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Skill bias in the labour market: Evidence from Iran

Mehdi Mohebi[1*], Akbar Komijani[2]

[1]Research Responsible, Training and Knowledge Development Department, Central Bank of Iran, Iran
[2]Faculty of Economics, University of Tehran, Tehran, Iran
*Corresponding author: meh_moh20@yahoo.com

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Author's email:
komijani@ut.ac.ir

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Abstract

Purpose — Most global economies are dealing with the issue of skill bias. In developing and underdeveloped countries, skill bias poses a problem by preventing the educated from participating in the economy's production function, especially in the long run. This paper expands on the skill-wage relationship and examines it in the case of Iran from 1981 to 2021.

Methods — The application of impulse response analysis from the VECM and Structural VAR models separates the relationship between skill and wages into short-run and long-run effects. The structural wage model was estimated using a structural vector autoregression.

Findings — The results show that skill played a significant role in wage determination for only three periods in the short run, and its effect was neutral in the long run. This means that skill accumulation through advancement in graduate and postgraduate study is unlikely to increase wages in the long run.

Implication — According to the findings, skill bias implies that educational attainment in the Iranian labour market can only improve wages to a minimum extent. This also proves that factors other than education determine wage growth in the economy.

Originality — The skill-wage relationship has not been a focus of studies in the field of education outcomes. Moreover, in the case of Iran, this investigation is novel, and there is a lack of studies on the relationship between compensation and skill.

Keywords — Skill bias, long-run wage model, human capital, bargaining

Introduction

The basic concept of wage-skill determination is captured by the Mincerian earnings function, which establishes a relationship between wages and skills. Jacob Mincer captures this concept in his 1974 study, which provided a strong background for many human capital studies. However, these investigations lack a focus on the assumption of stable effects of skill on wages, which is mostly supported by linear regression estimates of the Mincerian wage equation. Recently, it has been observed that although the number of university-educated individuals is increasing globally, this increase has failed to explain wage variations and has diminished their role in wage bargaining. This problem reflects the skill bias, characterized by high levels of human capital in a society with little power to set the equilibrium nominal wage. This study primarily focuses on the co-integration analysis of wages and the number of skilled workers in both the short- and long-run. It considers the case of Iran to conduct the co-integration analysis and determine how wages respond to

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variations in the number of university-educated workers. Given that the time series is I(1), the study provides sufficient evidence of co-movement between wages and skills of these workers. Although Lazear and Oyer (2007) discussed various types of wage compensation, including non-wage compensation, workers in Iran are mainly compensated through wages. Hence, this study uses wage as a proxy for compensation. Subsequently, the study constructs a long-run relationship between wages and skills. It concludes that skills can determine wages for 2 to 3 periods in the short run and, in longer horizons, the actual wage-skill curve lies below the potential curve. This finding implies that, at the same level of wages, the share of skilled workers in production in actual data is lower than the potential share. This pattern suggests the possibility of skill neutrality, which can lead to the underutilization of resources and the recruitment of low-productivity workers. Therefore, this will diminish the cost of damping skilled labour. According to Klenow and Blis (2000) and Tassaeva (2021), this will hamper economic growth and lead to a lack of equality in technological developments. This issue will then create negative externalities by increasing the social misbehavior of the unemployed. Concerning the long-run wage-skill relationships above, the study uses the vector error correction model (VECM) to solve the actual co-movement equation and estimate skill (which represents the number of workers with a university degree (Cunha et al., 2010; Hutter & Weber, 2021, 2022). The coefficient of skill in the wage model is 2.07, which is approximately equal to the coefficient in the structural vector auto-regression (SVAR) estimated in the subsequent section. To stabilize and filter the model, while accounting for unrelated shocks that prevent the accurate estimation of the coefficient of skill, the study incorporates the exogenous non-accelerating inflation rate of unemployment (NAIRU), estimated using a state-space model solved by the Kalman Filter (Kalman, 2006).

Many studies are dedicated to labour performance and compensation in world economies. Hendricks (2002) found that, in the case of Iran, human capital explains only 31 per cent of the wage difference between Iran and the US. Barro and Lee (2001) conducted a similar investigation for countries with lower revenue than the US. They concluded that higher skill, as measured by educational attainment, reduces earnings per worker by 20 percent in the wealthiest countries and by 40 percent in the poorest.

The primary goal of this study is to examine structural macroeconomic models based on microdata, rooted in the work of Becker (1964), Mincer (1974), Rosen (1976), Jones (2014), and Mankiw et al. (1992). The study highlights that, during the first decade of this century, firms did not adjust their wage structures in response to the accumulation of human capital. As a result, wages were determined by skills only for two to three periods in the short run, implying skill neutrality in the long run. The current study bridges the literature gap by applying the SVAR as a macro-econometric estimation method. The paper employs a specific identification procedure by imposing restrictions consistent with the observed behavior of wages, skills, and NAIRU. Following identification restrictions similar to those proposed by Blanchard and Perotti (2002) and Sims (1999), the model becomes fully identifiable and shows that a 1% increase in NAIRU reduces wages by approximately 10% in Iran.

The study solves the model and finds that the effects of skill shocks on wages last only for two to three periods in the short run. In the long run, skill accumulation, even after seven periods, leads to a decline in wages in the economy. Consequently, wage determination will not take effect from the demography of university-educated workers; therefore, skill is neutral in wage bargaining. This finding from the country case further reinforces the initial analysis of skill-biased labor markets. It suggests that although university attendance is rising in most countries, the share of educated workers may not significantly influence wage determination in the long run.

Methods

By running a unit root test, the study examined whether the model's variables are integrated. All data used in the VECM and structural models, including wages, equilibrium unemployment rates, and educated labour were found to be I(1). This implies that the data follow a light-tailed random walk. Hence, imposing a structural shock in SVAR will decay in the impulse-response function, which is essential to analyzing structural shocks to wages. These tend to be more short-run than long-run skill effects. Figures 1, 2, and 3 show each variable over time to assess the possibility of changes in the same direction.

