G²LM|LIC Working Paper No. 107 | July 2026

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ABSTRACT

# Social Connections and Skills Gap in Kenya*

This paper analyzed under-skilling across formal enterprises within Kenya's services and manufacturing sectors. The objective was to analyze the effect of under-skilling across related enterprises on under-skilling among focal enterprises. This paper utilized the 2016 STEP survey dataset comprising of 504 enterprise-level observations. The technique of ordinary least squares estimation was employed alongside negative binomial regression, while controlling for heterogeneity via incorporation of interaction terms. Empirical findings suggest that under-skilling in Kenya is quite high with 68% of enterprises having attracted an under-skilled job-seeker. These enterprises belonged to groups with a larger share of enterprises attracting under-skilled job-seekers, or with a larger number of vacant occupational positions attracting under-skilled applicants. Model estimation suggested that enterprises were less likely to attract under-skilled applicants as the number of vacant occupational positions with under-skilled applicants rose among peers. These findings further suggested that the number of vacant occupational positions with under-skilled applicants declined as either the share of peer enterprises with under-skilled applicants rose or the number of vacant occupational positions with under-skilled applicants rose among peers. This study concludes that enterprises in Kenya are less likely to attract under-skilled applicants when peers have more incidences of under-skilled job seekers. Furthermore, that enterprises have fewer vacant occupational positions with under-skilled applicants when either the share of peers with under-skilled applicants rises or the average number of vacant occupational positions with under-skilled applicants rises among peers.

**JEL Classification:**
D83, J24, J64, J82

**Keywords:**
Skills gap; Social connections

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* This paper benefitted from Mary Kehinde-Bello's mentorship under the G²LM|LIC initiative.

## INTRODUCTION

Kenya continues to experience a notable skills deficit, as one in every three formal enterprises indicate job applicants are under-skilled for available positions (State Department for Skills and Social Protection (SDSSP), 2022; State Department for Labour and Skills Development, 2023). Employers in Kenya highlight under-skilling as a serious challenge they face in filling available vacancies; this challenge is second only to relatively high reservation wages posted by some job seekers (SDSSP, 2022). However, its drivers in the country are not well understood. Previous research, like Guardia et al (2021), Meta (2022), and Muchira et al (2023), speculate a misfit between tertiary education curriculum development and the country's need for industry- and work-specific skills. These studies do not analyze under-skilling as an outcome of competition for skilled workers among related enterprises.

Existing research on under-skilling in Kenya focuses on describing skills gap across the labor market without modeling its drivers. This is because these studies were motivated exclusively by the desire to give an overview of skills gap and the labor market. These studies reveal failure of some enterprises in need of skilled workers to find them (Muchira et al, 2023; SDSSP, 2022), and highlight the prevalence of employee poaching as a disincentive to within-firm training of workers (Guardia et al, 2021; Meta, 2022). By failing to explain drivers of under-skilling in Kenya via model estimation, these studies fail to pin down observed under-skilling and its drivers. Absence of model estimation further implies that co-movement between under-skilling within an enterprise and under-skilling across related enterprises cannot be inferred from previous literature centered on Kenya. The present study is significant for it bridges the two aforementioned gaps.

This paper analyzes under-skilling among enterprises in Kenya as behavioral responses to skills gap across related firms. This is important because skills deficit constrains enterprises from creating skill-intensive tasks and jobs which are vital towards the realization of skills-driven industrialization in the country (Dhillon et al, 2020; Morris et al, 2020; Federico et al, 2019; Wolcott, 2021; McAdams, 2019). These deficits further impose binding labour constraints on enterprises which have to divert resources away from production towards training and skilling of workers. The problem is that enterprises are looking for skilled workers to drive productivity and raise enterprise profitability, and not unskilled workers who require training before executing skills-intensive tasks.

Against the aforementioned, this paper offers a natural extension to the literature by examining the effect of under-skilling across related enterprises on under-skilling within focal enterprises. In particular, it extends Munene (2021), Guardia et al (2021), Meta (2022), and SDSSP (2022)—which were descriptive studies focusing on Kenya—via way of model estimation.

Subsequent sections present an overview of models of search and matching—which are the basis of this paper— alongside highlights from some previous studies, followed by discussion of the methodology. Thereafter, empirical findings are presented and discussed before wrapping up.

## RELATED LITERATURE

## THEORETICAL FRAMING

The theoretical review of this paper is based on the Diamond-Mortensen-Pissarides search and matching model (Pissarides, 2000; Mortensen & Pissarides, 1994; Diamond, 1982). These three models in general consider a decentralized labour market which allows for a one-on-one meeting between workers looking for jobs and enterprises in need of workers. These models assume that:

available jobs are heterogeneous; workers differ in the level of skills; and each enterprise has its own specific needs for workers which differ from the needs of other firms. Both workers and enterprises have idiosyncratic preferences which have to be matched up in a costly process combining needs, skills, and preferences. Once an enterprise and a worker find a suitable match for each other, they must agree on how private gains (or the surplus) from hiring the worker are to be shared via Nash bargaining as a mathematical convenience. Nash bargaining is convenient but not a necessary condition for equilibrium existence in these models (l'Haridon et al, 2011). Existence of an equilibrium requires splitting private gains such that a match guarantees positive total private gains (efficiency) and no outside option offers either party more gains (individual rationality). This can also be achieved via alternative mechanisms such as requiring workers to pick the best wage from offers posted by enterprises, directed search, and alternating offers. However, if a Nash equilibrium exists, then an equilibrium in the search and matching model exists, implying that Nash bargaining is a sufficient but not necessary condition.

Models of search and matching highlighted above link to this paper in the following way. As firms part ways with skilled workers, vacancies which arise have to be filled by other skilled workers drawn from the pool of unemployed workers. Similarly, enterprises can create vacancies for skilled workers without a prior separation. Under-skilling becomes a problem when enterprises in need of skilled workers and skilled workers looking for employment which utilizes their skills fail to find/ match each other. From the firms' perspective, this constitutes skills deficits. Enterprises respond to these deficits in three ways:

One, enterprises roll over vacancies for skilled workers since successful matches between firms and workers become rare when skills deficits are pronounced. This is costly because firms incur vacancy maintenance costs (Schroeder, 2022). When skilled workers are hard to come by, indefinite rollover of vacancies undermines production due to unfilled vacancies (Brunello & Wruuck, 2021). Two, skills deficits raise competition for skilled workers via better counter-offers and bargaining (Braunerhjelm et al, 2020; Faberman et al, 2022). This in turn raises costs of hiring and retaining skilled workers while exposing enterprises to predatory poaching by competitors. These two issues induce enterprises to either destroy vacancies for skilled workers, outsource certain skill-intensive tasks, fill such vacancies with under-skilled workers, or mandate skilled employees to sign non-compete agreements (Bandiera et al, 2023; de Groot et al, 2021; Dhillon et al, 2020; Wolcott, 2021; McAdams, 2019). Enterprises settling for the latter either sacrifice the scope for innovation and worker productivity, or invest in costly within-firm employee training (Gelb et al, 2020). These studies collectively suggest that the burden of skills deficit is either borne by individual enterprises or shared across firms. These studies, however, do not indicate how enterprises respond when firms related to them face skills deficits.

