Unlucky and scarred: long-term consequences of labor market entry condition in Indonesia

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Abstract

This paper provides empirical evidence of the long-term consequences of labor market entrance conditions using Indonesian data. I exploit the fact that since the Asian Financial Crisis hit in 1997/1998, Indonesia suffered a spike in the unemployment rate that prolonged for almost a decade. I collect and harmonize a long series of Indonesian labor force surveys (SAKERNAS) spanning over 30 years to construct a pseudo-panel cohort of new labor market entrants from 1990 to 2019. Following Kahn (2010) and Oreopoulos et al. (2012), I exploit exogenous temporal variation of the unemployment rate at the national level and provincial level to test the existence of scarring effects. To deal with endogenous migration issues for the province-level specification, I constructed migration-weighted unemployment rates based on historical inter-province migration patterns from the Population Census. I find evidence of a scarring effect where a 1 percentage point increase in the unemployment rate at the year of labor market entrance causes about 15% loss in probability to be employed full-time and about 26% potential monthly income loss. The negative effects of the unemployment rate in the initial year on employment and income linger up to 11 years after entering the labor market. I find women and men share similar burdens in terms of negative employment effects, but larger negative income effects for women. My results highlight the significance of youth-specific support as part of recovery policies after an economic downturn.

Keywords: labor market entrants, unemployment rate, scarring, Asian Financial Crisis, labor economics, gender economics.

JEL Classification: J16, J24, J64, O17

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1 Introduction

The new entrants to the labor market, in comparison to the more experienced workers, are arguably one of the most affected groups during a labor market contraction. Reflecting on the recent pandemic-induced recession between 2019-2021, shreds of global evidence show that the young adult cohorts, compared to their older counterparts, suffer disproportionately in terms of increased mental health problems (Kwong et al., 2021), learning loss (Azevedo et al., 2021) and worsened quality of life (Favara et al., 2022). Not only short-run consequences but there are also rising concerns on long-term consequences such as future earnings and mental health according to the OECD report (2021).[1] Yet, as argued by the report, these particular cohorts rarely become the center of recovery policies. The lack of youth-specific support is even more evident in developing countries due to limited resources (World Bank, 2021).[2]

In the last decade, there has been growing evidence of lasting negative effects of these unlucky cohorts, as documented by Von Wachter (2020). Unfortunately, most studies focus on developed countries such as the United States (Kahn, 2010; Schwandt and Von Wachter, 2019) and Canada (Oreopoulos et al., 2012). To my knowledge, very limited studies have been done in developing countries. I argue that understanding developing countries offers important insights into the existing literature. Two unique features of developing economies, regarding the scarring effects, are their large share of informal sectors and low-income households in their economy. The informality of the labor market may provide a thicker job market compared to developed countries for new entrants during the recession. Next, as many of the new entrants were members of low-income households, they could not afford to be unemployed or delay their participation, to sustain their household livelihood. The interaction of such features could potentially provide new perspectives on scarring effect literature.

This paper uses Indonesia as a country of focus to study the existence of such scarring effects for those unlucky cohorts. In the last three decades, the Indonesian economy has been steadily growing, except when the Asian Financial Crisis hit between 1997 to 1999 and when the COVID-19 pandemic hit in 2019. The country shares one of the largest economies with the largest share of people working as unpaid workers and self-employed. About 60% of the labor force worked in informal sectors in the last decade (Allen, 2016). At the same time, before the crisis, Indonesia was on its way to transforming from a traditional to a modern economic sector. In the beginning, the agricultural sector shrunk as manufacturing grew for a short-lived period before the services sector start to take over a large portion of the economy (Suryahadi et al., 2012). These two features of a large share of the informal sector and premature decentralization are commonly shared among developing countries (Rodrik, 2016). Thus, I argue that Indonesia is an ideal study case to understand the scarring effects in

[1] See https://www.oecd.org/coronavirus/policy-responses/delivering-for-youth-how-governments-can-put-young-people-at-the-centre-of-the-recovery-92c9d060/

[2] See https://blogs.worldbank.org/voices/developing-countries-covid-19-crisis-has-not-affected-everyone-equally

a developing country context.

This paper lies within a growing bed of literature about the scarring effect of entering the labor market during bad times. Several empirical evidence of negative employment and income effects have been established in developed countries such as the United States (Kahn, 2010; Schwandt and Von Wachter, 2019), Canada (Oreopoulos et al., 2012), following the 1980's recession. Growing pieces of evidence emerge from another half of developed countries such as Japan (Genda et al., 2010), Australia (Andrews et al., 2020) and Korea (Choi et al., 2020). To the existing scarring literature, this paper is the closest to Choi et al. (2020)'s study which shows that, in Korea, young graduates who enter the labor market during the Asian Financial Crisis (AFC) suffer long-term negative income trajectories that last for about 10 years.

Previous literature provides several possible explanations on how one could expect a lasting effect of a bad economic situation on the new entrants' future employment and income trajectories. A relatively thin labor market during a recession would match many new entrants to lower-skilled jobs where these unlucky cohorts stay in this sector as job searching becomes costly over time (Topel and Ward, 1992). The longer these new entrants stay in the labor market potentially leads to job skill loss (Pissarides, 1992; Arulampalam et al., 2001). Related to this, being matched to lower-skilled jobs affects low human capital accumulation and investment of these new graduates (Gibbons and Waldman, 2004; Kahn, 2010).

My study contributes to the literature in several ways. First, knowledge of how the scarring effect would operate in a large share of the informal economy is limited. Except for several studies such as Tansel and Taşçı (2010) in Turkey, Martinoty (2016) in Argentine and Kuchibhotla et al. (2020) in Sri Lanka, systematic studies on the effect of bad economic conditions on the labor market new entrants are lacking. Most scarring literature relies on searching theory and matching which in the labor market with a large informal sector component has lesser relevance. Secondly, in regards to the role of informal sectors, unlike previous studies on the scarring (Von Wachter, 2020), I do not focus only on college graduates. Thirdly, from the country-specific perspective, despite the significance of the AFC in Indonesia, evaluation of long-term consequences in the labor market is lacking. Most studies focus on short-term responses of the AFC in the labor market that includes increased workers in agriculture and falling real wage in urban area (Manning and Junankar, 1998; Manning, 2000), workers found employment in the informal sector (Manning, 2000; Rothenberg et al., 2016), delaying the progress of absorption of workers to the manufacturing sector (Feridhanusthyawan and Arya, 2016). Consequently, from a welfare perspective, the AFC was also found to increase urban poverty (Suryahadi et al., 2005) and child labor incidence (Manning, 2000; Sim et al., 2017). It also affects other socio-economic issues, such as lower health care utilization (Waters et al., 2003), child nutrition deprivation (Giles and Satriawan, 2015), changes in intrahousehold bargaining power (Dong, 2016), and dropped school attendance in short term (Cameron, 2001). Lastly, to the best of my knowledge, this paper is the first effort to investigate the impact of the AFC focusing on the new entrants to the labor market in Indonesia.

To the best of my knowledge, there is only one existing study that shares the closest similarities to my study. Pritadrajati et al. (2021), using a longitudinal household survey (IFLS), finds that there is a strong positive correlation between current unemployment probability and past unemployment status. In her heterogeneity results, the study shows similar negative scarring effects for those who were unemployed as caused by the AFC. Compared to this paper, Pritadrajati et al. (2021) does not cover the entirety of cohort experience because of the limitation of the longitudinal household survey. This paper also differs since it allows the scarring effect to vary across time after entering the labor market instead of a cross-sectional correlation. This result provides more insights into the dynamics of scarring effects over time.

I follow previous literature to construct my estimation strategy for either national-level specification (Kahn, 2010; Choi et al., 2020) and province-level specification (Oreopoulos et al., 2012). The unit of observation is an aggregate cell of a cohort of labor market entrance, province, gender and time of the survey. Using a repeated cross-sections of the Indonesia labor force survey, SAKERNAS, from 1990 to 2019, I construct a synthetic-cohort panel that spans over 30 years. I match each cell observation to the corresponding unemployment rate based on the year of labor market entrance for national specification and province-year for the province-level specification. The estimated unemployment rate at labor market entry coefficients varies across years of experience after the year of entering the labor market. The estimated coefficients capture the effect of the economic situation when entering the labor market under national (province)-cohort-specific variation in unemployment rates.

I document significant negative employment and income effects of a high unemployment rate when entering the labor market. An Increase of 1 percentage point in the unemployment rate when entering the labor market leads to a drop in full-time employment probability by 3% for the first two years after entering the labor market. The negative effect was nullified after 9 to 11 years after entering the labor market. Overall, an increase of 1 percentage point in the unemployment rate when entering the labor market is associated with a 15% loss in the probability of full-time employment over 25 years of their working lifetime. With regards to income effects, I find that an increase of 1 percentage point in the unemployment rate translated to a 3% drop in monthly income for the first 2 years after entering the labor market. Similar to the employment effect, the negative effects start to disappear after at least 9 years.

The results from the province-level specification confirm my findings from the national-level specification. However, the estimated effects are less precise. On the one hand, similar results between the province and national specification suggest that temporal variation of the unemployment rate is unrelated to the change in cohort characteristics (Oreopoulos et al., 2012). On the other hand, this raises concern over the role of local labor market shocks that might be more relevant compared to the national level (Schwandt and Von Wachter, 2019). However, as discussed as threats to identification earlier, this disparity between the province and national specification may also point to endogenous migration issues.

I find that men and women share similar negative employment and income effects except for the following aspects. First, compared to women, men are more likely to be employed as unpaid workers. Second, women experienced higher income penalties despite small differences in comparison to their men counterparts. The differences however are not statistically significant. Third, more men switched to agriculture within the male group, compared to the women group.

My findings are robust over several sensitivity checks. To partially address the endogeneity of graduation years, I use the 3-year moving average of unemployment rates of labor market entrance. I find that for both national and province specifications the results are robust. Next, my results are also robust when I use youth-specific unemployment rates, e.g unemployment rates for 15-24 years old, which capture arguably more relevant unemployment rates faced by the new entrants. I also find that the results are robust when using the official unemployment rate produced by the national office of statistics (BPS)[3] although estimated less precisely. My results are also robust over alternative age restriction for sample selection for each cohort cell. Finally, I find external validity to my results from the alternative dataset in which I find a larger effect in the same direction as my preferred results.

The rest of the paper is organized as follows. Section 2 provides a brief overview of the Indonesian economy to the AFC event and labor market entrants profiles. Section 3 discusses the estimation strategy and threats to the identification. In Section 4, I describe the dataset used in this paper. I present the results in Section 5. I further discuss the gendered aspect of the results in Section 6. Section 7 provides several sensitivity tests to the results. Lastly, I conclude and suggest the direction of further research in Section 8.

2 Context

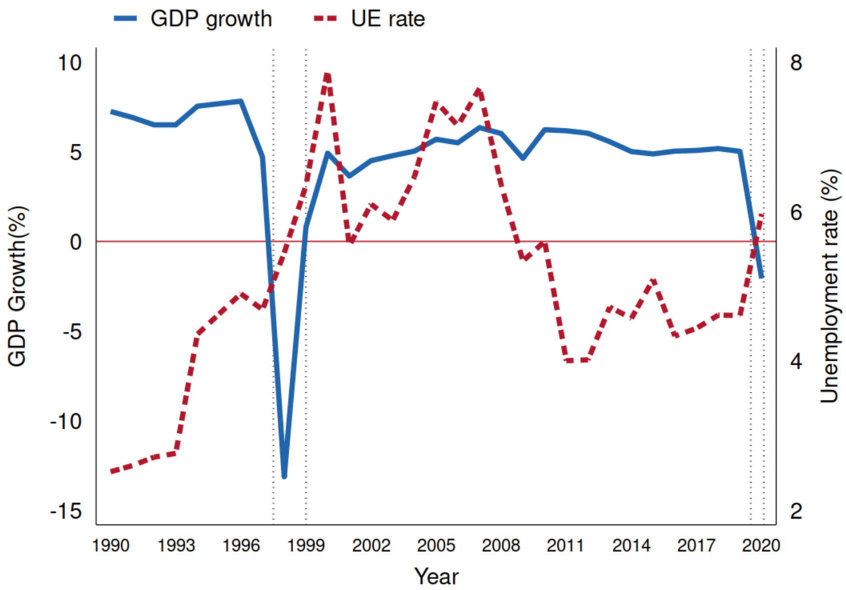
2.1 Indonesian economy and the Asian Financial Crisis

The AFC in Indonesia was marked by a 15% drop in economic growth between 1997-1998, the worst recession in the country since the 1960s. As summarized in Figure 1, the crisis contributes to the large upswing of the unemployment rate that follows in the next couple of years (Suryadarma et al., 2007; Nagib and Ngadi, 2008). In terms of employment, the recession pushed people away from the urban sector, where the crisis hit the most, to find employment in the agriculture sector as documented by Manning and Junankar (1998). Falling real wages in the paid job also pushed people to be employed in self-employment and unpaid job (Manning, 2000). Strauss et al. (2004) find that a relatively large drop in household incomes was responded to by increasing the labor supply of female household members. Not only in urban areas, poor women in rural areas noticeably joined the labor force. Rural areas during the period provide job availability to keep the unemployment rate increase in check. Further, the increase in the unemployment rate was accounted for by a huge increase in unemployment

[3] Also known as Statistics Indonesia. See https://www.bps.go.id/.

among youth by 4.4 percentage points, from 15.5 percent to 19.8 percent between 1997 to 1999 (World Bank, 2010).

Figure 1: Unemployment rate in Indonesia



Notes: Author's calculation. GDP growth retrieved from the World Development Index, The World Bank. The unemployment rate is calculated using SAKERNAS 1990-2020 following Suryadarma et al. (2007) approach to adjust for changes in labor market force definition and questionnaire. More details on the unemployment rate used in this graph are available in Section 4.2. The dotted black vertical line indicates the start and end of each recession event in Indonesia.

This crisis also temporarily reverses the structural transformation trend as many formal workers who lost their jobs return to farm activities as well as informal sectors. The SAKERNAS data recorded that the share of workers in formal sectors fell at a rate of 3.2 percentage points per year between 1998 to 1999. This decline was almost equally shared among the services and manufacturing sectors. However, manufacturing sectors recovered to the pre-crisis employment rate earlier than the service sectors. Declining formal sectors were also reflected by a real wage drop, around 31 percent between 1997 and 1999 (World Bank, 2010). Regarding poverty, the crisis ended positive trends of poverty reduction, as the poverty rate increased by 12% during the 1997-1999 period. It is also worth noting that Indonesia also suffered from drought[4] during the crisis period which lead to a significant hike in food prices.

From a female employment perspective, the increase in labor force participation among women, especially from low-income families, was motivated by sustaining a household level of income. This 'added worker effect' is a common coping mechanism, especially in low-income households (Attanasio et al., 2005). (Smith et al., 2002) find that female labor force

[4]El Nina brings a lengthy period of rain-less which significantly affects agricultural production. As a consequence, food crop retail prices increase which slightly benefits farmers, but overall there are no winners in this period given the share of net producers of rice in rural areas was smaller than net consumers

participation who live in poor families increased by 7 percent between 1997 to 1999. Most of these women worked as unpaid family workers and were mostly driven by low-educated women. Further, they also pointed out the significant impact of AFC on wage cuts and employment rates for the younger female group, especially in urban areas with low education.

The crisis was immediately followed by a significant increase in the poverty rate, especially in urban areas (Suryahadi et al., 2012). The poverty reduction trend slows down after the AFC. To sustain their livelihood, many children-aged household members became active in the labor market. This hardship also put more strain on younger members of the household. Manning (2000), in his study, shows that to obtain additional money, children-aged household members opt to work in informal sectors.

A body of literature presents the negative effect of the recession to other socioeconomic outcomes. First, as a response to the recession, many students dropped out of school in the short-term (Cameron, 2001). This phenomenon, however, did not last for a long time as students started to attend schooling not long after the recession ended. From a health perspective, Waters et al. (2003) suggest lower utilization of healthcare following the recession in Indonesia. A significant drop in income translates to lower expenditure including food. Giles and Satriawan (2015) argue, the social benefit has helped households to reduce child nutrition deprivation. Consistent with increased labor participation for women, Dong (2018) finds that the financial crisis has improved the bargaining power of women within a household.

The Indonesian economy started to positively grow in 2000.[5] Despite positive and steady economic growth, Indonesia records a rather disappointing employment growth, especially in the manufacturing sector. Some literature refers to the period between early 2000 and 2007 as a "jobless growth" period (World Bank, 2010; Manning and Pratomo, 2018). This period was also marked by persistently high unemployment rates. However, as discussed by Suryadarma et al. (2007), changes in labor for participation definition, by the BPS, were partly responsible for the trend of unemployment rates during the period (see Figure A1 in Appendix). Due to accommodating the ILO definition, the labor force survey includes discouraged workers in the labor force pool which inflate the unemployment rates. In section 4.2, I discuss this unemployment rate definition issue and its relation to my identification strategy.

