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

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15 February 2023

Abstract

This paper provides empirical evidence of the long-term consequences of labour market entrance conditions using Indonesian data. I collect and harmonize a long series of Indonesian labour force surveys (SAKERNAS) spanning over 30 years to construct a pseudo-panel cohort of new labour market entrants from 1990 to 2019. Following Kahn (2010) and Oreopoulos et al. (2012), My preferred specification use the variation of the unemployment rate at the national level to test the existence of scarring effects. I find evidence of a scarring effect where a 1 percentage point increase in the unemployment rate at the year of labour market entrance causes about 6.5% loss in probability to be employed full-time and about 21% potential monthly earning loss. The negative effects of the unemployment rate in the initial year on employment and earning linger up to 11 years after entering the labour market. I find women and men share similar burdens in terms of negative employment effects, but larger negative earning effects for women. My results highlight the significance of youth-specific support as part of recovery policies after an economic downturn.

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

JEL Classification: J16, J24, J64, O17

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1 Introduction

Shred of evidence on lasting negative effects of entering the labour market when unemployment rates are high have been well documented in developed countries (Kahn, 2010; Schwandt and Von Wachter, 2019; Oreopoulos et al., 2012; Andrews et al., 2020; Choi et al., 2020). Intriguingly, such studies in developing countries, which typically consist of a large share of the youth population, have been non-existent except for Berniell et al. (2023) work in Latin America.

Why is it important to examine such scarring effects in developing countries? First, the labour force profiles in developing countries are characterised by predominantly low-educated workers from low socioeconomic status households. To be unemployed is often not an affordable option, even more during bad economic conditions. In contrast, those people may potentially increase their working hours in informal sectors to sustain consumption. Second, unlike in developed countries, unemployment rates in developing countries are relatively high, more volatile and less attached to the economic growth movement (Fields, 2011). Thus, the effect of a high unemployment rate on the labour market outcomes may not be similar to the effect of a recession. Third, a relatively large share of informal sectors in the economy may indicate a thicker labour market than in developed countries. Thus, job search costs might be lower. Finally, developing countries typically have low female labour force participation (FLFP) due to traditional norms and lack of childcare support. Previous studies show that during an economic crisis women increased their labour supply to support household income (Skoufias and Parker, 2006; Stephens, 2002).

Therefore, this paper focuses on two questions. First, does the initial labour market condition, measured by the unemployment rate, has long-lasting negative implication for employment and earnings? If yes, how long does such an effect persist and at what magnitude compared to those in developed countries? Second, does the scarring effect has a heterogenous effect in regards to gender and education level?

To answer my research question, I use Indonesia as a case study for the following reasons. First, Indonesia possesses a long-series labour market survey that consistently collected than spans over 30 years. The availability of such dataset is one of the major challenges to conducting a study on scarring effects in developing countries. Second, despite robust economic growth, unemployment rates have been relatively volatile and high. In particular, there has been concern on high unemployment rates among the youth since the early 90s (Manning and Junankar, 1998). Third, about 60% of the labour force worked in informal sectors in the last decade (Allen, 2016). This provides an opportunity to test the role of informal sectors to cushion negative employment and earnings effects. Lastly, FLFP in Indonesia is relatively lower than the neighbouring countries in Southeast Asia, except for Malaysia, and has stagnated (Schaner and Das, 2016). This motivates us to test the added worker effect hypothesis, if any.

I follow previous literature (Oreopoulos et al., 2012; Schwandt and Von Wachter, 2019) by constructing a pseudo-cohort panel observation utilizing rich administrative data. Using a repeated cross-section of the Indonesia Labour Force survey, SAKERNAS, from 1990 to 2019, I construct a pseudo-cohort of new entrants who enter the labour market between 1990 and 2019 in which I can observe their employment and earnings trajectories up to 25 years. Unlike previous studies which focus only on college graduates, except for Schwandt and Von Wachter (2019), my sample covers the youth workers at any education level. Next, I match each cell observation to the corresponding unemployment rate based on the year of labour market entrance. It is important to note that I do not use official unemployment rates due to measurement issues as a result of changing labour force definition on several occasions in Indonesia. I use national unemployment rates in my preferred specification but also present results using provincial unemployment rates as a comparison. My specification allows the estimated unemployment rate at labour market entry coefficients to vary across years of experience after the year of entering the labour market. Thus, the coefficients capture an evolution of the negative (positive) effect of initial economic conditions on lifetime labour market outcomes.

In sum, I document significant negative employment and earnings effects of a high unemployment rate when entering the labour market. An Increase of 1 percentage point in the unemployment rate when entering the labour market leads to a drop in full-time employment probability by 3% for the first two years after entering the labour market. The negative effect was nullified after 5 to 8 years after entering the labour market. Overall, an increase of 1 percentage point in the unemployment rate when entering the labour market is associated with a 7% loss in the probability of full-time employment over 25 years of their working lifetime. With regards to effects on earnings, I find that an increase of 1 percentage point in the unemployment rate translated to a 3% drop in monthly earning for the first 2 years after entering the labour market. Similar to the employment effect, the negative effects start to disappear after at least 9 years.

Findings from my study contribute to the literature in several ways. First, it complements previous scarring literature by providing evidence that the size of the scarring effect is similar to those from developed countries. However, I find smaller negative effects and shorter scarring spells compared to previous studies in the United States (Schwandt and Von Wachter, 2019), Canada (Oreopoulos et al., 2012), and Australia (Andrews et al., 2020). It also adds knowledge of how the scarring effect remains significant though less severe even in the economy with a large share of informal jobs.

Secondly, my findings support the argument that the negative earnings effect might be driven by the allocation of workers to the lower-skilled jobs sectors (Gibbons and Waldman, 2004; Kahn, 2010), for instance as casual workers in the agriculture sector. At the same time, I also find that it pushes out people from high-income jobs such as in the services sector. Picking up lower-skilled jobs at the beginning of one's career seems to lead to low human capital accumulation and investment of the new graduates to find a high-skilled job (Gibbons and Waldman, 2004; Kahn, 2010).

Thirdly, I find that those with the least educated group deal with smaller within-group negative employment and earnings effects in comparison to their more educated counterparts. In fact, the least educated group found to be more likely to work longer hours when initial economic conditions worsen. This contradicts previous studies (Schwandt and Von Wachter, 2019) which found less educated youth workers bear more scarring effect in both employment and earnings. I also find that those with secondary education degree bear the worst scarring effect over working lifetime.

Fourthly, from gender perspectives, my findings agree with Schwandt and Von Wachter (2019); Oreopoulos et al. (2012) which suggests that men and women bear similar overall employment and earnings effects. I do not find strong evidence of added worker effect, since women also bear a negative employment effect in the analogous size as men. However, I do find women temporarily increased their working hours at the start of their careers when entering the labour market with high unemployment rates.

Lastly, in terms of the country's perspective, to the best of my knowledge, this study is the first effort to understand the long-term dynamics of labour market outcomes that focus on young workers. In regards to the scarring effect, there is only one existing study that shares a similar theme 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. Finally, this study also serves a new insights into the long-term consequences of the Asian Financial Crisis (AFC). The majority of existing studies on the impact of AFC, focus only on short-term response in the labour market. This includes increased workers in agriculture and falling real wages in urban areas (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).[1].

My findings are robust over several sensitivity checks. First of all, The results from the province-level specification confirm my findings from the national-level specification. Next, to partially address the potential endogeneity of graduation years, I use the 3-year moving average of unemployment rates of labour market entrance. I find that the results agree with my main specification. My results are also robust when I use 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 also similar, albeit almost halved when using the official unemployment rate produced by the national office of Statistics (BPS)[2]. Such results are

[1]Consequently, from a welfare perspective, the AFC was also found to increase urban poverty (Suryahadi et al., 2005) and child labour 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).

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

expected given the official unemployment rate is overstated. Concerning the mismeasurement of unemployment rates pre-1994, I perform the main specification using only survey years since 1994. I do find similar results as my main sample. Finally, my placebo test finds a null effect of initial unemployment rates to gender composition.

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

2 Context

In this section, I briefly discuss the Indonesian economy from several perspectives relating to the purpose of this study. Firstly, the long-run trend of Indonesia's economic growth and employment issues from the early 90s until today. Secondly, the evolution of labour force profiles. Thirdly, the issue of youth unemployment. Lastly, I discuss the issue of women's attachment to the labour market.

Literature often partitions the Indonesian economy from the early 1990s to the post-Global Financial Crisis into four periods, as summarised in (Bank, 2010). The first one is pre-AFC period. From the early 80s until before the AFC, the Indonesian economy has been accelerating mainly due to the commodities price boom (i:e oil and gas). This period was also marked by significant shifting in terms of labour absorption from the agriculture sector to the industrial and service sectors (Manning, 1993). The second period starts when the AFC. It 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). The third period started when the economy started to positively grow in 2000 until 2007.[3] Despite positive and steady economic growth, this period was also marked by persistently high unemployment rates. Such "jobless growth" is mainly attributed to the disappointing employment growth in manufacturing sectors (World Bank, 2010; Manning and Pratomo, 2018). Beyond the "jobless growth", Indonesia maintain positive economic and employment growth with minimum implication caused by the Global Financial Crisis.

The education profile of the labour force in Indonesia has improved significantly. The labour force predominantly to be having primary education for those who were born in the 60s, whereas the 90s cohort predominantly attends secondary school (Allen, 2016). Consequently, this implies delayed age of labour market entrance. Using the Indonesia Family Life

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

Survey (IFLS) Wave 5, I find that the age of having the first full-time job is, on average, 1.5 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 vocational secondary school becomes more important over time in Indonesia (Newhouse and Suryadarma, 2011). At the same time, the manufacturing-led economic growth, especially before the AFC, also benefits younger cohorts of new entrants with higher education profiles. 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).

Manning and Junankar (1998) firstly presents the issue of high unemployment rates among youth workers (aged 15-24), especially in urban areas. Since the early 90s until recently, youth unemployment consistently more than doubled the average unemployment rate. Such high unemployment rates are attributed to several potential sources. First, improved education access do not matched with sluggish growth in manufacturing sectors (Manning and Purnagunawan, 2011). Second, growing middle-class incomes may allow many young workers to afford a longer job-seeking process. Thirdly, the sequential increase in minimum wages between the 2000–07 periods may have unintended consequences on the absorption of youth workers in the labour market (Pratomo, 2016)

In regards to women's attachment in the labour market, in the last two decades, female labour force participation (FLFP) in Indonesia has stalled at around 55% (Schaner and Das, 2016). Such stagnation preserves despite declining fertility rate (Hull, 2016) and increased education access for women Schaner and Das (2016). Despite stagnation, from the SAKERNAS, between the early 90s and late 2010s, there has been a major shift where most women workers who were mostly absorbed in agriculture, now predominantly work in services. In regards to added worker effect, (Smith et al., 2002) find that the FLFP rate of those living in poor families increased by 7% between 1997 to 1999 using the Indonesia Family Life Survey (IFLS)[4]. 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.

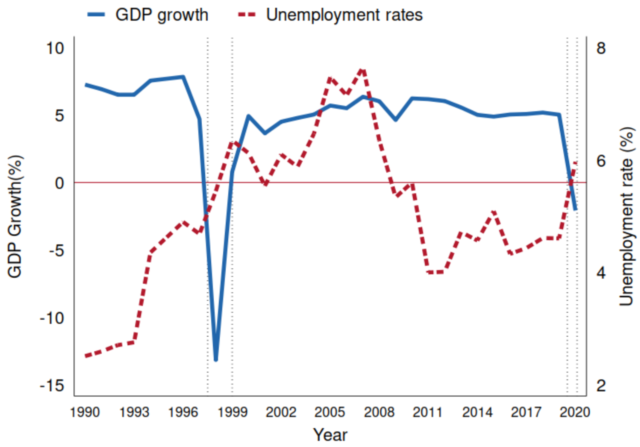
3 Data

3.1 SAKERNAS

The National Labour Force Survey, also known as SAKERNAS, is the national household survey purposely designed to produce the official labour force statistics in Indonesia. The timing, frequency, and sampling procedures of the survey have been changing over time since its first implementation in 1976. Before 1986, Indonesia's statistical office, known as BPS, collected SAKERNAS as a thematic module of the National Household Socioeconomic Survey (SUSE-

[4]Special survey known as IFLS2+

Figure 1: Unemployment rate in Indonesia



Notes: Author's calculation. Real GDP growth retrieved from the World Development Index, The World Bank. The unemployment rates is calculated using SAKERNAS 1990-2020 following Suryadarma et al. (2007) approach to adjust for changes in labour market force definition and questionnaire. I exclude 1995 observation. More details on the unemployment rate used in this graph are available in Section 3.2. The dotted black vertical line indicates the start and end of each recession event in Indonesia.

NAS) which is the main nationally representative household socioeconomic survey.[5] Since 1986 the BPS started to regularly survey except in 1995.[6] 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, plus May and November, if quarterly.[7] Designed to be nationally representative as it follows the SUSENAS sample frame, from 1986 to 2004,[8] 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. More details on the survey period, timing, sampling size and statistical representativeness are summarized in Table A1.

The survey collects labour market information on the working-age members of sampled households.[9] This includes household members as young as 10 years old. SAKERNAS becomes the main dataset to produce official labour force statistics including unemployment rate, labour force participation, level of wages and earnings. The SAKERNAS collects a rich array of information on individual engagement in the labour market. This includes several

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

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

[7] In the case of bi-annual data collection, from 2005-2010 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

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

[9] 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

key variables in the labour market which are not available in the SUSENAS such as wages, earnings and working hours. Important to note that SAKERNAS does not collect earnings information from those who work as employer and unpaid workers. However, compared to the SUSENAS, the survey provides limited non-labour 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 labour market outcomes which suit the purpose of this paper.[10]

I use individuals aged 15 to 40 years old in each survey year to construct an unbalanced pseudo-panel at the level of aggregation detailed in Section 4.1. Thus, I identify labour market entrants of males and females, who live in 26 provinces and completed either primary, secondary or tertiary education when entering the labour market between 1990 to 2019. I exclude observation in survey year 1995 to avoid mismeasurement of labour market information when using intercensal survey due to the absence of SAKERNAS. This yields potential 4,524 ($2 \times 26 \times 3 \times 29$) unique cells. I later drop cohort-cell observation if consists of less than ten individual observations. This brings my final observation to 4,411 unique cells.[11] Given the span of the dataset, I can observe up to 30 years of potential working experience, however, I restrict my observation up to 25 years of potential working experience. The final unbalanced-panel sample is 48,328 individual-year observations.[12]

Table 1 summarizes descriptive statistics of pseudo cohorts used in my analysis observed up to 11 years since they enter the labour market. Several key highlights emerge. First, from a gender perspective, it emerges that women are more likely to be in services sectors and accept lower wages compared to their men counterparts. Secondly, low-educated new entrants were likely to be employed in agriculture as casual workers in comparison to those has higher education degrees. Thirdly, over time Indonesian economy shifts from agriculture to services which is followed by a growing share of formal sectors. The descriptive statistics confirm the characterization of typical developing countries' labour market profiles in Section 1.

