European Research Studies,
Volume XIII, Issue (4), 2010

The Analysis of the Impact of Panel Attrition on Estimation of Regular-Irregular Worker Wage Gap in the KLIPS

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Abstract:

The aim of this paper is analyzing the effect of panel attrition on estimation of regular-irregular worker wage gap using KLIPS (Korean Labor and Income Panel Study). Using two wave sub-panels of KLIPS, we first analyze the characteristics of attritions. We find that the nonrandom attrition has occurred and it causes the underestimation of regular-irregular worker wage gap. Second, we decompose the attrition bias into 'ability bias' and 'distortion bias'. And third we develop the estimation strategies to reduce the bias. We have found that the bias is not negligible although it has been attenuated by change of job of workers.

JEL Classification: C40

Key words: Panel Attrition, Sample Selection, Wage Gap, IPW Method

1. Introduction

Since panel data controls for unobserved heterogeneity, it is essential for researchers in applied social science. But a panel data have a risk of attrition which may affect the value of some statistic, that is, an attrition bias.

There are several method suggested on reducing the attrition bias after the seminal paper of Hausman and Wise (1979). They applied Heckman estimator into social experimental data which show attrition. And Fitzgerald, Gottschalk and Moffit (1994) used weighted least square approach on PSID data. Most researches on attrition bias based on these two approaches.

The assumption of weighting approach is that the selection is occurred only on observable. But we find that the selection is occurred on both observable and unobservable. So we advanced weighting method by taking advantage of panel to also correct the bias occurred by selection on unobservable.

In this paper we explore the impact of panel attrition on regular-irregular worker wage gap among male worker. The empirical study is based on KLIPS (Korean Labor and Income Panel Study). We define the wage gap by difference of

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average wage of regular workers and that of irregular workers.

We find that the nonrandom attrition causes underestimation of wage gap. And we develop the method to correct two kind of bias (due to selection on observable and selection on unobservable) while former researches investigated only one of them. We conclude that the bias has been reduced because of workers' position (regular-irregular) change but it is still not negligible.

2. The Data and the Feature of Panel Attrition

2.1. The KLIPS and the Panel Attrition

KLIPS (Korean Labor and Income Panel Study) which began at 1998, has been created for 11th wave until now. The most recent available data is 2008 survey. At 1998, the beginning of the survey, 5000 households –the number of individual was 13321- living in urban area was surveyed, and they are inquired about their socio-economic state each year. The questionnaire is composed of personal level and household level question.

But the attrition has been occurred each year. By the 4th wave(2001), 72.4% of the original individual sample are remained in the KLIPS data. By the 11th wave (2008), 64.7% are remained. This implies that the average attrition rate of individual is approximately 1% from the 4th wave of the survey.

From now on, we will limit the scope of the research to the group of men who were employed at 2001 and in their twenties to thirties then, and study the effect of attrition to measurement of regular-irregular worker wage gap of the 2008 data.

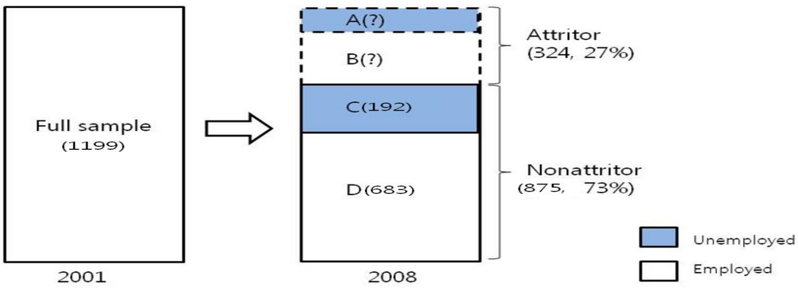
Table 1 show the number of samples in the two waves and attrition rate between them. 1198 samples are in the 2001 data, and then they were reduced to 878 at 2008 survey, which shows 27% of attrition rate. Besides, 193 samples out of remained 878 samples switched to unemployed. Accordingly, only 685 samples are remained in the 2008 data and employed, which are only 57% of former samples of 2001.

