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A NON-HEALING WOUND: LASTING CONSEQUENCES OF UNEMPLOYMENT AND INFORMAL SELF-EMPLOYMENT: AN EMPIRICAL EVIDENCE FROM INDONESIA

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Abstract

Economic inactivity has long been seen to lead to the deterioration of future labor market prospects. This negative effect on future labor outcomes potentially lasts for the individual's entire remaining working lifetime. Although there seems to be a consensus on the negative relationship between present spells of unemployment and future labor market outcomes, the literature discussing why and how this is the case, especially in developing countries, is limited. The challenges of labor market transitions are, without a doubt, complex, and the cases for developing countries could be different from those for developed countries. Therefore, to further extend the discussion in the literature, this paper attempts to investigate how self-employment in the informal sector, rather than unemployment per se, influences the scarring effects, especially in the context of Indonesia, where informality is prevalent. This paper finds that scarring effects due to previous unemployment and self-employment are more observable among senior workers. Besides, there is also evidence of scarring effect due to self-employment among young workers age 25-34 years, which is more substantial than that due to unemployment. The estimation results show that the duration of unemployment negatively affects subsequent earnings, particularly for senior workers and workers in the low-income group. In the meantime, years spent in self-employment has no significant effect on subsequent earnings, either when the sample is disaggregated by age, income distribution, gender, or location of residence. This evidence could indicate that the opportunity for human capital accumulation in self-employment is limited and/or employers may use this information as an indicator of low productivity.

Keywords: scarring effect, human capital, unemployment, self-employment

JEL Classifications: I25, I28, J24, J48

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1. Introduction

The global recession has left its mark, and many young people today have to encounter a higher level of economic and social uncertainty. The problem where young workers are unable to effectuate their full potential is not uncommon since the access to productive and decent jobs matching their qualifications and aspirations is limited. This issue is non-trivial for economic development, especially as the "demographic dividend" can turn into a source of instability provided that young people continue to face dissatisfactory outcomes in their search for employment. The question of how to enhance and support young persons' entry into a decent job has become even more pressing and complex, both in developed and developing countries. In Indonesia, while overall unemployment is at 5 percent, the youth (15-24) unemployment rate is at 15.8 percent in 2018, an increase of 0.5 percentage points compared to the previous year (ILO, 2019). This figure is relatively high compared to the average number in the region – Southeast Asia's youth unemployment rate is at 13.1 percent. Not to mention, the share of unemployed youth in total unemployment is substantial at 57.9 percent, which is nearly twice the global average of 30 percent (ILO, 2017).

Unemployment, nevertheless, is only the tip of the iceberg; the nature and quality of employment available to the young generation have also been an issue of concern. In developing countries, vulnerable and/or informal types of employment have come to dominate the youth labor market experience. Although workers who are engaged in the informal sector are typically categorized as employed, this type of employment has little, if any, access to pensions, health benefits, and formal training. In addition, the lengthy and challenging transition from school to work will leave "scars" and have enduring repercussions not only on young people themselves but also on their families and communities. During periods of economic inactivity, young workers may experience human capital reduction as they lose out on the opportunity of obtaining job-specific training and suffer from disparagement of general or transferable work skills (Gregory and Jukes, 2001). These two aspects of loss of human capital due to time spent in unemployment are regarded as giving rise to lower productivity and, thus, to worse employment prospects when returning to the labor market (Edin and Gustavsson, 2008; Mooi-Reci and Ganzeboom, 2012). This degradation of labor market outlook emerging directly from an early curse of unemployment is often labelled as "scarring". It can materialize in the form of higher unemployment propensity and/or lower subsequent earning, which conceivably continue throughout the rest of an individual's working lifetime.

As analysis on scarring requires panel surveys with a sufficiently long time-series observation, most of its existing research is conducted in the advanced economies, particularly in the US, UK, and some European countries where such data present. Although there seems to be a consensus that current unemployment spells and future labor outcomes are negatively correlated, the literature discussing why and how this is the case, especially in developing countries, is limited. The challenges of labor market transitions are, without a doubt, complex, and the cases for developing countries could be really different from those for developed countries. In many developing countries, including Indonesia, the adverse conditions experienced by workers are not essentially limited to unemployment. Most workers in Indonesia work in the informal sector as they cannot afford to be unemployed. Per data from the National Labor Force Survey (*Sakernas*) 2019, more than 55 percent of workers in Indonesia are involved in informal sector employment. This rate is higher among poor workers; approximately 65 percent of workers with income in the bottom 20 percent work in the informal sector. Workers who work in the informal sector tend to receive lower wages and are exempt from labor regulations and workplace benefits when compared to those who work in the formal sector (Maloney, 2004). In this context, Naidoo et al. (2015) has attempted to investigate the occupational mobility and job quality of workers in Indonesia using the duration of self-employment as the source of scarring. Beyond what has been done by Naidoo et al. (2015), this paper will also look at the effect of unemployment and self-employment *incidence*, in addition to their durations. Moreover, this paper employs a quasi-experimental research design using the difference-in-difference approach to analyze the scarring effects of previous unemployment and self-employment.

The limited research that attempts to address the issue of scarring effects from the perspective of previous informal employment indicates a serious gap in the literature. This paper makes three main contributions to the literature. First, it serves a further investigation on the effect of youth unemployment on adult labor market outcomes by introducing a dimension specific to emerging and developing economies – informality – to previous studies in advanced economies. Second, by using a rich longitudinal household survey from the Indonesian Family Life Survey (IFLS), it provides a fresh analysis of the variation in scarring effects based on individual and household background. Third, the quasi-experimental research design applied in this paper may provide a clear and straightforward interpretation of the scarring effects. This paper can be seen as a way to develop an evidence-based policy formation. If there is evidence for more marked scarring effects of informal employment, active labor market policies are required not only to promote employment by itself but desirably also formal employment. Besides, the government could intervene by facilitating a smooth transition from school to work and providing continuous training opportunities for human capital accumulation, especially for those working in the informal sector.

For ease of presentation, this paper is divided into the following chapters after this introduction. Chapter 2 will discuss the literature reviews on the unemployment scarring in the labor market, as well as scarring effects in certain types of employment. In Chapter 3, we will discuss the case of youth unemployment, human capital, and skill formation in Indonesia. Chapter 4 will explain the economic framework as the foundation of this research. Chapter 5 will explain the data characteristics and methodology used in this study. Next, Chapter 6 will present and discuss the empirical results. Chapter 7 will provide a robustness check of the analysis. Finally, Chapter 8 will provide conclusions and policy implications.

2. Literature Review

2.1 Unemployment Scarring in Labor Market

In the area of unemployment research, there is an expanding study that continues to investigate the long-run employment consequences of economic inactivity (i.e., time mostly spent in unemployment). Arulampalam et al. (2001) found that, in several countries, the present unemployment spell of an individual may intensify his/her possibility of being unemployed in the future. Specifically, the study finds evidence that interruptions during employment not only bring the immediate decline in the current earnings but impose a longer-term “scar” through the increase of future unemployment occurrence and the reduction in subsequent earnings. This condition is referred to as the “scarring effect” of unemployment.

The scarring theory of unemployment predicts that an individual experiencing present unemployment will function differently in the future to an otherwise comparable individual who does not have to undergo unemployment. In this regard, the human capital theory contributes feasible explanations for the scarring effects of previous labor market experiences (Becker, 1994). If workers suffer from unemployment, their firm-specific skills are permanently lost, while their general or transferable work skills depreciate, and as the time of economic inactivity lengthens, this process precipitates (Gregory and Jukes, 2001). This reduction of human capital arising from unemployment results in lower productivity and, therefore, a greater propensity of unemployment and/or a lower salary when entering back to employment. Meanwhile, from the labor demand’s point of view, this state dependence – or scarring – emerges because employers may use one's unemployment record as a screening device (Phelps, 1972; Lockwood, 1991; Blanchard and Diamond, 1994). Moreover, firms may open fewer vacancies following a demand contraction in the economy due to the decline in the perceived average quality of the unemployed (Pissarides, 1992; Bean, 1997). Another alternative explaining the mechanism behind is that workers who have been laid off are more inclined to take low-quality jobs characterized by high rates of job destruction (Arulampalam et al., 2000).

Using difference-in-difference estimation, Arulampalam (2001) and Gregory and Jukes (2001) investigate wage scarring, the effect of previous unemployment on subsequent earnings. The study by Arulampalam (2001), using British Household Panel Survey from 1991-1997, finds a significant wage penalty to employment interruptions, which takes an inverted U-shape and is estimated to be about 6 percent during the first year of re-entry. In support to that finding, Gregory and Jukes (2001), using British administrative data for the period 1984-1994, observes that the decrease in wage as an effect of a job interruption is estimated to be around 10 percent over the first year and a further wage penalty varying according to the length of the duration of unemployment. Meanwhile, Gregg (2001) examines the effect of present unemployment incidence on the potential of future unemployment. In other words, how unemployment experience at the beginning of a career contributes to the likelihood of being unemployed during adulthood. This paper demonstrates robust evidence of structural dependence induced by early unemployment experience, particularly among male workers, with only small persistence in unemployment.

The evidence pertaining to unemployment persistence is found to be dissimilar between young, possibly more agile and mobile workers, and for more mature workers. Arulampalam et al. (2000), using the first five waves of the British Household Panel Survey, discovers that "state dependence" for relatively older workers (aged 25 years and over) is much greater than that for young workers (aged less than 25 years). It is argued that, in accordance with the signaling hypothesis, unemployment occurrence and duration may be translated by employers as indications for unobservable worker productivity. The signaling hypothesis might operate in a distinct way for young and more mature workers. "Job-shopping" is perceived as a reasonable form of behavior for young workers; hence, employers may be less likely to take advantage of young workers' prior unemployment record as a negative signal (Arulampalam et al., 2000). In like manner, Gregory and Jukes (2001) observe that the effect of unemployment incidence is more marked among older workers; however, the effect of unemployment duration is more considerable for young workers. Gregory and Jukes (2001) also argue that the effect of unemployment incidence is only a temporary effect; by contrast, the effect of unemployment duration is permanent as any deterioration of transferable skills should be associated to time mostly spent in unemployment.

A number of studies also suggest that economic recessions may have a significant long-term impact on future earnings. Using an extensive longitudinal Canadian employer-employee-matched data set of male college graduates, Oreopoulos et al. (2012) uncover that new graduates may face substantial cost as an impact of recessions. This finding indicates that notably brief adverse labor market conditions have long-term consequences, in which a climb in unemployment rates by 5 percentage points suggests an initial loss in income of about 9 percent. They also find evidence for differential effects across different college graduates, in which those who graduated from more prestigious colleges and/or majors are hurt less by the unfavorable conditions of graduating in recessions as they have faster mobility to high-wage paying companies. On the other hand, the less advantaged graduates, in particular, have a higher propensity of early-career interruptions associated with persistent adverse effects on earnings. Meanwhile, a study by Kondo (2015) using the US database finds that the initial effect of an increasing unemployment rate due to a recession is more potent but fades faster for blacks and is weaker for women. This finding is in line with the economic theories, which posit less for persistence poorly qualified or disadvantaged workers, and smaller impacts among those with a weak attachment to the labor force.

2.2 Scarring Effects in Certain Types of Employment

The literature on scarring effects has been extended to take into account scarring effects from specific types of employment, as opposed to unemployment per se, including self-employment (Hyytinen and Rouvinen, 2008) and contingent (non-permanent) employment (Yu, 2012). The results of the study done by Hyytinen and Rouvinen (2008), using the European Community Household Panel reveal that individuals who re-enter formal wage employment after some time in self-employment have to endure a wage penalty. However, this finding is likely to be biased upward due to the negative relationship between self-selection to self-employment and unobserved ability and/or productivity. In addition, the study also finds that wage scarring due to the previous self-employment is relatively lower than that due to unemployment. In the context of Japan, Yu (2012) finds evidence that individuals' transition to formal employment may be delayed as an effect of working in a contingent type of employment, which could be more severe than remaining unemployed. This finding could be the case as the labor market in Japan is very segmented to no small extent, in which separation of labor supply for standard and contingent jobs is very harsh (Yu, 2012).

Scarring effects are copiously documented in developed countries, and only a few studies have been carried out in developing countries. As distinct from developed countries, two prominent features of the labor market in developing countries are: (1) the prevalence of the informal sector in which 93 percent of the world's informal employment is in developing countries (ILO, 2018); and, (2) the economic activity cannot be understood as the "derived demand for labor" (i.e., labor demand derived from product-market demand) as most self-employment is actually an effort at "demand creation" (Campbell and Ahmed, 2012). Moreover, among low-income households in developing countries, being self-employed is potentially selected not for the sake of its career prospects, but rather since it is the sole option available to generate income. For example, in Indonesia, according to the National Labor Force Survey (*Sakernas*) 2019, around 95 percent of self-employed workers are working in the informal sector. Therefore, a broader notion of scarring would be valuable in analyzing its impacts on labor outcomes. Especially for developing nations, in which a rigid distinction between unemployment and certain types of employment, such as casual work or self-employment, could be deceptive. Wage scarring from being in self-employment could emerge when its impacts on human capital are comparable to that of being in unemployment. This condition could be the case if an individual is no longer have the chance to accumulate firm-specific skill, and at the same time, his/her general human also deteriorates (Williams, 2000). In addition, not being able to achieve positive outcomes in self-employment may be perceived by employers as a cue that the individual is of low ability and/or productivity.

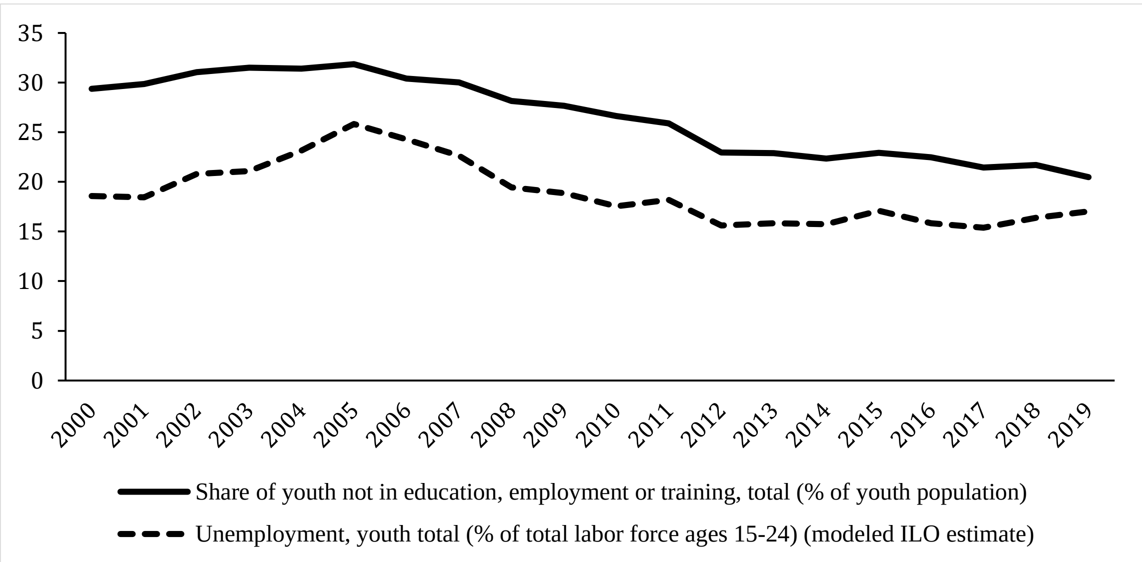
Using a database of Brazilian household surveys, Cruces et al. (2012) find robust and significant scarring effects among groups exposed to a higher propensity of working in the informal sector during their youth and are more severe among workers with a lower level of skill. However, they argue that the effects of scarring on income are mainly observable in the early years of adulthood, and tend to disappear as time goes by. In the context of Indonesia, Naidoo et al. (2015) investigate the occupational mobility and job quality among youth and relate these to the concept of scarring. Using the Indonesian Family Life Survey, they find that a year spent in self-employment corresponds to 3 to 4 percent wage penalty for young workers. Yet, there is no significant negative effect on income for older workers. In addition, there are evident patterns of persistence in self-employment, which are indicated by limited individuals succeeding in moving from frivolous self-employment (i.e., without permanent workers) to business with permanent workers (Naidoo et al., 2015). It is a concerning issue since young people who start their careers by being self-employed may not have the opportunity to develop their human capital further. In particularly on firm-specific skills, and may suffer zero or negative wage growth over time. Meanwhile, there are also studies claiming that periods of self-employment in the informal sector provide valuable skills for workers. Bosch and Maloney (2005) determine that experience working in the informal sector provides individuals with training for better jobs in the future that they might not be able to obtain right after completing their education. This finding is also supported by Cunningham and Salvagno (2011), who argue that young workers may initiate their careers in the labor market with temporary employment in the informal sector.

