Social Connections and Skills Gap in Kenya

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# **ABSTRACT**

Studies on inter-firm networks indicate that enterprises facing constraints related to the quality of employees rely on other enterprises for their own survival. These studies treat skills gap as given, and consider the poaching of highly-skilled and experienced employees as inevitable when firms face rising within-firm worker-training costs or when employee-employer referral system breaks down. What is less understood, especially from a developing-country context, is the extent to which focal enterprises respond to rising skills gap at the [sub]sector-region level. This paper analyzes the responsiveness of enterprises to under-skilling among related enterprises at the [sub]sector and region level in Kenya. The analysis utilizes the 2016 STEP survey dataset. This survey was conducted by the World Bank among firms within the services and manufacturing sectors. Findings suggest that under-skilling in Kenya is quite high with two in every three enterprises having attracted an under-skilled job seeker. In a regression discontinuity design setup, we show that focal enterprises were less likely to attract under-skilled job seekers when under-skilling was high among their peers relative to when low. We conclude that focal enterprises countered under-skilling among their peers by being less attractive to under-skilled job seekers. We then recommend regular coordination of skills training workshops at the sector-region level.

Key words: Skills gap; Social connections

JEL Codes: D83, J24, J64, J82

**INTRODUCTION**

Beginning the year 2007, Kenya embarked on an ambitious Vision 2030 project which was intended to transition the country into an upper-middle-income rapidly-industrializing country by the year 2030. The Project’s cornerstone was skills-driven industrialization. Towards meeting the country’s needs for skills for development, successive governments rolled out various initiatives targeting skills development and innovation. These initiatives included the Big Four Agenda in the 2013-2022 period, and the Bottom-Up Economic Transformation Agenda (BETA) from 2023 to the present. These initiatives were integrated within the fourth medium-term plan which emphasizes the creation of gainful and meaningful employment opportunities while expanding the pool of a skilled workforce. Kenya has also invested in talent and skills development via the State Department for Labour and Skills Development. This move was augmented by specific legislations and frameworks including the National Guidelines for Sector Skills Committees and the National Skills Development Policy. Both frameworks focus on enhancing the quality of workers, and thereby foster effective labour. Despite these initiatives and legislations, the country faces a skills deficit with the skills gap being more pronounced in some sectors and regions relative to others. Pronounced skills gaps could derail skills-driven industrialization, thereby rendering Vision 2030 unachievable.

The problem of skills deficit and slow industrialization is not unique to Kenya. For instance, industrialization on the continent is discouragingly low despite Africa’s massive industrial potential (Gelb et al, 2020; Newfarmer et al, eds, 2019). Africa is also argued to de-industrialize prematurely, thereby driving the destruction of decent industrial jobs (Naudé & Tregenna, 2023; Di Berardino et al, 2021; Ciccolini, 2023). Related studies, including Gillman (2021), Brunello & Wruuck (2021), and Bandiera et al (2023), indicate that the continent’s poor industrial development arises in part from the underutilization of a limited skilled workforce, widespread skills gap and skills deficits, underinvestment in skills development, and the replacement of skill-intensive jobs with less skill-sensitive jobs[[4]](#footnote-4). Widening skills deficit implies rising costs of labour sourcing and labour training (Gelb et al, 2020).

Skills are important for various reasons. One, a worker’s skills level is directly related to one’s ability, and the execution of tasks and productivity (Dhillon et al, 2020; Morris et al, 2020; Federico et al, 2019; McGuinness & Ortiz, 2016). This has direct implications on vacancy creation, hiring, and worker compensation decisions made by enterprises alongside the observed behavior of sourcing for new employees across firms (Bandiera et al, 2023; de Groot et al, 2021; Dhillon et al, 2020). Two, skills levels of available workers affect the rate at which new tasks and jobs are created, and the nature of these tasks (Wolcott, 2021; McAdams, 2019). This further affects unemployment across [sub]sectors and regions within an economy, and has the potential of inducing relative demand for specific skills thereby characterizing depreciation of less-demanded skills (Brunello & Wruuck, 2021; Barrios et al, 2020).

Studies including Liu et al (2019) and Chen et al (2023) indicate that enterprises treat the skills gap as given. This in turn induces firms to learn from each other, imitate hiring practices of related firms, and adopt sector-specific best practices. Sector-specific best practices could entail investment in customized firm-specific training or industry-educational institutions’ partnerships focusing on work-integrated learning/ vocational training/ employee training workshops (Bandiera et al, 2023; Lise & Postel-Vinay, 2020).