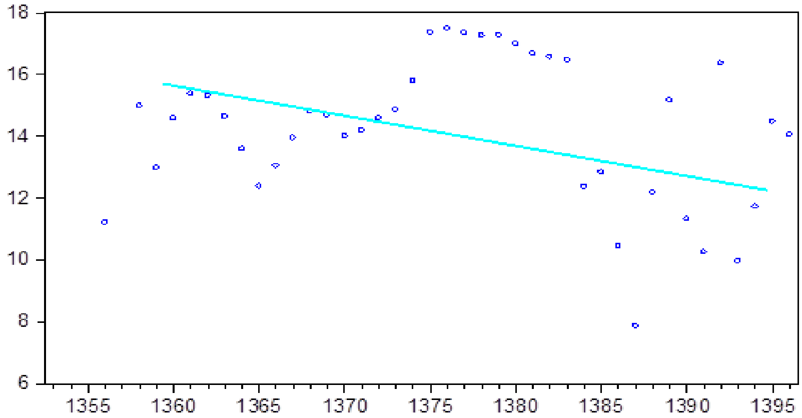

Figure 1. Unemployment in the Equilibrium Rate by Removing Inflationary Pressures

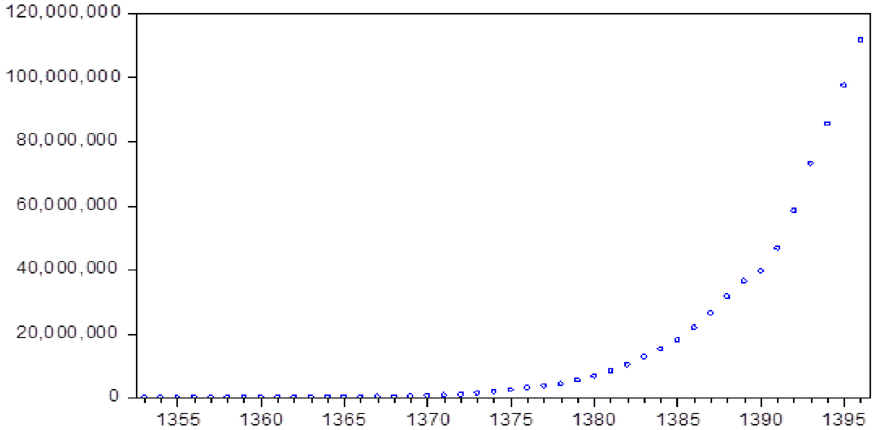

Figure 2. The Average Yearly Wage of All Agents in the Economy, According to Microdata of the National Census

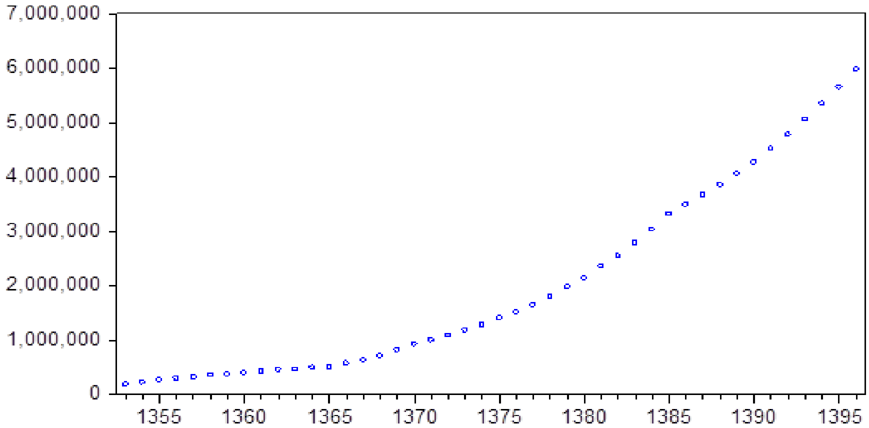

Figure 3. Number of Skilled Workers for the Whole Nation According to Microdata of Sample Firms on Census Data

Annual data analysis reveals paths for wages and skills that are partially similar; however, unemployment fluctuates around a point and exhibits a downward-sloping trend identical to the linear pattern in scatter plots. The co-integration of wage with skill versus unemployment will produce two strong co-integrating patterns in the data, which tend to decay to a level just as I(0). The weakening of these co-movements can also be triggered by exogenous stimuli, such as changes in working and job-matching arrangements, driven by changes in the economy's skilled labour stock. Jones (2014) highlighted the limitations of standard human capital accounting by applying marginal productivity analysis in a cross-country regression framework, focusing on cross-national variation in human capital. In practice, since the variation of human capital is modest, it appears to contribute negligibly to significant income variations. This study decomposes educated working labour into two parts, based on the significance of the short- and long-run in the structural wage model, constructed and solved using econometric tools. In the long run, the findings suggest that wages tend to be skill-neutral. This outcome reflects inefficiencies in the hiring process and labour-matching mechanisms, which are often hindered by weak institutional frameworks in developing countries.

Furthermore, the prevalence of a low-skilled workforce limits the potential contribution of the educated population. As of 2016, only 18/7 percent of high school graduates attained a bachelor's or higher university degree. This implies that any co-movement between wages and skills is not sustained in the long run and will decay in level.

Figures 2 and 3 illustrate changes in wages associated with a specific characteristic of each year: the proportion of workers who attended school for 2 or more years. This may reflect a labour-market bias, of which years of schooling are associated with short-term wage changes. In contrast, the impact of university education on wages appears unstable over the same period. Hendricks (2002) explained that human capital accounted for only 31 per cent of the wage difference in the US, as measured by the ratio of wages to the US wage. The coefficients for other countries are as follows: Iraq: 32.3; Venezuela: 47.4; Turkey: 23.5; and Thailand: 18.4. The coefficients for higher-income countries include Austria 72.6, Belgium 86.3, and France 82.6. Barro and Lee (2000) investigated the same condition for all source countries and found that educational attainment in countries' global data is lower than that in the US. This effect reduces earnings per worker by 20 percent for the wealthiest countries and by 40 percent for the poorest countries. The study investigated skill neutrality using Iran's microdata. It decomposed the time horizon into short- and long-run structural models, accounting for Iran's unique economic features, and ran an SVAR to estimate them. Subsequently, this study regresses wages on years of schooling. The model explains a substantial share of wage variation, with the schooling coefficient statistically significant at the 1% level and an adjusted R-squared of 99.3%. This further supports the assumption that other factors may undermine the impact of skills, rendering wages skill-neutral in the long run. The study investigates whether wages remain unresponsive to skill when short- and long-run co-movements are disentangled, thereby assessing the empirical validity of skill neutrality in the labour market. It used the features of two macro-econometric tools—VECM and restricted SVAR—to distinguish between the long and short horizons and probe whether the long-term bias is due to the economy's structure.

