The Effect of Food Delivery Platforms on the Wage Difference after Job Status Changing

By

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ABSTRACT

Since 2019, the food delivery platforms have become extremely prevalent in Taiwan. Many people have started engaging in this new kind of atypical job: food delivery riders. Wage differences, however, can be caused by the change of job status. The goal of this study is to estimate the impact from the rise in food delivery platforms on the labor market. Using data from the Manpower Utilization Quasi-Longitudinal Survey and specific definition of atypical employment, the estimation results suggest that for workers who changed from typical to atypical jobs from 2018 to 2019, even though they still suffered from the change of job status, the pain was less severe since they also received a significant alleviation of income losses. And workers who took atypical jobs from 2018 to 2019 also received additional income gains. The results also suggest people were more likely to take atypical jobs in 2019 even though the income equations in 2019 were not significantly different from those of previous years.

1. Introduction

In Taiwan, the proportion of atypical employment was about 7.13% in 2019 and this ratio is growing gradually in recent years. Also, wage differences can be generated by changing job status. From previous research results, we have seen some evidence showing that people changing their job status from atypical to typical usually enjoy income gains while people changing from typical to atypical suffer income losses. Atypical employment is more flexible, yet, this flexibility comes with a high cost of providing it since atypical workers need to face the risk of vulnerability and lower wages most of the time.

The growth of atypical employment may be attributed partially to global competition. Some firms may lay off typical workers and hire atypical workers to reduce the cost of employees. Yet, different from previous research results, this study focuses on the impact from the rise of the food delivery platforms.

The food delivery platforms have become extremely prevalent in Taiwan since 2019. Many people have become Foodpanda or Ubereats riders to make a living. This new kind of atypical jobs provide significant flexibility for the labor market. People who can't work regularly due to personal issues can now decide when and where to work. For example, college students can become Foodpanda riders after class. That is, the food delivery platforms provide more alternatives for atypical workers. Even workers who have typical jobs can take advantage of this new employment by becoming food delivery riders after work.

Besides the convenience that food delivery platforms provide, it's even possible for some people to earn a lot by doing jobs as food delivery riders. If this is the case, can the rise of this new kind of atypical jobs help reduce income losses people suffer after changing job status or even help them enjoy income gains? Also, will people become more willing to take atypical jobs like food delivery riders due to the rise of this new industry? To address these questions, I use the Manpower Utilization Quasi-Longitudinal Survey obtained from Academia Sinica to conduct the empirical research. I estimate the sign and the magnitude from the impact of the rise in food delivery platforms and its impact on the decision of becoming typical or atypical workers.

2. Literature Review

In Taiwan, some empirical research has shown the increase in atypical employment. Official statistics showed a sharp increase in the proportion of atypical workers. In 2009, The proportion of atypical workers rose from 6.24% to 6.71% due to the financial crisis in 2008 and this proportion still gradually increased despite the recovery of the economy in 2010 (Hsiao, 2013).

The study of the increase in atypical jobs matters since people usually suffer significant income losses from changing their job status to atypical employment. On average, compare to workers having had non-temporary jobs for two consecutive years, workers who move from non-temporary jobs to temporary jobs suffer significant income losses, about 5.8% of the average monthly income and workers who move from temporary to non-temporary jobs receive significant additional income, about 5.4% of the average income (Kuo, 2014).

The definition of atypical workers includes different kinds of jobs. According to Kalleberg (2002), part-time work, temporary agency employment, short-term employment, contingent work and independent contracting constitute atypical employment. Also, every country has different criteria to define atypical work. From the Manpower Utilization Quasi-Longitudinal Survey, however, we can only identify part-time work, temporary and dispatched jobs as atypical employment.

As for the choice of deciding to become full-time or part-time workers, studies have shown married men and people who are older have higher probability of choosing full-time work and non-temporary jobs and people who are divorced have higher probability of choosing atypical jobs (Lu and Chen, 2018).

3. Data Sources and Descriptive Statistics

This study uses the Manpower Utilization Quasi-Longitudinal Survey data from the Center for Survey Research, Research Center for Humanities and Social Sciences, Academia Sinica in Taiwan. This survey is a part of the Manpower Utilization Survey, which has been conducted every year since 1978.

This survey covers civilians in Taiwan who are 15 years or older in age. The data include personal information, such as gender, age, occupation and some information about job status and employment. I use the data from 2016 to 2019. Also, due to data limitation, I can only identify part-time workers, temporary workers and dispatched workers as atypical workers. The definition of food delivery workers is still not settled in Taiwan. In this study, I define them as atypical workers and I can only use available data to define atypical workers.