[10]The possible alternative to SAKERNAS is the Indonesia Family Life Survey (IFLS) a privately collected longitudinal dataset that was collected five times between 1993 to 2014 using SUSENAS 1993 as a sample frame.

[11]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 Australia. Tertiary education includes vocational and university degrees.

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

Table 1: Descriptive statistics, up to 11 years after entrance

	(1) Women	(2) Men	(3) Low	(4) Second	(5) Tertiary	(6) Up to	(7) Post-AFC
Employed	0.839	0.871	0.914	0.824	0.862	0.854	0.858
	(0.142)	(0.119)	(0.0928)	(0.139)	(0.129)	(0.133)	(0.130)
Full-time Job	0.491	0.574	0.471	0.524	0.615	0.529	0.538
	(0.182)	(0.182)	(0.178)	(0.185)	(0.169)	(0.198)	(0.181)
Waged worker	0.536	0.463	0.261	0.438	0.826	0.395	0.544
	(0.296)	(0.256)	(0.189)	(0.200)	(0.130)	(0.257)	(0.274)
Self-employed	0.137	0.203	0.177	0.204	0.112	0.233	0.145
	(0.121)	(0.142)	(0.137)	(0.141)	(0.103)	(0.165)	(0.111)
Casual and unpaid workers	0.326	0.333	0.563	0.358	0.0622	0.372	0.311
	(0.264)	(0.246)	(0.211)	(0.199)	(0.0781)	(0.247)	(0.256)
Monthly earnings (000s)	924.9	1130.6	659.8	917.4	1586.4	852.9	1115.9
	(587.7)	(623.0)	(319.4)	(444.1)	(707.5)	(591.9)	(608.6)
Total wage (000s)	918.7	1112.4	678.1	926.2	1494.8	843.4	1101.1
	(481.6)	(529.7)	(314.2)	(374.8)	(546.5)	(453.3)	(523.8)
Wage per hours (000s)	5.408	6.112	3.732	4.964	9.044	4.559	6.331
	(3.521)	(3.217)	(2.121)	(2.174)	(3.742)	(2.689)	(3.517)
Monthly working hours	155.5	165.2	150.9	163.8	164.1	167.0	157.9
	(35.86)	(30.94)	(35.69)	(34.05)	(29.07)	(37.89)	(31.08)
Agriculture	0.259	0.392	0.612	0.332	0.0628	0.414	0.291
	(0.263)	(0.267)	(0.232)	(0.205)	(0.0860)	(0.277)	(0.262)
Manufacturing	0.123	0.141	0.138	0.154	0.0882	0.148	0.125
	(0.132)	(0.117)	(0.128)	(0.129)	(0.100)	(0.133)	(0.120)
Services	0.618	0.467	0.249	0.514	0.849	0.438	0.583
	(0.273)	(0.253)	(0.179)	(0.177)	(0.133)	(0.248)	(0.272)
Observations	12727	14371	6726	13126	7246	8500	18525

Standard deviation in parentheses. Results are based on data from SAKERNAS 1990-2019, excluding the year of 1995. Sample restricted to be 15 to 40 years old in each survey. This table also restricts observation to be up to 11 years since entering the labour market. Unit observation is a cohort of labour market entrance by gender, education level and province of residence. Earnings referes to labour income including wage and salary. Wages only available for waged workers. All monetary values are inflation-adjusted using CPI with 1990 as base year.

3.2 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. labour 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 labour 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 labour force calculation. Since 1991, the survey follows the ILO to only include those who are at least 15 years old in the labour force. The second major change happened in 1994. Before 1994, to be included in the labour 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.[13] 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 labour force before 2001.

Figure B1 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 (which also corresponds to unemployment rate trends plotted in Figure 1). In regards to Figure B1, 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 inflate the number of discouraged workers in the labour 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 overestimated compared to the post-1994.

3.3 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.

4 Estimation strategy

4.1 Baseline specification

The main identification strategy relies on the assumption that changes in unemployment rates that deviate from their natural trend are mainly driven by labour demand rather than from

[13] 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.

the supply side. Hence, variation in unemployment rates should not be correlated with cohort (of labour entrance)-specific characteristics. I follow previous scarring literature (Kahn, 2010; Oreopoulos et al., 2012; Schwandt and Von Wachter, 2019), to estimate the relationship between a cohort's lifetime labour market outcomes and their corresponding unemployment rate at the time of labour market entrance. Since the labour market survey is a series of repeated cross-section data, I follow Oreopoulos et al. (2012) and Schwandt and Von Wachter (2019) to conduct a pseudo-panel analysis based on cohorts observation across surveys. In this study, the cohort is not defined by birth-year but on the year of the individual enter the labour market. In practice, I begin with mean-aggregating the individual-level observation at the year of labour market entrants (c), gender (g), education group (d), and residential province (p) for each survey year (t). In comparison to previous literature, our construction is similar to Schwandt and Von Wachter (2019), however, in this paper, I also add the gender dimension to the level of data aggregation. Thus, I estimate the following equation.

$$\bar{Y}_{cgdpt} = \alpha + \beta_e UR_0 + Exp_e + Pre94_c + \theta_c + \gamma_g + \delta_d + \pi_p + \tau_t + \epsilon_{cgdpt} \quad (1)$$

Where our outcome variable, $\bar{Y}$, is an average of each "cell" of aggregation. Each pseudo-cohort group is weighted according to the number of observations in each cell. My outcome variables cover an array of employment and earnings. From employment statuses, it includes binary variables of currently employed and worked full-time if individuals participate in the labour force, hence excluding those mainly in school. Next, I turn to job quality measured by the probability to be employed as wage workers and casual and unpaid workers, if they are employed.[14] For labour income, first, I use monthly earnings which is defined as all wages or salary either in cash or in-kind for those who were employed during the survey. Monthly wages as outcome variables are restricted for waged workers only. Important to note that SAKERNAS does not collect income information from those who work as employer and unpaid workers. Thus, any interpretation to my results on labour income should take into account such limitations. I also look into working hours in a week which I convert into monthly working hours by multiplying it by 52 and dividing by 12. Finally, I also look into wage rate which is defined as the ratio of monthly wage and working hours. In the estimation, I impose a logarithmic transformation for each earnings outcome including working hours. All monetary values are inflation-adjusted using Consumer Price Index (CPI) from World Development Indicator by the World Bank, with 1990 as the base year.

The main independent variable is the corresponding unemployment rate (UR) at the time of entering the labour market c. I use two different unemployment rates, one is at the national level, and the other is the provincial unemployment rate (UR_{pc}). Notice that some of the previous literature on the scarring effect, such as Oreopoulos et al. (2012) and Schwandt and Von Wachter (2019), prefer to use regional level unemployment rate, arguing the local

[14] Notice that I exclude self-employment since it reflects the rest of waged workers and unpaid workers.

labour 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 migration threat, as discussed further in Section 4.2, 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,[15] mostly for employment and education-related purposes. Hence, one could argue that internal mobility in Indonesia is relatively higher than in the US and Canada. Estimation using the provincial unemployment rate, despite its advantages in capturing local labour dynamics, potentially suffers from endogeneity issues. I will discuss more on the threats and procedure to deal with the potential endogenous migration problem to the provincial specification in the next section

The model allows the estimated effect of the initial unemployment rate to vary over years of potential experience since graduation year (β_e), such that mimics 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 labour market. To account for potential measurement bias due to change in the unemployment rate definition prior to 1994, I employ an additional control variable that captures the interaction of the unemployment rate and year prior to 1994 ($Pre94$). The model simply includes a set of dummy variables of labour market entrants cohort (θ_c), gender (γ_g), education level (δ_d), province (π_p) and survey year (τ_t). The error term ϵ is a zero-mean at the cell level. Finally, I cluster the standard error at the year of labour market entrance to capture the variation of the unemployment rate for the national employment rate specification. Meanwhile, for the provincial unemployment rate, I cluster my standard error at the province level.

Important to note that I proxy years of entering the labour market using years of highest completed education plus six years[16] because SAKERNAS does not collect an individual's exact year of graduation. To avoid cohort-specific labour 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.

4.2 Threats to identification

My estimation strategy relies on the assumption that temporal variation of the unemployment rate caused changes in labour demand and is not correlated with cohort-specific variation across time. In addition to potential endogeneity caused by the mismeasurement bias of unemployment rates discussed earlier in the model, the following may also raise some concerns

[15]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

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

about the validity of our assumption.

(i) Endogeneous education timing.– To avoid bad labour market prospects, a person may stay longer in school to delay their labour market participation. Thus, the scarring effect estimates would bias toward zero. To the best of my knowledge, there is no evidence of such behaviour 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. Thomas et al. (2004) using a specific micro-level data surveyed immediately after the AFC suggest that there is evidence that parental investment to children's education facing a trade-off. They find that households sustain investment for older children but reduce for younger children. In Figure B3 Panel A in Appendix B, I show that there is no observable change in terms of the distribution of educational attainment that could be attributed to the crisis. Over time, shifting towards a higher share of individuals who completed education at least a secondary degree, for instance, shows a smooth transition. Panel B provides clearer depictions in terms of the smoothness trends in gross enrollment rate during the crisis period. If manipulation happens, one shall expect a hump in any level of education enrollment around the time of crisis. It is clear to see that over time more children enrolled in secondary and tertiary. As additional evidence, I perform a similar test as the placebo test by regressing the share of secondary graduates on the initial unemployment rate as in 1. From Figure B4 Panel A and Figure B5 Panel A, I find null effects of initial unemployment rates on the share of secondary graduates.

(ii) Endogeneous migration timing.– Individuals could decide to migrate to another place with a better economic situation before entering the labour 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 labour 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). 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%. 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.

In regards to the endogeneity migration issue, I draw inspiration from Schwandt and Von Wachter (2019)'s bias correction procedure to the regional (provincial) level rate. They do so by weighting the initial unemployment rate with migration probability and graduation timing. In principle, they calculate the probability of working-aged individuals with a certain education level to migrate from their birth region to the residing province, then aggregate up across provinces and education profiles using the Population Census. This probability is then used as a weight to the unemployment rate of each labour market entrants cohort from the labour force survey observations. This double-weighted unemployment rate, they argue, is a biased-corrected unemployment rate to deal with both endogenous education and migration timing. In my case, as discussed previously, I do not concern with endogenous education timing but rather with the migration issue. So, I focus on applying migration weight to the provincial unemployment rate.

Recall that to apply such weight, one should rely on two key pieces of information, the birth and current residential province. That information must be available in both the population census and the labour force survey. Unfortunately, the SAKERNAS does not provide the birth of province information, thus to replicate Schwandt and Von Wachter (2019) procedure is non-viable. What I am able to do, however, is to tease out the migration pattern from one province to the other province at a particular time. The Population Census provides the provinces where the respondent resides 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.

$$UR_{pc}^{MW} = \sum_{p=1}^{26} Mig_{p_{-5}p} UR_{p0} \tag{2}$$

The migration-weight term, $Mig_{p_{-5},p}$ is the average share of those who live in province p that five years priors migrated from province p_{-5}. To match our main sample restriction, I only consider the migration pattern of respondents aged 15 to 40 in each census year. Thus, the migration share is used to weigh the unemployment rate of entering the labour market in year c of residential province p. Notice that, I use the provincial border definition in 1990, which is total 26 provinces (excluding East Timor), to preserve consistency across years as the number of provinces changes over time.[17] 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_{pc}^{MW}, suppose there are only two provinces, Province A and B. The average migration rates, during 1990-2010 period, from Province A to Province B were 25%, meaning a quarter of people living in Province A, between 1990 and 2010, 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 labour market in 1990 residing in 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_{pc}^{MW}) to modify equation 1. I matched each cohort of observations to

[17] Post Soeharto's regime, Indonesia experienced significant decentralisation including a process of regional proliferation. Between 1999 to 2012, new eight provinces emerge. For further discussion on the political economy of province proliferation process see Kimura (2013)

the migration-weighted unemployment rate terms (UR^{MW}_{pc}) using their province of residence p at market entrance year c. Equation 3 summarizes the provincial specification, as follows.

$$\bar{Y}_{cgdpt} = \alpha + \beta_e UR^{MW}_{p0} \times Exp_e + Exp_e + Pre94_{cp} + \theta_c + \gamma_g + \delta_d + \pi_p + \tau_t + \epsilon_{cgdpt} \quad (3)$$

In regards to the double-weighted specification by Schwandt and Von Wachter (2019), my provincial specification presents 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 increase 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.

I plot national unemployment rates on provincial unemployment rates and migration-weighted unemployment rates in Figure B2. It emerges that, despite a strong positive correlation between national and provincial unemployment rates, the variation within a year remains large. Even after detrending the series, as reflected in Panel B, in some years, we could see that provincial unemployment rates deviate up to 5 percentage points. It is also important to note that the migration-weighted unemployment rates (hollow circle) distribute closer to the national unemployment rates compared to the raw provincial unemployment rates (hollow triangle). The distribution of provincial-level unemployment rates displays higher degree of regional heterogeneity. Thus, it potentially correlated with characteristics of new entrants cohort which also aggregated at the province level. Thus, I prefer national exposure specification (Equation 1) results as my main results.

5 Results

5.1 Baseline estimation

I start with presenting the estimated scarring effects across years of experience since entering the labour market, following Equation 1. Table 2 summarises the results. As depicted in column 1, in the first two years after entering the labour market, the probability to be employed drops by about 2.8%. The negative effect lingers up to 6 to 8 years after first entering the labour market. The average effect over 25 years of a working lifetime is about 6.9% (see Table A2 in Appendix). A similar story emerges for the probability to work full-time, as presented in Column 2. Entering the labour market with a percentage point higher unemployment rates accounts for a lower likelihood to be employed by 3.2%. Once again, the effect lasts up to 6 to 8 years since entering the labour market. Compared to studies in the United States (Schwandt and Von Wachter, 2019), Korea (Choi et al., 2020) and Canada (Oreopoulos et al., 2012), my finding is half of their findings. I also find that the spell of negative employment effect is shorter than in those countries. These results may suggest two possible explanations: first, large informal sectors may cushion the negative employment effect and second, given the large share of workers with low socioeconomic backgrounds, unemployment is a luxury compared to the job seekers in developed countries. Later, I test such hypotheses by examining heterogeneity results based on education level.