Model Specification

Generalization of the wage and skill relationship

Co-integration based on the VECM model needs to be specified to investigate wage and human capital co-movements. Herrendorf and Schoellman (2018), Hutter and Weber (2021), and Klenow and Blais (2000) assumed that the logarithm of average years of schooling indicates skill affecting the logarithm of wage in Equation 1. To upgrade the indicator and make it suitable for the current job market and the production functions of firms with advanced technology, I used the number of workers with a specified contract period and university degrees as measures of their skill levels.

$$\mathrm{Log(Wage)} = \alpha \mathrm{Log(schooling)} + \varepsilon \tag{1}$$

Equation 1 implies that when an economy is at equilibrium, there is a balance between demand and supply. Additionally, the equation states that the returns to human capital from an additional year of education are equal to the rate of change of the logarithm of schooling, also known as wage returns (Mincer returns). The pace of technological advancements and the complexity of production processes require us to consider precise variables as proxies for human capital. According to Holmstrom (2017), the number of university-educated workers reflects the productive labour supplied by each individual, who is compensated through wages. Consequently, the co-movement between wages and worker performance is modeled through a generic principal-agent framework.

Examining the long-run relationship between wages and human capital is essential. Firms may be reluctant to alter production processes, increase the hiring of educated workers, or respond flexibly to economic shocks affecting wages, human capital, and unemployment. The wage and skill relationship can be inferred by the co-integration coefficient of wage and human capital being I(1). This implies that the long-run relationship between fluctuations in human capital and wages is neutral. Error correction can be achieved in two ways by assuming a linear long-run relationship. In the first method, error correction can be achieved by adjusting human capital. (Figure 4).

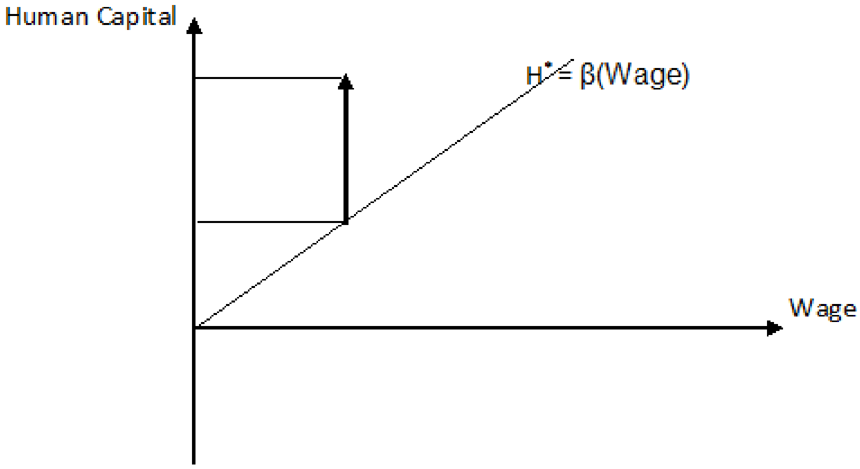

Figure 4. Long-run Relationship of Human Capital, Wage, and NAIRU by the Suppression of Inflationary

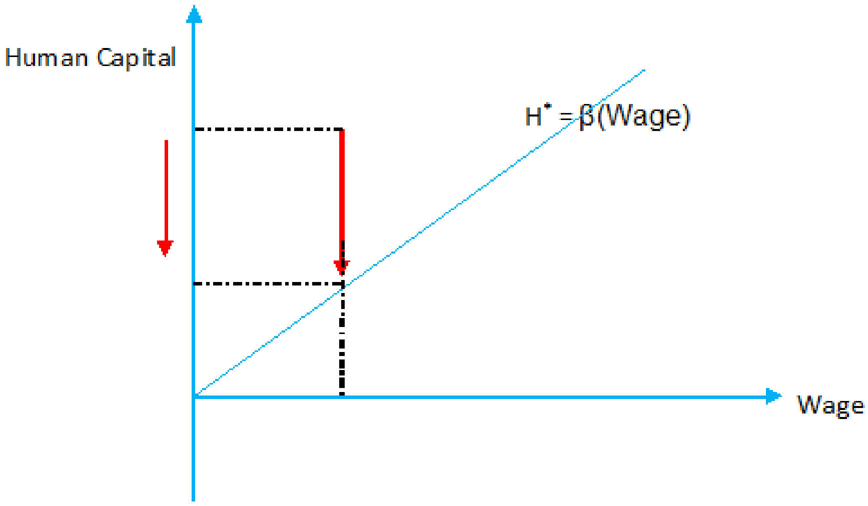

Figure 5. Convergence through Human Capital (by the Assumption of a Stabilizing Long-Run Unemployment Rate (NAIRU))

As shown in Figure 5, a hike in the number of educated workers creates a proportional gap. Assuming all points on the long-run line follow, it verifies the relationship H* = β(Wage). There is a long-run steady-state phase, and any deviation from this state will generate a gap. The dynamics of this co-movement require it to be placed at a point on the line. Similar results are obtained with the co-moving equation approach. These findings align with those of Jones (2014) and the Organisation for Economic Co-operation and Development (OECD), which also demonstrate a stable, steep linear relationship. Skill bias, reflected in the slope of the line, implies that lower wage variation in response to a one-percent shock to skilled labour mainly determines the structure of the economy.

Consequently, if the change in the gap follows a linear adjustment toward the long-run relationship, deviations from the steady state will gradually be corrected. Human capital, measured by the number of educated workers, will then decline when a positive error from the steady state arises. In such a case, α_h(error correction coefficient) should be below zero for the procedure not to diverge. Thus, the positive shock of an initial increase in educated workers would not last more than three periods. Therefore, the number of workers attaining a university degree will converge at initial wage levels.

$$H_t = \alpha_h(H_{t-1} - H^*_{t-1})\Delta \tag{2}$$

In the second method, adjustment takes place through wages. Assuming that H_t is fixed, both wages and H_t^*—the potential capacity of the economy determined by the long-run stock of human capital—adjust indirectly toward their equilibrium ratio. Another assumption is that wage changes follow a linear function of the extent of divergence from the potential path, with $\alpha_w > 0$, ensuring that H_t converges to the economy's long-run potential.