3. Indonesia Context

3.1. Youth Unemployment and Informality

In Indonesia, according to the National Labor Force Survey (*Sakernas*) 2019, approximately 4 million (18.85 percent) female and male youth between the age of 15 and 24 are unemployed, which is more than 56 percent of the total unemployment. The unemployment rate among young people is about 21 percent in rural and 35 percent in urban areas. Moreover, the great majority of youth at working age are engaged in some types of informal employment where they lack a decent working environment, adequate incomes, and job security. Open unemployment also consists of a large extent of youths who are mostly looking for their first job (Nagib and Ngadi, 2008). In addition to demand slump during the crisis periods, demographic factors also play a crucial role in explaining the high level of youth unemployment. In about thirty years, between 1971 and 2000, the population of young people aged 15-25 years grew by almost double the amount, from 19 million to 38 million. As a result of this massive growth, many young people are not able to be absorbed by the formal sector, which in turn leaving many struggling to make a living by working in the informal sector. Moreover, transitions from school to work are not well established; as a result, many young people are required to stay longer in economic inactivity than it would have been necessary otherwise.

Figure 1: Trends of Indonesia Youth Unemployment



Source: World Development Indicator (World Bank, 2020)

As represented in Figure 1, the share of young people (15-24 years) who are not in education, employment or training (NEET) as a proportion of the total number of young people in the corresponding age group is at 20 percent. These youths, either unemployed or inactive and not involved in education or training, are at stake of becoming socially excluded, in particular, to be with income lower than the poverty-line and inadequate skills to support their economic mobility (OECD, 2020). In fact, among these NEET youths, more than 63 percent of them are female, indicating the existence of substantial institutional barriers restricting women's participation in the labor market (World Bank, 2020). Moreover, although there has been a decreasing trend in youth NEET in Indonesia, this rate is still higher compared to other neighboring countries in the region. For instance, the rate of youth NEET is at 12 percent in Malaysia, 14 percent in Thailand, 14 percent in Vietnam, and 18 percent in the Philippines. The NEET group is primarily at the stake of both labor-market and social exclusion since this group is not involved in any activities related to human capital investment, either through training or employment experience, to improve their labor market prospects. The widespread youth NEET also hinders companies and countries' attempts to create innovation and develop competitive advantages that rely heavily on the quality of human capital, thereby damaging future economic outlook.

Numerous studies have shown that, for many developing countries, employment in the informal sector remains to be a substantial and, in fact, a growing component of the economies (Yamada, 1996; Bacchetta et al., 2009; Günther and Launov, 2012). As evidence, the National Labor Force Survey (*Sakernas*) 2019 finds that more than 55 percent of workers in Indonesia are engaged in some types of informal employment. This rate is higher among poor workers; approximately 65 percent of workers with income in the bottom 20 percent work in the informal sector. The rate of informal sector employment is around 70 percent in rural and 44 percent in urban areas. In particular, the share of young people (15-24 years) who work in the informal sector as a percentage of the total number of employed youths reached around 40 percent in 2019. While the informal sector is considered contributing significantly to Indonesia's economy, informal workers are especially at risk as they do not have access to the same social protection mechanisms associated with formal employment. Furthermore, broadly speaking, workers in the informal sector do not have adequate job security and often receive minimal benefits from employers (Cuevas et al., 2009).

3.2. Human Capital and Skill Formation

For Indonesia, a country predicted to undergo a demographic bonus between 2020 and 2035 with 70 percent of its population will be categorized as a productive working age group, the human capital – the knowledge, skills, and health that people accumulate throughout their lives – become the vital aspect to its future. The most recent Human Capital Index developed by the World Bank indicated that Indonesia scores 0.53. This score implies that a typical Indonesian worker of the next generation, on average, will only be 53 percent as productive as one could be under the benchmark of complete education and full health. This score is considered low compared to other neighboring countries in the region. For instance, the Human Capital Index is at 0.62 percent in Malaysia, 0.60 percent in Thailand, 0.67 percent in Vietnam, and 0.55 percent in the Philippines. Despite the rapid technological changes, significant fundamental bottlenecks continue to impede the labor markets, including low quality of human capital development, which results in a high likelihood of skill mismatch (World Bank, 2019). As technology and automation have inevitably reshaped the skills required and the way people work, Indonesia certainly needs an increasingly skilled labor force with the right level and combination of skills that are needed in the future job market.

In order to develop skilled workers and to promote better labor market outcomes, policymakers in developing countries, including Indonesia, often choose to increase access to vocational education. The distinct feature of vocational education is that it aims to produce “specific human capital”, which provides students with the chance to learn specific job-relevant skills that could help them to be more readily suitable for a given job (Tilak, 2002). The Indonesian Ministry of National Education and Culture (MNEC) enthusiastically embraces the idea of increasing the number of vocational schools (*Sekolah Menengah Kejuruan*, or SMK). It aims to increase the proportion of SMK, which is currently from 42.7 percent to become 70 percent in 2025 (Ministry of National Education and Culture, 2007). In response, the government halted several constructions of new general schools, whereas new vocational schools were built, and some existing general schools were being transformed into vocational schools. From 2009 to 2014, approximately 3,000 new SMK were built. In early 2017, the number of SMK in Indonesia reached 13,236 schools (3,434 were public and 9,802 were private) (MNEC, 2018).

Although vocational education surges, it continues to struggle with an image problem perceived by society. Vocational education is regarded to be less selective, less competitive, and less prestigious compared to general education (Shavit and Williams, 1985; Vanfossen et al., 1987). This negative presumption may lead to discrimination when candidates compete for limited employment opportunities. Therefore, instead of helping better transition to formal jobs, vocational education may worsen the scarring effects of unemployment and informality among young workers. According to the signaling hypothesis, this could be the case as employers may free-ride by using the information on worker’s histories to proxy for worker’s unknown productivity. In addition, as skills learned during vocational education are often too specific, a lengthy unemployment duration may lead to deterioration, or even loss, of skills, especially when they do not receive further training. This could be an area for further research, which could be done by exploring the effects of scarring based on different school types.

In April 2020, the Indonesian government launched the Pre-Employment Card (*Kartu Pra-Kerja*) program as part of the government’s stimulus package amid COVID-19, in which more than 2.8 million have been laid off. It is a form of social assistance analogues to unemployment benefit that intends to help workers who lost their jobs as a consequence of the temporary cessation of business operations during COVID-19. With a total budget of around Rp20 trillion, the program aims to provide social assistance to 5.6 million individuals aged 18 years or above who are currently not enrolled in formal education. The beneficiaries of this program will receive Rp3.5 million over four months, which includes Rp1 million for training to improve their skills further, and the remaining is in the form of cash assistance. Despite receiving many critics, particularly regarding its implementation, the Pre-Employment Card program can be viewed as the government effort to promote human capital development and to mitigate skill mismatch.

4. Economic Framework

The standard Mincer (1974) and Ben Porath's (1967) model are utilized to formalize the scarring effects on subsequent earnings due to previous unemployment or informal employment. The Mincer model illustrates the main tradeoffs in human capital investment, which allows a straightforward connection between the theory of human capital investment and the vast empirical literature on returns to education. The unique solution to the optimal schooling decision in the Mincer model is characterized by the first-order condition:

$$\frac{\eta'(S^*)}{\eta(S^*)} = r + v - g_w$$

where S represents an interval time in full-time schooling. It shows that higher interest rates (r) and higher value of flow rate of death (v) – corresponding to shorter planning horizons – decrease investment in human capital, whereas a higher value of wage growth (g_w) increases the value of human capital, and as a result, promotes further investments. Integrating both sides of this equation with respect to S:

$$ln\, \eta\, (S^*) = \text{constant} + (r + v\ -\ g_w)S^*$$

and the wage-earning of the worker age $\tau \geq S^*$ in the labor market at time t will be given by:

$$W(S, t) = \exp(g_w t) \exp(g_h(t - S))\, \eta(S)$$

where g_h shows the growth of human capital over time as the individual works. By taking logs, it implies that the earnings of the worker will be given by:

$$ln\, W(S^*, t) = \text{constant} + (r + v\ -\ g_w)S^* + g_w t + g_h(t - S^*)$$

where $t - S$ can be considered as work experience (time after schooling). In the event that a cross-sectional comparison across workers is utilized, the time trend term $g_w t$, will also move into the constant, so that the standard Mincer equation can be obtained where, in the cross-section, log wage earnings are proportional to schooling and experience:

$$ln\, W_j = \text{constant} + \gamma_s S_j + \gamma_s \text{experience}$$

where j refers to individual j. The Mincer empirical model suggests that the opportunity cost of one additional year of schooling is foregone earnings, implying that the return of schooling has to correspond to these foregone earnings, which would give rise to a proportional increase in the future earnings.

In the meantime, the Ben-Porath model allows for human capital investment and non-trivial labor supply decisions throughout the lifetime of the individual, which also connects to models of on-the-job human capital investment. In this model, the individual continues to accumulate human capital, even on-the-job, which can be interpreted as devoting time to attend training programs or allocating some of the working hours to learning. Moreover, since the time horizon is finite, the individual could decide to halt investment in human capital at some point in time. Therefore, the temporal profile of human capital investment produced by the canonical Ben-Porath model may have a hump-shaped, with a potential of a deteriorating portion at the end. Instead, the path of human capital (and the earning potential) in the current model is always increasing. There are two critical implications of the Ben-Porath model. First, it underlines that the path for human capital investment is not only through schooling; instead, there is a continuity between schooling investments and other investments in human capital. Second, it puts forward that individuals may also anticipate higher levels of on-the-job investments in human capital, particularly in societies where education investments are also high. This model also provides a useful lifecycle perspective of the individual, starting with higher investments in schooling, followed by investment in human capital during the period of "full-time" work, which then may increase earnings (Acemoglu and Autor, 2000).

In addition to the two models explained above, signaling theory also plays a crucial role in explaining the scarring effects. From the standard Mincer and Ben-Porath model of human capital investment, stock of knowledge and skills are accumulated in the course of time spent in education or at work (Becker, 1964; Pissarides, 1992). As a response, one way to indicate job-seekers' ability and productivity is by looking at the time invested in education and work experience, implying that periods of inactivity can be interpreted as lost opportunities to develop human capital. In addition, longer durations of inactivity may depreciate the previously acquired skills as they are not made use of and brought up to date through training and/or working

(Blanchard and Summers, 1986; Phelps, 1968; Pissarides, 1992). The signaling theory begins with the assumption that the recruitment process is a condition of asymmetric information because employers are not able to directly observe the ability and productivity of job-seekers at the moment of the hiring decision. As it would be too complicated, time-intensive, and costly to directly evaluate applicants' productivity, employers will make use of visible signals (Spense, 1973), to derive an estimate of productivity. Applicants' observable characteristics, for instance, education credentials, school grades, and previous job titles serve as signals for the candidates' unobserved productivity. Additionally, information can also be extracted from more indirect hints such as discontinuity in the resume or frequent change of employment. It has been argued that periods of inactivity could have detrimental effects on the likelihood of finding a job and on subsequent earnings (Arulampalam et al. 2000, 2001; Schmieder et al., 2016).

5. Data Characteristic and Methodology

5.1. Data Characteristic

The primary data source of this paper is from the Indonesia Family Life Survey (IFLS) wave 1, 3, 4, and 5, which was fielded in 1993, 2000, 2007, and 2014, covering for 21 years. It is a large-scare population-based longitudinal survey in which data are available for the same interview subjects from several points of time. Hence, it gives an avenue to comprehend the dynamics of behavior at the level of individual, household, and community. For the purpose of this study, the survey comprises abundant information collected at the individual and household levels, including education, labor market conditions, and outcomes, as well as historical details of employment. Although IFLS provides the breadth and depth of the longitudinal information on the labor market and other economic outcomes, the information was not collected in an entirely consistent way throughout the survey waves.

The IFLS wave 1 in 1993 covers 13 provinces, covering 83 percent of the population: all five of the Javanese provinces (DKI Jakarta, West Java, Central Java, DI Yogyakarta, and East Java), four provinces on Sumatra (North Sumatra, West Sumatra, South Sumatra, and Lampung), and four provinces covering the remaining major island groups (Bali, West Nusa Tenggara, South Kalimantan, and South Sulawesi). The subsequent waves then follow up with the same sample, with the average re-contact rate across waves of about 93.8 percent, which is as high as or even higher than most longitudinal surveys in the US and Europe. For this paper, IFLS wave 2 and wave 2+, which were conducted in 1997 and 1998, are not included in the analysis. It is because wave 2 does not provide information on the breakdown of different types of self-employment, and wave 2+ only covers 25 percent of the IFLS households, located in 7 of the 13 provinces that IFLS covers.

The dependent variable of the analysis, log of monthly income, is obtained by dividing the individual monthly income with its corresponding provincial CPI data in each year to index the variable in terms of 2010 rupiah. In Indonesia, the national CPI data is constructed based on CPI data available at the city or district level (CPI data at the provincial level is not directly available). In the case of this research, the authors attempt to construct provincial-level CPI using data at the city and district level by weighting cities that represent the province based on their GDP relative to the provincial GDP. These macro-economic variables, including the city or district GDP, provincial GDP, and inflation rate, are obtained from the Indonesian Bureau of Statistics. Moreover, the sample selected for this study are individuals age 15 or above and not currently at school during the survey. This sampling choice is in accordance with the fundamental Minimum Age Convention set by ILO in 1973, which indicates that the general minimum age for admission to employment is at 15 years old.

The variables of interest are previous unemployment and self-employment, which proxy for the experience of scarring. Using IFLS survey questions, the variable of unemployment is a dummy variable constructed with a value of one when someone does not work/try to work/help to earn income for pay for at least 1 hour during the past week, and zero otherwise. Meanwhile, the variable of self-employment is a dummy variable constructed with a value of one when someone is self-employed or self-employed with unpaid family worker/temporary worker, and zero otherwise. Notably, this paper only considers the informal type of self-employment, excluding self-employment with permanent workers as the latter is considered as a formal type of employment. It is in accordance with the National Labor Force Survey (*Sakernas*) 2019, that 95 percent of self-employed workers in Indonesia are in the informal sector. IFLS provides the historical information of employment based on an individual retrospective answers up until seven years before the survey, of which the variable of previous unemployment and self-employment are generated. Aside from the variables of interest, this paper also controls for some explanatory variables, including age, location of residence (urban/rural), gender, marital status, years of schooling, some work characteristics (sector and industry of employment), and some household characteristics (sanitation, cooking fuels, and water source) which could proxy for household's social-economic status. Table A1 below shows summary statistics for the variables that are included in the analysis.

Table A1: Summary Statistics

Variables	1993			2000			2007			2014		
	Mean	**Median**	**S.D.**	**Mean**	**Median**	**S.D.**	**Mean**	**Median**	**S.D.**	**Mean**	**Median**	**S.D.**
Log(wage_adj)	13.35	13.49	1.19	13.34	13.50	1.05	13.50	13.58	1.00	13.75	13.93	1.05
Ever unemployed	0.14	0.00	0.34	0.30	0.00	0.46	0.37	0.00	0.48	0.39	0.00	0.49
Ever self-employment	1.00	1.00	0.00	1.00	1.00	0.00	0.74	1.00	0.44	0.76	1.00	0.43
Years of unemployment	2.86	3.00	1.40	2.59	2.00	1.31	3.53	3.00	1.95	4.11	4.00	2.41
Years mostly in self-employment	4.35	5.00	1.26	4.43	5.00	1.95	5.88	6.00	3.32	7.02	6.00	4.64
Years mostly in private sector employment	3.95	5.00	1.45	3.81	4.00	1.75	4.23	4.00	2.35	4.99	5.00	3.37
Years mostly in government employment	4.55	5.00	1.06	4.55	5.00	1.15	5.95	6.00	3.00	6.99	6.00	4.50
Female	0.53	1.00	0.50	0.52	1.00	0.50	0.473	0.00	0.50	0.45	0.00	0.50
Age	36.23	33.00	16.49	36.67	33.00	16.79	36.86	33.00	15.88	38.20	35.00	15.57
Age^2	781.32	676.00	448.34	789.06	676.00	450.99	838.35	784.00	422.34	905.74	900.00	442.85
Urban	0.51	1.00	0.50	0.51	1.00	0.50	0.55	1.00	0.50	0.59	1.00	0.49
Married	0.63	1.00	0.48	0.63	1.00	0.48	0.61	1.00	.49	0.62	1.00	0.49
School years	5.45	6.00	4.09	6.83	6.00	4.11	7.65	9.00	3.96	8.31	9.00	3.73
Private sector	0.09	0.00	0.30	0.07	0.00	0.25	0.07	0.00	0.25	0.07	0.00	0.25
Agriculture, forestry, fishing, and hunting	.	.	.	0.35	0.00	0.48	0.32	0.00	0.46	0.27	0.00	0.44
Mining and quarrying	.	.	.	0.01	0.00	0.07	0.01	0.00	0.08	0.01	0.00	0.11
Manufacturing	.	.	.	0.14	0.00	0.34	0.13	0.00	0.34	0.12	0.00	0.33
Electricity, gas, water	.	.	.	0.003	0.00	0.05	0.003	0.00	0.05	0.005	0.00	0.07
Construction	.	.	.	0.04	0.00	0.21	0.05	0.00	0.21	0.05	0.00	0.21
Wholesale, retail, restaurant, and hotels	.	.	.	0.22	0.00	0.42	0.24	0.00	0.43	0.25	0.00	0.43
Transportation, storage & communications	.	.	.	0.04	0.00	0.20	0.04	0.00	0.18	0.02	0.00	0.15
Finance, insurance, real estate & business services	.	.	.	0.01	0.00	0.08	0.01	0.00	0.10	0.04	0.00	0.21
Social services	.	.	.	0.19	0.00	0.39	0.20	0.00	0.404	0.21	0.00	0.40
House with improved sanitation	0.53	1.00	0.50	0.67	1.00	0.47	0.77	1.00	0.42	0.84	1.00	0.37
House with improved cooking fuels	.	.	.	0.66	1.00	0.47	0.63	1.00	0.48	0.78	1.00	0.41
House with improved water source	.	.	.	0.60	1.00	0.49	0.69	1.00	0.46	0.80	1.00	0.40

5.2. Methodology

Based on the data characteristics explained above, the authors created a panel data set at the individual level to analyze the impacts of scarring, through unemployment or self-employment experience, on subsequent income when the individuals work in the formal sector. The panel data series modelling addresses the likely dependence across data observations within the same group. In fact, it allows for heterogeneity across groups and introduces individual-specific effects. In other words, the panel data set allows for controlling unobserved time-invariant heterogeneity that exists in the cross-sectional model. As a practical matter, the panel data series in this paper is constructed by taking two consecutive surveys, each as the baseline ($t = 0$) and after treatment ($t = 1$), and then stacked or pooled these two-period panel data from all waves to become one big two-period panel data set[1]. The treatment variable will be the retrospectives answers up to seven years prior obtained from the work history provided in the IFLS.

