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Estimating Gender Pay Gaps with Employment Selection

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Abstract:

In contrast to the United States and European countries, China has witnessed a widening gender pay gap in the past two decades. Nevertheless, the size of the gender pay gap could still be underestimated as a result of not accounting for the low-wage women who have dropped out of the labor force. As shown by a large and representative set of household survey data in China, since the 1980s the female employment rate has been falling and the gap between male and female employment rates has been increasing. We estimate the bounds of the raw gender pay gap in China, taking into consideration the different male and female employment rates. To tighten the bounds, we use an instrumental variable, having a child aged less than 6 years. The results support the view that the raw gender pay gap, as large as it has been, is still underestimated.

Keywords: Gender pay gap; gender employment gap; bounds; instrumental variable

JEL code: J3

1. Introduction

The gender pay gap is an important labor market phenomenon that has inspired a large and significant literature in labor economics. Recent research in this area has begun to pay great attention to the bias in the raw gender pay gap estimates due to employment selection. In the United States since the 1980s both the labor force participation rate and mean wages of women have been rising, while gender pay differentials have been narrowing. However, several studies have suggested that the narrowing gender pay gaps in the United States may have been overestimated as a result of overlooking changes in the composition of female workers. Mulligan and Rubinstein (2008) showed that selection of women for employment shifted from being negative in the 1970s to being positive in the 1980s. As more skilled women joined the labor force, women's relative wages increased. The researchers showed that most of the narrowing wage gap between genders was due to this change in the skill composition of female workers. Blau and Kahn (2006) found that the gender pay gap decreased more rapidly in the 1980s than in the 1990s in the United States, but after re-estimating gender pay gaps with a correction for sample selectivity, they found that the differences between the two decades were mostly due to different sample selectivity in the two decades. Machado (2010), however, reached a more positive conclusion that the gender pay gap in the United States had indeed narrowed substantially, and that the improvement in gender wage equality was not entirely a result of the selection effect.

Similar studies in Europe include Blundell et al. (2007), Albrecht et al. (2009), Picchio and Mussida (2011), and Beblo (2003). Blundell et al. (2007) used the U.K. Family Expenditure Survey data to estimate the non-parametric bounds to gender pay differentials for different age–education groups. Albrecht et al. (2009) extended the Machado-Mata (2005) method to account for employment selectivity in gender pay gaps in the Netherlands. They found that if all the non-working women were employed, the gender pay gap would be much larger, and that after correcting for employment selection gender differences in productivity characteristics played an important role in explaining the gender pay differentials. Picchio and Mussida (2011) adapted the hazard function estimator proposed by Donald et al. (2000) to estimate the gender wage gap in Italy. Their results also suggested an underestimation of gender pay gaps without selection correction, especially at the bottom of the wage distribution. Beblo et al. (2003) found that accounting for self-selection into work had an impact on gender wage estimates and wage gap decomposition in their study of five EU countries.

Employment selectivity is also useful to explain cross-country differences in the gender pay gap. Olivetti and Petrongolo (2008) showed that both the gender employment gap and the gender pay gap varied significantly across OECD countries, and that there was a negative relationship between the gender employment gap and gender pay gap. Their analysis suggested that the international variation in the gender pay gap would be smaller if the employment-rate differences across countries were taken into consideration.

Employment selection is also relevant to the racial wage gap. Chandra (2003) showed that the black–white wage gap among men was understated because of the selective withdrawal of black men from the labor market. In contrast to the large employment gap between black and white men, black and white women had a similar employment rate. Thus, prior to Neal (2004), it was believed that employment selection did not play an important role in the female black–white wage gap. Neal (2004), however, pointed out that employment selectivity still affected female racial wage gaps. They showed that typical black women who were not working were single mothers receiving welfare support, while their white counterparts were married with a relatively wealthier husband. As a result of different selection rules for working for black and white women, the female racial pay gap is also likely underestimated.

In contrast to the narrowing gender wage gap in the United States,[1] China has experienced a widening gender pay gap in recent decades.[2] China also provides an interesting contrast to other transition countries, such as Poland, Hungary, Russia, Estonia, and Slovenia, where the relative wages for women were unchanged or even improved during the transition from a centrally planned to a market economy.[3] In theory, on one hand, the gender wage gap could widen during the transition from a planned economy to a market economy as the result of deregulation of wage setting and rising discrimination in the labor market. On the other hand, increasing market forces could punish employers with discriminatory tastes and reduce the gender pay

[1] Blau and Kahn (2006, 1997); Blau (1998).

[2] Gustaffson and Li (2000); Appleton et al. (2005); Ng(2007); Chi and Li (2008).

[3] Glinskaya and Mroz (2000) and Reilly (1999) found that the gender pay gap in Russia has not changed during the transition from 1992 to 1996. Adamchik and Bedi (2003) found no change in women's relative wages in Poland during the transition. Jolliffe and Campos (2005) showed that the gender wage gap declined in Hungary from 1986 to 1988. The improvement in women's economic welfare has also been found for Estonia and Slovenia by Orazem and Vodopivec (2000).

gap (Becker, 1957). This mechanism has been confirmed in Hungary, where both the overall gender wage gap and the gap due to different returns to the endowments of men and women have declined (Jolliffe and Campos, 2005). The improved economic status for women in a transition country might be also explained by the change in the composition of the female labor force: Hunt (2002) showed that the gender wage gap fell by 10 points in East Germany during the economic transition, but a large part of the fall in the gender pay gap was due to the withdrawal of low-wage women from the labor market.

China has the world's largest labor force with an estimated number of actively working people approaching 0.78 billion as of 2010.[4] The male–female pay gap is one of the key issues concerning the nearly billion workers in China. Although prior research has examined the gender wage gap, occupation segregation, and discrimination in China,[5] most studies used samples of working individuals to estimate gender pay gaps, with very few addressing male and female employment rates or how the gender employment gap affects the pay gaps in China. According to Chi and Li (2008), employment rates declined from 1987–2004 for both men and women, but more so for women. With only 3 years of data, they could not show a trend in the employment rate or employment gap. We extend Chi and Li (2008) by using 20 years of data to study the trend in China's gender employment gap and gender pay gap. Appleton et al. (2005) suggested that the gender pay gap in China has stopped widening and has remained relatively static in recent years, suggesting that

[4] Data source: China Statistical Yearbook 2011, Table 4-1. http://www.stats.gov.cn/tjsj/ndsj/2011/indexch.htm

[5] Gustafsson and Li (2000); Appleton et al. (2005); Ng (2007); Meng and Miller (1995); Meng (1998a,b); Rozelle et al. (2002); and Dong et al. (2003).