2.2 Labor market entrants

In the last decades, the education profile of the labor force in Indonesia has improved significantly. Labor market profiles predominantly attend primary school for those who were born in the 60s, whereas the 90s cohort predominantly attends secondary school (Allen, 2016). Consequently, this implies delayed age of labor market entrance. Using the Indonesia Family Life Survey (IFLS) Wave 5, I find that the age of having the first full-time job is, on average, 1.5

[5] This is also followed by two major political events: a democratic presidential election and a large-scale decentralization.

years older for those born in the 90s onwards compared to their counterparts that were born before the 90s. This is also followed by the fact that the role of vocational secondary school also becomes more important over time in Indonesia (Newhouse and Suryadarma, 2011).

Before the AFC, as mentioned in the previous section, manufacturing-led economic growth also benefits younger cohorts of new entrants to the labor market. Growing formal sectors drive upward income mobility in terms of the real wage for both male and female new entrants as discussed by Skoufias and Suryahadi (2002). Using SAKERNAS from the early 1990s to 2019, I construct a pseudo panel of labor market entrants to track their corresponding employment and income over time. Figure 2 Panels A and B illustrate how the condition of labor market entry could affect new entrants' employment and income trajectory in the future. Notice that each of the plotted lines in Figure 2 represents employment (Panel A) and log of monthly income (Panel B) of each cohort of new entrants. In this Figure, entering the labor market is defined as the year when a cohort completed their education. I restrict individuals to be 20 to 65 years old in each survey year to reduce the possibility that individuals have not completed their education decisions. The starting point of each plotted line represents the probability of an individual's full-time employment (Panel A) and monthly income (Panel B) in the year of entering the labor market.

From Figure 2 Panel A, we could observe that full-time employment probabilities across years of entrance cohorts are relatively stable. A general pattern that plotted lines is slightly shifted toward the northeast indicating the likelihood of full-time employment improved over time. However, those, who entered the labor market between 1997 to 1999, printed as a solid line, were experiencing drops in full-time employability as represented by lower starting points compared to other lines. A more striking contrast is evident in terms of monthly incomes. Supporting Skoufias and Suryahadi (2002) findings, Figures 2 Panel B illustrates starting monthly incomes of new entrants during a recession are lower than their counterparts. Over time, however, new entrants receive better inflation-adjusted monthly incomes.

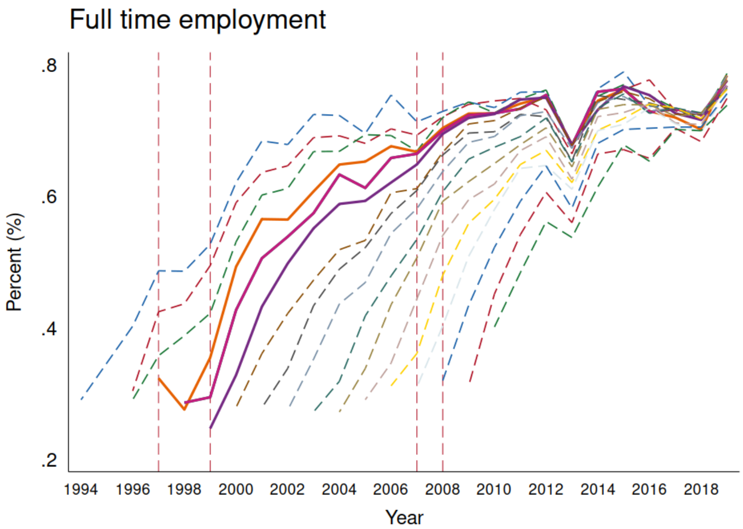
3 Estimation strategy

3.1 National exposure specification

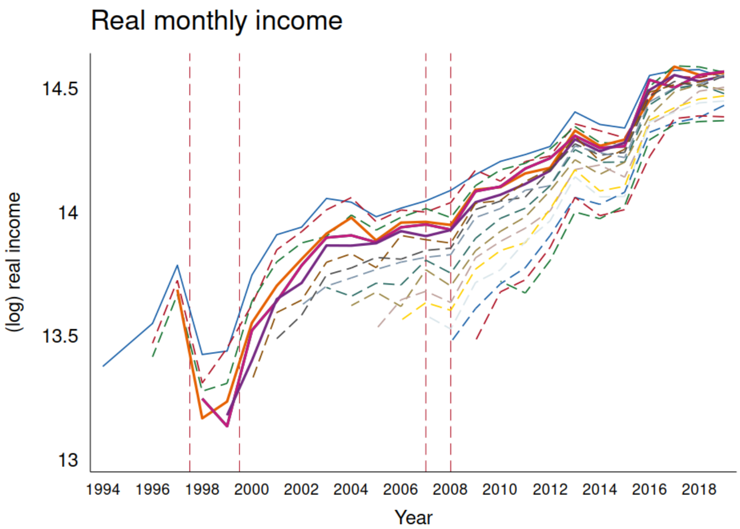
The main identification strategy relies on an unexpected increase in unemployment rates following the AFC in 1997-1998. The AFC hit the Southeast Asian region the hardest compared to other Asian regions. As for Indonesia, the GDP growth shrank by 15% within a year of the crisis. This is Indonesia's worst recession since the 1960s. While GDP started to recover and grew, the level of unemployment experienced a longer persistent effect. Notably, the unemployment rate has been increasing for two years before the AFC. Between 1997 and 2004, unemployment is recorded to increase by 6%. However, as later discussed in Section 4, there are measurement issues in unemployment rates between 1994 and 2003. From 2007,

Figure 2: Trends in employment and worker's income by entrance to labor market timing, SAKERNAS 1990-2019, Author's calculation

Panel A



Panel B



Notes: Own calculation using SAKERNAS 1994-2019. The starting year of each line represents the year the cohort enter the labor market. The employment rate in Panel A is restricted to those participating in the labor market. The income variable used in Panel B includes wages, salaries and profits. Each pseudo-panel observation is weighted with individual weight provided by the survey.

the unemployment rate started to decline. Important to note that the Global Financial Crisis (GFC) has had minimal impact on Indonesian economic performance and the labor market. Indonesia grows rather strongly at the 5-6% level and experiences a stagnant unemployment rate during the GFC (see Figure 1).

My baseline specification follows previous literature (Oreopoulos et al., 2012). We begin with mean-aggregating the individual-level observation at the level of labor market entrants cohort (c), gender (g), education group (d), residential province (p) and survey year (t). In comparison to previous literature, our construction differs by adding the gender dimension to the level of data aggregation. Thus, I estimate the following.

$$\bar{Y}_{cgdpt} = \alpha + UR_c + Exp_e + \theta_c + \gamma_g + \delta_d + \pi_p + \tau_t + \epsilon_{cgdpt} \tag{1}$$

$$\bar{Y}_{cgdpt} = \alpha + \beta_e UR_c + Exp_e + \theta_c + \gamma_g + \delta_d + \pi_p + \tau_t + \epsilon_{cgdpt} \tag{2}$$

By construction, our outcome variable $\bar{Y}$ is an average of each "cell" of aggregation, weighted according to the number of observations in each cell. Our outcome variables cover an array of employment statuses, earnings and working hours. From employment statuses, it includes binary variables of currently employed, employed full-time, self-employed and had jobs in formal sectors and had jobs informal sector at the time survey.[6] The rest of the outcome variables include monthly income.[7] The main independent variable is the corresponding national unemployment rate (UR) at the time of entering the labor market c. In our model, I vary the initial unemployment rate over years of potential experience since graduation year to mimic an event-study setup. The model also includes years of potential experience since graduation exp_e that is simply measured as differences between the survey year and the year of entering the labor market. The model simply includes a set of dummy variables of labor market entrants cohort (θ_c), gender (γ_g), education level (δ_d), province (π_p) and survey year (τ_t). Finally, the error term ϵ is a zero-mean at the cell level. To account for province variation, I cluster the standard error at the graduate cohort-provincial level.

Following Schwandt and Von Wachter (2019), I proxy years of schooling using years of highest completed education plus six years[8] because SAKERNAS does not collect individual's exact year of graduation. To avoid cohort-specific labor market changes, I use the unemployment rate at the national level for the working-age population rather than the cohort-specific unemployment rate. In the robustness section, I discuss the result of using the youth-age-specific unemployment rate.

3.2 Province exposure specification

Previous literature on the scarring effect, such as Oreopoulos et al. (2012) and Schwandt and Von Wachter (2019), commonly use provincial exposure, except for Kahn (2010) and Choi et al. (2020), arguing the local labor market conditions are more relevant to the new entrants. They argue that internal migration in US or Canada was relatively low, such that the endogenous

[6] Notice that by definition there is overlapping observation between self-employed and had a job in informal sectors. Job status in informal sectors includes family workers

[7] Income variable combines wage and salary to capture both formal and informal jobs. SAKERNAS asks the respondent to approximate the monetary value of their in-kind payment

[8] The legal age to enter primary school in Indonesia.

migration threat, as discussed previously in Section 3.3, becomes less significant. In Indonesia, internal migrations predominantly occur within the province border (Pardede et al., 2020). However, there has been increasing mobility in the last decades. The migration pattern is dominated by outside Java to Java island,[9] mostly for employment and education-related purposes. Related to the AFC, existing literature records a noticeable increase in urban-to-rural migration as people looked for employment in agricultural jobs when jobs were scarce in urban areas (Hugo, 2000). Based on the 2010 Population Census, for non-Java provinces, more than 90% of the population were born within the province border, whereas for Java provinces, the average of native-born residents was about 70%. Hence, one could argue that internal mobility in Indonesia is relatively higher than in the US and Canada. Estimation at the province level, despite its advantages in capturing local labor dynamics, potentially suffers from endogeneity issues.

In regards to the endogeneity migration issue, Schwandt and Von Wachter (2019) offers insightful and practical bias correction procedure to the regional level rate exposure by weight in the initial unemployment rate with migration probability and education level. In principle, they calculate the probability of working-aged individuals with a certain education level to migrate from their birth region to the residence's region, then aggregate up across provinces and education profiles using the Population Census. This probability is to be assigned as a weight to the unemployment rate of each labor market entrants cohort from the labor force survey observations. This double-weighted unemployment rate, they argue, is a biased-corrected unemployment rate exposure.

To apply such weight, I rely on two key pieces of information, the birth and residential province. That information must be available in both the population census and the labor force survey. Unfortunately, the SAKERNAS does not provide the birth of province information. However, the Population Census provides the provinces where the respondent resided in the last five years. Hence, I can calculate an average migration pattern across provinces using a series of population censuses. Thus, in the similar spirit of Schwandt and Von Wachter (2019), I construct a migration-weighted average graduation year unemployment rate as summarized below.

$$UR_{pc}^{MW} = \sum_{p=1}^{27} Mig_{p_{-5}p} UR_{pc} \tag{3}$$

The migration-weight term, $Mig_{p_{-5},p}$ is the historical share of those who live in province p that five years priors migrated from province p_{-5}. To match our preferred sample, I only consider the migration pattern of respondents aged 15 to 45 in each census year. Thus, the migration share is used to weigh the unemployment rate of entering the labor market in year c of

[9]Java island is the fourth largest island in Indonesia, yet has inhabited more than 60% of the population since the 90s. Historically, it became the center of the economy and the administration of the colonial government, since the Dutch's occupation. It is also the location of Jakarta, the nation's capital city since 1945

residential province p. I use provincial border definition in 1990, which in total 27 provinces, to preserve consistency across years as the number of provinces grows especially post-1998 due to decentralization as response to the end of Soeharto-era.[10] The data to construct migration share $Mig_{p_{-5},p}$ is drawn from subsamples of the Population Census in 1990, 2000 and 2010. Hence, the migration share reflects the average migration pattern between 1990 and 2010. To illustrate the construction of UR^{MW}_{pc}, suppose there are only two provinces, Province A and B. The historical migration rates from Province A to Province B were 25%, meaning a quarter of people living in province A today migrated from province B. Suppose in 1990, the unemployment rate in Province A was 5%, whereas in Province B was 2%. For those entering the labor market in 1990 and Province A, the migration-weighted unemployment rate was 4.5% (2% × 0.25 + 5% × 0.75), instead of 5%. Finally, I use the migration-weighted unemployment rate (UR^{MW}_{pc}) to modify equation 2. I matched each cohort of observations to the migration-weighted unemployment rate terms (UR^{MW}_{pc}) using their province of residence p at market entrance year c. Equation 4 summarizes provincial specification, as follows.

$$\bar{Y}_{cgdpt} = \alpha + \beta_e UR^{MW}_{pc} + Exp_e + \theta_c + \gamma_g + \delta_d + \pi_p + \tau_t + \epsilon_{cgdpt} \tag{4}$$

In regards to the double-weighted specification by Schwandt and Von Wachter (2019), my provincial specification has some obvious limitations. First, I only rely on historical inter-province migration by assuming migration patterns are similar across birth cohorts. Despite using 20 years of average migration pattern, this measure could not capture a specific birth cohort confounding factors to mobility decisions, if any. As discussed earlier, there has been a significant improvement in terms of inter-province mobility in the last decades. Second, my migration-weighted approach ignores the specific education level factors that might also relate to the migration status. Pardede et al. (2020), in particular, points to the important role of education level in increasing the likelihood of migration decisions. Given these caveats, I use the provincial specification as part of supporting results and sensitivity checks for the national specification. As additional rationale to use national specification, in Figure A5 in Appendix A, I show evidence of a strong correlation between the national level and the province level unemployment rate. From Figure A5, the variation of unemployment at the province level follows closely the variation at the national level. The correlation coefficient of national and provincial unemployment rates also suggests a strong positive correlation between the two. Thus, I prefer national exposure specification (Equation 2) results as my main results.

3.3 Threats to identification

My estimation strategy relies on the assumption that temporal variation of the unemployment rate, as a product of the unexpected economic recession, could have a lasting effect on those entering the labor market. To draw this inference, each new entrant will be matched with

[10] For further discussion on political economy of province proliferation process see Kimura (2013)

the corresponding unemployment rate. To begin with, I discuss several potential issues that could threaten the identification of scarring effect estimates.

(i) Endogenous temporal variation of the unemployment rate.– The identification strategy relies on the assumption that temporal variation in unemployment caused by the unexpected recession should not correlate with the change in cohort-specific characteristics. From what we know, the 1997/1999 recession was caused by a regional-wide currency crisis that started in Thailand and quickly spread across the Southeast Asian region. I argue that this unexpected crisis supposedly not correlated with the characteristics of the cohort during the time.

To support my claim, I follow Schwandt and Von Wachter (2019) to estimate a balancing regression. This procedure simply checks if the variation of the unemployment rate would change the composition of fixed factors of the cohort such as gender composition. In the balancing regression, I estimate Equation 2, using the indicator variable of being a female as a dependent variable. Figure A4 reports the result. It emerges that there is not enough evidence to show the effect of unemployment on sex composition is different from zero over time. Further, I follow (Oreopoulos et al., 2012) who argue the similarity in terms of results between the national and the provincial specification as partial evidence to the 'exogeneity' of unemployment rate variation.

(ii) Endogeneous migration timing.– Individuals could decide to migrate to another place with a better economic situation before entering the labor market. This positive sorting potentially leads to attenuation bias. As people move to a less crisis-affected area with better employment opportunities, the effect of the unemployment rate when entering the labor market bias toward zero. For the national specification, this should not be a concern as Indonesia has relatively low inter-national mobility (Bazzi et al., 2016). On the other hand, interregional mobility predominantly happens within the province border (Pardede et al., 2020). However, as raised by Hugo (2000), the increased inter-province migration as a response to the crisis is not trivial. He argues that post-AFC, the inter-regional mobility of Indonesia has significantly increased. Considering it, in the province specification, I apply migration-weighted unemployment rate using historical inter-province migration patterns drawing from the pooled subsample of the Population Census from 1990 to 2010.

(iii) Endogeneous education timing.– To avoid bad labor market prospects, a person may stay longer in school to delay their labor market participation. Thus, the scarring effect estimates would bias toward zero. To the best of my knowledge, there is no evidence of such behavior in the existing literature. Cameron (2001) find a temporary increase in school drop-out in a short time, but within months education participation bounced back to the pre-crisis trend.

4 Data

4.1 SAKERNAS

The National Labor Force Survey, also known as SAKERNAS, is the national household survey purposely designed to produce the official labor force statistics in Indonesia. The timing, frequency, and sampling procedures of the survey have been changing over time since its first implementation in 1976. Prior to 1986, Indonesia's statistical office, known as BPS, collected SAKERNAS as a thematic module of the National Household Socioeconomic Survey (SUSENAS) which is the main nationally representative household socioeconomic survey.[11] Since 1986 the BPS started to regularly conduct the survey except in 1995.[12] Initially, the data collection was implemented once a year but later on conducted bi-annually as well as quarterly. The BPS surveys larger respondents in August, and smaller samples in February, when bi-annually, or May, if quarterly.[13] Designed to be nationally representative as it follows the SUSENAS sample frame, from 1986 to 2004,[14] the sampling frame preserve representativeness up to provincial level. Since 2005, the SAKERNAS has been represented at the district level, except in 2014. For this paper, I mainly use SAKERNAS August, except for the years before 2006.

