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Decoding Joblessness in Pakistan: A Generational and Temporal Analysis

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CONTENTS

List of Tables

List of Figures

ABSTRACT

Unemployment has been acknowledged as one of the most important socioeconomic problems faced by developing nations, especially Pakistan. It is a sign of underlying structural imbalance in the economy, in addition to reflecting the labour market inefficiencies. It is argued that due to the higher education expansion in Pakistan during the last two decades and due to high youth bulge in the country, the young cohort entering the labour market are experiencing high unemployment. So, to understand and analyse this complex phenomenon, the Age-Period-Cohort (APC) model provides a nuanced approach in understanding unemployment rates simultaneously with other control variables. For analysis, data was acquired from the labour Force Survey (LFS) 2001-02 to 2024-25 covering twelve alternative waves. The results indicate that higher education, with increase in skills and productivity, helps individuals to escape from unemployment. However, cohort analysis shows vulnerability of young, educated cohorts to unemployment as compared to the older cohorts. This effect is more pronounced in tertiary education.

1. INTRODUCTION

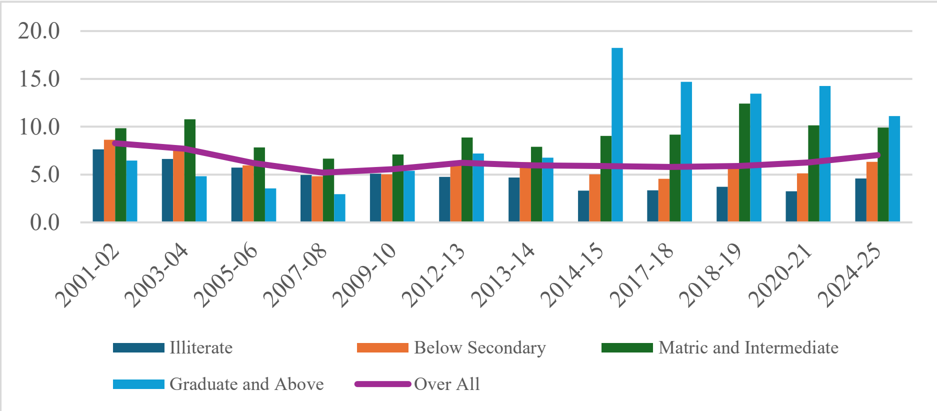
Unemployment has long been recognised as one of the most pressing socio-economic challenges faced by the developing economies, including Pakistan. It not only reflects inefficiencies in the labour market but also serves as an indicator of underlying structural imbalances in the economy. A significant number of theories try to highlight different reasons for this unemployment. One of these is the Cohort Crowding Hypothesis. It claims that a cohort effect exists when large young labour force entering the job market faces tough competition and experiences unemployment and underemployment due to excess supply of labour force (Freeman, 1979; Welch, 1979; Korenman & Neumark, 1991).

Pakistan's population is also going through a demographic transition, as young population is touching numbers much higher than past due to high birth rate and declining mortality rate. Najam & Bari (2017) observed that 64 percent of the population is below 30 years of age and 29 percent lies between 15 to 29 years' age group. In Pakistan, higher population growth rate leads to higher labour force availability and higher unemployment rate consequently (Hafeez, et al. 2020).

Another reason for the cohort effect on unemployment is excess supply of higher education in the labour market. Though no one can deny the important role higher education plays in the development of a country by enhancing its human capital, promoting innovation, and supporting the transition towards a knowledge-based economy. However, true benefits of higher education manifest only if it is really needed in the labour market or is consistent with technological change, industrial revolution and macroeconomic environment of a country (Haim, 2019). Therefore, when labour markets were not adequately responsive, led to unemployment and low earnings in many countries, a phenomenon known as "Overeducation" (Freeman, 1976; Sicherman, 1991) or "Education Inflation" (Collins, 1979) in literature. In such a scenario younger cohort with higher education face significantly higher unemployment, low earnings and mismatch of education as compared to older cohorts (Wang, et al. 2012; Haim, et al. 2019; Boto-García & Escalonilla, 2022).

In case of Pakistan, a great change was witnessed in higher education when the University Grant Commission was transformed to Higher Education Commission in 2002. As a result, the average growth rate of higher education was increased by 16 percent, whereas the average growth rate of primary education remained just 5 percent during the last two decades. However, weak institutional management, labour markets inability to absorb increased supply, and poor education quality made it difficult to translate these increased years of schooling into improved human capital (Mustafa, 2023). Moreover, due to worsening economic situation, the labour market in Pakistan was unable to absorb the huge number of skillful labour force that Pakistan was producing (see British Council, 2015). As a result, the average unemployment rate in Pakistan remained between 5 percent and 10 percent during 2006 to 2012, whereas the unemployment rate among the tertiary educated individuals became more alarming as it reached about 18 percent in the year 2014 whereas the average unemployment rate of young graduate was 31 percent. Figure 1 depicts the given scenario.

Fig. 1. Unemployment Rate by Education Level from 2001-02 to 2024-25



Source: Author's calculations from various LFS.

Hence, rapid expansion of education along with demographic changes may bring problems instead of opportunities for a developing country like Pakistan. This is because when economic growth is not enough and labour markets are not developed, this expansion could lead to unemployment and lower earnings as many individuals may accept jobs not at par with their educational abilities (Ahsan, 2024).). Therefore, it is imperative to analyse whether individuals are becoming well off overtime or this huge increase in labour force is making matters worse in terms of employment opportunities.

To understand and analyse the complex phenomenon, the Age-Period-Cohort (APC) model provides a nuanced approach in understanding unemployment rates by simultaneously analysing the effects of age, time, and birth cohort. Cohort refers to a group of people who experience certain events such as birth year or entry into a college at the same time. Cohort effects are defined as the formative effects of social events on individuals at a specific period during their life course (Ryder,1965). Therefore, cohort effects are generated by the interaction between individuals' life histories and macro-socioeconomic environment. In Pakistan massive increase in education expansion, especially higher education, may have affected the employment opportunities when large young and educated cohorts entered the labour market.

Age effect represents the social and biological process of aging and is used to measure the impact of age-related characteristics like experience, physical and mental strength, etc. on employment prospects across their life span. Period effects are variations in the time that affect all population in a society regardless of age and cohort (Yang & Land, 2013) and these may reflect in the form of macroeconomic movements, such as secular and cyclical changes in unemployment and inflation rate, etc.

Each of these three time-related factors have conceptually independent pathways to affect individuals' employment prospects and are equally important to measure the true returns to education. Therefore, to understand the long-term changes manifesting unemployment rate, the study has used the APC model to capture the effects of age, period and cohort simultaneously as these are important to analyse the impact on unemployment along with other control variables e.g. gender, education level and region etc. For the analysis the data has been acquired from the Labour Force Survey (LFS) 2001-02 to 2024-25 covering twelve alternative waves.