An extension of models of search and matching builds on the reliance on referrals and recommendations for new employees. Referrals and recommendations enable enterprises to onboard the best talent, and act as assisted search (Bandiera et al, 2023; Lise & Postel-Vinay, 2020). These studies also indicate that referrals signal a worker's ability without guaranteeing the resilience of referrals to skills deficits. This suggests that referred workers are just likely to be under-skilled as their counterparts without referrals. Since a firm's decision to use referrals is independent of the hiring practices of other enterprises, the literature assumes that under-skilling within enterprises is independent of skills deficits across related enterprises. The central idea is the literature is that it is individuals and employees who refer workers, and not enterprises although it is enterprises which hire or poach employees. This theoretical prediction is not aligned with existing empirical evidence. When skilled workers are few, long-term contracts with punitive terms for leavers render it difficult for workers to accept outside job offers. A small pool of skilled workers further implies that enterprises relying on new hires cannot raise the pool of skilled workers without poaching from other firms. As a consequence, the level of skills across enterprises is important in shaping skills deficits within firms.

The relevance of models of search and matching to this paper rests in the prediction that widespread under-skilling results in unsuccessful matches when enterprises in need of skilled workers meet under-skilled job seekers. What is less studied in the literature relates to the extent to which under-skilling in enterprises is affected by under-skilling across enterprises related to them. In particular, previous studies—e.g., (Onsomu et al, 2006; Manda et al, 2002; Söderbom et al, 2006; Gethin, 2023; Psacharopoulos & Patrinos, 2018)— focusing on Kenya emphasized either returns to education or the importance of skills towards realizing development imperatives. These studies did not look at the responsiveness of enterprises to under-skilling across enterprises which are related to them.

This paper extends the search and matching model by looking at the extent to which enterprises respond to under-skilling across enterprises related to them. This extension is in line with Calvó-Armengol & Jackson (2004) which suggests that networks affect skills gap.

**EMPIRICAL STUDIES**

Previous studies related to ours consider either descriptive statistics, explicit model estimation, or both. Some of the previous studies with a focus on Kenya—e.g., SDSSP (2022), Meta (2022), and Guardia et al (2021)— discussed descriptive statistics based on frequency tables, means, and proportions. Collectively, these studies concur that enterprises in Kenya acknowledge under-skilling as a bottleneck to their production processes. These studies also indicate under-skilling as multi-dimensional (certain skills could be missing among workers but not others) and heterogenous (under-skilling could be more common across certain occupations, sectors/ industries, and regions but not others; and workers differ in the composition of their skills set). The aspect of under-skilling as multi-dimensional and heterogenous is also established in various studies which explicitly estimate regression models. These studies include Beaman & Magruder (2010) and Montana (2020). A survey of studies reporting model estimation reveals a variety of estimation techniques employed—ranging from ordinary least squares (OLS) to Heckman selection (Beaman & Magruder, 2010), negative binomial regression (Braunerhjelm et al, 2020), multinomial logit (McGuinness & Ortiz, 2016), and calibration and simulation (Lise & Postel-Vinay, 2020; Montana, 2020). Other studies—e.g., Marcolin & Quintini (2023) and Brunello & Wruuck (2021)—survey the literature on skills gap, its measurement, and consequence.

The literature on under-skilling also distinguishes between skills gap from the demand and under-skilling from the supply side. Demand-side studies, e.g., Beaman & Magruder (2010), Glitz & Vejlin (2021), and Braunerhjelm et al (2020) reveal that networks affect under-skilling by shaping the pattern of within-firm knowledge transfer, exposure to counter-offers, and co-worker/ supervisor referrals. Supply-side studies, e.g., Bandiera et al (2023), McGuinness et al (2024), McGuinness & Staffa (2025), and Carranza & McKenzie (2024), indicate that short-term programs focusing on specific skills and assisted job search raise the likelihood of enterprises in need of specific skills meeting workers with those skills. We leave out studies which do not link skills gap to networks, e.g., Hjort & Poulsen (2019), Bustos et al (2022) and Federico et al (2019). These latter studies indicate that skills gaps arise from sectoral reallocation of unskilled and skilled workers during the process of structural transformation or exposure to technological shocks.

Beaman & Magruder (2010) analyze referral to jobs based on social networks and worker ability in India's Kolkata. In a multi-round laboratory experiment involving 18-65-year-old men, the authors introduce performance pay as an incentive. Worker ability was given by performance on a cognitive test that assessed speed and accuracy. Employing the Heckman model, the authors indicate high-ability individuals being referred by high-ability original participants given strong incentives. Referrers were less likely to recruit low-ability family members compared to co-workers. The findings further suggest that network members were effectively screened by high-ability original participants. According to the authors, the preference for high-ability co-workers over low-ability relatives was driven by performance pay. This implies that it never paid referrers to recruit low-ability relatives when payment stakes were high. A shortcoming in the study is that rainfall was a weak instrument for attending the interview when low-ability referrals were considered. That is, a low-ability referral may opt not to show up in any case.

Glitz & Vejlin (2021) analyze coworker referrals and match quality based on administrative data among 25-54-year-olds from 1980 to 2005 in Denmark. Referrals were proxied by whether or not an individual worked in the same firm with a former coworker. In the regressions, the authors control for overexposure proxied by the network size—number of coworkers in the previous ten years. The results suggest that workers received significantly higher wages, and were less likely to exit at the beginning of tenure in a new establishment when a coworker was present compared to when absent. The authors further reveal much lower distortions of a worker's productivity signals in the referral market relative to external markets. This was attributed to much longer contact durations, and shorter separation durations between the referral, and the coworker. In the long-run, turnover probability and wages received converge for workers hired from the external market and those referred. The convergence in wages was attributed to externally-hired workers that formed bad matches being weeded out.

Bandiera et al (2023) analyze job matching and vocational training in Uganda. In the intent-to-treat model, offer of a job match was deployed as an intervention. Job match entailed linking vocational trainees to job offers. The authors indicate vocational training raising sector-specific skills among the trained relative to untrained counterparts. Skills accumulation rose insignificantly in job matching regardless of training. In terms of long-run outcomes, unskilled youth experienced long unemployment spells (lasting 14 months) relative to vocational trainees (1-2 months after graduation). This was attributed to differences in search behaviors, and expectations, between the vocational trained and the untrained youth.

Goel & Lang (2019) consider social networks among 6524 15-64-year-old immigrants within Canada's twenty-three metropolis. Network strength was given by presence of a friend or relative in Canada during entry. Employing the difference-in-differences model, the authors indicate significant job creation within strong networks for immigrants. The results further suggest negligible skills bias such that immigrant wages were insignificantly affected by observed skills. This was true with the exception of the third decile. Within the third decile, immigrants with network jobs were less likely to have language skills (fluency in French or English), or to have worked before migrating, and were likely to have lower educational attainment. The authors argue that networks increased the number of jobs without dictating the type of offer received.