Table 1: ***The number of samples in 2001 data and 2008 data***

	Employed (%)	Unemployed (%)	Total (%)
2001	1199 (100)	0 (0)	1199 (100)
2008	683 (57.0)	192 (16.0)	875 (73.0)

Note: *New sample in the 2008 data are excluded. And Parenthesis shows the percentage of the total sample of the 2001 data.*

Figure 1: ***Dividing samples into four groups***



Then we can group whole 1199 samples into four groups (See Figure 1). First, they are grouped into two groups, attrition and non-attrition. Attritions which have been suffered from attrition between 2001 and 2008 are not appeared in 2008 data, while non-attritions are in the 2008 data. And each of above two groups has two subgroups respectively, one is employed and another is unemployed in 2008. Thus there are four groups, which can be seen in the figure 1. (A: attrition-employed, B: attrition-unemployed, C: non-attrition-employed, D: non-attrition-unemployed).

2.2. The Characteristics of Attritions

We are now interested in properties of group B+D, employed men in 2008 who were also employed in 2001, but we can only observe D in 2008 data. Let's assume that we are interested in a variable X in 2008 data. Then a question is posed whether group B and D has homogenous distribution about variable X. If they don't, a mean value of drawn from group D can be biased. This statement can be represented algebraically:

If $\bar{X} \mid B \neq \bar{X} \mid D$ then $\bar{X} \mid B \neq \bar{X} \mid B \cup D$,

Where $\bar{X} \mid B \cup D$ is an unbiased estimator of expectation value of X of employed men in 2008.

Therefore we must check whether group B and D are drawn from same population. But there is an awkward problem in checking this issue. That is, we cannot pick out group B from group A+B (attrition), because we don't know who are employed in 2008 among them. Alternatively, we compared group A+B (attrition) and C+D (non-attrition) about 7 important variables.[2)] If they have different properties we can suppose B and D are also different. We conducted this comparative analysis with 2001 data.

1. Schooling means the period of schooling year, and tenure means the period of working year in current job.

Table 2: Comparison of mean value of some variables between attrition and non-attrition

	Attrition (324)	**Non-attrition (875)**	**Total (1199)**	**P-value**
Log hourly wage	1.48 (0.56)	1.52 (0.52)	1.51 (0.53)	0.12
Age	30.8 (4.60)	31.8 (4.67)	31.5 (4.67)	0
Schooling	13.5 (2.55)	13.6 (2.34)	13.6 (2.40)	0.73
Tenure	2.93 (3.56)	4.05 (4.06)	3.75 (3.91)	0
Worktime (per day)	7.70 (1.90)	7.74 (2.06)	7.73 (2.04)	0.32
Rate of the married	0.49	0.64	0.6	0
Rate of the regular worker	0.87	0.89	0.89	0.18

Notes: *p-value denotes probability that mean value of non-attrition isn't larger than that of attrition. Bold typed variable name: significant at 1% level.*

Table 2 shows mean value of some variable of group A+B (attrition) and C+D (non-attrition) with 2001 data. Actually we need to figure out whether they are different in 2008 data, but if they are different in 2001, it is presumed that they are also different in 2008. The result says that all variables are larger in 2008 than in 2001. Three of them are statistically significant, namely age, tenure and rate of the married. Judging from this fact, we can see that these two groups are not having same distribution, if we only focus on above seven variables.

To see the casual relationship between characteristics of individual and attrition, we employed Probit model. The result says that the married and long time work tends to have larger probability of survival in the data. But age doesn't turn out to be a major factor affecting the attrition probability (Table 3).

Table 3: Non-attrition Probit Result

	Coefficient	Std. Err.	dP/dx	Z
Interviewed personally(d)	0.1086	0.099	0.03613	1.1
Interviewed face to face(d)	0.0403	0.094	0.01325	0.43
Times of interview	0.1649	0.174	0.05386	0.95
Work on short term position(d)	-0.1986	0.177	-0.06828	-1.12
Living in capital area(d)	-0.0977	0.081	-0.03189	-1.21
Be in college(d)	-0.2823	0.175	-0.09877	-1.61
Regular worker(d)	0.0438	0.128	0.01446	0.34
Married(d)***	0.2954	0.097	0.09805	3.06
Divorced(d)	0.2755	0.498	0.0817	0.55
Age	-0.1561	0.108	-0.05099	-1.45
Square of age	0.0024	0.002	0.00079	1.39
Schooling	0.0079	0.018	0.00257	0.45
Tenure**	0.0349	0.012	0.0114	2.83
Monthly work time	-0.0001	0.001	-0.00002	-0.1
Sample size(N)	1199			
Pseudo R^2	0.03			

