China's Wage Premium: A Comparison of Provincial Capitals and Non-provincial Capitals[1]

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Abstract

In this paper, I estimate the urban wage premium and the provincial capital wage premium of China using data from the China Health and Nutrition Survey (CHNS) of the year 2015. Controlling for unobservable worker characteristics using a propensity score method, I confirm that there exists a significant urban wage premium and a provincial capital wage premium in China. However, when I take cost of living into account, I find little evidence supporting the economic agglomeration effects of living in urban areas or provincial capitals.

Keywords: urban economics, wage premium, urban agglomeration effect, propensity score matching.

JEL Code: R11, R12

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1 Introduction

According to United Nations' statistics, more than half of the population in the world are living in urban regions, and urbanization keeps spreading throughout the world[2]. Regional opportunity structures attract a lot of investigations of the urban labor market at a micro level. High-income level and fast income growth of workers in populated regions are in contrast with the wage level of workers in the rural area and less dense places. A vast literature studies the urban wage premium, particularly in the U.S. context.

China led the global urbanization of the past few decades and according to the World Bank is expected to have 70% of its population living in urban areas by the year 2030[3]. Although China has been going through such a dramatic scale of urbanization, currently there is not a lot of literature on urban wage premium in China. The goal of this paper is to investigate China's urban wage premium with a special focus on its provincial capitals.

China's provincial capitals are different from America's capital cities because of political and cultural reasons which makes it very interesting and relevant to the urban wage premium problem. Provincial capitals in China are both the political and economic centers of a province; it is the most populated and dense city of a province and the one that has the highest GDP compared to all the other cities in the same province.

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[2] See for example "68% of the world's population projected to live in urban areas by 2050, says UN," United Nations Department of Economics and Social Affairs News, 5/16/2018, available at https://www.un.org/development/desa/en/news/population/2018-revision-of-world-urbanization-prospects.html

[3] See "By 2030, up to 70% of the Chinese population - some one billion - will be living in cities." the World Bank and the Development Research Center of China's State Council, available at http://www.worldbank.org/en/country/china/publication/urban-china-toward-efficient-inclusive-sustainable-urbanization

Using data front China Health and Nutrition Survey(CHNS), a representative sample of the Chinese population, in Section 3 I describe the positive relationship between the city population density in China and the average log wage. It is possible that people receive higher wages because the cost of living is much higher in cities. It could also be possible that cities attract high-skilled workers working for white collar jobs which leads to higher wages. The empirical challenge is to find a research design capable of overcoming these biases.

My goal is to determine if there exist urban/provincial capital agglomeration effects in China that contribute to the wage premium accounting for the cost of living and the unobservable ability bias of workers. To account for potential sources of endogeneity, I adopt a variety of empirical approaches. Specifically, I compare standard Ordinary Least Squares Regressions (OLS) to the results from a Propensity Score Matching (PSM) specification. In both specifications, I control for various confounders.

Results show that there is a 6.0% and 7.9% wage premium for urban workers and provincial capital workers respectively. However, when I control for the cost of living by using the average housing price per unit, the urban wage premium becomes negative, and the provincial capital wage premium becomes very small and insignificant. The results using PSM is similar to my OLS results. I am not able to find strong evidence that indicates there exist urban/ provincial capital agglomeration effects in China that contribute to the wage premium. Instead, the cost of living contributes mostly to the urban and provincial capital wage premium.

My contribution to the existing literature is applying a propensity score matching(PSM) technique to overcome the unobservable ability bias of workers, and to account for local cost of living. The paper is organized as follows. I review the urban wage premium literature in Section

2. The next two sections describe my data and my empirical strategy of the econometrics models I use respectively. In Section 4, I discuss the empirical results. Section 5 concludes the paper.

2 Related Literature

My methodology draws from an extensive literature on the urban wage premium. Currently, there are three common explanations for such premium: ability bias, the difference in cost of living, and the agglomeration economy effect.

Wages of workers living in urban areas may differ because people with higher skills self-select to reside in cities(perhaps with a preference for provincial capitals), generating an ability bias in standard OLS regression of wages on the place of residence.

To solve this identification challenge, Glaeser and Mare (1996) use a fixed effect regression model, finding that the urban wage premium in the U.S. which is about 33% appears to be both the effect of wage level and wage growth effect because of the accumulation of human capital.

Yankow(2006) argues that there exists a significant amount of urban wage premium that is not simply the result of observed and omitted ability bias. For the cost of living point of view, he (2006) finds that urban workers are compensated for the higher cost of living in cities, but after controlling for the cost of living, he still finds a significant urban wage premium in both of his OLS estimates and fixed effect model.