Rest of the paper is arranged in the following manner. In the next section, we reviewed literature related to cohort effect on employment prospects. Section 3 describes the data and discusses the methodology. Descriptive analysis and empirical results for determinants of unemployment rate through APC Model are presented and discussed in Section 4 and last section concludes the study.

2. LITERATURE REVIEW

Research on the impact of cohort effect on unemployment rate flourished after World War II, especially during period 1950-60, when the baby boom was at its high and the age structure in the USA and Europe was changing dramatically (Perry, et al. 1970).

It has been argued that larger cohorts entering the labour market experience greater competition for jobs, resulting in higher unemployment rates, lower starting wages, and underemployment due to stagnant demand in labour market. Moreover, there exists imperfect substitution between old and younger cohorts since young and old workers do not compete for the same jobs and this elasticity of substitution is low for higher levels of education. This low elasticity of substitution is because people associated with jobs demanding higher levels of education undergo a long training, so the new entrants need considerable time to become close substitutes of these old cohorts (Welch ,1979; Shimer, 2001).

Perry, et al. (1970) predicted that the entry of the baby boomers into the labour market would push up the unemployment rate during the 1970s. Later various studies estimated that there is a direct as well as indirect effect of baby boomers on unemployment rate (Flaim, 1979; Biagi & Lucifora, 2008). Shimer (1998) ascertained that the direct effect of baby boomers resulted in 84 basis point increase in the aggregate unemployment rate from 1954 to 1978 and an 81-basis point decrease from 1978 to 1998. According to neoclassical growth model, a rapid increase in labour force may disturb the capital-labour ratio, increase interest rates and lower wages ultimately lead to unemployment. Moreover, if a perfect substitution does not exist between younger and older workers in the labour market then an increase in the youth labour force may affect both cohorts differently. Shimer (1998) found that such demographic shifts, like the baby boom, significantly influenced overall unemployment trends across time.

Subsequent studies confirmed Welch's findings in different economic contexts. Easterlin (1980) expanded on Welch's theory, showing that countries with large youth cohorts often experience higher unemployment rates due to the inability of labour markets to absorb the excess labour supply. For instance, Korenman & Neumark (2000) found that larger cohorts in the U.S. labour market experienced higher unemployment and slower wage growth. Their estimates show that large cohort size causes youth unemployment rate by elasticities 0.5 to 0.6. While explaining how labour market dynamics work, they added that with flexible wages the entry of the large young cohort results in employment adjusted with lower equilibrium wage rate. On the other hand, if jobs are fixed and wages are rigid, the unemployment rate of youth declines more sharply. In this case unemployment rate of youth rises more sharply as wages cannot adjust to increase labour supply. They suggested the view that wage rigidity intensifies cohort crowding effects on youth unemployment.

Moffat & Roth (2017) found that the negative impact of cohort size on unemployment is stronger for highly educated groups as compared to less educated groups and most of the effect comes in the early years of their career. Moreover, the rapid expansion of higher education has created conditions like those experienced during the baby boom era, with young graduates facing increased competition and skill mismatches. So, the other reason behind the cohort effect regarding graduate unemployment primarily revolves around the idea of over-education or credential inflation in the labour market, as discussed by Freeman (1976) and it got due attention after publication of his book "The Over-Educated American" in 1976. Freeman's research ascertains that excess supply of graduates contributes to unemployment, underemployment, and wage compression for graduates. As when labour market does not grow with the education expansion the young, educated cohort faces more competition and subsequently higher unemployment in comparison to their old cohort counterpart.

Theoretical frameworks highlight that the cohort effect on unemployment among young graduates arises from interactions between demographic transitions, macroeconomic conditions, institutional structures, and individual characteristics. Cohorts entering the labour market during recessions or periods of structural change face significant disadvantages in terms of employment opportunities. Wang, et al. (2012) found that graduate unemployment issue in China has grown rapidly and one of the leading arguments attributes it to the quantitative growth of higher education, which leads to a surplus of knowledge-based workforce in the labour market while job opportunities do not grow at the same pace. This formed distinct cohort effects, which caused fierce competition among college graduates in getting appropriate jobs (Bai, 2006). Similarly, Mok & Jiang (2018) also found that higher education expansion in China has increased rapidly in 2000. As a result, on one side unemployment of young graduates increased, and on the other side they were likely to work in informal sector and face lower economic returns as compared to earlier cohorts. It is suggested that the expansion pace of higher education be slowed down nationwide to limit the quantity of graduates.

Moreover, higher education institutions remain weak in training highly skilled workforce to satisfy the technological advancement in the labour market. As it has been argued that structural problem stems from the call for higher education expansion in terms of quantitative growth without the careful mapping of diverse and changing labour market requirements (Mok & Jiang, 2018; Tam & Jiang, 2015).

In case of Pakistan various studies have been conducted to analyse how demographic and individual characteristics influence the unemployment. Like Khan & Yousaf (2013) found that chance of unemployment of young graduates of public university is high as compared to those who graduate from private university. Females have higher chance to being an unemployment as compared to male. Similarly, various studies found that age is negatively related to the rate of unemployment. Moreover, training can play a significant role in securing job. They also found that married people are less unemployed as compared to single due to acceptance of low paying jobs. Whereas rural people are less unemployed than urban people, that may show that urban areas have less opportunities or overcrowded due to large internal migration on one side, while on the other side, it is possible that in rural area people are involved in informal economy (Qayyum, 2007). However, despite the extensive research on unemployment dynamics, no research has been done that analyse that how cohort effects the unemployment in context of Pakistan's economy. As Pakistan faces a unique demographic transition that is characterised by a large youth bulge population and on the other side higher education expansion after the 2003-04, increases the rapid labour force growth. So, with the persistent structural imbalances and ignoring the cohort-specific labour market experiences may lead to an incomplete understanding of unemployment dynamics.

3. DATA

To analyse the returns to education via APC model, longitudinal and panel data are needed, which provide the information of the same set of individuals or households over time. However, in case of Pakistan these data are outdated, extremely limited and not useful for the analysis under consideration. The alternative is to create pooled cross section APC model using independent but repeated cross sectional data sets. Therefore, our analysis is based on pooled cross section derived from the national level data and acquired by Pakistan Labour Force Survey (LFS). The data are created for the period 2001-02 to 2024-25 comprising twelve annual data sets.

4. METHODOLOGICAL FRAMEWORK

We begin the analysis with pooled cross-sectional data constructed from multiple rounds of the Pakistan Labour Force Surveys (2001-02 to 2024-25). Pooling allows us to combine repeated cross-sections over time to increase the sample size and capture overall variations in individual employment outcomes, while controlling for observable characteristics such as age, education, gender, and region.