Morris et al (2019) link productivity of firms within the United Kingdom (UK) to skill shortage and skills gap. Skills gap within a firm was given by the share of employees facing below-required level job proficiency. Skills gaps were then averaged across industries and regions to yield a region-industry skill shortage share. Productivity was proxied by gross value addition, and total factor productivity. In a fixed effects model, the authors indicate that regional firm productivity differences in the 2008-2014 period were driven by skill shortage at the industry-region level. This was attributed to operational issues and loss of requisite knowledge that aggravated skill shortage.

Andreoni et al (2021) analyze skills development within South Africa's industrialization and digitalization context. The authors argue that interactions among enterprises enhance skills acquisition via institutional learning. Inter-firm interactions also catapult joint capacity building ventures, collaborative research and development (R & D), and process innovation.

Braunerhjelm et al (2020) look at innovation, knowledge diffusion, and mobility of highly-educated individuals on the Swedish labor market. The analysis was based on a dataset drawn from the Statistics Sweden's Business Register containing 91688 employee-employer observations across 21662 firms from 1987 to 2008. Firms without an R & D worker were excluded from the sample. Workers poached from other firms and retained employees were categorized as experienced. Fresh university graduates that joined enterprises were considered inexperienced workers. Innovation was proxied by patent applications in the 2001-2008 period. In a negative binomial regression, the authors indicate significant increments in patent applications as joiners increased relative to stayers. This effect was large when new R & D hires came from firms that were already patenting compared to non-patenting counterparts. The authors argue that superior absorptive capacity among recipient firms for new hires enabled them to raise patent applications. In addition, patent applications significantly rose in the size of R & D workforce, and firm's stock of capital. Patent applications were insignificantly affected by university graduates that were inexperienced as well as by leavers regardless of the firm. Similarly, patent applications insignificantly declined in the number of associate professionals and technicians; i.e., less-skilled R & D workers.

Audretsch et al (2023) focus on product innovation among SMEs and the co-generation of knowledge in the UK. The analysis was based on six waves of the UK Innovation Survey (UKIS) covering 9213 SMEs from 2002 to 2014. UKIS was matched to Business Enterprise Research and Development Survey, and the Business Registry datasets, both compiled biannually. Product innovation was given by the turnover arising from introduction of new commodities to the market as a share of total turnover to the firm. In both instrumental variable Tobit, and random-effects Tobit models, knowledge collaboration between SMEs and universities and customers significantly raised product innovation. This was attributed to integration of high-quality knowledge, international diversity, and sticky knowledge which is embedded locally. Knowledge collaboration with other UK-based enterprises significantly raised product innovation. This effect withered away when collaboration was extended to enterprises within Europe or other countries globally.

Studies focusing on Africa and Kenya are largely descriptive, and indicate that the depth and severity of under-skilling vary across professions and industries. These studies also reveal that under-skilling is an important constraint facing enterprises in need of new employees. SDSSP (2022) indicates that the challenge of under-skilling is second only to high reservation wages among some job seekers. In a focus group discussion involving 89 university stakeholders drawn from Tanzania, Kenya, and Uganda, Guardia et al (2021) document that the stakeholders believed graduates had skills gap which were partial. This was attributed to training across universities failing to equip learners with skills which are aligned to work- and industry-specific contexts. Meta (2022) reviews a limited number of studies on skills gap. The author indicates that skills gap in Kenya is shaped by professional and curriculum development, area of skill utilization, and training. Munene (2021) also indicates that curriculum development across tertiary institutions in the country has not been sufficiently responsive to the industry's need for skilled workforce. This is further aggravated by almost non-existent university career advisory services.

Among empirical studies outside Kenya, Audretsch et al (2023), Morris et al (2019), McGuinness et al (2024), and McGuinness & Staffa (2025) are closest to ours. The first two papers consider inter-firm networks via geographical proximity or region-industry identification, respectively. However, these studies respectively explain SMEs' product innovation and enterprise productivity instead of within-enterprise under-skilling. The last two studies explain the probability that a worker is under-skilled without looking at inter-firm networks. We bridge this gap by utilizing geographical proximity and region-sector identification in explaining within-enterprise under-skilling. We also bridge a gap in data and geographical coverage by narrowing down to Kenya, a country which was not considered in both studies. Studies which focused on Kenya, or included Kenya in the analyses—e.g., SDSSP (2022), Guardia et al (2021), Meta (2022), and Munene (2021)—were descriptive, and did not look at inter-firm networks. We bridge this methodological gap via utilization of model estimation. This enables us to tease out the extent to which under-skilling within an enterprise is affected by under-skilling across enterprises related to it.

## METHODOLOGY

The theoretical model for this study is the Pissarides (2000) version of search and matching models whereby the number of unemployed workers (u) in an economy depends on labour market tightness ($\theta$), vacancy-filling rate ($h(\theta)$), and the rate at which employed workers breakup with enterprises ($\lambda$).

Following Pissarides (2000), we consider an economy populated with many identical infinitely-lived workers and many enterprises which are identical. Each worker is either employed or unemployed at any point in time. There are E employed workers and U unemployed workers with the mass of workers normalized to 1, implying that $E = 1 - U$. There is at most 1 vacancy in each enterprise, and payoffs in the future are discounted by enterprises and workers at rate $\tau > 0$. Payoffs are given by value functions, which capture maximum gains accrued to each agent. Workers in search for a job and enterprises in need of workers are matched via the constant returns to scale function $G(u, v)$ –which determines the flow of hires—where the number of unemployed workers and number of vacancies are respectively denoted by u and v. Labour market tightness is given by $\theta = \frac{v}{u}$, where the larger is $\theta$, the tighter is the labour market, implying that unemployed workers find jobs faster than enterprises with vacancies fill them. Vacancies are filled at the rate $h(\theta) = \frac{G(u,v)}{v} = G\left(\frac{u}{v}, 1\right) = G\left(\frac{1}{\theta}, 1\right)$, which is the vacancy transition rate. Unemployed workers find jobs at the rate $\frac{G(u,v)}{u} = G\left(1, \frac{v}{u}\right) = G(1, \theta) = \frac{v}{u}\frac{G(u,v)}{v} = \theta G\left(\frac{u}{v}, 1\right) = \theta G\left(\frac{1}{\theta}, 1\right) = \theta h(\theta)$. A filled job can be destroyed at no cost, and worker-enterprise separation follows a Poisson process with job separation rate $\lambda$. Unemployment rate evolves according to:

$$\dot{u} = \lambda E - \theta h(\theta)u = \lambda(1 - u) - \theta h(\theta)u$$

In the long-run, $\dot{u} = 0$ since flows into unemployment, $\lambda(1-u)$, and flows from unemployment, $\theta h(\theta)u$, are equal. The number of unemployed workers in the steady-state is then given by:

$$u = \frac{\lambda}{\lambda + \theta h(\theta)} = \frac{1}{1 + \frac{\theta h(\theta)}{\lambda}}$$

This implies that the number of unemployed workers is high when either the labour market is loose, vacancy filling rate is small, or job separation rate is high. λ, θ, and $h(\theta)$ depend on respective value functions for unemployed workers, employed workers, enterprises with filled vacancies, and enterprises with unfilled vacancies (Carrillo-Tudela et al, 2023). Since, the model's transitory dynamics are complicated, we consider the relationship between u, θ, $h(\theta)$, and λ in the steady state with the specification:

$$u = \frac{\lambda}{\lambda + \theta h(\theta)} = \frac{1}{1 + \frac{\theta h(\theta)}{\lambda}}$$

Which, upon making vacancy-filling rate the subject, is rewritten as:

$$h(\theta) = \frac{\lambda(1-u)}{u\theta} = \frac{\lambda\left(\frac{1}{u} - 1\right)}{\theta}$$

With $0 < \lambda < 1$. In the absence of binding non-compete agreements (McAdams, 2019), λ reflects employed workers' responsiveness to counter-offers by other enterprises (Faberman et al, 2022). When θ is low, i.e., a loose labour market, $h(\theta)$ is high, implying that available vacancies in the economy are filled faster than the rate at which job seekers find employment. Conversely, in a tight labour market, $h(\theta)$ is low, and enterprises find it increasingly difficult to fill available vacancies. $h(\theta)$ is also low when $u$ is high.