In this study, workers are divided into two types of job status, atypical and typical jobs. In the first model, the definition of atypical workers includes part-time workers, temporary workers and dispatched workers. Only those who are not only non-temporary and non-dispatched but also full-time workers are considered as typical workers. For example, if a worker is a full-time and temporary worker, even though he is a full-time worker, he will still be considered as atypical worker according to the first definition. Under the first definition, typical workers must be full-time workers and atypical workers may be full-time but temporary and dispatched workers or part-time but non-temporary and non-dispatched workers.

In the second model, the definition of atypical workers only includes temporary workers and dispatched workers. And typical workers are those who are full-time, non-temporary and non-dispatched. That is, the definition of typical worker is largely the same but I use a different definition of atypical workers. Part-time workers are excluded. Therefore, under the second definition, both atypical and typical workers are full-time workers.

We use these two definitions to test whether estimation results are sensitive to different definitions.

Every observation in the sample has data of two consecutive years and all of them are divided into four groups: (S1) workers employed in atypical jobs for two consecutive years; (S2) workers employed in atypical jobs in the first year but changed to typical jobs in the second year; (S3) workers employed in typical jobs in the first year but changed to atypical jobs in the second year; and (S4) workers employed in typical jobs for two consecutive years.

Some data that are not suitable for this study are deleted from the sample. People who did not provide records of monthly income or the records did not show the actual value are excluded. Also, if the personal information, such as age, gender, marital status, educational level or work location, etc., is missing, then these data are excluded from the sample as well. In addition, since this study only focuses on Taiwan, people whose work locations are not in Taiwan (e.g. Mainland China and other countries) are excluded as well.

Some variables are included to control for personal characteristics. These variables are: gender, years of education, potential work experience, marital status, the number of children, work location and industry.

Gender is a dummy variable. It equals one if the respondent is male, and equals zero if the respondent is female. Marital status is also a dummy. It equals one if the respondent is married, and equals zero if the respondent is single, divorced, separated, or widowed.

According to the National Comprehensive Development Plan, work locations are divided into four different regions: northern region, western region, southern region, and eastern and outlying island region. Work industries are divided into three types, corresponding to the three sectors of the economy.

From the original data, we can only see the level of education. Therefore, I transformed the data into years of education. People whose education levels are 1 to 3 (illiterate, self-educated and primary school) are viewed as having 6 years of education. Education level 4 (junior high school) is viewed as having 9 years of education. Education level 5 (senior high school) and 6 (Vocational school) are viewed as having 12 years of education. Education level 7 (Junior college) is viewed as having 14 years of education. Education level 8 (University) is viewed as having 16 years of education. Education level 9 (Master's) is viewed as having 18 years of education. Education level 10 (PhD's) is viewed as having 21 years of education.

Also, we use potential work experience to represent years of experience in the model since using the actual value of work experience may exclude temporary workers and this will cause more difficulties in identifying food delivery riders. Potential work experience is computed as followed:

$$\textbf{potential work experience} = \textbf{age} - \textbf{years of edu} - \textbf{6}(\textbf{preschool})$$

People whose potential work experience is negative are deleted since their years of education are shorter than most people.

Table 1 and 2 present the summary of the variables used in this study. After pooling all available data from 2016 to 2019, there are 35837 respondents using the first definition and 34788 respondents using the second definition. The first four variables are the four groups divided by job status. The following variables include personal information. The descriptive statistics for work location and industry are not provided in both tables since the information is meaningless.

4. Empirical Design

4.1 Model 1

$$Y_i = \alpha + \beta_1 S_{1i} + \beta_2 S_{2i} + \beta_3 S_{3i} + \beta_4 S_{1i}T + \beta_5 S_{2i}T + \beta_6 S_{3i}T + X_i^{'}\boldsymbol{\lambda} + \varepsilon_i \ , i = 1, \dots, N$$

Where Y_i is the difference between wages in the two consecutive years for respondent i, namely, the monthly income in the second year minus the monthly income in the first year. As for $\mathrm{S_i}$, they are a set of dummies indicating the group where individual i belongs:

$\mathrm{S_{1i}}$: This variable indicates workers employed in atypical work for two consecutive years, worker i.

$\mathrm{S_{2i}}$: This variable indicates workers employed in atypical work in the first year but switching to typical work in the second year, worker i.

$\mathrm{S_{3i}}$: This variable indicates workers employed in typical work in the first year but switching to atypical work in the second year, worker i.