Since our dependent variable employment status is binary variable that takes the value “1” for unemployed and “0” for employed therefore the appropriate estimation technique is Logit model. The model is given below.

$$Log\left[\frac{P_{unemployed}}{1-P_{unemployed}}\right] = \beta_j X + U_i \qquad (1)$$

Here $P_{unemployed}$ is the probability of being unemployed, while $P_{unemployed}$ / (1-$P_{unemployed}$) shows the odd ratio of being unemployed and “X” is vector of explanatory variables. Whereas explanatory variables include gender, age, education, vocational training, marital status and geographical region. These are all key determinants for an individual’s risk of unemployment and included in the empirical model to capture heterogeneity in labour-market outcomes. For instance, gender matters because women often face structural barriers to employment (such as discrimination, domestic responsibilities or limited mobility), and empirical evidence from Pakistan shows significantly lower labour force participation and higher unemployment risks for females compared to males (Msigwa & Kipesha, 2013; Isengard, 2003; Rodriguez-Modroño, 2019). Age is important since the labour market outcome tends to follow a life-cycle pattern: younger workers may lack experience and face higher unemployment, while older workers may face obsolescence or health constraints, so age differences help capture those life-cycle risks. It is also maintained that due to lack of experience, weak exposure to working environment and failure to acquire required skills, young people are more vulnerable to unemployment (Tangtipongkul & Wangmo, 2017; Baah-Boateng, 2015; Alawad, 2020).

Education and vocational training enhance human capital, increasing employability, lowering unemployment risks and enabling individuals to adapt to changing job-market demands. However, when education does not match with demand in the labour market it causes unemployment as traditional education system mainly focuses on theoretical knowledge rather than field experience (Rajarshi & Mukherjee, 2013).

Similarly, the limited capacity of formal sectors to absorb the growing number of graduates leads to graduates' unemployment. Rapid expansion of higher education without proportional job creation has created a mismatch between supply and demand in the labour market. In contrast, illiterate or less-educated workers often find employment in informal or unskilled labour markets, where entry barriers are lower and demand for low-skilled labour remains steady (Shabbir, 2019).

To analyse the impact of household burden on unemployment, marital status is taken as an important explanatory variable. Marital status reflects the level of family and domestic responsibilities that can influence an individual's participation in the labour market (Korenman & Neumark, 1991). Geographical region (urban/rural or province) is critical because labour-market opportunities, industrial structure, infrastructure and public policy differ significantly across regions, altering the unemployment risk by location. By incorporating all these determinants, the model better accounts for both individual-level and contextual sources of unemployment variation, thus reducing omitted-variable bias and improving the credibility of the estimates.

This above model provides baseline estimates of the determinants of unemployment across all survey years, without explicitly separating the temporal or generational influences that might be embedded in the data. After establishing these baseline associations through the pooled Logit estimation, we extend the analysis using an Age-Period-Cohort (APC) framework to disentangle the distinct effects of individuals' age (life-cycle stage), survey period (macroeconomic or policy context), and birth cohort (generation-specific characteristics).

Although the APC framework has usually been used for continuous outcomes like earnings (Charni, 2019; Beaudry & Lemieux, 1999), its application to the binary dependent variables using logistic model is both methodologically correct and well supported in the literature (Chauvel & Smits, 2015; Lee, 2019)

The APC model explains the outcome variables through the combined effect of three influences i.e. age period and cohort: This leads to the following equation in which "Unemployed" is the outcome variable

$$Log\left[\frac{P_{unemployed}}{1-P_{unemployed}}\right]= a_0 + \beta\, D_{age} + \gamma\, D_{cohort} + \pi\, D_{period} + \beta_j X + \mu_i \qquad (2)$$

As again we are interested to analyse the determinants of unemployment that is measured through dummy variables so "1" stands for unemployed and "0" for employed. Therefore, in above equation U is unemployment of individual i, D_{age} is vector of age dummies, D_{cohort} is vector of cohort dummies, D_{period} is vector of period dummies, X is vector of control variables as we have taken in pooled model given in Equation (2) and μ_i is error term.

The APC model can detect how an outcome is explained by position in the life cycle age effect (a), time of measurement period effect (p), and date of birth cohort effect (c). That is, each variable is a combination of the other two as given below:

$$a = c + p$$

Above equation shows that there is a linear relationship between age, period and cohort. We can refer to cohort's age with 'a' if we choose to label cohort 'c' with age of the individual in the period p = 0, and here 'p' represents the date.

Since age, period and cohort form a linear combination, we cannot estimate equation "2" through any standard estimation technique. Put differently, it is not possible to identify all the three slope parameters representing age, period and cohort effects. (i.e., there is no uniquely defined vector of coefficient estimates) due to the perfect collinearity between the three variables. This identification problem is well known in literature, and several methods have been developed by researchers to identify and measure the age period and cohort effects separately.

To solve the identification problem different methods have been used in literature (Mason & Fienberg ,1985). Each of the methods has their own advantages and limitations to solving the identification problem. In practice, the appropriate method will be the one that is well-matched with objectives and data.

This study made use of proxy-variable method (Kapteyn, et al. 2005; Browning, et al. 2016). Instead of using year dummies as period indicators, which may lead to perfect multicollinearity, the annual inflation rate is used as a continuous proxy to highlight period effect. This substitution has its theoretical roots in Phillips Curve relationship between inflation and unemployment and is empirically consistent with a large body of literature which uses period dummies instead of time series to achieve identification. This approach helps to measure the age and cohort effect more clearly without arbitrary constraints on the parameter space. Incidents of macroeconomic variable usage as a proxy for the period effect in APC models can be frequently found the labour economics literature. Beaudry & Lemieux (1999) used unemployment rate as a proxy for the period effect in their cohort-based analysis of female labour force participation in Canada, hence addressing the APC identification problem along with capturing the prevailing macroeconomic conditions. Likewise, Charni (2019) took unemployment rate as a proxy variable for the period effect within an APC framework to isolate and analyse the cohort effect on earning patterns of the older workers in France and Great Britain.

Moreover, as Mason & Fienberg (1985) have pointed out, imposing just one constraint on parameters may not fully resolve the identification problem. Hence, we also supplement all the cohort and education dummies with the interaction terms. To analyse how education contributes to employment status across the cohort, we used interaction between cohort groups with educational levels which includes below-secondary, secondary and intermediate, and graduate and above.

Pakistan's labour market was interrupted by three discrete macroeconomic shocks during 2001–2024 which affected employment distinctly from the variation captured by the inflation-based period proxy. These are Global Financial Crisis, China-Pakistan Economic Corridor investment, and COVID-19.

The Global Financial Crisis of 2008-09 transmitted to Pakistan through a contraction in export demand, a sharp decline in workers' remittances, and a tightening of external financing conditions, collectively depressing aggregate labour demand in a manner inconsistent with normal inflationary dynamics (World Bank, 2009; Obstfeld & Rogoff, 2009).