For simplicity, let available vacancies across enterprises be for skilled workers. The rate at which vacancies for skilled workers are filled reflects the rate at which enterprises with vacancies meet under-skilled applicants, and the rate at which skilled workers leave jobs in other related enterprises. Some enterprises could be meeting under-skilled job seekers because skilled workers have already been hired by other firms (Morris et al, 2020; Marcolin & Quintini, 2023). This implies that incidences of under-skilled applicants rise in the enterprise which is unable to meet and hire skilled workers relative to firms which hire skilled workers. Separation of skilled workers from current employment hints at possible poaching whereby enterprises hire workers offered employment elsewhere (Calvó-Armengol & Jackson, 2004). Poaching renders networks/ enterprise proximity—in terms of shared attributes such as geographical closeness and line of operation/ sector— relevant.

For the setup presented to be relevant to this analysis, we place enterprises into network group such that enterprises are related if they belong to the same group on the basis of metropolitan region, sector, and enterprise size. This is in line with Morris et al (2020) which treats enterprises in the same industry and region to be related, with the relation enabling the authors to analyze spillover effects of vacancies arising from skill shortage. We then make three modifications to the model. First, we separately replace the number of unemployed workers by the share of enterprises within a given firm's network which attracted under-skilled applicants—hereafter, skill share,

$u_{0j}$— and the share of vacant occupational positions across enterprises within the network for which under-skilled applicants were attracted—or simply, share, $u_{1j}$—. Second, we replace vacancy-filling rate by two variables: whether an enterprise attracted a job seeker who was under-skilled, $h_{0f}(\theta)$, and the number of occupational positions within an enterprise for which under-skilled applicants were attracted, $h_{1f}(\theta)$. Third, we split jobs into two categories on the basis of the required level of skills: white-collar/ type-A jobs requiring high skills and blue-collar/ type-B jobs requiring low skills. This dichotomy is in line heterogenous skills requirements across different occupational positions within an enterprise (Wolcott, 2021). It further implies that a worker is either white-collar (type-A) with high skills or blue-collar (type-B) with low skills (World Bank, 2016, 2018). Let $b$ denote job type/ worker type. Since employed workers breaking up with enterprises are likelier to find jobs in other firms within firm $f$'s network, job separation rate is absorbed in the network.

We then have a theoretical relationship with the specification:

$$h_{kf} = h_{kf}\left(u_{mj}^{b}\right), k = 0,1;\ m = 0,1$$

Where $h(.)$ is read as "function of". In this relationship, incidences of under-skilled applicants in firm f depend on incidences across $j$ enterprises in the network of (or related to) f. The explained variable in this model is similar to that in McGinness et al (2024) and McGuinness & Staffa (2025) except that both papers focus on under-skilling from the supply side. Both papers only focused on estimating a worker's under-skilling without analyzing behavioural aspects. Our main explanatory variable in the theoretical arrangement follows Wolcott (2021), Morris et al (2019), and Audretsch et al (2023). We then incorporate other explanatory variables—including enterprise-specific characteristics—and parameterize the model. In so doing, we adopt and modify the analytical model estimated in McGuinness et al (2024) and McGuinness & Staffa (2025), where both studies estimate the same model. This modification is in the following respects.

One, we focus on under-skilling as captured from enterprises' perspective rather than from the workers' perspective. Two, we explain two outcome variables in separate regression models—$h_{0f}(\theta)$ and $h_{1f}(\theta)$—instead of merely focusing on the probability that an enterprise attracted under-skilled job seekers. Three, we consider $u_{1j}$ and $u_{0j}$ as the main explanatory variables—these variables are missing in both McGuinness et al (2024) and McGuinness & Staffa (2025). Four, we omit any other variable related to the dimension of skills—numeracy, technical, or social skills—from the vector of explanatory variables. Last, standard errors are clustered at the group level, and not at the country level. With this in mind, the analytical model follows the specification:

$$h_{kf} = \beta_0 + \beta_1 u_{mj}^{b} + \gamma W_f + v_f$$

Where $\beta_0$ is a constant term, $\beta_1$ is a slope coefficient corresponding to $u_{mj}$, and $\gamma$ is a vector of slope coefficients corresponding to control variables captured in W. These control variables are: the number of sources for new type-A and type-B employees, enterprise size, educational attainment for type-B employees, metropolitan region, and workforce expansion. V is an error term. Share and skill share are transformed using the inverse hyperbolic sine (arcsine) function of the actual value multiplied by 100; i.e., $arcsine(100 \times share)$ and $arcsine(100 \times skillshare)$.

Workforce expansion allows enterprises to raise the share of skilled workers. Marcolini & Quintini (2023) indicate that type-A and type-B workers tend to be attracted to enterprises with a large share of high-skill workers to take advantage of learning opportunities. For our analysis, this implies that the effect of workforce expansion on attracting under-skilled applicants balances out with its effect on attracting skilled workers. Thus, workforce expansion may insignificantly affect under-skilling.

A priori, a higher skills gap across other enterprises within a group is associated with a decline in under-skilling within the focal firm— e.g., due to poaching from other firms, and retention of highly-skilled employees. This in turn implies that a higher relative separation also translates into a reduction in under-skilled applicants to any particular enterprise.

We cluster standard errors at the group level, which allows us to adjust for potential heterogeneity across groups. This is in line with Morris et al (2020), McGuinness et al (2024), and McGuinness & Staffa (2025). Morris et al (2020) cluster standard errors at the region-industry level whereas McGuinness et al (2024) and McGuinness & Staffa (2025) cluster at the country level.

## TECHNIQUE OF ESTIMATION

To estimate the probability of an enterprise attracting under-skilled applicants, we employ maximum likelihood estimation via probability unit model, and subsequently report marginal effects. This is in line with McGuinness et al (2024) and McGuinness & Staffa (2025) which utilize probit models. In practice, marginal effects reported under probability unit model are similar to those under logit model, and marginal effects from both models are closely approximated in a linear probability model using OLS. Probit, logit, and linear probability models are suitable since the outcome variable is not censored. Furthermore, in testing for sample selection in the next section, the Heckman model simplifies to OLS. This hints at absence of selection bias which would otherwise have arisen from sample selection.

The number of vacant occupational positions for which under-skilled applicants were attracted is estimated in a negative binomial model[5]. The choice of negative binomial model was based on the goodness of fit test [between it and Poisson model] and the information criterion test between it and zero-inflated Poisson model.