The aforementioned studies offered a description of skills gap – revealing its heterogeneity across sectors and regions—alongside explaining some of its drivers. These drivers include differences in educational investment, vocational training, technological disruptions, and within-firm upskilling of employees. These studies alongside the ones we reviewed in the next section, however, considered enterprises as being unresponsive to under-skilling among firms related to them. Against this background, this paper offers an analysis of skills gap within focal firms as behavioral responses to under-skilling among enterprises which are related to them. That is, the paper looks at social connections among enterprises, and the extent to which these connections affect skills gap in Kenya. The paper considers enterprises as being socially connected or related when they belong to the same subsector and region. [Sub]sector-region analysis is important because enterprises are not equally exposed to skills-related problems. Enterprises facing similar skills-related challenges also tend to respond differently. One of the behavioral responses entails enterprises diversifying sources for new hires. The 2016 Employer Satisfaction Survey (STEP) reveals that 66% and 53% of enterprises within services and manufacturing sectors, respectively, relied on more than one source for new employees (World Bank, 2016, 2018). We further treat returns to education as given. This is because an additional year of schooling in Kenya has returns in the range 2-36% depending on the level with returns exceeding 15% for post-primary education (Onsomu et al, 2006; Manda et al, 2002; Söderbom et al, 2006; Gethin, 2023; Psacharopoulos & Patrinos, 2018)

Skills gap is operationalized as either relational (Meta, 2022; Guardia et al, 2021; Munene, 2021) or relative to a benchmark level desired by employers/ firms (de Groot et al, 2021; Carranza & McKenzie, 2024). Skills gap is relational when existing tasks within a firm require a skillset which differs from skills embodied by employees. The gap is relative when workers’ skills level either exceeds or falls below the threshold set by the firm for the execution of specific tasks or jobs.

Subsequent sections contextualize this paper within the relevant literature, discuss the analytical approach, and present empirical analyses for Kenya alongside a discussion, and conclusion.

# **RELATED LITERATURE**

## **THEORETICAL FRAMING**

The underlying theory is the Diamond-Mortensen-Pissarides search and matching model (Pissarides, 2000; Mortensen & Pissarides, 1994; Diamond, 1982). This model indicates that it is always beneficial to both jobseekers and hiring enterprises agreeing on job offers whenever the two parties meet. An implication of it is that when an enterprise in need of skilled workers meets unskilled or skill-mismatched job seekers, the former incurs additional costs in its failure to hire unskilled job seekers. These costs arise from maintenance expenses related to a vacancy created within the firm, and foregone output when a firm has to keep searching for workers. Similarly, a firm incurs expenses related to filling a vacancy requiring skilled workers with unskilled workers. These expenses include within-firm training, re-skilling, and upskilling new employees. Although searching models assume that vacancies are created and destroyed without a cost, there are many barriers to job creation and destruction in practice—including legal suits over unfair employee dismissal, and legislative provisions mandating the compensation of workers whose jobs have been destroyed[[5]](#footnote-5).

It is these costs associated with upskilling unskilled workers, costly continuous search for skilled workers when such workers are hard to come by, and costly legal suits which incentivize enterprises to rely on referrals, networks, and poaching skilled employees from other firms (Calvó-Armengol & Jackson, 2004; Faberman et al, 2022; de Groot et al, 2021; Glitz & Vejlin, 2021). Beaman & Magruder (2010), Pieper et al (2019), Faberman et al (2022), and Glitz & Vejlin (2021) indicate that between one-third and one-half of new vacancies are filled via referrals. This is driven by noise and signal distortion on external hiring markets which interfere with the efficient matching of workers to enterprises across a skills profile. Theory, therefore, predicts that networks and referrals grease the job matching function, and both explain part of the reported skills gap across enterprises.