The survey collects labor market information on the working-age members of sampled households.[15] This includes household members as young as 10 years old. SAKERNAS becomes the main dataset to produce official labor force statistics including unemployment rate, labor force participation, level of wages and income. The SAKERNAS collects a rich array of information on individual engagement in the labor market. This includes several key variables in the labor market which are not available in the SUSENAS such as wages, income and working hours. However, compared to the SUSENAS, the survey provides limited non-labor market information on individuals as well as households. Survey limitation includes unavailability of household expenditure, assets, fertility, and complete household member roster information which arguably are potentially important factors for one's employment outcomes and decisions (Dong, 2016). Despite the survey's limitations, the SAKERNAS remains the only long-series and consistently collected dataset to proxy key labor market outcomes which suit the purpose of this paper.[16]

[11] SUSENAS has been the main resource to estimate welfare indicator, including poverty, collected since 1963

[12] The BPS uses a 5-yearly intercensal population survey, SUPAS, to estimate labor market indicators in the absence of SAKERNAS

[13] In case of bi-annual data collection, from 2006-2011 the BPS collected smaller samples in February with a lower level of representativeness. After 2012, when the survey implementation was done quarterly, the BPS collected mid-quarter data in May

[14] except for 2000-2001, as the sampling was representative at regional level due to big-bang decentralization following the reformation era

[15] The survey does collect limited information on those younger than 10 years old as part of the household members listing process. The information includes, at least, name, gender, marital status and age. However, the information is not available in the released dataset

[16] The possible alternative to SAKERNAS is the Indonesia Family Life Survey (IFLS) a privately collected lon-

I use individuals aged 15 to 45 years old in each survey year to construct an unbalanced pseudo-panel at the level of aggregation detailed in Section 3.1. Hereby, I identify labor market entrants of males and females who were born between 1969 to 2003, live in 27 provinces and completed either primary, secondary or tertiary education when entering the labor market between 1990 to 2019.[17] Given the span of the dataset, I observe up to 25 years of potential working experience. The baseline estimation of Equation 2 yields a total of 64,147 cell observations.[18]

4.2 Unemployment rate

The BPS releases the annual unemployment rate following the collection of SAKERNAS. Hence, the statistics have become available regularly every year since 1990, except for 1995. In 1995, due to budget problems, the BPS did not conduct the SAKERNAS survey. Labor market statistics in 1995 were inferred from the intercensal population survey in that year. BPS has changed the implementation of the survey that affects the calculation of the unemployment rate at least three times, between 1990 to 2003, to accommodate the ILO definition of the labor force and unemployment as summarized in Suryadarma et al. (2007). The first major adjustment is the changes in the working age definition. From 1980 to 1990, the official unemployment rate includes individuals aged 10 to 14 years old in the labor force calculation. Since 1991, the survey follows the ILO to only include those who are at least 15 years old in the labor force. The second major change happened in 1994. Before 1994, to be included in the labor force as unemployed, the BPS required that a person be looking for a job for at least a week following the survey. From 1994 onwards, the BPS removed the qualifying time condition.[19] The third major change happened in 2001. The BPS added those who are not working and not actively looking for a job as they believe no job position is available (discouraged worked), those who had a job but have not started the job and those who preparing for business. These three groups of people were considered out of the labor force before 2001.

Figure A1 illustrates the unemployment rate trends over the study period. The solid line represents the official unemployment statistics from the BPS as recorded in their annual releases. The dashed line represents the unemployment rate using the pre-2001 definition of the unemployment rate. In regards to Figure A1, Suryadarma et al. (2007) argue changes in the survey implementation, as mentioned previously, contribute to a positive trend of the unemployment rates between the AFC and 2004. In particular, they find that the new statistics

gitudinal dataset that was collected five times between 1993 to 2014 using SUSENAS 1993 as a sample frame.

[17] Completing primary education includes those who never had an education up to completing primary school. Secondary education includes junior and senior high school or equivalent to year 7 to year 12 in most western countries such as US and Australia. Tertiary education includes vocational and university degrees.

[18] On average, each cell observation consists of 42 unique individual-year observations with a maximum of 610 individual-year observations.

[19] As mentioned in Suryadarma et al. (2007), Manning and Junankar (1998) show that this change in definition responsible for about 2.8 percentage point increase in the unemployment rate between 1993-1994.

inflate the number of discouraged workers in the labor force. Unfortunately, there is no way to precisely recalculate the unemployment rate to a definition before 1994, as the structure of the questionnaire has changed. As mentioned earlier, before 1994, BPS excluded those who look for jobs longer than a week before the survey. While maintaining the pre-2001 definition to obtain 'consistent' unemployment rates over time, it is worth noting that the calculation of the unemployment rates before 1994 potentially was underestimated compared to the post-1994.

4.3 Population Census

This paper uses a sample of population census data available from the Integrated Public Use Microdata Series (IPUMS) to calculate the proportional migration across cohorts and education levels over time. The IPUMS version of the population census represents 5% of the total population in 1990, and 10% of the total population in the 2000 and 2010 waves. This yields between 912,544 (1990) and 23,603,049 (2010) observations. The population census provides key information on where people live five years before the Census year. Using this information, I construct a matrix of migration patterns by pooling three Population Census as one. With this matrix, I obtain, on average, the share of individuals living in current residential provinces that lived in other 26 provinces five years ago between 1990 to 2010.

5 Results

5.1 National estimates

I start with presenting the lifetime results as summarized in Table 3. This estimation refers to a modified version of Equation 2, where I drop the interaction terms between initial unemployment rates and years of experience dummies. Table 3 reports the coefficients of the initial unemployment rate separately for each outcome across columns. From column (1), it emerges that a one percentage point increase in the unemployment rate at the time of labor market entry would decrease the probability to be employed by 15% over a working lifetime. Respectively, as shown in columns (2)-(5), we learn that an increased unemployment rate causes a lower probability to have a full-time job, increases the probability to have an unpaid job, lowers the probability to be in a self-employed job and increases the probability to be in an informal job.

Table 1: Descriptive statistics of new labor market entrants between 1990 to 2019 aged 20–65 years old

	By gender		
	Male	Female	Total
Labor market outcomes			
Employed (%)	0.917	0.892	0.907
	(0.101)	(0.123)	(0.111)
Full-time Job (%)	0.659	0.530	0.610
	(0.158)	(0.161)	(0.171)
Waged worker (%)	0.434	0.454	0.441
	(0.207)	(0.283)	(0.239)
Unpaid Job (%)	0.255	0.334	0.285
	(0.194)	(0.232)	(0.213)
Self-employed Job (%)	0.312	0.212	0.274
	(0.173)	(0.142)	(0.169)
Total wage (000s)	1264.2	999.7	1163.3
	(561.7)	(533.0)	(565.7)
Monthly income (000s)	1461.2	1136.0	1337.3
	(1007.3)	(837.8)	(959.4)
Monthly Working hours	175.8	159.5	169.6
	(25.69)	(30.07)	(28.57)
Agriculture (%)	0.400	0.314	0.367
	(0.234)	(0.268)	(0.251)
Manufacturing (%)	0.0901	0.108	0.0970
	(0.0926)	(0.128)	(0.108)
Education profiles			
Low education (%)	0.272	0.253	0.265
	(0.445)	(0.435)	(0.441)
Secondary education (%)	0.592	0.538	0.571
	(0.492)	(0.499)	(0.495)
Tertiary education (%)	0.136	0.209	0.164
	(0.343)	(0.407)	(0.370)
Year of entering labor market			
1990–1994 (%)	0.271	0.262	0.267
	(0.444)	(0.440)	(0.443)
1995–1999 (%)	0.260	0.246	0.255
	(0.439)	(0.431)	(0.436)
2000–2004 (%)	0.216	0.212	0.215
	(0.412)	(0.409)	(0.411)
2005–2010 (%)	0.170	0.182	0.174
	(0.375)	(0.386)	(0.379)
2011–2019 (%)	0.083	0.098	0.089
	(0.276)	(0.297)	(0.284)
Years of experience			
0-2 (%)	0.0879	0.119	0.100
	(0.283)	(0.324)	(0.300)
3-5 (%)	0.149	0.167	0.156
	(0.356)	(0.373)	(0.363)
6-8 (%)	0.146	0.138	0.143
	(0.353)	(0.345)	(0.350)
9-11 (%)	0.139	0.125	0.134
	(0.346)	(0.330)	(0.340)
12-14 (%)	0.139	0.125	0.133
	(0.346)	(0.330)	(0.340)
15-17 (%)	0.134	0.125	0.130
	(0.340)	(0.330)	(0.336)

Table 2: Descriptive statistics of new labor market entrants between 1990 to 2019 aged 20–65 years old

	Years of labor market entrants					
	1990/1994	1995/1999	2000/2004	2005/2010	2011/2019	Total
Labor market outcomes						
Female (%)	0.369	0.369	0.378	0.400	0.423	0.381
	(0.482)	(0.482)	(0.485)	(0.490)	(0.494)	(0.486)
Employed (%)	0.949	0.934	0.900	0.859	0.822	0.907
	(0.0788)	(0.0928)	(0.114)	(0.123)	(0.116)	(0.111)
Full-time Job (%)	0.638	0.641	0.614	0.560	0.525	0.610
	(0.170)	(0.160)	(0.157)	(0.174)	(0.180)	(0.171)
Waged worker (%)	0.357	0.399	0.468	0.524	0.578	0.441
	(0.225)	(0.223)	(0.228)	(0.234)	(0.233)	(0.239)
Unpaid Job (%)	0.264	0.273	0.291	0.311	0.313	0.285
	(0.208)	(0.200)	(0.213)	(0.225)	(0.228)	(0.213)
Self-employed Job (%)	0.378	0.328	0.241	0.165	0.109	0.274
	(0.179)	(0.153)	(0.128)	(0.102)	(0.0770)	(0.169)
Total wage (000s)	1143.9	1209.5	1172.1	1101.4	1188.2	1163.3
	(584.3)	(598.5)	(569.7)	(519.3)	(472.1)	(565.7)
Monthly income (000s)	1139.9	1360.8	1370.3	1377.3	1680.4	1337.3
	(925.7)	(1033.6)	(987.4)	(881.5)	(771.6)	(959.4)
Monthly working hours	172.9	175.3	173.7	164.4	143.7	169.6
	(28.56)	(25.89)	(24.79)	(27.47)	(30.87)	(28.57)
Agriculture (%)	0.430	0.399	0.361	0.302	0.238	0.367
	(0.250)	(0.248)	(0.249)	(0.235)	(0.215)	(0.251)
Manufacturing (%)	0.0853	0.0871	0.0916	0.117	0.134	0.0970
	(0.0996)	(0.0980)	(0.104)	(0.125)	(0.119)	(0.108)
Services & construction (%)	0.485	0.514	0.547	0.581	0.628	0.536
	(0.224)	(0.220)	(0.224)	(0.217)	(0.197)	(0.224)
Education profiles						
Low education (%)	0.392	0.306	0.241	0.143	0.0598	0.265
	(0.488)	(0.461)	(0.428)	(0.350)	(0.237)	(0.441)
Secondary education (%)	0.512	0.566	0.582	0.640	0.601	0.571
	(0.500)	(0.496)	(0.493)	(0.480)	(0.490)	(0.495)
Tertiary education (%)	0.0960	0.128	0.177	0.217	0.339	0.164
	(0.295)	(0.334)	(0.382)	(0.412)	(0.473)	(0.370)
Years of experience						
0-2 (%)	0.0276	0.0266	0.0392	0.219	0.441	0.100
	(0.164)	(0.161)	(0.194)	(0.414)	(0.497)	(0.300)
3-5 (%)	0.0829	0.0527	0.161	0.301	0.375	0.156
	(0.276)	(0.223)	(0.368)	(0.459)	(0.484)	(0.363)
6-8 (%)	0.0509	0.0805	0.264	0.205	0.184	0.143
	(0.220)	(0.272)	(0.441)	(0.404)	(0.388)	(0.350)
9-11 (%)	0.0550	0.179	0.197	0.179	0	0.134
	(0.228)	(0.384)	(0.397)	(0.383)	(0)	(0.340)
12-14 (%)	0.104	0.226	0.146	0.0954	0	0.133
	(0.305)	(0.418)	(0.354)	(0.294)	(0)	(0.340)
15-17 (%)	0.218	0.162	0.143	0	0	0.130
	(0.413)	(0.368)	(0.350)	(0)	(0)	(0.336)

Table 3: Long-term consequences of the unemployment rate at labor market entry to lifetime employment

	(1) Employed	(2) Full-time Job	(3) Waged worker	(4) Unpaid Job	(5) Self-employed Job
Unemployment rate at entry	-0.070***	-0.062***	0.008	0.114***	-0.122***
	(0.007)	(0.007)	(0.012)	(0.012)	(0.006)
Observation	64,147	64,147	63,457	63,457	63,457
Mean	0.887	0.563	0.487	0.289	0.224
Adjusted R2	0.635	0.622	0.751	0.639	0.621
Fixed effects	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Long-term consequences of the unemployment rate at labor market entry - event study results

	(1) Employed	(2) Full-time Job	(3) Waged worker	(4) Unpaid Job	(5) Self-employed Job
Unemployment rate × years since					
0-2 years	-0.027***	-0.029***	-0.006**	0.017***	-0.012***
	(0.002)	(0.001)	(0.002)	(0.003)	(0.002)
3-5 years	-0.009***	-0.010***	0.004**	0.006**	-0.010***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
6-8 years	-0.002**	0.000	0.006***	0.001	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
9-11 years	0.002***	0.004***	0.004***	-0.000	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
12-14 years	0.003***	0.005***	0.002*	-0.002*	0.000
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
15-17 years	0.003***	0.004***	-0.000	-0.002**	0.002***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Observation	64,147	64,147	63,457	63,457	63,457
Mean	0.887	0.563	0.487	0.289	0.224
Adjusted R2	0.631	0.620	0.750	0.638	0.620
Fixed effects	Yes	Yes	Yes	Yes	Yes

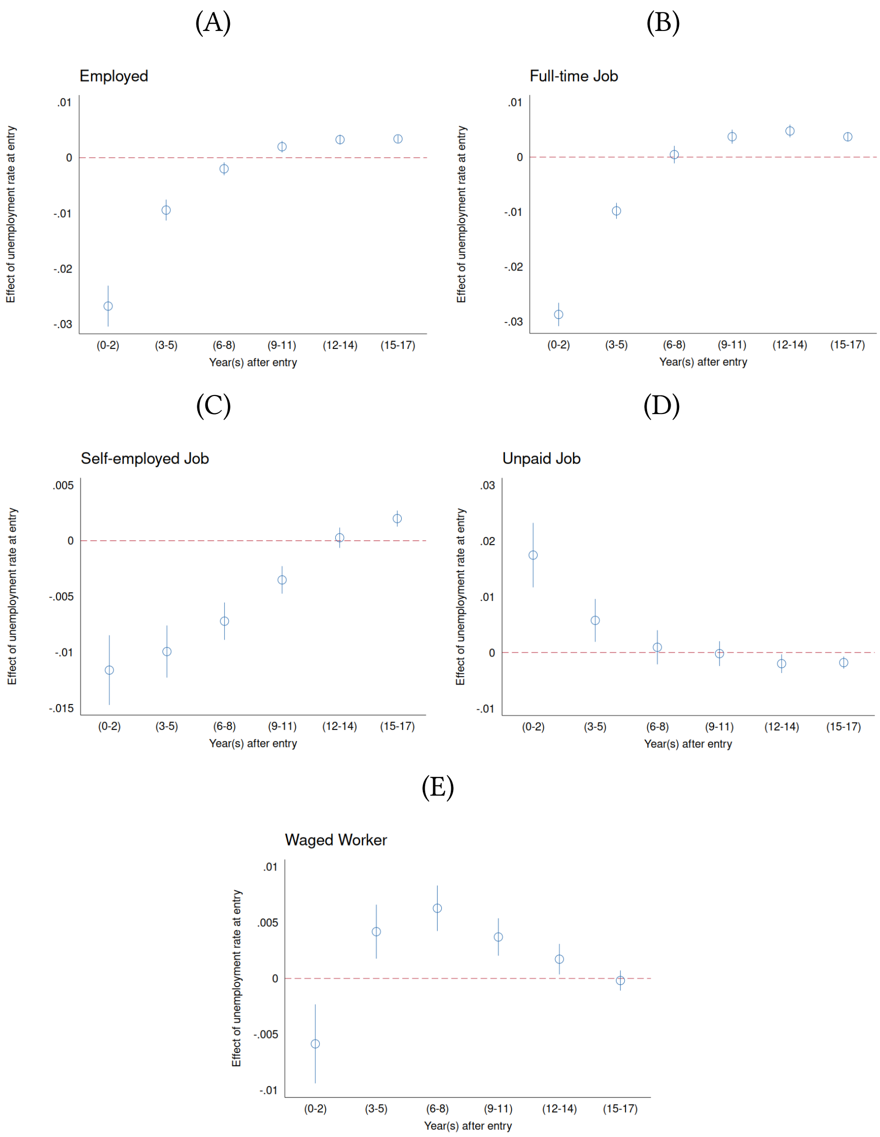
Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Next, I present the main results by plotting the scarring effects across years of experience since entering the labor market, following Equation 2. Figure 3 depicts the persistence of scarring effects on employment outcomes. As depicted in Figure 3 Panel (A), in the first two years after entering the labor market, the probability to be employed drops by about 3%. The negative effect lingers up to 9 to 11 years after first entering the labor market. An almost identical story emerges for the probability to get a full-time job, as illustrated in Panel B. This finding is comparable in magnitude with previous studies in the United States (Schwandt and Von Wachter, 2019) and Canada (Oreopoulos et al., 2012).