Therefore, many urban economists seek to identify the agglomeration effects of cities, which are based on the size and density per se; such effects make workers more productive and lead to higher wages. Wheaton and Lewis (2001) showed evidence of the agglomeration economy in cities that leads to the urban wage premium. In cities that are populated and concentrated in economic activities, consumers and suppliers are more accessible to firms that are located there. Thus, it is easier for workers to find ideal jobs that fit their skills. Both firms and workers benefit from lower costs and higher efficiency. Places with dense markets will lead to a higher level of productivity which explains a higher wage level in cities. Other economists such as Baum-Snow and Pavan (2012) argued that returns to experience are the most important contributors to the city size wage premium. They also find significant wage-level effects (intercepts of cross-sectional location categories) explaining the differences between middle and small cities. Differences in wage intercepts from cross-sectional location categories are more important for generating wage gaps between medium and small cities while differences in returns to experience are more important for generating large–small city size wage gaps.

My paper builds on these three mainstream explanations for the urban wage premium to investigate the specific case of China's urban wage premium and provincial capital wage premium. Peng(2016) used China's Comprehensive Social Survey (CGSS) in 2010 and applied an instrumental variable method. To control for ability bias, he instrumented urban location with urban scale data from 10 years ago. He discovered that there exists a significant urban scale wage premium in larger cities with a population of more than 5 million for both high-skilled and low-skilled workers. Huang's(2008) study focuses on China's provincial capitals, as this paper does. Without controlling for the cost of living, he finds that there exists about a 14% wage premium in provincial capital cities. He also finds that there is a 7% provincial capital premium for workers because of the agglomeration economic effects using Mundlak-Chamberlain's random-effect model to control for the cost of living. However, he uses the average monthly expenses on childcare in cities to control for the cost of living. Building on his work, I use the average housing price per unit to account for different levels of costs of living in different locations. My results show that the agglomeration economic effects are a lot smaller and insignificant when I control for the costs of living compared to his.

One of the concerns of using OLS model to estimate the urban wage premium and provincial capital wage premium is that workers' location choice is not random. It is very possible that people choose to work in urban areas or provincial capitals for some unobservable characteristics, thus casual interference cannot be made. If people with higher ability are more likely to choose to work in an urban or provincial capital setting, I would be overestimating the agglomeration economic effect that contributes to the wage premium(Glaeser and Mare 1996). My data does not allow me to run a fixed effect regression because workers in the panel are not followed out of rural locations. My contribution, related to the literature, is to identify this causal effect using a propensity score matching methodology, and by taking into account the effect of the cost of living.

3 Data

I use data from the China Health and Nutrition Survey (CHNS), a nationally representative sample of Chinese population running from 1997 to 2015. While there is a lot of restricted access to Chinese government population statistics, the CHNS covers 15 representative provinces that vary substantially in demography, economics, and public resources. It used a multistage, random cluster process in drawing samples statistics from each province. The overall survey contains about 7,200 households and covers roughly 30,000 individuals with residential location type classified as urban neighborhood, rural villages, county town neighborhoods, and suburban villages. In urban areas, the provincial capital and a lower income city were selected randomly if possible. In rural areas, counties were stratified by income, and a weighted scheme was used to randomly select four counties within each province. This includes detailed household and individual economic and social information.

Even though follow-up levels are high, families that migrate from one community to a new one are not recorded as movers exit the sample. The CHNS does not provide the floating population information since it stopped keeping track of people once they moved. Conducting an OLS regression model by controlling for different characteristics that might cause biases would also give a good prediction for the urban wage premium in provincial capitals in China.

In the empirical analysis, I use the information on gender, education status, marital status, years of experience, white-collar dummy, housing price per square meter, provincial capital dummy, urban dummy, the interaction between white-collar dummy and urban dummy, and the interaction between white-collar dummy and the provincial capital dummy.. In order to compute the provincial capital wage premium, I drop all the individuals who live in rural areas and created the provincial capital dummy variable indicating whether the individuals who live in urban areas are from provincial capitals.