The China-Pakistan Economic Corridor investment boom of 2014-18, by contrast, represented an exogenous positive demand shock driven by large-scale foreign-financed infrastructure expenditure in construction, energy, and transport sectors whose labour intensity is sufficiently high to generate measurable employment gains beyond what prevailing inflation trends would predict (Blanchard & Perotti, 2002; Kumar, et al. 2022).

Finally, the COVID-19 pandemic of 2020–21 induced simultaneous supply and demand contractions through mobility restrictions and the collapse of contact-intensive service-sector activity, producing an unemployment surge qualitatively different from a standard recessionary episode (ILO, 2021).

Since none of these episodes is adequately characterised by changes in the general price level alone, relying exclusively on the inflation proxy risks attributing their employment effects to spurious age or cohort variation. Accordingly, the APC model is augmented with three dummy variables to capture the net contribution of each shock to individual unemployment probability, holding constant the age, cohort, period, and individual-level covariates that form the remainder of the specification. The theoretical rationale for including these dummies rests on the argument demonstrated by Blanchard & Wolfers (2000) that macroeconomic shocks interact with labour market conditions in ways that produce unemployment changes that cannot be attributed to secular trends alone; failing to account for such episodes, risks biasing the estimated period, cohort, and age coefficients by confounding their independent contributions with the effects of these concentrated disruptions. Each shock dummy is therefore treated as an orthogonal shift in the employment probability schedule for the relevant survey period, isolating the net effect of the shock on individual unemployment status after controlling for all other model components. In the light of above discussion, we considered the following augmented APC model.

$$\log U_{it} = \alpha_0 + \sum_{k=2}^{7}\gamma_k C_{ik} + \sum_{j=2}^{4}\theta_{1j} X_{ij} + + \sum_{k=2}^{7}\sum_{j=2}^{4}\gamma_{kj} C_{ik} X_{ij} + \sum_{j=2}^{5}\pi_a A_{ia} + \beta_1 I_t + \lambda_1 \mathrm{GFC}_t + + \lambda_2 CPEC_t + \lambda_3 COVID_t + \lambda_4 M_i + \lambda_5 MAR_i + \lambda_6 VOC_i + \lambda_7 URB_i + \sum_{j=1}^{4}\lambda_8 PRO_{ip} + + \varepsilon_{it} \quad (3)$$

The notations are defined below.

U_{it} = Dummy variable=1 if individual i is unemployed at time t.
C_{ik} = Dummy variable = 1 if the observation of individual i belongs to cohort group k;
X_{ij} = Dummy variable, = 1 if individual i has attained the education level j;
A_i = Dummy variable=1 if individual i belongs to age group a;
I_t = Inflation rate at period t.
GFC_t = Dummy variable =1 for survey waves 2007-08 and 2008-09, capturing global financial crises and 0 otherwise;
$CPEC_t$ = Dummy variable = 1 for survey waves 2014 − 15 through 2018 − 19, capturing the CPEC infrastructure investment boom, and 0 otherwise;
$COVID_t$ = Dummy variable =1 for survey wave 2020 -21, capturing the labour market disruption associated with the COVID-19, and 0 otherwise.
M_i = Dummy variable, = 1 if individual i is male;
MAR_i =Dummy variable = 1 if individual i is married;
VOC_i= Dummy variable = 1 if individual i is attends the vocational training;
URB_i = Dummy variable = 1 if individual i lives in a urban area;
PRO_i =Dummy variable = 1 if individual i belongs to province P;
ε_{it} = Error term;
i = 1, . . ., n;
t = 2001, . . ., 2024

The detailed construction of variables is given in Appendix Table 3.

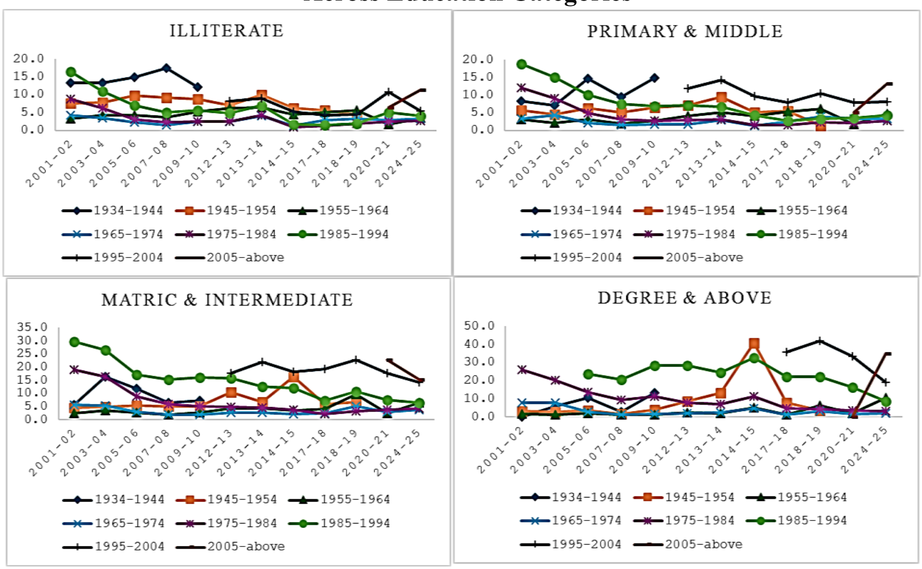
5. DESCRIPTIVE AND EMPIRICAL ANALYSIS

The synthetic cohort diagram, presented in Fig. 2, shows the differences in unemployment between birth cohorts and across periods. Here periods are on horizontal axis, and the y-axis shows unemployment rates (percent) for that cohort during different survey years. Each line represents a particular cohort group. It enables tracking different birth-cohorts (generations) through time as observed under labour force surveys. These diagrams allow to assess how various birth cohorts face unemployment over different periods, and how the unemployment of the various birth cohorts differ in a given period.

Fig. 2 presents the unemployment status for various education levels (illiterate, primary and middle, matric and intermediate, graduate and above) and birth cohorts (1934–44, 1945–54, up to the cohort 2005 and above). First panel of the figure examines the unemployment level for illiterate across various birth-cohorts. The figure reveals that the elderly cohorts, i.e. from 1934-54, show higher unemployment although they are declining after 2009-10. The unemployment patterns have mixed trends for illiterate workers as the highest unemployment rate is observed for the cohort 1985-94, however over time the unemployment rate has declined. From this panel, it seems that unemployment among illiterates has reduced significantly over the periods. This may be due to the lesser number of illiterates in the labour force and increased demand for low-skill jobs in the informal sector.