China may have "crossed the river." We argue that this view may be overly optimistic because it does not consider the decline in female employment rates in China.

From a methodological perspective, our study adapts the bound method (Manski, 1994; Manski and Pepper, 2000; Blundell et al., 2007) to the gender pay gap, and uses an instrumental variable and exclusive restriction to tighten the bounds. Blundell et al. (2007) illustrated this method in their article, and they computed the bounds to the change in the gender wage differentials from 1978–1998 for four age–education groups, while we calculate the bounds to the gender pay differential for each year from 1988–2009 to show a trend. We also estimate the bounds not only for each age–education subgroup, but for the entire sample.

Our main findings are that the employment rates in China have generally decreased since 1989, and declined more for women than for men, which resulted in a widening gender gap in the employment rate. Our data also show widening gender pay gaps among working people. We estimate the bounds to the gender pay gap with correction for employment selection and find that the bounds lie almost entirely above the uncorrected gender pay gap. We interpret this result as an indication that the uncorrected gender pay gap is very likely underestimated. We further show that the underestimation bias has increased over time and in recent years has been greater for less-educated workers.

The remainder of this article is organized as follows: Section 2 describes the data and presents descriptive results on gender employment gaps and gender pay gaps in China. Section 3 describes the bound methods. Section 4 reports the results divided into several sub-sections, including estimates of the raw gender pay gap over time, the worst-case bounds and the stochastic dominance bounds, as well as the instrumental variable (IV) and IV-bounds. Section 5 discusses the results and concludes the article.

2. Data

2.1 China's Urban Household Surveys

This study uses data collected from China's Urban Household Surveys from 1988 to 2009. The Urban Household Survey has been conducted by China's National Bureau of Statistics (NBS) every year since 1987. We do not use 1987 data because data quality is poor in the first year of the survey. The survey gathers information from a large random sample of urban households through interviews. The NBS uses this data to produce aggregate statistics on employment and income, which are published in China Statistical Yearbooks. The overview of the survey methodology can be found in the yearbooks.

The NBS urban household surveys use a stratified random sampling method. In the first stage, cities and counties are selected based on population size. In total, 146 cities and 80 counties are selected to be surveyed. In the second stage, within each selected city or county, sub-districts (street committees), resident committees, and households are sampled, successively. To ensure that the sample is representative, each year one-third of the households from the second stage are rotated out and replaced by new households. Thus the household sample is completely renewed every three years. The survey begins with a monthly accounting of an individual's basic information on demographics, education, employment status, industry, and occupation, as well as the total monthly income, earnings, and other income components. The survey, then, asks a set of questions about household living arrangement, housing type, and all kinds of household expenditures. The monthly data are then aggregated into yearly data and reported to the NBS. We used the yearly data provided by the NBS. Ideally, we would like to use the hourly wage rate to examine gender pay differentials rather than earnings. However, a drawback of the NBS data is that hours of work were only asked in the 2003-2006 survey. As a result, we could not calculate the hourly wage rate. This problem may not be too serious since part-time jobs are limited and workers have little flexibility to work fewer hours in China.[6]

2.2 Sample

Our study focuses on primary-working age individuals. We select men aged 16–60 and women 16–55. The upper limit is set to exclude retired people because the normal retirement age is 60 for men and 55 for women in China. Individuals with missing values are excluded. The final sample is composed of 214,296 women and 222,243 men. Appendix Table 1 shows the number of observations for each survey year.

The survey asks about the relationship between the respondent and the household head, such as whether the respondent is the household head herself, or it is her spouse, child, or parent. Based on this question, we generate a dummy indicator of whether an individual has a young child aged less than or equal to 6 years. Appendix Table 2 shows the percentage of men and women who have a young child. Those with a young child are mostly aged 25–35 years. Since the beginning of the 1980s, China has

[6] The 2006 data shows that the monthly hours of work for men and women differed by only 3 hours. Ng (2007) also pointed out that variation in hours worked in China was not as serious as in developed countries, so omitting working hours may not cause a large bias in the estimation.

enforced its one-child policy in urban areas. Most couples have only one child, except for those having twins.[7] Therefore, the difference between whether a couple has a young child and the number of young children is small. Based on the family relationship code, we are also able to identify a household head and her/his spouse. For all years, we identify a total of 152,788 couples.

Two measures of employment can be generated from the survey data. One is the self-reported employment status, and the other is the dummy indicator of positive earnings. In the survey, self-reported employment status takes a value from 1–15 with 1–7 indicating employment in a state-owned, foreign, or private company, or in the government or other sectors, and 8–15 indicating non-working individuals, including retired and disabled persons, household wives, enrolled students, and individuals waiting for jobs. Because the employment status question has non-standard phrasing (i.e., whether an individual is out of a job but actively looking for one), we could not identify unemployed individuals. Therefore, we focus on the employment rate instead. We define employment as equal to 1 if the self-reported status takes the value of 1–7. Alternatively, we define employment equal to 1 if an individual reported positive earnings. The two measures of employment are significantly correlated with a correlation coefficient of 0.80. However, because self-employment status pertains to status in the last month of the survey year, typically December, while positive earnings indicate that an individual has done some work during the year, the two measures are not always consistent. For people who did not change work status during

[7] A couple is allowed to have a second child only if their first-born is disabled or has other serious diseases.

the year, the two measures give the same value. We report results based on the second measure—an individual is employed if her earnings are positive.

Figure 1 shows male and female employment rates from 1988–2009. Both male and female employment rates declined during the 20-year period. Since 2000, the female employment rate decreased rapidly while the male employment rate was stagnant and even increased slightly after 2005. As a result, the gender employment gap has widened notably since 2005.