I included in my regressions individuals who are between the age of 22 to 65. I recorded the occupation categorical variable and created a dummy variable for white-collar workers vs. blue-collar workers. The estimated wage premiums in urban areas and provincial capitals do not take into account cross-city price differences. Based on the Penn-effect, typically for each 1% increase in nominal wage, price levels increase by 0.5%: the real wage premium increase is half the nominal amount. Thus it is necessary to take cost of living into consideration as other literature do. To correct for the difference in cost of living, I use the average housing prices per unit at each location as a proxy for the cost of living. Data for the housing information is collected in the asset section in CHNS at the household level. Housing price per square meter is calculated by dividing the price of the house by its size measured in square meters. Then I compute the average housing price per unit for each location and included it in my regression for each individual. Although there are not sufficient micro-panels of prices for baskets of goods in rural areas in China, the available data on the cost of housing price at the household level can be used to control for cost of living.

For the purpose of this research, I selected the sample of workers whose monthly working hours to be greater than 20 hours per week for a full-time job and focused on the survey year 2015. Following the literature, I only kept those who work full-time because wage differs a lot between full-time and part-time employment. Hourly wages were estimated by dividing the average monthly wage of an individual last year by the usual hours they worked per month.

In Figure 1, I plot the predicted logarithm average wage across the different levels of city population density. It illustrates that there exist a positive correlation between the size of a city and the logarithm average wage of individuals in that city. The bigger and denser a city is, the higher the average wage is.

Figure 1: City Population Density and Average Wage

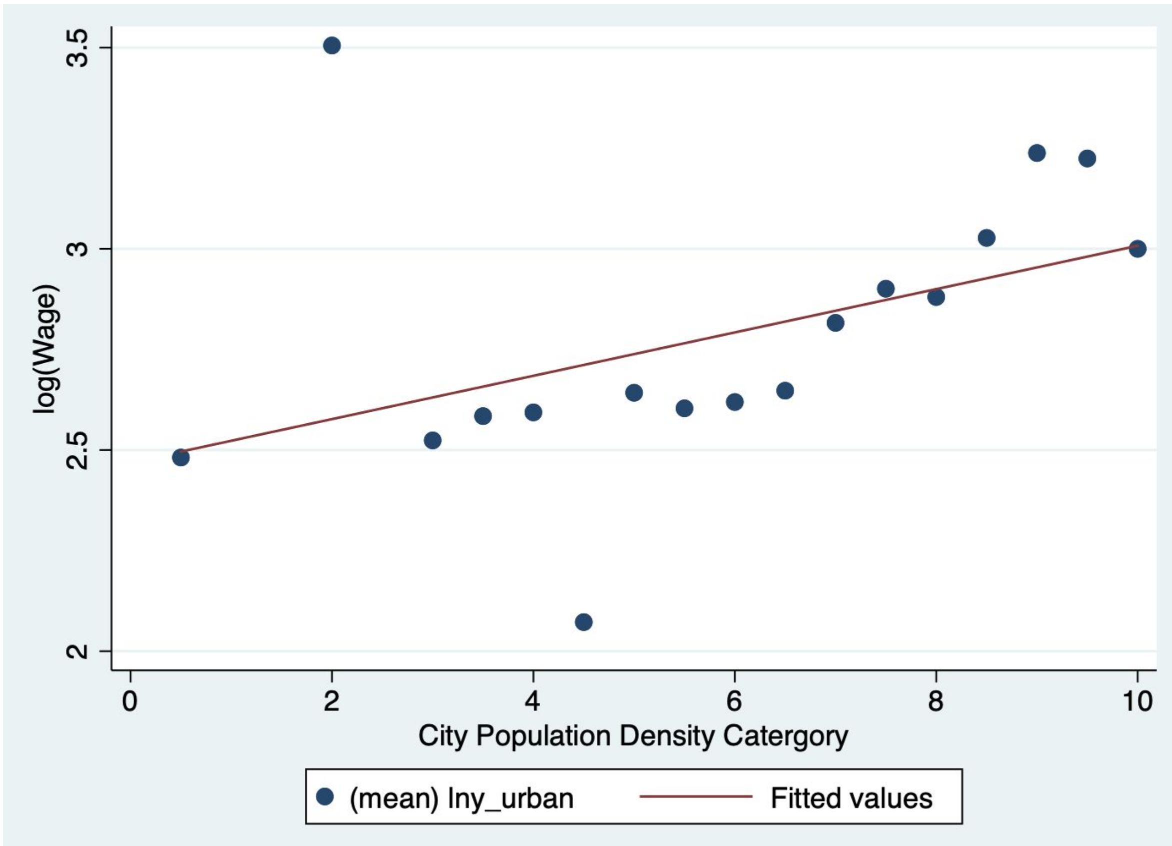


Table 1 gives descriptive statistics for the variables in my regression. For the year 2015, I have 3441 observations in total, 1495 individuals in the urban area and 1946 individuals living in the rural area. Within those who live in the urban area, I have 637 individuals who live in provincial capitals and 556 individuals who live in non-provincial cities.