Panel 2 of Fig. 2. shows fluctuation in unemployment of primary and middle education, however with time their unemployment declines slightly. The two older cohorts spanning over 1934–54 have moderate unemployment, about 5 percent to 10 percent, while the youngest cohorts (cohorts 2005 and above) face the high unemployment in the year 2024-25. However, in case of secondary and intermediate, education slightly improves employment stability when compared with the situation of illiterates and those having basic education. It has been observed that at the beginning of their career all the cohorts face unemployment but with time it decreases significantly.

Fig. 2. Synthetic Cohort Trends of Unemployment Rate Across Education Categories



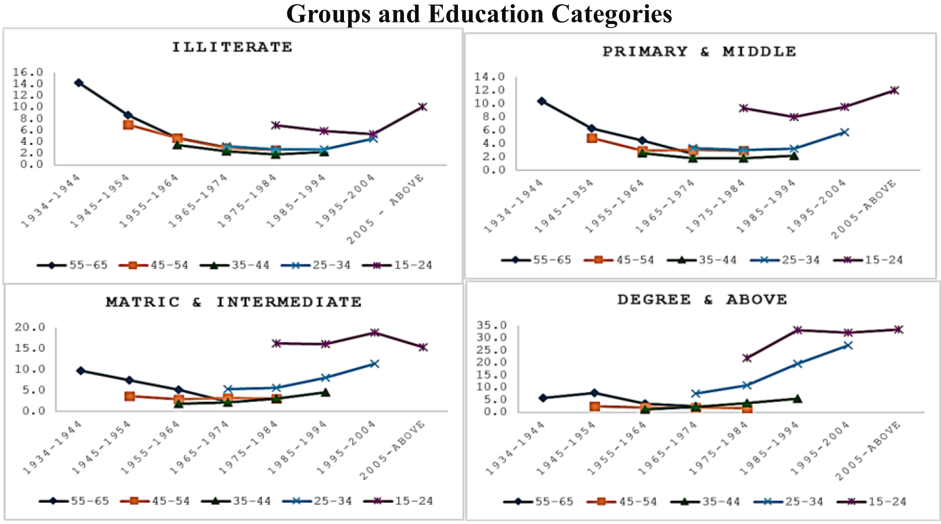
Whereas the highest and most volatile unemployment is observed for Graduate and Above group. The unemployment among 1955–1974 cohorts fluctuate between 15 percent to 30 percent, with a visible spike, reaching about 40 percent in 2014–15 for some groups. The youngest cohorts (2005 and above) show increasing unemployment, rising above 40 percent, during 2024-25. Despite higher education, graduates of younger generations face high unemployment. The other interesting finding is that in 2013-14 to 2014-15 and 2018-19 employment opportunities are depressing for all education groups, and highest for graduate and above level of education.

More education no longer guarantees employment, especially for Graduate and above level of education. It is evidence of a structural transformation lag leading to graduate unemployment crisis indicating education-labour market mismatch, where higher education is expanding faster than high-skill job creation. Labour market reforms and vocational industry linkages are needed to align skills with market needs.

Fig 3 shows the cohort trend in which cohorts are on the horizontal axis and each line represent a particular age group. Here we can compare the unemployment of different cohorts within a given age group by moving horizontally along the corresponding employment opportunities profile. The four panels (illiterate, primary and middle, matric and intermediate and graduate and above) of the figure show mixed trends.

It has been observed that older age groups (45–54 and 55–65) that were born later face low unemployment as compared to earlier cohorts in almost all education categories. Age group 25-34 and 15-24 years, which are younger age groups in our sample, and the cohorts born later of this age group, face higher unemployment than earlier born cohorts in all education categories and the effect is more pronounced for graduates and above. As the unemployment rate is 20 percent for the cohorts who were born between 1975-84 and it reached 35 percent for cohorts born during 2005 or later, both belonging to age group 15-24. Across all education levels, cohort effects are stronger for younger generations than for older ones. Moreover, trend shows that unemployment decreased from 16 percent in 2020-21 to 11 percent in 2024-25, but this decrease has not been reflected for young age group as the young graduates have been facing the highest unemployment as compared to earlier cohorts.

Fig. 3. Cohort Trends of Unemployment Rate within Age Groups and Education Categories



The reason for cohort effect being stronger for graduates and above is the rapid expansion of higher education during the last two decades compared with other levels of education. Hence when graduates enter the labour market, they face more competition and low demand and do not get jobs according to their qualifications and often work as over-educated. Moreover, this excess supply of educated labour resulted in their diversion to low paying jobs, thereby creating unemployment and depressing wages for the less educated workers as well.

5.1. Logistic Model: Determinants of Unemployment Using Pooled Data

The first model examined the unemployment structure in the presence of several features. The estimates based upon the proposed model augmented with control variables are given in Table 1. Column 1 provides the results in terms of marginal effects of Logit model as estimated in equation1. To analyse how various demographic and socio-economic factors impact unemployment status across gender we also disaggregated the unemployment across gender, where column 1 shows the results for male and column 2 is for female.

The first feature used to identify the impact on unemployment is the effect of differences in gender. Being male significantly reduces the likelihood of unemployment, with a marginal effect is 5 percent, implying that males are less likely to be unemployed than females. One of the major reasons is that males are socially expected to work and keenly search for jobs, which may increase their employment opportunity even in low-quality or informal jobs.

The exploration of the effect of education levels on unemployment is studied by taking illiterate as base category. Various educational levels, such as primary and middle, indicate 1.3 percent more chances of being unemployed than illiterate. The category matric and intermediate shows a probability of being unemployed 4.08 percent higher than illiterate. Similarly, the category degree and above shows that individuals with higher education are 5.6 percent more likely to be unemployed compared to illiterate individuals. Hence, all education levels yield greater chances of unemployment than the illiterate group. The impact of education on unemployment is notably differed across gender. The probability of unemployment for females is higher as marginal effects of Degree and above is 13.2 percent for female and 3.9 percent for male compared to illiterate. This may suggest that educated females face more hurdles in getting jobs that are even well matched with their qualifications.

Overall, the results reflect the oversupply of educated workers and a mismatch in labour market skills, particularly for new graduates. It also supports the notion that the impact of demographic transition in Pakistan in the form of youth bulge is causing the oversupply in labour market. Further, the labour force attending vocational training yields 2.1 percent less chance of being unemployed as compared to those having no vocational training.

Examining the age group effect, keeping all other factors constant, indicates that the younger age groups yield less chance of unemployment as compared to oldest age group. Particularly, the age group 15-24, with estimated probability of 1.75 percent and age group 25-34 having 3.5 percent less chance of being unemployed than the individuals from age group 55-60. Similarly, the chance of being unemployed has been further decreasing with age, indicates the negative relationship of age with unemployment, suggesting that older age groups may experience lower unemployment due to enhanced experience. However after 55 years of age the chance of unemployment becomes higher due to low productivity. The result of unemployment across gender are consistent with overall, however the prime working age female faces relatively low probability of unemployment compared to older workers.