And T is a dummy. If the second year is 2019 or beyond, then T equals one. The way I define T is because I take 2019 as the year when food delivery platforms started flourishing in Taiwan.

β_1, β_2 and β_3 are the impacts of these groups by job status. One job status dummy is dropped from the equation, the group where workers were employed in typical work for two consecutive years.

β_4, β_5 and β_6 are the impacts of different groups by job status along with the rise of food delivery platforms. One dummy is also dropped from the equation, the group where workers were employed in typical work for two consecutive years along with the impact of food delivery platforms.

The vector X_i' contains the characteristics of individual i : gender, potential experience and its square, marital status, years of education, work location and the industry of the job, and all these are used to control for the individuals' characteristics.

Before conducting the empirical research, I used the Breusch-Pagan test to see whether there is heteroskedasticity. According to the results from STATA, the LM statistics is about 27.3738 using the first definition and 26.8778 using the second definition and the corresponding p-value is 0.0375 and 0.0429 respectively. Both are smaller than 0.05, that is, we should reject the null hypothesis at 5% significance level. I use robust standard error to address the problem of heteroskedasticity.

4.2 Model 2

$$I_i^* = \alpha T + \boldsymbol{Z}_i \boldsymbol{W}_i + v_i$$

$$\begin{cases} I_i = 1, & if\ I_i^* \geq 0 \\ I_i = 0, & if I_i^* < 0 \end{cases}$$

Where I_i^* indicates whether the respondent i is an atypical worker in the second year or not. It is a latent variable. $\boldsymbol{Z}_i$ is a vector containing the personal characteristics that will affect the probability of choosing between atypical work and typical work. The personal characteristics include: potential work experience and its square, gender, years of education, marital status, the number of children, work location and industry. T is the same dummy that I defined in the previous model. Also, I_i is the observed decision. If a worker decides to engage in atypical work in the second year, then I_i=1, and I_i=0 if the worker decides to engage in typical work in the second year.

In this probit model, we want to see whether the impact of the rise in food delivery platforms is significant in affecting the probability of choosing atypical work. The coefficient of T, namely α, is the focus of interest.

4.3 Model 3

In this part, I use the Heckman model to estimate the impact of the rise in food delivery platforms on monthly income for those who are atypical workers or typical workers originally. The estimation results of this model can tell us whether income gain arises from the flourishing food delivery platforms for atypical workers and typical workers.

The Hackman model is a sample selection model. Sample selection usually occurs when people select themselves into a group. In this study, we want to see the impact of the rise in food delivery platforms on monthly income for both atypical and typical workers respectively. We have the selection decision, whether people choose atypical work or not and whether people choose typical work or not. The reason why we consider typical workers is because it is also possible for typical workers to work as food delivery riders during their free time.

The income equations are as followed:

$$\log(Income_{typ}) = \alpha_{typ}T + \boldsymbol{X}_{typ}\boldsymbol{\beta}_{typ} + u_{typ}$$

$$\log(Income_{atyp}) = \alpha_{atyp}T + \boldsymbol{X}_{atyp}\boldsymbol{\beta}_{atyp} + u_{atyp}$$

Where the vector $\boldsymbol{X}$ contains the same personal characteristics in model 1. T is the same dummy that I defined in the previous models. In the first income equation, we can only observe typical workers. And in the second income equation, we can only observe atypical workers.

Running regression on truncated samples suffers from omitted variable bias if correlation of unobserved income determinants and unobserved determinants of the work decision is negative for atypical workers and positive for typical workers. Observed atypical workers will have lower income than expected from their characteristics (negative selection) and observed typical workers will have higher income than expected from their characteristics (positive selection).

Based on model 2, we can calculate the estimated inverse Mills ratio.

$$\lambda_{iatyp}(\alpha T + \boldsymbol{Z}_i\boldsymbol{W}_i) = \frac{\varphi(\alpha T + \boldsymbol{Z}_i\boldsymbol{W}_i)}{\boldsymbol{\Phi}(\alpha T + \boldsymbol{Z}_i\boldsymbol{W}_i)}$$

$$\lambda_{ityp}(\alpha T + \boldsymbol{Z}_i\boldsymbol{W}_i) = -\frac{\varphi(\alpha T + \boldsymbol{Z}_i\boldsymbol{W}_i)}{\boldsymbol{1} - \boldsymbol{\Phi}(\alpha T + Z_i'W_i)}$$

Where φ is the probability density function of normal distribution and $\boldsymbol{\Phi}$ is the cumulative density function of normal distribution.