To assess the causal effects of some forms of scarring on subsequent employment outcomes, the authors make use of the difference-in-difference method with propensity score matching. The difference-in-difference technique is utilized to gauge the difference in the effects at the time after the intervention between a treatment group and its counterfactual relative to the initial condition observed at the pre-intervention baseline survey (Lechner, 2011). In the case of this research, the treatment is the condition when someone has previously been unemployed or self-employed. In contrast to propensity score matching alone, the difference-in-difference estimator allows for unobserved heterogeneity, which is assumed to be time-invariant; thus, the bias gets offset over differencing. To put it in simple mathematical terms, given a two-period setting where $t = 0$ and $t = 1$, respectively, denote periods before and after the treatment; and let Y_t^T and Y_c^T be the respective outcomes for treated and non-treated individuals in time t; the difference-in-difference approach will estimate the average treatment effect as follows:

$$DD = E(Y_1^T - Y_0^T | T_1 = 1) - E(Y_1^C - Y_0^C | T_1 = 0)$$

where $T_1 = 1$ denotes treatment at $t = 1$, whereas $T_1 = 0$ denotes control individuals. In other words, the difference is measured between the observed average outcomes for the test and control groups before and after the treatment.

The critical assumption for the use of the difference-in-difference approach is that unobserved heterogeneity is constant across time and uncorrelated with the treatment over time. This condition is also known as parallel-trend assumptions. Although the difference-in-difference approach relaxes the premise of conditional exogeneity or selection only on *observed* characteristics, this notion of time-invariant selection bias should be justified, provided that treatment could be targeted or happened by choice (voluntarily). In regard to this research, previous unemployment or self-employment may be more likely if there is a temporary shock-induced drop in income prior to the treatment of previous unemployment or self-employment. Hence, the test group might have experienced more rapid growth in income. In this case, a difference-in-difference method is likely to overestimate the treatment's effect. Likewise, when previous unemployment or self-employment is voluntary, a difference-in-difference method is likely to be biased upward due to self-selection from paid- into unemployment or self-employment that has a negative correlation with the unobserved ability and/or productivity.

In practical terms, ex-ante, time-varying unobserved heterogeneity could be accounted for by ensuring that control and treatment groups share similar pre-treatment characteristics

[1] In this case, stacking or pooling the two-period panel data will not be a problem since the log of monthly income variable has been adjusted in terms of 2010 rupiah, and later the year fixed effect will also be included in difference-in-difference estimation to take into account other potential structural changes over time.

(Khandker et al., 2010). If control and treatment groups are not similar, it could be the case that the effects observed in the outcome across time are functions of this difference, which as a result, will bias the difference-in-difference. To ensure similar pre-treatment characteristics, this paper is applying difference-in-difference with propensity score matching, in which the propensity score matching is run on the baseline and then perform a difference-in-difference on the individuals that stay in the common support. Previous studies are able to demonstrate that weighting the control group according to its propensity score yields a fully efficient estimator (Hirano et al., 2003), particularly when careful attention is given to characteristics that determine treatment during the baseline. However, it is worthwhile to note that propensity score matching develops a counterfactual that is as similar to the treatment group as possible with regard to the *observed* characteristics.

In this paper, the propensity score matching approach will help in constructing a statistical comparison group by using the probability model of participating in the treatment (i.e., being unemployed or self-employed), based on the observed characteristics. In particular, the propensity score matching using data from the base year will ensure that the counterfactual group is similar to the treatment group before applying difference-in-difference to the matched sample. By using the "pscore" command in Stata, the participation variable in $t = 1$ (i.e., whether an individual has ever been unemployed or self-employed within the years in between two consecutive surveys) is regressed with exogenous variables in $t = 0$ to obtain propensity scores from the baseline data. The observed exogenous variables controlled in this case include age, location of residence (urban/rural), gender, marital status, and years of schooling. An essential assumption of propensity score matching is the common support condition, ensuring that treatment observations have comparison observation "nearby" in the propensity score distribution (Heckman et al., 1999). As a practical matter, the effectiveness of propensity score matching relies on the availability of a large and roughly equal number of participant and non-participant observations; as such, a significant region of common support can be established. Figure A1 below shows the regions of common support, both for previous unemployment and previous self-employment, which is [3.473e-70, .51482645] and [.32055533, .99999797] respectively, indicating a large area of common support. The observations with weak common support are dropped, as only in the area of common support can inference be made about causality (Heckman et al., 1997). The matched observations in the baseline year ($t = 0$) are kept and merged with the corresponding panel data ($t = 1$), and the difference-in-difference estimation is implemented.

Figure 2 Region of Common Support for Previous Unemployment Propensity Score

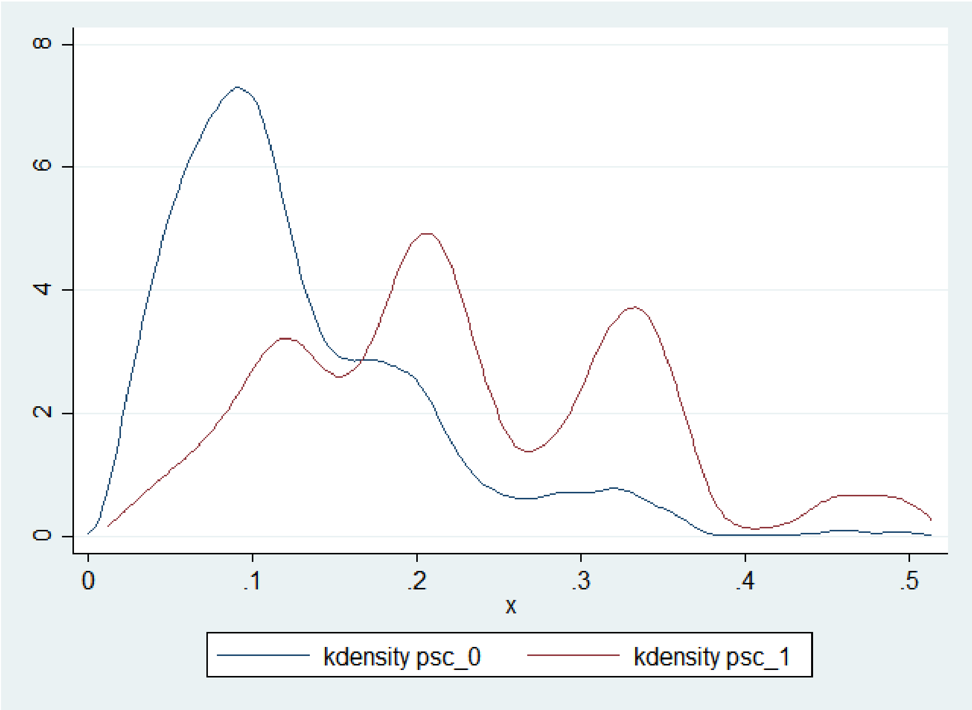
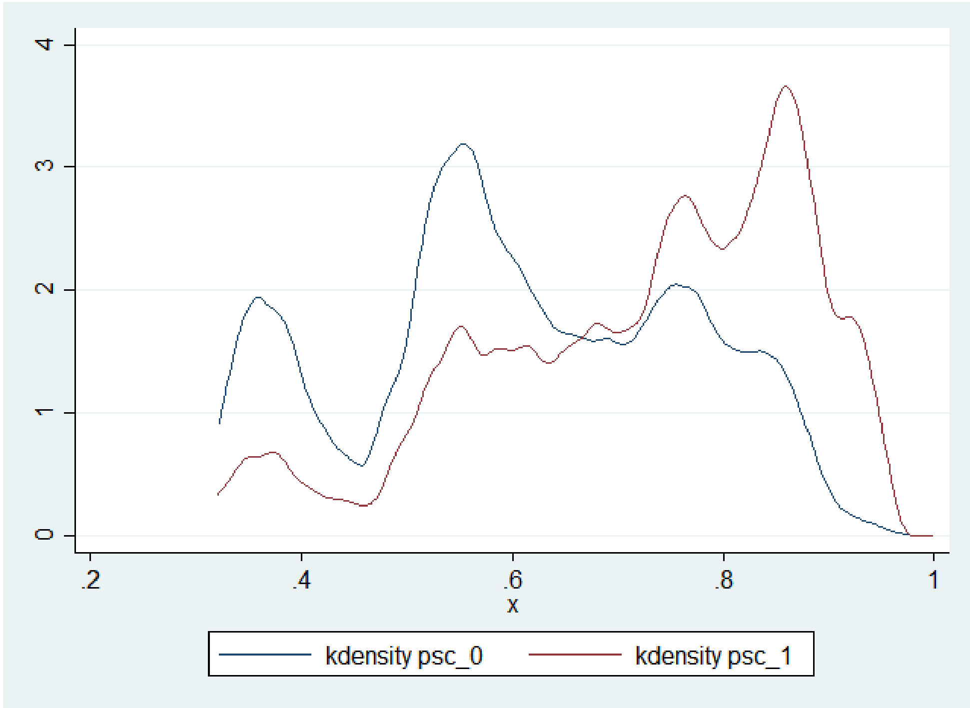


Figure 3 Region of Common Support for Previous Self-Employment Propensity Score



For panel data analysis, it is crucial to consider serial correlation within clusters as observations in the data set are related to each other, which will bias the standard errors and causes the results to be less efficient (Drukker, 2003). Magruder (2013) also asserts the importance of considering serial correlation within each cluster to avoid very misleadingly small standard errors (underestimation) and, consequently, narrow confidence intervals, large *t*-statistics, and low *p*-values (over-rejection). Despite its significance, Bertrand et al. (2004) point out that many difference-in-difference studies do not control for clustered errors, and those that do often cluster at the incorrect level. Cameron and Miller (2015) provide guiding principles that determine what to cluster over. First, if there is a justification for believing that the regressors and the errors might be correlated within-cluster, clustering should be defined in a broad enough way to account for that correlation. Second, the bias-variance trade-off should be considered when clustering (it is advisable to be conservative and avoid bias by using more aggregate clusters up to the point at which there is concern about having too few clusters). In this paper, the standard error is at the individual level as the analysis uses multiple time periods, and the unit of randomization is individual; thus, it is very likely that the model errors are to be serially correlated at the individual level (Abadie et al., 2017).

6. Effects of Scarring on Subsequent Earnings

6.1. Empirical Approach

a. Effects of Previous Unemployment and Self-Employment

The estimation of scarring effects using a difference-in-difference approach can be measured within a regression framework. Primarily, the estimating equation would be specified as follows:

$$Y_{it} = \alpha + \beta T_{it} t + \delta T_{it} + \gamma t + \boldsymbol{X}'_{i,t}\pi + \alpha_j + \delta_t + \varepsilon_{it}$$

where Y_{it} is the log of monthly income, adjusted in terms of 2010 rupiah, for individual i at time t. The coefficient β on the interaction between the post-treatment variable (T_{it}) and time ($t = 0\ and\ 1$, where 0 suggests period before treatment and 1 suggests period after treatment) gives the average difference-in-difference effect of the treatment. In other words, the coefficient β picks up the impact of scarring as a result of previous unemployment or self-employment. Apart from the interaction term, the variables t and T_{it} are controlled separately to capture individually any average effects of time as well as the effect of being targeted versus not being targeted (Khandker et al., 2010). Moreover, the mean difference in outcomes between treatment and control units after the treatment would be $\beta + \delta$, which is the effect of scarring plus the initial difference across the two samples. T_{it} is a dummy variable indicating whether individual i has ever been unemployed or self-employed. In the meantime, $\boldsymbol{X}_{i,t}$ is a vector of individual-, work-, and household-specific control variables. α_j is the provincial fixed effect, whereas δ_t is the year dummy used to capture structural change over time.

The estimation of scarring effects due to previous unemployment and self-employment will be explicitly discussed in Section 6.2 and Section 6.3, respectively. For the purpose of robustness check, the difference-in-difference regressions are estimated, both by involving and omitting of work- and household-specific control variables. Particularly, since the data for some work- and household-specific control variables are only available in wave 3, 4, and 5. The complete results of the regression are presented in Table A2-A7 below, which shows no significant difference between the regression results that involve the complete set of variables and those that do not.

Table A2: Scarring Effects of Previous Unemployment on Subsequent Earnings, by Age

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Full Sample	Age 15-24	Age 25-34	Age 35-44	Age 45-60	Full Sample	Age 15-24	Age 25-34	Age 35-44	Age 45-60
Time	0.0157***	0.00256	0.00446	-0.000370	0.00946**	0.0170***	0.00516	0.00532	-0.000185	0.0109**
	(0.00288)	(0.00806)	(0.00316)	(0.00287)	(0.00426)	(0.00293)	(0.00916)	(0.00325)	(0.00294)	(0.00444)
Ever unemployed	-0.0270*	0.00508	0.0258	-0.0176	0.0144	-0.0272*	0.00821	0.0271*	-0.0167	0.0163
	(0.0148)	(0.00922)	(0.0159)	(0.0187)	(0.0387)	(0.0150)	(0.0104)	(0.0163)	(0.0192)	(0.0407)
Time * Ever unemployed	-0.0274	-0.00752	-0.0337	0.0130	-0.134**	-0.0312*	-0.0135	-0.0375*	0.0108	-0.154**
	(0.0169)	(0.0173)	(0.0208)	(0.0336)	(0.0671)	(0.0171)	(0.0198)	(0.0213)	(0.0343)	(0.0702)
Age	0.0755***	-0.341	-0.216	-0.0998	0.136	0.0778***	-0.256	-0.212	-0.0948	0.182*
	(0.0122)	(0.330)	(0.168)	(0.183)	(0.109)	(0.0123)	(0.353)	(0.168)	(0.184)	(0.110)
Age^2	-0.000777***	0.00807	0.00356	0.00156	-0.00158	-0.000812***	0.00519	0.00362	0.00147	-0.00199*
	(0.0000759)	(0.00724)	(0.00260)	(0.00229)	(0.00103)	(0.0000771)	(0.00792)	(0.00265)	(0.00230)	(0.00102)
Urban	0.0509*	0.351	0.0286	-0.00621	0.0592	0.0697**	0.430	0.0374	-0.00734	0.0860
	(0.0303)	(0.270)	(0.105)	(0.109)	(0.127)	(0.0305)	(0.303)	(0.108)	(0.105)	(0.128)
Married	0.0374	-0.00776	0.0343	-0.128	-0.142	0.0430	0.147	0.0330	-0.147	-0.153
	(0.0271)	(0.186)	(0.0669)	(0.116)	(0.126)	(0.0273)	(0.184)	(0.0677)	(0.115)	(0.133)
School years	0.0398***	0.209***	0.0394**	-0.0174	-0.00383	0.0404***	0.221***	0.0388**	-0.0222	-0.00744
	(0.00783)	(0.0489)	(0.0174)	(0.0221)	(0.0212)	(0.00794)	(0.0462)	(0.0178)	(0.0220)	(0.0215)
Private sector	0.165***	-0.808	0.261***	0.0536	0.291**					
	(0.0415)	(0.599)	(0.0700)	(0.121)	(0.113)					
Mining and quarrying	0.127	-0.0931	0.232	0.230	0.833***					
	(0.0898)	(0.407)	(0.168)	(0.204)	(0.185)					
Manufacturing	0.195***	0.479**	0.266***	0.0365	0.177					
	(0.0393)	(0.230)	(0.101)	(0.140)	(0.141)					
Electricity, gas, water	0.132	0	0.332	0.197	-0.237					
	(0.111)	(.)	(0.399)	(0.268)	(0.201)					
Construction	0.157***	0.337	0.213	0.0805	0.226					
	(0.0440)	(0.269)	(0.132)	(0.187)	(0.149)					
Wholesale, retail, restaurant & hotels	0.123***	0.122	0.184*	0.00698	0.130					
	(0.0434)	(0.269)	(0.108)	(0.141)	(0.178)					
Transportation, storage & communications	0.152***	-0.148	0.302**	-0.00250	0.226					
	(0.0522)	(0.409)	(0.134)	(0.159)	(0.194)					
Finance, insurance, real estate & business services	0.202***	0.470	0.287	0.00724	0.0237					
	(0.0558)	(0.705)	(0.179)	(0.152)	(0.196)					
Social services	0.00935	-0.231	0.0867	0.0366	-0.0810					
	(0.0402)	(0.280)	(0.104)	(0.137)	(0.160)					
Other household characteristics	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	38293	8236	12888	9471	6692	38293	8236	12888	9471	6692

Note: The dependent variable is the log of monthly wage adjusted to the 2010 value. All estimations include all the control variables described in Chapter 5 as well as year and district fixed effects. Robust clustered standard errors are reported in parentheses below coefficient estimates. Significance at the 1 percent, 5 percent, and 10 percent levels are denoted respectively by ***, **, and *.

