
Junior College	0.191 (0.154)	0.072 (0.067)	0.191 (0.154)	0.072 (0.067)	-0.06
College	0.217 (0.170)	0.053 (0.050)	0.217 (0.170)	0.053 (0.050)	-0.00
Graduate School	0.024 (0.023)	0.005 (0.005)	0.024 (0.023)	0.005 (0.005)	0.14
Observations	1,060	8,011	1,060	8,011	

Notes: Variances in parentheses. (a) t-tests for equality of means in the two samples (before and after matching if option both is specified) based on pstest in Stata 15. T-tests are based on a regression of the variable on a treatment indicator. Before matching or on raw samples this is an unweighted regression on the whole sample, after matching the regression is weighted using the matching weight variable _weight or user-given weight variable in mweight and based on the on-support sample. T-tests are based on Rosenbaum and Rubin (1985).

TABLE A.2 Over-identification Test for Covariate Balancing

Survey Source /Year	CHIP 1988[a]	CHS 1993[b]	CHIP 2002[c]	CGSS 2003[d]	CGSS 2013[e]
	(1)	(2)	(3)	(4)	(5)
chi2(12)= 16.0546	60.4384	16.0546	46.053	22.631	56.39
Prob > chi2	0.00	0.1887	0.0000	0.031	0.000
Observations	19,323	1,994	11,817	4,491	9,071

Notes: A formal test based on Imai and Ratkovic (2014) tests the null hypothesis that the IPW model balanced the covariates used in matching. ***, ** and * indicate significance at 1, 5 and 10%, respectively.

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TABLE A.3 Earnings Equation (2SLS)

Dependent Variable:	ln (Monthly Earnings, in RMBs)	
Survey Source /Year:	CHIP 2002[a,b]	CGSS 2013[a]
	(1)	(2)
Communist Party Membership	0.170 (0.388)	0.277 (0.465)
District Fixed Effects	YES	YES
F-statistic	66.87	345.07
R-squared	0.060	0.3489
Observations	6,706	9,071

Notes: (a) The instrumental variable is parental Communist Party affiliation. (b) Based on the urban sample. ***, ** and * indicate significance at 1, 5 and 10%, respectively.

Online Appendix B

TABLE B.1 Propensity Stratified Regressions

Propensity Score Strata	Coefficient Estimate				
	CHIP 1988	CHS 1988	CHIP 2002	CGSS 2003	CGSS 2013
	(1)	(2)	(3)	(4)	(5)
1	0.230	0.061	-0.088	0.345***	0.545***
	(0.272)	(0.089)	(0.631)	(0.095)	(0.124)
2	0.168	0.107	0.343***	0.247**	0.254**
	(0.141)	(0.083)	(0.106)	(0.112)	(0.098)
3	0.232***	0.132***	0.323***	0.274***	0.075
	(0.037)	(0.047)	(0.056)	(0.083)	(0.108)
4	0.447*	0.087	0.199	0.219***	-0.066
	(0.263)	(0.062)	(0.155)	(0.052)	(0.073)
5	0.152***	0.033	0.172***	0.163	0.049
	(0.053)	(0.082)	(0.035)	(0.163)	(0.071)
6	-0.080	0.150***	0.160*	0.194**	0.034
	(0.200)	(0.078)	(0.091)	(0.065)	(0.073)
7	0.177	0.007	0.031	-0.313***	-0.214**
	(0.350)	(0.052)	(0.035)	(0.095)	(0.079)
Observations	51,681	1,994	11,887	4,491	9,071

Notes: Standard Errors in parantheses. ***, ** and * indicate significance at 1, 5 and 10%, respectively.

TABLE B.2 Matching Algorithms

	Dependent Variable: Monthly Earnings (in RMB)				
Algorithm Method	NN 2:1 Matching with replacement	NN 1:1 Matching Mahalonobis	IPW	Radius Caliper (0.20)	Kernel
	(1)	(2)	(3)	(4)	(5)
Panel A (CHIP 1988):					
Communist Party Membership	0.177***	0.181***	0.189***	0.191***	0.189***
	(0.010)	(0.010)	(0.009)	(0.009)	(0.009)
Controls	YES	YES	YES	YES	YES
Observations	19,323	19,323	19,323	19,323	19,323
Panel B (CHS 1993):					
Communist Party Membership	0.094***	0.090***	0.085***	0.131***	0.0825***
	(0.024)	(0.024)	(0.024)	(0.024)	(0.025)
Controls	YES	YES	YES	YES	YES
Observations	1,994	1,994	1,994	1,994	1,994
Panel C (CHIP 2002):					
Communist Party Membership	0.188***	0.191***	0.209***	0.188***	0.209***
	(0.022)	(0.023)	(0.022)	(0.022)	(0.022)
Controls	YES	YES	YES	YES	YES
Observations	11,817	11,817	11,817	11,817	11,817
Panel D (CGSS 2003):					
Communist Party Membership	0.233***	0.237***	0.245***	0.237***	0.227***
	(0.032)	(0.032)	(0.031)	(0.032)	(0.035)
Controls	YES	YES	YES	YES	YES
Observations	4,491	4,491	4,491	4,491	4,491
Panel E (CGSS 2013):					
Communist Party Membership	0.212***	0.214***	0.253***	0.199***	0.257***
	(0.052)	(0.052)	(0.047)	(0.054)	(0.048)
Controls	YES	YES	YES	YES	YES
Observations	9,071	9,071	9,071	9,071	9,071