Then the income equation can be rewritten as followed:

$$\log(Income_{typ}) = \alpha_{typ}T + \boldsymbol{X}_{typ}\boldsymbol{\beta}_{typ} + \sigma_{typ,u}\rho_{typ,uv}\lambda_{typ} + \varepsilon_{typ}$$

$$\log(Income_{atyp}) = \alpha_{atyp}T + \boldsymbol{X}_{atyp}\boldsymbol{\beta}_{atyp} + \sigma_{atyp,u}\rho_{atyp,uv}\lambda_{atyp} + \varepsilon_{atyp}$$

Where ρ_{uv} is the correlation between the discrete decision and the continuous decision, namely, the income equations that sample selection assumes and σ_u is the standard error of the error term from the income equations.

Some assumptions are needed when using Heckman model. A standard assumption is that **z** from model 2 is exogenous:

$$\mathrm{E}(u|\mathbf{x},\mathbf{z})=0.$$

We also require that **x** be a strict subset of **z**, and we have some elements of **z** that are not also in **x**.

The error term v in the sample selection equation is assumed to be independent of **z** (and therefore **x**). We also assume that v has a standard normal distribution. Assuming that $(u,\ v)$ is independent of **z**, we can derive:

$$\mathrm{E}(\mathrm{y}|\mathbf{z}, v)= \mathbf{x}\boldsymbol{\beta}+ \mathrm{E}(u|\mathbf{z}, v)= \mathbf{x}\boldsymbol{\beta}+ \mathrm{E}(u|\ v),$$

where $\mathrm{E}(u|\mathbf{z}, v)= \mathrm{E}(u|\ v)$ because $(u,\ v)$ is independent of **z**. Now, if u and v are jointly normal (with zero mean), then $\mathrm{E}(u|\ v) = \rho v$ for some parameter ρ. Therefore,

$$\mathrm{E}(\mathrm{y}|\ \mathbf{z}, v)= \mathbf{x}\boldsymbol{\beta}+ \rho v.$$

We do not observe v, but we can use this equation to compute $\mathrm{E}(\mathrm{y}|\ \mathbf{z},\ I)$ and then specialize this to I =1. We now have:

$$\mathrm{E}(\mathrm{y}|\ \mathbf{z},\ I)= \mathbf{x}\boldsymbol{\beta}+ \rho \mathrm{E}(v|\mathbf{z},\ I).$$

Because I and v are related by sample selection equation, and v has a standard normal distribution, we can show that $\mathrm{E}(v|\mathbf{z}, I)$ is simply the inverse Mills ratio, $\lambda(\alpha T + \boldsymbol{ZW})$, when I =1. This leads to the important equation :

$$\mathrm{E}(\mathrm{y}|\ \mathbf{z},\ I=1)= \mathbf{x}\boldsymbol{\beta}+ \rho\ \lambda(\alpha T + \boldsymbol{ZW}).$$

When u and v are uncorrelated, $\rho = 0$.

Because $\boldsymbol{W}$ and α are unknown, we can not evaluate $\lambda(\alpha T + \boldsymbol{Z}_i\boldsymbol{W})$ for each i. However, from the assumptions we have made, I given $\mathbf{z}$ follows a probit model:

$$P(I = 1|\mathbf{z}) = \boldsymbol{\Phi}(\alpha T + \boldsymbol{ZW}).$$

Therefore, we can estimate $\boldsymbol{W}$ and α by probit of I_i on $\boldsymbol{z}_i$ and T, using the entire sample.

5. Estimation Results

5.1 Model 1

Table 3 presents OLS estimates for income difference in two consecutive years according to the groups by job status along with the rise in food delivery platforms and the personal characteristics.

Using the first definition, workers in group S2, who had atypical work in the first year and changed to typical work in the second year, benefited from the change of job status. The average monthly income for workers in group S2 is more than workers employed in typical jobs for two consecutive years by about $3521 NTD.

Workers in group S3, who had typical work in the first year and changed to atypical work in the second year, suffered from the change of job status. The average monthly income for workers in group S3 is less than workers employed in typical jobs for two consecutive years by about $3006 NTD.

Unexpectedly, using the first definition, workers who were in group S2 from 2018 to 2019 got more benefits from the change of job status. This result may suggest there were factors other than the rise in food delivery platforms in 2019 or the existence of the channel for food delivery platforms to affect workers in group S2.

Using the second definition, workers in group S2, who had atypical work in the first year and changed to typical work in the second year, benefited from the change of job status. The average monthly income for workers in group S2 is more than workers employed in typical jobs for two consecutive years by about $2032 NTD.