Notes: *** Significant at 5% level, *** Significant at 1% level.*

3. Analyzing the Impact of Attrition on Regular-irregular Worker Wage Gap

3.1. The Comparison of Attritions and Non-Attritions

We restrict our analysis to relationship between attrition and regular-irregular worker wage gap in 2008. Table 4 shows the wage gap in 2001 and 2008 respectively. Wage gap in 2001 was 0.27 and it increased to 0.33 by 2008. But we cannot conclude that the wage gap increased 0.06 for 7 years, since that measurement isn't obtained with the same group of sample. So we also calculate it with 683 samples of group D which can be observed both in 2001 and 2008 –see figure 1. Regular-irregular worker wage gap among the group D in 2001 was 0.23, which is smaller than wage gap obtained with whole sample. In that case, therefore, the increase in amount of wage gap between 7 years is observed 0.10 that is larger than above result

A statement of above paragraph, that is to say the fact that the wage gap among whole samples is larger than among the group D in 2001, implies the wage gap among group A+B+C is larger than among group D in 2001. And because it is, from a commonsense point of view, unrealizable that wage gap among group C is very high so this increases the wage gap of A+B+C, we can conjecture that wage gap among group A+B is higher than that among group C+D. In a word, the wage gap is larger among attritions than among non-attritions in 2001. Table 5 shows this supposition is true. First row and second row display the wage gap among attritions, and among non-attritions respectively.

Table 4: Wage gap among whole sample and group D

		Log wage	Wage gap
Year 2001 (whole sample, 1199)	regular (1066)	1.54(0.53)	0.27
	rregular(133)	1.27(0.50)	
Year 2001 (group D, 683)	regular (615)	1.55(0.52)	0.23
	irregular (68)	1.32(0.48)	
Year 2008 (group D, 683)	regular (590)	2.24(0.54)	0.33
	irregular (93)	1.91(0.54)	

Table 5: Wage gap among attrition and non-attrition in 2001

		Log wage	Wage gap
Attrition (324)	regular (283)	1.53(0.54)	0.44
	Irregular (41)	1.09(0.47)	
Non-attrition (875)	regular (783)	1.54(0.52)	0.19
	irregular (92)	1.35(0.49)	
Total (1199)	regular (1066)	1.54(0.53)	0.27
	irregular (133)	1.27(0.50)	

As expected, wage gap among attritions shows much larger than that of non-attritions. The wage gap among attritions (0.44) is more than twice as large as that of non-attritions (0.19). This result alludes to possibility of underestimation of regular-irregular worker wage gap in 2008, since samples showing large wage gap attrited.

3.2 The Decomposition of Wage Gap

Let's represent hourly wage a worker by below equation.

$$\ln w_i = \beta_0 + \boldsymbol{\beta_1}\mathbf{x}_i + \beta_2 reg_i + e_i$$

$\mathbf{x}_i$ is a vector that characteristics of the worker which affect his wage. It consists of tenure, age, square age, period of education, daily worktime and married(dummy). Variable tenure is a year of working experience on current job. And reg_i is a dummy variable which is 1 if he is a regular worker. And e_i is a synthesis of all other factors which influence his wage. Let's define the front part of above equation –from first term to third term- be 'explained wage', and e_i be 'unexplained wage'. Then we can represent regular-irregular worker wage gap(WG) in our data as below. (refer to the equation 1)

$$WG = (\overline{\ln w} \mid reg = 1) - (\overline{\ln w} \mid reg = 0)$$

$$= \left(\overline{\beta_0 + \boldsymbol{\beta_1}\mathbf{x}_i + \beta_2 reg_i + e_i}\,\middle|\, reg = 1\right) - \left(\overline{\beta_0 + \boldsymbol{\beta_1}\mathbf{x}_i + \beta_2 reg_i + e_i}\,\middle|\, reg = 0\right)$$

$$= \beta_1 [(\bar{x} \mid reg = 1) - (\bar{x} \mid reg = 0)] + \beta_2 + [(\bar{e} \mid reg = 1) - (\bar{e} \mid reg = 0)]$$

$$= WG1 + WG2 \qquad (1)$$

Where WG1 is gap in average explained wage and WG2 is gap in average unexplained wage. Above formulation can be applied at any group in any wave.