Our identification strategy entails controlling for heterogeneity via introducing interaction terms on specific explanatory variables.

## DATA

Secondary data was sourced from the 2016 Employer Satisfaction Survey (STEP), compiled by the World Bank (World Bank 2016, 2018), which focused on formal private sector enterprises with at least five employees. 504 enterprises were surveyed in Kenya with data being captured on skills shortage and skills gap for white-collar (type-A) workers, and blue-collar (type-B) workers. Workers in type-A perform high-skill jobs; covered type-A workers were: technicians, professionals, and managers. Type-B workers engage in low-skill jobs; these workers include those in elementary occupations. STEP sheds light on the quality of job applicants in terms of job-related skills, experience, and expectations about salary within select municipalities in Kenya. Overall, enterprises reported on vacancies across nine occupational positions[6].

[5] None of the previous studies reviewed estimated a model for the number of occupational positions for which under-skilled applicants were attracted.

[6] Job applicants captured were: managers, professionals, technicians/ associate professionals, support and clerical workers, service workers, sales workers, construction workers, drivers/ machine operators, and elementary workers. We exclude agriculture (including fishery and forestry) workers.

EMPIRICAL FINDINGS

## DESCRIPTIVE STATISTICS

This subsection discusses key demographics which are summarized in Table 1 with a focus on the arithmetic mean. 341 firms attracted under-skilled applicants in at least one or more vacant occupational position; this represents 68% of sampled enterprises. Enterprises which attracted under-skilled workers tended to be large relative to firms which never attracted under-skilled applicants or were not hiring. Enterprises which attracted under-skilled applicants in at least 2 or more vacant occupational positions had 51 full-time permanent employees. This estimate is high relative to an average of 36.5 and 21.5 permanent employees reported among enterprises which attracted under-skilled applicants in 1 occupational position or none/ not hiring. Enterprises with under-skilled applicants in 2 or more occupational positions created vacancies in about 4.2 occupational positions. This is much higher than the 2.4 occupational positions reported across enterprises with under-skilled applicants in 1 occupational position. In terms of networks, enterprises with under-skilled applicants in at least 2 occupational positions belonged belonged to networks in which 63% of enterprises attracted under-skilled applicants. This contrasts with 62% and 58% reported for enterprises with under-skilled applicants in 1 occupational position or none/ not hiring, respectively. There are noticeable differences in the educational attainment of type-B workers. Typical type-B workers had tertiary education in 31.7% of enterprises with under-skilled applicants in 1 occupational position. This contrasts with 7.8% of enterprises without under-skilled applicants.

A test of independence was conducted using $\chi^2$ test with corresponding probability values reported. This test suggested significant linear associations across enterprises which either were not hiring or experienced no under-skilled applicants and enterprises with under-skilled applicants in 1 and 2 or more occupational positions. These significant associations were evident with regard to the number of full-time permanent employees (enterprise size), the number of vacant occupational positions, number of hiring sources deployed for new type-A and type-B workers, expansion of the workforce, the share of type-B workers with at least a Bachelor's degree, and the sahre of enterprises with under-skilled applicants within their networks.

*Table 1: Demographics*

| | Reported number of occupational positions with under-skilled applicants | | | | |
|---|---|---|---|---|---|
| | 0 or not hiring (N = 156) | 1 (N = 171) | 2+ (N = 170) | Total (N = 497) | p-value |
| | Mean (SD) | | | | |
| Enterprise age (years) | 17.31 (10.78) | 16.71 (11.03) | 17.90 (13.13) | 17.21 (11.43) | 0.674 |
| Enterprise size (no. of full-time permanent workers) | 21.51 (61.15) | 36.52 (92.38) | 51.33 (143.71) | 34.21 (97.78) | 0.034 |
| Group share of firms with under-skilled applicants* | 0.58 (0.13) | 0.62 (0.15) | 0.63 (0.16) | 0.61 (0.15) | 0.010 |
| Group mean no. of occupational positions with under-skilled applicants | 0.93 (0.39) | 1.07 (0.45) | 1.15 (0.55) | 1.04 (0.46) | <0.001 |
| No. of occupational positions with vacancies | 1.65 (1.24) | 2.40 (1.33) | 4.23 (1.67) | 2.53 (1.69) | <0.001 |
| Firm size-sector-region average of occ positions hiring excl. focal firm | 2.42 (0.70) | 2.69 (0.88) | 2.84 (0.93) | 2.62 (0.84) | <0.001 |
| Group share of occupational positions with under-skilled applicants | 0.38 (0.09) | 0.40 (0.08) | 0.39 (0.09) | 0.39 (0.09) | 0.404 |

| | | | | | |
|---|---|---|---|---|---|
| Number of firms in each group | 26.93 (13.81) | 27.72 (13.39) | 25.06 (12.50) | 26.82 (13.37) | 0.240 |
| Arcsine wage bill ratio | 0.98 (0.50) | 1.02 (0.71) | 1.04 (0.60) | 1.01 (0.61) | 0.672 |
| No. of hiring sources for type-A workers | 1.84 (1.24) | 2.16 (1.05) | 2.76 (1.26) | 2.18 (1.22) | <0.001 |
| No. of hiring sources for type-B workers | 1.66 (1.01) | 1.93 (1.08) | 2.70 (1.28) | 2.01 (1.17) | <0.001 |
| Group share of firms with under-skilled applicants in 2+ positions | 0.22 (0.11) | 0.26 (0.13) | 0.27 (0.16) | 0.25 (0.13) | 0.003 |
| | Percentage | | | | |
| Enterprise size | | | | | <0.001 |
| Small: 5-19 workers | 83.8 | 64.3 | 52.2 | 68.9 | |
| Medium: 20-99 workers | 12.7 | 29.7 | 39.2 | 25.5 | |
| Large: >99 workers | 3.4 | 5.9 | 8.6 | 5.6 | |
| Type-A worker's education: tertiary | 65 | 66.7 | 65.6 | 65.8 | 0.886 |
| Type-B worker's education: tertiary | 7.8 | 31.7 | 34.3 | 23.2 | 0.023 |
| Type A or type B worker trained in the firm | 15.1 | 11.2 | 11.4 | 12.7 | 0.697 |
| Within-firm type-A worker training | 15.1 | 9.3 | 7 | 10.9 | 0.678 |
| Within-firm type-B worker training | 5.5 | 5.1 | 5.1 | 5.2 | 0.540 |
| Negotiable worker salaries | 69.5 | 72.5 | 79.7 | 73.1 | 0.065 |
| Workforce expansion between 2014 and 2015 | 23.8 | 44.5 | 58.4 | 39.8 | 0.001 |
| Sector | | | | | 0.571 |
| Manufacture incl. elec supply, agric, and mining | 18.5 | 15.4 | 15.7 | 16.6 | |
| Wholesale or retail trade | 30.5 | 25.2 | 34 | 29.2 | |
| Other services | 51 | 59.4 | 50.3 | 54.2 | |

*Source: Authors' computation using STEP dataset*

We reconcile these enterprise-level demographics with previous studies. Alfonsi et al (2020) reveal 67% of enterprises in Uganda having under-skilled workers. This suggests that under-skilling is not unique to Kenya.