$$W_t = \alpha_w(H_{t-1} - H_{t-1}^*)\Delta \tag{3}$$

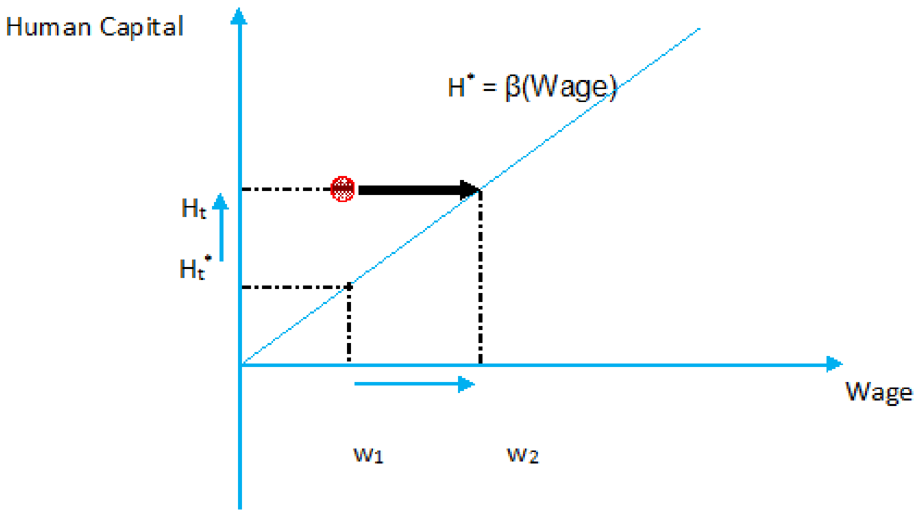

Figure 6. Convergence Through Wages to Long-run Skill/Wage Potential Levels

As shown in Figure 6, wages move from W1 to W2 after divergence from the linear path. Therefore, there is a movement from the subsequent increase in the number of educated workers in the workplace (H_t) to the potential long-run value of the number of educated workers (H*). The fundamental intuition behind the above graphs is that, despite a new shock and an increased number of educated workers, the ratio of wages to the number of educated workers remains constant across various wage levels. Thus, human capital would not affect wages, and consequently, educated workers would not influence wage determination. This study refers to this effect as skill gap bias in the labour market.

The third method achieves error correction through two cointegration relationships specified in Equation (4). These relationships, imposed by the structure of the labor market, guide the economy toward its potential path.

$$H_t = \alpha_h(H_{t-1} - H_{t-1}^*) \qquad \alpha_h < 0\Delta$$
$$W_t = \alpha_w(H_{t-1} - H_{t-1}^*) \qquad \alpha_w > 0\ \Delta \tag{4}$$

The magnitudes of the coefficients explain the pace at which wages and human capital will adjust in the long run (Figure 7).

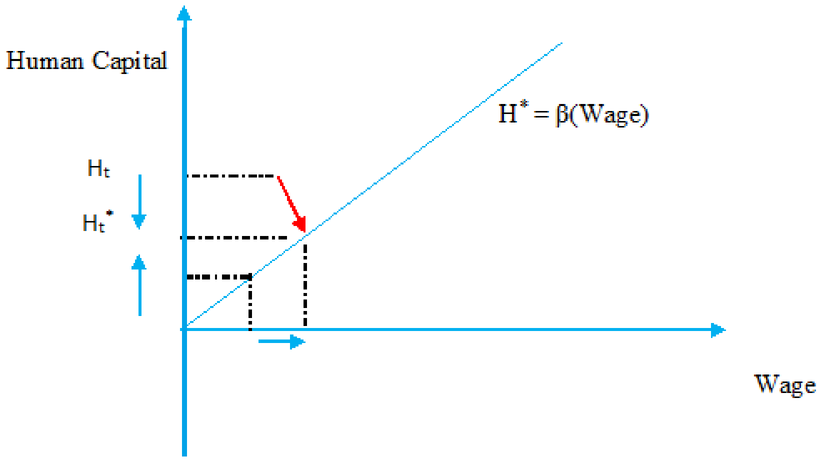

Figure 7. Convergence Achieved Through both Human Capital Wages to Long-run Skill/Wage Potential Levels

Assuming that job search behaviour is homogeneous and remains constant across the labour force at a given wage level, it follows that β can be treated as a constant, irrespective of differences in workers' abilities. The assumption is made in the procedures explained above. Conversely, suppose that structural inadequacies in the economy make the job search process more complex. Under such conditions, the probability of a worker's success depends on the extent of participation in complex job search procedures. As a result, the success of a worker with an average level of human capital is directly influenced by expectations about the labor market (Equation 5).

$$\text{Prob(Search Participation)} = e^{\delta w}\zeta \tag{5}$$

In the above probability function, the parameter e represents the expected compensation for the labour force, and δ specifies the worker's expectations regarding the complexity of a job search. If δ is perceived to be greater than or equal to 1 (δ>1), then the worker would expect the job search in a closed labour market to be complicated and costly. On the other hand, δ<1 reflects a partial improvement in the business environment, with the temporary elimination of international sanctions. This facilitates the job search process for workers. W denotes the general levels of nominal wages that positively correlate with the probability of being involved in a job search, and ζ is a deterministic indicator of the current situation of the labour market. As expected, the increased involvement of a worker in search attempts leads to a decline in the rate of increase in δ, making the long-run steady state vertical. Thus, the probability of labour participation multiplied by the labour force gives the number of workers that attained university degrees in the entire labour force. A β reflects the probability of the job search; hence,

$$\beta = e^{\delta w}\zeta \tag{6}$$

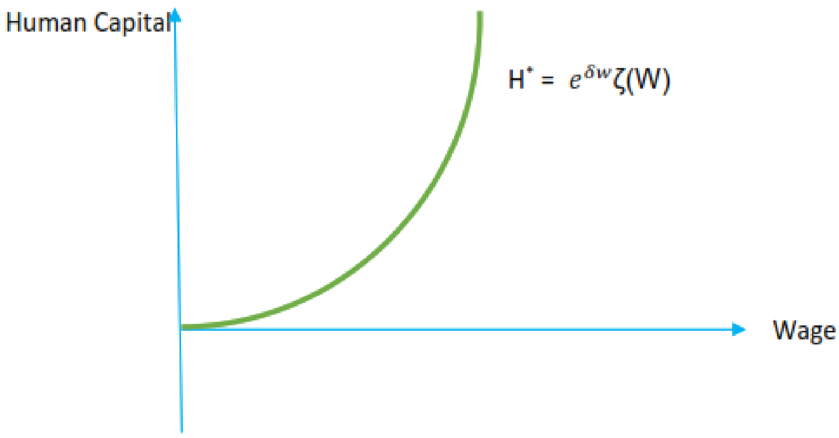

Figure 8. Dynamic Long-run Relationship with Search Probability

Considering workers' innate skills, Herrendorf and Schoellman (2018) show that workers are endowed with one unit of unskilled labour that requires no education and can be supplied to the market immediately. Alternatively, individuals may become skilled by acquiring human capital, characterized by a high amount of abstract knowledge that facilitates innovation and the development of new ideas. This is reflected in the intercept of the curve, denoted by β as the capital-wage long-run relationship rate (Figure 8).