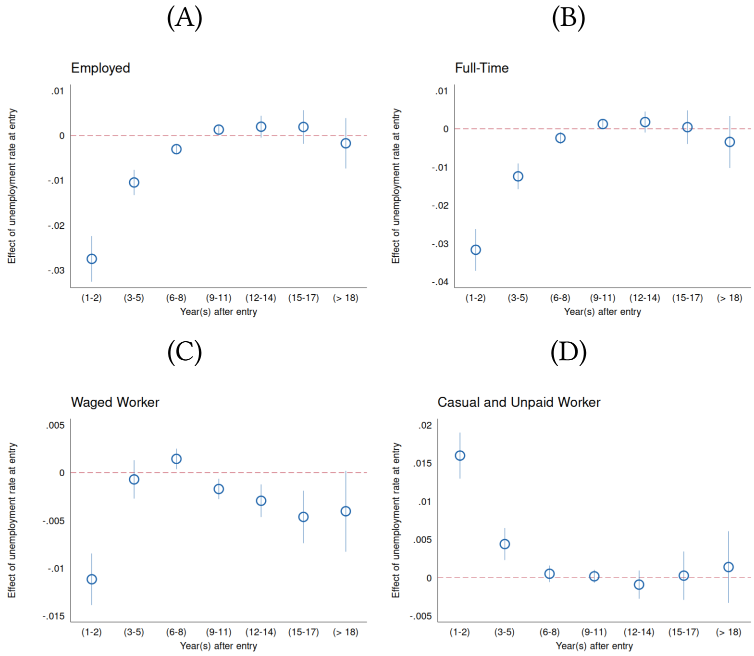
Table 2: Long-term consequences of the unemployment rate at labour market entry to lifetime occupational sectors

	(1) Employed	(2) Full-time Job	(3) Formal Job	(4) Unpaid Job
Unemployment rate × years since				
1-2 years	-0.028***	-0.032***	-0.011***	0.016***
	(0.002)	(0.003)	(0.001)	(0.001)
3-5 years	-0.010***	-0.012***	-0.001	0.004***
	(0.001)	(0.002)	(0.001)	(0.001)
6-8 years	-0.003***	-0.002**	0.001*	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
9-11 years	0.001*	0.001*	-0.002**	0.000
	(0.001)	(0.001)	(0.001)	(0.000)
12-14 years	0.002	0.002	-0.003**	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
15-17 years	0.002	0.000	-0.005**	0.000
	(0.002)	(0.002)	(0.001)	(0.002)
$\geq$ 18 years	-0.002	-0.003	-0.004	0.001
	(0.003)	(0.003)	(0.002)	(0.002)
Observation	46,613	46,613	46,613	46,613
Mean	0.904	0.575	0.456	0.299
Adjusted R2	0.654	0.637	0.765	0.641
Fixed effects	Yes	Yes	Yes	Yes
Clustered S.E.	Yes	Yes	Yes	Yes

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses. Observation drawn from SAKERNAS 1990-2019, excluding the 1995 observation. I restrict the sample to those entering labour market between 1990 to 2019 and age 15 to 40 years old in each survey year. Unit observation is a cell of a cohort of labour market entrance by gender, education level and province of residence. Reported coefficients correspond to β_e of Equation 1 using national unemployment rates. The dependent variable is indicated by the title of each column. Specification controls for years of experience, labour market entry fixed effects, education fixed effects, gender fixed effects and survey year fixed effects. Standard errors are clustered at the year of labour market entrance.

From Table 2 columns (3) and (4), I find evidence that many new entrants are sorted into unpaid jobs and at the same time sorted out from waged workers. As depicted in Panel The probability to be employed in unpaid jobs is positively associated with the unemployment rate at entrants in the first 5 years after graduation. This finding is consistent with previous findings (Manning and Junankar, 1998; Manning, 2000) that find many waged workers switch to unpaid jobs in rural areas. Such effects are short-lived compared to the employment effects indicating the role of casual workers to absorbing workers during bad economic conditions. For the new entrants, this could be the type of job that they can get sorted too with minimum barriers to entry. However, it is interesting to see that the negative effect on the likelihood to be in formal sectors lasts longer. This may indicate young workers may choose to be self-employed (categories not presented in the graph due to redundancy). I provide a visual illustration of the results of Table 2 in Figure 2. For the rest of the discussion in the paper, I refer to graphical illustrations with corresponding tables available in the Appendix.

Figure 2: Scarring effects on employment, National UR



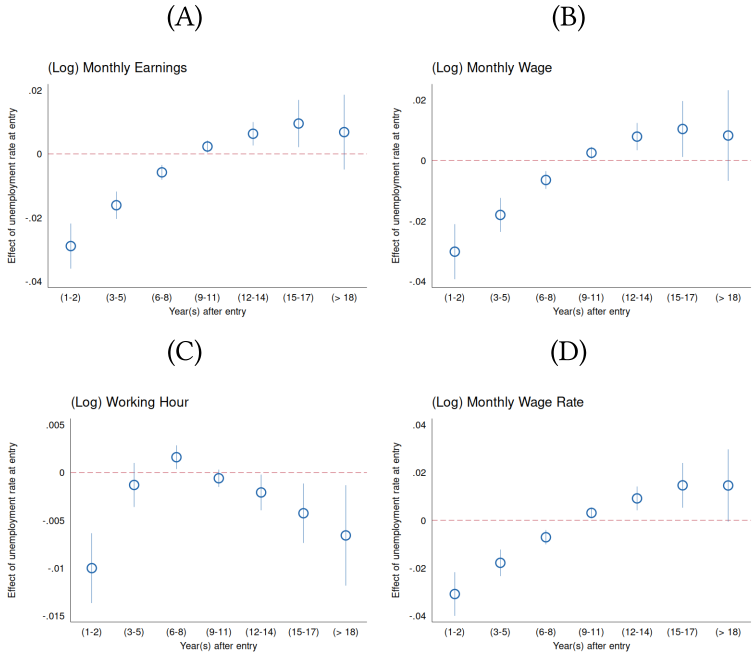
Notes: Observation drawn from SAKERNAS 1990-2019, excluding the 1995 observation. I restrict the sample to those entering labour market between 1990 to 2019 and age 15 to 40 years old in each survey year. Unit observation is a cell of a cohort of labour market entrance by gender, education level and province of residence. Plotted coefficients correspond to β_e of Equation 1 using national unemployment rates. Specification controls for labour market entry fixed effects, education fixed effects, gender fixed effects and survey year fixed effects. The whisker of each dot plot represents a 95% confidence interval. The dependent variable is indicated by the title of each graph. Each panel represents separate regression. For Panel C, the formal sector includes wage workers and the employer who has permanent workers. Standard errors are clustered at the year of labour market entrance.

Further investigation, looking at the occupational sector, confirms the role of agriculture in the increase in casual workers. It emerges that the new entrants are likely to be in the agriculture sector when the unemployment rate is high, as illustrated in Figure B6 Panel A in Appendix A.[18] 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), for instance. While most existing studies refer to already-in-labour 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 and rural is a typical response of workers in Indonesia when the labour market con-

[18]Lifetime results of the scarring effects estimation on occupational sectors are presented in Table A4 in Appendix A

tracted as experienced during the AFC (Hugo, 2000). I do find a negative effect towards the probability to be employed in manufacturing, as shown in Figure B6 Panel B. However, the effect is short-lived and small. I do find that bad economic conditions push out new entrants from the services sectors (see Figure B6 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 in 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.

Figure 3: Scarring effects on earnings, ational UR



Notes: Observation drawn from SAKERNAS 1990-2019, excluding the 1995 observation. I restrict the sample to those entering labour market between 1990 to 2019 and age 15 to 40 years old in each survey year. Unit observation is a cell of cohort of labour market entrance by gender, education level and province of residence. Plotted coefficients correspond to β_e of Equation 1 using national unemployment rates. Specification controls for labour market entry fixed effects, education fixed effects, gender fixed effects and survey year fixed effects. Monthly earnings are measured as total labour income, salary or wages except for those working as employers and unpaid workers. Wage information is conditional on being a waged worker. For casual workers, the survey also includes the estimated value of non-cash remuneration. All monetary values are inflation-adjusted using CPI with 1990 as base year. The whisker of each dot plot represents a 95% confidence interval. The dependent variable is indicated by the title of each graph. Each panel represents separate regression. Standard errors are clustered at the year of labour market entrance.

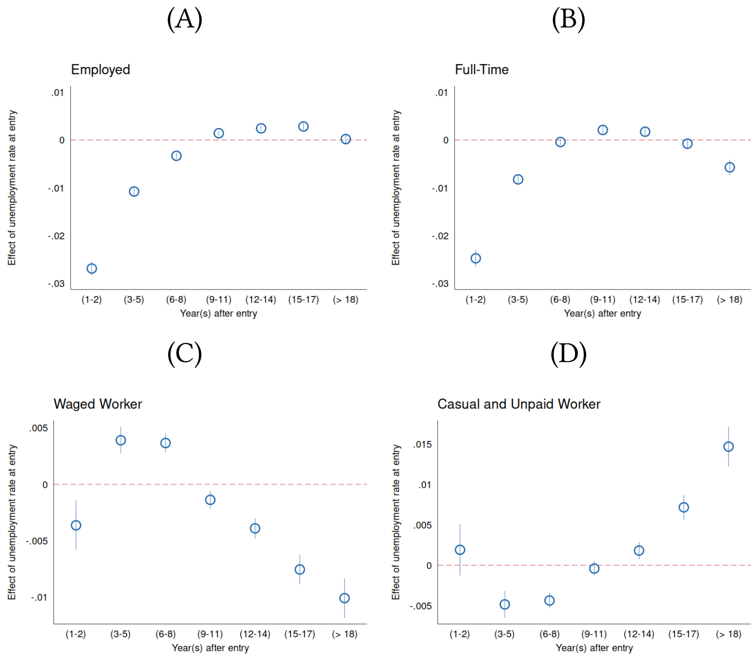
From the previous section, we observe evidence that bad economic conditions at labour market entry would affect new entrants' employability and job placement. As a bad economic condition is associated with the likelihood to be in a lower-skilled job, we should expect it would also be reflected in their earnings trajectories. Analogous to Figure 2, the results on earnings outcome depicted in Figure 3 (see Table A5). 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 2.9% less earnings in the first two years of their career. The effect starts to be nullified after 9 to 11 years after graduation. The size of labour income loss is about a third-quarter to developed countries' experience such as Canada (Oreopoulos et al., 2012) and about half of the AFC effect in Korea (Choi et al., 2020). In regards to aggregate, It emerges that a percentage point increase in the unemployment rate in labour market entrance causes more than 22% (16%) loss of earnings (wage) during the 25 years of working experience (see A3 Columns 1 and 2). This loss of earnings is statistically significant and substantive. It also affects working hours as well as wage rate consequently (see column 3 and column 4)

There is a significant drop in wage rate for the new entrants (see Panel D) in the early years of their careers as working hours also dropped along with their total monthly earnings. However, it is interesting to see that the negative effect on working hours immediately recovered and become positive after 3 years (Panel C). I take this as evidence that low-income workers need to compensate for potential earning loss by working more

5.2 Province estimates

Overall, the province estimates share similar insights to the national estimates as summarized in Figure 4 (also see Table A7). A higher unemployment rate at labour 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 years. The magnitude of the negative effect of labour market entrance conditions is similar to the national estimates. However, interesting results emerge in the probability of being in waged workers and unpaid job outcomes. In Figure 4 Panel C and D, respectively, the effect of bad economic conditions only last for 2 years after entering the labour market before but returns and amplified after 9-11 years.

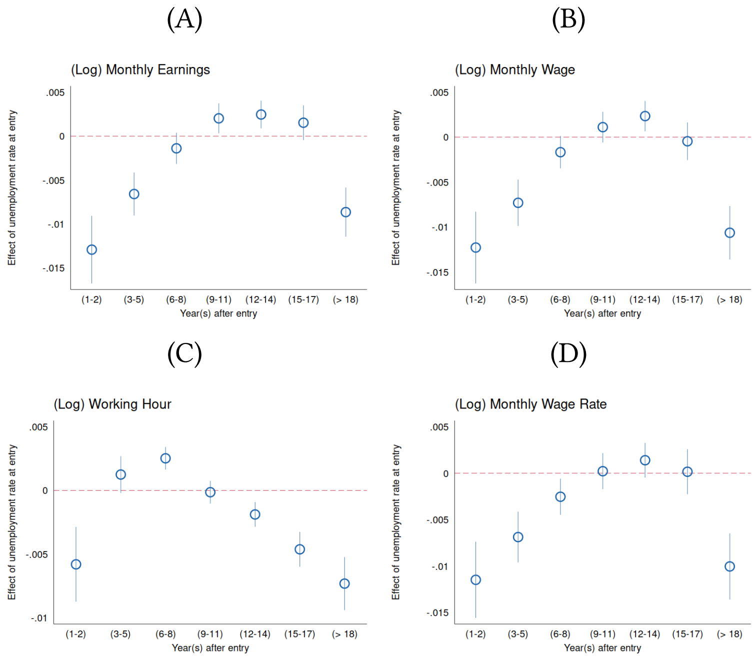
Figure 4: Scarring effects on employment, Province UR



Notes: Observation drawn from SAKERNAS 1990-2019, excluding the 1995 observation. I restrict the sample to those entering labour market between 1990 to 2019 and age 15 to 40 years old in each survey year. Unit observation is a cell of a cohort of labour market entrance by gender, education level and province of residence. Plotted coefficients correspond to β_e of Equation 3 using migration-weighted provincial unemployment rates. Specification controls for labour market entry fixed effects, education fixed effects, gender fixed effects and survey year fixed effects. The whisker of each dot plot represents a 95% confidence interval. The dependent variable is indicated by the title of each graph. Each panel depicts separate regression. Standard errors are clustered at the year of labour market entrance and residential province.

Now, I turn to the earning effect point of view as depicted in Figure 5. I find that, overall, the negative earning effect emerges but is smaller in magnitude. For the monthly earnings and wages outcome, see Panel A and B of Figure 5, the negative effect trends throughout an individual's work life are less than half of the national estimates. Similar to national estimates, I also find that individuals take fewer working hours (see Panel C of Figure 3) but immediately reversed after 2 years since entering labour market.

Figure 5: Scarring effects on earnings, Province UR



Notes: Observation drawn from SAKERNAS 1990-2019, excluding the 1995 observation. I restrict the sample to those entering labour market between 1990 to 2019 and age 15 to 40 years old in each survey year. Unit observation is a cell of cohort of labour market entrance by gender, education level and province of residence. Plotted coefficients correspond to β_e of Equation 3 using migration-weighted provincial unemployment rates. Specification controls for labour market entry fixed effects, education fixed effects, gender fixed effects and survey year fixed effects. Monthly earnings are measured as total labour income, salary or wages except for those working as employers and unpaid workers. Wage information is conditional on being a waged worker. For casual workers, the survey also includes the estimated value of non-cash remuneration. All monetary values are inflation-adjusted by CPI with 1990 as base year. The whisker of each dot plot represents a 95% confidence interval. The dependent variable is indicated by the title of each graph. Each panel depicts separate regression. Standard errors are clustered at the year of labour market entrance and residential 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 year of labour market entrance.