Workers in group S3, who had typical work in the first year and changed to atypical work in the second year, suffered from the change of job status. The average monthly income for workers in group S3 is less than workers employed in typical jobs for two consecutive years by about $1830 NTD.

In addition, workers who were in group S1 from 2018 to 2019, that is, those who had atypical jobs from 2018 to 2019, enjoyed a significant income gain. Their average monthly income was more than those who had typical jobs for two consecutive years from 2018 to 2019 by about $1124 NTD.

Workers who were in group S3 from 2018 to 2019, that is, those who had typical work in 2018 and atypical work in 2019, enjoyed alleviation of income loss by about $1431 NTD. Even though workers in this group still suffered from the change of job status overall, those who did the job status change from 2018 to 2019 suffered significantly less than those who did during other periods of time.

The reason why these two estimation results differ is probably because whether we include part-time workers as atypical workers or not. Using the first definition, we include part-time workers as atypical workers and the estimation results turn out to be unexpected. Using the second definition, however, we exclude all part-time workers. The definition of atypical employment simply includes those who are temporary and dispatched workers. Even though temporary workers, dispatched workers, and part-time workers can all be considered as atypical workers in general, the first two types of workers still differ from part-time workers. One possible explanation is part-time work actually has more restrictions than temporary and dispatched work. Part-time work is pretty similar to typical work. The biggest difference between part-time work and typical work is usually only the degree of work involvement like work hours. Also, there may exist trade-offs between food delivery riders and part-time workers. For example, food delivery riders have much more freedom to choose when and where to work, their 'mobility' is why part-time workers are less like food delivery riders. In other words, using temporary and dispatched workers to represent food delivery riders may be more suitable and the inclusion of part-time workers may lead the estimation results to be unclear.

5.2 Model 2

Probit model is estimated using the maximum likelihood method. And we can only interpret the sign of the coefficient but not the magnitude. The magnitude cannot be interpreted using the coefficient because different models have different scales of coefficients. Therefore, we will use the average marginal effects from table 5 to interpret the estimation results.

Using the first definition of atypical workers, we can see T is statistically significant, which is what we expected. In 2019, the likelihood of taking atypical work became about 0.7% more likely. Those who work in Eastern and outlying island region are about 2% more likely to work as atypical workers than those who work in the northern region. It is also about 2% more likely for those who work in secondary industry to choose atypical work than those who work in tertiary sector.

It is about 1% less likely for men to work as atypical workers than women. For each additional year in education, individuals are about 1% less likely to become atypical workers. Those who are married are about 3% less likely to work as atypical workers than those who are single, divorced, separated, or widowed. It is about 3% less likely for people who work in primary industry to choose atypical work than those who work in tertiary sector as well.

Using the second definition, the estimation results are a little bit different. In 2019, the likelihood of taking atypical work became about 0.4% more likely. Also, people who work in other regions are more likely to choose atypical work than people who work in the northern region. It is also about 3% more likely for those who work in secondary industry to choose atypical work than those who work in tertiary sector.

For each additional year in education, individuals are about 0.9% less likely to become atypical workers. Those who are married are about 2% less likely to work as atypical workers than those who are single, divorced, separated, or widowed.

The sign of potential work experience is positive for both definitions. This may suggest for people who have zero years of potential work experience, an additional year of potential work experience will increase the likelihood of becoming atypical workers but the marginal effect is decreasing since the sign of the square of potential work experience is negative.

5.3 Model 3

From table 6 and table 7, we can see the coefficient of T is not statistically significant at 5% level for both typical and atypical workers no matter using the first or the second definition of atypical workers. We may conclude that the benefits resulting from the rise in food delivery platforms were only reaped by those who change their job status and there is no significant difference between income equations in 2019 and income equations in previous years.

6. Discussion

The main restriction of this study is resulted from the dummy variable T, which is expected to capture the impact of rise in food delivery platforms in this study.

Yet, the assumption that the impact of T can be attributed simply to the rise of food delivery platforms is quite strong. Other factors may influence workers' income during 2019. From model 1 and model 2, we've seen people were more likely to choose atypical work using either the first definition or the second definition in 2019. Also, people who are in group S2 enjoy additional income benefit in 2019 using the first definition and people who are in group S1 and group S3 enjoy additional income benefit in 2019 using the second definition. But it is possible that these statistically significant results are the outcome from other economic or social factors. Another restriction is even though most counties in Taiwan had had the food delivery service in 2019, they were covered by the service in different months. Therefore, the estimation results may be overestimated.