From Figure 3 Panel C, interesting results emerge. The unlucky new entrants were unlikely to be employed in self-employed jobs. While this may contradict the fact that after the crisis many people became self-employed as the wage sector contracted, these results show that new entrants might find it difficult to begin their career in self-employed jobs. One possible explanation is the set-up cost of starting a self-employed job. Though for most workers, switching to self-employed occupations is an effective strategy Rothenberg et al. (2016), this might not be the most affordable strategy.

Finally, from Figure 3 Panel D, I find evidence that many new entrants are sorted into unpaid jobs. The probability to be employed in unpaid jobs is positively associated with the unemployment rate at entrants up to 9-11 years after graduation. This fact is consistent with previous findings (Manning and Junankar, 1998; Manning, 2000) that find many waged workers switch to unpaid jobs in rural areas. For the new entrants, this could be the type of job that they can get sorted too with minimum barriers to entry.

Figure 3: Scarring effects on employment



Notes: Results are based on national specification as summarized in Equation 2 using data from SAKERNAS 1990-2019. Plots represent coefficients on unemployment rate at the year and current province residence of labor market entrance. Specification controls for labor market entry fixed effects, gender fixed effects and survey year fixed effects. The whisker of each dot plot represents a 95% confidence interval. Standard errors are clustered at the graduate cohort-provincial level.

Next, I turn to occupational sector results. It emerges that the new entrants are likely to be in the agriculture sector when the unemployment rate is high, as illustrated in Figure A2 Panel A in Appendix A.[20] This is consistent with previous literature that finds agriculture as a safety net employment for those who were affected by the recession in 1997/1998 Manning and Junankar (1998). While most existing studies refer to already-in-labor market employer responses, my results confirm that the new entrants follow a similar path. Increased likelihood to work in agriculture is tightly correlated with the fact that reverse migration from urban

[20]Lifetime results of the scarring effects estimation on occupational sectors are presented in Table A1 in Appendix A

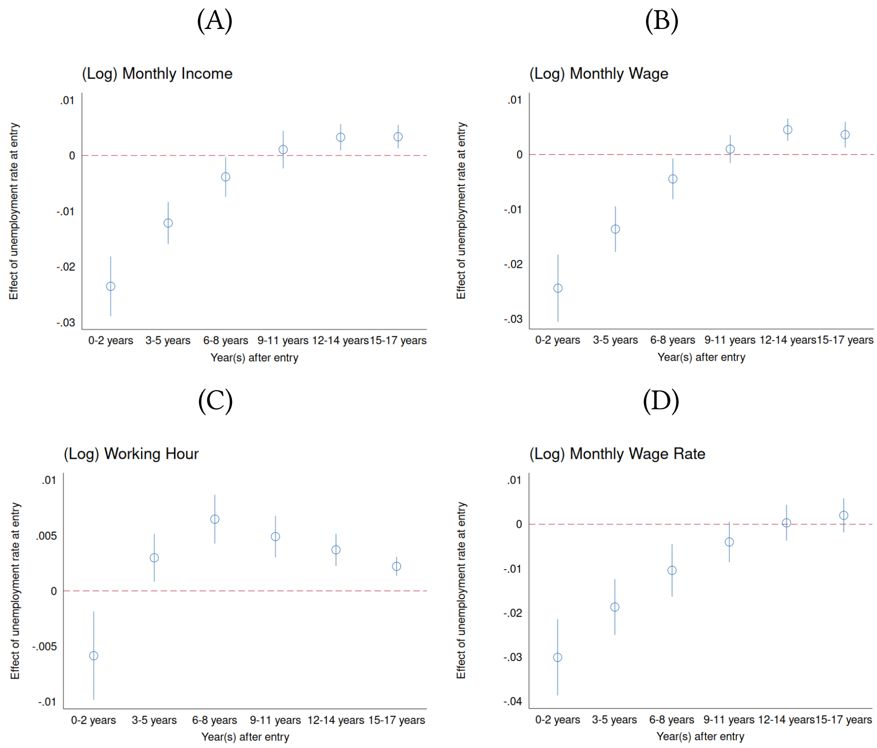
and rural is a typical response of workers in Indonesia when the labor market contracted as experienced during the AFC (Hugo, 2000). However, in contrast to employed workers, I do not find a significant effect towards the probability to be employed in manufacturing, as shown in Figure A2 Panel B. Existing literature shows that manufacturing employment has shrunken, as the recession hit in 1997/1998. For the new entrants, the unemployment rate does not significantly affect the probability to find a job in manufacturing. I do find that bad economic conditions push out new entrants from the services and construction sectors (see Figure A2 Panel C). The negative effect on services and construction sectors persists throughout their working lifetime. This persistent negative effect, in particular, is interesting as it suggests that the new entrants may fail to accumulate the necessary skills to be engaged in services and construction when they started in the non-services sectors. One possible interpretation is the service sector consists of high-skilled occupations such as education, finance, technology, etc. Human capital investment in an earlier stage of a career is even more important compared to other sectors such as agriculture and manufacturing. However, one should carefully interpret the results, as service sectors also include lower-skilled occupations such as retails and trade which do not require such accumulation of human capital.

Table 5: Long-term consequences of the unemployment rate at labor market entry to lifetime occupational sectors

	(1) Log monthly income	(2) Log total wage	(3) Log working hours	(4) Log wage per hours
Unemployment rate × years since				
0-2 years	-0.024***	-0.024***	-0.006**	-0.030***
	(0.003)	(0.003)	(0.002)	(0.004)
3-5 years	-0.012***	-0.014***	0.003**	-0.019***
	(0.002)	(0.002)	(0.001)	(0.003)
6-8 years	-0.004*	-0.004*	0.006***	-0.010**
	(0.002)	(0.002)	(0.001)	(0.003)
9-11 years	0.001	0.001	0.005***	-0.004
	(0.002)	(0.001)	(0.001)	(0.002)
12-14 years	0.003**	0.005***	0.004***	0.000
	(0.001)	(0.001)	(0.001)	(0.002)
15-17 years	0.003**	0.004**	0.002***	0.002
	(0.001)	(0.001)	(0.000)	(0.002)
Observation	61,563	59,276	62,775	59,208
Mean	13.734	13.844	5.072	8.672
Adjusted R2	0.903	0.740	0.539	0.720
Fixed effects	Yes	Yes	Yes	Yes

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure 4: Scarring effects on income



Notes: Results are based on national specification as summarized in Equation 2 using data from SAKERNAS 1990-2019. Plots represent coefficients on unemployment rate at the year and current province residence of labor market entrance. Specification controls for labor market entry fixed effects, gender fixed effects and survey year fixed effects. The whisker of each dot plot represents a 95% confidence interval. Standard errors are clustered at the graduate cohort-provincial level.

From the previous section, we observe evidence that bad economic conditions at labor market entry would affect new entrants' employability and job placement. As a bad economic condition is associated with the likelihood to be in a lower-skilled job, we should expect it would also be reflected in their income trajectories. The results are presented in Table 6. From Table 6, it emerges that a percentage point increase in the unemployment rate in labor market entrance causes more than 26% loss of income or wage during the 25 years of working experience (see Columns 1 and 2). This loss of income is statistically significant and substantive. It also affects working hours as well as wage rate consequently (see column 3 and column 4).

Table 6: Long-term consequences of the unemployment rate at labor market entry to lifetime income

	(1) Log monthly income	(2) Log total wage	(3) Log working hours	(4) Log wage per hours
Unemployment rate at entry	-0.313***	-0.269***	-0.173***	-0.314***
	(0.015)	(0.018)	(0.012)	(0.026)
Observation	61,563	59,276	62,775	59,208
Mean	13.734	13.844	5.072	8.672
Adjusted R2	0.903	0.740	0.541	0.720
Fixed effects	Yes	Yes	Yes	Yes

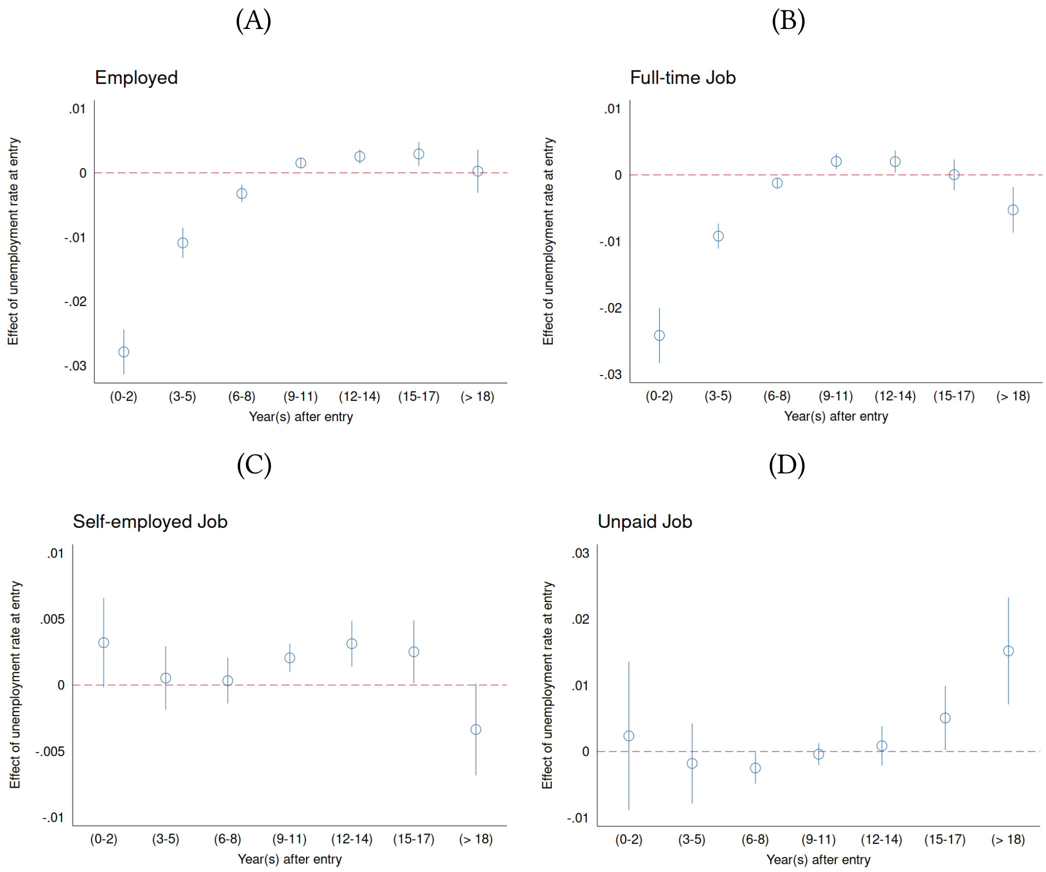
Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Decomposing the effect to be varied across years after entering the labor market, for total income and wage, I find a similar pattern as the negative effect towards probability to be employed. A bad economic situation in the initial year correlates with more than 3% less income or wage in the first two years of their career. The effect starts to be nullified after 9 to 11 years after graduation. There is a significant drop in wage rate for the new entrants in the early years of their career as working hours also dropped along with their total monthly income. As the picture depicts both waged workers and informal jobs, it may mask a more pronounced effect for the waged worker group. The size of income loss is similar to developed countries' experience such as the US (Schwandt and Von Wachter, 2019; Kahn, 2010) and Canada (Oreopoulos et al., 2012).

5.2 Province estimates

Overall, the province estimates share similar insights to the national estimates as summarized in Figure 5. A higher unemployment rate at labor market entry leads to a drop in the probability of being employed and having a full-time job. The negative effect is found the largest in the first two years and starts to recover after 9 to 11 years. The magnitude of the negative effect of labor market entrance conditions is similar to the national estimates. However, interesting results emerge in the probability of being self-employed and working at unpaid jobs outcomes. In Figure 5 Panel C and D, respectively, the effect of bad economic conditions is less precisely estimated and not significant for the earlier career for both self-employed and unpaid job outcomes. For the self-employment outcomes, the estimate using provincial exposure provides the opposite effect compared to the national estimates. From the provincial specification, there is a positive effect of a bad economic situation for the new entrants, while not statistically significant. As for the unpaid job, the increased likelihood of the unpaid job from national estimates in the earlier stage of new entrants' work life is less detectable.

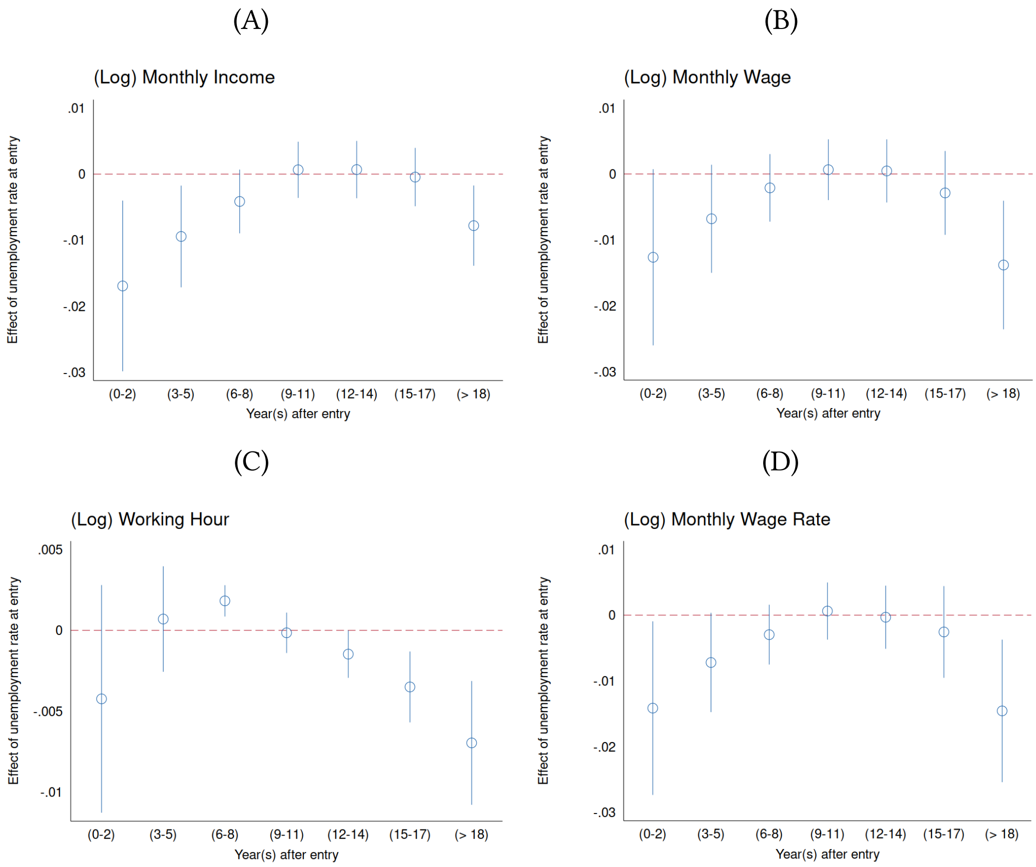
Figure 5: Province estimate: Scarring effects on employment



Notes: Results are based on provincial specification as summarized in Equation 4 using data from SAKERNAS 1990-2019. Plots represent coefficients on unemployment rate at the year and current province residence of labor market entrance. Unemployment rates are weighted using historical inter-province migration patterns in Indonesia between 1990 to 2010. I construct the inter-province migration pattern using a sub-sample of Population Census 1990, 2000 and 2010 provided by IPUMS. Specification controls for labor market entry fixed effects, gender fixed effects, provincial fixed effects and survey year fixed effects. The whisker of each dot plot represents a 95% confidence interval. Standard errors are clustered at the graduate cohort-provincial level.

Now, I turn to the income effect point of view as depicted in Figure 6. I find that, overall, the negative income effect emerges but is smaller in magnitude and less precisely estimated. For the monthly income outcome, see Panel A of Figure 6, the negative effect trends throughout an individual's work life are similar to the national estimates. For the monthly wage, see Panel B, while sharing a similar trend and direction with the national estimates, the negative income effects are no longer statistically significant. Similar to national estimates, I also find that individuals take fewer working hours (see Panel C of Figure 4) but the negative effect estimates are also no longer statistically significant. Consequently, the estimated scarring effect on unpaid job likelihood follows a similar pattern.