Table 6: ***Explained and unexplained wage gap among attrition and non-attrition in 2001***

		explained wage	unexplained wage	explained wage gap	unexplained wage gap	total wage gap
Attri-tion (324)	Regular (283)	1.50(0.37)	0.031(0.38)	0.33	0.11	0.44
	Irregular (41)	1.17(0.37)	-0.077(0.41)			
Non-attri-tion (875)	Regular (783)	1.55(0.39)	-0.012(0.34)	0.23	-0.04	0.19
	Irregular (92)	1.32(0.41)	0.030(0.43)			
Total 1199	Regular (1066)	1.54(0.53)	0 (0.35)	0.27	0	0.27
	Irregular (133)	1.27(0.50)	0 (0.43)			

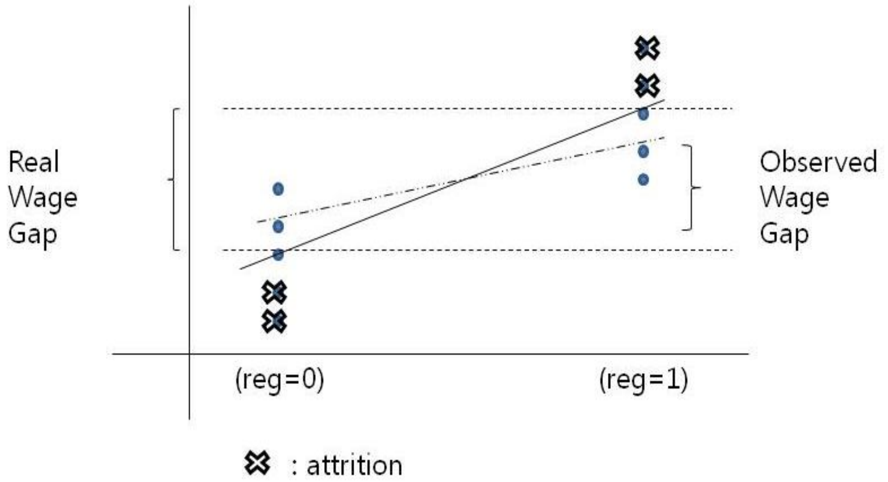
Note: *Unexplained wage of total sample is 0 for both regular and irregular worker. It is because of orthogonality of error term and independent variable ('reg' is independent variable.)*

First, we estimated β_0, β_1 and β_2 with whole sample of 2001 data, and calculated explained wage and unexplained wage for all person. Table 6 summarizes the average of above two values within six groups, and regular-irregular worker wage gap among attritions and among non-attritions. Like the preceding, wage gap is small among non-attritions compare with wage gap among attritions. And we find that both explained wage gap and unexplained wage gap are also small among non-attritions.

4. Estimating Strategies

Since unexplained wage includes the effect of unobserved skill or his other characteristics that last permanently, one's unexplained wage wouldn't change pretty much for seven years. Therefore table 6 says that unexplained wage may be high for irregular worker and low for regular worker in 2008 data. If we assume that the estimation of unexplained wage in 2001 be unbiased, the estimation of unexplained wage in 2008 would be biased because higher unexplained wage workers are attrited among regular worker and the opposite is happened among irregular worker. The mechanism of bias is represented at figure 2. Because higher unexplained wage workers are dropped among regular worker, we would underestimate unexplained wage of regular worker in 2008, and irregular workers are similar except the sign of bias. Thus we underestimate the regular-irregular worker wage gap in 2008.

Figure 2: ***Underestimation of regular-irregular wage gap in 2008***



We want to get unbiased estimator of regular-irregular worker wage gap in 2008. Let's define two kind of bias in the estimation of wage gap. The first is similar to ability bias in returns to schooling literatures that is a bias caused by selection on unobserved ability of workers. We named it as 'ability bias' following traditional terminology. And the second kind of bias, we named it 'distortion bias', is caused by selection on observable. The sum of above two kind of bias is the attrition bias in which we are interested. We will describe these in detail at next section.

4.1 The Ability Bias and Distortion Bias

In this section we will analyze formally the cause of bias defined above. Let's define the attrition equation as below.

Attrition equation: $a_i^* = \gamma_1 \mathbf{x}_{1,i} + \gamma_2 \mathbf{v}_i + \theta_i$ $\qquad \theta \sim N_{iid}(0,1)$

Observable response: (non-attrition) a=1 if a*≥0
(attrition) a=0 if a*<0

Sign 1 at vector $\mathbf{x}_1$ means it is the variable observed in 2001. (First wave compared with 2008, which we will call second wave) And $\mathbf{v}_i$ is a vector of characteristics of the worker which are not contained in the vector $\mathbf{x}_i$. It contains interview related variable such as times of interview, whether he was interviewed personally, etc. and whether he was working on short-term position. And it would be appropriate that contain the interaction of dummy variable 'reg' and unexplained wage in 2001, because it was observed that unexplained wage affect the attrition probability and the effect is opposite between regular and irregular worker.