Figure 2 demonstrates average earnings for men and women from 1988–2009 based on the sample of employed individuals. Although both male and female earnings increased significantly during the period under study, the gender pay gap also increased. Figure 3 shows that the raw gender pay gap increased from 0.2 to the maximum of 0.4 during the mid-2000s, and then decreased to 0.35 in 2008 and 2009.

Similar to Olivetti and Petrongolo (2008), we conduct simulations to show potential underestimations of the gender earnings gap because of positive employment selection. Let W and X denote the logarithm of wage and the conditional vector (including gender, age, education, and year). When W is observed, the indicator variable employment (E) equals 1, and when W is not observed, E equals 0. Assume that non-employed individuals earn a wage equal to a proportion (r) of the wage of employed individuals. If there is a positive selection into employment, non-working individuals would earn a lower wage than working ones even if they worked. In such a case r is less than 1. If there is a negative selection, non-working individuals would earn a higher wage than those who are working, and r would be greater than 1. The actual average wage for each subgroup with characteristics x can be calculated from the observed average wage as equation (1) (see also equation (1) in Olivetti and Petrongolo, 2008),

$$E(W|x) = E(W|x, E = 1)[r + (1 - r)P(x)] \qquad (1)$$

Here $P(x) = P(E = 1|x)$ is the employment rate for the subgroup.

We simulate three scenarios where r = 0.9, 0.7, and 0.5. This implies that had the non-working individuals been employed, they would have earned 90%, 70%, or 50% of what the working individuals with the same characteristics x earn. Figure 3 shows the simulated gender pay gaps from 1988–2009. Two patterns emerge from the results. First, as the gender employment gap rises over time, the extent to which the gender pay gap is underestimated increases. Second, for a given year, the smaller r is, the greater the extent to which the gender pay gap is underestimated. These simulations show that, given male and female employment rates in China, and given the assumption of positive selection into employment, the actual gender pay gaps would be much larger than the raw gap estimated based on the people already working.

3. Method

There are several methods that can be used to estimate the gender pay gap correcting for employment selection. First, if panel data are available, a researcher can impute an individual's missing wages in year t, using that individual's own wage data from the nearest wave (Blau and Kahn, 2006; Olivetti and Petrongolo, 2008). The wage imputation can also be done based on the observed characteristics. Second, the Heckman-selection correction can be used (Heckman, 1979; Mulligan and Rubinstein, 2008; Beblo, 2003). Instrumental variables are needed to perform Heckman selection. The instrumental variables should be able to predict the employment probability but are uncorrelated with wages. Third, the Machado-Mata (2005) technique can be extended to estimate quantile wage regressions with sample selection (Albrecht et al., 2009). Fourth, Donald's (2005) hazard function estimator can be applied to estimate the wage density and gender wage gap across the wage distribution with employment selection. Finally, the bounds can be estimated without explicitly modeling the selection process (Manski, 1994; Blundell et al., 2007).

Because our data are time-series cross-sectional data, we cannot apply the imputation method that takes advantage of the panel nature of a data set. Among the latter four techniques, we choose the bound method because it does not require any identifying assumptions. However, the bound can be loose and uninformative. Therefore we apply assumptions that are fairly general to tighten the bounds and provide more informative results. We also use an instrumental variable to tighten the bounds. As a robustness check, we use the same instrumental variable to perform the Heckman-selection correction and show the corrected gender pay gaps over time in the Appendix Figure.

In the rest of this section, we discuss the worse case bounds and the bounds with the assumption of stochastic dominance and with the use of IV. For the sake of completeness, we briefly review in the following the bound methods proposed in

Blundell et al (2007).

3.1 The worse case bounds

We are interested in $F(w|x)$, which can be written as

$$F(w|x) = F(w|x, E = 1)P(x) + F(w|x, E = 0)[1 - P(x)]$$

Here $F(w|x,E=1)$ and $P(x)=P(E=1|x)$ can be identified from the data. Whereas $F(w|x,E=0)$ is unidentified. The worst case bounds of the conditional cumulative distribution function (cdf) $F(w|x)$ can be derived from the following inequality,

$$F(w|x, E = 1)P(x) \leq F(w|x) \leq F(w|x, E = 1)P(x) + 1 - P(x)$$

The bounds can then be translated to give worst case bounds on the conditional quantiles (Manski, 1994). Denoting by $w^q(x)$ the qth quantile of $F(w|x)$, we then have

$$w^{q(l)}(x) \leq w^q(x) \leq w^{q(u)}(x) \qquad (*)$$

where $w^{q(l)}(x)$is the lower bound and $w^{q(u)}(x)$ is the upper bound that, respectively, solves the equation

$$q = F(w|x, E = 1)P(x) + [1 - P(x)]$$

and

$$q = F(w|x, E = 1)P(x)$$

with respect to w.

3.2 Use the stochastic dominance to tighten the bounds

The bounds in the preceding subsection are universally correct, but could be too crude and hence uninformative. To tighten the bounds, one can impose a positive selection assumption which posits that individuals with higher wages will be more likely to work. The positive selection assumption can be translated to a *stochastic dominance* premise, which can be mathematically phrased as:

$$F(w|x, E = 1) \leq F(w|x, E = 0), \quad \text{for all } w, x$$

It follows from stochastic dominance that

$$F(w|x, E = 1) \leq F(w|x) \leq F(w|x, E = 1)P(x) + [1 - P(x)]$$

The left bound is tighter than the previous version. This transcends to smaller $w^{q(u)}(x)$, the upper bound for $w^q(x)$.

3.3 The IV bounds

Instrumental variables can be employed to tighten the bounds as well. Suppose z are some determinants of employment but unrelated to wages, i.e.,

$$F(w|x, z) = F(w|x) \text{ and } P(x, z) \neq P(x)$$

Whether having a young child, the number of young children or non-labor welfare income is often used as IV in this case. The IV we will use is a dummy variable of whether having a young child under age 6.