While exploring the impact of marital status on unemployment, it is observed that married individuals have a lower likelihood of unemployment i.e. 4.8 percent probability, possibly due to a greater sense of job stability or different labour force participation patterns the result.

Table 1

Determinants of Unemployment Status by Using Pooled Data

Variables	Overall	Male	Female
Male	-0.0524***		
Ref: Female	(0.000586)		
Primary and Middle	0.0136***	0.00424**	0.0550***
	(0.000703)	(0.000698)	(0.00211)
Matric and Intermediate	0.0408***	0.0259***	0.114***
	(0.000695)	(0.000698)	(0.00201)
Degree and Above	0.0569***	0.0394***	0.132***
Ref: Illiterate	(0.000846)	(0.000948)	(0.00208)
Vocational Training	-0.0218***	-0.0174***	-0.0339***
	(0.000780)	(0.000827)	(0.00203)
Age 15-24	-0.0175***	-0.0174***	-0.0521***
	(0.00109)	(0.00121)	(0.00277)
Age 25-34	-0.0354***	-0.0335***	-0.0756***
	(0.00100)	(0.00112)	(0.00260)
Age 35-44	-0.0629***	-0.0512***	-0.122***
	(0.00115)	(0.00125)	(0.00293)
Age 45-54	-0.0409***	-0.0309***	-0.0849***
Ref: Age: 55 and Above	(0.00114)	(0.00122)	(0.00299)
Married	-0.0485***	-0.0582***	-0.0135***
Ref: Unmarried	(0.000752)	(0.000878)	(0.00188)
Urban	0.0170***	0.0122***	0.0291***
Ref: Rural	(0.000526)	(0.000536)	(0.00147)
Punjab	0.00670***	0.0121***	-0.0206***
	(0.000919)	(0.000902)	(0.00290)
Sindh	-0.0113***	-0.0122***	-0.0105***
	(0.00103)	(0.00102)	(0.00319)
KPK	0.0346***	0.0300***	0.0415***
Ref: Balochistan	(0.000989)	(0.000979)	(0.00311)
Observations	848,535	671,202	177,333

Note: Standard errors are given in parentheses. The parameters significant at 10 percent, 5 percent and 1 percent levels of significance one indicated by *, ** and *** respectively.

For examining the impact of geographical structure on the labour force of Pakistan facing unemployment, urban areas of Punjab and KPK regions exhibit different unemployment characteristics. Urban areas yield 1.7 percent higher probability of being unemployed than rural ones, possibly due to a larger, more competitive labour force and lesser opportunities and moreover, it is possible that in rural areas people are mostly engaged in informal sector. The different provinces also show mixed effects, as in Sindh the probability of unemployment is low compared to Balochistan. The labour force from Punjab and KPK, on average, yields minor yet significant and positive likelihood of being unemployed than those from Balochistan. The reason possibly is due to a larger, more competitive labour force.

5.2. Model: Determinants of Unemployment Status Across the Age Period and Cohort

Table 2 provides the marginal effects of Logit model based on the proposed APC model augmented with control variables for overall individuals and across gender. It examines how chances of unemployment vary across different birth-cohorts, age and period with several control variables. The cohort effect shows the differences in the probability of being unemployed for illiterate group. The chances of being unemployed are lower in recent cohorts as compared to older (base) cohorts 1934-44. Comparing the successive cohorts indicate that the individuals born during 1945-54 have about 2.7 percent less chance of being unemployed than those who were born between 1934-44. Similarly, the youngest cohort belonging to the cohort 2005 and above have less chance to being an unemployed by 9.9 percent, 4.5 percent and 28.1 percent for overall, male and female respectively.

This significant decrease in unemployment across the cohorts for the illiterate category may indicate the improved conditions like increased labour-market integration and increased demand for low-skill jobs in the informal sector.

The second feature explored how education affects unemployment, for which various education levels have been taken where illiterate is the base category. Here the category, primary and middle yield slightly lower unemployment chances than illiterate but that is not statistically significant. While the other two higher education categories are showing statistically significant lower unemployment with probabilities i.e. 1.3 percent for matric and intermediate category and 4.9 percent for degree and above category. It is apparent that the attainment of higher education reduces chances of unemployment as compared to illiterate, implying that schooling still offers protection against joblessness. The result of unemployment across the gender shows that males who are graduates have significantly less chance of being unemployed, 2.1 percent as compared to illiterate. However, in case of female the probability that education, in comparison to one being illiterate, improves the chances of being employed is not statistically significant. This may show that after controlling the cohort effect the education helps male to escape unemployment but for educated females, limited employment opportunities and social and cultural constraints, still make it difficult to translate their educational attainments into employment opportunities.

To explore how education affects unemployment across the cohorts, we have taken the interaction of cohort with education level. For primary and middle educated groups: the cohort related to 1945-64 do not significantly face unemployment as compared to the cohort 1934-44. However, the chance of being unemployed for recent cohorts (1975-84) is 2.52 percent more than the base category cohort and is statistically significant and the probability of being unemployed reaches 3.89 percent for cohort 1995-04. However, the corresponding coefficients for males and females are statistically insignificant, showing that the observed relationship is not strong within gender-specific subsamples. The lack of significance may be the result of reduced sample size and lower statistical power in the disaggregated estimations.

The individuals with matric and intermediate education born after 1965 face rising unemployment risk, as the cohorts who belong to 1985–94 are 6.9 percent more likely to be unemployed than those with the same education level but belonging to cohorts 1934-44 and it is highly statistically significant. Furthermore, the recent cohorts have higher probability of being unemployed as unemployment level for matric and intermediate appears to be significantly higher for recent birth cohorts. This might be because the mid-level education has lost labour-market value for younger generations.

The cohort effect for degree and above level of education shows that young cohorts for this educational category have faced more unemployment than their older cohort counterparts. Cohorts from 1965-74 have 5.2 percent more chance of being unemployed than the base category. Similarly, the young graduates, belonging to 1995-04 cohorts are 13.3 percent more likely to be unemployed compared to the older cohort counterpart. This situation highlights a serious graduate unemployment crisis indicating the mismatch between highly educated individuals and the job demand which is quite stale. The youngest cohort belonging to 2005 and above have the chance of being unemployed statistically significant by 12.4 percent, 8.9 percent and 20.4 percent for overall, and for male and female respectively.

Young cohorts, despite having high education levels, are not a ready substitute for older cohorts due to lack of experience. Secondly expansion in higher education was more rapid in Pakistan than other levels of education in the last two decades, whereas the labour market did not develop with the same pace to accommodate this huge surge of educated individuals. Therefore, young cohorts have less opportunities compared to old cohorts in high education levels and female graduates even face more struggle.