Let's analyze the process of the bias formally. Below equation is the covariance of a* and ln w_2 (2 denote the wage in 2008. EW is explained wage, and UW is unexplained wage).

$$\begin{aligned}\mathrm{Cov}(a^*, \ln w_2) &= \mathrm{Cov}(\gamma_1 \mathbf{x}_1 + \gamma_2 \mathbf{v} + \theta,\ \beta_0 + \boldsymbol{\beta}_1 \mathbf{x}_2 + \beta_2 \mathrm{reg}_2 + \mathbf{e}_2) \\ &= \mathrm{Cov}(\gamma_1 \mathbf{x}_1 + \gamma_2 \mathbf{v} + \theta,\ EW_2 + UW_2) \\ &= \mathrm{Cov}(\gamma_1 \mathbf{x}_1 + \gamma_2 \mathbf{v},\ EW_2) + \mathrm{Cov}(\gamma_1 \mathbf{x}_1 + \gamma_2 \mathbf{v},\ UW_2) + \mathrm{Cov}(\theta,\ EW_2 + UW_2) \\ &= \mathrm{Cov}(\gamma_1 \mathbf{x}_1 + \gamma_2 \mathbf{v},\ EW_2) + \mathrm{Cov}(\gamma_1 \mathbf{x}_1 + \gamma_2 \mathbf{v},\ UW_2) + \mathrm{Cov}(\theta,\ EW_2 + UW_2)\end{aligned}$$

Let's assume that Cov(θ, EW_2+UW_2) be zero, other variable except UW_1 doesn't affect UW_2. Then above equation is reduced to below equation.

$$\mathrm{Cov}(a^*, \ln w_2) = \begin{cases} \mathrm{Cov}(\gamma_1 \mathbf{x}_1 + \gamma_2 \mathbf{v}, EW_2) + \delta_{reg} \mathrm{Cov}(UW_1, UW_2) < 0 & (\textit{for regular worker}) \\ \mathrm{Cov}(\gamma_1 \mathbf{x}_1 + \gamma_2 \mathbf{v}, EW_2) + \delta_{irreg} \mathrm{Cov}(UW_1, UW_2) > 0 & (\textit{for irregular worker}) \end{cases}$$

Our basic assumption is that Cov(a*, ln w_2| reg_1=1)<0 and Cov(a*, ln w_2| reg_1=0)>0, as we explained previously. This propensity causes the bias in estimation of regular-irregular wage gap as below.

$$E[\ln w_2 \mid reg_1=1,\ a=1] < E[\ln w_2 \mid reg_1=1]$$
$$E[\ln w_2 \mid reg_1=0,\ a=1] > E[\ln w_2 \mid reg_1=0]$$

If there is strong positive correlation between reg_1 and reg_2,

$$E[\ln w_2 \mid reg_2=1,\ a=1] < E[\ln w_2 \mid reg_2=1]$$
$$E[\ln w_2 \mid reg_2=0,\ a=1] > E[\ln w_2 \mid reg_2=0] .$$

And so

$$E[\ln w_2 \mid reg_2=1,\ a=1] - E[\ln w_2 \mid reg_2=0,\ a=1] < E[\ln w_2 \mid reg_2=1] - E[\ln w_2 \mid reg_2=0]$$

which means underestimation of wage gap, and we named it as attrition bias.

Above attrition bias consists of ability bias and distortion bias. In equation (1), the inequality holds for both first and second term. Thus,

$E[EW_2 \mid reg_2{=}1, \ a{=}1] - E[EW_2 \mid reg_2{=}0, \ a{=}1] < E[EW_2 \mid reg_2{=}1] - E[EW_2 \mid reg_2{=}0]$
and

$E[UW_2 \mid reg_2{=}1, \ a{=}1] - E[UW_2 \mid reg_2{=}0, \ a{=}1] < E[UW_2 \mid reg_2{=}1] - E[UW_2 \mid reg_2{=}0]$.

The first inequality represents the 'distortion bias', and the second inequality represents the 'ability bias'. The sum of two inequalities makes inequality XXX, which represents 'attrition bias'.