With the availability of a binary IV z, we can tighten the bounds for $F(w|x)$ by observing the following inequalities:

$$max\{F(w|x, z = 0, E = 1)P(x, 0), F(w|x, z = 1, E = 1)P(x, 1)\}$$

$$\leq F(w|x) \leq$$

$$Min\{F(w|x, z = 0, E = 1)P(x, 0) + [1 - P(x, 0)], F(w|x, z = 1, E = 1)$$

$P(x,1) + [1-P(x,1)]\}$

We have a similar inequality $(*)$ with $w^{q(l)}(x)$ being the larger one of the solution of

$q = F(w|x,z=1,E=1)P(x,z=1) + [1-P(x,z=1)]$ and

$q = F(w|x,z=0,E=1)P(x,z=1) + [1-P(x,z=0)]$ with respect to w;

$w^{q(u)}(x)$ is the smaller one of the solution of $q = F(w|x,z=1,E=1)P(x,z=1)$ and

$q = F(w|x,z=0,E=1)P(x,z=0)$ with respect to w.

3.4 Estimating the bounds of wage differentials between genders

Given the bounds for a quantile for each gender group, one can easily derive the bounds for the differences between genders in the corresponding quantile. Specifically, suppose that we have obtained the bounds for the quantile of both genders:

$$w_m^{q(l)}(x) \le w_m^q(x) \le w_m^{q(u)}(x),$$
$$w_f^{q(l)}(x) \le w_f^q(x) \le w_f^{q(u)}(x)$$

The bounds for the difference between genders in a quantile are given by:

$$w_m^{q(l)}(x) - w_m^{q(u)}(x) \le w_m^q(x) - w_f^q(x) \le w_m^{q(u)}(x) - w_f^{q(l)}(x).$$

4. Results

4.1 Evidence of positive employment selection

Table 1 shows the gender employment gap and the gender pay gap by marital status, age, and education. Because of space limitations, we report descriptive results for only 3 years—1992, 2002, and 2009. These years are selected to represent their corresponding decades. We select 2009 because it is the most recent year within the period under study; 2002 because the survey queried marital status only since 2002; and 1992 because it is exactly a decade before 2002.

We discover the following patterns from the results reported in Table 2. First, the employment rate increased with education. More educated individuals had a higher employment rate than less educated individuals. This is true for both men and women. This pattern became more pronounced in recent years. We interpret this result as evidence of positive employment selection. The only exception is for men in 1992, where men with a primary education had a 90% employment rate while those with a secondary education had a 83% employment rate, and the earnings of the two groups were similar. In 1992 the earnings differential between men and women was relatively small, while it became larger in the latter two year points. For all the three year points, the gender employment gap and the gender pay gap were the largest for the least educated.

Second, we find an interesting pattern with respect to marital status. In general the employment rate was lower for singles. This is likely because of their young age and hence the fact that they would still be enrolled in school. However, single women had a higher employment rate than single men. Single women also had relatively higher pay, so that the gender pay gap was markedly smaller for singles (0.04) than for married (0.40) women.

Third, regarding the gender employment gap by age, we find that the employment rate generally increased with age for both men and women. For the youngest group (aged 18–22 years), the employment rate was fairly low and became even lower in recent years. This is most likely because of increasing college availability and enrollment. Interestingly, both the gender employment gap and the gender pay gap were the smallest for the youngest group; women from this age group actually had a higher employment rate than their male counterparts even though this pattern attenuated over time, and for this group female earnings were close to male earnings. Over time, the second youngest group (aged 23–27 years) started to show a similar pattern: women began to have a higher employment rate than men, and the male-female pay differentials declined, suggesting that female relative wages became more competitive over time for this group.

Table 1 shows a general pattern where the gender employment gap and the gender pay gap were positively correlated across groups. This suggests that when women in a group had a higher wage relative to men, they also had a relatively higher employment rate.

To further provide evidence for positive selection, we use the matched set of husbands and wives, and divide the sample by a husband's income level into five groups: a husband's income is in either the bottom 20%; 20–40%, 40–60%, 60–80%, or the top 20%. Subsequently, we calculate the wives' employment rates for each of the five groups in 1992, 2002, and 2009. Table 2 shows the results. Women whose husband's income is in the lowest quintile have a 9–12% lower employment rate than that of the other four groups of women; the employment rate of the other four groups of women is actually similar. We do not find that women with a relatively wealthier husband are less likely to work. On the contrary, in recent years it seems they become even more likely to work than other women. This evidence points to positive selection into employment among women in urban China, with a pattern that has not changed over time.

4.2 Worst case bounds and stochastic dominance bounds[8]

Figure 4 shows the raw gender pay gap and the bounds estimates for 1988–2009. The worst-case bounds are the least informative, as the lower bound crosses zero for most of the years from 1995–2009. To tighten the bounds, we assume positive selection into employment, but impose only a weak assumption that the wage distribution of working individuals first-order stochastically dominates the wage distribution of the non-working individuals. Including this assumption tightens the lower bound of the raw gender pay gap significantly, making it above zero for all years. Before 1995, male and female employment rates were high and the gender employment gap was small; hence the bounds are rather tight. After 2000, the gender employment gap widened significantly, and the bounds became loose. As can be seen, however, the lower bound remained steady while the upper bound increased. In 2009, the lower and upper bound with the assumption of stochastic dominance were 0.02 and 0.88, respectively, in contrast with the raw gender pay gap which was 0.27.

4.3 IV bounds

The IV we use is a dummy variable of whether an individual has a young child aged less than or equal to 6 years. This variable is widely used in the relevant literature as an IV for employment selection. To demonstrate the validity of this IV,

[8] Throughout we use the same kernel estimation in Section 4 of Blundell et al (2007) to estimate the conditional cdfs and the conditional probabilities.

we report the employment rate and earnings for men and women both with and without a young child (Table 3). Our calculation is based on the sample of men and women aged 25–35 years because those with a young child are almost exclusively from this age group. Pooling people of all ages in the calculation could confound the result.[9]

Table 3 shows that among those aged 25–35 years, women without a young child have a higher employment rate than those with a young child. The difference is less than 1 percentage point but is statistically significant at the 1% level, based on the data from all years. We also divide the data into two periods, the 1990s and 2000s, and find that the impact of having a young child on females' employment is more evident in the 2000s. For many years Chinese women have been under the influence of Mao's ideology—"women holding up a half sky"—which promotes equal participation in market work for men and women. The female labor force participation rate and employment rate had been high until recent decades. As the collectivism becomes less dominant and individual freedom becomes more prevalent, some women have decided to revert to the traditional role in the family.[10] Moreover, the increased cost of child-care service has also caused some women with a young child to stay home. In contrast to the employment differences between women with and without a young child, we find that the earnings differences between them are small and insignificant.