General Structural Model of Wage

Assuming human capital is the production agent, the recruitment decisions of firms will be based on the expected function of these agents. For better analysis, assume that production is labour-intensive, and therefore, in the wage model, we can consider the complete substitution of both human and physical capital as follows:

$$Log(\text{wage}) = \alpha Log(\text{Equilibrium Job Demand}) + \beta \iint \left(\frac{\text{Physical Capital}}{\alpha}\right)\left(\frac{\text{Human Capital}}{\beta}\right) \text{dpdh} + \Omega_t \quad (7)$$

Human capital tends to accumulate over time, so we used the double integration index as the capital part of our formula. In the above equation, *dpdh* is the first difference between physical and human capital. To mitigate the cost effects of job search and promote homogeneity in job demand, inflation is excluded from the expectations that influence workers' job search strategies. Inflation is calculated according to the Phillips Curve.

$$\text{Log(Equilibrium Job demand)} = \text{Log}\left(\frac{Gross\ Job\ Demand}{net\ inflation}\right) \quad (8)$$

such that,

Equilibrium Job Demand = (Equilibrium Job Demand Rate) (Labour Force);
Gross Job Demand = (Labour Force) (Unemployment Rate)

Substituting Equation 8 by its components gives:

$$\text{Log}\left(\frac{\text{(Labour Force)(Unemployment Rate)}}{\text{Inflation}}\right) = \text{Log}\big(\text{(Equilibrium Job demand Rate)(Labour Force)}\big) \quad (9)$$

Eliminating the Labour Force factor from both sides will give the form $\log\left(\frac{\text{(Unemployment Rate)}}{\text{Net inflation}}\right)$.
On the right-hand side, this shows the unemployment rate filtered by the effects of inflation. It is also known as NAIRU, or the equilibrium job demand rate.

The total capital in the production process by a firm in the second part of Equation 7, based on the assumption of the Leontief-type production process, can be substituted by human capital because technology growth requires workers of a higher quality. The wage-determining equation for the equilibrium unemployment will eventually take the following form:

$$\text{Log(wage)} = \alpha \text{log(Equilibrium Job Demand)} + \beta \log\left(\int_{t=12}^{t=18} \text{Human Capital}\right) dH + \Omega_t \quad (10)$$

where t is the number of years of university attendance (between 12 and 18 years) of a sample worker. It takes 12 years to complete pre-college education in Iran. As the summation implies, human capital accumulation is similar to that of Manuelli and Seshadri (2014). They assume that technological accumulation is constant during schooling, which will positively affect average wages.

Procedure for Estimating the Structural Wage-Human Capital Model for Iran

The SVAR is the most beneficial macroeconometric tool proposed by Christopher Sims and applied to aggregated microdata. To understand the effects of skill on wages, we use the intuition that an increase in workers' skills leads to better job placement and puts them in a stronger position in negotiations with firms, thereby leading to higher wages through matching procedures. To estimate the effects of variations in skilled labour on wages, it is necessary to identify and isolate purely exogenous and independent shocks to the variable of interest. The response of wages to these shocks can then be examined. The reaction is reflected in the impulse responses. To identify skill shocks, we need to identify the structural model. The structural model facilitates the isolation of purely structural shocks and responds to exogenous variables after the economy is affected by them. Getting the structural model means determining the proper identification for our models. Identification is the interpretation of historical variation in data that enables prediction of the consequences of an action not yet undertaken. Hence, the main challenge is to identify pure shocks. Suppose the structural model follows the following form;

$$AX_t = \beta_0 + \beta_1 X_{t-1} + u_t \tag{11}$$

In our model, the vector X_t depends on its own lag and structural shocks u_t. These structural shocks are independently distributed. Suppose that X has the following three variables: $X_t = \begin{bmatrix} \text{W} \\ \text{NAIRU} \\ \text{Skill} \end{bmatrix}$, where W denotes the Wage, NAIRU denotes the equilibrium unemployment to suppress the inflationary movements in the model, and the number of employees with graduate-level studies is denoted by skill. In such variable specifications, the system will be expressed through the following three equations;

$$\begin{aligned} &W_t + \alpha_{12}NAIRU_t + \alpha_{13}Skill_t = \beta_{10} + \beta_{11}W_{t-1} + \beta_{12}NAIRU_{t-1} + \beta_{13}Skill_{t-1} + u_{wt} \\ &\alpha_{12}W_t + NAIRU_t + \alpha_{23}Skill_t = \beta_{20} + \beta_{21}W_{t-1} + \beta_{22}NAIRU_{t-1} + \beta_{23}Skill_{t-1} + u_{NAIRUt} \\ &\alpha_{31}W_t + \alpha_{23}NAIRU_t + Skill_t = \beta_{30} + \beta_{31}W_{t-1} + \beta_{23}NAIRU_{t-1} + \beta_{33}\, Skill_{t-1} + u_{Skillt} \end{aligned} \tag{12}$$

If we pre-multiply this VAR specification by the inverse of matrix $A(A^{-1})$, then we will get the reduced form VAR;

$$\begin{aligned} &A^{-1}AX_t = A^{-1}\beta_0 + A^{-1}\beta_1 X_{t-1} + A^{-1}u_t \\ &X_t = G_0 + G_1\, X_{t-1} + \varepsilon_t \ \ (G_0 = A^{-1}\beta_0 \text{ and } G_1 = A^{-1}\beta_1) \end{aligned} \tag{13}$$

We impose $\alpha_{12} = \alpha_{21} = \alpha_{32} = 0$, reflecting the stable nature of the NAIRU. Therefore, the wage is unaffected by shocks to the equilibrium unemployment rate. NAIRU is also neutral, and surprises to NAIRU will not affect the number of educated firms. Shocks to NAIRU will only affect wage and skill with a lag, but shocks to skill will change the equilibrium.

Results and Discussion

According to data on average years of schooling, including primary, secondary, and high school, workers with a certificate of secondary education exhibit positive comovement for 56 years, as shown in Figure 9. Upper secondary education is not compulsory in Iran. The government provides free schooling to the entire population. It includes primary schooling and higher schooling 1 and 2, where higher schooling 1 is equivalent to secondary education at an international level.

As shown in the figure, the average years of schooling are 7 to 8, and the average wage growth is about 20 percent. Herrendorf and Schoellman (2018) utilize this relationship to assess the impact of schooling by removing the error term from the right-hand side of the equation, thereby disregarding the influence of skill-related shocks on wages. Specifically, this study identifies and decomposes structural skill shocks into their short-run and long-run components.