Turning to the age group, the young ones in our sample, belonging to the age group 15-24 and 25-34, significantly face high unemployment by a probability of 2.5 percent and 0.5 percent respectively compared to the age group 55-60. While the individuals from the age cohort (35–54) have low chance of unemployment in reference to the base age cohort (55 and above) so the unemployment risk is highest among youth, declines with age, and is lowest for mid-career workers. One of the interesting results we observed is that in pooled estimation given in table 1 all age groups have less chance of being unemployed compared to the oldest age group 55-60 (base category). However, when we disaggregate unemployment into APC model, we observe that the chance of being unemployed is higher for young people and this is also consistent with the descriptive statistics and previous research (Haque & Nayab, 2022; Mansoor, 2024).

Turning to the period effect which has been measured by inflation as a proxy of period, it shows that a one percentage point rise in inflation is reciprocated with a 0.1 percent lesser chance of unemployment. This empirical behavior is consistent with the short run Phillips-Curve trade-off concept.

Accounting for the influence of macroeconomic shocks like Global Financial Crises 2008, it is positive and statistically significant at 1 percent across all three samples. Pakistan's economy was adversely affected through multiple transmission channels during this period: a contraction in export demand, a marked decline in workers' remittances, and a tightening of external financing conditions, all of which compressed aggregate labour demand and elevated unemployment for both males and females relative to the pre-crisis baseline (World Bank, 2009; Obstfeld & Rogoff, 2009). The CPEC dummy enters with a negative and statistically significant coefficient at 1 percent level across all specifications. This result is consistent with the expectation that large-scale public infrastructure investment generates significant direct and indirect employment: CPEC-related activities in construction, energy, and transport expanded labour demand substantially during 2014–18, reducing the probability of unemployment for both males and females. Notably, the magnitude of the effect is considerably larger for women than for men, suggesting that infrastructure-led growth opened employment channels in sectors and localities where female participation had previously been limited (Kumar, et al. 2022). These findings align with Blanchard & Perotti's (2002) theoretical framework, which establishes that positive public investment raises output and employment through multiplier effects on aggregate demand. Finally, the COVID-19 dummy is positive and highly significant at the 1 percent level for all three samples and represents the largest single unemployment shock in the estimation window. The pandemic induced simultaneous supply and demand contractions through lockdowns, disrupted supply chains, and a collapse in contact-intensive service-sector activity, producing a sharp and broad-based rise in unemployment that was particularly severe for females. This outcome is consistent with extensive international evidence on asymmetric labour. The effect of control variables on unemployment is same as we observed in model 1 given under Table 1.

Table 2

Determinants of Unemployment Status Across the Age Period and Cohort

Variables	Overall	Male	Female
Cohort_1945-54	-0.0273***	-0.0161***	-0.0733***
	(0.00252)	(0.00301)	(0.00598)
Cohort_1955-64	-0.0607***	-0.0370***	-0.148***
	(0.00259)	(0.00303)	(0.00640)
Cohort 1965-74	-0.0871***	-0.0467***	-0.216***
	(0.00282)	(0.00324)	(0.00700)
Cohort 1975-84	-0.103***	-0.0618***	-0.244***
	(0.00302)	(0.00347)	(0.00744)
Cohort 1985_94	-0.106***	-0.0625***	-0.249***
	(0.00307)	(0.00347)	(0.00769)
Cohort_1995-04	-0.112***	-0.0622***	-0.271***
	(0.00325)	(0.00363)	(0.00829)
Cohort_2005 & Above	-0.0988***	-0.0446***	-0.281***
	(0.00386)	(0.00409)	(0.0113)
Primary & Middle	-0.00763	0.00632	0.0645*
	(0.00544)	(0.00520)	(0.0342)
Matric & Intermediate	-0.0130*	0.00273	0.0588
	(0.00749)	(0.00690)	(0.0575)
Degree & Above	-0.0489***	-0.0281**	-0.0578
	(0.0146)	(0.0141)	(0.0543)
Primary_& Middle Cohort_1945-54	0.00225	-0.00497	-0.0130
	(0.00614)	(0.00593)	(0.0359)
Primary & Middle Cohort_1955-64	0.00639	-0.00634	-0.0317
	(0.00591)	(0.00570)	(0.0351)
Primary & Middle cohort 1965-74	0.0166***	-0.00662	-0.0129
	(0.00585)	(0.00566)	(0.0348)
Primary & Middle Cohort 1975-84	0.0252***	0.00230	0.00216
	(0.00568)	(0.00550)	(0.0345)
Primary & Middle Cohort 1985-94	0.0284***	0.00268	0.00102
	(0.00558)	(0.00535)	(0.0344)
Primary_& Middle_Cohort_1995-04	0.0389***	0.00575	0.0199
	(0.00563)	(0.00539)	(0.0345)
Primary_& Middle Cohort 2005 & Above	0.0215***	-0.00727	-0.0469
	(0.00636)	(0.00602)	(0.0370)
Matric &Intermediate Cohort 1945-54	0.00765	0.00125	-0.0256
	(0.00821)	(0.00761)	(0.0598)
Matric_& Intermediate Cohort 1955-64	0.00579	-0.00384	-0.0838
	(0.00797)	(0.00738)	(0.0587)
Matric &_Intermediate Cohort 1965-74	0.0259***	-0.000423	0.00460
	(0.00782)	(0.00728)	(0.0578)
Matric & Intermediate Cohort 1975-84	0.0560***	0.0274***	0.0515
	(0.00764)	(0.00710)	(0.0576)
Matric & Intermediate Cohort 1985-94	0.0696***	0.0348***	0.0742
	(0.00759)	(0.00701)	(0.0576)
Matric & Intermediate Cohort 1995-04	0.0777***	0.0352***	0.0953*
	(0.00762)	(0.00704)	(0.0576)