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[9] Because individuals with a young child are mostly aged 25–35 years, while those who do not have a young child are older, the employment rate differences between them could be because of age rather than the effect from having a young child.

[10] A survey of women in Beijing showed that 60% of respondents indicated that they were willing to be a household wife if their family financial situations allowed them to stay home. http://news.xinhuanet.com/newscenter/2003-01/12/content_686805.htm

For men, having a young child had a different impact on the employment probability and earnings than for women. Table 4 shows that men with a young child are more likely to work and also have higher earnings than their counterparts without a young child. This finding indicates that having a young child may have motivated men to work harder in China. Because having a young child is correlated with both employment probability and earnings, it cannot be used as an IV to correct males' employment selectivity. Therefore, we use this IV to obtain the corrected earnings estimates for women, and then use the IV bounds of women's earnings and the stochastic dominance bounds of men's earnings to create the gender pay gap bounds. These estimated bounds are shown in Figure 4 as the "IV bounds". The IV bounds are tighter than the stochastic dominance bounds. After 2000, the lower IV bound almost overlaps with the raw gap. For example, in 2009 the IV lower bound and upper bound is 0.28 and 0.75, respectively, while the raw gender pay gap is 0.27. These estimates suggest that the raw gap is likely to be underestimated.

As a robustness check, we run the Heckman selection regressions using the same instrumental variable as in the IV bound estimation. The Appendix Figure shows the OLS estimate and the Heckman regression estimate of the gender earnings gap from 1988–2009. Before 2000, because the female employment rate was high and the gender employment gap was low, the Heckman regression estimates are close to the OLS estimates, suggesting that selection bias is fairly small. After 2000, as results show a widening gender employment gap and more low-wage women withdrawing from the labor market than men, the raw gender pay gap is evidently underestimated.

This result is in accordance with the IV bounds estimates.

4.4 Bounds for sub-groups

Furthermore, we estimate the gender pay gap bounds for age–education sub-groups for 1992, 2002, and 2009 (Figure 5). In 1992, the bounds are quite tight for most of the groups except for age 20 and age 50 groups with an education of junior high or below, and the age 20 group with a high school education. For the age 50 group with an education of junior high or below, the estimated bounds lie above the raw gender pay gap, while for the other two groups, the bounds are less informative because the lower bound is below the raw gap.

For 2002 and 2009, the bounds are still relatively tight for college-educated individuals aged 30–50 years. For those aged 25 years with at least a college education, the bounds are loose. This is likely because some people from this group might still be enrolled in school and the employment rate is relatively low for this group. The bounds are generally loose for the groups with no more than a high school education. Figure 5 shows that in general the bounds to the raw gender pay gap are the tightest for the college-educated and primary-working age groups.

5. **Conclusion**

Men and women often have different employment rates, and because of non-random selection into employment, the gender pay gap estimate is likely to be biased. If employment selection is positive, low-wage workers would be more likely to stay out of the labor force. Because women often have a lower employment rate than men, the gender pay gap estimate is thus likely subject to downward bias as the result of omitting low-wage women in the sample. Our article is motivated by the observation that little is known about the male–female employment rate gap in China, or the extent to which the gender employment gap causes underestimation of the gender pay gap.

We show the trend in the gender employment gap and gender pay gap in China during the period 1988–2009, and estimate the bounds to the raw gender pay gap. The worse-case bounds are uninformative because the lower bound crosses zero for many of the years. However, with the weak assumption of stochastic dominance of the earnings of working people over those not working, the lower bound is tightened significantly. The results support the notion that the raw gender pay gap is likely underestimated. We further tighten the bound using the IV—whether an individual has a young child aged less than or equal to 6 years—which is often used to correct employment selection. We also estimate the bounds for different age-education subgroups, and find that the bounds are narrowest for college-educated individuals.

Our article contributes to the literature on the gender pay gap in transition countries, specifically in China, by estimating the bounds to the raw gender gap with correction for employment selection. We also assessed whether employment selection is positive or negative for Chinese women, and found evidence of positive selection. These results help to better understand the functioning of China's labor market, by far the largest in the world. Methodologically, our article is most similar to Blundell et al. (2007) although we use a different IV and apply the method extensively. We also examine the validity of the IV because it has rarely been tested in the context of China.