Figure 10 depicts the history of labour demography in Iran from the years before the revolution that occurred from 1978 to 1988. The figure shows that the workers hired through the pre-revolution system had not retired and continued to work in an environment with outdated infrastructure and institutional systems after the revolution. In these years, the variation in the growth of skilled workers was higher than that in wages. This can be primarily attributed to a firm's tendency to hire more skilled labour. Subsequently, the imposition of institutional changes on the economy and structural shocks, such as war, worsened the distance rate. According to 2016 census data from 3,904 individuals in urban and rural areas of Iran, only 18.7% of active workers held a bachelor's degree or higher. Given the rapid growth in the number of university graduates over the past decade, this mismatch contributes to labour market inefficiencies.

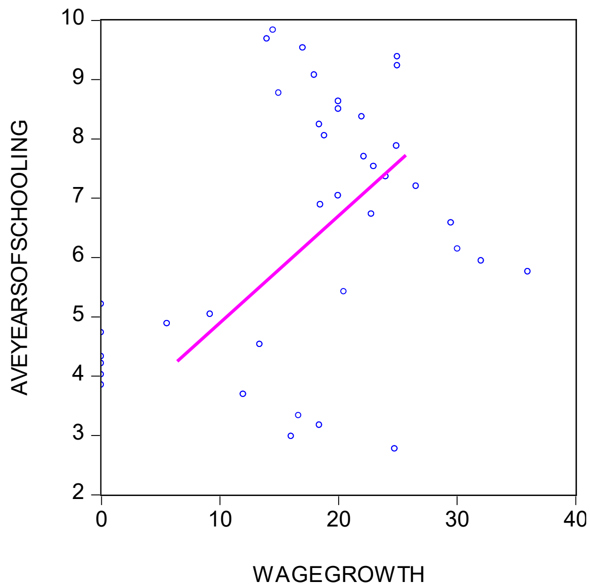

Figure 9. Scatter of Wage Variations and Long-run Changes in the Number of Workers with School Education Attainments

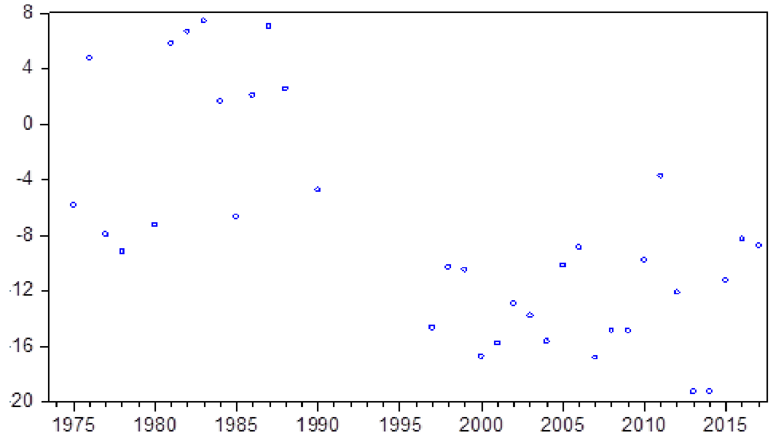

Figure 10. The Distance Between Skilled Labor Force Growth and Minimum Compensation Growth

The results in Table 1 show that short-run human capital shocks lead to higher wages. This finding is consistent with the impulse-response function presented in Figure 13. The effect lasts for about 2 to 3 periods and is reflected in a coefficient of 2.07, which is statistically significant at the 5% level according to Table 1. This result implies that a 1% unexpected increase in the number of workers with a university degree raises wages by approximately 2.07% in the short run. On the other hand, in the long run, structural shocks to human capital lead to a decline in wages. As shown in Table 1, wages decrease by 2.217%, and the effect is statistically significant at the 5% level. These results support the initial assumption that educated workers play a minimal role in wage bargaining relative to other workers with different qualities, suggesting that firms' stock of human capital does not primarily drive wage changes. This result aligns with the study conducted by Hendricks (2002), which found that human capital can account for the low wage difference (approximately 31 percent) in Iran. This phenomenon produces a smooth curve in Figure 11, illustrating a general upward shift in wage levels along the horizontal axis. Structural shocks of NAIRU to human capital are positive, which implies that being unemployed will drive skilled workers to increase their job-search efforts. These workers search for jobs using complicated methods, such as costly registration for private job campaigns, which, according to statistics, have increased significantly among the educated in recent years. Despite an increase in the share of university-educated workers, their share in firms' wages fails to increase accordingly, as supported by studies by Becker (1964), Mincer (1974), Rosen (1976), Mankiw et al. (1992), and Jones (2014). In developing countries, education does not guarantee job attainment without sufficient effort by educated job seekers. Moreover, an increase in the number of PhD students in recent years is another adjustment considered in the study to show how these students can contribute toward increasing the share of university-educated workers in firms. This is reflected in the increase in the unemployment rate over the past 25–30 years, a period roughly comparable to the time required for a student to complete a PhD.

Table 1. Results of Estimation of the VECM Model and Co-movement Equations

Variables	Dependent variable wage		Mean	Standard Error	P-value
Exogenous variable	Skill	2.076	7.9	1.05	0.0375
Independent variable	NAIRU	-2978279	12	0.5	0.042
R-squared			0.909		
F-statistic			114.25		

The coefficient of NAIRU in the solved model is -2978279, implying that a one-unit increase in unemployment will result in a fall in general wage levels to IRR 2,978,279, as revealed by the empirical data of private firms. The Mincer coefficient for Iran is estimated at 2.076%. In the short run, this implies that a 1% increase in skill raises wages by approximately 2.076%. However, according to the specification of the structural wage model, economic theory, and impulse-response analysis, this effect is not persistent beyond two to three periods, after which it gradually decays and the impact of human capital becomes negative. Subsequently, the model was estimated for the sampled period to see whether real-world data could confirm the dynamic long-run correlation in Figure 11. Results of the solving model with the baseline scenario are presented against actual values for each of the three variables in Figure 12. Figure 11 shows that the relationship between human capital and wages is approximately zero at low wage levels. This finding is based on the sampled years between 1978 and 1988, a period surrounding the Iranian Revolution. During this time, education was the primary criterion for hiring, and increases in the minimum wage led to a significant increase in the number of workers with university degrees.