Notes: Variables used in estimating propensity score: sex dummy (1 if respondent is male and 0 if female), ethnicity dummy (1 if respondent is of the Han majority ethnicity and 0 if of a minority ethnicity), married dummy (1 if the respondent is married and 0 if single), dummies for education (1 if the respondent achieved the specified level of education and 0 if not) and religion (1 if the respondent is religious and 0 if town). Values can be interpreted as the percent change in monthly earnings. Communist party membership in a dummy equal to 1 if the subject is a member of the Communist party and 0 if otherwise. Standard Errors in Parentheses.
***, ** and * indicate significance at 1, 5 and 10%, respectively.

TABLE B.3 Quantile Regressions

	Dependent Variable: Monthly Earnings (in RMB)		
	0.25 Quantile	0.50 Quantile	0.75 Quantile
	(1)	(2)	(3)
Panel A (CHIP 1988):			
Communist Party Membership	0.194***	0.159***	0.135***
	(0.008)	(0.007)	(0.008)
Controls	YES	YES	YES
Observations	19,323	19,323	19,323
Panel B (CHS 1993):			
Communist Party Membership	0.102***	0.040	0.029
	(0.315)	(0.030)	(0.031)
Controls	YES	YES	YES
Observations	1,994	1,994	1,994
Panel C (CHIP 2002):			
Communist Party Membership	0.136***	0.115***	0.119***
	(0.030)	(0.022)	(0.020)
Controls	YES	YES	YES
Observations	11,887	11,887	11,887
Panel D (CGSS 2003):			
Communist Party Membership	0.038***	0.020	0.033
	(0.056)	(0.036)	(0.038)
Controls	YES	YES	YES
Observations	9,071	9,071	9,071
Panel E (CGSS 2013):			
Communist Party Membership	0.223***	0.233***	0.182***
	(0.068)	(0.051)	(0.053)
Controls	YES	YES	YES
Observations	4,491	4,491	4,491

Notes: ***, ** and * indicate significance at 1, 5 and 10%, respectively.

TABLE B.4-1 Rosenbaum Bounds (CHIP 1988)

Gamma	Sig+	Sig-	t-hat+	t-hat-	CI+	CI-
1	0	0	0.165212	0.165212	0.157635	0.172853
2	0	0	0.088251	0.243723	0.080331	0.251972
3	0	0	0.044552	0.289714	0.036123	0.298698
4	0.001225	0	0.014213	0.322239	0.00511	0.332039
5	0.973904	0	-0.00905	0.347436	-0.01875	0.357977
6	1	0	-0.02783	0.368033	-0.03817	0.379353
7	1	0	-0.04379	0.385449	-0.05473	0.397537
8	1	0	-0.05752	0.400675	-0.06909	0.413432
9	1	0	-0.06966	0.414064	-0.08193	0.427514
10	1	0	-0.08066	0.426081	-0.09346	0.440351

Notes: gamma - log odds of differential assignment due to unobserved factors. sig+ - upper bound significance level. sig- - lower bound significance level. t-hat+ - upper bound Hodges-Lehmann point estimate. t-hat- - lower bound Hodges-Lehmann point estimate. CI+ - upper bound confidence interval (a= .95). CI- - lower bound confidence interval (a= .95)

TABLE B.4-2 Rosenbaum Bounds (CHS 1993)