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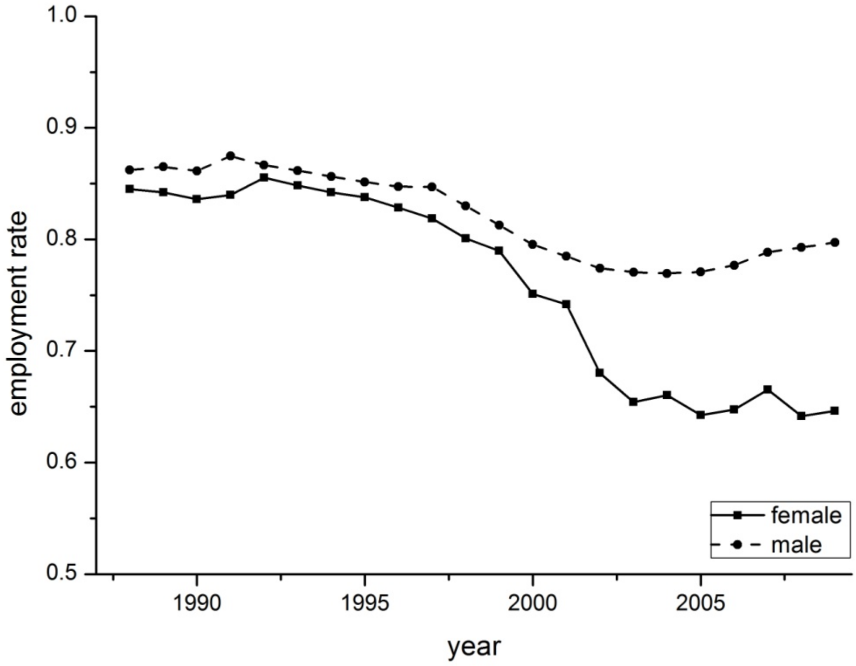
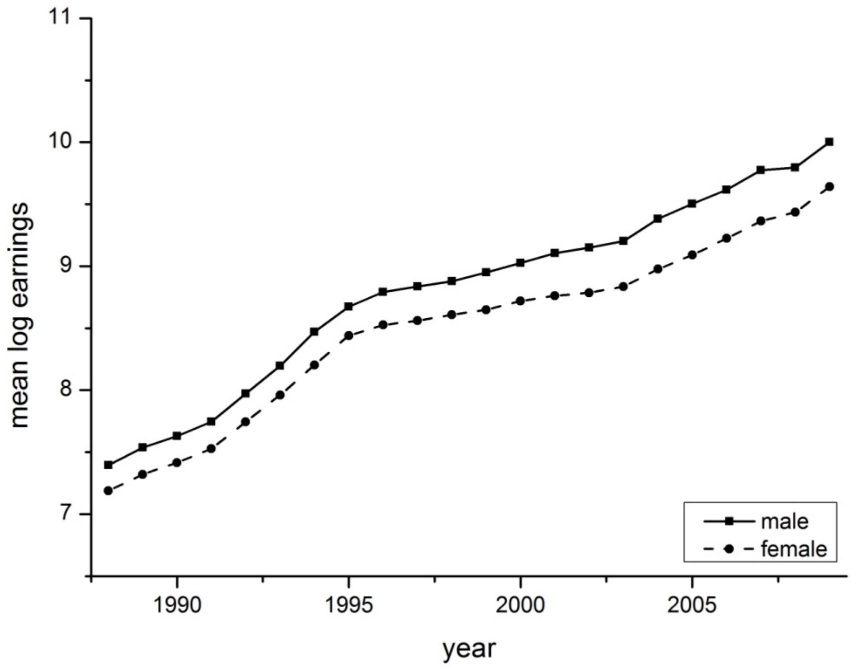
Figure 1: male and female employment rates



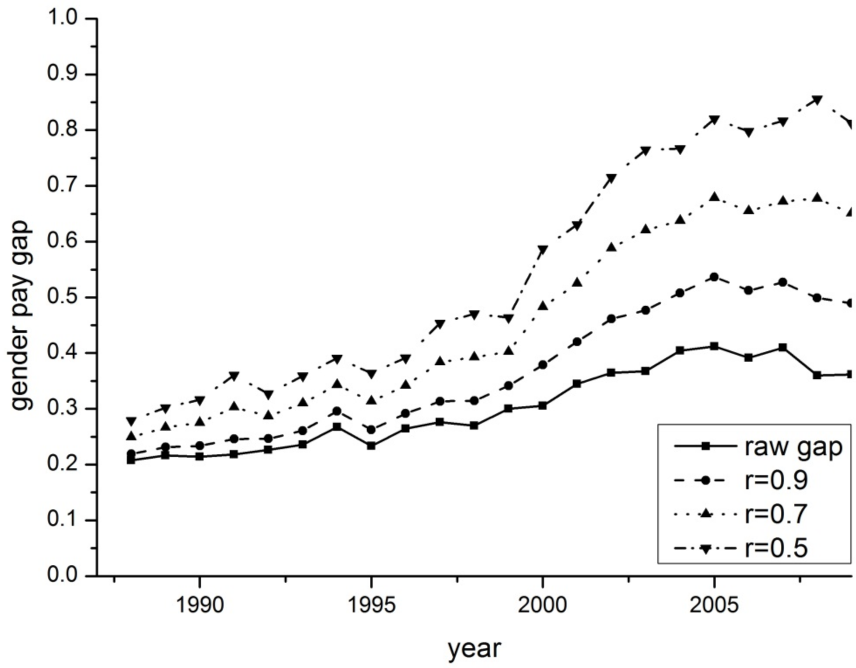
Source: NBS Urban Household Survey data 1989-2009; author's own calculation

Figure 2: male and female mean earnings



Source: NBS Urban Household Survey data 1989-2009; author's own calculation
Note: the earnings shown in this figure are nominal earnings.

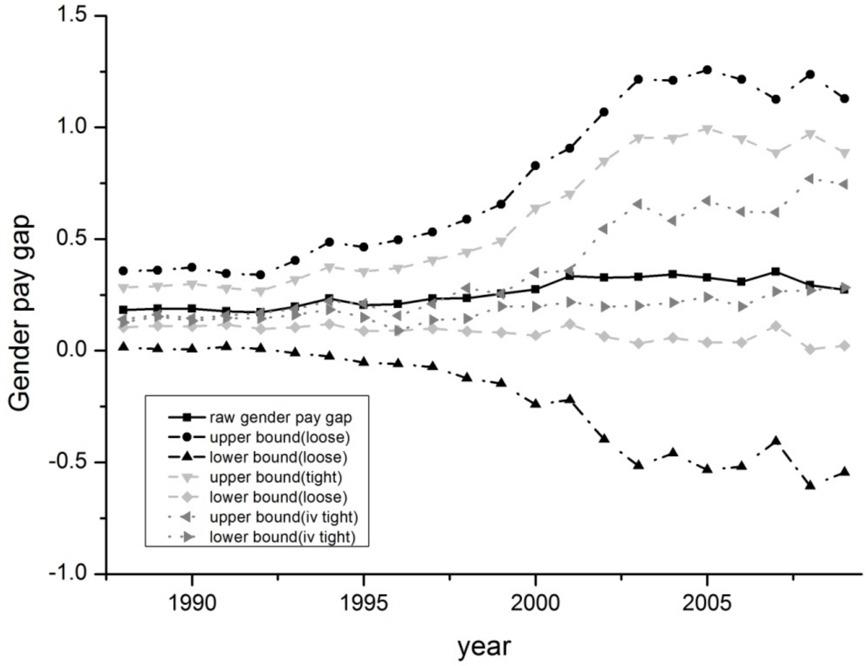
Figure 3: raw and simulated gender pay gaps



Source: NBS Urban Household Survey data 1989-2009; author's own calculation

Note: this figure shows the raw gender pay gap and simulated ones based on equation (X). Positive employment selection is assumed. r=0.9, 0.7, and 0.5 assumes unemployed workers can potentially earn 90, 70, or 50% of wages of employed workers. Male and females' actual employment rates in each year are used in the simulation.