## **EMPIRICAL STUDIES**

Studies on skills gap and networks focus almost exclusively on referrals, poaching, or collaborations (Beaman & Magruder, 2010; Glitz & Vejlin, 2021; Braunerhjelm et al, 2020; Goel & Lang, 2019; Andreoni et al, 2021; Shingou et al, 2022; Audretsch et al, 2023). These referrals are largely drawn from coworkers, social networks, and inter-firm linkages, with the consensus being that referrals reduce the costs of screening new employees, and reduce the need for on-the-job training. Some studies offer a job-matching context of skills gap by matching beneficiaries of study programs to available jobs (Bandiera et al, 2023). Other studies, and which we leave out, consider skills gap without linking them to networks. 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 (Acemoglu et al, 2022; Diao et al, 2021; Bustos et al, 2022; Federico et al, 2019; Halim et al, 2019); relative importance of certain skills (Getahun & Mersha, 2020; Fink, 2023; Shingou et al, 2022); and limited interactions among employees in a firm (Wuni et al, 2021; Gregersen, 2022). We also omit studies focusing on the nexus between curriculum development, coverage of syllabus, fields of study, and skills shortage (Tomar-Mishra et al, 2019; Amutabi & Wambugu, 2020; John et al, 2020; Zervoudi, 2020; Costan et al, 2021; Wolcott, 2021; Munga et al, 2021; Ngware et al, 2022; Muchira et al, 2023; Conzelman et al, 2023)

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.

Among the reviewed studies, Audretsch et al (2023) and Morries et al (2019) are the closest to this paper. The former considers geographical proximity of enterprises to partners in understanding skills shortage. The latter analyzes region-sector skills shortage and productivity. These studies, however, shed no light on enterprises’ responsiveness to skills shortage across firms related to them. In particular, Morris et al (2019) considers a general region-industry skills gap average which masks skills evolution across individual, although related, enterprises. A major gap across the reviewed literature is that skills gap within enterprises was treated as being unresponsive to skills gap among other enterprises which are related to them. This paper bridges this gap by looking at skills gap as a behavioral response to under-skilling among related firms with a focus on enterprises within the manufacturing and services sectors in Kenya.

# **METHODOLOGY**

Skills gaps exist, and are given irrespective of a worker’s educational attainment (Morris et al, 2020; de Groot et al, 2021; Glitz & Vejlin, 2021; Bandiera et al, 2023; McGuinness & Ortiz, 2016). Firms in turn search for prospective employees with minimal skills gap in order to slash down costs of worker training and leapfrog others (Brunello & Wruuck, 2021). We further assume that enterprises are not penalized for poaching employees, and that firms learn from the errors of others (Morris et al, 2020; Liu et al, 2019). Whereas skills gap is given, it is not homogenous across sectors and regions (Morris et al, 2020; Marcolin & Quintini, 2023).

Similarly, employees differ in the level of skills depending on their type. For simplicity, we associate a white-collar (type-A) worker with high skills, and a blue-collar (type-B) worker with low skills (Wolcott, 2021). Both worker types prefer enterprises with a larger share of Type-A workers or the pattern of skills gap between the types is unrelated (Marcolin & Quintini, 2023). Lastly, we assume that skills gap in a focal firm is declining when the share of related enterprises facing skills shortage is rising. The focal firm realizes this via either contacting educational institutions directly, poaching skilled and experienced workers, or investing in costly on-the-job training (Morris et al, 2020; McGuinness & Ortiz, 2016). Skills gap then assumes the theoretical functional form with the specification:

$$G\_{f}^{b}=G\_{f}\left(G\_{j}^{b},Q\_{f}^{b}\right)$$

Where firm f’s skills gap G for worker type b depends on skills gap in related firms j, and other factors, Q. These other factors include: skills gap share across related enterprises, firm size, within-firm training, contact with educational institutions, sector, wage bill, and number of occupational positions for which vacancies were available.

We estimate skills gap probability in a robust linear-in-means regression discontinuity design (RD)[[6]](#footnote-6). The explained variable is the probability that a firm attracted under-skilled applicants in at least one of the nine occupational positions it had desired filling[[7]](#footnote-7). This is explained separately by three running variables—centered number of within-firm employees; centered share of enterprises at the region-sector level which attracted under-skilled applicants; and centered workforce ratio at the firm size-sector-region level[[8]](#footnote-8). Number of employees in a firm is centered by subtracting from it the average number of employees at the respective firm size-sector-region level, excluding the focal firm. Workforce ratio captures the number of employees in the firm in 2015 as a ratio of the number of employees in 2014. This ratio indicates workforce expansion, and reflects relative worker separation. Where worker ratio exceeds 1, it is assumed that the number of workers joining the firm exceeded that leaving. This variable further shed light on the possibility of poaching such that poaching is evident when a firm’s workforce shrinks while simultaneously experiencing skills gap. We then average for the sector, region, and firm size level before subtracting this firm size-region-sector average from the respective firms’ values. Centering necessarily implies that the threshold of the centered variable is at 0.