Figure 6: Province estimate: Scarring effects on income



Notes: Results are based on provincial specification as summarized in Equation 4 using data from SAKERNAS 1990-2019. Plots represent coefficients on unemployment rate at the year and current province residence of labor market entrance. Unemployment rates are weighted using historical inter-province migration patterns in Indonesia between 1990 to 2010. I construct the inter-province migration pattern using a sub-sample of Population Census 1990, 2000 and 2010 provided by IPUMS. Specification controls for labor market entry fixed effects, gender fixed effects, provincial fixed effects and survey year fixed effects. The whisker of each dot plot represents a 95% confidence interval. Standard errors are clustered at the graduate cohort-provincial level.

These findings, I argue, lead to two possible explanations. First, the disparity between national and provincial estimates could reflect that the local labor market, as well-proxied by the provincial unemployment rate, is more relevant to the outcomes compared to the national level. Second, the less precision in province specification estimates may also indicate endogenous migration problems that have not been resolved fully. However, in general, national estimates and province estimates are consistent with each other except for the self-employment job likelihood. This gives us more confidence in the exogeneity of temporal variation of the unemployment rate. The change in the unemployment rate is less likely to be correlated with changes in cohort-specific characteristics.

6 Heterogeneity results

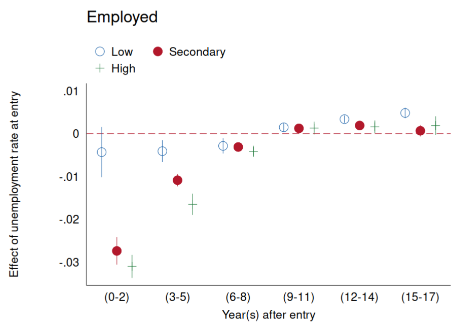
6.1 Education

Education profiles of the new entrants matters in employment decisions and potential incomes, hence the scarring effect should potentially vary across education level. As discussed in Section 2, the AFC hit the waged workers sector the most. Hence, one possible hypothesis would be more educated workers are more affected by the recession due to their job prospects, especially in an earlier stage of their careers. Furthermore, the more educated new entrants could recover better in the long run as they endowed human capital than the lower educated. On the contrary, it is also possible to hypothesize otherwise. The less educated might suffer more in terms of employment as they were to compete with more educated new entrants who were looking for low-level jobs.

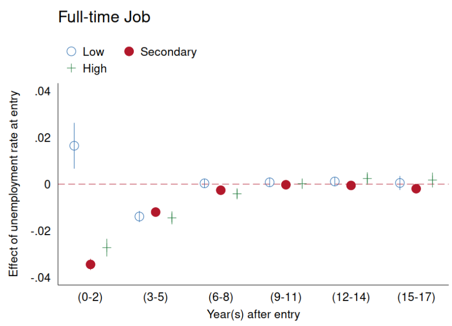
Figure 7 summarizes the estimation of the scarring effect by education level. From Panel A, confirmed our earlier hypothesis that more educated new entrants experience a larger drop in employment probability in the first 5 years of their career compared to their less educated counterparts. This suggests evidence that shrinking waged employment disadvantaged the more educated workers. Investigating the likelihood to have a full-time job, the striking gap between more and less educated becomes more evident. Surprisingly, the low-educated new entrants were more likely to have full-time jobs. I connect this evidence to the fact that low-educated individuals, largely come from lower-level income families who could not afford to be unemployed to sustain their livelihood. Finally, as shown in Panel C of Figure 7, both low-educated and high-educated new entrants matched to unpaid jobs in the first 5 years of their career and share similar recovery over time.

Figure 7: Scarring effects on employment by education

(A)

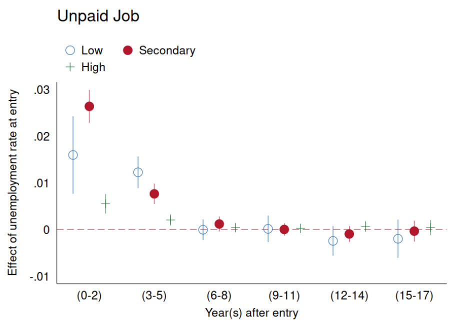


(B)



(C)

(D)



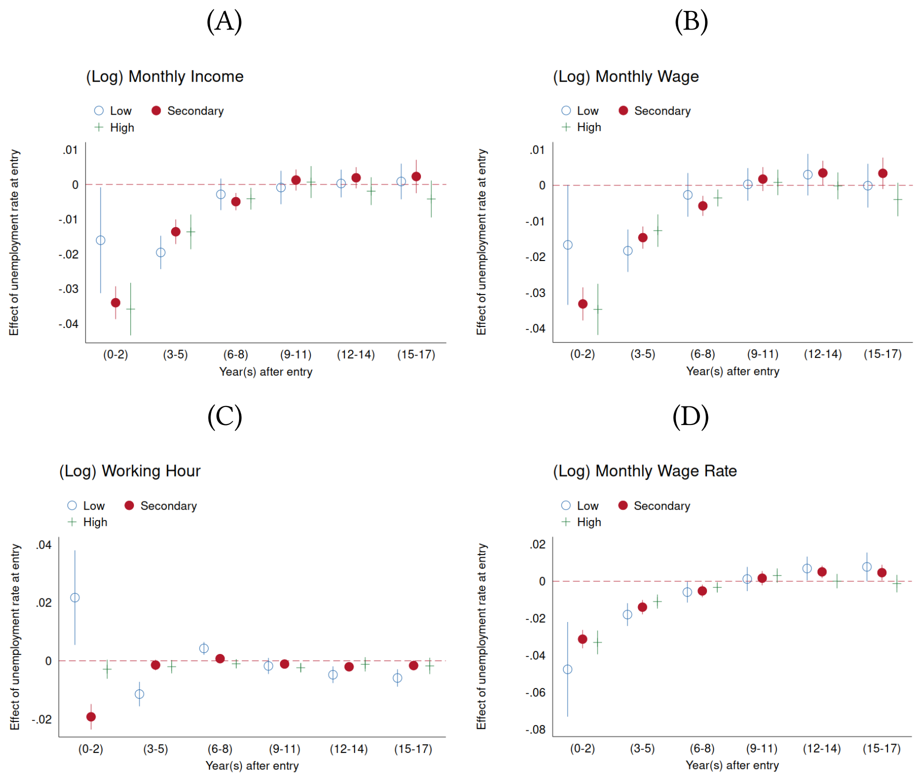
Notes: Results are based on national specification as summarized in Equation 2 using data from SAKERNAS 1990-2019. Each colored line represents separate regression by education level. Plots represent coefficients on unemployment rate at the year and current province residence of labor market entrance. Specification controls for labor market entry fixed effects, gender fixed effects and survey year fixed effects. The whisker of each dot plot represents a 95% confidence interval. Standard errors are clustered at the graduate cohort-provincial level.

Previous literature Topel and Ward (1992) suggests that as the cost of job searching increased over time, less educated young workers would search intensely after being allocated to lower-quality jobs. On the other hand, more educated individuals could afford longer job search costs for a longer time. From Figure 7, it emerges that the recovery trajectories do not vary much across education levels in terms of employment. There seems no strong evidence that the endowed with better human capital helped them to recover quicker than the less endowed. However, it is possible to have different trajectories in terms of income, as more educated individuals could be matched to much better jobs when the scarring effect starts to wear off. Figure 8 summarizes the results on income by education level. Several interesting results emerge. First, from Panel A, B and C of Figure 8, scarring effects were more pronounced for less educated individuals, though not statistically significant compared to the more educated. Second, there is no evidence of better recovery trajectories across levels of education. Thus, from our results, there is no strong evidence that supports the argument of the more educated new entrants would recover better compared to the less educated new entrants. This may point to the argument that the more educated young workers invested in the 'wrong' human capital due to bad initial job matching as discussed by Gibbons and

Waldman (2004). Thus, their income and employment trajectories follow a similar path as lesser-educated cohorts.

The provincial specification confirms the overall findings from the national specification. As summarized in Figure A6, the more educated new entrants experience a larger drop in terms of the probability to be employed and having a full-time job. Level of education also seems to have no effect in determining the length of recovery spells (i.e null scarring effect). In contrast, from Figure A7, it emerges that in terms of monthly income and wage, more educated workers were found to be recovered in a shorter period compared to the low-educated workers. Overall, similar to previous results, the provincial specification yields less precise estimates but supports the national specification findings.

Figure 8: Scarring effects on income by education



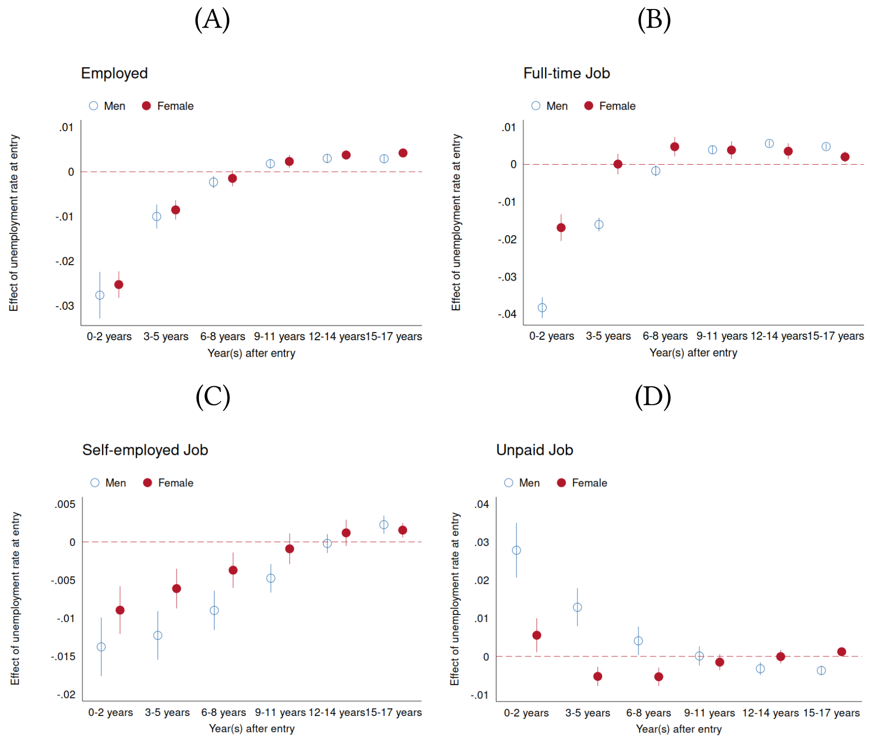
Notes: Results are based on national specification as summarized in Equation 2 using data from SAKERNAS 1990-2019. Each colored line represents separate regression by education level. Plots represent coefficients on unemployment rate at the year and current province residence of labor market entrance. Specification controls for labor market entry fixed effects, gender fixed effects and survey year fixed effects. The whisker of each dot plot represents a 95% confidence interval. Standard errors are clustered at the graduate cohort-provincial level.

6.2 Gendered results

In this section, I focus on investigating whether there are any differences in the bad economic situation when entering the labor market between men and women. As the gender gap, either in employment and income, in the labor market in Indonesia remains a big issue (Schaner and Das, 2016), the more relevant comparison would be within their gender group.

First, from an employment perspective, gender comparison reveals that the negative employment effect is shared similarly among men and women. Figure 9 captures this result. Both women and men experience about 3% less likely to be employed during the first 2 years of their careers. After 9 to 11 years, the negative employment effect starts to disappear. Among women, however, they experience less likely to be employed in an unpaid job compared to the men group by about 1%.

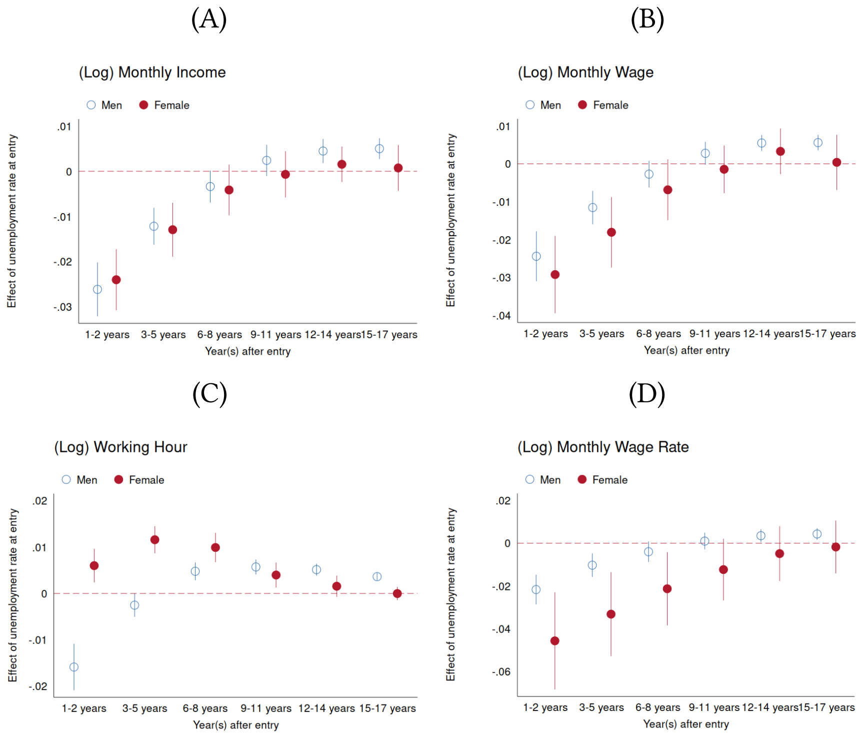
Figure 9: Scarring effects on employment by gender



Notes: Results are based on national specification as summarized in Equation 2 using data from SAKERNAS 1990-2019. Each colored line represents separate regression by gender. Plots represent coefficients on unemployment rate at the year and current province residence of labor market entrance. Specification controls for labor market entry fixed effects and survey year fixed effects. The whisker of each dot plot represents a 95% confidence interval. Standard errors are clustered at the graduate cohort-provincial level.

Secondly, an almost mimicking story emerges from income perspectives. Both gender group experiences similar pattern in terms of negative income effect among themselves as illustrated in Figure 10. The only exception is the effect on working hours. The initial unemployment rate has the opposite effect across gender. Within the men group, the effect is positive such that an increase in the initial unemployment rate leads to increased working hours. On the other hand, the scarring effect leads to a drop in working hours among the women group.

Figure 10: Scarring effects on income by gender



Notes: Results are based on national specification as summarized in Equation 2 using data from SAKERNAS 1990-2019. Each colored line represents separate regression by gender. Plots represent coefficients on unemployment rate at the year and current province residence of labor market entrance. Specification controls for labor market entry fixed effects and survey year fixed effects. The whisker of each dot plot represents a 95% confidence interval. Standard errors are clustered at the graduate cohort-provincial level.

Lastly, some interesting results emerge from sectoral results. The labor market entry condition affects increased participation in agriculture largely among men. As for women, surprisingly within the first two years, the results are negative (see Figure A3 Panel A. This result could relate to the fact that at the initial stage, more women may already be absorbed in agriculture, compared to men. In terms of services, as expected, the men's group has been impacted more by the scarring effect as seen in Figure A3 Panel C. This strongly correlated with the fact that these sectors include construction which was a male-dominated job that happened to be hit the hardest during the AFC.

7 Sensitivity tests

7.1 Alternative unemployment rates

I first test the sensitivity of national estimate results using a set of alternative unemployment rate choices. First, I use the 3-year moving average of the unemployment rate. While endogenous migration is less likely in national estimates, endogenous graduation of timing might affect our estimates. Using 3-year moving average unemployment rates, we averaged out the possibility of individuals delaying or starting their careers early in the labor market. In Figure A8 and Figure A9, my results are robust using a 3-year moving average of the unemployment rate. Second, one might expect that a cohort-specific unemployment rate would be more relevant to the new entrants. Thus, I use the unemployment rate for people aged 15-24 years old as a proxy for the youth-specific unemployment rate.[21] I find that my results are robust using such a youth-specific unemployment rate for all outcomes as depicted in FigureA10 and Figure A11.

7.2 BPS official unemployment rates

In Section 4.2, I discuss the argument to use a consistent unemployment rate definition as opposed to using BPS official unemployment rate. Assigning BPS's official unemployment rate as the initial labor market condition for the new entrants would be an appropriate sensitivity check to my results. The results are presented in Figure A12 and A13.

From employment outcomes perspectives, in general, we find a similar effect to our preferred national specification in Section 5. Negative and persistent scarring-effect emerges for both employment probability and having a full-time job outcome. However, notice that the results are less precise and share more similarities to the province specification estimates. This resemblance could also be observed for unpaid jobs and self-employment as shown in Figure A12 Panel C and D, respectively. This could indicate that the province estimates might still suffer from the potential endogeneity.