The demographics indicate greater prevalence of under-skilled applicants across enterprises having typical type-B workers with tertiary education. Marcolin & Quintini (2023) indicate that some workers look for employment in enterprises offering greater opportunities to learn. These opportunities arise when enterprises have a large pool of educated employees (World Bank2016, 2018). The literature also indicates that some workers look for employment in fields of work which differ substantively from their respective fields of study (Conzelmann et al, 2023). Since some skills are specific to certain fields of work, some workers had skills which were different from the ones enterprises with vacancies sought out for.

Under-skilled workers were drawn towards enterprises with a large number of permanent employees. This is in line with Marcolin & Quintini (2023) which indicate that large enterprises compensate workers better and have higher worker retention chances. Both attributes incentivize workers to seek employment in relatively large enterprises although their chances of being employed in high-skill jobs are low due to better screening.

Enterprises with under-skilled applicants were related to other enterprises facing similar problems. This reflects slow-to-almost non-existent cross-group reallocation of labour rather than enterprise- and worker-sorting (Brunello & Wruuck, 2021). Since skilled workers tend to strategically search for jobs, they were more likely absorbed by enterprises due to reduced need for firm training, or received assisted job search (Alfonsi et al, 2020; Bandiera et al, 2023). The pool of job seekers then had increasingly fewer numbers of skilled workers since many of them find jobs early.

## ESTIMATED MODEL

We consider a baseline model without interaction terms, and employ OLS alongside alternative logit and probability unit specifications. The non-causal effect of various explanatory variables on the probability of an enterprise attracting under-skilled job applicants is given by the marginal effects in Table 2.

The marginal effect of the share of enterprises attracting under-skilled applicants (arcsine skill share) is negative but not statistically different from zero. This suggests that the probability of enterprises attracting under-skilled job seekers was independent of other enterprises attracting under-skilled applicants. The marginal effect of the share of occupational positions with under-skilled applicants in other enterprises (arcsine share) is, however, negative and statistically non-zero. In particular, a 1% increase in occupational positions with under-skilled applicants in other enterprises is associated with a 0.19-0.23% reduction in the probability that a focal enterprise attracts under-skilled applicants. We reconcile this latter finding with the literature in two ways. One, job search costs are significant implying that the larger the number of under-skilled applicants looking for employment in other firms, the fewer the number of them looking for work in focal enterprises (Kettanurak, 2025). Two, other firms hire following the believe that skilled applicants are hard to come by whereas focal enterprises strategically delay hiring (Cintio, 2022; Kettanurak, 2025; Schroeder, 2022).

Enterprises whose typical type-B workers had tertiary education were 11-12% more likely to attract under-skilled applicants than enterprises whose typical type-B workers had lower educational attainment. Since educational attainment of a typical worker in an enterprise is not private information, workers looking for employment in enterprises whose typical employees have tertiary education must themselves be having a similar educational attainment. This finding then hints at some job seekers being educated yet under-skilled (Muchira et al, 2023).

Raising the number of sources for new type-A hires by 1 is associated with a 3.4-3.6% increase in the probability of an enterprise attracting under-skilled applicants. This magnitude corresponds with 5.0-5.5% for type-B workers. Since workers with low skills tend to search for jobs using multiple modalities (Wolcott, 2021), diversifying sources for new hires raises the odds of enterprises meeting under-skilled workers. A natural question which arises is why enterprises would increase the number of hiring sources when such a move raises the odds of meeting under-skilled applicants. It turns out enterprises in Kenya do not genuinely care much about the quality of workers. This is the case in at least two respects. One, low labor quality matches its corresponding compensation which is low (Dhillon et al, 2020). We showed in Table 1 that there are no significant differences in employee compensation (arcsine wage bill ratio) among enterprises with no under-skilled applicants and firms attracting under-skilled workers. An analysis of labour incomes based on the 2016, 2018, 2021, and 2024 Financial Access Household Survey datasets suggests median labour earnings which are quite low. Two, under-skilled workers implies that labour is constraint to activities of enterprises. However, the 2007, 2013, 2018, and 2025 Enterprise Surveys conducted by the World Bank reveals only a small share of formal enterprises in Kenya facing major or very severe constraints related to labour—in terms of quality/ skills, hiring expenses, and regulations.

A medium enterprise was 20.5-26.6% more likely to attract under-skilled applicants than a small counterpart. A large enterprise was 17.3-23.6% more likely to attract under-skilled applicants than a small counterpart. This finding is in line with Marcolin & Quintini (2023) indicating that job seekers, irrespective of their skills set, tend to be attracted to large enterprises due to better compensation and greater prospects for mobility up the job ladder (Marcolin & Quintini, 2023). Under-skilled applicants may further believe that medium and large enterprises are not any better at discerning who to offer jobs to than small enterprises (Carranza & McKenzie, 2024). This belief, alongside the belief that some under-skilled applicants stood a chance of being employed (Brunello & Wruuck, 2011), inclined under-skilled applicants towards medium and large enterprises.

Enterprises within Nakuru metropolis were 14.2-17.7% more likely to attract under-skilled applicants than counterpart enterprises within Kisumu metropolis. However, enterprises within Mombasa and Nairobi metropolises were just likely to attract under-skilled applicants as counterpart firms within Kisumu metropolis. This finding is tandem with Ngware et al (2022) which indicate ambiguous geographical effects on skills relevant for whole youth development. At the time of STEP survey, Nakuru metropolis—including Uasin Gishu and Kericho—had no special economic zones/ export-processing zones or industrial clusters unlike the other metropolises (Newman & Page, 2017); these industrial clusters were designated for development in 2023, about 7 years later (Ministry of Trade & Industry, 2023). König & Brenner (2022) indicate that industrial clusters tend to attract skilled workers.