Matric & Intermediate Cohort 2005 &Above	0.0358***	0.00137	0.0385
	(0.00828)	(0.00768)	(0.0587)
Degree & AboveCohort1945-54	0.0370**	0.0338**	-0.0243
	(0.0153)	(0.0147)	(0.0584)
Degree & Above Cohort 1955-64	0.0202	0.0107	0.000850
	(0.0152)	(0.0147)	(0.0563)
Degree & Above Cohort 1965-74	0.0524***	0.0247*	0.0840
	(0.0149)	(0.0144)	(0.0548)
Degree & Above Cohort 1975-84	0.101***	0.0697***	0.160***
	(0.0147)	(0.0142)	(0.0545)
Degree & Above Cohort1985-94	0.138***	0.0922***	0.234***
	(0.0147)	(0.0142)	(0.0544)
Degree &Above Cohort1995 -04	0.133***	0.0860***	0.244***
	(0.0147)	(0.0142)	(0.0545)
Degree & Above Cohort 2005 & Above	0.124***	0.0899***	0.204***
	(0.0194)	(0.0191)	(0.0637)
Age 15-24	0.0255***	0.00464**	0.0830***
	(0.00207)	(0.00221)	(0.00544)
Age 25-34	0.00550***	-0.0128***	0.0548***
	(0.00190)	(0.00203)	(0.00504)
Age 35-44	-0.0189***	-0.0273***	0.00775*
	(0.00173)	(0.00184)	(0.00458)
Age 45-54	-0.0094***	-0.0124***	0.00352
	(0.00137)	(0.00144)	(0.00371)
Inflation rate	-0.0014***	-0.0021***	0.00191***
	(0.000142)	(0.000148)	(0.000392)
Global Financial Crises	0.00353***	0.00877***	0.0173***
	(0.00105)	(0.00110)	(0.00281)
CPEC-Shock	-0.0074***	-0.0041***	-0.0167***
	(0.000763)	(0.000806)	(0.00201)
COVID-19 Shock	0.00649***	0.0171***	0.0362***
	(0.000952)	(0.000990)	(0.00265)
Male	-0.0504***		
	(0.000584)		
Attending Vocational training	-0.0204***	-0.0174***	-0.0273***
	(0.000783)	(0.000831)	(0.00202)
Married	-0.0457***	-0.0568***	-0.00831***
	(0.000752)	(0.000875)	(0.00189)
Urban	0.0178***	0.0130***	0.0331***
	(0.000568)	(0.000574)	(0.00163)
Punjab	0.00564***	0.0118***	-0.0269***
	(0.000914)	(0.000899)	(0.00285)
Sindh	-0.0103***	-0.0116***	-0.00913***
	(0.00102)	(0.00102)	(0.00314)
KPK	0.0325***	0.0287***	0.0348***
	(0.000983)	(0.000976)	(0.00306)
Observations	848,535	671,202	177,333

Note: Standard errors are given in parentheses. The parameters significant at 10 percent, 5 percent and 1 percent levels of significance one indicated by *, ** and *** respectively.

6. CONCLUSION

This study tried to evaluate the determinants of unemployment through APC model, which is a more appropriate instrument for analysing employment status over a long period of time. To accomplish the task comprehensive and national level data of LFS collected for period 2001-02 to 2024-25 for Pakistan was used.

Results of pooled model 1 show that individuals with higher education are more likely to be unemployed compared to illiterate individuals. This may reflect the over-supply of educated workers and a mismatch of their skills in the labour market, particularly for graduates. Whereas the results of APC model show that although higher education helps to escape from unemployment on one hand, as education increases skills and productivity, making individuals more attractive to employers however when disaggregated into cohorts, it shows that young, educated cohorts are more vulnerable to unemployment when compared to older cohorts and the effect is more pronounced in the tertiary education.

This continuous increase in unemployment rate among the tertiary educated individuals in the past decade relates to the findings of the British Council (2015) which show a significant gap between supply and demand of the educated individuals in the labour market. Further a weak industry-university linkage means that graduates being produced are not what is being demanded by industries. Finally, the shrinking state of economy and macroeconomic imbalances are some of the attributes responsible for high unemployment rate of graduates for Pakistan economy.

From policy point of view great emphasis needs to be put on developing countries' labour markets so it can easily accommodate the increasing labour force, especially those with high levels of education. This will not only help to reduce unemployment but will also help individuals in getting earnings as per their educational credentials and capabilities.

Finally, government needs to focus on the development of small cities both in terms of quality education and to have decent job opportunities to reduce income disparities with big cities. This will also help governments in reducing massive flow of young population from small to big cities thus helping to manage the issue of urbanisation as well.

APPENDIX

Table 3: Variables Construction

Variables	Description
U_{it} (Unemployed)	Employment status of individual i. Here employment status is binary variable that takes the value "1" for unemployed and "0" for employed for individual i in period t.
C_{ik}(Cohort)	Cohort is defined as the year of birth of individual i, the cohort will be taken as dummy variable by grouping ten-year birth cohorts. The cohort who lies in that group is assigned value 1 and 0 otherwise. The group of cohorts starts form 1934-44 and ends 2005 and above.
X_{ij} (Education Level)	A set of dummy variables that represents the highest level of education that the individual i has attained. = 1 if the education level of individual i is Below Secondary, that is greater than 4 but less than 9 years of schooling, = 0 otherwise. = 1 if the education level of individual i is Secondary or Intermediate, that is equal to or greater than 9 but less than 14 years of education, = 0 otherwise. = 1 if the education level of individual i is Graduate and Above, that is equal to or greater than 14 years of education, = 0 otherwise. The illiterate group is taken as the reference category.
A_i (Age)	Age is taken from 15 to 65 as International Labour Organisation (ILO) has defined 15 as the legal minimum working age, while retirement typically occurs between 60 and 65 years of age. The age group will be taken as dummy variable by grouping 10-year age. The individual who lies in this age assigns the value "1" and "0" otherwise.
I_j(Inflation)	Inflation rate at period t.
M_i (Male)	A dummy variable that takes value one if individual is a male and zero otherwise.
MAR_i (Married)	A dummy variable that takes values one if the individual is a married, and zero otherwise.
VOC_i(Vocational training)	A dummy variable that takes the value equal to one if individual attends the training and zero otherwise.
URB_i(Urban)	A dummy variable that takes the value equal to one if the individual belongs to urban area, and zero otherwise
PRO_i(Province)	A dummy variable that takes the value equal to one if the individual belongs to that province and zero otherwise GFC(Global Financial Crisis)A binary dummy variable equal to 1 for survey waves 2007–08 and 2008–09, corresponding to the period of the Global Financial Crisis, and 0 otherwise. The GFC transmitted to Pakistan through trade contraction, a decline in workers' remittances, and tightened external financing conditions, producing a negative aggregate demand shock with adverse effects on employment (World Bank, 2009; Obstfeld & Rogoff, 2009).
CPEC (China–Pakistan Economic Corridor Boom)	=A binary dummy variable equal to 1 for survey waves 2014–15 through 2018–19, corresponding to the peak CPEC construction and investment period, and 0 otherwise. CPEC-linked infrastructure, energy, and transport projects generated substantial direct and indirect employment, constituting a positive labour demand shock that is theoretically distinct from the secular period trend captured by the inflation proxy (Blanchard and Perotti, 2002; Kumar, et al. 2022).

COVID-19 Shock	A binary dummy variable equal to 1 for the survey wave 2020–21, capturing the labour market disruption associated with the COVID-19 pandemic, and 0 otherwise. The pandemic induced simultaneous supply and demand contractions through mobility restrictions, business closures, and the collapse of contact-intensive sectors, producing a sharp and broad-based rise in unemployment (ILO, 2021).

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