Comparing the national and provincial unemployment rate estimates implies two important points. First, similar results between the two gives us more confidence in the exogeneity of temporal variation of the unemployment rate. The change in the unemployment rate at national level is less likely to be correlated with changes in cohort-specific characteristics. Secondly, the disparity between national and provincial estimates could reflect that the local labour market, as well-proxied by the provincial unemployment rate, is more relevant to the outcomes compared to the national level. However, it may also point to the endogeneity problem as raised by placebo test in Section 4.2.

6 Heterogeneity results

6.1 Gendered results

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

First, from the employment perspective, gender comparison reveals that the negative employment effect is shared similarly among men and women. Table 3 summarizes the results. 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. However, women were found to be less affected in terms of full-time employment. Since full-time employment is defined by the length of working hours, these findings suggest that women may work more compared to men. This provide indicative evidence of the added worker hypothesis, where during bad economic situation, women tend to provide more labour supply to sustain household income. I also find that men disproportionately to find employment as casual workers during bad economic condition. Similar to previous discussion, Figure 6 provides visual illustration of the findings.

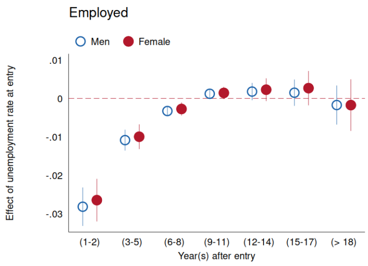
Table 3: Long-term consequences of the unemployment rate at labour market entry to lifetime occupational sectors

	(1) Employed	(2) Full-time Job	(3) Formal Job	(4) Unpaid Job
A. Men				
1-2 years	-0.028***	-0.041***	-0.021***	0.025***
	(0.002)	(0.003)	(0.002)	(0.002)
3-5 years	-0.011***	-0.018***	-0.006***	0.010***
	(0.001)	(0.002)	(0.001)	(0.001)
6-8 years	-0.003***	-0.004***	-0.001	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
9-11 years	0.001*	0.002*	-0.001	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
12-14 years	0.002	0.002	-0.002	-0.002
	(0.001)	(0.002)	(0.001)	(0.001)
15-17 years	0.001	0.001	-0.004	-0.001
	(0.002)	(0.003)	(0.002)	(0.002)
$\geq$ 18 years	-0.002	-0.004	-0.005	0.002
	(0.002)	(0.004)	(0.003)	(0.003)
Observation	24,548	24,548	24,548	24,548
Mean	0.914	0.634	0.452	0.264
Adjusted R2	0.680	0.702	0.786	0.740
Fixed effects	Yes	Yes	Yes	Yes
Clustered S.E.	Yes	Yes	Yes	Yes
B. Women				
1-2 years	-0.026***	-0.021***	-0.001	0.007***
	(0.003)	(0.003)	(0.001)	(0.002)
3-5 years	-0.010***	-0.004*	0.008***	-0.004**
	(0.002)	(0.001)	(0.001)	(0.001)
6-8 years	-0.003**	0.001	0.005***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
9-11 years	0.001	0.000	-0.003***	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
12-14 years	0.002	0.000	-0.005***	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
15-17 years	0.003	-0.001	-0.007***	0.005**
	(0.002)	(0.002)	(0.001)	(0.002)
$\geq$ 18 years	-0.002	-0.004	-0.004*	0.003
	(0.003)	(0.003)	(0.002)	(0.002)
Observation	22,065	22,065	22,065	22,065
Mean	0.893	0.508	0.461	0.339
Adjusted R2	0.662	0.578	0.825	0.776
Fixed effects	Yes	Yes	Yes	Yes
Clustered S.E.	Yes	Yes	Yes	Yes

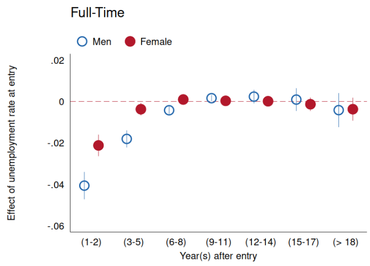
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses. Observation drawn from SAKERNAS 1990-2019, excluding the 1995 observation. I restrict the sample to those entering labour market between 1990 to 2019 and age 15 to 40 years old in each survey year. Unit observation is a cell of a cohort of labour market entrance by gender, education level and province of residence. Reported coefficients correspond to β_e of Equation 1 using national unemployment rates estimated separately for men (Panel A) and women (Panel B). Specification controls for year of experience, labour market entry fixed effects, education fixed effects, gender fixed effects and survey year fixed effects. Standard errors are clustered at the year of labour market entrance.

Figure 6: Scarring effects on employment by gender, National UR

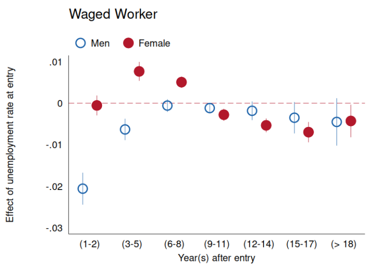
(A)



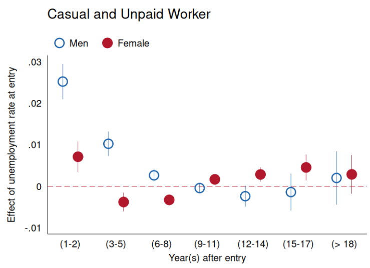
(B)



(C)



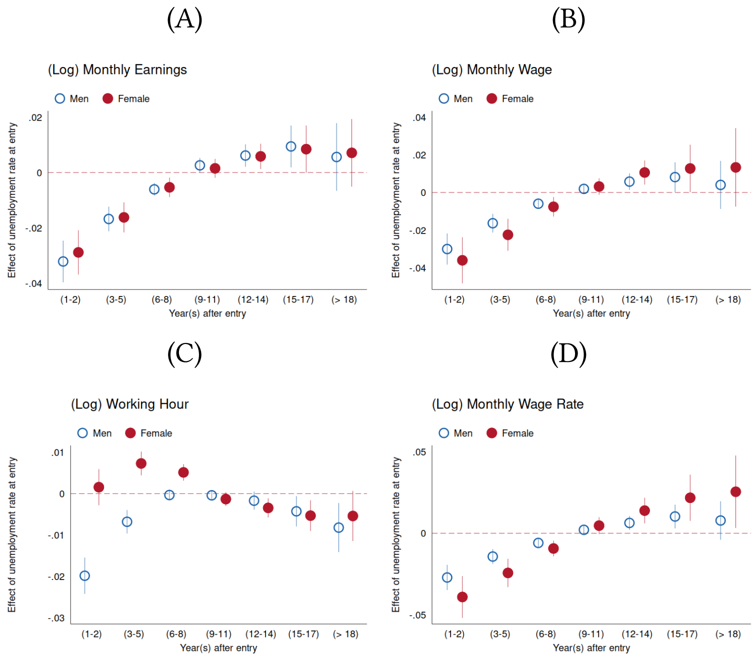
(D)



Notes: Observation drawn from SAKERNAS 1990-2019, excluding the 1995 observation. I restrict the sample to those entering labour market between 1990 to 2019 and age 15 to 40 years old in each survey year. Unit observation is a cell of a cohort of labour market entrance by gender, education level and province of residence. Plotted coefficients correspond to β_e of Equation 1 using national unemployment rates. Specification controls for labour market entry fixed effects, education fixed effects and survey year fixed effects. The whisker of each dot plot represents a 95% confidence interval. The dependent variable is indicated by the title of each graph. Male and female coefficients are drawn from a separate regression. Standard errors are clustered at the year of labour market entrance and residential province.

Further, both men and women experience similar trajectories in terms of negative earning effect as illustrated in Figure 7. 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. These findings support our earlier claim that added worker effect may exists.

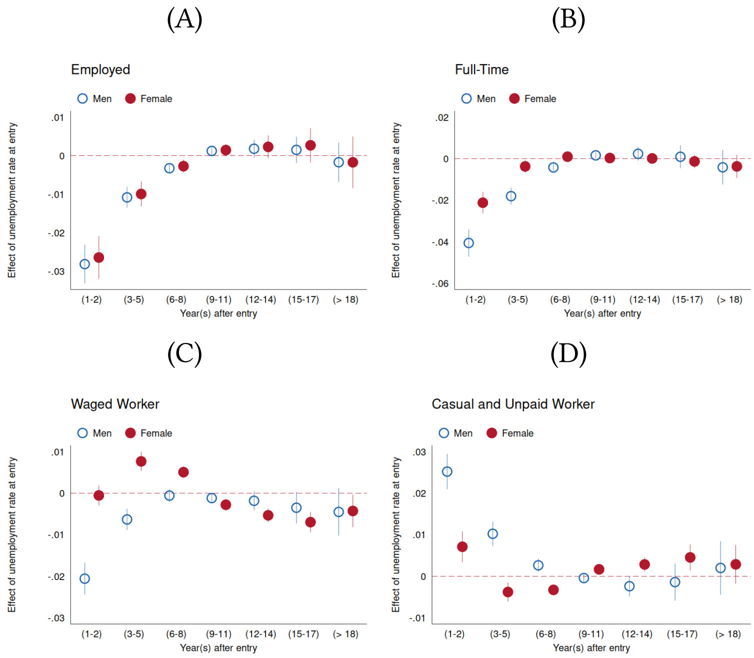
Figure 7: Scarring effects on earnings by gender, National UR



Notes: Observation drawn from SAKERNAS 1990-2019. I restrict the sample to those entering the labour market between 1990 to 2019 and age 15 to 40 years old in each survey year. Unit observation is a cell of cohort of labour market entrance by gender, education level and province of residence. Plotted coefficients correspond to β_e of Equation 1 using national unemployment rates. Specification controls for labour market entry fixed effects, education fixed effects, gender fixed effects and survey year fixed effects. The whisker of each dot plot represents a 95% confidence interval. The dependent variable is indicated by the title of each graph. Male and female coefficients are drawn from a separate regressionEach panel represents separate regression. Standard errors are clustered at the year of labour market entrance.

Lastly, some interesting results emerge from sectoral results. The labour 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 B7 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 B7 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.

Figure 8: Scarring effects on employment by gender



Notes: Observation drawn from SAKERNAS 1990-2019, excluding the 1995 observation. I restrict the sample to those entering labour market between 1990 to 2019 and age 15 to 40 years old in each survey year. Unit observation is a cell of a cohort of labour market entrance by gender, education level and province of residence. Plotted coefficients correspond to β_e of Equation 1 using national unemployment rates. Specification controls for labour market entry fixed effects, education fixed effects, gender fixed effects and survey year fixed effects. The whisker of each dot plot represents a 95% confidence interval. The dependent variable is indicated by the title of each graph. I regress men and women sample in separate regression. Each panel represents separate regression. For Panel C, the formal sector includes wage workers and the employer who has permanent worker. Standard errors are clustered at the year of labour market entrance.

6.2 Education

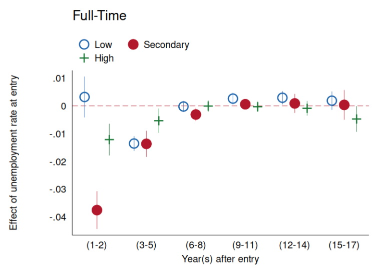
The scarring effect potentially varies across education level. One possible hypothesis would be more educated workers are more affected by the recession due to their expectation to be employed in high-income jobs. Furthermore, the more educated new entrants could recover better in the long run as they 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 9 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. Unsurprisingly, 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 9, 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.

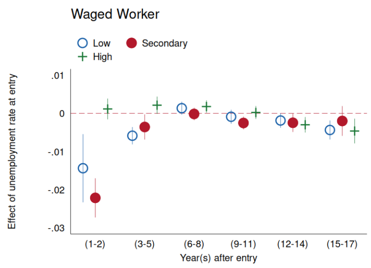
Figure 9: Scarring effects on employment by education, National UR

(A)

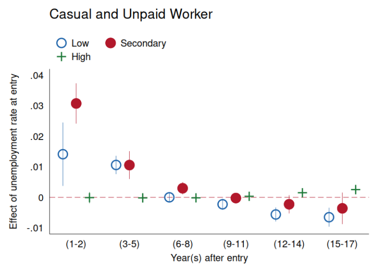
(B)



(C)



(D)



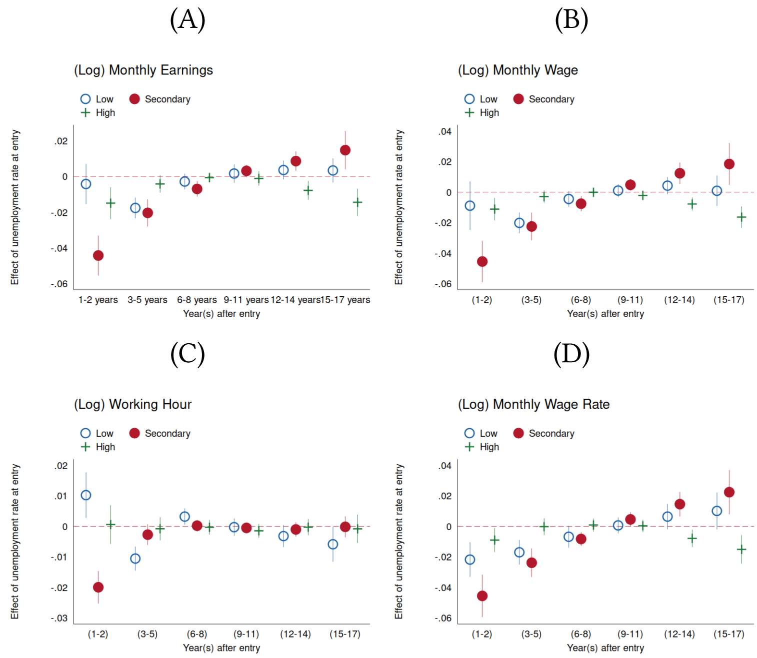
Notes: Observation drawn from SAKERNAS 1990-2019, excluding the 1995 observation. I restrict the sample to those entering labour market between 1990 to 2019 and age 15 to 40 years old in each survey year. Unit observation is a cell of cohort of labour market entrance by gender, education level and province of residence. Plotted coefficients correspond to β_e of Equation 1 using national unemployment rates. Specification controls for labour market entry fixed effects, education fixed effects and survey year fixed effects. The whisker of each dot plot represents a 95% confidence interval. The dependent variable is indicated by the title of each graph. Low-educated, secondary educated and high-educated coefficients are drawn from a separate regression. Standard errors are clustered at the year of labour market entrance and residential province.