To justify this main assumption, we need to be confident to argue that if there is no flourishing in the food delivery platforms industry, then Y_i should be stable. We can see whether Y_i before 2019 is stable or not. If this is the case, then we can be more confident to argue it is the rise in food delivery platforms that results in the differences in 2019. It is also important to check whether the statistically significant results are similar in 2020 since the food delivery platforms were still growing during 2020. Yet, since the data of the Manpower Utilization Quasi-Longitudinal Survey has not been released, we don't have available data to check.

Table 8 and table 9 show the average monthly income difference from 2016 to 2019. Table 8 uses the first definition and S2*T is statistically significant in model 1. Therefore, we check whether the average monthly income difference for group S2 in 2017 and 2018 is stable or not and it seems that the number does not vary a lot from 2017 to 2018.

Table 9 uses the second definition and both S1*T and S2*T are statistically significant in model 1. Therefore, we check whether the average monthly income difference for both groups S1 and S3 in 2017 and 2018 are stable or not. The numbers are largely negative around -1000 from 2017 to 2018 for group S3. But the number varies quite significantly from 2017 to 2018 for group S1.

To justify our assumption more carefully, we run the regression from model 1 again. Instead of using data from 2016 to 2019 like table 3, we only use data from 2016 to 2018. Also, instead of using T as a dummy, I define another dummy, G, which equals one if the second year is 2018, otherwise G=0. Table 10 shows the estimation results. And we can see the coefficients of S1*G, S2*G, and S3*G, no matter using the first or the second definition, are not statistically significant at 5% level and most of them are even negative.

From the discussion above, we can have faith in our assumption to some extent. In the future, using data from 2015 and 2020 may give us much more clear information of the impact from the rise in food delivery platforms. In addition, it is also possible to conduct a Difference-in-Differences estimation method. As we mentioned earlier, counties in Taiwan were covered by the food delivery service in different months in 2019. We can thus take counties that were covered by the service later in 2019 as control groups. But this approach is less feasible since we don't have monthly income data of every individual. Another approach is more feasible. If we take a glance at the Foodpanda service region, we will find that even though a county is classified as having the food delivery service, it may not be fully covered. We can thus use towns or cities as work locations and divide them into fully covered, partially covered, and not covered since the Foodpanda service regions are not adhered to the administrative regions. Taking towns that are not covered as control groups is appropriate to some extent since Foodpanda is the biggest food delivery platform in Taiwan and people who use Foodpanda service are mostly overlapped with people who use other food delivery platforms such as Ubereats.

Appendix

Table 1

Summary of pooled data using the first definition

Variable	N	Mean	Std.Dev	Min	Max
S1(atyp to atyp)	35837	0.0328	0.1782	0	1
S2(atyp to typ)	35837	0.0262	0.1597	0	1
S3(typ to atyp)	35837	0.0202	0.1406	0	1
S4(typ to typ)	35837	0.9208	0.2700	0	1
Income_1	35837	38730.35	25007.99	1000	989800
Income_2	35837	39649.64	22575.51	1000	970000
Deltainc	35837	919.2935	16583.76	-932200	920000
Gender	35837	0.6028	0.4893	0	1
Age	35837	43.9309	12.2858	17	90
Potential work experience	35837	24.8381	14.0411	0	78
Years of Edu	35837	13.0928	3.1502	6	21
Married	35837	0.5685	0.4953	0	1
The number of children	35837	1.6126	0.4872	1	2

Table 2

Summary of pooled data using the second definition

Variable	N	Mean	Std.Dev	Min	Max
S1(atyp to atyp)	34788	0.0172	0.1301	0	1
S2(atyp to typ)	34788	0.0185	0.1348	0	1
S3(typ to atyp)	34788	0.0157	0.1242	0	1
S4(typ to typ)	34788	0.9486	0.2208	0	1
Income_1	34788	39261.02	25064.33	1000	989800
Income_2	34788	40151.44	22579.44	1000	970000
Deltainc	34788	890.4201	16698.13	-932200	920000
Gender	34788	0.6071	0.4884	0	1
Age	34788	43.8494	12.2083	17	90
Potential work experience	34788	24.7218	13.9440	0	78
Years of Education	34788	13.1276	3.1296	6	21