Gamma	Sig+	Sig-	t-hat+	t-hat-	CI+	CI-
1	4.30E-10	4.30E-10	0.121024	0.121024	0.084781	0.157868
2	0.310705	0	0.01046	0.234923	-0.03038	0.276998
3	0.996879	0	-0.0516	0.299525	-0.0908	0.347857
4	1	0	-0.09083	0.347921	-0.13138	0.400047
5	1	0	-0.11937	0.38523	-0.16277	0.434136
6	1	0	-0.1428	0.411439	-0.1875	0.464085
7	1	0	-0.1618	0.433158	-0.2081	0.491797
8	1	0	-0.17666	0.451299	-0.22549	0.51259
9	1	0	-0.18966	0.469065	-0.23943	0.532992
10	1	0	-0.20179	0.484703	-0.25231	0.547123

Notes: gamma - log odds of differential assignment due to unobserved factors. sig+ - upper bound significance level. sig- - lower bound significance level. t-hat+ - upper bound Hodges-Lehmann point estimate. t-hat- - lower bound Hodges-Lehmann point estimate. CI+ - upper bound confidence interval (a= .95). CI- - lower bound confidence interval (a= .95)

TABLE B.4-3 Rosenbaum Bounds (CHIP 2002)

Gamma	Sig+	Sig-	t-hat+	t-hat-	CI+	CI-
1	0	0	0.362942	0.362942	0.29483	0.43134
2	0.712764	0	-0.02075	0.718146	-0.0986	0.785225
3	1	0	-0.25135	0.91118	-0.33769	0.97952
4	1.00E+00	0	-0.41325	1.03916	-0.50755	1.10976
5	1	0	-0.5407	1.13236	-0.64361	1.20491
6	1	0	-0.64415	1.20532	-0.75438	1.27913
7	1	0	-0.72989	1.26395	-0.84877	1.33872
8	1	0	-0.80675	1.31265	-0.927	1.38968
9	1	0	-0.87374	1.35433	-0.99846	1.43385
10	1	0	-0.92896	1.3905	-1.0613	1.47297

Notes: gamma - log odds of differential assignment due to unobserved factors. sig+ - upper bound significance level. sig- - lower bound significance level. t-hat+ - upper bound Hodges-Lehmann point estimate. t-hat- - lower bound Hodges-Lehmann point estimate. CI+ - upper bound confidence interval (a= .95). CI- - lower bound confidence interval (a= .95)

TABLE B.4-4 Rosenbaum Bounds (CGSS 2003)

Gamma	Sig+	Sig-	t-hat+	t-hat-	CI+	CI-
1	0	0	0.480354	0.480354	0.395073	0.558735
2	4.00E-07	0	0.265161	0.679859	0.169027	0.762688
3	5.63E-03	0	0.135897	0.794804	0.030456	0.875794
4	0.183534	0	0.045364	0.866592	-0.074153	0.959258
5	0.636796	0	-0.022168	0.919445	-0.152859	1.01638
6	0.915482	0	-0.080858	0.966481	-0.224391	1.06903
7	0.987802	0	-0.133331	0.999042	-0.28097	1.103
8	0.998736	0	-0.173593	1.03078	-0.334802	1.14278
9	0.999896	0	-0.214004	1.063	-0.384472	1.17452
10	0.999993	0	-0.238746	1.0828	-0.426642	1.1951

Notes: gamma - log odds of differential assignment due to unobserved factors. sig+ - upper bound significance level. sig- - lower bound significance level. t-hat+ - upper bound Hodges-Lehmann point estimate. t-hat- - lower bound Hodges-Lehmann point estimate. CI+ - upper bound confidence interval (a= .95). CI- - lower bound confidence interval (a= .95)

TABLE B.4-5 Rosenbaum Bounds (CGSS 2013)

Gamma	Sig+	Sig-	t-hat+	t-hat-	CI+	CI-
1	0	0	0.422942	0.422942	0.370801	0.468287
2	6.50E-08	0	0.169048	0.65102	0.111045	0.699623
3	3.74E-01	0	0.012907	0.776261	-0.05407	0.825773
4	9.99E-01	0	-0.10476	0.862256	-0.18496	0.915829
5	1	0	-0.20274	0.926319	-0.28698	0.983245
6	1	0	-0.27867	0.974446	-0.37912	1.03708
7	1	0	-0.35319	1.02181	-0.4511	1.08279
8	1	0	-0.41144	1.05917	-0.52012	1.12308
9	1	0	-0.46545	1.08799	-0.58164	1.15766
10	1	0	-0.50778	1.11764	-0.63061	1.19141

Notes: gamma - log odds of differential assignment due to unobserved factors. sig+ - upper bound significance level. sig- - lower bound significance level. t-hat+ - upper bound Hodges-Lehmann point estimate. t-hat- - lower bound Hodges-Lehmann point estimate. CI+ - upper bound confidence interval (a= .95). CI- - lower bound confidence interval (a= .95)