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 9, 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 earnings, as more educated individuals could be matched to much better jobs when the scarring effect starts to wear off. Figure 10 summarizes the results on earnings by education level. Several interesting results emerge. First, from Panel A, B and C of Figure 10, 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 earning 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 B12, 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 B13, it emerges that in terms of monthly earning 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 10: Scarring effects on earnings by education, National UR



Notes: Observation drawn from SAKERNAS 1990-2019, excluding the 1995 observation. I restrict the sample to those entering labour market between 1990 to 2019 and age 15 to 40 years old in each survey year. Unit observation is a cell of a cohort of labour market entrance by gender, education level and province of residence. Plotted coefficients correspond to β_e of Equation 1 using national unemployment rates. Specification controls for labour market entry fixed effects, education fixed effects, gender fixed effects and survey year fixed effects. The whisker of each dot plot represents a 95% confidence interval. The dependent variable is indicated by the title of each graph. I regress men and women sample in separate regression. Each panel represents separate regression. For Panel C, the formal sector includes wage workers and the employer who has permanent worker. Low-educated, secondary educated and high-educated coefficients are drawn from a separate regression. Standard errors are clustered at the year of labour market entrance.

7 Sensitivity tests

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 labour market.

In Figure B14 and Figure B15, 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.[19] I find that my results are robust using such a youth-specific unemployment rate for all outcomes with smaller magnitude, as depicted in FigureB16 and Figure B17.

In Section 3.2, 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 labour market condition for the new entrants would be an appropriate sensitivity check to my results. The results are presented in Figure B18 and B19. 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 magnitude of the effect is smaller. Such results are expected since the official unemployment rates overestimate the unemployment rates and hence underestimate the scarring effect.

Next, I test the potential mismeasurement bias in observation before 1994 due to changes in unemployment rate calculation and survey design. To do so, I exclude observations from the survey before 1994. The results are presented in Figure B20 and B21. I find that, in general, the results are similar to my main specification.

Lastly, I perform a placebo test following previous literature Schwandt and Von Wachter (2019). This procedure simply checks if the variation of the unemployment rate would change characteristics that are pre-determined before entering the labour market. Given the unavailability of parental and childhood information in SAKERNAS, I test for two outcomes: the share of females and the share of secondary graduates. While the choice of the former outcome is quite obvious, the latter outcomes could be thought as predetermined to each cohort of labour market ent. I estimate Equation 1, using three aforementioned outcomes as outcome variables. Figure B4 Panel A in Appendix A presents the results. It emerges that initial unemployment rates has a null effect on gender composition within each cohort. I also claim these results as evidence that unemployment rate variation is seemingly unrelated to other policies that might affect demographic outcomes. During the period of study, some major national policy changes were likely to affect those outcomes. However, I find evidence that using provincial unemployment rates may be endogenous to the gender composition as depicted in Figure B5 Panel A.

[19] 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.

8 Conclusion

In this study, I provide evidence of the scarring effect of bad economic conditions when entering the labour market in Indonesia. I use 30-year long cross-sectional labour force surveys to construct a synthetic cohorts panel to capture employment and labour income dynamics over a lifetimeworking-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 labour 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 labour markets despite potentially picking up more relevant local labour market situations.

I find a significant and substantive negative scarring effect of the unemployment rate at labour market entrance on the cohort's employment earning 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 labour 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 labour market. The bad economic situation on the labour market entrance also matches this cohort to casual and unpaid jobs. From the labour income perspective, a similar story emerges. The negative earning effect is measured by about a 3% drop in total monthly earning and monthly wage in the first 2 years after entering the labour 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 labour market entrance consequences in two fashions. First, the matching to casual and unpaid jobs is more apparent within the men group compared to within the women group. Second, within the women group, worsening labour market conditions at the entrance translate to more working hours while the opposite results emerge for men groups. I interpret this as supporting evidence for the added worker hypothesis. Lastly, the allocation to the agricultural sector is more pronounced within the men's group.

I find that those with secondary education degrees bear the most negative employment and earnings effects. In contrast to findings from the US Schwandt and Von Wachter (2019), the least educated group was consistently less affected by the scarring effects of both employment and earnings outcomes. These findings show that in developing countries, high unemployment rates mostly relate to high-income jobs (e.g. formal sectors) rather than informal sectors. Hence, the scarring effects is less pronounced in the group that is more attached to the informal sectors.

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 labour supply side. Addressing the aforementioned caveats should motivate the direction of future research agendas.

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Appendix A

Table A1: SAKERNAS survey and sample representativeness 1986–2019

Series	Survey period (month)	Survey coverage	Representativeness
1976	Annual	Excluding East Timor	National
1977	Quarterly	Excluding East Timor	National
1978	Quarterly	Limited sampling in Maluku and Papua	National
1986-1993	Quarterly (February, May, August, November)	All provinces	Province
1994	Annual (August)	All provinces	Province
1995	Not collected, replaced with SUPAS	All provinces	Province
1996-2001	Annual (August)	All provinces	Province
2002-2004	Quarterly (February, May, August, November)	All provinces	Province
2005-2010	Biannual (February, August)	All provinces	District (August), Province (February)
2011-14	Quarterly (February, May, August, November)	All provinces	District (August), Province (Feb, May, November)
2015-now	Biannual (February, August)	All provinces	District (August), Province (February

Source: Statistics of Indonesia

Table A2: Long-term consequences of the unemployment rate at labour market entry to lifetime employment

	(1) Employed	(2) Full-time Job	(3) Formal Job	(4) Unpaid Job
UR at entry	-0.067**	-0.064*	0.008	0.151***
	(0.024)	(0.031)	(0.019)	(0.021)
Observation	46,613	46,613	46,613	46,613
Mean	0.904	0.575	0.456	0.299
Adjusted R2	0.660	0.639	0.765	0.642
Fixed effects	Yes	Yes	Yes	Yes
Clustered S.E.	Yes	Yes	Yes	Yes

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses. Observation drawn from SAKERNAS 1990-2019, excluding the 1995 observation. I restrict the sample to those entering labour market between 1990 to 2019 and age 15 to 40 years old in each survey year. Unit observation is a cell of a cohort of labour market entrance by gender, education level and province of residence. Reported coefficients based on modified Equation 1, where national unemployment rates do not interact with dummies of year experiences. The dependent variable is indicated by the title of the column. Specification controls for years of experience, labour market entry fixed effects, education fixed effects, gender fixed effects and survey year fixed effects. Standard errors are clustered at the year of labour market entrance.

Table A3: Long-term consequences of the unemployment rate at labour market entry to life-time employment

	(1) log monthly earnings	(2) log total wage	(3) log working hours	(4) log wage/ hours
UR at entry	-0.218***	-0.164**	-0.178***	-0.205***
	(0.040)	(0.053)	(0.024)	(0.054)
Observation	46,407	45,799	46,613	45,766
Mean	11.747	11.583	164.044	6.679
Adjusted R2	0.774	0.732	0.571	0.707
Fixed effects	Yes	Yes	Yes	Yes
Clustered S.E.	Yes	Yes	Yes	Yes

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses. Observation drawn from SAKERNAS 1990-2019, excluding the 1995 observation. I restrict the sample to those entering labour market between 1990 to 2019 and age 15 to 40 years old in each survey year. Unit observation is a cell of a cohort of labour market entrance by gender, education level and province of residence. Reported coefficients based on modified Equation 1, where national unemployment rates do not interact with dummies of year experiences. The dependent variable is indicated by the title of each column. Monthly earnings are measured as total labour income, salary or wages except for those working as employers and unpaid workers. Wage information is conditional on being a waged worker. For casual workers, the survey also includes the estimated value of non-cash remuneration. All monetary values are inflation-adjusted using CPI with 1990 as base year. Specification controls for years of experience, labour market entry fixed effects, education fixed effects, gender fixed effects and survey year fixed effects. Standard errors are clustered at the year of labour market entrance.

Table A4: Long-term consequences of the unemployment rate at labour market entry to life-time employment

	(1) Agriculture	(2) Manufacturing	(3) Services
UR at entry	0.038*	0.015*	-0.053***
	(0.014)	(0.005)	(0.013)
Observation	46,613	46,613	46,613
Mean	0.344	0.134	0.522
Adjusted R2	0.832	0.642	0.775
Fixed effects	Yes	Yes	Yes
Clustered S.E.	Yes	Yes	Yes

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses. Observation drawn from SAKERNAS 1990-2019, excluding the 1995 observation. I restrict the sample to those entering labour market between 1990 to 2019 and age 15 to 40 years old in each survey year. Unit observation is a cell of a cohort of labour market entrance by gender, education level and province of residence. Reported coefficients based on modified Equation 1, where national unemployment rates do not interact with dummies of year experiences. The dependent variable is indicated by the title of each column. Specification controls for years of experience, labour market entry fixed effects, education fixed effects, gender fixed effects and survey year fixed effects. Standard errors are clustered at the year of labour market entrance.

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

	(1) log monthly earnings	(2) log total wage	(3) log working hours	(4) log wage/ hours
Unemployment rate × years since				
1-2 years	-0.029***	-0.030***	-0.010***	-0.031***
	(0.003)	(0.004)	(0.002)	(0.004)
3-5 years	-0.016***	-0.018***	-0.001	-0.018***
	(0.002)	(0.003)	(0.001)	(0.003)
6-8 years	-0.006***	-0.006***	0.002*	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
9-11 years	0.002*	0.003*	-0.001	0.003**
	(0.001)	(0.001)	(0.000)	(0.001)
12-14 years	0.006**	0.008**	-0.002*	0.009***
	(0.002)	(0.002)	(0.001)	(0.002)
15-17 years	0.010*	0.010*	-0.004**	0.015**
	(0.004)	(0.005)	(0.002)	(0.005)
≥ 18 years	0.007	0.008	-0.007*	0.015
	(0.006)	(0.007)	(0.003)	(0.007)
Observation	46,407	45,799	46,613	45,766
Mean	11.747	11.583	164.044	6.679
Adjusted R2	0.774	0.732	0.570	0.707
Fixed effects	Yes	Yes	Yes	Yes
Clustered S.E.	Yes	Yes	Yes	Yes

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses. Observation drawn from SAKERNAS 1990-2019, excluding the 1995 observation. I restrict the sample to those entering labour market between 1990 to 2019 and age 15 to 40 years old in each survey year. Unit observation is a cell of a cohort of labour market entrance by gender, education level and province of residence. Reported coefficients correspond to β_e of Equation 1 using national unemployment rates. The dependent variable is indicated by the title of each column. Monthly earnings are measured as total labour income, salary or wages except for those working as employers and unpaid workers. Wage information is conditional on being a waged worker. For casual workers, the survey also includes the estimated value of non-cash remuneration. All monetary values are inflation-adjusted using CPI with 1990 as base year. Specification controls for years of experience, labour market entry fixed effects, education fixed effects, gender fixed effects and survey year fixed effects. Standard errors are clustered at the year of labour market entrance.

Table A6: Long-term consequences of the unemployment rate at labour market entry to life-time occupational sectors

	(1) Agriculture	(2) Manufacturing	(3) Services
Unemployment rate × years since			
1-2 years	0.006***	0.000	-0.006***
	(0.001)	(0.001)	(0.001)
3-5 years	0.002**	0.001*	-0.003***
	(0.001)	(0.000)	(0.001)
6-8 years	0.000	0.001*	-0.001
	(0.000)	(0.000)	(0.001)
9-11 years	0.001	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
12-14 years	0.001	-0.001	-0.000
	(0.001)	(0.000)	(0.001)
15-17 years	0.001	-0.001**	0.000
	(0.001)	(0.000)	(0.001)
≥ 18 years	0.000	-0.002*	0.001
	(0.002)	(0.001)	(0.002)
Observation	46,613	46,613	46,613
Mean	0.344	0.134	0.522
Adjusted R2	0.832	0.642	0.775
Fixed effects	Yes	Yes	Yes
Clustered S.E.	Yes	Yes	Yes

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses. Observation drawn from SAKERNAS 1990-2019, excluding the 1995 observation. I restrict the sample to those entering labour market between 1990 to 2019 and age 15 to 40 years old in each survey year. Unit observation is a cell of a cohort of labour market entrance by gender, education level and province of residence. Reported coefficients correspond to β_e of Equation 1 using national unemployment rates. The dependent variable is indicated by the title of each column. Specification controls for years of experience, labour market entry fixed effects, education fixed effects, gender fixed effects and survey year fixed effects. Standard errors are clustered at the year of labour market entrance.

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

	(1) Employed	(2) Full-time Job	(3) Formal Job	(4) Unpaid Job
Unemployment rate × years since				
1-2 years	-0.027***	-0.025***	-0.004**	0.002
	(0.001)	(0.001)	(0.001)	(0.002)
3-5 years	-0.011***	-0.008***	0.004***	-0.005***
	(0.000)	(0.000)	(0.001)	(0.001)
6-8 years	-0.003***	-0.000	0.004***	-0.004***
	(0.000)	(0.000)	(0.000)	(0.000)
9-11 years	0.001***	0.002***	-0.001***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
12-14 years	0.002***	0.002***	-0.004***	0.002***
	(0.000)	(0.000)	(0.000)	(0.001)
15-17 years	0.003***	-0.001	-0.008***	0.007***
	(0.000)	(0.001)	(0.001)	(0.001)
$\geq$ 18 years	0.000	-0.006***	-0.010***	0.015***
	(0.001)	(0.001)	(0.001)	(0.001)
Observation	45,744	45,744	45,744	45,744
Mean	0.903	0.574	0.459	0.299
Adjusted R2	0.669	0.634	0.761	0.656
Fixed effects	Yes	Yes	Yes	Yes
Clustered S.E.	Yes	Yes	Yes	Yes

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses. Observation drawn from SAKERNAS 1990-2019, excluding the 1995 observation. I restrict the sample to those entering labour market between 1990 to 2019 and age 15 to 40 years old in each survey year. Unit observation is a cell of a cohort of labour market entrance by gender, education level and province of residence. Reported coefficients correspond to β_e of Equation 3 using national unemployment rates. The dependent variable is indicated by the title of each column. Specification controls for years of experience, labour market entry fixed effects, education fixed effects, gender fixed effects and survey year fixed effects. Standard errors are clustered at the year of labour market entrance.