Table A3: Scarring Effects of Previous Unemployment on Subsequent Earnings, by Income Distribution

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	<20%	20-40%	40-60%	60-80%	>80%	<20%	20-40%	40-60%	60-80%	>80%
Time	0.0156***	-0.0000298	0.000378	0.00163**	0.00210	0.0167***	-0.0000652	0.000205	0.00172**	0.00231
	(0.00581)	(0.00124)	(0.000792)	(0.000745)	(0.00142)	(0.00595)	(0.00122)	(0.000813)	(0.000783)	(0.00146)
Ever unemployed	0.0250	0.00364	-0.0000234	0.00392	0.00922	0.0291*	0.00311	-0.000300	0.00418	0.0107
	(0.0163)	(0.00394)	(0.00359)	(0.00510)	(0.0236)	(0.0166)	(0.00395)	(0.00360)	(0.00508)	(0.0230)
Time * Ever unemployed	-0.0516**	-0.00262	-0.00111	-0.00897	-0.0224	-0.0567***	-0.00214	-0.000378	-0.00952	-0.0251
	(0.0209)	(0.00548)	(0.00457)	(0.00607)	(0.0261)	(0.0214)	(0.00544)	(0.00460)	(0.00616)	(0.0262)
Age	0.0314	0.00101	0.000980	0.0155	0.0110	0.0404	0.00154	0.00251	0.0158	0.00888
	(0.0451)	(0.0107)	(0.00868)	(0.0111)	(0.0175)	(0.0450)	(0.0112)	(0.00843)	(0.0111)	(0.0173)
Age^2	-0.000198	-0.000141**	-0.0000940*	-0.000178**	-0.000215	-0.000238	-0.000140*	-0.0000907*	-0.000178**	-0.000197
	(0.000167)	(0.0000710)	(0.0000538)	(0.0000713)	(0.000154)	(0.000170)	(0.0000733)	(0.0000536)	(0.0000713)	(0.000150)
Urban	0.00846	-0.00147	-0.0166	0.00772	0.0331	-0.00251	0.00928	-0.0224	0.00218	0.0224
	(0.107)	(0.0440)	(0.0283)	(0.0281)	(0.0372)	(0.104)	(0.0423)	(0.0280)	(0.0282)	(0.0372)
Married	0.0778	-0.00691	-0.00931	0.00344	0.114*	0.0723	-0.0116	-0.0127	0.0116	0.134**
	(0.0922)	(0.0294)	(0.0206)	(0.0300)	(0.0602)	(0.0935)	(0.0291)	(0.0201)	(0.0292)	(0.0592)
School years	0.0199	0.00544	-0.00795	0.000178	-0.00724	0.00995	0.00508	-0.00759	0.000546	-0.00959
	(0.0216)	(0.00892)	(0.00525)	(0.00740)	(0.0193)	(0.0214)	(0.00882)	(0.00517)	(0.00730)	(0.0198)
Private sector	-0.142	0.0295	-0.0554	0.0591	0.0816					
	(0.124)	(0.0807)	(0.0438)	(0.0414)	(0.0636)					
Mining and quarrying	-0.237	0.0763	-0.0159	-0.0541	0.0203					
	(0.392)	(0.108)	(0.0591)	(0.0662)	(0.101)					
Manufacturing	0.00366	0.0140	0.00853	0.00270	0.0498					
	(0.105)	(0.0366)	(0.0289)	(0.0377)	(0.0632)					
Electricity, gas, water	0	-0.257	-0.00121	0.0631	-0.0870					
	(.)	(0.282)	(0.0634)	(0.0591)	(0.109)					
Construction	-0.0850	-0.0182	0.0353	-0.0229	0.140					
	(0.145)	(0.0405)	(0.0338)	(0.0431)	(0.0986)					
Wholesale, retail, restaurant & hotels	-0.0501	0.0180	0.0216	0.0216	0.0368					
	(0.131)	(0.0403)	(0.0335)	(0.0423)	(0.0769)					
Transportation, storage & communications	0.0122	-0.0622	0.0676	-0.0356	0.177					
	(0.183)	(0.0716)	(0.0412)	(0.0502)	(0.109)					
Finance, insurance, real estate & business services	-0.164	-0.102	0.0568	-0.0358	0.0519					
	(0.186)	(0.0896)	(0.0461)	(0.0514)	(0.0851)					
Social services	0.0665	-0.00107	0.0338	-0.0219	-0.0232					
	(0.112)	(0.0386)	(0.0308)	(0.0368)	(0.0505)					
Other household characteristics	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7803	8370	8399	7351	6370	7803	8370	8399	7351	6370

Note: The dependent variable is the log of monthly wage adjusted to the 2010 value. All estimations include all the control variables described in Chapter 5 as well as year and district fixed effects. Robust clustered standard errors are reported in parentheses below coefficient estimates. Significance at the 1 percent, 5 percent, and 10 percent levels are denoted respectively by ***, **, and *.

Table A4: Scarring Effects of Previous Unemployment on Subsequent Earnings, by Gender and Residence

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Male	**Female**	**Rural**	**Urban**	**Male**	**Female**	**Rural**	**Urban**
Time	0.0143***	0.0212***	0.0156***	0.0195***	0.0151***	0.0255***	0.0163***	0.0216***
	(0.00325)	(0.00643)	(0.00497)	(0.00354)	(0.00331)	(0.00667)	(0.00503)	(0.00366)
Ever unemployed	-0.0433**	-0.0138	0.00767	-0.0385***	-0.0442**	-0.0139	0.00799	-0.0390***
	(0.0185)	(0.0139)	(0.0205)	(0.0125)	(0.0189)	(0.0144)	(0.0207)	(0.0129)
Time * Ever unemployed	-0.0246	-0.0403**	-0.0562**	-0.0337**	-0.0268	-0.0500**	-0.0586**	-0.0392**
	(0.0214)	(0.0189)	(0.0247)	(0.0154)	(0.0219)	(0.0196)	(0.0251)	(0.0159)
Age	0.0288**	0.0102	0.0165	0.00944	0.0295**	0.00910	0.0140	0.00963
	(0.0128)	(0.0117)	(0.0228)	(0.00877)	(0.0126)	(0.0117)	(0.0234)	(0.00897)
Age^2	-0.0000263**	-0.0000103	-0.0000146	-0.00000945	-0.0000270**	-0.00000893	-0.0000122	-0.00000944
	(0.0000121)	(0.0000111)	(0.0000217)	(0.00000831)	(0.0000120)	(0.0000111)	(0.0000222)	(0.00000850)
Urban	0.0627*	0.0479	0	0	0.0867**	0.0485	0	0
	(0.0345)	(0.0645)	(.)	(.)	(0.0346)	(0.0661)	(.)	(.)
Married	0.234***	0.0507	0.191***	0.131***	0.246***	0.0577	0.194***	0.146***
	(0.0302)	(0.0408)	(0.0584)	(0.0281)	(0.0304)	(0.0415)	(0.0588)	(0.0282)
School years	0.0399***	0.0375**	0.0633***	0.0323***	0.0404***	0.0385**	0.0665***	0.0311***
	(0.00922)	(0.0184)	(0.0167)	(0.0103)	(0.00934)	(0.0184)	(0.0167)	(0.0104)
Private sector	0.121**	0.277***	0.111	0.186***				
	(0.0517)	(0.0747)	(0.0996)	(0.0511)				
Mining and quarrying	0.182*	-0.00443	0.254	0.140				
	(0.0945)	(0.286)	(0.159)	(0.124)				
Manufacturing	0.210***	0.224**	0.197***	0.211***				
	(0.0444)	(0.0876)	(0.0673)	(0.0614)				
Electricity, gas, water	0.220*	-0.188	0.621	0.135				
	(0.119)	(0.255)	(0.501)	(0.117)				
Construction	0.182***	0.275	0.204**	0.0905				
	(0.0469)	(0.189)	(0.0796)	(0.0656)				
Wholesale, retail, restaurant & hotels	0.131***	0.140	0.142	0.115*				
	(0.0496)	(0.0944)	(0.0968)	(0.0609)				
Transportation, storage & communications	0.178***	0.233*	0.132	0.169**				
	(0.0564)	(0.136)	(0.114)	(0.0677)				
Finance, insurance, real estate & business services	0.231***	0.197	0.324*	0.184***				
	(0.0626)	(0.135)	(0.173)	(0.0703)				
Social services	0.0477	-0.0249	0.0631	-0.0293				
	(0.0465)	(0.0837)	(0.0740)	(0.0589)				
Other household characteristics	Yes	Yes	Yes	Yes	No	No	No	No
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	26048	13878	14097	25829	26048	13878	14097	25829

Note: The dependent variable is the log of monthly wage adjusted to the 2010 value. All estimations include all the control variables described in Chapter 5 as well as year and district fixed effects. Robust clustered standard errors are reported in parentheses below coefficient estimates. Significance at the 1 percent, 5 percent, and 10 percent levels are denoted respectively by ***, **, and *.

Table A5: Scarring Effects of the Previous Self-Employment on Subsequent Earnings, by Age

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
	Full Sample	**Age 15-24**	**Age 25-34**	**Age 35-44**	**Age 45-60**	**Full Sample**	**Age 15-24**	**Age 25-34**	**Age 35-44**	**Age 45-60**
Time	0.0394***	0.00326	0.0169**	0.0164*	0.0288*	0.0425***	0.00323	0.0158**	0.000487	0.0326*
	(0.00672)	(0.00621)	(0.00733)	(0.00969)	(0.0163)	(0.00679)	(0.00638)	(0.00746)	(0.00665)	(0.0168)
Ever self-employed	-0.00713	0.00714	0.0000307	0.000763	0.000324	-0.0104	0.00828	-0.00201	0.00160	-0.00371
	(0.00709)	(0.00608)	(0.00618)	(0.00684)	(0.0131)	(0.00714)	(0.00656)	(0.00637)	(0.00810)	(0.0136)
Time * Ever self-employed	-0.0487***	-0.00922	-0.0241**	-0.0217	-0.0355	-0.0512***	-0.00989	-0.0215*	-0.00169	-0.0384
	(0.0106)	(0.0122)	(0.0122)	(0.0139)	(0.0227)	(0.0107)	(0.0127)	(0.0124)	(0.0141)	(0.0235)
Age	0.0967***	0.0228	-0.0428	-0.216	0.111	0.0981***	-0.0167	-0.0173	-0.0954	0.155*
	(0.00833)	(0.299)	(0.146)	(0.182)	(0.0841)	(0.00843)	(0.308)	(0.148)	(0.184)	(0.0841)
Age^2	-0.000931***	0.000885	0.000865	0.00354	-0.000953	-0.000961***	0.00133	0.000513	0.00148	-0.00139*
	(0.0000532)	(0.00686)	(0.00239)	(0.00229)	(0.000779)	(0.0000537)	(0.00705)	(0.00243)	(0.00230)	(0.000779)
Urban	0.0432*	0.364	0.0196	0.145	0.0768	0.0578**	0.416	0.0356	-0.00751	0.0878
	(0.0260)	(0.258)	(0.0871)	(0.0915)	(0.0845)	(0.0263)	(0.283)	(0.0884)	(0.105)	(0.0852)
Married	0.0410*	0.0378	0.0165	-0.0684	0.0281	0.0438*	0.135	0.00868	-0.147	0.0233
	(0.0238)	(0.158)	(0.0657)	(0.139)	(0.0959)	(0.0239)	(0.159)	(0.0669)	(0.115)	(0.0976)
School years	0.0238***	0.195***	0.0206	0.000444	-0.00858	0.0248***	0.197***	0.0214	-0.0222	-0.00710
	(0.00598)	(0.0420)	(0.0169)	(0.0192)	(0.0150)	(0.00600)	(0.0413)	(0.0171)	(0.0220)	(0.0152)
Private sector	0.222***	-0.184	0.124	0.0759	0.636***					
	(0.0424)	(0.527)	(0.0986)	(0.116)	(0.135)					
Mining and quarrying	0.222***	0.280	0.481**	0.491***	0.245					
	(0.0711)	(0.391)	(0.221)	(0.187)	(0.329)					
Manufacturing	0.245***	0.365*	0.320***	0.118	0.222**					
	(0.0319)	(0.198)	(0.0993)	(0.114)	(0.0970)					
Electricity, gas, water	0.239**	0	0.311	0.238	-0.186					
	(0.0932)	(.)	(0.268)	(0.259)	(0.179)					
Construction	0.287***	0.179	0.289**	0.230*	0.313***					
	(0.0386)	(0.258)	(0.129)	(0.133)	(0.106)					
Wholesale, retail, restaurant & hotels	0.189***	0.130	0.269**	0.143	0.151					
	(0.0318)	(0.220)	(0.109)	(0.110)	(0.0967)					
Transportation, storage & communications	0.154***	-0.283	0.304***	-0.0536	0.139					
	(0.0423)	(0.271)	(0.116)	(0.153)	(0.113)					
Finance, insurance, real estate & business	0.264***	-0.441	0.357**	0.108	0.203					
services	(0.0490)	(0.579)	(0.150)	(0.150)	(0.150)					
Social services	0.0637**	-0.124	0.179*	0.108	-0.0957					
	(0.0311)	(0.233)	(0.0990)	(0.106)	(0.0878)					
Other household characteristics	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	54422	10017	19559	9474	15372	54422	10017	19559	9474	15372

Note: The dependent variable is the log of monthly wage adjusted to the 2010 value. All estimations include all the control variables described in Chapter 5 as well as year and district fixed effects. Robust clustered standard errors are reported in parentheses below coefficient estimates. Significance at the 1 percent, 5 percent, and 10 percent levels are denoted respectively by ***, **, and *.

Table A6: Scarring Effects of the Previous Self-Employment on Subsequent Earnings, by Income Distribution

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	<20%	20-40%	40-60%	60-80%	>80%	<20%	20-40%	40-60%	60-80%	>80%
Time	-0.000112	0.00774***	0.00484***	0.00105	-0.00180	-0.00149	0.00860***	0.00478***	0.00178	-0.00218
	(0.0121)	(0.00258)	(0.00166)	(0.00164)	(0.00269)	(0.0122)	(0.00264)	(0.00167)	(0.00166)	(0.00272)
Ever self-employed	-0.00820	0.00574**	0.000914	0.00111	-0.00433	-0.00854	0.00608**	0.00117	0.00194	-0.00369
	(0.0110)	(0.00270)	(0.00207)	(0.00282)	(0.00873)	(0.0115)	(0.00271)	(0.00213)	(0.00290)	(0.00895)
Time * Ever self-employed	0.00479	-0.0147***	-0.00843**	-0.00262	0.00702	0.00682	-0.0162***	-0.00847**	-0.00448	0.00731
	(0.0198)	(0.00487)	(0.00350)	(0.00436)	(0.0111)	(0.0202)	(0.00497)	(0.00356)	(0.00444)	(0.0113)
Age	0.0314	0.000809	0.00101	0.0156	0.0115	0.0404	0.00129	0.00252	0.0160	0.00936
	(0.0451)	(0.0106)	(0.00868)	(0.0111)	(0.0175)	(0.0449)	(0.0111)	(0.00844)	(0.0111)	(0.0173)
Age^2	-0.000200	-0.000139**	-0.0000941*	-0.000180**	-0.000220	-0.000241	-0.000138*	-0.0000906*	-0.000180**	-0.000202
	(0.000167)	(0.0000708)	(0.0000537)	(0.0000714)	(0.000155)	(0.000170)	(0.0000731)	(0.0000535)	(0.0000714)	(0.000151)
Urban	0.00789	-0.000763	-0.0166	0.00770	0.0331	-0.00290	0.00975	-0.0224	0.00208	0.0223
	(0.107)	(0.0438)	(0.0282)	(0.0281)	(0.0371)	(0.104)	(0.0421)	(0.0280)	(0.0282)	(0.0372)
Married	0.0757	-0.00704	-0.00961	0.00356	0.115*	0.0703	-0.0115	-0.0131	0.0116	0.135**
	(0.0922)	(0.0294)	(0.0206)	(0.0300)	(0.0603)	(0.0935)	(0.0291)	(0.0201)	(0.0292)	(0.0594)
School years	0.0199	0.00564	-0.00782	0.000198	-0.00738	0.00990	0.00532	-0.00746	0.000554	-0.00976
	(0.0216)	(0.00890)	(0.00524)	(0.00739)	(0.0194)	(0.0215)	(0.00880)	(0.00517)	(0.00729)	(0.0199)
Private sector	-0.142	0.0286	-0.0556	0.0592	0.0813					
	(0.123)	(0.0804)	(0.0439)	(0.0414)	(0.0637)					
Mining and quarrying	-0.248	0.0709	-0.0142	-0.0546	0.0213					
	(0.396)	(0.107)	(0.0591)	(0.0661)	(0.101)					
Manufacturing	0.00282	0.0127	0.00889	0.00286	0.0502					
	(0.105)	(0.0366)	(0.0288)	(0.0377)	(0.0633)					
Electricity, gas, water	0	-0.250	0.000348	0.0624	-0.0885					
	(.)	(0.281)	(0.0632)	(0.0592)	(0.110)					
Construction	-0.0876	-0.0179	0.0353	-0.0226	0.144					
	(0.145)	(0.0405)	(0.0337)	(0.0432)	(0.0985)					
Wholesale, retail, restaurant & hotels	-0.0540	0.0175	0.0219	0.0221	0.0375					
	(0.131)	(0.0403)	(0.0334)	(0.0423)	(0.0771)					
Transportation, storage & communications	0.00732	-0.0628	0.0678*	-0.0356	0.177					
	(0.184)	(0.0711)	(0.0412)	(0.0503)	(0.109)					
Finance, insurance, real estate & business services	-0.164	-0.100	0.0583	-0.0350	0.0514					
	(0.186)	(0.0897)	(0.0459)	(0.0515)	(0.0852)					
Social services	0.0633	-0.000431	0.0343	-0.0218	-0.0227					
	(0.112)	(0.0386)	(0.0307)	(0.0368)	(0.0507)					
Other household characteristics	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7832	8376	8400	7349	6368	7832	8376	8400	7349	6368

Note: The dependent variable is the log of monthly wage adjusted to the 2010 value. All estimations include all the control variables described in Chapter 5 as well as year and district fixed effects. Robust clustered standard errors are reported in parentheses below coefficient estimates. Significance at the 1 percent, 5 percent, and 10 percent levels are denoted respectively by ***, **, and *.