7.3 External validity using the IFLS dataset

As my last sensitivity check, I use the Indonesian Family Life Survey (IFLS)[22] to investigate the scarring effect. Since the IFLS is a longitudinal household survey, it allows me to conduct individual-panel estimates. The dataset covers the period from 1993 to 2014. There are at least three potential benefits of utilizing IFLS compared to official labor force survey data. First, the IFLS possesses a more detailed questionnaire on labor market history as they explicitly ask the year when the respondent starts their first full-time job. Second, the survey also provides more detailed education information as it records the highest grade of each education year such that it is possible to more accurately measure the years of schooling. Third, the survey provides information on the province of residence when individuals aged 12 years old.[23]

[21] I follow the World Bank and the OECD definition of the youth unemployment rate that restricts an individual to be 15 to 24 years old. See https://data.worldbank.org/indicator/SL.UEM.1524.ZS for World Bank statistics and https://data.oecd.org/unemp/youth-unemployment-rate.htm for OECD statistics. Alternatively, ILO considers 15-29 years old in their calculation of the youth unemployment rate. See https://ilostat.ilo.org/resources/concepts-and-definitions/description-youth-labour-market-statistics/ for ILO statistics.

[22] Collected by RAND Cooperation, available in 5 waves. The survey is regarded as high-quality household survey data with a very low attrition rate.

[23] The IFLS also provides information on migration history, however for simplicity, I argue that using residence at age 12 could be able to more precisely predict the

However, I argue that there are at least two major caveats to using the IFLS for my study. First, the IFLS sampling coverages may limit the cohort representation of each cohort that enters the labor market during the study period. The sample of IFLS is designed to be representative of 83% of the Indonesian population in 1993. The survey then follows the household including the split-off household over time in the next four waves. I argue that the sample construction would be less representative of cohorts that enter the labor market between 1993 to 2014. Second, as the survey was collected within, on average, 5 years intervals, the employment and income history rely on the quality of respondent recalls. While overall attrition of the IFLS across waves is low, the collected retrospective information was prone to recall bias and missing values, especially for income information.

Nevertheless, I follow a similar procedure in the spirit of my identification strategy to estimate the scarring effects using the IFLS. The major differences in terms of identification strategy are the following. First, the IFLS allows me to estimate at the individual-panel level instead of synthetic-cohort observation. Second, the time of entering the labor market is defined as the year of the first full-time job. Next, the data also allows me to identify the province of entering the labor market as the province when an individual was 15 years old. Given a better approximation to the year and province of entering the labor, than provided by SAKERNAS, I estimate the results following Equation 4 with unweighted province-level unemployment rates. Notice that I only estimate the employment probability as it least suffered from missing values issues. The IFLS results, as summarized in Table A8, in general, agree with my preferred estimation results. The IFLS estimate captures a larger scarring effect over a lifetime compared to my preferred specification results in Table 3. On one hand, this result gives external validity to my estimate. On other hand, these results also suggest that using more precise province information might improve the estimation using province specification, hence suggesting that province specification might remains suffer from endogenous migration issues.

8 Conclusion

In this study, I provide evidence of the scarring effect of bad economic conditions when entering the labor market in Indonesia. The AFC triggered a massive economic contraction which I argue is significant enough to create a temporal variation of the unemployment rate during and years after the crisis. I follow scarring effect literature (Kahn, 2010; Oreopoulos et al., 2012; Schwandt and Von Wachter, 2019) to use exposure to the unemployment rate at the year of labor market entrance as a treatment variable for the corresponding cohort. I use 30-year long cross-sectional labor force surveys to construct a synthetic cohorts panel to capture employment and labor income dynamics over a lifetime. In the preferred specification, I match the national-level unemployment rate to pseudo-panel observations aggregated at a cohort of graduation and province of residence by year of labor market entrance. Alternatively, I provide an estimation using province-level unemployment rate weighted by historical migration share across provinces. The latter specification is prone to endogenous migration issues and persistent unemployment at local labor markets despite potentially picking up more relevant local labor market situations.

I find a significant and large negative scarring effect of the unemployment rate at labor market entrance on the cohort's employment and income outcomes. For the likelihood to be employed and having full-time job outcomes, the effect persists up to nine to eleven years after entering the labor market. An increase in the unemployment rate by 1 percentage point leads to a 3% drop in the likelihood of having a full-time job in the first 2 years since entering the labor market. The bad economic situation on the labor market entrance also matches this cohort o unpaid jobs. From the income perspective, a similar story emerges. The negative income effect is measured by about a 3% drop in total monthly income and monthly wage in the first 2 years after entering the labor market and starts to fade away after 9 to 11 years. I also find that individual work more hours which lead to a subsequent drop in the wage rate. That unlucky cohort is also more likely to find a job in agriculture and less likely to be involved in services and construction. This is consistent with findings from previous literature (Manning, 2000) that show the agriculture sector absorbs more workers from non-agriculture following the crisis as more people move temporarily from urban areas where most job opportunities contracted (Hugo, 2000).

From gender viewpoints, I find that, in general, the scarring effect is shared similarly among men and women groups. Women and men groups experience different labor market entrance consequences in two fashions. First, the matching to unpaid jobs is more apparent within the men group compared to within the women group. Second, within the women group, worsening labor market conditions at the entrance translate to more working hours while the opposite results emerge for men groups. Lastly, the allocation to the agricultural sector is more pronounced within the men's group.

Overall, comparing national and province specification results brings two important insights. First, the similarity in direction of the scarring effect between national and province specification encourages us to that exogenous temporal variation in the unemployment rate to cohort characteristic changes holds. Second, province specifications show less precise estimation. This could be related to the fact that the migration-weighted unemployment rates strategy might not be able to fix the endogenous migration issue. On the other hand, it could be suggestive evidence that local labor market shock may be more relevant compared to the national level, especially for income results.

Understanding the magnitude and mechanism of the scarring effect for new entrants becomes an even more important issue for policymakers than before given the latest pandemic-induced recession. Hence, this study offers at least two important insights to policymakers. First, it raises the importance of providing economic support for young people to afford costly job-matching processes to avoid allocation to low-skilled jobs. Second, providing job training could help the new entrants to not lose important human capital accumulation. Finally, I acknowledge that this study has several caveats. First, the design of the study was unable to test the explicitly possible mechanism behind the scarring effect. Second, this paper has very limited insight into firm-side stories which interact with the labor supply side. Addressing the aforementioned caveats should motivate the direction of future research agendas.

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9 Appendix

Table A1: Long-term consequences of the unemployment rate at labor market entry to lifetime occupational sectors

	(1) Agriculture	(2) Manufacturing	(3) Services & construction
Unemployment rate at entry	0.048***	0.029*	-0.077***
	(0.008)	(0.011)	(0.012)
Observation	63,457	63,457	63,457
Mean	0.343	0.071	0.586
Adjusted R2	0.808	0.604	0.751
Fixed effects	Yes	Yes	Yes

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A2: Long-term consequences of the unemployment rate at labor market entry to lifetime occupational sectors

	(1) Agriculture	(2) Manufacturing	(3) Services & construction
Unemployment rate × years since			
0-2 years	0.007***	-0.002	-0.005***
	(0.001)	(0.001)	(0.001)
3-5 years	0.002*	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
6-8 years	-0.000	-0.001	0.001
	(0.001)	(0.001)	(0.001)
9-11 years	-0.000	-0.001	0.001
	(0.001)	(0.001)	(0.001)
12-14 years	-0.000	-0.000	0.001
	(0.001)	(0.000)	(0.001)
15-17 years	0.001	-0.000	-0.000
	(0.000)	(0.000)	(0.001)
Observation	63,457	63,457	63,457
Mean	0.343	0.071	0.586
Adjusted R2	0.807	0.604	0.751
Fixed effects	Yes	Yes	Yes

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A3: Long-term consequences of the unemployment rate at labor market entry to lifetime occupational sectors

	(1) Agriculture	(2) Manufacturing	(3) Services & construction
Unemployment rate × years since			
0-2 years	0.007***	-0.002	-0.005***
	(0.001)	(0.001)	(0.001)
3-5 years	0.002*	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
6-8 years	-0.000	-0.001	0.001
	(0.001)	(0.001)	(0.001)
9-11 years	-0.000	-0.001	0.001
	(0.001)	(0.001)	(0.001)
12-14 years	-0.000	-0.000	0.001
	(0.001)	(0.000)	(0.001)
15-17 years	0.001	-0.000	-0.000
	(0.000)	(0.000)	(0.001)
Observation	63,457	63,457	63,457
Mean	0.343	0.071	0.586
Adjusted R2	0.807	0.604	0.751
Fixed effects	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A4: Long-term consequences of the unemployment rate at labor market entry to lifetime occupational sectors

	(1) Employed	(2) Full-time Job	(3) Waged worker	(4) Unpaid Job	(5) Self-employed Job
A. Male					
1-2 years	-0.028***	-0.038***	-0.014***	0.028***	-0.014***
	(0.003)	(0.001)	(0.002)	(0.003)	(0.002)
3-5 years	-0.010***	-0.016***	-0.001	0.013***	-0.012***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
6-8 years	-0.002**	-0.002*	0.005***	0.004*	-0.009***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
9-11 years	0.002**	0.004***	0.005***	0.000	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
12-14 years	0.003***	0.006***	0.003***	-0.003***	-0.000
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
15-17 years	0.003***	0.005***	0.001**	-0.004***	0.002***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Observation	32,041	32,041	31,746	31,746	31,746
Mean	0.887	0.563	0.487	0.289	0.224
Adjusted R2	0.659	0.685	0.772	0.729	0.685
Fixed effects	Yes	Yes	Yes	Yes	Yes

	(1) Employed	(2) Full-time Job	(3) Waged worker	(4) Unpaid Job	(5) Self-employed Job
B. Female					
1-2 years	-0.025***	-0.017***	0.003	0.006*	-0.009***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
3-5 years	-0.009***	0.000	0.011***	-0.005***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
6-8 years	-0.001	0.005***	0.009***	-0.005***	-0.004**
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
9-11 years	0.002**	0.004**	0.002	-0.002	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
12-14 years	0.004***	0.004**	-0.001	-0.000	0.001
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
15-17 years	0.004***	0.002**	-0.003***	0.001*	0.002**
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
Observation	32,106	32,106	31,711	31,711	31,711
Mean	0.887	0.563	0.487	0.289	0.224
Adjusted R2	0.636	0.548	0.804	0.757	0.576
Fixed effects	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A5: Long-term consequences of the unemployment rate at labor market entry to lifetime occupational sectors

	(1) Log monthly income	(2) Log total wage	(3) Log working hours	(4) Log wage per hours
A. Male				
1-2 years	-0.026***	-0.024***	-0.016***	-0.022***
	(0.003)	(0.003)	(0.002)	(0.003)
3-5 years	-0.012***	-0.012***	-0.003*	-0.010***
	(0.002)	(0.002)	(0.001)	(0.003)
6-8 years	-0.003	-0.003	0.005***	-0.004
	(0.002)	(0.002)	(0.001)	(0.002)
9-11 years	0.002	0.003	0.006***	0.001
	(0.002)	(0.001)	(0.001)	(0.002)
12-14 years	0.004**	0.005***	0.005***	0.003*
	(0.001)	(0.001)	(0.001)	(0.001)
15-17 years	0.005***	0.006***	0.004***	0.004**
	(0.001)	(0.001)	(0.000)	(0.001)
Observation	31,139	30,270	31,406	30,243
Mean	13.734	13.844	5.072	8.672
Adjusted R2	0.932	0.805	0.598	0.769
Fixed effects	Yes	Yes	Yes	Yes

	(1) Log monthly income	(2) Log total wage	(3) Log working hours	(4) Log wage per hours
B. Female				
1-2 years	-0.024***	-0.029***	0.006**	-0.046***
	(0.003)	(0.005)	(0.002)	(0.011)
3-5 years	-0.013***	-0.018***	0.012***	-0.033**
	(0.003)	(0.005)	(0.001)	(0.010)
6-8 years	-0.004	-0.007	0.010***	-0.021*
	(0.003)	(0.004)	(0.002)	(0.008)
9-11 years	-0.001	-0.001	0.004**	-0.012
	(0.002)	(0.003)	(0.001)	(0.007)
12-14 years	0.002	0.003	0.002	-0.005
	(0.002)	(0.003)	(0.001)	(0.006)
15-17 years	0.001	0.000	-0.000	-0.002
	(0.002)	(0.004)	(0.001)	(0.006)
Observation	30,424	29,006	31,369	28,965
Mean	13.734	13.844	5.072	8.672
Adjusted R2	0.872	0.674	0.513	0.679
Fixed effects	Yes	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A6: Long-term consequences of the unemployment rate at labor market entry to lifetime occupational sectors

	(1) Agriculture	(2) Manufacturing	(3) Services & construction
A. Male			
1-2 years	0.012***	-0.001	-0.011***
	(0.002)	(0.001)	(0.002)
3-5 years	0.004**	-0.000	-0.004**
	(0.001)	(0.001)	(0.001)
6-8 years	-0.001	0.000	0.001
	(0.001)	(0.000)	(0.001)
9-11 years	-0.002*	0.000	0.002**
	(0.001)	(0.000)	(0.001)
12-14 years	-0.002***	0.001*	0.002*
	(0.001)	(0.000)	(0.001)
15-17 years	-0.001	0.000	0.001
	(0.001)	(0.000)	(0.001)
Observation	31,746	31,746	31,746
Mean	0.343	0.071	0.586
Adjusted R2	0.839	0.650	0.772
Fixed effects	Yes	Yes	Yes

	(1) Agriculture	(2) Manufacturing	(3) Services & construction
B. Female			
1-2 years	0.000	-0.002	0.002
	(0.001)	(0.002)	(0.002)
3-5 years	-0.001	-0.002*	0.003
	(0.001)	(0.001)	(0.001)
6-8 years	0.000	-0.002	0.001
	(0.001)	(0.001)	(0.001)
9-11 years	0.002*	-0.002	-0.001
	(0.001)	(0.001)	(0.001)
12-14 years	0.002**	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
15-17 years	0.003***	-0.001	-0.002*
	(0.001)	(0.001)	(0.001)
Observation	31,711	31,711	31,711
Mean	0.343	0.071	0.586
Adjusted R2	0.812	0.612	0.791
Fixed effects	Yes	Yes	Yes

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A7: Long-term consequences of the unemployment rate at labor market entry to lifetime occupational sectors