*Table 2: Baseline Estimation—prob of attracting under-skilled job applicants*

| Variables | LPM | Logit | Probit | LPM | Logit | Probit |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Arcsine skill share | -0.178** | -0.271 | -0.283 | | | |
| | (0.0730) | (0.190) | (0.194) | | | |
| Type-A sources | 0.0339* | 0.0351* | 0.0341* | 0.0350* | 0.0355** | 0.0345** |
| | (0.0174) | (0.0179) | (0.0175) | (0.0172) | (0.0177) | (0.0173) |
| Type-B sources | 0.0534*** | 0.0541*** | 0.0547*** | 0.0503*** | 0.0504*** | 0.0506*** |
| | (0.0151) | (0.0176) | (0.0173) | (0.0149) | (0.0170) | (0.0166) |
| Tertiary type-B education | 0.120** | 0.121** | 0.120** | 0.117* | 0.114* | 0.114** |
| | (0.0576) | (0.0579) | (0.0545) | (0.0577) | (0.0599) | (0.0556) |
| Workforce expansion | 0.150*** | 0.144*** | 0.150*** | 0.155*** | 0.149*** | 0.155*** |
| | (0.0407) | (0.0406) | (0.0403) | (0.0408) | (0.0407) | (0.0406) |
| Medium firms | 0.235*** | 0.260*** | 0.266*** | 0.210*** | 0.205*** | 0.209*** |
| | (0.0518) | (0.0846) | (0.0821) | (0.0455) | (0.0526) | (0.0506) |
| Large enterprises | 0.207*** | 0.231*** | 0.236*** | 0.178*** | 0.173*** | 0.177*** |
| | (0.0546) | (0.0841) | (0.0815) | (0.0492) | (0.0555) | (0.0530) |
| Metropolis | | | | | | |
| Kisumu (rf) | | | | | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| Nairobi | 0.0255 | 0.0375 | 0.0383 | 0.00595 | 0.00425 | 0.00545 |
| | (0.0571) | (0.0653) | (0.0657) | (0.0522) | (0.0521) | (0.0521) |
| Nakuru | 0.158** | 0.180** | 0.177** | 0.143** | 0.142** | 0.142** |
| | (0.0767) | (0.0847) | (0.0843) | (0.0677) | (0.0668) | (0.0651) |
| Mombasa | 0.0485 | 0.0617 | 0.0610 | 0.0505 | 0.0504 | 0.0531 |
| | (0.0659) | (0.0691) | (0.0698) | (0.0580) | (0.0546) | (0.0555) |
| Arcsine share | | | | -0.192*** | -0.220* | -0.230** |
| | | | | (0.0652) | (0.117) | (0.117) |
| Observations | 485 | 485 | 485 | 485 | 485 | 485 |

*Source: Authors' computation using STEP dataset*

Parentheses indicate standard errors which are adjusted for 32 clusters. * p<0.1, ** p<0.05, and *** p<0.01. Skill share: share of enterprises in a group with under-skilled workers in at least 1 occupational position, excluding focal firm. Share: mean # of occupational positions in a group which attracted under-skilled applicants divided by the mean # of occupational positions in a group which were vacant. Arcsine skill share=arcsine (100*skill share). Arcsine share=arcsine(100*share).

Within-firm number of vacant occupational positions which attracted under-skilled job seekers is then estimated in a baseline OLS, followed by negative binomial with enterprise age utilized as exposure variable. Deviance test suggested over-dispersion, and thereby ruled out Poisson model. Information criterion based on Akaike procedure hinted at greater parsimony in negative binomial than under the zero-inflated negative binomial model. Marginal effects after OLS and negative binomial are captured in Table 3.

Raising the average number of occupational positions with under-skilled applicants among peer enterprises by 1% is associated with a 0.01 reduction in the number of occupational positions with under-skilled applicants within the focal enterprise. Raising the share of peer enterprises with under-skilled applicants by 1% is associated with a 0.011 reduction in the number of occupational positions with under-skilled applicants within the focal enterprise. These suggest that some under-skilled applicants were absorbed in the other peer enterprises, thereby reducing incidences of focal firms attracting under-skilled applicants (Marcolin & Quintini, 2023). Alternatively, some enterprises waited for other firms to hire believing that other enterprises had lower reservation skill (Schroeder, 2022), or that the delay was strategic so that laggards would then avail counter-offers to workers already screened and hired by other enterprises.

Table 3: Baseline Estimation—number of occupational positions with under-skilled job applicants

| Variables | OLS | Negative binomial | OLS | Negative binomial |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Arcsine share | -0.378** | -0.995*** | | |
| | (0.178) | (0.317) | | |
| Type-A sources | 0.146** | 0.157** | 0.143** | 0.149** |
| | (0.0675) | (0.0764) | (0.0665) | (0.0733) |
| Type-B sources | 0.175*** | 0.276*** | 0.183*** | 0.291*** |
| | (0.0593) | (0.0878) | (0.0593) | (0.0854) |
| Tertiary type-B education | 0.291* | 0.520** | 0.299* | 0.545** |
| | (0.151) | (0.240) | (0.153) | (0.247) |
| Workforce expansion | 0.599*** | 0.974*** | 0.590*** | 0.941*** |
| | (0.140) | (0.209) | (0.140) | (0.198) |
| Medium firms | 0.628*** | 0.915*** | 0.703*** | 1.065*** |

| | | | | |
|---|---|---|---|---|
| | (0.134) | (0.293) | (0.140) | (0.289) |
| Large enterprises | 0.633*** | 0.502*** | 0.714*** | 0.659*** |
| | (0.140) | (0.174) | (0.139) | (0.185) |
| Metropolis | | | | |
| Kisumu (rf) | | | | |
| Nairobi | 0.175 | 0.154 | 0.221 | 0.248 |
| | (0.153) | (0.238) | (0.132) | (0.199) |
| Nakuru | 0.346** | 0.957*** | 0.394** | 1.073*** |
| | (0.155) | (0.278) | (0.161) | (0.286) |
| Mombasa | 0.588*** | 0.707** | 0.591*** | 0.666** |
| | (0.180) | (0.323) | (0.161) | (0.273) |
| Arcsine skill share | | | -0.424* | -1.074** |
| | | | (0.227) | (0.434) |
| Observations | 485 | 485 | 485 | 485 |

*Source: Authors' computation using STEP dataset*

Parentheses indicate standard errors which are adjusted for 32 clusters. * p<0.1, ** p<0.05, and *** p<0.01.

## ROBUSTNESS CHECK

We analyze heterogeneity by incorporating interaction terms. These terms are: enterprise size separately interacted with type-B worker's educational attainment, metropolis, and workforce expansion, and; workforce expansion interacted with metropolis. The analysis is also repeated with ana alternative specification for skill gap—focusing on at least 2 or more occupational positions with under-skilled job seekers (skill gap II). Marginal effects after logit and negative binomial are captured in Table 4. Reported coefficients in Table 4 closely match corresponding coefficients in Table 2 and Table 3 in terms of statistical significance and direction of effect. The magnitudes differ slightly but remain within allowable bounds. This suggests absence of pronounced heterogeneities.