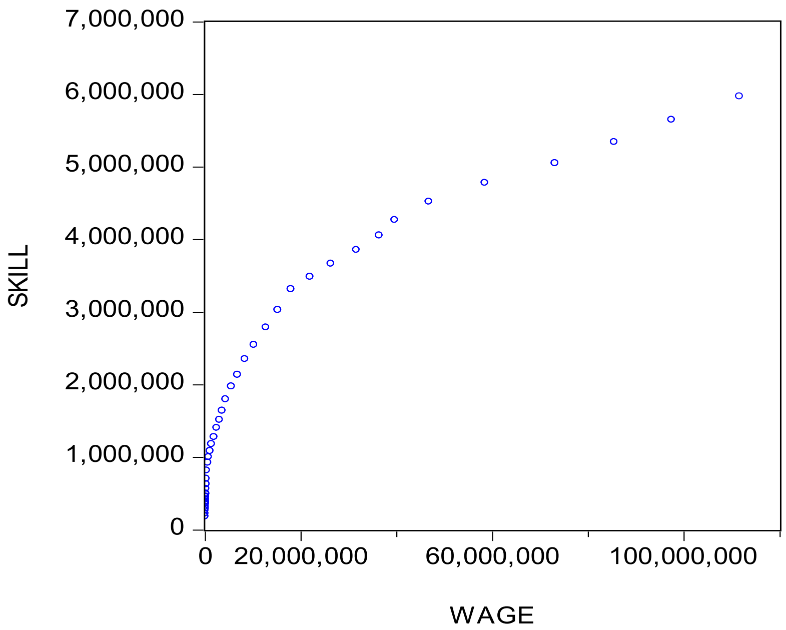

Figure 11. Skill Bias in the Iranian Economy

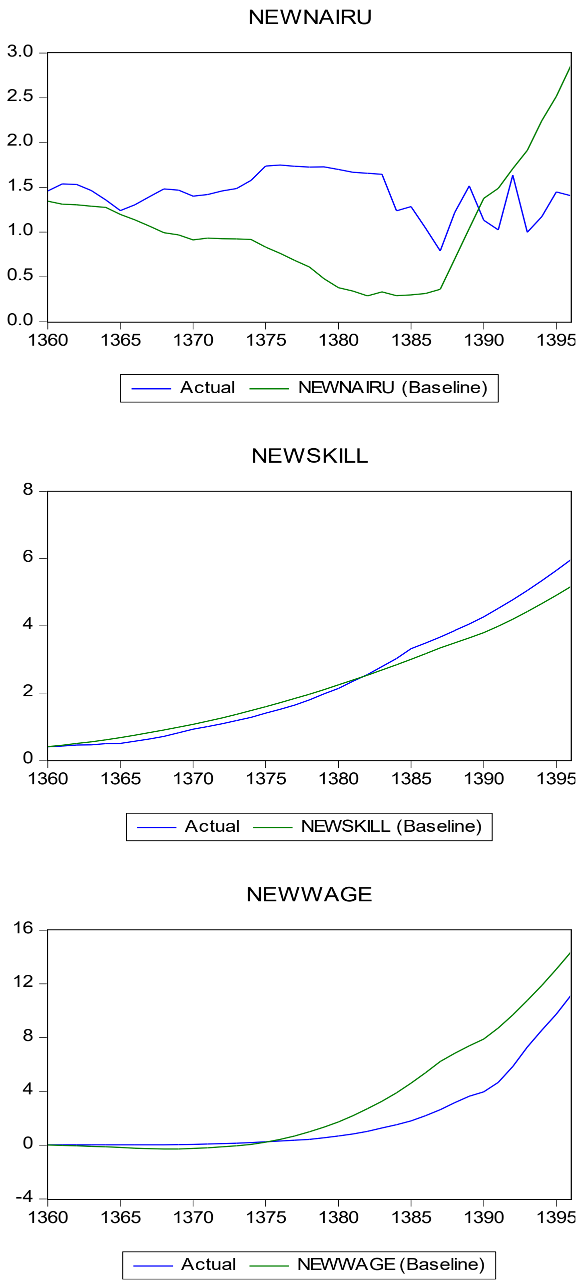

Figure 12. Solving Model with Baseline Scenario

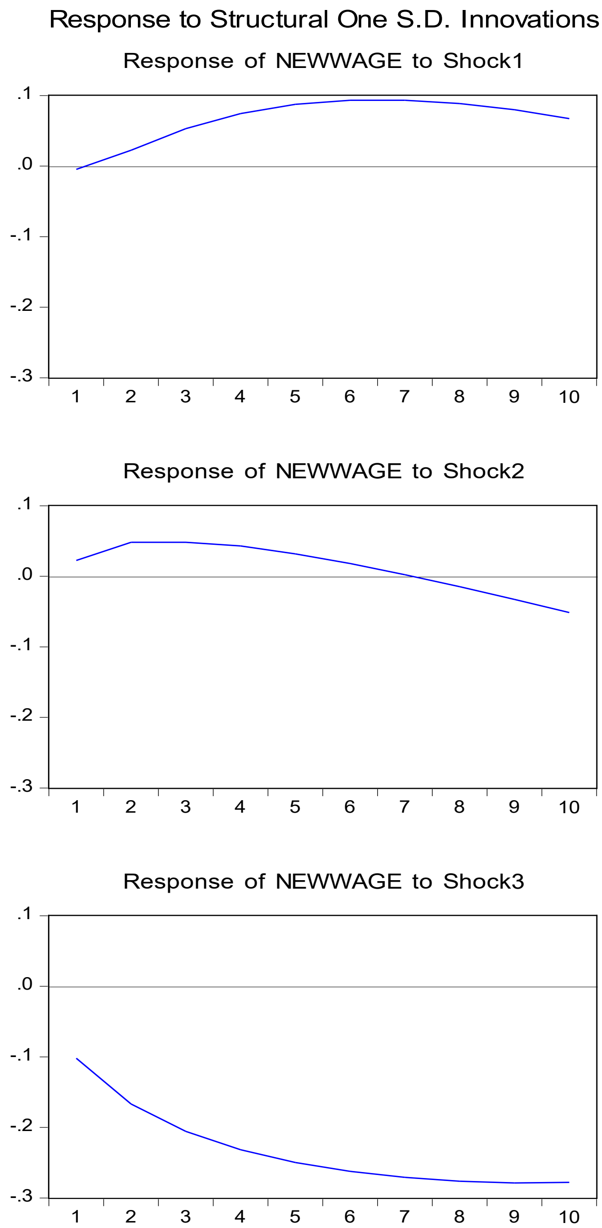

Figure 13. Response of Wages to a One-Standard Structural Shock Hit of Three Endogenous Variables

The error-correction feature of the wage model ensures the existence of significant cointegration. It observed this at the individual level in the microdata, in the form of co-movements. A scatter plot of wage and human capital indicates that, due to firms' inflexible production function, new technological shocks will not alter their labour employment capacity. This situation is described as an adverse selection when wages, taking into account the effects of human capital, are presumed by the macro-production function. Still, wages mostly change due to an error term in the wage model. This is approved by a study done by Carbonero et al. (2022).