In this table, workers in urban areas generally have more years of education usually around two years. Workers in urban areas also are more likely to have white-collar occupations and occupations that require more years of schooling. Experience is similar in urban areas and rural areas. There is not a big difference between years of education for workers who live in provincial capitals and those who live in other cities. There is also not a big difference between the experience of workers in provincial capitals and other cities. These patterns do not show a huge difference between human capital between workers who live in urban areas and rural areas. They also demonstrate that the level of human capital in the provincial capital is very similar to the level of human capital in other cities.

Table 1: Summary Statistics

	Urban Area			Rural Area			Provincial Capital			Non-provincial Capital Cities		
CHNS:2015	N	mean	sd	N	Mean	sd	N	Mean	sd	N	Mean	sd
gender	1,495	0.535	0.499	1,946	0.58	0.494	637	0.551	0.498	556	0.531	0.5
Age	1,477	46.7	18.6	1,770	41.6	17.9	1867	45.38	20.55	1707	47.7	20.45
White-Collar	1,495	2.205	0.772	1,946	2.425	0.713	637	2.276	0.748	556	2.212	0.786
Potential experience	1,472	26.82	12.73	1,871	25.68	14.01	622	25.33	13.27	549	26.72	12.55
Housing Price	1,477	16,118	23,626	1,863	4,159	11,511	1781	20730	47131	1797	17006	11577
Hourly Wage	1,450	28.6	53.7	1,240	18.1	43.7	622	37.6	29.4	546	29.6	36.1

4. Empirical Strategy

4.1 The ordinary least squares (OLS) regression

To establish a point of reference, I start my analysis by running a standard mincerian regression using OLS. I adopt the following specification:

$$log(W_k) = \sum_{i=1}^{h} \beta_i X_{ik} + \gamma\ Urban_k + \alpha_k + \varepsilon_k, \tag{1}$$

$$log(W_k) = \sum_{i=1}^{h} \beta_i X_{ik} + \gamma Capital_k + \alpha_k + \varepsilon_k, \tag{2}$$

where W_k is the hourly wage for an individual k, and X_{ik} is an individual characteristic that includes gender, years of schooling, potential experience (years of schooling minus age) and its square, a white-collar job occupation dummy[4], log of the housing price per unit, and an interaction term between white-collar dummy and urban or capital dummy. $Urban_k$ is a dummy variable describing whether the individual lives in an urban area, and $Capital_k$ is a dummy variable describing whether the individual lives in a provincial capital.

4.2 Propensity Score Matching

To better account for the possibility of the ability bias and strengthen the causal interpretation of my results, I adopt a Propensity Score Matching (PSM hereafter) method in addition to the OLS model (Rosenbaum and Rubin 1983). Rubin (2008) argues that this methodology approximates a randomized trial.

The PSM technique is implemented in two stages. In the first stage, the treatment probability (the "propensity score") is estimated to find how likely an individual is to be treated, given covariates. In my application, treatment corresponds to living in an urban area or capital city, depending on the specification. Then, in the second stage, treated and non-treated individuals are matched so that people with similar propensity scores, but different treatment, can be compared. The procedure purports to capture the causal effect of the treatment by comparing otherwise identical individual, using the propensity score to identify similar people. The underlying assumption behind this strategy is that conditional on the propensity score, the locational choice is random.

As defined by Rosenbaum and Robins(1983), the estimated propensity score for subject *i*, (*i = 1,…, N*) is the conditional probability of assignment to work in an urban area or a provincial capital as the treatment condition given a set of observed covariates X_i :

[4] See the Appendix for details on the job classification I used

$$e(x_i) = Pr(Z_i = 1 | X_i) \qquad (3)$$

where $Z_i = 1$ indicates when an individual work in an urban area or a provincial capital.

To implement (5) I adopted one of the most commonly used methods, logistic regression, calculating the propensity scores according to the following specification:

$$log\frac{e(x_i)}{1-e(x_i)} = log\frac{Pr(Z = 1|X_i)}{1-Pr(Z = 1|X_i)} = \alpha + \beta^T X_i \qquad (4)$$

Appendix B presents probit estimates of coefficients used for propensity score matching.