Observations with values either on or above the threshold constitute the treated group with the remainder forming the untreated/ control group (Marinescu et al, 2022). In the separate RD models, control factors include: [number of] sources[[9]](#footnote-9) for new white-collar hires[[10]](#footnote-10), educational attainment, sector of the enterprise, size of the firm, wage bill ratio (transformed using inverse hyperbolic sine function), within-firm employee training, firm age, and provision for employer-employee salary negotiation[[11]](#footnote-11). A distinction is made between type-A, and type-B (blue-collar) workers based on educational attainment.

Analytically, the model follows the specification:

$$G\_{f}^{r}=β\_{0}+β\_{1}G\_{f}^{0}+β\_{2}Z\_{cjf}+β\_{3}G\_{f}^{r}×Z\_{cf}+γ^{1r}W\_{f}^{r}+θ\_{m\_{r}}^{r}+v\_{fr}^{0}$$

Where G0 is the treatment assignment for firm f belonging to [firm size-] region-sector r based on centered running variable Z. Centering relies on linear-in-means approach whereby the focal firm is excluded in the computation of means. The assignment rule is given by:

$$G\_{f}^{0}=\left\{\begin{array}{c}1(Z\geq 0)\\0(Z<0)\end{array}\right.$$

Skills gap G in firm f within [firm size]-region-sector group r is explained by firm-specific characteristics, W, sector-specific characteristics, m, size of the group, L, and the running variable alongside assignment rule. Centering implies that β1 captures the local average treatment effect. The estimates are reliable over a wide range of bandwidths provided that β3=0, which captures the treatment effect derivative. Stochastic disturbance is captured in v whereas m and W are exogenous covariates.

A priori, a higher skills gap at the firm size-sector-region level 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 a focal firm. We associate a large workforce within the focal firm relative to related enterprises with firms serving as worker upskilling academies. Where the workforce is large relative to others, the referral system may unintentionally present under-skilled job applicants.

We employ bunching as a robustness check to complement the treatment effect derivative (Song, 2025; Bertanha et al, 2021, 2024; Caetano et al, 2021; Boerma et al, 2022). In this exercise, we analyze whether firms bunch at the centered threshold on each of the three running variables. This is because in the RD estimation, there were mass points detected. The central idea is that related enterprises could be competing for workers both already within the focal firm and outside on the labour market. This in turn affects a firm’s workforce and the skills set of its employees. As a result, enterprises are likely to bunch at the average workforce size and the average skills set of related firms. This follows from the assumption that employment level and the quality of job applicants within enterprises depends on employment levels and the quality of job applicants attracted by other enterprises within the same sector and region.

Our analysis is based on the 2016 Employer Satisfaction Survey (STEP) (World Bank 2016, 2018). This dataset was compiled by the World Bank, and focused on private sector enterprises with at least five employees. 504 enterprises were surveyed with data being captured on skills shortage and skills gap for white-collar (type-A) workers, and blue-collar (type-B) workers (World Bank, 2016, 2018). Workers in type-A perform high-skill jobs, such as technicians, professionals, and managers. Type-B workers engage in low-skill jobs, such as 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.

In the STEP dataset, we are unable to observe the total number of job applicants that each firm attracted within the three-year period captured. Thus, we cannot establish the share of unskilled job applicants that received an offer. However, sampled enterprises reported on the skills gap, and size of the difference in the skills gap, for the average job applicant.

# **EMPIRICAL FINDINGS**

## **DESCRIPTIVE STATISTICS**

Key demographics are summarized at the sector level based on the mean, and captured in Table 1. There are noticeable sectoral differences with respect to social connections, sources for hiring new white-collar workers, and firm size. 70% of sampled enterprises within manufacturing attracted under-skilled job applicants in at least one occupational position. This share is high relative to the 66% and 67% reported, respectively, for retail or whole trade and other services. Sources for new white-collar workers were fewest within the manufacturing sector which trailed behind the services sector. These sources were about 2-3 on average. In terms of size, enterprises within manufacturing were much larger compared to services sector. A firm in manufacturing had 83 employees, on average, which was about 3-4 times that reported within the services sector.

Across the three sectors, enterprises were, on average, similar with respect to the duration of operation within the country, growth of annual per worker wage, under-skilled job applicants and occupational skills gaps, within-firm training, workers’ educational attainment, workforce expansion, and the status of salary setting.