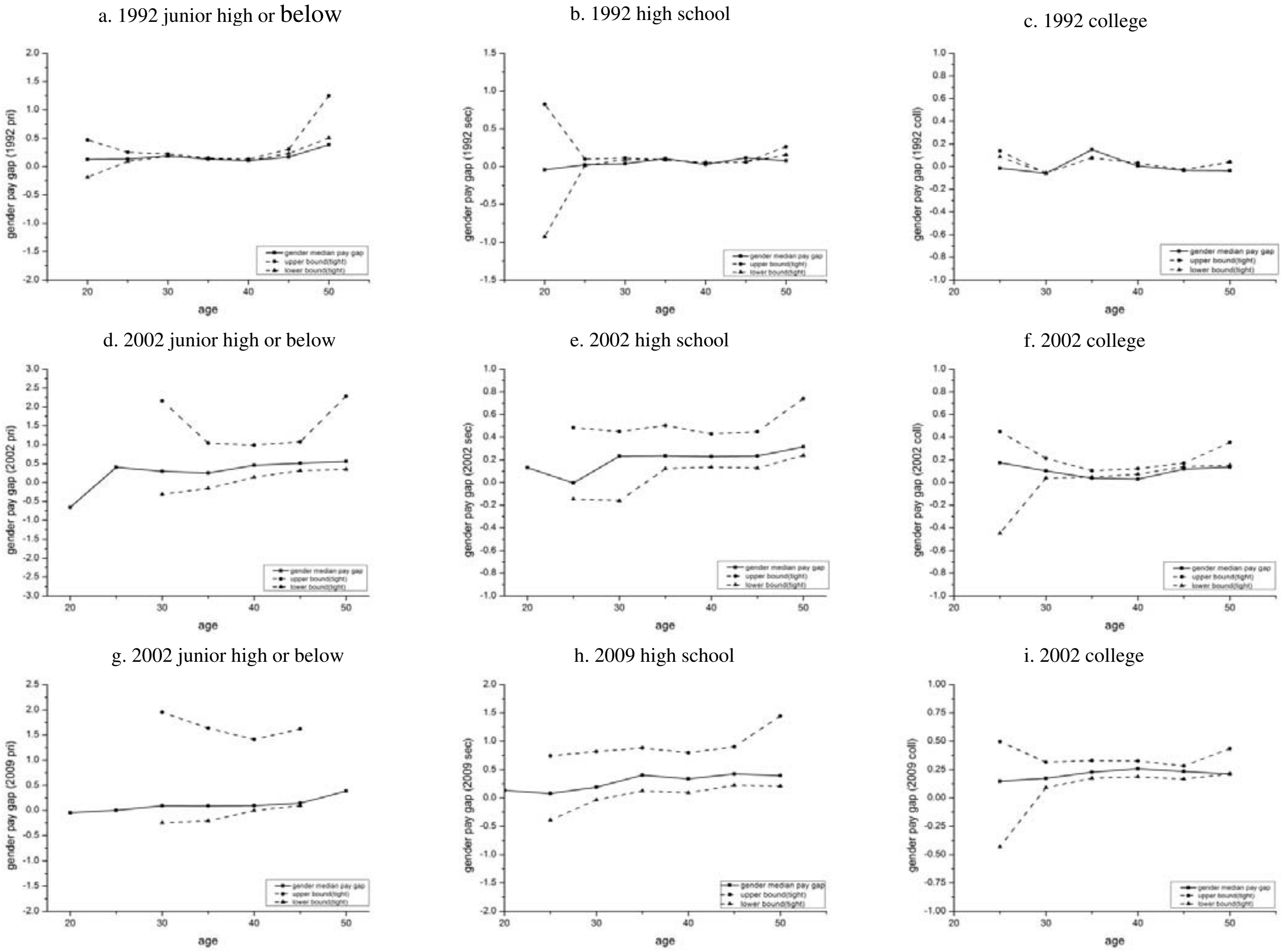
Figure 4: employment selection and estimated gender pay gap bounds



Source: NBS Urban Household Survey data 1989-2009; author's own calculation

Notes: the figure shows the raw gender pay gap and estimated upper and lower bounds on the gap after taking into consideration employment selection. The worst case and stochastic dominance bounds are estimated.

Figure 5: raw gender pay gaps and bounds by education and age, 1992, 2002, 2009



Notes: the figure shows the raw gender pay gap and estimated upper and lower bounds on the gap for each subgroup and year. The stochastic dominance bounds are reported.