Table A8: Long-term consequences of the unemployment rate at labour market entry to lifetime occupational sectors

	(1) log monthly earnings	(2) log total wage	(3) log working hours	(4) log wage/ hours
Unemployment rate × *years since*				
1-2 years	-0.013***	-0.012***	-0.006***	-0.011***
	(0.002)	(0.002)	(0.001)	(0.002)
3-5 years	-0.007***	-0.007***	0.001	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
6-8 years	-0.001	-0.002	0.003***	-0.003*
	(0.001)	(0.001)	(0.000)	(0.001)
9-11 years	0.002*	0.001	-0.000	0.000
	(0.001)	(0.001)	(0.000)	(0.001)
12-14 years	0.002**	0.002**	-0.002***	0.001
	(0.001)	(0.001)	(0.000)	(0.001)
15-17 years	0.002	-0.000	-0.005***	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
≥ 18 years	-0.009***	-0.011***	-0.007***	-0.010***
	(0.001)	(0.002)	(0.001)	(0.002)
Observation	45,554	45,014	45,744	44,983
Mean	11656.857	11485.905	164.065	6624.267
Adjusted R2	0.773	0.731	0.568	0.705
Fixed effects	Yes	Yes	Yes	Yes
Clustered S.E.	Yes	Yes	Yes	Yes

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses. Observation drawn from SAKERNAS 1990-2019, excluding the 1995 observation. I restrict the sample to those entering labour market between 1990 to 2019 and age 15 to 40 years old in each survey year. Unit observation is a cell of a cohort of labour market entrance by gender, education level and province of residence. Reported coefficients correspond to β_e of Equation 3 using province unemployment rates. The dependent variable is indicated by the title of each column. Monthly earnings are measured as total labour income, salary or wages except for those working as employers and unpaid workers. Wage information is conditional on being a waged worker. For casual workers, the survey also includes the estimated value of non-cash remuneration. All monetary values are inflation-adjusted using CPI with 1990 as base year. Specification controls for years of experience, labour market entry fixed effects, education fixed effects, gender fixed effects and survey year fixed effects. Standard errors are clustered at the year of labour market entrance.

Table A9: Long-term consequences of the unemployment rate at labour market entry to lifetime occupational sectors

	(1) Agriculture	(2) Manufacturing	(3) Services
Unemployment rate × years since			
1-2 years	0.003^{***}	0.003^{***}	-0.006^{***}
	(0.001)	(0.001)	(0.001)
3-5 years	0.001	0.003^{***}	-0.004^{***}
	(0.000)	(0.001)	(0.001)
6-8 years	-0.001	0.002^{***}	-0.002^{***}
	(0.000)	(0.000)	(0.000)
9-11 years	0.001^{*}	0.001	-0.001^{***}
	(0.000)	(0.000)	(0.000)
12-14 years	0.002^{***}	-0.001	-0.001^{*}
	(0.000)	(0.000)	(0.000)
15-17 years	0.003^{***}	-0.002^{***}	-0.001
	(0.001)	(0.000)	(0.001)
≥ 18 years	0.003^{***}	-0.004^{***}	0.001
	(0.001)	(0.001)	(0.001)
Observation	45,744	45,744	45,744
Mean	0.339	0.136	0.525
Adjusted R2	0.826	0.638	0.770
Fixed effects	Yes	Yes	Yes
Clustered S.E.	Yes	Yes	Yes

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses. Observation drawn from SAKERNAS 1990-2019, excluding the 1995 observation. I restrict the sample to those entering labour market between 1990 to 2019 and age 15 to 40 years old in each survey year. Unit observation is a cell of a cohort of labour market entrance by gender, education level and province of residence. Reported coefficients correspond to β_e of Equation 3 using province unemployment rates. The dependent variable is indicated by the title of each column. Specification controls for years of experience, labour market entry fixed effects, education fixed effects, gender fixed effects and survey year fixed effects. Standard errors are clustered at the year of labour market entrance.

Table A10: Long-term consequences of the unemployment rate at labour market entry to lifetime earnings by gender

	(1) log monthly earnings	(2) log total wage	(3) log working hours	(4) log wage/ hours
A. Men				
1-2 years	-0.032***	-0.030***	-0.020***	-0.027***
	(0.004)	(0.004)	(0.002)	(0.004)
3-5 years	-0.017***	-0.016***	-0.007***	-0.014***
	(0.002)	(0.002)	(0.001)	(0.002)
6-8 years	-0.006***	-0.006***	-0.000	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
9-11 years	0.003	0.002	-0.000	0.002
	(0.001)	(0.001)	(0.000)	(0.001)
12-14 years	0.006**	0.006*	-0.002	0.006**
	(0.002)	(0.002)	(0.001)	(0.002)
15-17 years	0.009*	0.008*	-0.004*	0.010**
	(0.004)	(0.004)	(0.002)	(0.004)
$\geq$ 18 years	0.006	0.004	-0.008**	0.008
	(0.006)	(0.006)	(0.003)	(0.006)
Observation	24,487	24,311	24,548	24,300
Mean	13.190	12.912	171.845	7.114
Adjusted R2	0.824	0.797	0.628	0.757
Fixed effects	Yes	Yes	Yes	Yes
Clustered S.E.	Yes	Yes	Yes	Yes
B. Women				
1-2 years	-0.029***	-0.036***	0.002	-0.039***
	(0.004)	(0.006)	(0.002)	(0.006)
3-5 years	-0.016***	-0.022***	0.007***	-0.024***
	(0.003)	(0.004)	(0.001)	(0.004)
6-8 years	-0.005**	-0.008**	0.005***	-0.009***
	(0.002)	(0.003)	(0.001)	(0.002)
9-11 years	0.001	0.003	-0.001	0.005
	(0.002)	(0.002)	(0.001)	(0.003)
12-14 years	0.006*	0.011**	-0.003**	0.014**
	(0.002)	(0.003)	(0.001)	(0.004)
15-17 years	0.008	0.013*	-0.005**	0.022**
	(0.004)	(0.006)	(0.002)	(0.007)
$\geq$ 18 years	0.007	0.013	-0.005	0.025*
	(0.006)	(0.010)	(0.003)	(0.011)
Observation	21,920	21,488	22,065	21,466
Mean	10.135	10.079	155.364	6.186
Adjusted R2	0.713	0.665	0.557	0.663
Fixed effects	Yes	Yes	Yes	Yes
Clustered S.E.	Yes	Yes	Yes	Yes

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses. Observation drawn from SAKERNAS 1990-2019, excluding the 1995 observation. I restrict the sample to those entering labour market between 1990 to 2019 and age 15 to 40 years old in each survey year. Unit observation is a cell of a cohort of labour market entrance by gender, education level and province of residence. Reported coefficients correspond to β_e of Equation 1 using national unemployment rates estimated separately for men (Panel A) and women (Panel B). The dependent variable is indicated by the title of each column. Monthly earnings are measured as total labour income, salary or wages except for those working as employers and unpaid workers. Wage information is conditional on being a waged worker. For casual workers, the survey also includes the estimated value of non-cash remuneration. All monetary values are inflation-adjusted using CPI with 1990 as base year. Specification controls for years of experience, labour market entry fixed effects, education fixed effects, gender fixed effects and survey year fixed effects. Standard errors are clustered at the year of labour market entrance.

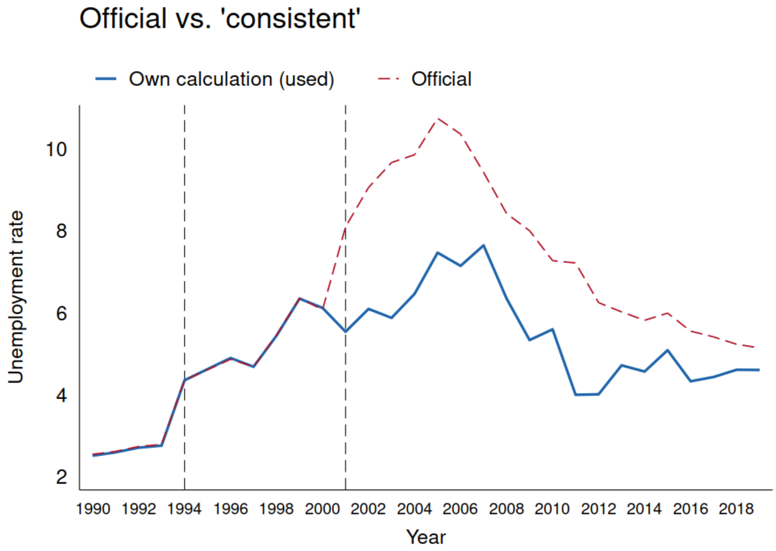
Table A11: Long-term consequences of the unemployment rate at labour market entry to lifetime occupational sectors by gender

	(1) Agriculture	(2) Manufacturing	(3) Services
A. Men			
1-2 years	0.013***	-0.001	-0.012***
	(0.002)	(0.001)	(0.002)
3-5 years	0.006***	0.001	-0.006***
	(0.001)	(0.000)	(0.001)
6-8 years	0.001	0.001	-0.002*
	(0.001)	(0.000)	(0.001)
9-11 years	0.000	-0.000	-0.000
	(0.000)	(0.001)	(0.001)
12-14 years	0.001	-0.001	0.000
	(0.001)	(0.001)	(0.001)
15-17 years	0.002	-0.002***	0.000
	(0.001)	(0.001)	(0.001)
$\geq$ 18 years	0.002	-0.003**	0.001
	(0.002)	(0.001)	(0.002)
Observation	24,548	24,548	24,548
Mean	0.389	0.151	0.461
Adjusted R2	0.859	0.704	0.802
Fixed effects	Yes	Yes	Yes
Clustered S.E.	Yes	Yes	Yes
B. Women			
1-2 years	-0.002*	-0.000	0.003
	(0.001)	(0.001)	(0.001)
3-5 years	-0.003***	0.001	0.002*
	(0.001)	(0.001)	(0.001)
6-8 years	-0.002**	0.001	0.001
	(0.001)	(0.000)	(0.001)
9-11 years	0.001**	-0.001	-0.001
	(0.001)	(0.000)	(0.001)
12-14 years	0.001*	-0.000	-0.001
	(0.001)	(0.000)	(0.001)
15-17 years	0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
$\geq$ 18 years	-0.002	-0.000	0.002
	(0.001)	(0.001)	(0.002)
Observation	22,065	22,065	22,065
Mean	0.294	0.116	0.590
Adjusted R2	0.835	0.678	0.799
Fixed effects	Yes	Yes	Yes
Clustered S.E.	Yes	Yes	Yes

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors in parentheses. Observation drawn from SAKERNAS 1990-2019, excluding the 1995 observation. I restrict the sample to those entering labour market between 1990 to 2019 and age 15 to 40 years old in each survey year. Unit observation is a cell of a cohort of labour market entrance by gender, education level and province of residence. Reported coefficients correspond to β_e of Equation 1 using national unemployment rates estimated separately for men (Panel A) and women (Panel B). The dependent variable is indicated by the title of each column. Specification controls for year of experience, labour market entry fixed effects, education fixed effects, gender fixed effects and survey year fixed effects. Standard errors are clustered at the year of labour market entrance.

Appendix B

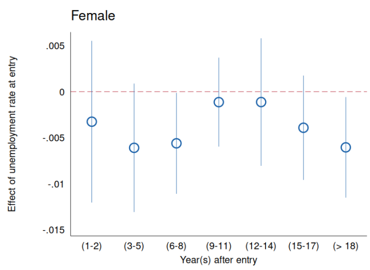
Figure B1: Unemployment rate in Indonesia



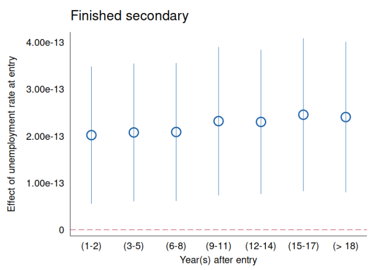
Notes: Own calculation using SAKERNAS 1990-2019. I exclude the unemployment rate in 1995.

Figure B4: Placebo test using national unemployment rates

(A)



(B)

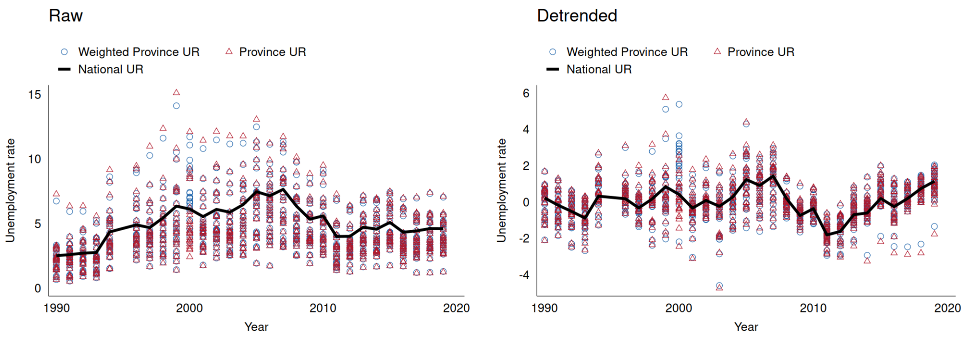


Notes: Results are based on national specification as summarized in Equation 1 using data from SAKERNAS 1990-2019. The dependent variables are the share of female individuals (Panel A), the share of married individuals (Panel B) and the share of secondary graduates (Panel C) in each cohort cell observation. Plots represent coefficients on unemployment rate at the year and current province residence of labour market entrance. Specification controls for labour 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 year of labour market entrance.

Figure B2: Provincial unemployment rates and national unemployment rates

(A) Correlation = 0.80*** (0.25)

(B) Correlation = 0.91*** (0.05)

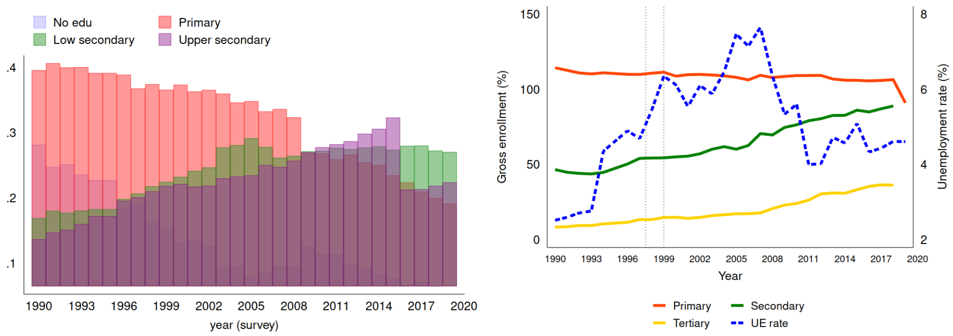


Notes: Own calculation using SAKERNAS data 1990-2019. I exclude the unemployment rate in 1995. The correlation coefficient in Panel A is a linear square estimation of provincial unemployment rates on national unemployment rates with year-fixed effects. Standard error in parentheses. In Panel B, detrended unemployment rates depict residual terms of linear estimation of corresponding unemployment rates on the cubic function of years and province fixed effect. The correlation coefficient in Panel A and B are the linear square estimation of provincial unemployment rates on national unemployment rates with year-fixed effects.