Once the estimated propensity score for each individual is obtained, I match individuals with similar propensity scores, but different location choices, using the nearest neighbor matching algorithm (Austin 2011). This algorithm minimizes the absolute differences between the calculated propensity scores for the treatment and the control groups. Individuals in the control group are matched up with individuals in the treatment group who have the closest propensity score to each other.

$$C(p_i) = min_j|p_i - p_j| \qquad (5)$$

where p_i is the estimated propensity score of an individual working in a provincial capital while p_j is the estimated propensity score of an individual working in a non-provincial capital city. $C(p_i)$ is the group of treated individuals that match with the controlled individuals based on the smallest differences of their estimated propensity scores. Figures 2 and 3 illustrate the post-match distributions of the mean of each covariate against the estimated propensity scores between treated individuals and controlled individuals: if the treatment and control groups have similar means of covariates at each propensity score, the matching can be considered to be good. The average treatment effect among the treated (ATT) can be computed as follows:

$$ATT = \frac{1}{N^T} \sum_{i \in T} [Y_i^T - \sum_{j \in C(pi)} w_{ij} Y_j^C] \quad (6)$$

where N^T is the number of individuals who live in a provincial capital, and weights w_{ij} = $\frac{1}{N_i^C}$ $if\ j \in C(p_i)$; 0 otherwise. N_i^C is the number of individuals who live in non-provincial capital cities matched to N^T based on the estimated propensity scores.

4. Results

The main results are reported in tables 2 (urban wage premium using OLS), 3 (provincial capital wage premium using OLS), and 4 (urban wage premium and provincial capital wage premium using PSM). The first column in Table 2 shows that the living in cities implies a wage premium of 6.0% relative to living in rural areas, when controlling for gender, marital status, years of education and potential experience. Adding controls for occupation (a white-collar job dummy), the urban wage premium is about the same.

The magnitude of the urban wage premium of China using the CHNS for the year 2015 is much smaller than the U.S' wage premium presented in Glaeser and Mare's (1996) paper which is 25.6%, which remains high even when controlling for unobservable characteristics using workers' fixed effects. The premium might be higher in provinces with lower wages overall.

Table 3 demonstrates the wage premium effect of living in a provincial capital. The first column shows that the wage premium from living in provincial capitals is 7.5% when I control for the same variables as I do in Table 2. When I control the workers' occupations (second column), the premium is 7.9%.

The effect of living in a provincial capital in comparison of living in another city is bigger than the premium of living in an urban area in comparison to living in a rural area in

China; this suggests an important role for provincial capitals in shaping labor market effects. Workers who work in provincial capitals largely benefit from living there.

In tables 2 and 3, column 3 reports results when costs of living are controlled for by using a measure of housing price. I find a wage penalty for living in urban areas (-4.5%) and 2.0% premium, not statistically significant, of living in provincial capitals. Therefore, costs of living are an important component of the urban wage premium and the provincial capital wage premium in China when we take the average price of housing per unit into account. In column 4 for both table 2 and 3, I find that there is a premium for white-collar workers living in the urban areas or provincial capitals cities.

Table 2: Urban Wage Premium Using OLS

	(1)	(2)	(3)	(4)
Male	.218***	0.204***	.21936***	0.1984***
	(.0285)	(.0284)	(.02807)	(0.03196)
Marital Status	.0577121	.0090258	.0043514	0.006524
	(.0605)	(.0613956)	(.0618103)	(0.15844)
Urban	.0598**	.060**	-.04500*	-0.092508
	(.0290)	(.0288)	(0.0256)	(0.16582)
Years of Education	.05495***	.04013***	.028407***	0.010886***
	(.00469)	(.00514)	(.005232)	(0.00487)
Potential Exp	.00722	.006626	.0061335	-0.0169*
	(.004639)	(.0046076)	(.0045455)	(0.0070)
Potential Exp2	-.0001522**	-.00015**	-.0001561**	2.81e^-06
	(.0000694)	(.0000689)	(.000068)	(0.00008)
White Collar		.183232***	.1508213 **	0.1807***
		(.0651835)	(.0643957)	0.04410
ln(Housing Price)			.1077752***	.07184955***
			(.0116468)	.01465833
ln(Housing Price)2			.0106626**	0.004499
			(.0055024)	0.0016846
Price_urban				0.00144
				(0.00245)
white_collar_urb				0.1433*
				(0.0677)
Constant	1.958***	2.20356***	1.487193***	1.2119***
	(.099)	(.1167)	(.1387478)	(0.2292)

(Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1)