Table 1: Demographics

|

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|   | Manufacture | Wholesale or retail trade | Other services | Total |   |
|   | (N = 128) | (N = 129) | (N = 233) | (N = 490) | p-value |

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|

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Firm age |   |   |   |   |  0.055 |
|  Mean (SD) | 19.65 (13.06) | 16.22 (8.22) | 17.19 (10.32) | 17.30 (10.30) |  |
|  Min, Max | 3.0, 58.0 | 3.0, 50.0 | 3.0, 58.0 | 3.0, 58.0 |  |
| # of workers |  |  |  |  | <0.001 |
|  Mean (SD) | 83.11 (179.94) | 20.88 (47.46) | 27.15 (78.41) | 34.38 (98.37) |  |
|  Min, Max | 5.0, 2347.0 | 5.0, 602.0 | 5.0, 2500.0 | 5.0, 2500.0 |  |
| Skills gap share |  |  |  |  | <0.001 |
|  Mean (SD) | 0.70 (0.08) | 0.66 (0.06) | 0.67 (0.03) | 0.67 (0.05) |  |
|  Min, Max | 0.5, 1.0 | 0.6, 0.8 | 0.6, 0.8 | 0.5, 1.0 |  |
| Wage bill ratio |  |  |  |  |  0.947 |
|  Mean (SD) | 1.33 (0.86) | 1.35 (1.04) | 1.31 (1.01) | 1.33 (0.99) |  |
|  Min, Max | 0.2, 6.0 | 0.2, 6.0 | 0.2, 6.0 | 0.2, 6.0 |  |
| # of hiring sources for type-A workers |  |  |  |  |  0.049 |
|  Mean (SD) | 1.95 (1.16) | 2.11 (1.14) | 2.31 (1.28) | 2.20 (1.22) |  |
|  Min, Max | 0.0, 6.0 | 0.0, 5.0 | 1.0, 7.0 | 0.0, 7.0 |  |
|  | Percentage  |  |
| Under-skilled applicants | 60.8 | 61.2 | 64.7 | 63.1 |  0.288 |
| Occupational skills gap |  |  |  |  |  0.514 |
|  No gap or not hiring | 39.2 | 38.8 | 35.3 | 36.9 |  |
|  Skills gap in 1 position | 39.0 | 34.7 | 43.7 | 40.3 |  |
|  Skills gaps in 2+ positions | 21.8 | 26.5 | 21.0 | 22.8 |  |
| Firm size |  |  |  |  | <0.001 |
|  Small: 5-19 workers | 43.9 | 72.4 | 73.7 | 68.4 |  |
|  Medium: 20-99 workers | 37.0 | 25.7 | 22.5 | 25.8 |  |
|  Large: 100+ workers | 19.1 | 1.9 | 3.8 | 5.7 |  |
| Type-A worker education | 66.8 | 65.2 | 66.0 | 65.9 |  0.493 |
| Type-B worker education | 19.9 | 18.8 | 27.5 | 23.6 |  0.752 |
| Type-A worker training | 17.0 | 12.2 | 7.3 | 10.2 |  0.074 |
| Type-B worker training | 17.6 | 2.1 | 2.9 | 5.1 |  0.362 |
| Negotiable salaries | 67.6 | 76.3 | 72.7 | 73.1 |  0.619 |
| Workforce expansion | 33.6 | 33.8 | 45.7 | 40.1 |  0.563 |

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See **APPENDIX** for additional information.

### **ESTIMATED MODEL**

We estimate three RD models using three separate running variables. These running variables are centered, and are the following: number of within-firm employees, share of enterprises at the region-sector level which attracted under-skilled applicants, and workforce ratio at the firm size-sector-region level. RD results are presented in Table 2. The estimated local average treatment effect (LATE) suggests that enterprises with a workforce larger than the average within the respective sector-region group were 21.2% more likely to attract under-skilled job applicants compared to enterprises below the threshold. Among groups with average share of firms attracting under-skilled job applicants above the national threshold, focal firms were 32.6% less likely to attract under-skilled job applicants relative to counterpart firms below the threshold. Expansion of the workforce insignificantly mattered. Reported LATE estimates are reliable since the treatment effect derivative, which is not reported, was not statistically different from zero. A key implication of these findings is that, since under-skilling is given, specific incentives could be given to enterprises to address skills gap. These incentives could include wage subsidies for within-firm worker training (Alfonsi et al, 2020; Marcolin & Quintini, 2023), aided job-search whereby matching vocational-trained workers with available jobs (Bandiera et al, 2023), and worker-centered workshops to help employees find purpose at work[[12]](#footnote-12) (Ashraf et al, 2024).