Table A7: Scarring Effects of the Previous Self-Employment on Subsequent Earnings, by Gender and Residence

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Male	Female	Rural	Urban	Male	Female	Rural	Urban
Time	0.0241***	0.0153*	0.0114	0.0188***	0.0229***	0.0169*	0.0141	0.0187***
	(0.00759)	(0.00860)	(0.0115)	(0.00603)	(0.00766)	(0.00877)	(0.0116)	(0.00607)
Ever self-employed	-0.00917	0.00541	-0.0277***	-0.00154	-0.00990	0.00335	-0.0263**	-0.00275
	(0.00777)	(0.0102)	(0.0105)	(0.00693)	(0.00785)	(0.0104)	(0.0106)	(0.00702)
Time * Ever self-employed	-0.0360***	-0.0288*	-0.0118	-0.0327***	-0.0340***	-0.0311*	-0.0159	-0.0324***
	(0.0128)	(0.0172)	(0.0178)	(0.0117)	(0.0129)	(0.0176)	(0.0180)	(0.0118)
Age	0.0297**	0.0102	0.0170	0.00975	0.0305**	0.00904	0.0145	0.00996
	(0.0127)	(0.0117)	(0.0229)	(0.00889)	(0.0126)	(0.0118)	(0.0235)	(0.00911)
Age^2	-0.0000272**	-0.0000102	-0.0000150	-0.00000977	-0.0000280**	-0.00000888	-0.0000127	-0.00000979
	(0.0000121)	(0.0000111)	(0.0000218)	(0.00000843)	(0.0000120)	(0.0000112)	(0.0000223)	(0.00000864)
Urban	0.0646*	0.0494	0	0	0.0887**	0.0500	0	0
	(0.0345)	(0.0646)	(.)	(.)	(0.0346)	(0.0663)	(.)	(.)
Married	(0.0282)	(0.0282)	(0.0282)	(0.0282)	0.258***	0.0597	0.198***	0.156***
	(0.0282)	(0.0282)	(0.0282)	(0.0282)	(0.0305)	(0.0416)	(0.0590)	(0.0283)
School years	0.0401***	0.0377**	0.0631***	0.0325***	0.0406***	0.0387**	0.0664***	0.0312***
	(0.00925)	(0.0184)	(0.0166)	(0.0103)	(0.00938)	(0.0185)	(0.0167)	(0.0104)
Private sector	0.118**	0.278***	0.108	0.184***				
	(0.0518)	(0.0749)	(0.0995)	(0.0513)				
Mining and quarrying	0.182*	-0.00542	0.255	0.143				
	(0.0947)	(0.292)	(0.159)	(0.124)				
Manufacturing	0.209***	0.224**	0.196***	0.212***				
	(0.0444)	(0.0877)	(0.0672)	(0.0615)				
Electricity, gas, water	0.219*	-0.195	0.614	0.132				
	(0.119)	(0.255)	(0.503)	(0.117)				
Construction	0.182***	0.279	0.204**	0.0919				
	(0.0469)	(0.188)	(0.0794)	(0.0656)				
Wholesale, retail, restaurant & hotels	0.129***	0.139	0.142	0.114*				
	(0.0496)	(0.0946)	(0.0967)	(0.0611)				
Transportation, storage & communications	0.177***	0.233*	0.130	0.169**				
	(0.0564)	(0.136)	(0.114)	(0.0679)				
Finance, insurance, real estate & business services	0.239***	0.201	0.331*	0.192***				
	(0.0627)	(0.135)	(0.174)	(0.0704)				
Social services	0.0462	-0.0289	0.0615	-0.0310				
	(0.0464)	(0.0838)	(0.0738)	(0.0589)				
Other household characteristics	Yes	Yes	Yes	Yes	No	No	No	No
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25527	13238	13760	25005	25527	13238	13760	25005

Note: The dependent variable is the log of monthly wage adjusted to the 2010 value. All estimations include all the control variables described in Chapter 5 as well as year and district fixed effects. Robust clustered standard errors are reported in parentheses below coefficient estimates. Significance at the 1 percent, 5 percent, and 10 percent levels are denoted respectively by ***, **, and *.

b. Effects of Duration of Unemployment and Self-Employment

Besides, this paper also attempts to examine the connection between the duration of unemployment or self-employment and subsequent earnings. In order to capture the relationship, a panel data analysis using fixed-effect estimation is utilized, with control for individual-, work-, and household-specific control variables. In that regard, the regression will be estimated according to the following specification:

$$Y_{it} = \alpha + \beta D_{it} + \boldsymbol{X}'_{i,t}\pi + \alpha_j + \delta_t + \varepsilon_{it}$$

where Y_{it} is the log of monthly income, adjusted in terms of 2010 rupiah, for individual i at time t. The coefficient of interest is β, capturing the relationship between the duration of unemployment or self-employment and subsequent earnings. In the meantime, $\boldsymbol{X}_{i,t}$ is a vector of individual-, work-, and household-specific control variables. α_j is the provincial fixed effect, whereas δ_t is the year dummy used to capture structural change over time. The individual-, work-, and household-specific control variables used in this fixed-effect analysis are the same as those used in the difference-in-difference analysis on the effects of previous unemployment and self-employment.

Section 6.4 and Section 6.5, respectively, will discuss in detail the results of the fixed-effect estimation analyzing the effects of unemployment and self-employment. Furthermore, for the purpose of robustness check, the difference-in-difference regressions are estimated, both by involving and omitting of work- and household-specific control variables. Particularly, since the data for some work- and household-specific control variables are only available in wave 3, 4, and 5. The complete results of the regression are presented in Table A8 below, which shows no significant difference between the regression results that involve the complete set of variables and those that do not.

Table A8: Effects of Years of Unemployment on Subsequent Earning, by Age

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Full Sample	**Age 15-24**	**Age 25-34**	**Age 35-44**	**Age 45-60**	**Full Sample**	**Age 15-24**	**Age 25-34**	**Age 35-44**	**Age 45-60**
Years of unemployment	-0.0346***	-0.0507	-0.0316	-0.0299	-0.0997***	-0.0391***	-0.0745	-0.0366	-0.0318	-0.110***
	(0.00700)	(0.0577)	(0.0238)	(0.0310)	(0.0269)	(0.00703)	(0.0565)	(0.0237)	(0.0306)	(0.0267)
Age	0.0832***	-0.210	-0.149	-0.0921	0.192*	0.0865***	-0.0857	-0.141	-0.0835	0.240**
	(0.0102)	(0.372)	(0.158)	(0.197)	(0.0999)	(0.0103)	(0.371)	(0.157)	(0.193)	(0.100)
Age^2	-0.000834***	0.00427	0.00252	0.00139	-0.00211**	-0.000878***	0.000461	0.00247	0.00126	-0.00252***
	(0.0000610)	(0.00883)	(0.00256)	(0.00247)	(0.000938)	(0.0000613)	(0.00875)	(0.00255)	(0.00241)	(0.000943)
Urban	0.0497*	0.329	0.0334	-0.0168	0.0564	0.0671**	0.409	0.0331	-0.0111	0.0811
	(0.0280)	(0.257)	(0.0878)	(0.0946)	(0.0995)	(0.0280)	(0.250)	(0.0874)	(0.0931)	(0.0997)
Married	0.0447*	0.0275	0.0130	-0.165	-0.140	0.0508**	0.156	0.0120	-0.186	-0.150
	(0.0248)	(0.197)	(0.0640)	(0.124)	(0.110)	(0.0249)	(0.190)	(0.0636)	(0.122)	(0.112)
School years	0.0400***	0.218***	0.0393*	-0.0150	-0.00169	0.0407***	0.236***	0.0386*	-0.0201	-0.00539
	(0.00667)	(0.0504)	(0.0202)	(0.0249)	(0.0162)	(0.00672)	(0.0506)	(0.0201)	(0.0246)	(0.0164)
Private sector	0.152***	-0.681	0.239*	0.0316	0.261**					
	(0.0415)	(0.508)	(0.132)	(0.118)	(0.117)					
Mining and quarrying	0.150**	-0.136	0.192	0.270	0.819**					
	(0.0764)	(0.868)	(0.250)	(0.227)	(0.353)					
Manufacturing	0.183***	0.464*	0.262***	0.0209	0.175					
	(0.0330)	(0.260)	(0.0969)	(0.112)	(0.113)					
Electricity, gas, water	0.176*	0	0.412	0.272	-0.227					
	(0.0993)	(.)	(0.278)	(0.284)	(0.356)					
Construction	0.148***	0.334	0.187	0.0248	0.278**					
	(0.0393)	(0.313)	(0.119)	(0.132)	(0.132)					
Wholesale, retail, restaurant & hotels	0.125***	0.176	0.191*	0.0336	0.132					
	(0.0370)	(0.287)	(0.108)	(0.127)	(0.129)					
Transportation, storage & communications	0.152***	-0.158	0.309**	-0.00175	0.175					
	(0.0475)	(0.439)	(0.122)	(0.159)	(0.166)					
Finance, insurance, real estate & business services	0.200***	0.409	0.323**	-0.0158	-0.0264					
	(0.0523)	(0.661)	(0.164)	(0.177)	(0.209)					
Social services	-0.00185	-0.168	0.0727	0.0432	-0.0786					
	(0.0331)	(0.297)	(0.0963)	(0.113)	(0.111)					
Other household characteristics	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25918	5974	8728	6269	4296	25918	5974	8728	6269	4296

Note: The dependent variable is the log of monthly wage adjusted to the 2010 value. All estimations include all the control variables described in Chapter 5 as well as year and district fixed effects. Robust clustered standard errors are reported in parentheses below coefficient estimates. Significance at the 1 percent, 5 percent, and 10 percent levels are denoted respectively by ***, **, and *.

Table A9: Effects of Years of Unemployment on Subsequent Earning, by Income Distribution

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	<20%	20-40%	40-60%	60-80%	>80%	<20%	20-40%	40-60%	60-80%	>80%
Years of unemployment	-0.0373**	-0.0117	-0.00427	-0.0158	-0.00369	-0.0390**	-0.0121	-0.00131	-0.0145	-0.00705
	(0.0184)	(0.00852)	(0.00778)	(0.00965)	(0.0255)	(0.0181)	(0.00845)	(0.00755)	(0.00949)	(0.0253)
Age	0.0381	0.000460	0.000536	0.0160	0.00967	0.0473	0.00151	0.00189	0.0164	0.00783
	(0.0346)	(0.0110)	(0.00886)	(0.0116)	(0.0184)	(0.0341)	(0.0107)	(0.00874)	(0.0114)	(0.0184)
Age^2	-0.000251	-0.000145**	-0.0000831	-0.000193***	-0.000178	-0.000298*	-0.000150**	-0.0000780	-0.000194***	-0.000167
	(0.000171)	(0.0000736)	(0.0000577)	(0.0000737)	(0.000135)	(0.000169)	(0.0000723)	(0.0000568)	(0.0000722)	(0.000133)
Urban	-0.0392	-0.00101	-0.0217	0.00105	0.0446	-0.0461	0.0124	-0.0285	-0.00487	0.0354
	(0.105)	(0.0434)	(0.0253)	(0.0286)	(0.0467)	(0.104)	(0.0423)	(0.0246)	(0.0278)	(0.0460)
Married	0.0709	-0.0128	-0.00139	-0.00533	0.110*	0.0614	-0.0207	-0.00575	0.00331	0.131**
	(0.0916)	(0.0307)	(0.0223)	(0.0281)	(0.0578)	(0.0906)	(0.0301)	(0.0214)	(0.0276)	(0.0573)
School years	0.0163	0.00973	-0.00903	-0.00146	-0.00892	0.00655	0.00980	-0.00865	-0.00111	-0.0110
	(0.0267)	(0.00938)	(0.00575)	(0.00606)	(0.0140)	(0.0264)	(0.00924)	(0.00568)	(0.00596)	(0.0139)
Private sector	-0.145	0.0151	-0.0491	0.0535	0.103					
	(0.210)	(0.0624)	(0.0361)	(0.0413)	(0.0628)					
Mining and quarrying	-0.141	0.101	-0.0178	-0.0566	0.0259					
	(0.354)	(0.135)	(0.0603)	(0.0851)	(0.112)					
Manufacturing	0.0454	0.0244	0.000564	0.00311	0.0474					
	(0.107)	(0.0381)	(0.0318)	(0.0356)	(0.0793)					
Electricity, gas, water	0	-0.246	-0.00303	0.0473	-0.0799					
	(.)	(0.194)	(0.0896)	(0.0771)	(0.145)					
Construction	-0.0561	-0.0184	0.0314	-0.00879	0.141					
	(0.173)	(0.0409)	(0.0368)	(0.0426)	(0.108)					
Wholesale, retail, restaurant & hotels	-0.0181	0.0370	0.0126	0.0193	0.0287					
	(0.126)	(0.0394)	(0.0357)	(0.0399)	(0.0868)					
Transportation, storage & communications	0.0664	-0.0555	0.0661	-0.0433	0.169*					
	(0.248)	(0.0686)	(0.0411)	(0.0437)	(0.0985)					
Finance, insurance, real estate & business services	-0.125	-0.0762	0.0460	-0.0439	0.0559					
	(0.262)	(0.0836)	(0.0532)	(0.0477)	(0.0912)					
Social services	0.124	0.0188	0.0247	-0.0218	-0.0117					
	(0.108)	(0.0390)	(0.0336)	(0.0338)	(0.0743)					
Other household characteristics	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5102	5391	5580	5350	4495	5102	5391	5580	5350	4495

Note: The dependent variable is the log of monthly wage adjusted to the 2010 value. All estimations include all the control variables described in Chapter 5 as well as year and district fixed effects. Robust clustered standard errors are reported in parentheses below coefficient estimates. Significance at the 1 percent, 5 percent, and 10 percent levels are denoted respectively by ***, **, and *.