Married	34788	0.5698	0.4951	0	1
The Number of children	34788	1.6110	0.4875	1	2

Table 3

Estimation results of model 1

	Using the first definition	Using the second definition
(S1) atyp to atyp	176.8047 (318.6845)	-317.1439 (353.7275)
(S2) atyp to typ	3520.758*** (573.5731)	2032.458*** (710.8112)
(S3) typ to atyp	-3006.384*** (426.1571)	-1829.979*** (434.1265)
(S1*T)	124.0088 (442.115)	1124.329** (532.7858)
(S2*T)	1768.608** (857.3087)	940.1361 (876.8456)
(S3*T)	379.2289 (893.5097)	1430.643** (703.9547)
Years of Education	47.7719 (50.5144)	52.7935 (52.0902)
Potential work experience	-23.8881 (21.1386)	-14.4692 (21.8605)
Potential work experience square	0.1024 (0.3510)	-0.0282 (0.3655)
Male	10.1060 (157.8655)	5.8822 (160.3468)
Married	-119.109 (168.3174)	-131.0143 (172.1273)
Work location	Included	Included
Industry	Included	Included
Constant	750.1551 (853.1756)	565.7144 (878.4462)
R-squared	0.0033	0.0015
N	35837	34788

NOTE: The OLS estimation uses the robust standard error to address heteroskedasticity and the data are from 2016 to 2019.

***Significant at the 1 percent level

**Significant at the 5 percent level
*Significant at the 10 percent level

Table 4
Estimation results from model 2

	Using the first definition	Using the second definition
T	0.0700*** (0.0239)	0.0621** (0.0295)
Potential work experience	0.0056* (0.0031)	0.0125*** (0.0040)
Potential work experience square	-0.0001** (0.00005)	-0.0003*** (0.00007)
Male	-0.1075*** (0.0242)	0.0276 (0.0305)
Years of education	-0.0960*** (0.0050)	-0.1306*** (0.0065)
Married	-0.2460*** (0.0322)	-0.2626*** (0.0396)
The number of children	0.0714* (0.0378)	0.0087 (0.0457)
Western region	-0.0179 (0.0296)	0.1001*** (0.0360)
Southern region	0.0265 (0.0277)	0.0888** (0.0348)
Eastern and outlying island region	0.2363*** (0.0559)	0.3491*** (0.0679)
Primary industry	-0.3082*** (0.0530)	-0.0916 (0.0623)
Secondary industry	0.2232*** (0.0250)	0.4671*** (0.0311)
Constant	-0.5120*** (0.0959)	-0.4874*** (0.1205)
Pseudo R-squared	0.0617	0.1094
N	35837	34788

NOTE: The data are from 2017 to 2019.
***Significant at the 1 percent level
**Significant at the 5 percent level

*Significant at the 10 percent level

Table 5

Average marginal effects from model 2

	Using the first definition	Using the second definition
T	0.0071*** (0.0024)	0.0041** (0.0020)
Potential work experience	0.0006* (0.0003)	0.0008*** (0.0003)
Potential work experience square	-0.00001** (5.06e-06)	-0.00002*** (4.37e-06)
Male	-0.0110*** (0.0025)	0.0018 (0.0020)
Years of education	-0.0098*** (0.0005)	-0.0087*** (0.0005)
Married	-0.0251*** (0.0033)	-0.0175*** (0.0027)
The number of children	0.0073* (0.0039)	0.0006 (0.0030)
Western region	-0.0018 (0.0030)	0.0067*** (0.0024)
Southern region	0.0027 (0.0028)	0.0059** (0.0023)
Eastern and outlying island region	0.0241*** (0.0057)	0.0232*** (0.0045)
Primary industry	-0.0315*** (0.0054)	-0.0061 (0.0041)
Secondary industry	0.0228*** (0.0026)	0.0311*** (0.0022)

NOTE: The data are from 2017 to 2019.

***Significant at the 1 percent level

**Significant at the 5 percent level

*Significant at the 10 percent level

Table 6

Estimation results for atypical workers from model 3

	Using the first definition	Using the second definition
T	0.0817* (0.0478)	0.2658 (0.2873)
Years of Education	-0.0446 (0.0540)	-0.3881 (0.5548)
Potential work experience	0.0226*** (0.0053)	0.0486 (0.0572)
Potential work experience square	-0.0004*** (0.00009)	-0.0012 (0.0015)
Male	0.1738** (0.0694)	0.2834 (0.1835)
Married	-0.0899 (0.1188)	-0.7148 (1.0837)
Western region	0.0364 (0.0354)	0.3017 (0.4480)
Southern region	-0.0842** (0.0347)	0.1552 (0.4036)
Eastern and outlying island region	0.0655 (0.1430)	0.8743 (1.4805)
Primary industry	-0.2804 (0.1782)	-0.5108 (0.4451)
Secondary industry	0.3962*** (0.1278)	1.5401 (1.9891)
Constant	8.6878*** (0.6824)	5.9817 (5.2518)
Uncensored obs	1899	1144
Censored obs	33938	33644
Number of obs	35837	34788

NOTE: The data are from 2017 to 2019.