Table 3: Provincial Capital Wage Premium Using OLS

	(1)	(2)	(3)	(4)
Male	.2049512***	.1916811***	.1946853***	.2299***
	(.039064)	(.0388186)	(.0431742)	(.0447)
Marital Status	-.0406873	-.0435625	.0071824	-.0042325
	(.0868496)	(.0863892)	(.0863541)	(.086527)
Provincial Capital	.074505*	.0794967**	.0203765	.00533140
	(.0385091)	(.038278)	(.0450232)	(.0064318)
Years of Education	.0684249***	.0511513***	.0515672***	.0466051***
	(.0066017)	(.0073793)	(.0081863)	(.0085275)
Potential Exper	.002702	.0023067	.0002125	-.0087063
	(.0064495)	(.0064013)	(.0073829)	(.0088388)
Potential Exper^2	-.0000837	-.0000902	-.0000681	.0000855
	(.0001014)	(.0001005)	(.0001165)	(.0001325)
White Collar		.0367173	-.0168239	.1661121***
		(.0803073)	(.0916794)	(.05082)
ln(Housing Price)			.0571339***	.0297172***
			(.0154218)	(.0177533)
ln(Housing Price)^2			-.0115489	-.0059657
			(.0094952)	(.010228)
Price_capital				-.0551601
				(.0397226)
white_collar_capital				.0981111*
				(.045122)
Constant	1.810805***	2.099138***	1.702977***	1.754775***
	(.1434125)	(.1639937)	(.2097142)	(.1604594)

(Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1)

Turning to the description of the results using the PSM method as described in the previous section, Figure 2 and 3 show the post matching estimates of the mean of each covariate, by treatment status, at each value of the propensity score. Matching is conducted to balance the covariate distribution across the treatment and control group. Figure 2 plots such relationship for urban vs. rural, and Figure 3 plots for provincial capital vs. non-provincial capital cities. From a visual inspection, although the treatment and control groups do not have identical means of each covariate for every propensity score, most of the means of the covariates do show clear resemble with some minor differences.

Figure 2: Post-matched Mean of Each Covariate Against the Estimated Propensity Score(Urban)