Table A10: Effects of Years of Unemployment on Subsequent Earning, by Gender and Residence

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Male	**Female**	**Rural**	**Urban**	**Male**	**Female**	**Rural**	**Urban**
Years of unemployment	0.00588	-0.0585***	-0.0520**	-0.0372***	0.00294	-0.0649***	-0.0531**	-0.0429***
	(0.0157)	(0.0124)	(0.0210)	(0.0122)	(0.0157)	(0.0124)	(0.0207)	(0.0123)
Age	0.0931***	0.0652***	0.0617***	0.0831***	0.0968***	0.0652***	0.0634***	0.0861***
	(0.0138)	(0.0235)	(0.0239)	(0.0137)	(0.0137)	(0.0245)	(0.0243)	(0.0136)
Age^2	-0.000975***	-0.000441***	-0.000635***	-0.000900***	-0.00102***	-0.000480***	-0.000682***	-0.000931***
	(0.0000849)	(0.000145)	(0.000162)	(0.0000890)	(0.0000857)	(0.000148)	(0.000164)	(0.0000906)
Urban	0.0575*	0.0435	0	0	0.0762**	0.0494	0	0
	(0.0338)	(0.0632)	(.)	(.)	(0.0338)	(0.0644)	(.)	(.)
Married	0.0860***	0.00774	0.108*	-0.00174	0.0933***	0.00874	0.106*	0.0106
	(0.0327)	(0.0463)	(0.0641)	(0.0309)	(0.0329)	(0.0467)	(0.0643)	(0.0310)
School years	0.0348***	0.0401**	0.0594***	0.0281***	0.0352***	0.0406**	0.0623***	0.0266***
	(0.00857)	(0.0185)	(0.0159)	(0.00982)	(0.00868)	(0.0186)	(0.0158)	(0.00994)
Private sector	0.117**	0.246***	0.0895	0.163***				
	(0.0494)	(0.0721)	(0.0944)	(0.0484)				
Mining and quarrying	0.174*	0.0225	0.259*	0.164				
	(0.0911)	(0.325)	(0.152)	(0.119)				
Manufacturing	0.162***	0.248***	0.184***	0.169***				
	(0.0420)	(0.0873)	(0.0619)	(0.0595)				
Electricity, gas, water	0.219*	-0.165	0.554	0.167				
	(0.114)	(0.236)	(0.426)	(0.121)				
Construction	0.138***	0.241	0.161**	0.0600				
	(0.0457)	(0.199)	(0.0810)	(0.0644)				
Wholesale, retail, restaurant & hotels	0.0953**	0.186**	0.159*	0.0898				
	(0.0467)	(0.0924)	(0.0903)	(0.0587)				
Transportation, storage & communications	0.132**	0.271**	0.141	0.135**				
	(0.0551)	(0.130)	(0.111)	(0.0656)				
Finance, insurance, real estate & business services	0.193***	0.220	0.272*	0.158**				
	(0.0594)	(0.140)	(0.161)	(0.0685)				
Social services	0.00651	0.0117	0.0540	-0.0533				
	(0.0447)	(0.0840)	(0.0710)	(0.0575)				
Other household characteristics	Yes	Yes	Yes	Yes	No	No	No	No
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17049	8869	9006	16912	17049	8869	9006	16912

Note: The dependent variable is the log of monthly wage adjusted to the 2010 value. All estimations include all the control variables described in Chapter 5 as well as year and district fixed effects. Robust clustered standard errors are reported in parentheses below coefficient estimates. Significance at the 1 percent, 5 percent, and 10 percent levels are denoted respectively by ***, **, and *.

Table A11: Effects of Years of Self-Employment on Subsequent Earning, by Age

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Full Sample	**Age 15-24**	**Age 25-34**	**Age 35-44**	**Age 45-60**	**Full Sample**	**Age 15-24**	**Age 25-34**	**Age 35-44**	**Age 45-60**
Years mostly in self-employment	-0.00356	0.00289	-0.0124	-0.0218	0.00630	-0.00424	0.0188	-0.00845	-0.0249	0.00572
	(0.00417)	(0.0440)	(0.0165)	(0.0169)	(0.0150)	(0.00416)	(0.0438)	(0.0165)	(0.0167)	(0.0150)
Years mostly in private sector employment	0.00791*	0.0424	0.00445	-0.00310	0.0232	0.00785*	0.0515	0.00619	-0.00386	0.0202
	(0.00444)	(0.0426)	(0.0165)	(0.0176)	(0.0172)	(0.00445)	(0.0421)	(0.0166)	(0.0175)	(0.0172)
Years mostly in government employment	0.0294***	0.444***	0.00885	0.0433*	0.0113	0.0316***	0.276**	0.0162	0.0406*	0.0141
	(0.00633)	(0.167)	(0.0324)	(0.0227)	(0.0197)	(0.00629)	(0.135)	(0.0303)	(0.0223)	(0.0199)
Age	0.0961***	0.0532	-0.0293	-0.193	0.158*	0.0976***	0.120	-0.00160	-0.187	0.203**
	(0.00820)	(0.309)	(0.145)	(0.181)	(0.0829)	(0.00824)	(0.304)	(0.146)	(0.181)	(0.0835)
Age^2	-0.000912***	-0.000117	0.000675	0.00311	-0.00135*	-0.000942***	-0.00270	0.000259	0.00299	-0.00179**
	(0.0000476)	(0.00753)	(0.00239)	(0.00227)	(0.000777)	(0.0000478)	(0.00741)	(0.00241)	(0.00227)	(0.000782)
Urban	0.0410	0.312	0.00944	0.112	0.0711	0.0547**	0.405*	0.0163	0.105	0.0770
	(0.0255)	(0.241)	(0.0834)	(0.0881)	(0.0851)	(0.0256)	(0.236)	(0.0838)	(0.0877)	(0.0857)
Married	0.0327	0.0185	-0.0297	-0.0963	-0.000890	0.0360	0.111	-0.0340	-0.121	-0.00660
	(0.0238)	(0.164)	(0.0668)	(0.115)	(0.0923)	(0.0239)	(0.161)	(0.0670)	(0.115)	(0.0930)
School years	0.0236***	0.196***	0.0230	0.00301	-0.00224	0.0248***	0.194***	0.0237	0.00101	-0.00175
	(0.00582)	(0.0431)	(0.0204)	(0.0186)	(0.0158)	(0.00586)	(0.0432)	(0.0205)	(0.0186)	(0.0159)
Private sector	0.193***	-0.926*	0.119	-0.0199	0.670***					
	(0.0460)	(0.525)	(0.159)	(0.146)	(0.130)					
Mining and quarrying	0.231***	0.160	0.410	0.447**	0.244					
	(0.0755)	(0.689)	(0.271)	(0.222)	(0.289)					
Manufacturing	0.235***	0.305	0.320***	0.121	0.203**					
	(0.0287)	(0.224)	(0.0886)	(0.0956)	(0.0898)					
Electricity, gas, water	0.285**	0	0.354	0.375	-0.133					
	(0.113)	(.)	(0.284)	(0.354)	(0.522)					
Construction	0.286***	0.198	0.296***	0.225*	0.336***					
	(0.0369)	(0.271)	(0.113)	(0.123)	(0.114)					
Wholesale, retail, restaurant & hotels	0.187***	0.119	0.289***	0.166*	0.139*					
	(0.0277)	(0.242)	(0.0898)	(0.0934)	(0.0829)					
Transportation, storage & communications	0.142***	-0.184	0.322***	-0.0226	0.132					
	(0.0402)	(0.320)	(0.114)	(0.128)	(0.128)					
Finance, insurance, real estate & business services	0.250***	-0.474	0.384**	0.114	0.217					
	(0.0543)	(0.517)	(0.172)	(0.179)	(0.219)					
Social services	0.0555**	-0.0876	0.165*	0.112	-0.0817					
	(0.0281)	(0.240)	(0.0880)	(0.0955)	(0.0845)					
Other household characteristics	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	44648	7218	13304	11388	9848	44648	7218	13304	11388	9848

Note: The dependent variable is the log of monthly wage adjusted to the 2010 value. All estimations include all the control variables described in Chapter 5 as well as year and district fixed effects. Robust clustered standard errors are reported in parentheses below coefficient estimates. Significance at the 1 percent, 5 percent, and 10 percent levels are denoted respectively by ***, **, and *.

Table A12: Effects of Years of Self-Employment on Subsequent Earning, by Income Distribution

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	<20%	20-40%	40-60%	60-80%	>80%	<20%	20-40%	40-60%	60-80%	>80%
Years mostly in self-employment	0.0235	0.00511	0.00277	0.0103	0.00970	0.0266*	0.00604	0.00190	0.00978	0.00583
	(0.0159)	(0.00728)	(0.00521)	(0.00659)	(0.0218)	(0.0155)	(0.00702)	(0.00506)	(0.00648)	(0.0217)
Years mostly in private sector employment	0.0231	0.0160**	0.00828*	0.00891	-0.00828	0.0260	0.0174***	0.00765*	0.00938*	-0.00851
	(0.0164)	(0.00693)	(0.00475)	(0.00562)	(0.00993)	(0.0159)	(0.00674)	(0.00459)	(0.00552)	(0.00974)
Years mostly in government employment	0.0457	0.0515***	0.0124*	0.0126*	0.0107	0.0367	0.0447***	0.00837	0.0135**	0.00916
	(0.0426)	(0.0148)	(0.00736)	(0.00645)	(0.00981)	(0.0400)	(0.0131)	(0.00686)	(0.00632)	(0.00965)
Age	0.0366	-0.00119	0.00235	0.0186	0.0230	0.0463	0.000242	0.00320	0.0187	0.0206
	(0.0346)	(0.0108)	(0.00889)	(0.0117)	(0.0187)	(0.0342)	(0.0106)	(0.00877)	(0.0115)	(0.0187)
Age^2	-0.000217	-0.000135*	-0.0000872	-0.000219***	-0.000331**	-0.000262	-0.000129*	-0.0000792	-0.000217***	-0.000313**
	(0.000170)	(0.0000726)	(0.0000586)	(0.0000766)	(0.000141)	(0.000169)	(0.0000712)	(0.0000578)	(0.0000749)	(0.000140)
Urban	-0.0365	0.0134	-0.0225	-0.00377	0.0406	-0.0421	0.0227	-0.0287	-0.00935	0.0315
	(0.105)	(0.0430)	(0.0251)	(0.0288)	(0.0464)	(0.104)	(0.0418)	(0.0246)	(0.0280)	(0.0457)
Married	0.0655	-0.0176	-0.00738	-0.00497	0.121**	0.0604	-0.0263	-0.0121	0.00295	0.141**
	(0.0920)	(0.0303)	(0.0224)	(0.0281)	(0.0575)	(0.0910)	(0.0296)	(0.0216)	(0.0276)	(0.0571)
School years	0.0164	0.0108	-0.00822	-0.000904	-0.0116	0.00560	0.0117	-0.00794	-0.000623	-0.0140
	(0.0269)	(0.00926)	(0.00572)	(0.00607)	(0.0140)	(0.0265)	(0.00912)	(0.00567)	(0.00597)	(0.0139)
Private sector	-0.186	-0.0856	-0.0592	0.0491	0.0609					
	(0.225)	(0.0700)	(0.0380)	(0.0416)	(0.0637)					
Mining and quarrying	-0.147	0.0657	0.00198	-0.0577	0.0299					
	(0.355)	(0.134)	(0.0605)	(0.0854)	(0.112)					
Manufacturing	0.0446	0.0149	0.00338	0.00475	0.0483					
	(0.107)	(0.0377)	(0.0317)	(0.0357)	(0.0788)					
Electricity, gas, water	0	-0.206	0.00644	0.0492	-0.0922					
	(.)	(0.191)	(0.0893)	(0.0773)	(0.144)					
Construction	-0.0497	-0.0202	0.0362	-0.00752	0.160					
	(0.173)	(0.0402)	(0.0366)	(0.0432)	(0.107)					
Wholesale, retail, restaurant & hotels	-0.0194	0.0351	0.0140	0.0204	0.0266					
	(0.127)	(0.0388)	(0.0355)	(0.0400)	(0.0863)					
Transportation, storage & communications	0.0547	-0.0693	0.0657	-0.0377	0.168*					
	(0.249)	(0.0678)	(0.0409)	(0.0439)	(0.0978)					
Finance, insurance, real estate & business services	-0.0376	-0.0496	0.0624	-0.0338	0.0515					
	(0.270)	(0.0841)	(0.0537)	(0.0479)	(0.0908)					
Social services	0.116	0.0212	0.0280	-0.0204	-0.0214					
	(0.108)	(0.0384)	(0.0334)	(0.0339)	(0.0738)					
Other household characteristics	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5102	5391	5580	5350	4495	5102	5391	5580	5350	4495

Note: The dependent variable is the log of monthly wage adjusted to the 2010 value. All estimations include all the control variables described in Chapter 5 as well as year and district fixed effects. Robust clustered standard errors are reported in parentheses below coefficient estimates. Significance at the 1 percent, 5 percent, and 10 percent levels are denoted respectively by ***, **, and *.

Table A13: Effects of Years of Self-Employment on Subsequent Earning, by Gender and Residence

Variables	(1) Male	(2) Female	(3) Rural	(4) Urban	(5) Male	(6) Female	(7) Rural	(8) Urban
Years mostly in self-employment	-0.0142**	0.0109	0.00110	-0.00484	-0.0159***	0.0117	-0.00108	-0.00535
	(0.00563)	(0.00821)	(0.00929)	(0.00603)	(0.00554)	(0.00826)	(0.00921)	(0.00603)
Years mostly in private sector employment	-0.00172	0.0206**	0.0130	0.00488	-0.00263	0.0220***	0.0145	0.00466
	(0.00550)	(0.00819)	(0.00973)	(0.00565)	(0.00545)	(0.00823)	(0.00974)	(0.00568)
Years mostly in government employment	0.0218***	0.0414***	0.0230*	0.0306***	0.0225***	0.0453***	0.0275**	0.0318***
	(0.00700)	(0.00879)	(0.0123)	(0.00661)	(0.00678)	(0.00873)	(0.0119)	(0.00652)
Age	0.0988***	0.0915***	0.0940***	0.0971***	0.102***	0.0894***	0.0957***	0.0987***
	(0.0101)	(0.0156)	(0.0133)	(0.0118)	(0.0102)	(0.0157)	(0.0135)	(0.0119)
Age^2	-0.000955***	-0.000814***	-0.000853***	-0.000956***	-0.000997***	-0.000817***	-0.000889***	-0.000975***
	(0.0000653)	(0.000101)	(0.0000920)	(0.0000731)	(0.0000659)	(0.000101)	(0.0000927)	(0.0000741)
Urban	0.0566*	-0.00310	0	0	0.0760***	-0.00223	0	0
	(0.0291)	(0.0530)	(.)	(.)	(0.0294)	(0.0536)	(.)	(.)
Married	0.114***	-0.0656	-0.00105	0.0295	0.116***	-0.0623	-0.00573	0.0363
	(0.0290)	(0.0403)	(0.0493)	(0.0296)	(0.0290)	(0.0405)	(0.0490)	(0.0297)
School years	0.0232***	0.0171	0.0422***	0.0136*	0.0245***	0.0167	0.0436***	0.0136*
	(0.00675)	(0.0124)	(0.0108)	(0.00773)	(0.00678)	(0.0124)	(0.0108)	(0.00777)
Mining and quarrying	0.167***	0.200**	0.232**	0.156***				
	(0.0537)	(0.0814)	(0.102)	(0.0512)				
Manufacturing	0.263***	-0.0887	0.236**	0.246**				
	(0.0747)	(0.259)	(0.102)	(0.110)				
Electricity, gas, water	0.257***	0.175**	0.197***	0.252***				
	(0.0352)	(0.0683)	(0.0507)	(0.0515)				
Construction	0.343***	-0.229	0.731**	0.271***				
	(0.0932)	(0.228)	(0.324)	(0.103)				
Wholesale, retail, restaurant & hotels	0.306***	0.172	0.330***	0.175***				
	(0.0402)	(0.145)	(0.0651)	(0.0576)				
Transportation, storage & communications	0.211***	0.125**	0.162***	0.177***				
	(0.0364)	(0.0635)	(0.0491)	(0.0513)				
Finance, insurance, real estate & business services	0.158***	0.251*	0.170**	0.134**				
	(0.0429)	(0.133)	(0.0808)	(0.0559)				
Social services	0.267***	0.0419	0.228*	0.210***				
	(0.0521)	(0.139)	(0.128)	(0.0646)				
Other household characteristics	Yes	Yes	Yes	Yes	No	No	No	No
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	27885	16763	18787	25861	27885	16763	18787	25861

Note: The dependent variable is the log of monthly wage adjusted to the 2010 value. All estimations include all the control variables described in Chapter 5 as well as year and district fixed effects. Robust clustered standard errors are reported in parentheses below coefficient estimates. Significance at the 1 percent, 5 percent, and 10 percent levels are denoted respectively by ***, **, and *.

6.2. Scarring Effects of Previous Unemployment on Subsequent Earnings

This section begins by discussing the effect of previous unemployment incidence on subsequent earnings. The difference-in-difference with propensity score matching model is tested on various subsets of data, including sample disaggregated by age, income distribution, gender, and location of residence.

Table 1 presents the results of estimation based on subsets of different age groups. The whole sample ranges from 15 to 60 years of age, representing the working-age population, which is then breakdown into four different groups, namely 15-24, 25-34, 35-44, and 45-60. In particular, those aged 15-24 years could be characterized as young workers who just entered the labor market. Meanwhile, those aged 25-44 are mid, and upper-midrange workers who are in their primary working lives, and those aged 45-60 are more senior workers who are at the peak of their career and also those who are approaching retirement. According to Table 1, the scarring effect due to previous unemployment, represented by the interaction term, is more observed among older workers. It can be inferred that among workers age 45-60 years, those who have been previously unemployed received earning 13.4 percent lower relative to those who have not, significant at 1 percent level. Meanwhile, there is no significant effect of scarring due to previous unemployment among other age groups.

Table 1: Scarring Effects of Previous Unemployment on Subsequent Earnings, by Age

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
	Full Sample	**Age 15-24**	**Age 25-34**	**Age 35-44**	**Age 45-60**
Time	0.0157***	0.00256	0.00446	-0.000370	0.00946**
	(0.00288)	(0.00806)	(0.00316)	(0.00287)	(0.00426)
Ever unemployed	-0.0270*	0.00508	0.0258	-0.0176	0.0144
	(0.0148)	(0.00922)	(0.0159)	(0.0187)	(0.0387)
Time * Ever unemployed	-0.0274	-0.00752	-0.0337	0.0130	-0.134**
	(0.0169)	(0.0173)	(0.0208)	(0.0336)	(0.0671)
Other individual characteristics	Yes	Yes	Yes	Yes	Yes
Other work characteristics	Yes	Yes	Yes	Yes	Yes
Other household characteristics	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	38,293	8,236	12,888	9,471	6,692

Note: The dependent variable is the log of monthly wage adjusted to the 2010 value. All estimations include all the control variables described in Chapter 5 as well as year and district fixed effects. Robust clustered standard errors are reported in parentheses below coefficient estimates. Significance at the 1 percent, 5 percent, and 10 percent levels are denoted respectively by ***, **, and *.