The short-term effects of human capital shocks can be proven further by estimating the response of wages to skill shocks, as in Figures 14 and 15. According to the IR figure, the response of wages to human capital shocks—as indicated by the intercept of the impulse response in the short run—starts at approximately 2%. This suggests that a one-unit shock to human capital leads to a 2% increase in wages. The positive effect intensifies to around 5% in the second and third periods, but gradually declines, turning negative after the seventh period. This pattern supports our finding that, in the long run, increases in firm-level human capital may lead to lower wages. Such a result implies weak bargaining power and a smoother, less responsive long-run relationship between human capital and wages.

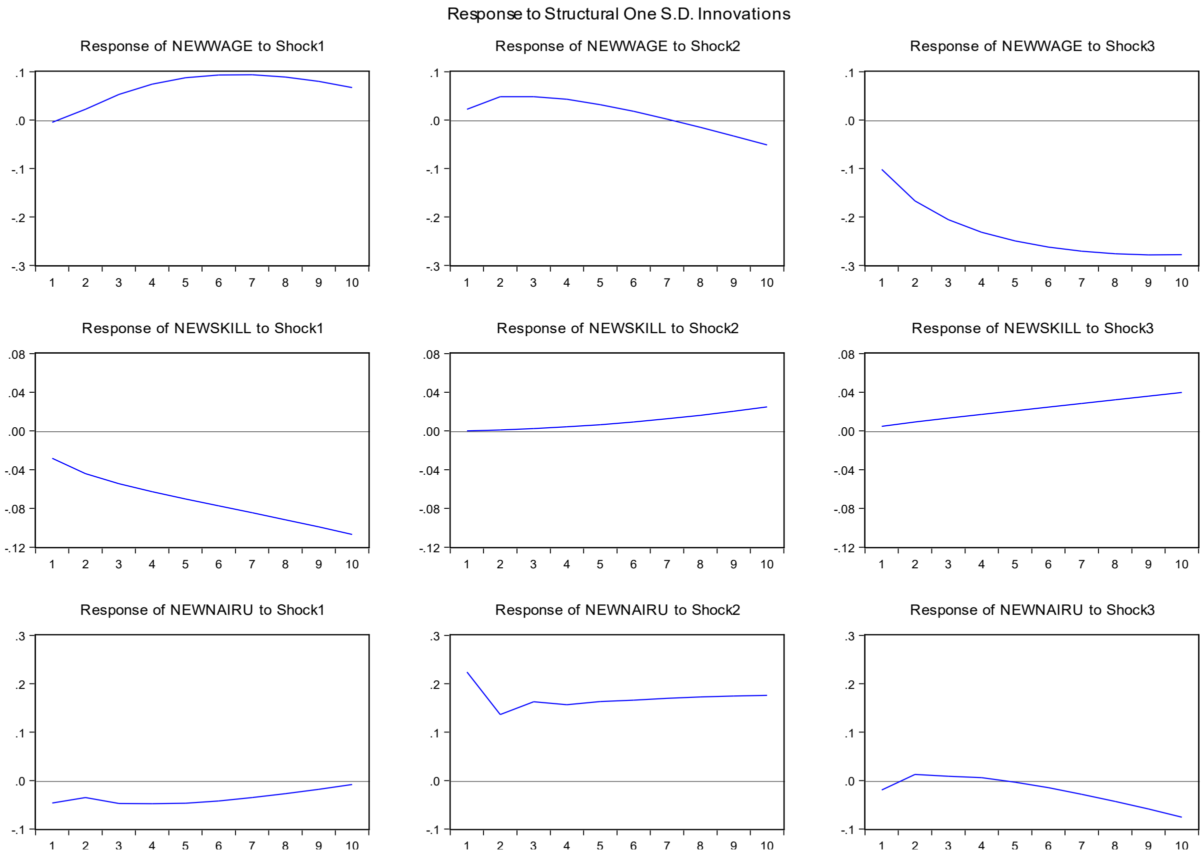

Figure 14. Responses of Three Endogenous Variables to One Structural Shock in Wage Model

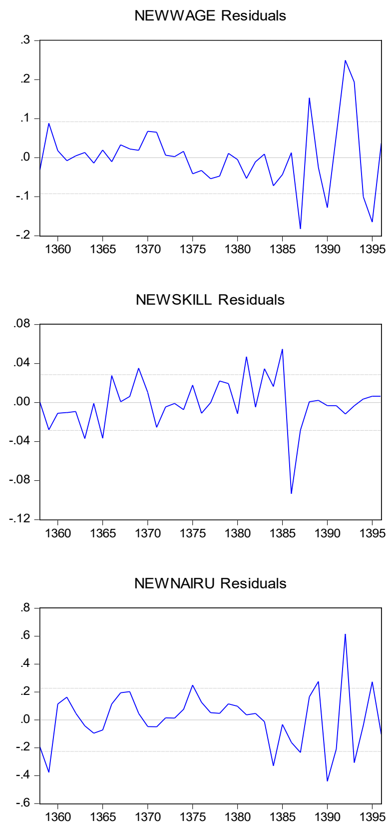

Figure 15. Residuals of Endogenous Variables in SVAR Model

Conclusion

This study puts forward the missing link in the existing literature on wage and human capital models. In other words, despite the recent expansion of university education and the resulting increase in human capital, the employment of educated workers in firms and their influence in wage bargaining have not kept pace. This problem reflects the bias of highly educated workers. Their neutrality has led to a decline in firms' human capital, which, in this study, is defined as skill bias. This study fit data from Iran, derived from microdata of rural and urban centers, to the model specification of the time series.

Additionally, according to the co-movement equation approach, co-movement in the long-run wage-skill relationship is lower than the actual curve would suggest. It implies that the recruitment of university-educated workers is below the optimal level. An estimate of the co-movement equation using a VECM yielded a coefficient of 2.07 for skill; the SVAR estimation also supported this. This study specified a wage model for the Iranian economy and subsequently estimated it using the SVAR approach on aggregated microdata. It is concluded that skilled workers play a significant role in wage bargaining for two to three periods, while in the longer horizons, comprising approximately seven periods, the educated population has a negative impact on wage levels. The results imply that human capital generates negative externalities for both the macroeconomy and individuals, thereby minimizing the significance of job search efforts among the educated, thwarting their expectations, and isolating them from the labour market. This study describes this phenomenon as skill bias, in which education, originally intended to facilitate wage bargaining in the labor market, gradually loses its effectiveness and becomes neutral, as illustrated by the case of Iran.

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