Estimated coefficients for the covariates suggest that firms were less likely to attract under-skilled job applicants when either older, with fewer sources for new white-collar workers, or small. A decline in the probability of enterprises attracting under-skilled applicants as firms focused on fewer sources could arise from less exposure to noisy signals in external hiring markets. Older firms could have solidified sources for new workers which, together with prestige, disincentivized under-skilled workers from seeking employment in older firms.

Educational attainment of blue-collar workers is associated with the increased likelihood of enterprises attracting under-skilled job applicants. When controlling for the share of enterprises, in column 2, white-collar workers’ educational attainment and within-firm training are associated with enterprises attracting under-skilled job applicants. It could be that such job applicants considered enterprises with a large share of educated workers as offering extensive opportunities for learning and job shadowing, thereby resulting into self-selection (Kemeny & Storper, 2020).

Table 2: Estimated skills gap

|  |  |
| --- | --- |
|  | Probability of attracting under-skilled applicants |
| Variables | (1) | (2) | (3) |
| Running variable | -0.00232 | 0.306\*\*\* | 0.0458 |
|  | (0.00216) | (0.111) | (0.462) |
| RD Estimate | 0.212\*\*\* | -0.326\*\*\* | 0.00117 |
|  | (0.0617) | (0.0484) | (0.0944) |
| Bandwidth  | 61.984 | 0.500 | 0.176 |
| Type-A education | -0.0415 | 0.144\*\*\* | -0.0678 |
|  | (0.0452) | (0.0389) | (0.0441) |
| Type-B education | 0.201\*\*\* | 0.141\*\*\* | 0.127\*\*\* |
|  | (0.0498) | (0.0404) | (0.0479) |
| Type-A training | 0.0958 | 0.144\*\* | 0.0889 |
|  | (0.0761) | (0.0584) | (0.0748) |
| Type-B training | -0.0524 | -0.0652 | -0.126 |
|  | (0.135) | (0.107) | (0.121) |
| Firm size |  |  |  |
| Small (rf) |  |  |  |
| Medium  | 0.199\*\*\* | 0.148\*\*\* | 0.183\*\*\* |
|  | (0.0622) | (0.0477) | (0.0552) |
| Large  | 0.211 | 0.126\*\* | 0.167\*\* |
|  | (0.146) | (0.0583) | (0.0699) |
| Negotiable wage | 0.115\*\* | 0.0628 | 0.0848\* |
|  | (0.0538) | (0.0444) | (0.0508) |
| Sector  |  |  |  |
| Manufacture (rf) |  |  |  |
| Retail or wholesale | -0.0194 | 0.00999 | -0.00382 |
|  | (0.0701) | (0.0567) | (0.0684) |
| Other service  | -0.0613 | -0.0845 | -0.0777 |
|  | (0.0668) | (0.0540) | (0.0622) |
| Wage bill ratio | 0.0441\* | 0.0405\*\* | 0.0404\* |
|  | (0.0235) | (0.0206) | (0.0239) |
| Type-A sources | 0.0442\*\* | 0.0607\*\*\* | 0.0735\*\*\* |
|  | (0.0185) | (0.0157) | (0.0179) |
| Firm age | -0.00528\*\*\* | -0.00411\*\* | -0.00554\*\*\* |
|  | (0.00197) | (0.00161) | (0.00182) |
| Observations | 367 | 459 | 388 |

The explained variable captures the probability that a firm attracted under-skilled job applicants for at least one occupational position. Reported coefficients capture marginal effects after probability unit model estimation using analytical weights computed following sharp RD, where the estimates are available.

## **ADDITIONAL ROBUSTNESS CHECK**

We analyze bunching around the thresholds for respective running variables. For bunching to be absent, the truncated Tobit plot closely matches the histogram reflecting no sudden drops/ jumps/ spikes around the threshold (Bertanha et al, 2024). This corresponds with a horizontal elasticity line. Plots captured in Figure 1, Figure 2, and Figure 3 indicate bunching around the respective cutoffs.