4.2 Correction of Ability Bias by Using Unexplained Wage in 2001 as a Proxy

The ability bias can be resolved by controlling for one's unobserved ability. We do not know one's exact value of unobserved ability, but assuming that the UW_1 includes the outcome of his unobserved ability gives alternative solution. On this assumption, we can get rid of ability bias wage gap by adding UW_1 as an independent variable. Below is true model for the wage in 2008.

$$\ln w_2 = WG \cdot reg_2 + \zeta_0 + \zeta_1 \cdot ability + \varphi_2$$

WG is wage gap in which we are interested. ζ_0 is a constant term and ζ_1 is premium for ability. φ_2 is a error term which satisfies classical OLS assumption. But if we ignore the unobserved ability then estimation of WG is biased since Cov (reg_2, ability) < 0 so lead to simultaneity.

We use UW_1 as a proxy for ability, since UW_1 consist of premium of time invariant ability and other time variant terms. Then simultaneity problem is resolved and estimator of WG is consistent.

4.3 Correction of Attrition Bias by IPW(inverse probability weight estimator)

In this section, we will describe the weighting approach. We want get the estimator of wage gap among group B+D but we can only observe group D in 2008 data. In section xxx we introduced attrition equation. By estimating this equation with Probit we can get the expected probability of attrition among group B+D. Before estimation of attrition equation we should selected employed in 2008 among attritions, say group B. We conducted this task by applying 'employed Probit model' to non-attritions and obtain group B using that coefficient and standard normal random number generator.

We denote the estimated non-attrition probability $\hat{w}$ and apply weighted least square method by using $\hat{w}^{-1}$ as a weight to get IPW estimator.

5. Empirical Results

We described two estimators. The first is proxy basis estimator, which is free from ability bias. And the second is IPW estimator. If we assume that unemployment in 2008 follow same rule for attritions and non-attritions, it is consistent estimator which is free from ability bias and distortion bias, say attrition bias. We can obtain distortion bias only by subtracting ability bias from attrition bias.

Table 7: *Estimation of regular-irregular wage gap for the model*

Model	Wage Gap
OLS	0.323(0.060)
Proxy	0.332(0.058)
IPW	0.341(0.059)

Table 7 summarizes outcomes of three estimators. The OLS is just the difference of average log hourly wage between regular worker and irregular worker in 2008. As mentioned earlier, the OLS estimator would underestimate the real wage gap. The result in table 7 says that ability bias is about 0.01 and attrition bias is about 0.02, so it is estimated that distortion bias is 0.01.

But the bias is quite smaller than we expected, hence we before find that the wage gap is underestimated by 0.08 in 2001 if we restrict our samples to non-attritions (See table 5). Since there is no reason to wage gap shrink from 0.07 to 0.02, we assumed that many of each group members would have moved to other group, that is to say that many of regular worker has been transferred to irregular position or the otherwise. Therefore the initial attrition bias has been attenuated for seven years. Table 8 shows the transfer of position of non-attrited workers. We find that the half of irregular worker in 2001 has been transferred to regular position while regular workers in 2001 don't show much change of position.

Table 8: Transfer of position of non-attrited workers

2001	**2008**	**N**
regular	regular	556
regular	irregular	59
irregular	regular	34
irregular	irregular	34
total		683

We apply above estimator but only to no-transferred workers this time.(Table 9) Then the attrition bias is measured by 0.046 which is more than twice large as attrition bias measured with whole non-attritions. Therefore we can conclude that underestimation of wage gap is attenuated by transference between groups (regular worker, irregular worker), and the bias is still quite large if we restrict our samples to no-transferred workers.

Table 9: Estimation of Regular-irregular wage gap within no-transferred workers (N=590)

Model	Wage Gap
OLS	0.247(0.094)
Proxy	0.279(0.090)
IPW	0.293(0.093)

6. Conclusion

We analyzed the characteristics of attritions among male worker and find that attrition causes an underestimation of regular-irregular worker wage gap. And we decomposed the bias into two kinds. The first is ability bias which is occurred due to selection on unobservable, and the second is distortion bias occurred due to selection on observable.

We developed two strategies to correct these biases. The first is to use unexplained wage on the first wave data as a proxy of unobserved ability. This method can correct the ability bias. And the second method is weighting approach which can correct two kinds of bias together. We find that the wage gap in 2008 is underestimated about 2% by attrition bias. It is less than we have expected. That is because of transference of position (regular-irregular) of workers.

Our findings indicate that the attrition bias in KLIPS is not negligible and researchers investigating wage gap with KLIPS must consider it. And the most important implication is that we find the estimator which corrects the two kind of bias we explained above.

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