***Significant at the 1 percent level

**Significant at the 5 percent level

*Significant at the 10 percent level

Table 7

Estimation results for typical workers from model 3

	Using the first definition	Using the second definition

T	0.0026 (0.0231)	0.0142 (0.0194)
Years of Education	0.0978*** (0.0106)	0.0905*** (0.0069)
Potential work experience	0.0178*** (0.0028)	0.0169*** (0.0025)
Potential work experience square	-0.0002*** (0.00005)	-0.0002*** (0.00004)
Male	0.2465*** (0.0249)	0.1999*** (0.0193)
Married	0.1679*** (0.0321)	0.1483*** (0.0242)
Western region	-0.0587** (0.0269)	-0.0854*** (0.0237)
Southern region	-0.1051*** (0.0256)	-0.1126*** (0.0225)
Eastern and outlying island region	-0.1628** (0.0638)	-0.1475*** (0.0534)
Primary industry	-0.2456*** (0.0567)	-0.3311*** (0.0407)
Secondary industry	-0.1167*** (0.0329)	-0.1393*** (0.0298)
Constant	8.6035*** (0.2023)	8.8367*** (0.1153)
Uncensored obs	33938	33644
Censored obs	1899	1144
Number of obs	35837	34788

NOTE: The data are from 2017 to 2019.

***Significant at the 1 percent level

**Significant at the 5 percent level

*Significant at the 10 percent level

Table 8

Average monthly income difference over time

Definition1	Year_2	Mean	Std.Dev	Freq.
S1	2017	345.1345	8004.9759	342
	2018	1448.7283	7746.1026	368

	2019	1062.2318	7087.1131	466
S2	2017	4422.0266	17412.919	338
	2018	4228.4437	9961.1346	311
	2019	6155.0173	11037.98	289
S3	2017	-1970.1843	9285.7103	293
	2018	-2619.467	8893.7012	212
	2019	-1864.8624	11803.809	218
S4	2017	835.6132	17244.777	11323
	2018	946.0644	18118.804	10489
	2019	836.9929	15580.195	11188
Total	2017	853.6975	16927.243	12296
	2018	985.5993	17584.886	11380
	2019	923.5701	15212.142	12161

Table 9

Average monthly income difference over time

Definition2	Year_2	Mean	Std.Dev	Freq.
S1	2017	923.1954	6203.3539	174
	2018	11.4462	6181.3405	195
	2019	1578.6957	6367.1255	230
S2	2017	2939.5311	19152.457	241
	2018	2772.1429	8260.5438	217
	2019	3815.0538	7228.8677	186
S3	2017	-881.5688	8893.4847	218
	2018	-1251.1274	6425.319	157
	2019	410.5882	7443.905	170
S4	2017	835.6132	17244.777	11323
	2018	946.0644	18118.804	10489
	2019	836.9929	15580.195	11188
Total	2017	847.9867	17062.703	11956
	2018	934.2222	17723.773	11058
	2019	892.3710	15271.397	11774

Table 10

Estimation results of model 1 from 2016 to 2018

	Using the first definition	Using the second definition
(S1) atyp to atyp	-331.7744	261.7799

	(460.6426)	(505.5082)
(S2) atyp to typ	3713.69*** (958.5733)	2220.343* (1244.12)
(S3) typ to atyp	-2630.817*** (569.9738)	-1569.844** (632.5701)
(S1*G)	1113.528* (593.5051)	-903.0376 (648.5904)
(S2*G)	-319.9662 (1104.034)	-328.7486 (1360.569)
(S3*G)	-633.6195 (811.2287)	-347.99 (788.3766)
Years of Education	81.8246 (51.3466)	79.9563 (52.9513)
Potential work experience	-19.3383 (28.0303)	-10.7244 (29.0245)
Potential work experience square	-0.0231 (0.4888)	-0.1568 (0.5103)
Male	-11.49049 (197.9788)	0.4492 (201.1272)
Married	-131.0119 (223.2177)	-152.8862 (228.5606)
Work location	Included	Included
Industry	Included	Included
Constant	379.3554 (883.7469)	313.6201 (909.5658)
R-squared	0.0031	0.0017
N	23676	23014

NOTE: The OLS estimation uses the robust standard error to address heteroskedasticity and the data are from 2016 to 2018.
***Significant at the 1 percent level
**Significant at the 5 percent level
*Significant at the 10 percent level

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