The estimation results by age groups indicate that the older workers' difficulty to reintegrate into the labor market after being dismissed from employment is more severe than that of the younger unemployed. It could happen due to older workers' accumulated job-specific skills are not easily transferred to new jobs, while their general transferable skills may have been obsolete. This finding is consistent with the studies done by Coen et al. (2010) and Böheim et al. (2011), showing that as workers get older, the period of their unemployment lengthens and the opportunity of finding a new job decreases. As an aging population will exacerbate this adverse effect, Henkens et al. (1996) suggest that reorientation and retraining efforts must be initiated as early as possible to protect older workers from the trap of long-term economic inactivity, and in many cases, total exclusion from the labor market.

The results of the difference-in-difference estimation according to groups of the income distribution are displayed in Table 2. It is interesting to point out that the effect of scarring is more pronounced among the low-income group, particularly those who are in the bottom 20 percent of income. Those who have been previously unemployed received earning 5.16 percent lower relative to those who have not, significant at 1 percent level. Observing the pattern of the result, we can see that unemployment scarring is disproportionately affecting the poorest as low-paid jobs may be the only income-generating options that offer a suitable way to reintegrate those who are unemployed back into the labor market. Specifically, this group may be constantly transiting between periods of unemployment and low-paid and low-skilled work. Nevertheless, there have been ongoing debates regarding low-paid jobs and whether they are beneficial to workers. In view of this, engaging in low-paid jobs may prevent the scarring effects of unemployment and could be used as a stepping stone onto higher-paid employment (McCormick, 1990; Cai, 2014). Yet, on the other hand, workers can be entrapped in low-paid jobs where the accumulation of human capital is often limited (Mosthaf et al., 2014).

Table 2: Scarring Effects of Previous Unemployment on Subsequent Earnings, by Income Distribution

Variables	Income Distribution				
	(1)	(2)	(3)	(4)	(5)
	<20%	20-40%	40-60%	60-80%	>80%
Time	0.0156***	-0.0000298	0.000378	0.00163**	0.00210
	(0.00581)	(0.00124)	(0.000792)	(0.000745)	(0.00142)
Ever unemployed	0.0250	0.00364	-0.0000234	0.00392	0.00922
	(0.0163)	(0.00394)	(0.00359)	(0.00510)	(0.0236)
Time * Ever unemployed	-0.0516**	-0.00262	-0.00111	-0.00897	-0.0224
	(0.0209)	(0.00548)	(0.00457)	(0.00607)	(0.0261)
Other individual charcs.	Yes	Yes	Yes	Yes	Yes
Other work charcs.	Yes	Yes	Yes	Yes	Yes
Other household charcs.	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	7,803	8,370	8,399	7,351	6,370

Note: The dependent variable is the log of monthly wage adjusted to the 2010 value. All estimations include all the control variables described in Chapter 5 as well as year and district fixed effects. Robust clustered standard errors are reported in parentheses below coefficient estimates. Significance at the 1 percent, 5 percent, and 10 percent levels are denoted respectively by ***, **, and *.

Table 3: Scarring Effects of Previous Unemployment on Subsequent Earnings, by Gender and Residence

Variables	(1)	(2)	(3)	(4)
	Male	Female	Rural	Urban
Time	0.0143***	0.0212***	0.0156***	0.0195***
	(0.00325)	(0.00643)	(0.00497)	(0.00354)
Ever unemployed	-0.0433**	-0.0138	0.00767	-0.0385***
	(0.0185)	(0.0139)	(0.0205)	(0.0125)
Time * Ever unemployed	-0.0246	-0.0403**	-0.0562**	-0.0337**

	(0.0214)	(0.0189)	(0.0247)	(0.0154)
Other individual characteristics	Yes	Yes	Yes	Yes
Other work characteristics	Yes	Yes	Yes	Yes
Other household characteristics	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	26,048	13,878	14,097	25,829

Note: The dependent variable is the log of monthly wage adjusted to the 2010 value. All estimations include all the control variables described in Chapter 5 as well as year and district fixed effects. Robust clustered standard errors are reported in parentheses below coefficient estimates. Significance at the 1 percent, 5 percent, and 10 percent levels are denoted respectively by ***, **, and *.

Table 3 displays the results of estimation from subsets divided by gender and place of residence. Previous unemployment experience affects both male and female workers; however, subsequent earning penalty is higher for females, in which those who have been previously unemployed received earning 4.03 percent lower relative to those who have not, significant at 1 percent level. Likewise, residents of rural areas are more heavily affected by previous unemployment relative to those of urban areas, by receiving earning 5.62 percent less to the counterfactuals who have never experienced previous unemployment. This magnitude of scarring among rural workers is almost double than that of urban workers. Also, it is worth noting that the mean difference in subsequent earnings among male workers is somewhat influenced by the initial difference between the two groups, rather than the scarring effect of unemployment per se, which amounts to 4.33 percent. It could indicate that among males, workers are able to accumulate human capital and/or show better signals to employers despite previous unemployment experience. Also, as male traditionally holds the role of breadwinners in the family, it is too costly for a male to be unemployed.

6.3. Scarring Effects of the Previous Self-Employment on Subsequent Earnings

This section will discuss the results of the difference-in-difference estimation using previous self-employment experience – which includes self-employed workers and self-employed with unpaid family/temporary workers – as the source of scarring. The coefficient on the interaction term gives the average difference-in-difference effect, i.e., the scarring effect of the previous self-employment.

Table 4: Scarring Effects of the Previous Self-Employment on Subsequent Earnings, by Age

Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
	Full Sample	**Age 15-24**	**Age 25-34**	**Age 35-44**	**Age 45-60**
Time	0.0394***	0.00326	0.0169**	0.0164*	0.0288*
	(0.00672)	(0.00621)	(0.00733)	(0.00969)	(0.0163)
Ever self-employed	-0.00713	0.00714	0.0000307	0.000763	0.000324
	(0.00709)	(0.00608)	(0.00618)	(0.00684)	(0.0131)
Time * Ever self-employed	-0.0487***	-0.00922	-0.0241**	-0.0217	-0.0355
	(0.0106)	(0.0122)	(0.0122)	(0.0139)	(0.0227)
Other individual characteristics	Yes	Yes	Yes	Yes	Yes
Other work characteristics	Yes	Yes	Yes	Yes	Yes
Other household characteristics	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	54,422	10,017	19,559	9,474	15,372

Note: The dependent variable is the log of monthly wage adjusted to the 2010 value. All estimations include all the control variables described in Chapter 5 as well as year and district fixed effects. Robust clustered standard errors are reported in parentheses below coefficient estimates. Significance at the 1 percent, 5 percent, and 10 percent levels are denoted respectively by ***, **, and *.

As presented in Table 4, the scarring effect due to previous engagement in self-employment activities is more observable among the early-mid level workers aged 25-34 years. Those who have been previously self-employed earn 2.41 percent lower relative to those who have not, significant at 5 percent level. This finding could indicate that, among young workers age 25-34 years, scarring effects due to self-employment is more substantial than that due to unemployment. During periods of working in the informal sector, young workers may suffer from human capital reduction as they miss out on the opportunity of obtaining job-specific training. Although having a low-paid job may be better than being unemployed, the opportunity

Table 5: Scarring Effects of the Previous Self-Employment on Subsequent Earnings, by Income Distribution

Variables	**Income Distribution**				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
	<20%	**20-40%**	**40-60%**	**60-80%**	**>80%**
Time	-0.000112	0.00774***	0.00484***	0.00105	-0.00180
	(0.0121)	(0.00258)	(0.00166)	(0.00164)	(0.00269)
Ever self-employed	-0.00820	0.00574**	0.000914	0.00111	-0.00433
	(0.0110)	(0.00270)	(0.00207)	(0.00282)	(0.00873)
Time * Ever self-employed	0.00479	-0.0147***	-0.00843**	-0.00262	0.00702
	(0.0198)	(0.00487)	(0.00350)	(0.00436)	(0.0111)
Other individual characteristics	Yes	Yes	Yes	Yes	Yes
Other work characteristics	Yes	Yes	Yes	Yes	Yes
Other household characteristics	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	7,832	8,376	8,400	7,349	6,368

Note: The dependent variable is the log of monthly wage adjusted to the 2010 value. All estimations include all the control variables described in Chapter 5 as well as year and district fixed effects. Robust clustered standard errors are reported in parentheses below coefficient estimates. Significance at the 1 percent, 5 percent, and 10 percent levels are denoted respectively by ***, **, and *.

for human capital accumulation in low-quality jobs is inadequate, and is probably not much better than during unemployment, especially if the unemployed individuals obtain training measures from the government or employment agency (Moshtaf et al., 2014). Moreover, for young workers, their general skills gained during schools are likely to depreciate during the time spent in self-employment, which then creates long-term consequences, including lower subsequent earnings. In developing countries where the informal sector characterizes a large set of economic activities, low-skilled young workers may engage in self-employment as it is the only option available to earn income. Meanwhile, young workers who can “afford” unemployment tend to be high-skilled and their unemployment status are temporary or frictional, i.e., in the process of first joining the workforce or moving from one job to another.

Table 5 presents the effects of scarring due to previous self-employment experience on future earnings based on different income groups. Unlike the previous estimation of scarring effects due to unemployment, the harmful effects of the previous self-employment on subsequent earnings are seen to affect mainly the aspiring-middle- and middle-class individuals, those who are between 20 to 60 percent of the income distribution. It is interesting to note how scarring effects due to previous self-employment, similar to that due to previous employment, has the tendency of affecting certain income groups disproportionately. In this case, relative to the counterfactuals who have never been self-employed, workers of aspiring-middle- and middle-class suffer from earning a penalty after spending some time in self-employment. It could be the case as those who continuously have wage employment will be able to accumulate their human capital without interruption by receiving regular on-the-job training.

Moreover, in Indonesia, around 60 percent of workers in the 2nd and 3rd quintile of the income distribution are engaged in some types of informal employment (BPS, 2019). These groups of the income distribution are often categorized as the "missing middle" because they are unqualified for poverty-targeted social assistance and yet also ruled out from employment-based benefits. Meanwhile, there are no observable scarring effects due to the previous self-employment among the bottom 20 percent of incomes. It might be the case that these people live in poverty or even extreme poverty. These people have no adequate opportunities to accumulate human capital even when they work at wage employment, as it tends to be a low-paid and/or low-quality job. Schnable (2016) asserts that low-wage employment is a problem when it tends to be persistent, which may drive individuals into repeated spells of unemployment with a low-pay and no-pay cycle.

Table 6: Scarring Effects of the Previous Self-Employment on Subsequent Earnings, by Gender and Residence

Variables	**(1)**	**(2)**	**(3)**	**(4)**
	Male	**Female**	**Rural**	**Urban**
Time	0.0241***	0.0153*	0.0114	0.0188***
	(0.00759)	(0.00860)	(0.0115)	(0.00603)
Ever self-employed	-0.00917	0.00541	-0.0277***	-0.00154
	(0.00777)	(0.0102)	(0.0105)	(0.00693)
Time * Ever self-employed	-0.0360***	-0.0288*	-0.0118	-0.0327***
	(0.0128)	(0.0172)	(0.0178)	(0.0117)
Other individual characteristics	Yes	Yes	Yes	Yes
Other work characteristics	Yes	Yes	Yes	Yes
Other household characteristics	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	25,527	13,238	13,760	25,005

Note: The dependent variable is the log of monthly wage adjusted to the 2010 value. All estimations include all the control variables described in Chapter 5 as well as year and district fixed effects. Robust clustered standard errors are reported in parentheses below coefficient estimates. Significance at the 1 percent, 5 percent, and 10 percent levels are denoted respectively by ***, **, and *.

Table 6 displays the effects of the previous self-employment on subsequent earnings analyzed on data subsets divided by gender and place of residence. The estimation based on gender shows that male experience reduced earnings caused by the previous self-employment, shown by the statistically significant coefficients for the interaction term between time and post-treatment variable. Male workers are estimated to lose 3.6 percent on average due to previous self-employment, significant at 1 percent level. Meanwhile, when the data set is disaggregated by place of residence, only urban workers experience a reduction in subsequent earnings as an effect of the previous self-employment. In terms of the magnitude, the reduction in subsequent earnings for urban workers who have ever been self-employed amounts to 3.27 percent. Correspondingly, a study by Gindling et al., (2016) finds that non-professional own-account workers and informal wage employees encounter a more severe income penalty relative to formal wage employees.

6.4. Effects of Years of Unemployment on Subsequent Earning

This section will further examine the effect of unemployment, in terms of its duration, to subsequent earnings. Using fixed-effect estimation, the model is tested on different data subsets, including sample disaggregated by age, income distribution, gender, and location of residence.

Table 7: Effects of Years of Unemployment on Subsequent Earning, by Age

Variables	(1)	(2)	(3)	(4)	(5)
	Full Sample	**Age 15-24**	**Age 25-34**	**Age 35-44**	**Age 45-60**
Years of unemployment	-0.0346***	-0.0507	-0.0316	-0.0299	-0.0997***
	(0.00700)	(0.0577)	(0.0238)	(0.0310)	(0.0269)
Other individual characteristics	Yes	Yes	Yes	Yes	Yes
Other work characteristics	Yes	Yes	Yes	Yes	Yes
Other household characteristics	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	25,918	5,974	8,728	6,269	4,296

Note: The dependent variable is the log of monthly wage adjusted to the 2010 value. All estimations include all the control variables described in Chapter 5 as well as year and district fixed effects. Robust clustered standard errors are reported in parentheses below coefficient estimates. Significance at the 1 percent, 5 percent, and 10 percent levels are denoted respectively by ***, **, and *.

Table 7 indicates that, particularly for workers age 45-60 years, the duration of unemployment negatively affects subsequent earnings, in which an additional year of unemployment will reduce subsequent earnings by 9.97 percent, significant at 1 percent level. It is in line with the result of Gregory & Jukes (2001), stating that longer unemployment spells can exacerbate the negative effect of scarring and cause a permanent effect.

Table 8: Effects of Years of Unemployment on Subsequent Earning, by Income Distribution

Variables	(1)	(2)	(3)	(4)	(5)
	<20%	**20-40%**	**40-60%**	**60-80%**	**>80%**
Years of unemployment	-0.0373**	-0.0117	-0.00427	-0.0158	-0.00369
	(0.0184)	(0.00852)	(0.00778)	(0.00965)	(0.0255)
Other individual characteristics	Yes	Yes	Yes	Yes	Yes
Other work characteristics	Yes	Yes	Yes	Yes	Yes
Other household characteristics	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	5,102	5,391	5,580	5,350	4,495

Note: The dependent variable is the log of monthly wage adjusted to the 2010 value. All estimations include all the control variables described in Chapter 5 as well as year and district fixed effects. Robust clustered standard errors are reported in parentheses below coefficient estimates. Significance at the 1 percent, 5 percent, and 10 percent levels are denoted respectively by ***, **, and *.

The results of the fixed-effect estimation according to groups of the income distribution are displayed in Table 8. It is interesting to point out that the effect of years of unemployment is more evident among the low-income group, particularly those who are in the bottom 20 percent of income, in which one year of unemployment leads to a reduction of 3.73 percent in subsequent earnings, significant at 5 percent level.

Table 9: Effects of Years of Unemployment on Subsequent Earning, by Gender and Residence

Variables	(1) Male	(2) Female	(3) Rural	(4) Urban
Years of unemployment	0.00588	-0.0585***	-0.0520**	-0.0372***
	(0.0157)	(0.0124)	(0.0210)	(0.0122)
Other individual characteristics	Yes	Yes	Yes	Yes
Other work characteristics	Yes	Yes	Yes	Yes
Other household characteristics	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	17,049	8,869	9,006	16,912

Note: The dependent variable is the log of monthly wage adjusted to the 2010 value. All estimations include all the control variables described in Chapter 5 as well as year and district fixed effects. Robust clustered standard errors are reported in parentheses below coefficient estimates. Significance at the 1 percent, 5 percent, and 10 percent levels are denoted respectively by ***, **, and *.

Table 9 displays the results of fixed-effects estimation using sample subsets divided by gender and place of residence. Relative to male workers, female workers are affected more heavily by a more prolonged duration of unemployment, in which an additional year of unemployment will reduce their subsequent earning by 5.85 percent, significant at 1 percent level. Meanwhile, there is no significant result among male workers, which could indicate that they may benefit from conventional gender identity signals and/or that longer period of job search leads to better employment matches. Furthermore, when the estimation is tested based on place of residence, both residents of rural and urban areas are affected by the duration of unemployment. However, the subsequent earning penalty is higher for workers who live in rural areas, with 5.20 percent lower subsequent earnings corresponding one-year economic inactivity, significant at 5 percent level.

The analysis of duration of unemployment in this section is closely related to the study done by Gregory and Jukes (2001), that the time spent in unemployment, and not the occurrence of job displacement in itself, that counts the more for prospective earnings in the future. Moreover, it is also in line with the finding of Cooper (2014), using data from the US, that workers who are out of work beyond 26 weeks encounter a much larger income penalty and have lower subsequent earnings even after 10 or 15 years than those workers that experienced shorter-duration of unemployment. The finding is, in general, consistent with unemployment resulting in human capital loss, which leads to lower labor prospects in the future.