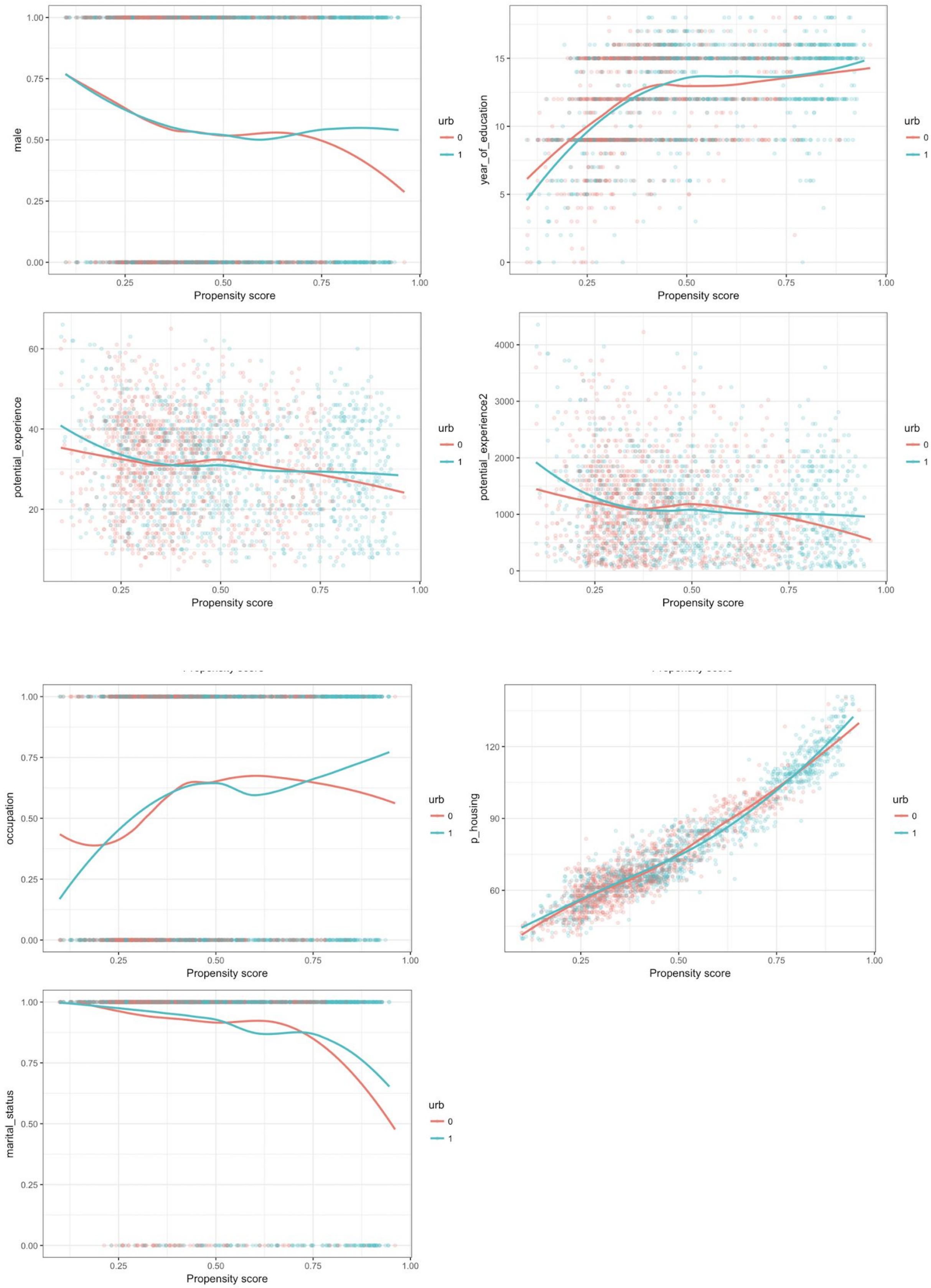
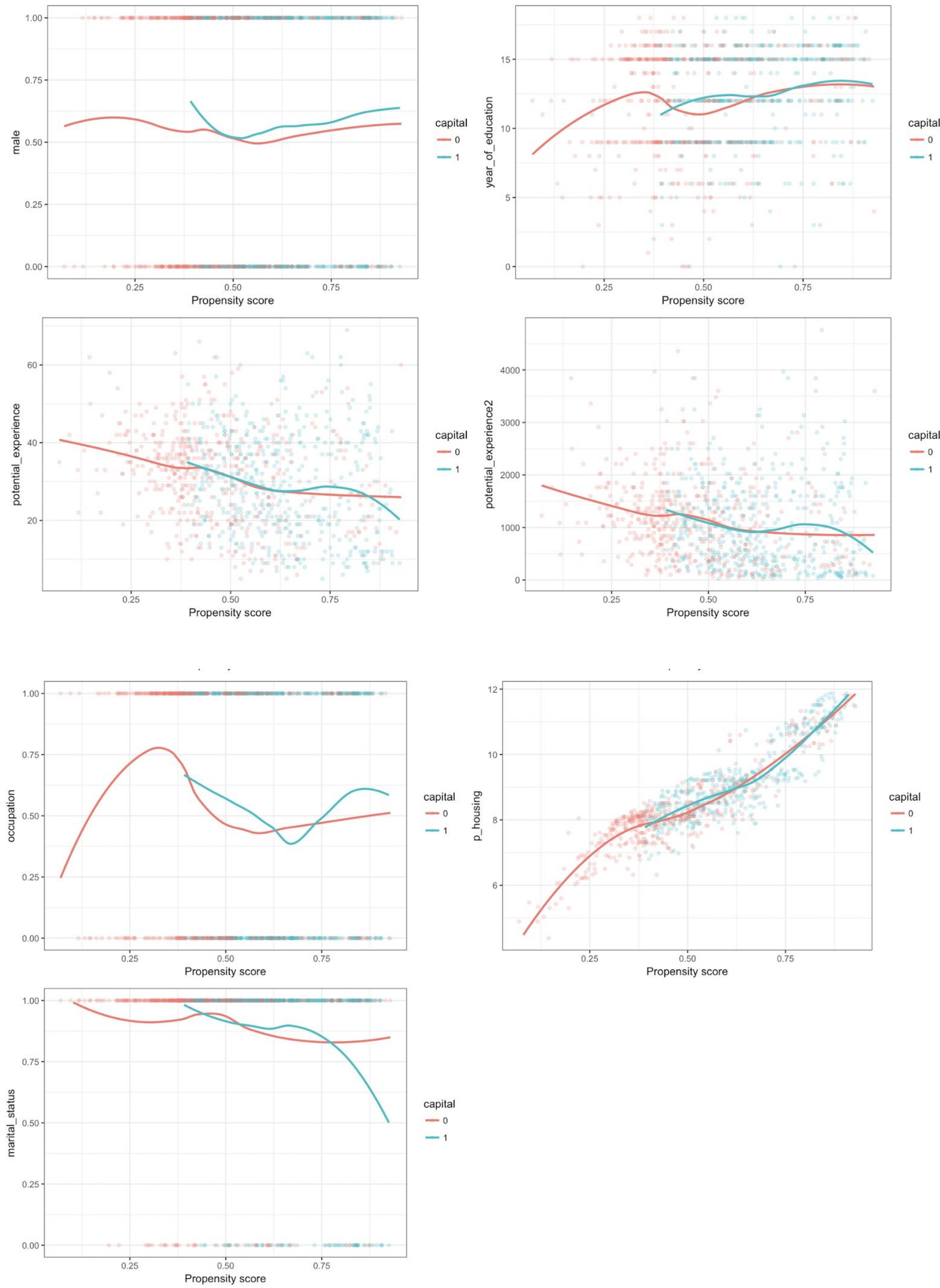