Figure B3: Education attaintment trends in Indonesia

(A)

(B)

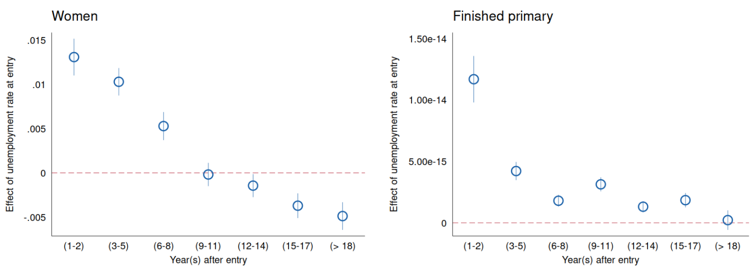


Notes: Panel (A): Own calculation using SAKERNAS 1990-2019, excluding the educational attainment in 1995. Panel (B): World Development Indicator, The World Bank.

Figure B5: Placebo test using provincial unemployment rates

(A)

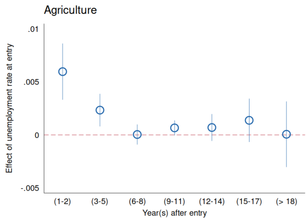
(B)

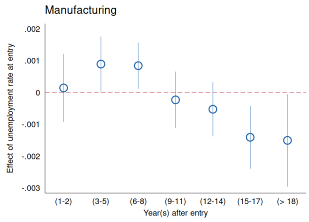


Notes: Results are based on the migration-weighted provincial unemployment rate as summarized in Equation 3 using data from SAKERNAS 1990-2019. The dependent variables are the share of female individuals (Panel A), the share of married individuals (Panel B) and the share of secondary graduates (Panel C) in each cohort cell observation. Plots represent coefficients on unemployment rate at the year and current province residence of labour market entrance. Specification controls for labour 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 year of labour market entrance.

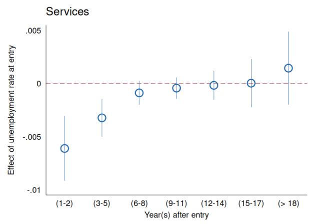
Figure B6: Scarring effects on employment sector

(A) (B)





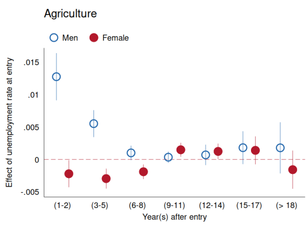
(C)

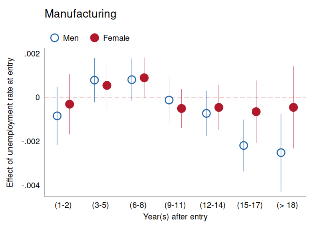


Notes: Results are based on national specification as summarized in Equation 1 using data from SAKERNAS 1990-2019. Plots represent coefficients on unemployment rate at the year and current province residence of labour market entrance. Specification controls for labour market entry fixed effects, gender fixed effects and survey year fixed effects. The whisker of each dot plot represents a 95% confidence interval. Standard errors are clustered at the year of labour market entrance.

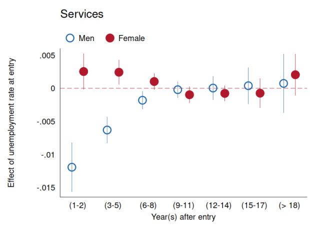
Figure B7: Scarring effect on employment sector by gender

(A) (B)





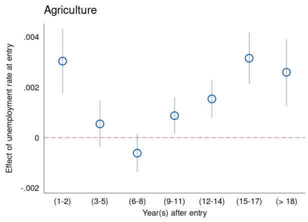
(C)



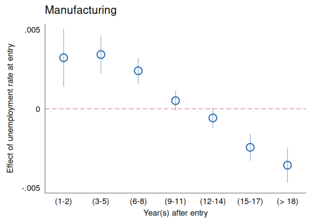
Notes: Results are based on national specification as summarized in Equation 1 using data from SAKERNAS 1990-2019. Each colored line represents separate regression by gender. Plots represent coefficients on unemployment rate at the year and current province residence of labour market entrance. Specification controls for labour 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 year of labour market entrance.

Figure B8: Scarring effects on employment sector, Province UR

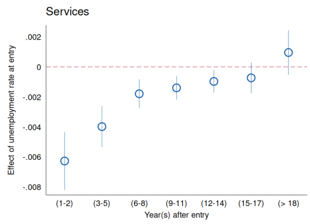
(A)



(B)



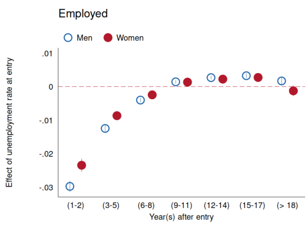
(C)



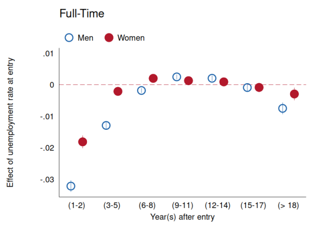
Notes: Observation drawn from SAKERNAS 1990-2019, excluding the 1995 observation. I restrict the sample to those entering labour market between 1990 to 2019 and age 15 to 40 years old in each survey year. Unit observation is a cell of a cohort of labour market entrance by gender, education level and province of residence. Plotted coefficients correspond to β_e of Equation 3 using migration-weighted provincial unemployment rates. Specification controls for labour market entry fixed effects, education fixed effects, gender fixed effects and survey year fixed effects. The whisker of each dot plot represents a 95% confidence interval. The dependent variable is indicated by the title of each graph. Each panel depicts separate regression. Standard errors are clustered at the year of labour market entrance and residential province.

Figure B9: Scarring effects on employment by education, Province UR

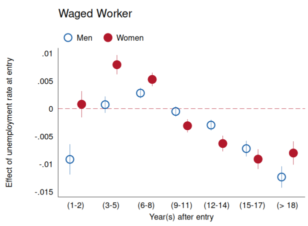
(A)



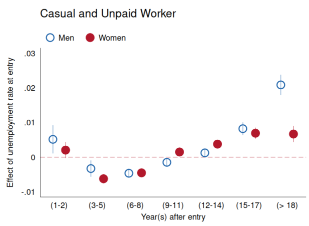
(B)



(C)



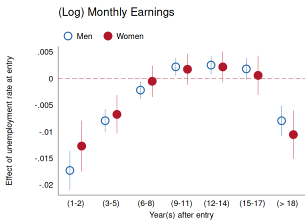
(D)



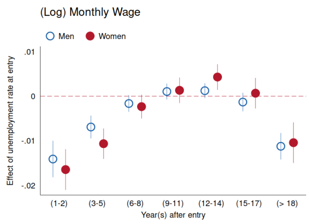
Notes: Observation drawn from SAKERNAS 1990-2019, excluding the 1995 observation. I restrict the sample to those entering labour market between 1990 to 2019 and age 15 to 40 years old in each survey year. Unit observation is a cell of a cohort of labour market entrance by gender, education level and province of residence. Plotted coefficients correspond to β_e of Equation 3 using migration-weighted provincial unemployment rates. Men and women coefficients are estimated separately. Specification controls for labour market entry fixed effects, education fixed effects, gender fixed effects and survey year fixed effects. The whisker of each dot plot represents a 95% confidence interval. The dependent variable is indicated by the title of each graph. Each panel depicts separate regression. Standard errors are clustered at the year of labour market entrance and residential province.

Figure B10: Scarring effects on earnings by education, Province UR

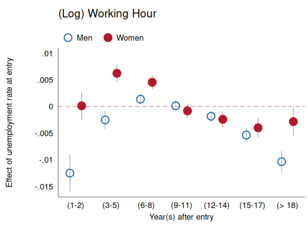
(A)



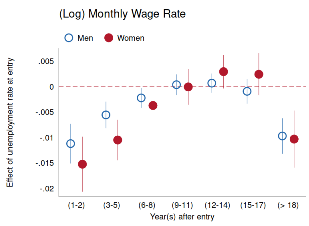
(B)



(C)



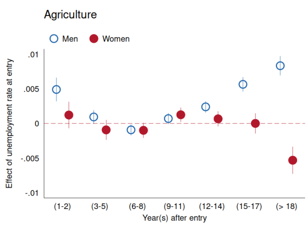
(D)



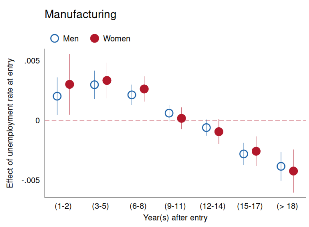
Notes: Observation drawn from SAKERNAS 1990-2019, excluding the 1995 observation. I restrict the sample to those entering labour market between 1990 to 2019 and age 15 to 40 years old in each survey year. Unit observation is a cell of cohort of labour market entrance by gender, education level and province of residence. Plotted coefficients correspond to β_e of Equation 3 using migration-weighted provincial unemployment rates. Men and women coefficients are estimated separately. Specification controls for labour market entry fixed effects, education fixed effects, gender fixed effects and survey year fixed effects. Monthly earnings are measured as total labour income, salary or wages except for those working as employers and unpaid workers. Wage information is conditional on being a waged worker. For casual workers, the survey also includes the estimated value of non-cash remuneration. All monetary values are inflation-adjusted by CPI with 1990 as base year. The whisker of each dot plot represents a 95% confidence interval. The dependent variable is indicated by the title of each graph. Each panel depicts separate regression. Standard errors are clustered at the year of labour market entrance and residential 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 year of labour market entrance.

Figure B11: Scarring effect on income by gender, Province UR

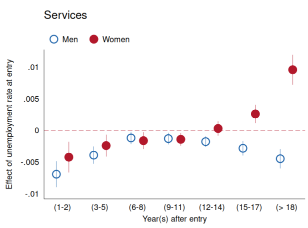
(A)



(B)

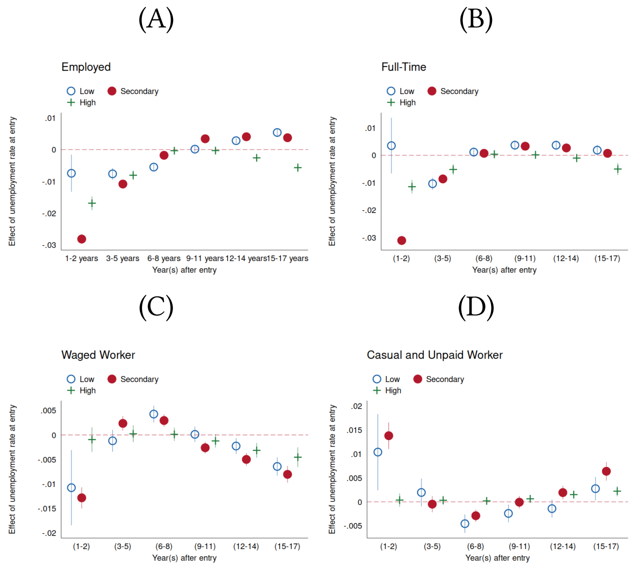


(C)



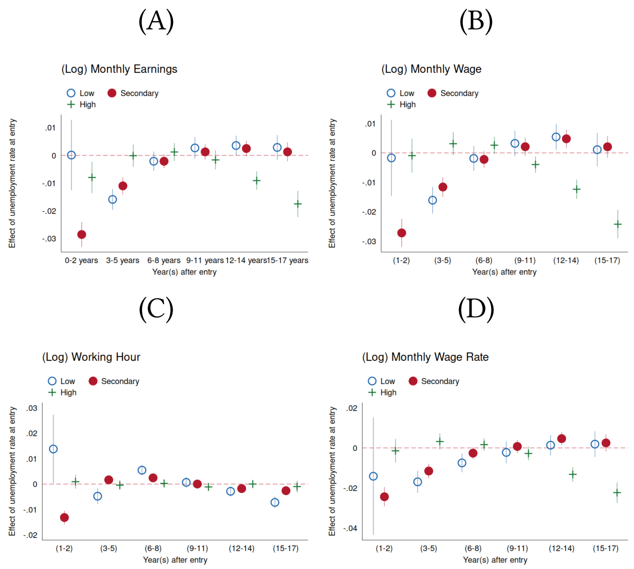
Notes: Results are based on provincial specification as summarized in Equation 3 using data from SAKERNAS 1990-2019. Plots represent coefficients on unemployment rate at the year and current province residence of labour market entrance. Unemployment rates are weighted using historical inter-province 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 labour 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 year of labour market entrance.

Figure B12: Scarring effects on employment by education, Province UR



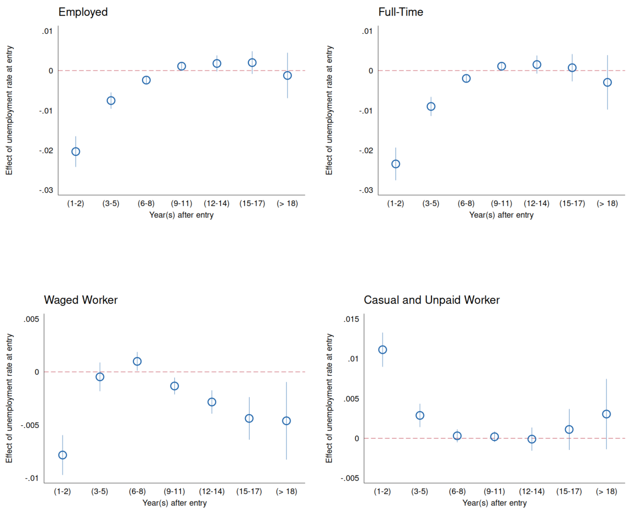
Notes: Results are based on provincial specification as summarized in Equation 3 using data from SAKERNAS 1990-2019. Plots represent coefficients on unemployment rate at the year and current province residence of labour market entrance. Unemployment rates are weighted using historical inter-province 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 labour 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 year of labour market entrance.