6.5. Effects of Years of Self-Employment on Subsequent Earning

Similar to Section 6.4, this section will further examine the effect of self-employment, in terms of its duration, to subsequent earnings. Self-employment, in this case, includes self-employed workers and self-employed with unpaid family/temporary workers. Using fixed-effect estimation, the model is tested on various subsets of data, including sample disaggregated by age, income distribution, gender, and location of residence.

Table 10: Effects of Years of Self-Employment on Subsequent Earning, by Age

Variables	(1)	(1)	(2)	(3)	(4)
	Full Sample	**Age 15-24**	**Age 25-34**	**Age 35-44**	**Age 45-60**
Years mostly in self emply.	-0.00356	0.00289	-0.0124	-0.0218	0.00630
	(0.00417)	(0.0440)	(0.0165)	(0.0169)	(0.0150)
Other individual characteristics	Yes	Yes	Yes	Yes	Yes
Other work characteristics	Yes	Yes	Yes	Yes	Yes
Other household characteristics	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	44,648	7,218	13,304	11,388	9,848

Note: The dependent variable is the log of monthly wage adjusted to the 2010 value. All estimations include all the control variables described in Chapter 5 as well as year and district fixed effects. Robust clustered standard errors are reported in parentheses below coefficient estimates. Significance at the 1 percent, 5 percent, and 10 percent levels are denoted respectively by ***, **, and *.

The effects of duration in self-employment by age groups are presented in Table 10. It can be observed that experience working in self-employment does not have any significant effect on subsequent earnings across different age groups. These results could indicate limited human capital accumulation during self-employment and/or hiring managers may use this information as an indicator of low productivity since periods spent during self-employment are not associated with higher income in the future.

Table 11: Effects of Years of Self-Employment on Subsequent Earning, by Income Distribution

Variables	(1)	(2)	(3)	(4)	(5)
	<20%	**20-40%**	**40-60%**	**60-80%**	**>80%**
Years mostly in self emply.	0.0235	0.00511	0.00277	0.0103	0.00970
	(0.0159)	(0.00728)	(0.00521)	(0.00659)	(0.0218)
Other individual characteristics	Yes	Yes	Yes	Yes	Yes
Other work characteristics	Yes	Yes	Yes	Yes	Yes
Other household characteristics	Yes	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	5,102	5,391	5,580	5,350	4,495

Note: The dependent variable is the log of monthly wage adjusted to the 2010 value. All estimations include all the control variables described in Chapter 5 as well as year and district fixed effects. Robust clustered standard errors are reported in parentheses below coefficient estimates. Significance at the 1 percent, 5 percent, and 10 percent levels are denoted respectively by ***, **, and *.

On a similar note, Table 11 shows that years spent in self-employment also do not significant effect on future earnings, when the sample is disaggregated by income distribution. The insignificant effects of self-employment duration on future earnings could indicate that the opportunity for human capital accumulation in low-quality jobs is inadequate and/or employers may use this information as an indicator of low productivity. Besides, these results could potentially imply limited opportunities for upward wage mobility for self-employed workers. According to research by Chen (2012), self-employed workers have higher poverty risk and are concentrated in low-average-earnings categories.

Table 12: Effects of Years of Self-Employment on Subsequent Earning, by Gender and Residence

Variables	(1) Male	(2) Female	(3) Rural	(4) Urban
Years mostly in self emply.	-0.0142**	0.0109	0.00110	-0.00484
	(0.00563)	(0.00821)	(0.00929)	(0.00603)
Other individual characteristics	Yes	Yes	Yes	Yes
Other work characteristics	Yes	Yes	Yes	Yes
Other household characteristics	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	27,885	16,763	18,787	25,861

Note: The dependent variable is the log of monthly wage adjusted to the 2010 value. All estimations include all the control variables described in Chapter 5 as well as year and district fixed effects. Robust clustered standard errors are reported in parentheses below coefficient estimates. Significance at the 1 percent, 5 percent, and 10 percent levels are denoted respectively by ***, **, and *.

Table 12 demonstrates the results of fixed-effects estimation using sample subsets divided by gender and place of residence. Among male workers, additional year of self-employment is associated with 1.42 percent lower future earnings. This result may suggest that male workers suffer the most due to experience in self-employment, particularly in terms of their potential earnings. Meanwhile, when the sample is disaggregated by location of residence, experience in self-employment does not affect future wages, both for workers in rural and urban areas. In that regard, the study of Lazear and Moore (1984) also finds that income patterns were flatter for own-account workers than formal salary workers as they do not have to utilize a tilted-up wage profile as a screening device. Moreover, in the context of developing countries, most workers are self-employed since they have no better alternatives; hence, self-employment, in this case, is not the same as entrepreneurship (Fields, 2019).

7. Robustness Check

a. Alternative Identification Strategy

This section will discuss the effects of previous unemployment and self-employment on subsequent earnings using a natural experiment as an alternative identification strategy. In contrast to the quasi-experiment using propensity score matching carried out in the previous section, the natural experiment employs the occurrence of (natural) external events to generate random assignment of individuals into control and treatment groups. In this case, the adverse labor market consequence of the Asian financial crisis of 1997-1998, including the incidence of involuntary unemployment and self-employment, provides a natural experiment to measure the scarring effects. The panel data series for the analysis using a natural experiment is constructed by taking IFLS wave 1 fielded in 1993 as the baseline ($t = 0$) and IFLS wave 5 fielded in 2014 as after treatment ($t = 1$). The treatment variable will be the incidence of involuntary unemployment and self-employment during the Asian financial crisis of 1997-1998. This scarring analysis, therefore, examines the impacts of previous unemployment or self-employment of subsequent earnings over 21 years.

Individuals in the sample are grouped into three different cohorts: old, middle, and young cohorts. Those who were born from 1949 to 1958 are categorized as the old cohort. Those who were born from 1959 to 1968 are categorized as the middle cohort. Meanwhile, those who were born from 1969 to 1978 are categorized as the young cohort. In 1993, individuals in the young cohort group were aged 15-24 years, those in the middle cohort group were aged 25-34, and those in the old cohort group were aged 35-44. During the Asian financial crisis of 1997-1998, individuals in the young cohort group were aged 19-28 years, those in the middle cohort group were aged 29-38, and those in the old cohort group were aged 39-48. Meanwhile, later in 2014, individuals in the young cohort group were aged 36-45 years, those in the middle cohort group were aged 46-55, and those in the old cohort group were aged 56-65.

Table 13: Scarring Effects of Previous Unemployment due to 1997-1998 Financial Crisis on Subsequent Earnings, by Cohort

	(1)	(2)	(3)	(4)
	Full Sample	**Young Cohort**	**Middle Cohort**	**Old Cohort**
Average Treatment Effect	-0.354**	-0.109	-0.441**	-0.259
	(0.140)	(0.476)	(0.220)	(0.345)
Other individual characteristics	Yes	Yes	Yes	Yes
Other work characteristics	Yes	Yes	Yes	Yes
Other household characteristics	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	4,260	1,311	1,915	1,034

Note: The dependent variable is the log of monthly wage adjusted to the 2010 value. All estimations include all the control variables described in Chapter 5 as well as year and district fixed effects. Robust clustered standard errors are reported in parentheses below coefficient estimates. Significance at the 1 percent, 5 percent, and 10 percent levels are denoted respectively by ***, **, and *.

Table 13 displays the estimation results of involuntary unemployment due to the Asian financial crisis of 1997-1998 on subsequent earnings disaggregated by the cohort group. The estimation results indicate that the treated individuals in the middle cohort receive 44.1 percent lower subsequent earning relative to the controlled individuals, significant at 5 percent level. Those in the middle cohort, aged 29-38 years, were at the beginning or the peak of their mid-level careers when the crisis occurred. During a crisis, from the labor demand's point of view, it is economically convenient for companies to layoff well-paid workers, as there is a more significant amount of money saved. Companies are more likely to flatten out hierarchy by cutting out layers of middle management; thus, a disproportionate number of experienced workers are likely to be displaced. However, from the workers' perspective, this could be a traumatic event. If their economic inactivity continues for an extended period, it will be difficult for them to reintegrate back to the labor market.

Similar to the case of older workers, the scarring effect among mid-level workers could occur since the accumulated job-specific skills of more experienced workers are not easily transferred to new jobs. At the same time, their general transferable skills may have been outdated. Moreover, the case of the aging population will worsen this adverse effect where productive older-workers are not able to support their retirement as well as their children who still need financial help. Therefore, the provision of reorientation and retraining for this type of worker, in particular, is necessary to avoid the trap of long-term economic inactivity or, even worse, total exclusion from the labor market. Instruments of the active labor market are crucial, especially those that provide qualifications in improving job match quality and employment prospects.

Table 14: Scarring Effects of Previous Self-Employment due to 1997-1998 Financial Crisis on Subsequent Earnings, by Cohort

	(1)	(2)	(3)	(4)
	Full Sample	**Young Cohort**	**Middle Cohort**	**Old Cohort**
Average Treatment Effect	-0.315**	0.121	-0.359*	-0.281
	(0.132)	(0.838)	(0.190)	(0.241)
Other individual characteristics	Yes	Yes	Yes	Yes
Other work characteristics	Yes	Yes	Yes	Yes
Other household characteristics	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	4,009	1,152	1,846	1,011

Note: The dependent variable is the log of monthly wage adjusted to the 2010 value. All estimations include all the control variables described in Chapter 5 as well as year and district fixed effects. Robust clustered standard errors are reported in parentheses below coefficient estimates. Significance at the 1 percent, 5 percent, and 10 percent levels are denoted respectively by ***, **, and *.

As presented in Table 14, the scarring effect due to previous engagement in self-employment activities is more apparent among workers in the middle cohort groups. Significant at 10 percent level, the magnitude of scarring due to self-employment is less severe relative to that due to unemployment; those who have been previously self-employed receive 35.9 percent lower subsequent earnings relative to those who have not. Nevertheless, these results could indicate that the scarring effects on human capital due to self-employment are relatively comparable to that of being in unemployment. It could be the case as the opportunity to accumulate human capital is very limited in the informal type of self-employment. Like in many other developing countries, self-employment in Indonesia cannot be directly associated with entrepreneurship as over 90 percent of self-employed workers are in the informal sector. These findings are relevant to policymakers that social assistance and entrepreneurship programs are required not only to increase self-employment per se, but desirably also a formal type of self-employment reflected by the presence of paid permanent workers.

b. Time-Varying Treatment Effects

Besides, to examine the time-varying treatment effects, lagging values of the treatment variable are included in the standard difference-in-difference model. The event study framework investigates how the initial effect of treatment dissipates over time. To capture the phase-in effects, the estimation equation of scarring effects using a difference-in-difference approach is specified as follows:

$$Y_{i,t} = \alpha + \beta T_{i,t} t + \sum_{m}^{M} \eta_m T_{i,t-m}\, t + \delta T_{i,t} + \gamma t + \boldsymbol{X}'_{i,t}\boldsymbol{\pi} + \alpha_j + \delta_t + \varepsilon_{i,t}$$

η_m measures any additional effects of a treatment that occur m periods after adoption. If the initial effect of the treatment is positive, then negative values of η_m imply that the initial effect of the treatment dissipates over time, and positive values of η_m suggest that the treatment has larger effects over time; and vice versa, if the initial effect of the treatment is negative.

Figure 4: Time-Varying Treatment Effects due to Previous Unemployment

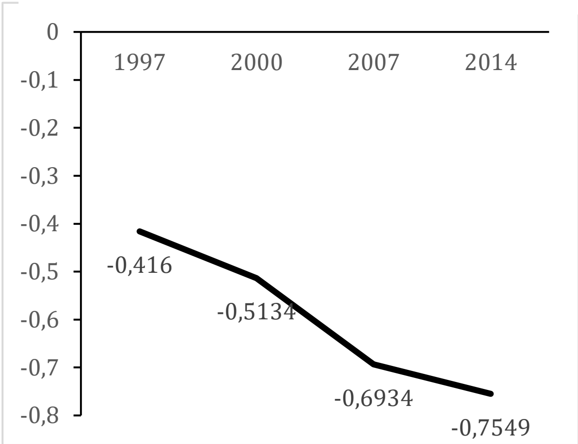


Figure 5: Time-Varying Treatment Effects due to Previous Self-Employment

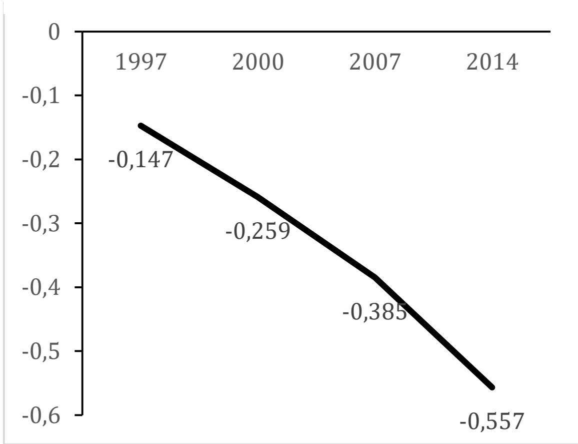


Figure 2 shows the time-varying treatment effects due to unemployment incidence during the 1997-1998 financial crisis. The results indicate persistence negative impacts on subsequent earnings, and the treatment has a larger effect over time. Similarly, as displayed in Figure 3, treatment effects due to the previous self-employment also show persistence adverse effects; however, the effects fluctuate over time. It can be observed that – although the treatment effects due to previous unemployment are larger – the slope of treatment effects due to the previous self-employment is steeper, which suggests that the additional scarring effects are increasing over the years. This result could indicate that the opportunity for human capital accumulation in the informal type of self-employment is lacking. It is even nothing better than during unemployment, especially in the event that the unemployed individuals are eligible to receive social assistance and/or employment benefits, including reorientation and retraining programs.

8. Conclusion and Policy Implications

The results of this paper suggest that scarring effects due to previous unemployment and self-employment are more observable among senior workers. In addition, there is also evidence of scarring effect due to self-employment among young workers age 25-34 years, which is more substantial than that due to unemployment. These findings could indicate that, in developing countries where the informal sector characterizes a large set of economic activities, low-skilled young workers may engage in self-employment as it is the only alternative available to generate income. Meanwhile, young workers who can "afford" unemployment tend to be high-skilled and their unemployment status are temporary or frictional, i.e., in the process of first joining the workforce or moving from one job to another. Thus, there are no apparent scarring effects among them. The scarring effect due to unemployment is disproportionately affecting the poorest, mainly the bottom 20 percent of the income distribution. It could occur as low-paid jobs may be the only income-generating options that offer a suitable way to reintegrate those who are unemployed back into the labor market.

In terms of scarring effects from the perspective of years spent in unemployment or self-employment, the estimation results show that the duration of unemployment negatively affects subsequent earnings, particularly for senior workers and workers in the low-income group. Female workers are also more heavily affected by a more prolonged duration of unemployment. Meanwhile, there is no significant result among male workers, which could indicate that they may benefit from conventional gender identity signals and/or that a more extended period of job-seeking may result in better employment matches. In the meantime, years spent in self-employment has no significant effect on subsequent earnings, either when the sample is disaggregated by age, income distribution, gender, or location of residence. This evidence could indicate that the opportunity for human capital accumulation in self-employment is limited and/or employers may use this information as an indicator of low productivity. Moreover, in the context of developing countries, most workers are self-employed since they have no better alternatives. Hence, self-employment, in this case, is not the same as entrepreneurship since there is no career effect where people have views for lucrative business activities and strive to become successful entrepreneurs.

In Indonesia, low-quality self-employment has become a significant feature of the labor market, despite its contentious topic for debate. For most people, engaging in informal sector employment may be better than having no job at all. However, this type of employment offers limited – or even non-existent – job security and formal training. Moreover, self-employment and poverty are closely correlated, even though not perfectly (Fields, 2019). The limited opportunity for human capital accumulation during self-employment may trap people in low-quality jobs, making it harder to improve their chances to progress to better employment. This issue demands labor market policies that provide continuous learning opportunities for better skills to these vulnerable workers. A comprehensive approach through empowerment and capacity building strategy could be adopted based on lifelong investment in education and training. It could enhance workers' individual powers to negotiate with employers and increase their opportunities for upward wage mobility. Moreover, public policy must place more focus on human capital investment, especially childhood development and education, to prevent individuals from being disadvantaged at the start of their working life.

Furthermore, amid the COVID-19 pandemic, those working in the informal sector are indeed heavily affected as lockdowns severely downscaled economic activities leading to an immediate loss of revenue, likely without savings or other financial cushions. Most owners of informal businesses may have no choice but to use their inconsequential business capital to cover their daily needs. Accordingly, they may be forced to shut down their informal businesses temporarily or permanently, leading to further job losses and an increase in poverty. In addition to immediate health response to reduce the risk of contagion, comprehensive social protection measures should be in place to support businesses, including targeted cash and/or in-kind transfer scheme, to compensate for the loss of economic activity. In the case where income replacement is absent, mainly if social protection systems are inadequate and coverage is low, formal businesses could be pushed into informality resulting in the growth of the informal economy.

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