*Table 4: Heterogeneity Estimation*

| | Logit | | | | Negative binomial | | |
|---|---|---|---|---|---|---|---|
| Variables | Skill gap | Skill gap | Skill gap II | Skill gap II | Number of positions | y1 | y1 |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Arcsine skill share | -0.366* | | | | -1.159** | | |
| | (0.187) | | | | (0.480) | | |
| Type-A sources | 0.0332** | 0.0343** | 0.0363* | 0.0346* | 0.135* | 0.141* | 0.151* |
| | (0.0169) | (0.0166) | (0.0198) | (0.0206) | (0.0796) | (0.0814) | (0.0811) |
| Type-B sources | 0.0569*** | 0.0516*** | 0.0645*** | 0.0695*** | 0.297*** | 0.279*** | 0.260*** |
| | (0.0171) | (0.0169) | (0.0190) | (0.0195) | (0.0853) | (0.0879) | (0.0911) |
| Tertiary type-B education | 0.144*** | 0.149*** | 0.168*** | 0.155*** | 0.938*** | 0.954*** | 0.984*** |
| | (0.0389) | (0.0386) | (0.0399) | (0.0403) | (0.181) | (0.191) | (0.201) |
| Workforce expansion | 0.139*** | 0.134*** | 0.124** | 0.119** | 0.602*** | 0.583*** | 0.608*** |
| | (0.0406) | (0.0418) | (0.0570) | (0.0578) | (0.225) | (0.220) | (0.230) |
| Medium firms | 0.262*** | 0.193*** | 0.199*** | 0.135*** | 1.139*** | 1.008*** | 1.079*** |
| | (0.0765) | (0.0480) | (0.0684) | (0.0508) | (0.272) | (0.291) | (0.362) |
| Large enterprises | 0.238*** | 0.176*** | 0.187*** | 0.156*** | 0.660*** | 0.536*** | 0.568*** |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | (0.0736) | (0.0494) | (0.0434) | (0.0375) | (0.146) | (0.109) | (0.131) |
| Metropolis | | | | | | | |
| Kisumu (rf) | | | | | | | |
| Nairobi | 0.0512 | -0.00789 | 0.0245 | -0.0348 | 0.268 | 0.157 | 0.349 |
| | (0.0488) | (0.0424) | (0.0706) | (0.0568) | (0.187) | (0.232) | (0.231) |
| Nakuru | 0.214*** | 0.143** | 0.253*** | 0.134** | 0.980*** | 0.839*** | 1.100*** |
| | (0.0631) | (0.0589) | (0.0843) | (0.0668) | (0.260) | (0.253) | (0.302) |
| Mombasa | 0.0724 | 0.0352 | 0.201*** | 0.0994* | 0.787*** | 0.833*** | 1.024*** |
| | (0.0600) | (0.0451) | (0.0756) | (0.0511) | (0.203) | (0.270) | (0.383) |
| Arcsine share | | -0.260* | | -0.117 | | - 1.130*** | |
| | | (0.135) | | (0.0827) | | (0.422) | |
| Arcsine skill share II | | | -0.157** | | | | -0.501* |
| | | | (0.0687) | | | | (0.268) |
| Observations | 485 | 485 | 485 | 485 | 485 | 485 | 485 |

*Source: Authors' computation using STEP dataset*

Parentheses indicate standard errors which are adjusted for 32 clusters. * $p<0.1$, ** $p<0.05$, and *** $p<0.01$. Skill share II: share of other enterprises in a group with under-skilled workers in at least 2 occupational positions.

## SUMMARY OF KEY FINDINGS

This paper analyzed the extent to which under-skilling among related enterprises affect under-skilling within focal firms. In line with the paper's objective, these findings are summed up as follows:

i. The probability of an enterprise having under-skilled applicants was not affected by other peer enterprises attracting under-skilled applicants.
ii. The probability of an enterprise attracting under-skilled applicants declines in the average number of occupational positions for which peer enterprises attracted under-skilled applicants.
iii. The number of occupational positions with under-skilled applicants in an enterprise decline in the average number of occupational positions with under-skilled applicants among peer enterprises.
iv. The number of occupational positions with under-skilled applicants in an enterprise decline in the share of peer enterprises with under-skilled applicants.

## POLICY IMPLICATION

Key findings from this paper imply the following for policy:

i. Enterprises are less likely to attract under-skilled applicants as under-skilling rises among peer enterprises [based on the average number of occupational positions with under-skilled applicants]. This raises a challenge whereby some enterprises may strategically delay hiring workers while hoping for peers to employ under-skilled workers [only for delayers to later poach them].
ii. Enterprises have fewer vacant occupational positions with under-skilled applicants when an increasing number of vacant occupational positions among peers attract under-skilled applicants. This, again, may induce enterprises to delay filling vacant occupational positions when faced with under-skilled applicants. The problem is that in the long-run, no enterprise hires.

## CONCLUSION

This paper analyzed how under-skilled among enterprises in Kenya is affected by under-skilling across related enterprises. Two outcome variables were considered; i.e., the probability of an enterprise attracting under-skilled applicants, and the number of a firm's vacant occupational positions for which under-skilled applicants were attracted. The former outcome was estimated using OLS alongside computing marginal effects from probit and logit models. The latter outcome was estimated in a negative binomial model.

Key findings were as follows: the probability of an enterprise having under-skilled applicants was not affected by under-skilling across related enterprises; enterprises were less likely to attract under-skilled applicants when the number of occupational positions for which related enterprises attracted under-skilled applicants rose; the number of occupational positions with under-skilled applicants in an enterprise declined in the average number of occupational positions with under-skilled applicants among related enterprises; and the number of occupational positions with under-skilled applicants in an enterprise declined in the share of peer enterprises with under-skilled applicants.

This paper concludes that enterprises in Kenya are less likely to attract under-skilled applicants when peers have more incidences of under-skilled job seekers. The paper further concludes that enterprises have fewer vacant occupational positions with under-skilled applicants when either the share of peers with under-skilled applicants rises or the average number of vacant occupational positions with under-skilled applicants rises among peers.

As a suggestion for policy action, programs which encourage within-enterprise training of workers would go a long way in addressing under-skilling in Kenya. This is because the negative co-movements between focal enterprises' under-skilling and that among peers could be due to enterprises adopting a "wait-and-see" approach in which hiring is delayed until under-skilled applicants are absorbed by other firms. One such program is wage subsidy which enables enterprises to free up resources towards worker upskilling and within-enterprise training.

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## APPENDIX

### SECTORS AND REGIONS

Enterprises in this analysis were regrouped into three sectors—manufacturing, retail or wholesale trade, and other services. Municipalities were regrouped into four regions. These municipalities were: Ahero, Juja, Kajiado, Katito, Kericho, Kericho, Kiambu, Kisumu, Mombasa, Muhoroni, Nairobi, Nakuru, Thika, and Uasin Gishu.

### OPERATIONALIZATION OF VARIABLES IN THE RESULTS SECTION

In Table 1, 4 firms from mining and extraction, agriculture, and supply of electricity, steam, and gas were included among manufacturing sector enterprises. A firm expanded its workforce if the number of employees in 2015 exceeded that in 2014. Type-A or type-B worker is negotiable for firms which set wages via employer-employee negotiation. Worker training is assigned 1 for a firm which offered within-firm employee training, and 0 otherwise. Worker education assumes 1 for average worker with tertiary education (Bachelor and above), and 0 otherwise. Occupational skills gap refers to the number of occupational positions for which under-skilled job applicants were attracted. Under-skilled applicants are assigned 1 for enterprises which attracted under-skilled job applicants in at least one occupational position; 0 includes enterprises which never hired.

Wage bill ratio captures the annual per worker wage in 2015 as a ratio of the respective costs in 2014. This is transformed using inverse hyperbolic sine function. Skill share: share of enterprises in a group with under-skilled workers in at least 1 occupational position, excluding focal firm. Share: mean # of occupational positions in a group which attracted under-skilled applicants divided by the mean # of occupational positions in a group which were vacant. Arcsine skill share=arcsine (100*skill share). Arcsine share=arcsine(100*share). In computing these shares, focal firms are excluded. Sectors are trade (wholesale or retail), other services, and manufacturing. Enterprises are regrouped into four regions—Kisumu (including Ahero and Muhoroni municipalities), Nakuru (including Uasin Gishu and Kericho), Nairobi (including Juja, Kiambu, Thika, Kajiado, and Katito), and Mombasa. Firm age captures the duration, in years, for which the enterprises had operated in Kenya up to 2016.