Figure B13: Scarring effects on earnings by education, Province UR



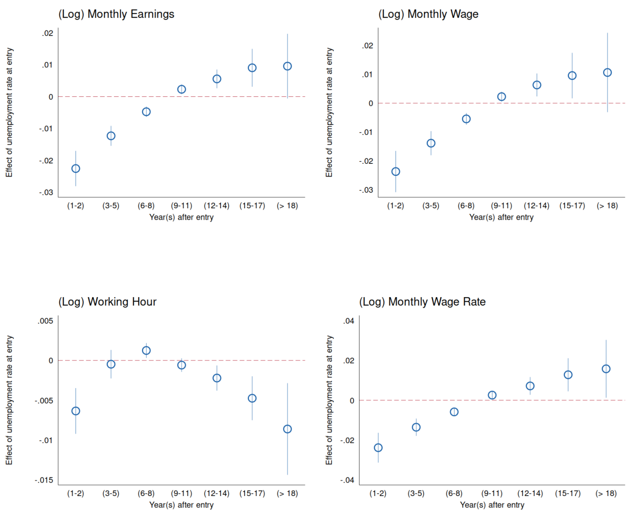
Notes: Results are based on provincial specification as summarized in Equation 3 using data from SAKERNAS 1990-2019. Plots represent coefficients on unemployment rate at the year and current province residence of labour market entrance. Unemployment rates are weighted using historical inter-province 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 labour 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 year of labour market entrance.

Figure B14: Scarring effects of 3-year moving average unemployment rate



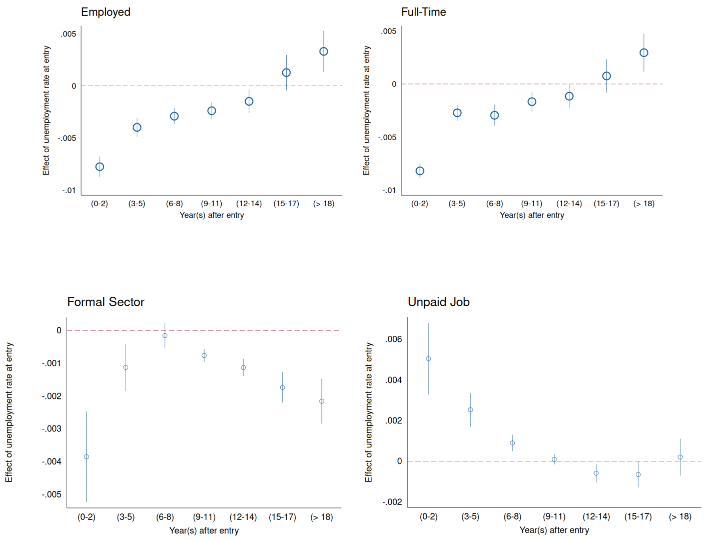
Notes: Observation drawn from SAKERNAS 1990-2019, excluding the 1995 observation. I restrict the sample to those entering labour market between 1990 to 2019 and age 15 to 40 years old in each survey year. Unit observation is a cell of a cohort of labour market entrance by gender, education level and province of residence. Plotted coefficients correspond to β_e of Equation 1 using 3-year moving average national unemployment rates. Specification controls for labour market entry fixed effects, education fixed effects, gender fixed effects and survey year fixed effects. The whisker of each dot plot represents a 95% confidence interval. The dependent variable is indicated by the title of each graph. Each panel represents separate regression. For Panel C, the formal sector includes wage workers and the employer who has permanent workers. Standard errors are clustered at the year of labour market entrance.

Figure B15: Scarring effects of 3-year moving average unemployment rate



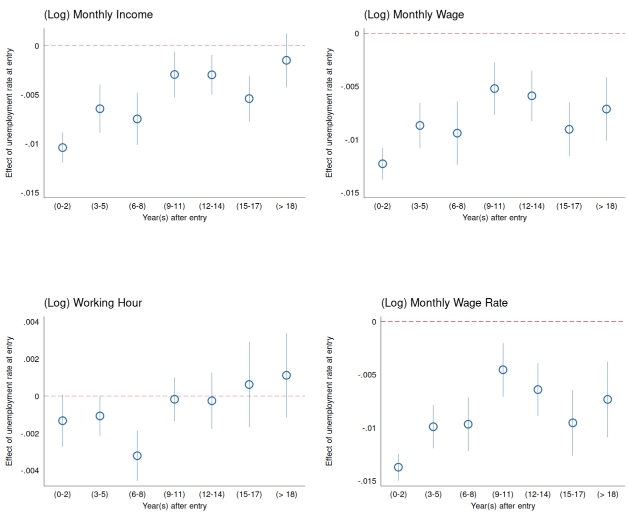
Notes: Observation drawn from SAKERNAS 1990-2019, excluding the 1995 observation. I restrict the sample to those entering labour market between 1990 to 2019 and age 15 to 40 years old in each survey year. Unit observation is a cell of cohort of labour market entrance by gender, education level and province of residence. Plotted coefficients correspond to β_e of Equation 1 using 3-year moving average national unemployment rates. Specification controls for labour market entry fixed effects, education fixed effects, gender fixed effects and survey year fixed effects. Monthly earnings are measured as total labour income, salary or wages except for those working as employers and unpaid workers. Wage information is conditional on being a waged worker. For casual workers, the survey also includes the estimated value of non-cash remuneration. All monetary values are inflation-adjusted using CPI with 1990 as base year. The whisker of each dot plot represents a 95% confidence interval. The dependent variable is indicated by the title of each graph. Each panel represents separate regression. Standard errors are clustered at the year of labour market entrance.

Figure B16: Scarring effects using unemployment rate of 15-24 years old



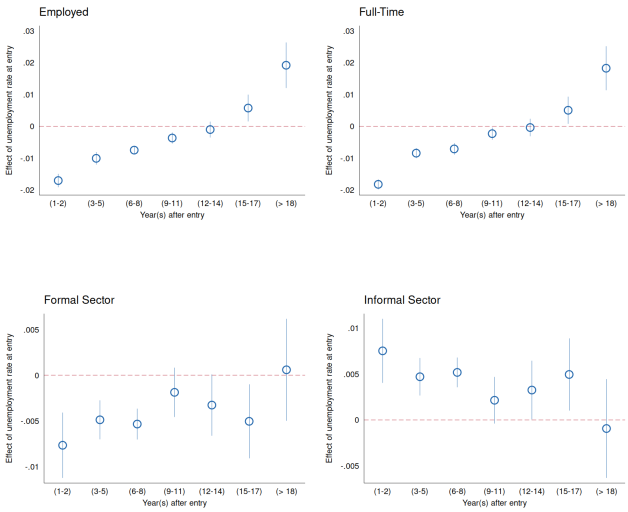
Notes: Observation drawn from SAKERNAS 1990-2019, excluding the 1995 observation. I restrict the sample to those entering labour market between 1990 to 2019 and age 15 to 40 years old in each survey year. Unit observation is a cell of a cohort of labour market entrance by gender, education level and province of residence. Plotted coefficients correspond to β_e of Equation 1 using national unemployment rates for 15-24 years old population. Specification controls for labour market entry fixed effects, education fixed effects, gender fixed effects and survey year fixed effects. The whisker of each dot plot represents a 95% confidence interval. The dependent variable is indicated by the title of each graph. Each panel represents separate regression. For Panel C, the formal sector includes wage workers and the employer who has permanent workers. Standard errors are clustered at the year of labour market entrance.

Figure B17: Scarring effects using unemployment rate of 15-24 years old



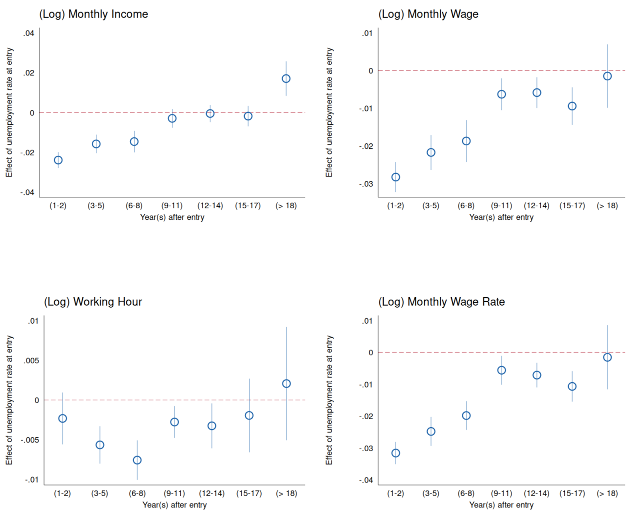
Notes: Observation drawn from SAKERNAS 1990-2019, excluding the 1995 observation. I restrict the sample to those entering labour market between 1990 to 2019 and age 15 to 40 years old in each survey year. Unit observation is a cell of cohort of labour market entrance by gender, education level and province of residence. Plotted coefficients correspond to β_e of Equation 1 using national unemployment rates for 15-24 years old population. Specification controls for labour market entry fixed effects, education fixed effects, gender fixed effects and survey year fixed effects. Monthly earnings are measured as total labour income, salary or wages except for those working as employers and unpaid workers. Wage information is conditional on being a waged worker. For casual workers, the survey also includes the estimated value of non-cash remuneration. All monetary values are inflation-adjusted using CPI with 1990 as base year. The whisker of each dot plot represents a 95% confidence interval. The dependent variable is indicated by the title of each graph. Each panel represents separate regression. Standard errors are clustered at the year of labour market entrance.

Figure B18: Scarring effects of official BPS unemployment rate



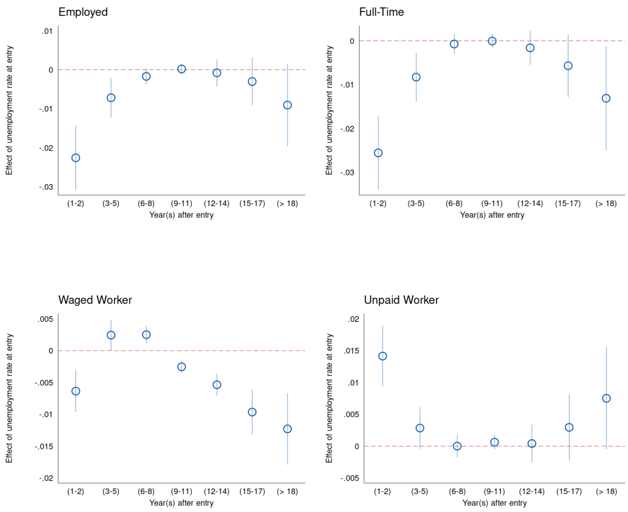
Notes: Observation drawn from SAKERNAS 1990-2019, excluding the 1995 observation. I restrict the sample to those entering labour market between 1990 to 2019 and age 15 to 40 years old in each survey year. Unit observation is a cell of a cohort of labour market entrance by gender, education level and province of residence. Plotted coefficients correspond to β_e of Equation 1 using the official national unemployment rates from BPS. Specification controls for labour market entry fixed effects, education fixed effects, gender fixed effects and survey year fixed effects. The whisker of each dot plot represents a 95% confidence interval. The dependent variable is indicated by the title of each graph. Each panel represents separate regression. For Panel C, the formal sector includes wage workers and the employer who has permanent workers. Standard errors are clustered at the year of labour market entrance.

Figure B19: Scarring effects of official BPS unemployment rate



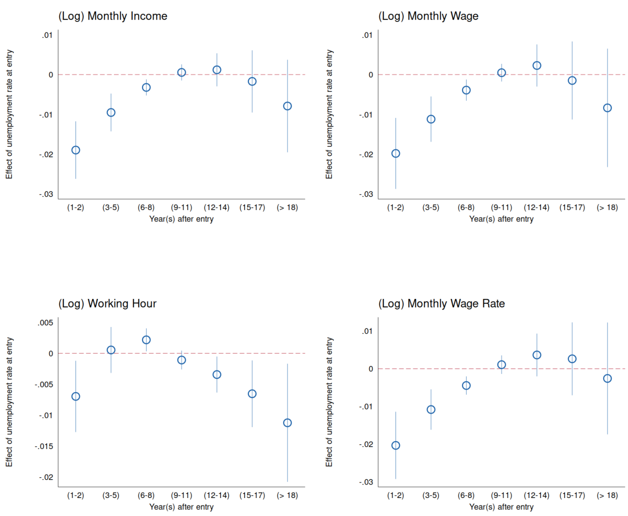
Notes: Observation drawn from SAKERNAS 1990-2019, excluding the 1995 observation. I restrict the sample to those entering labour market between 1990 to 2019 and age 15 to 40 years old in each survey year. Unit observation is a cell of cohort of labour market entrance by gender, education level and province of residence. Plotted coefficients correspond to β_e of Equation 1 using the official national unemployment rates from BPS. Specification controls for labour market entry fixed effects, education fixed effects, gender fixed effects and survey year fixed effects. Monthly earnings are measured as total labour income, salary or wages except for those working as employers and unpaid workers. Wage information is conditional on being a waged worker. For casual workers, the survey also includes the estimated value of non-cash remuneration. All monetary values are inflation-adjusted using CPI with 1990 as base year. The whisker of each dot plot represents a 95% confidence interval. The dependent variable is indicated by the title of each graph. Each panel represents separate regression. Standard errors are clustered at the year of labour market entrance.

Figure B20: Scarring effects on employments, excluding pre 1994 observation



Notes: Observation drawn from SAKERNAS 1990-2019, excluding the 1995 observation. I restrict the sample to those entering labour market between 1990 to 2019 and age 15 to 40 years old in each survey year. I exclude observations from the surveys dated prior to 1994. Unit observation is a cell of a cohort of labour market entrance by gender, education level and province of residence. Plotted coefficients correspond to β_e of Equation 1 using national unemployment rates. Specification controls for labour market entry fixed effects, education fixed effects, gender fixed effects and survey year fixed effects. The whisker of each dot plot represents a 95% confidence interval. The dependent variable is indicated by the title of each graph. Each panel represents separate regression. For Panel C, the formal sector includes wage workers and the employer who has permanent workers. Standard errors are clustered at the year of labour market entrance.

Figure B21: Scarring effects on earnings, excluding pre 1994 observation



Notes: Observation drawn from SAKERNAS 1990-2019, excluding the 1995 observation. I restrict the sample to those entering labour market between 1990 to 2019 and age 15 to 40 years old in each survey year. I exclude observations from the surveys dated prior to 1994. Unit observation is a cell of cohort of labour market entrance by gender, education level and province of residence. Plotted coefficients correspond to β_e of Equation 1 using national unemployment rates. Specification controls for labour market entry fixed effects, education fixed effects, gender fixed effects and survey year fixed effects. Monthly earnings are measured as total labour income, salary or wages except for those working as employers and unpaid workers. Wage information is conditional on being a waged worker. For casual workers, the survey also includes the estimated value of non-cash remuneration. All monetary values are inflation-adjusted using CPI with 1990 as base year. The whisker of each dot plot represents a 95% confidence interval. The dependent variable is indicated by the title of each graph. Each panel represents separate regression. Standard errors are clustered at the year of labour market entrance.