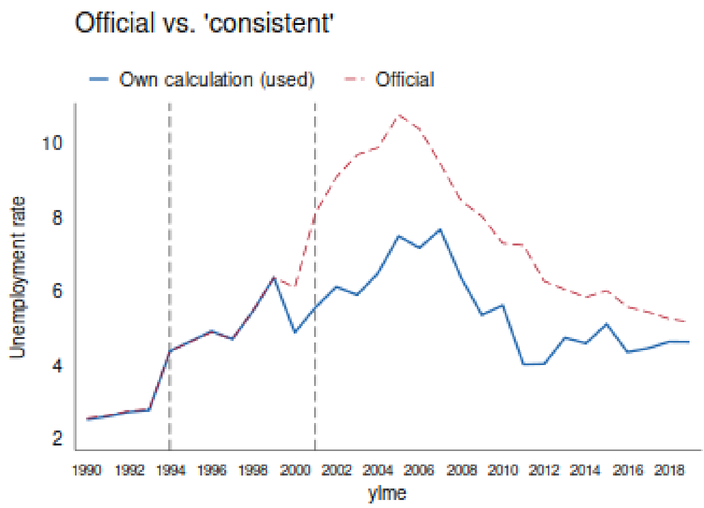
	(1) Employed	(2) Full-time Job	(3) Waged worker	(4) Unpaid Job	(5) Self-employed Job
Male	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
Female	-0.018**	-0.128***	-0.014	0.096***	-0.082***
	(0.005)	(0.011)	(0.012)	(0.022)	(0.013)
yeare	0.006***	0.015***	0.003*	-0.017***	0.014***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Unemployment rate × years since					
0-2 years	-0.027***	-0.029***	-0.006**	0.017***	-0.012***
	(0.002)	(0.001)	(0.002)	(0.003)	(0.002)
3-5 years	-0.009***	-0.010***	0.004**	0.006**	-0.010***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
6-8 years	-0.002**	0.000	0.006***	0.001	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
9-11 years	0.002***	0.004***	0.004***	-0.000	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
12-14 years	0.003***	0.005***	0.002*	-0.002*	0.000
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
15-17 years	0.003***	0.004***	-0.000	-0.002**	0.002***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Low education	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
Secondary	-0.022***	0.107***	0.169***	-0.218***	0.049***
	(0.004)	(0.007)	(0.014)	(0.011)	(0.008)
High education	-0.013	0.161***	0.512***	-0.439***	-0.073***
	(0.010)	(0.010)	(0.029)	(0.024)	(0.012)
year of labor market entry=1990	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)
year of labor market entry=1991	-0.006***	0.007**	0.006*	-0.008**	0.002
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
year of labor market entry=1992	-0.009***	0.013***	0.012***	-0.014***	0.002
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)
year of labor market entry=1993	-0.008*	0.020***	0.023***	-0.019***	-0.004
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
year of labor market entry=1994	-0.009*	0.028***	0.023***	-0.024***	0.001
	(0.004)	(0.004)	(0.005)	(0.005)	(0.003)
year of labor market entry=1995	-0.010	0.035***	0.026***	-0.028***	0.001
	(0.006)	(0.005)	(0.005)	(0.005)	(0.004)
year of labor market entry=1996	-0.010	0.042***	0.040***	-0.035***	-0.005
	(0.007)	(0.005)	(0.007)	(0.006)	(0.005)
year of labor market entry=1997	-0.008	0.049***	0.045***	-0.043***	-0.002
	(0.008)	(0.007)	(0.007)	(0.007)	(0.005)
year of labor market entry=1998	-0.010	0.057***	0.058***	-0.052***	-0.006
	(0.008)	(0.007)	(0.008)	(0.008)	(0.005)
year of labor market entry=1999	-0.008	0.067***	0.064***	-0.061***	-0.003
	(0.010)	(0.008)	(0.009)	(0.009)	(0.007)
year of labor market entry=2000	-0.008	0.070***	0.070***	-0.070***	0.000
	(0.011)	(0.010)	(0.010)	(0.011)	(0.008)
year of labor market entry=2001	-0.011	0.082***	0.092***	-0.079***	-0.013
	(0.011)	(0.010)	(0.011)	(0.011)	(0.008)
year of labor market entry=2002	-0.006	0.096***	0.103***	-0.093***	-0.010
	(0.013)	(0.012)	(0.012)	(0.012)	(0.009)
year of labor market entry=2003	-0.004	0.105***	0.115***	-0.105***	-0.010
	(0.014)	(0.013)	(0.013)	(0.012)	(0.009)
year of labor market entry=2004	-0.001	0.112***	0.120***	-0.114***	-0.007
	(0.015)	(0.014)	(0.014)	(0.013)	(0.011)
year of labor market entry=2005	0.014	0.127***	0.126***	-0.129***	0.003
	(0.016)	(0.016)	(0.015)	(0.015)	(0.011)
year of labor market entry=2006	0.017	0.136***	0.139***	-0.140***	0.002
	(0.017)	(0.016)	(0.015)	(0.016)	(0.012)
year of labor market entry=2007	0.027	0.156***	0.142***	-0.154***	0.013
	(0.019)	(0.018)	(0.016)	(0.017)	(0.012)
year of labor market entry=2008	0.019	0.160***	0.155***	-0.160***	0.005
	(0.018)	(0.019)	(0.016)	(0.017)	(0.012)
year of labor market entry=2009	0.012	0.158***	0.160***	-0.164***	0.004
	(0.020)	(0.020)	(0.018)	(0.019)	(0.013)
year of labor market entry=2010	0.022	0.187***	0.166***	-0.178***	0.012
	(0.020)	(0.022)	(0.019)	(0.021)	(0.013)
year of labor market entry=2011	0.005	0.175***	0.178***	-0.176***	-0.002
	(0.021)	(0.022)	(0.019)	(0.021)	(0.014)
year of labor market entry=2012	0.001	0.182***	0.185***	-0.186***	0.001
	(0.023)	(0.024)	(0.021)	(0.023)	(0.014)
year of labor market entry=2013	0.009	0.206***	0.192***	-0.208***	0.015
	(0.025)	(0.023)	(0.021)	(0.023)	(0.017)
year of labor market entry=2014	0.004	0.198***	0.193***	-0.211***	0.018
	(0.025)	(0.026)	(0.022)	(0.023)	(0.017)

Table A8: Long-term consequences of the unemployment rate at labor market entry to employment using IFLS

	(1)	(2)	(3)
	All	Urban	Rural
UR at entry	-0.032***	0.029***	0.037***
	(0.0004)	(0.0006)	(0.0007)
Covariates	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Province Fixed Effects	Yes	Yes	Yes
Observation	13022	7236	5766

* p<0.05, ** p<0.01, *** p<0.001. Standard errors in round parentheses. Results are based on a pooled sample of Indonesia Family Life Survey Waves 1-5. Observation is at the individual level. The sample is restricted to individuals aged 20 to 65 years old. Specification controls for covariates, labor market entry fixed effects, years fixed effects and provincial fixed effects. Unemployment rates are matched to each individual using the year when the individual worked full-time and the province of residence when the individual aged 15 years old. Covariates include individual characteristics such as age, education level and gender. Standard errors are clustered at the individual level.

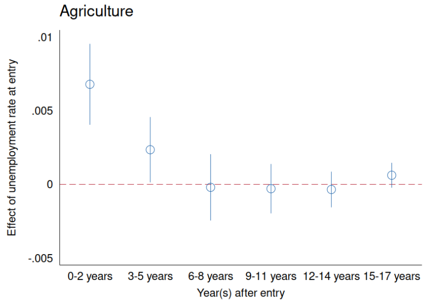
Figure A1: Unemployment rate in Indonesia



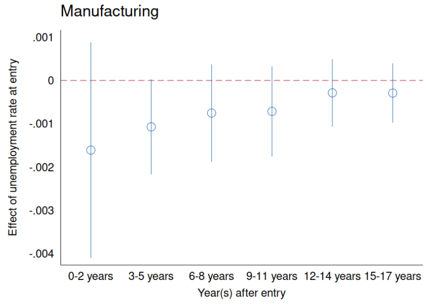
Notes: Own calculation using SAKERNAS 1990-2019. I exclude the unemployment rate in 1995.

Figure A2: Scarring effects on employment sector

(A)



(B)

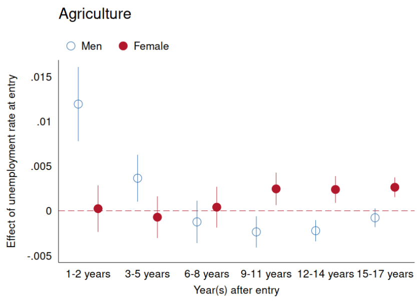


(C)

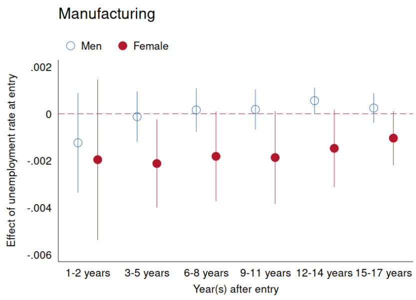
Notes: Results are based on national specification as summarized in Equation 2 using data from SAKERNAS 1990-2019. Plots represent coefficients on unemployment rate at the year and current province residence of labor market entrance. Specification controls for labor market entry fixed effects, gender fixed effects and survey year fixed effects. The whisker of each dot plot represents a 95% confidence interval. Standard errors are clustered at the graduate cohort-provincial level.

Figure A3: Scarring effect on income by gender

(A)



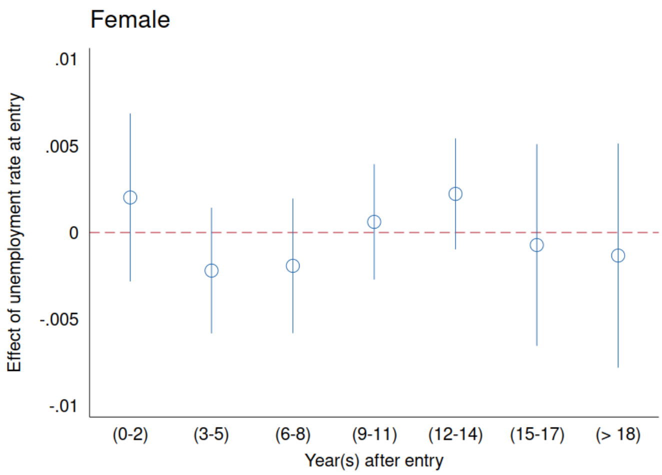
(B)



(C)

Notes: Results are based on national specification as summarized in Equation 2 using data from SAKERNAS 1990-2019. Each colored line represents separate regression by gender. Plots represent coefficients on unemployment rate at the year and current province residence of labor market entrance. Specification controls for labor market entry fixed effects and survey year fixed effects. The whisker of each dot plot represents a 95% confidence interval. Standard errors are clustered at the graduate cohort-provincial level.

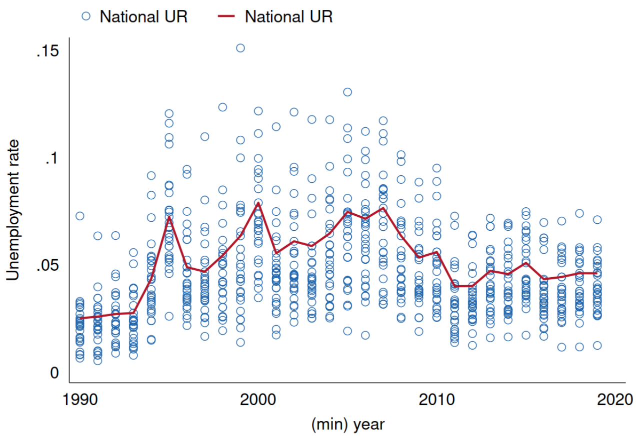
Figure A4: Balancing regression



Notes: Results are based on national specification as summarized in Equation 2 using data from SAKERNAS 1990-2019. The dependent variable is the share of female individuals in each cell. Plots represent coefficients on unemployment rate at the year and current province residence of labor market entrance. Specification controls for labor market entry fixed effects and survey year fixed effects. The whisker of each dot plot represents a 95% confidence interval. Standard errors are clustered at the graduate cohort-provincial level.

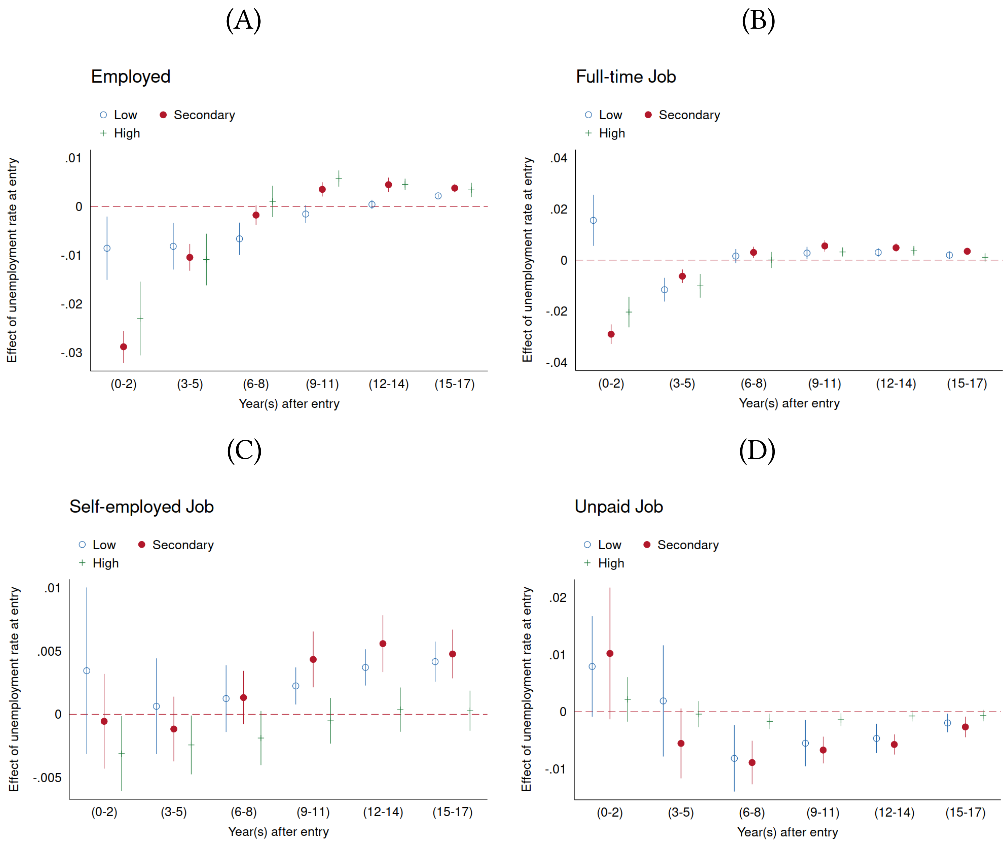
Figure A5: Unemployment rates at province level vs. national level

Correlation = 0.87*** (0.05)



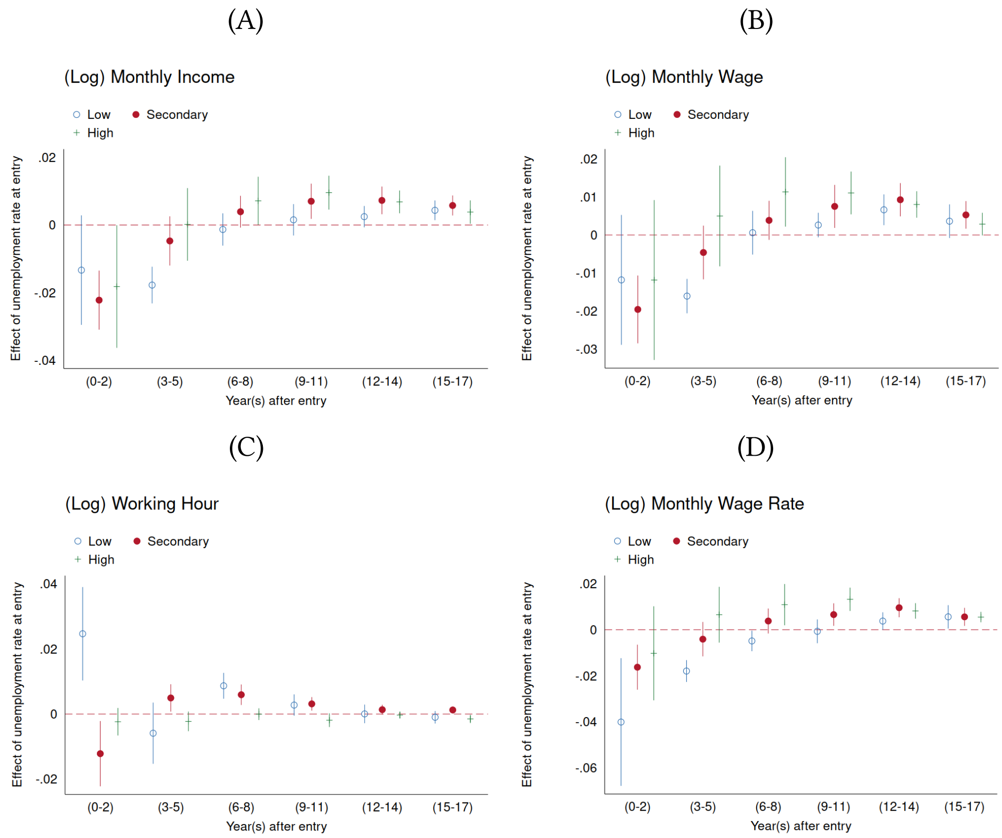
Notes: Own calculation using SAKERNAS data 1990-2019. The correlation coefficient is a linear square estimation of national unemployment rates to provincial unemployment rates at each survey year.

Figure A6: Scarring effects on employment by education



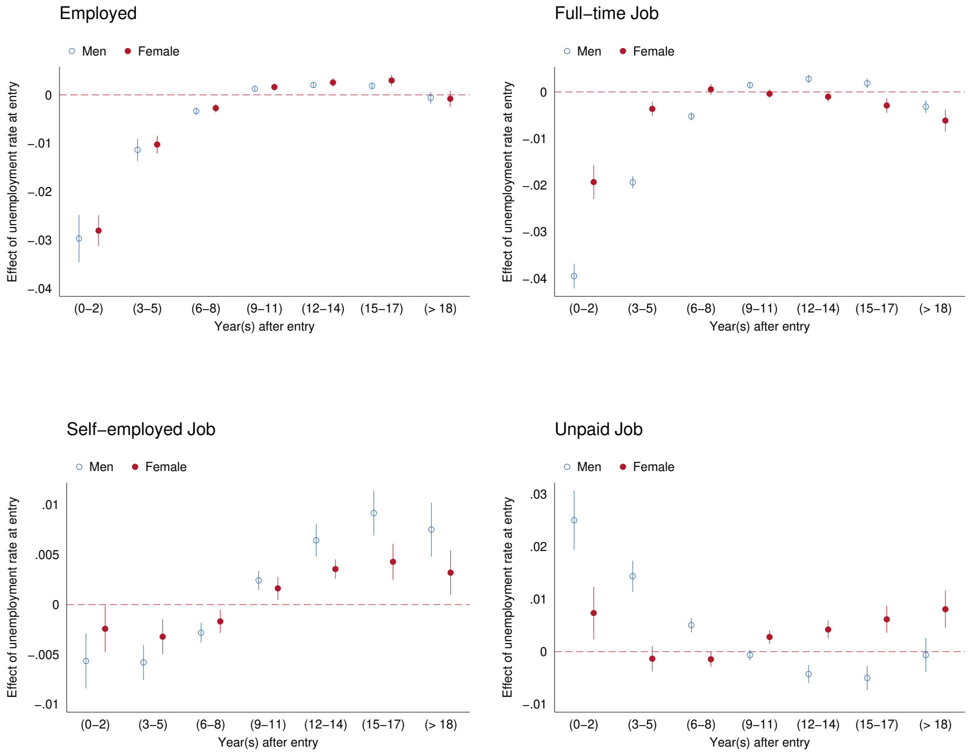
Notes: Results are based on provincial specification as summarized in Equation 4 using data from SAKERNAS 1990-2019. Plots represent coefficients on unemployment rate at the year and current province residence of labor market entrance. Unemployment rates are weighted using historical inter-province migration patterns in Indonesia between 1990 to 2010. I construct the inter-province migration pattern using a sub-sample of Population Census 1990, 2000 and 2010 provided by IPUMS. Specification controls for labor market entry fixed effects, gender fixed effects, provincial fixed effects and survey year fixed effects. The whisker of each dot plot represents a 95% confidence interval. Standard errors are clustered at the graduate cohort-provincial level.