Figure 1: Truncated Tobit Method for Workforce Size



Figure 2: Truncated Tobit Method for Workforce Expansion



Figure 3: Truncated Tobit Method for Share of Firms Which Attracted Under-skilled Job Applicants



## **SUMMARY OF KEY FINDINGS**

This paper aimed at analyzing the extent to which under-skilling among related enterprises affect under-skilling within focal firms. Across the three sectors—manufacture, retail or wholesale, and other services—under-skilled was high, with 66-70% of enterprises reporting to have attracted under-skilled job applicants. Parametric estimation suggested that focal enterprises were less likely to attract under-skilled job seekers when under-skilling was high among their peers relative to when low. This finding hints at social norm deviation as a behavioral response across enterprises—which could have been actualized via targeted employee sourcing, e.g., via high-quality referral mechanism or poaching. In terms of other factors, analyses hint at self-selection such that under-skilled job applicants were more likely to seek for employment in enterprises with a large number of employees relative to their peers. The first robustness check suggested that the reported regression discontinuity results were reliable. The second robustness check indicated bunching around the threshold for respective running variables.

In line with the paper’s objective, and based on the findings, we conclude that focal enterprises countered under-skilling among their peers by being less attractive to under-skilled job seekers. Since focal firms’ behavior could drive up under-skilling among peers, by pulling skilled applicants, we recommend broad-based measures in combating under-skilling at the sector-region level. One such a measure could be regular coordination of skills training workshops at the sector-region level.

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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.

## **DESCRIPTION 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. Skills gap share captures the share of enterprises at the [firm size]-region-sector level which attracted under-skilled job applicants in at least one occupational position. In computing this share, 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 has operated in Kenya up to 2016.

In Table 2, sharp RD bandwidths were utilized in situations where analytical weights led to inestimability. Column 2 bandwidth was set manually due to absence of observations within the optimal bandwidth. Parentheses capture standard error which are robust. \*\*\*, \*\*, and \*, respectively, indicate a statistically non-zero coefficient at 1, 5, and 10 percent levels. Running variables are respectively number of employees in 2016 (column 1), number of occupational positions which attracted under-skilled applicants (column 2), and number of employees in 2015 as a ratio of that in 2014 (column 3). These running variables are centered. Type-A sources refer to the number of sources for new type-A workers.

1. The author is a doctoral student at the University of Nairobi, and is affiliated to the Economics Scholar Panel. He is reachable via keffasimiyu@gmail.com or +254711454732. [↑](#footnote-ref-1)
2. The co-author is an Economics and Statistics’ graduate from the same institution, and is affiliated to Economics Scholar Panel. She is reachable via mbinyabettym@gmail.com or +254797310017. [↑](#footnote-ref-2)
3. Intern at the World Bank, the co-author is an Economics graduate from the same institution, and will commence graduate studies at Yale University in 2025. He is reachable via karypeters2018@gmail.com or +254743092414. [↑](#footnote-ref-3)
4. Job losers do not easily find new jobs (Di Berardino et al, 2021). [↑](#footnote-ref-4)
5. Think of insiders and outsiders in Lindbeck & Snower (2001) as unskilled and skilled, respectively. Unskilled insiders have strong incentives to oppose creation of vacancies for skilled outsiders. [↑](#footnote-ref-5)
6. Skills gap assumes 0 for a firm which either never hired in the 3-year period preceding the survey or did not attract under-skilled job applicants. [↑](#footnote-ref-6)
7. 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. [↑](#footnote-ref-7)
8. We assume that mobility barriers confine workers to finding employment within proximate geographical distances. We further assume that workers from large firms never transit to medium or small firms. [↑](#footnote-ref-8)
9. These sources are: public employment services, private employment services, job fairs, poaching (from offers to experienced people in other firms), educational institutions, Internet postings, media postings (excluding Internet), informal channels, and other sources. [↑](#footnote-ref-9)
10. New hires covered the following positions: elementary workers, machine operators/ drivers, construction/ craft workers, sales workers, service workers, support/ clerical workers, technicians/ associate professionals, professionals, and managers. [↑](#footnote-ref-10)
11. We restrict our analysis to enterprises which had been in operation for at least three years and not longer than sixty years at the time of the survey. This represents 97% of the surveyed enterprises. [↑](#footnote-ref-11)
12. These countries were: Thailand, South Africa, Singapore, Russia, Philippines, Nigeria, Mexico, Italy, Indonesia, India, Greece, Ghana, El Salvador, and Costa Rica. [↑](#footnote-ref-12)