Table 1: gender employment gaps and gender pay gaps for subgroups

	year 1992						year 2002						year 2009					
	male		**female**		**differentials**		**male**		**female**		**differentials**		**male**		**female**		**differentials**	
	employment rate (100%)	mean lgearn	employment rate (100%)	mean lgearn	employment gap	gender pay gap	Employment rate (100%)	mean lgearn	employment rate (100%)	mean lgearn	employment gap	gender pay gap	employment rate (100%)	mean lgearn	employment rate (100%)	mean lgearn	employment gap	gender pay gap
all	86.67	7.97	85.54	7.74	1.12	0.23	77.41	9.15	68.01	8.79	9.41	0.36	79.73	10.00	64.61	9.64	15.12	0.36
marital status																		
married							88.38	9.21	75.48	8.81	12.90	0.40	83.60	10.05	70.26	9.65	13.34	0.40
not married							37.44	8.67	40.24	8.63	-2.80	0.04	39.03	9.58	42.21	9.55	-3.18	0.02
education																		
primary	90.52	7.93	84.39	7.63	6.13	0.29	70.42	8.86	55.10	8.31	15.32	0.55	65.17	9.61	49.29	9.11	15.88	0.50
secondary	83.25	7.92	84.69	7.78	-1.44	0.13	73.55	9.08	71.61	8.83	1.94	0.25	69.77	9.88	60.60	9.50	9.17	0.38
college	94.62	8.13	93.01	8.01	1.61	0.12	87.40	9.48	83.36	9.27	4.04	0.22	85.66	10.31	83.59	10.05	2.07	0.26
age																		
18-22	56.28	7.32	61.50	7.26	-5.22	0.06	17.80	8.17	21.50	8.23	-3.70	-0.05	13.10	9.02	15.94	8.87	-2.84	0.15
23-27	95.21	7.70	94.19	7.55	1.02	0.14	72.88	8.78	74.70	8.68	-1.82	0.10	71.63	9.71	72.53	9.62	-0.90	0.09
28-32	98.61	7.93	98.54	7.78	0.07	0.16	84.49	9.04	79.16	8.81	5.33	0.23	86.56	10.05	80.27	9.80	6.29	0.25
33-37	100.00	8.02	99.54	7.87	0.46	0.15	90.88	9.20	83.31	8.88	7.57	0.32	86.50	10.14	79.57	9.75	6.93	0.39
38-42	99.90	8.07	98.05	7.94	1.85	0.13	92.41	9.26	84.99	8.91	7.42	0.35	85.79	10.09	78.90	9.68	6.89	0.41
43-47	99.33	8.14	96.38	7.92	2.95	0.22	92.97	9.26	83.08	8.86	9.89	0.41	87.00	10.09	75.99	9.63	11.01	0.47
48-52	99.20	8.18	77.89	7.70	21.31	0.48	90.31	9.23	66.34	8.69	23.97	0.54	87.28	10.02	57.80	9.50	29.48	0.52

Source: NBS Urban Household Survey data 1989-2009; author's own calculation

Table 2: Female employment selection

	Husband's income quintiles				
Wife's employment rate	1	2	3	4	5
1992	85.22	93.88	91.14	90.91	91.97
2002	67.98	79.95	80.42	77.90	79.88
2009	60.03	71.23	74.70	74.87	77.34

Source: NBS Urban Household Survey data 1989-2009; author's own calculation

Notes: only a household head and his/her spouse are selected for matching.

Table 3: Employment rates of females and males with and without young child in the 1990s and 2000s

Panel A:

Employment rates	1990s	2000s	All years
Female with young children	96.64	79.75	85.80
Female without young children	96.79	81.01*	86.65*
Male with young children	99.26	89.67	93.86
Male without young children	96.74*	83.95*	87.62*

Panel B:

Log earnings	1990s	2000s	All years
Female with young children	7.74	7.40	7.52
Female without young children	7.80	7.48	7.58
Male with young children	8.11	8.62	8.40
Male without young children	7.95*	7.91*	7.92*

Source: NBS Urban Household Survey data 1989-2009; author's own calculation

Notes: calculation is based on males and females aged 25-35. "*" indicates that Pearson Chi2 test is significant at the 1% level.

Appendix Table 1: Sample description

	The number of obs.
1988	11286
1989	10502
1990	11144
1991	10967
1992	12393
1993	11788
1994	11854
1995	11867
1996	11888
1997	12058
1998	12021
1999	12102
2000	11884
2001	11967
2002	28299
2003	31930
2004	34327
2005	36052
2006	36306
2007	36267
2008	35088
2009	34549
Total	436539

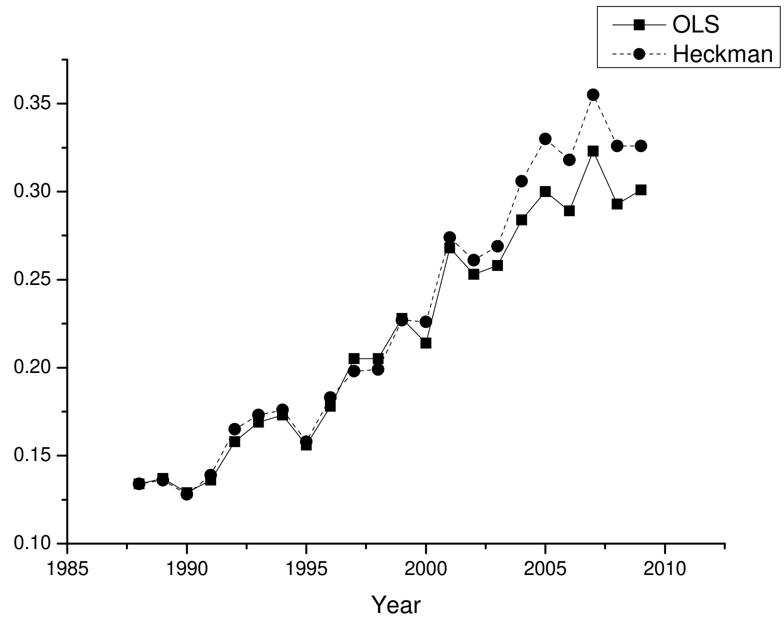
Source: NBS Urban Household Survey data 1989-2009; author's own calculation

Appendix Table 2: having a young child by age

Male	Num. of obs.	% having a young child	Female	Num. of obs.	% having a young child
<25 years old	39,597	1.32	<25 years old	38,427	4.03
25-35	39,347	43.98	25-35	47,200	42.32
>35	143,299	3.66	>35	128,669	1.88

Source: NBS Urban Household Survey data 1989-2009; author's own calculation

Appendix Figure: OLS and Heckman selection-correction estimates of gender earnings gap in China



Source: NBS Urban Household Survey data 1989-2009; author's own calculation

Notes: The instrumental variable used in the Heckman selection-correction is whether an individual has a young child under age 6.