Figure 3: Post-matched Mean of Each Covariate Against the Estimated Propensity Score(Provincial Capital)



The estimation results from the PSM method are presented in Table 4. Results show that living in urban areas negatively affects wages by about -6.8%. This negative urban wage premium is consistent with my previous results using OLS regressions but slightly larger in magnitude when I take cost of living into account. Thus, by controlling for unobservable characteristics, I observe a more negative urban wage premium. The provincial capital wage premium is 0.3% but not significant at the 5% level. The results using the PSM method agree with the results using OLS regression. I don't find evidence showing that there is a positive agglomeration economics effect per se.

Table 4: Urban Wage Premium and Provincial Capital Wage Premium Using PSM
OLS Regressions: (Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1)

	(1)	(2)
	Urban	Provincial Capital
Male	.1989***	.2250***
	(0.0287)	(0.04465)
Marital Status	0.0734	0.002284
	(0.06162)	(0.08604)
Treatment	-0.06838*	0.003178
	(0.02760)	(0.04608)
Years of Education	.03385***	.04775***
	(.005379)	(0.008395)
Potential Experience	-0.0044	-.00738
	(0.0055)	(0.008811)
Potential Experience^2	0.00003	0.00006
	(-.00008)	(.0001319)
White Collar	0.2015***	.1696***
	(0.03218)	(0.05097)
ln(Housing Price)	0.007131***	0.09058***
	(0.000706)	(0.1881)
Constant	1.745***	1.364***
	(0.1121)	(0.2087)
Total	2963	1745

6. Conclusion

Using an OLS regression model and a propensity score matching method, this paper investigates whether there is an urban wage premium and a provincial capital wage premium in China. The data I use is from the China Health and Nutrition Survey. I account for the cost of living using the average housing price in addition to other observable individual characteristics. In my results, I find that urban or provincial capital wage premia are entirely offset by higher costs of living in urbanized settings. I find a negative urban premium and small but insignificant premium of living in capital cities. The urban wage premium and provincial capital wage premium are mostly compensated for the cost of living. Results are consistent across OLS and propensity score matching specifications.

These results should be interpreted with caution. First, data limitations prevented me to adopt a fixed effect model to account for individual unobserved characteristics more directly than using propensity scores. Only a panel following an individual's migration status would allow better inference on whether there exists urban and provincial capital agglomeration economics effect in China. Moreover, regional price indexes are hard to find for China, therefore using housing prices can only approximate differences in the overall costs of living between urban and rural areas. As better data become available, better accounting for individual heterogeneity and regional differences in costs of living may be an interesting area of further research.

A Appendix:

Jobs category Stratification

Occupation	Group
1. Senior Professional (Doctor, Professor, Lawyer, Architect,Engineer)	White-collar (1-6)
2. Junior Professional(midwife, nurse, teacher, editor)	
3. Office staff(secretary, office helper)	
4. Skilled worker (foreman, group leader, craftsman)	
5. Administrator/manager/executive	
6. Army officer, police officer	Blue-collar (7-11)
7. Farmer, fisherman, hunter	
8. Non-skilled worker (ordinary laborer, logger)	
9. Ordinary soldier, policeman	
10. Driver	
11. Service worker	

B Appendix:

Probit Estimates of Coefficients Used for PSM

	(1) Urban	(2) Provincial Capital
Male	-.165***	.13335***
	(0.089)	(0.139)
Marital Status	-0.648**	0.527
	(0.200)	(0.275)
Years of Education	.105***	-0.020
	(.017)	(0.026)
Potential Experience	0.041*	-.092***
	(0.018)	(0.027)
Potential Experience^2	-0.00003	0.0011**
	(-.0002)	(0.00042)
White Collar	-.221*	-0.4022*
	(0.1)	(0.1596)
ln(Housing Price)	0.040***	0.6218***
	(0.00)	(0.064)
Constant	-4.53***	-3.668***
	(0.0024)	(0.6835)
Total	2963	1745

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