Figure A7: Scarring effects on income by education



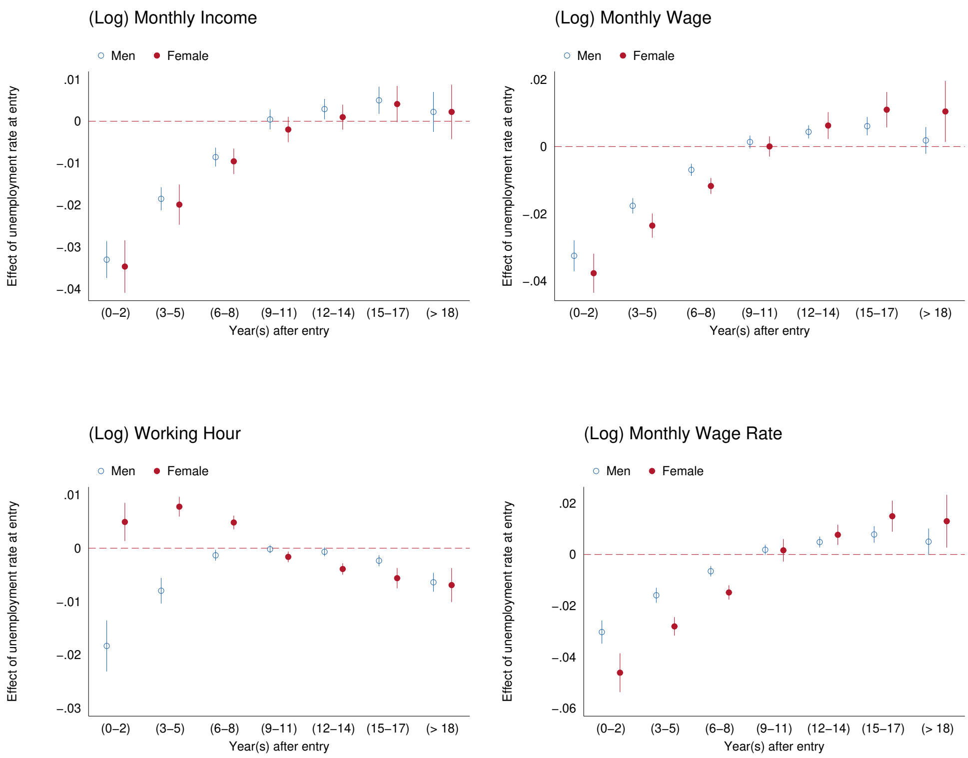
Notes: Results are based on provincial specification as summarized in Equation 4 using data from SAKERNAS 1990-2019. Plots represent coefficients on unemployment rate at the year and current province residence of labor market entrance. Unemployment rates are weighted using historical inter-province migration patterns in Indonesia between 1990 to 2010. I construct the inter-province migration pattern using a sub-sample of Population Census 1990, 2000 and 2010 provided by IPUMS. Specification controls for labor market entry fixed effects, gender fixed effects, provincial fixed effects and survey year fixed effects. The whisker of each dot plot represents a 95% confidence interval. Standard errors are clustered at the graduate cohort-provincial level.

Figure A8: Scarring effects of 3-year moving average unemployment rate



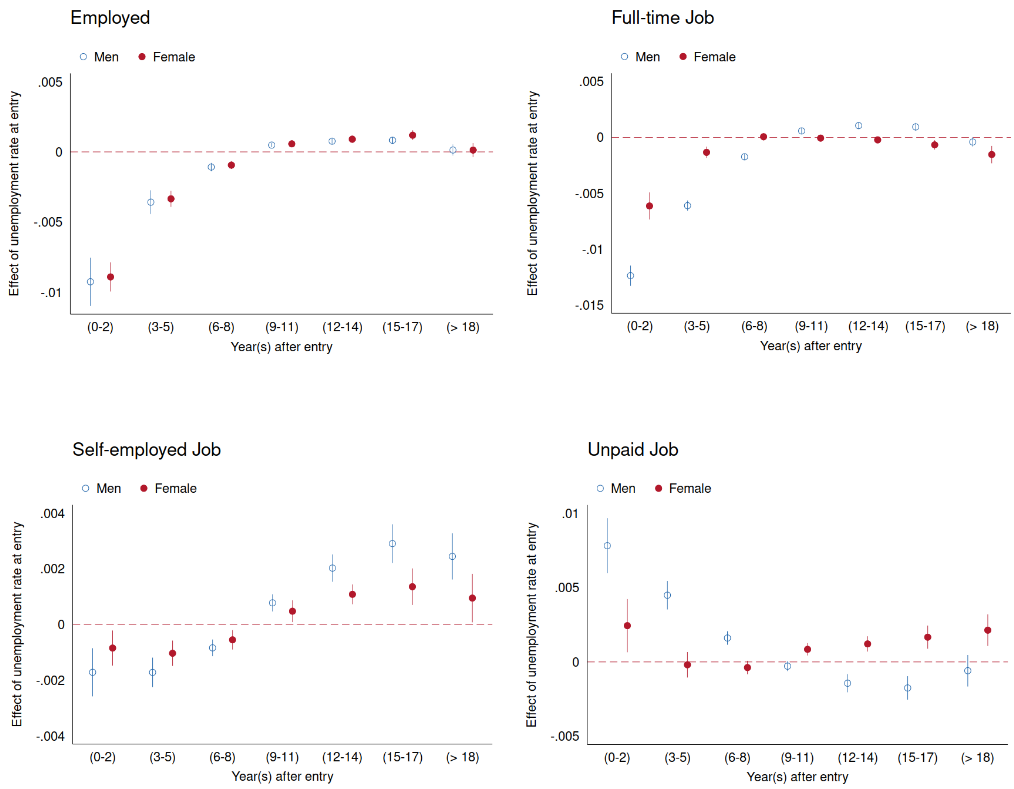
Notes: Results are based on national specification as summarized in Equation 2 using data from SAKERNAS 1990-2019. Each colored line is estimated separately by gender. Plots represent coefficients on the 3-year moving average unemployment rate at the year and current province residence of labor market entrance. Specification controls for labor market entry fixed effects and survey year fixed effects. The whisker of each dot plot represents a 95% confidence interval. Standard errors are clustered at the graduate cohort-provincial level.

Figure A9: Scarring effects of 3-year moving average unemployment rate



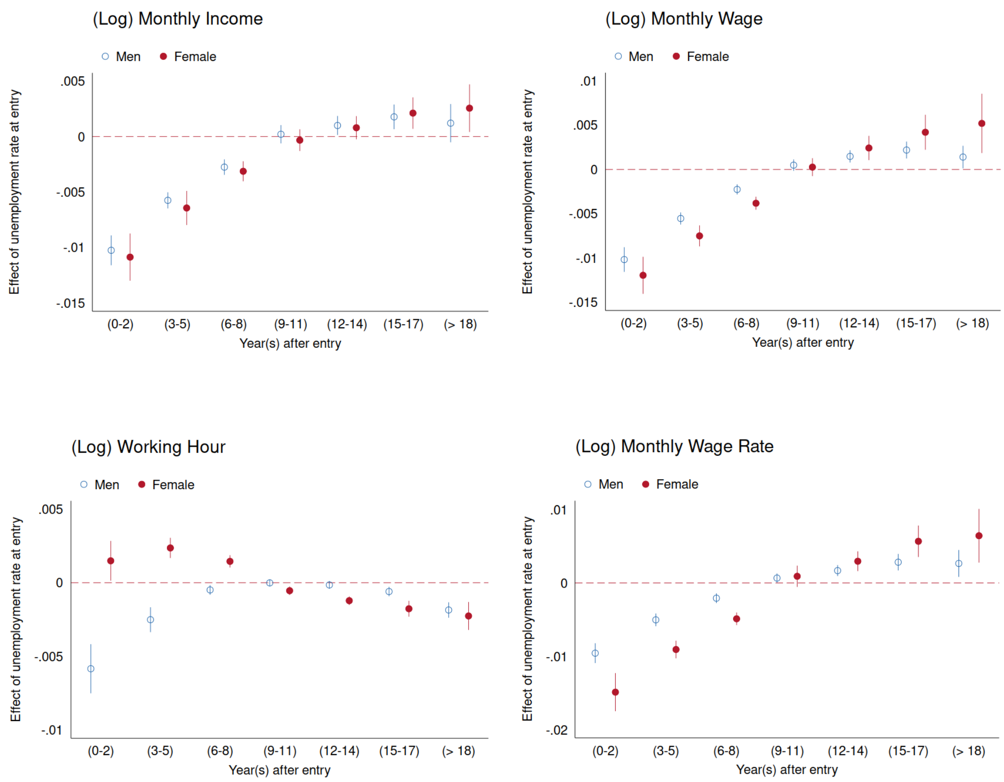
Notes: Results are based on national specification as summarized in Equation 2 using data from SAKERNAS 1990-2019. Each colored line is estimated separately by gender. Plots represent coefficients on the 3-year moving average unemployment rate at the year and current province residence of labor market entrance. Specification controls for labor market entry fixed effects and survey year fixed effects. The whisker of each dot plot represents a 95% confidence interval. Standard errors are clustered at the graduate cohort-provincial level.

Figure A10: Scarring effects using unemployment rate of 15-24 years old



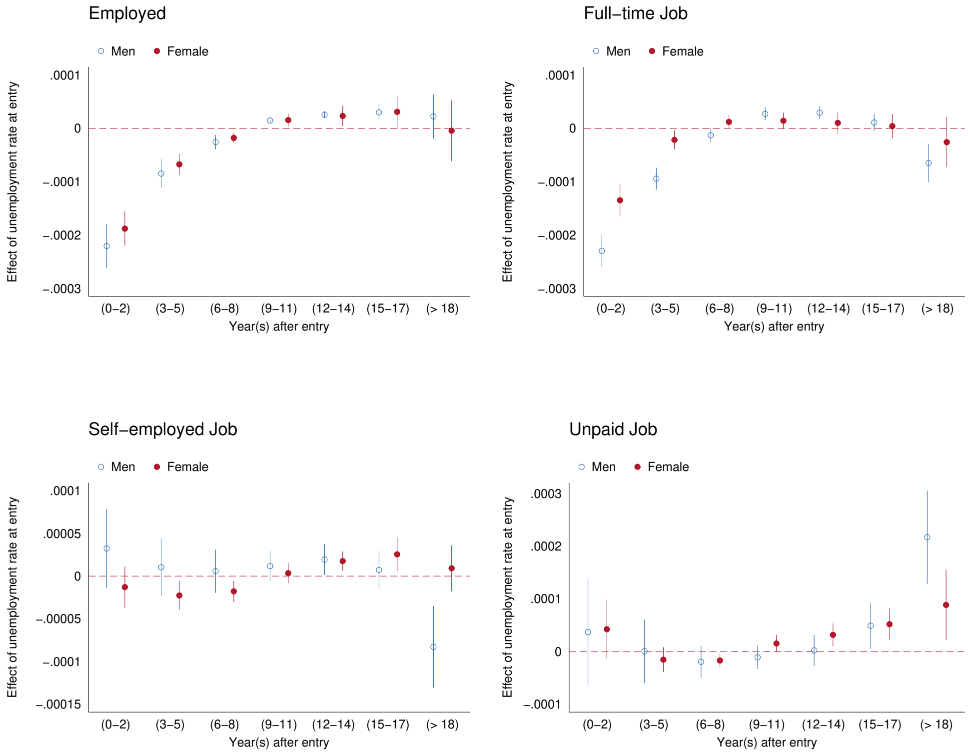
Notes: Results are based on national specification as summarized in Equation 2 using data from SAKERNAS 1990-2019. Each colored line is estimated separately by gender. Plots represent coefficients on youth-specific (aged 15-24 years old) unemployment rate at the year and current province residence of labor market entrance. Specification controls for labor market entry fixed effects and survey year fixed effects. The whisker of each dot plot represents a 95% confidence interval. Standard errors are clustered at the graduate cohort-provincial level.

Figure A11: Scarring effects using unemployment rate of 15-24 years old



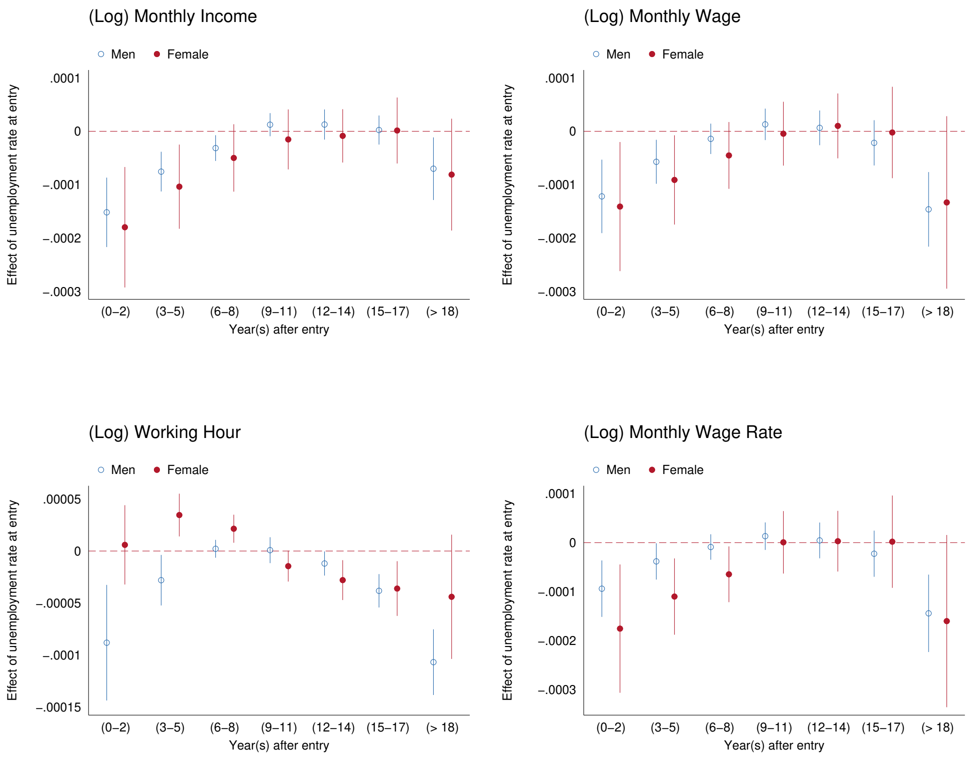
Notes: Results are based on national specification as summarized in Equation 2 using data from SAKERNAS 1990-2019. Each colored line is estimated separately by gender. Plots represent coefficients on youth-specific (aged 15-24 years old) unemployment rate at the year and current province residence of labor market entrance. Specification controls for labor market entry fixed effects and survey year fixed effects. The whisker of each dot plot represents a 95% confidence interval. Standard errors are clustered at the graduate cohort-provincial level.

Figure A12: Scarring effects of official BPS unemployment rate



Notes: Results are based on national specification as summarized in Equation 2 using data from SAKERNAS 1990-2019. Each colored line is estimated separately by gender. Plots represent coefficients on the official unemployment rate produced by BPS at the year and current province residence of labor market entrance. Specification controls for labor market entry fixed effects and survey year fixed effects. The whisker of each dot plot represents a 95% confidence interval. Standard errors are clustered at the graduate cohort-provincial level.

Figure A13: Scarring effects of official BPS unemployment rate



Notes: Results are based on national specification as summarized in Equation 2 using data from SAKERNAS 1990-2019. Each colored line is estimated separately by gender. Plots represent coefficients on the official unemployment rate produced by BPS at the year and current province residence of labor market entrance. Specification controls for labor market entry fixed effects and survey year fixed effects. The whisker of each dot plot represents a 95% confidence interval. Standard errors are clustered at the graduate cohort-provincial level.