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Film Productivity and Matching Frictions in the Labor Markets: Is This Unending Curse to Employers?

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Abstract

Firm productivity behavior is heavily influenced by labor market frictions in both emerging and established countries. Kenya keeps pushing for more effective measures to raise productivity, but the significance of friction in the labor market remains unclear. This study uses cross-sectional data from the Skills Toward Employment Productivity (STEP) Household Survey 2016–2017 for Kenya, sourced from the World Bank database, to examine the impact of market friction on firm productivity. Market friction is defined in terms of overeducation, undereducation, education, and skills mismatch. The findings, which were derived from an estimate of the endogenous switching regression (ESR) using the Full specification of the Maximum Likelihood model, demonstrated that undereducation and skills mismatch considerably lower firm production, whereas the effect of overeducation was negligible. In addition, the marginal treatment effect that is crucial for policymaking revealed that overeducation was substantially linked to higher levels of firm productivity, whereas the education and skills mismatch was linked to lower levels of firm productivity. Implications for policy highlight the need of matching graduates with jobs that are well-suited to their degree and experience levels.

Keywords: Firm productivity, labor market, friction, overeducation, undereducation, mismatch

Introduction

The discrepancy in cross-country labour productivity can be attributed to the allocation of skills, which accounts for a substantial portion of this difference. Additionally, it has been found that the allocation of skills explains approximately 30-40 percent of the variation in aggregate labour productivity across countries, as reported by the OECD in 2013. Haltiwanger, Hyatt, and McEntarfer (2017) posit that individuals with higher levels of education exhibit a greater propensity to engage in employment with firms that demonstrate higher levels of productivity. Nevertheless, it is worth noting that individuals with higher levels of education are less inclined to be matched with firms characterized by low productivity. However, it is improbable for these individuals to disassociate themselves from such firms. Organizations employing a workforce with lower levels of education exhibited a higher propensity to experience employee turnover during periods of expansion, as well as a greater likelihood of encountering challenges in maintaining upward mobility within the organizational hierarchy. According to Braconier et al. (2014), the presence of a higher percentage of employees with advanced education levels has a substantial positive impact on labor productivity. However, it is anticipated that the rate of growth in the accumulation of human capital will decrease. According to Braconier et al. (2014), it is anticipated that the increasing economic significance of knowledge will lead to higher rewards for individuals with advanced skills, consequently resulting in a rise in income disparities within nations in the forthcoming years.

On examining the impact of skill and qualification mismatch on productivity may be different, Allen and Van der Velden (2001) showed qualification and skill mismatch leads to low productivity and thus a lack of efficiency in resource allocation. The more efficient matching of qualifications and skills, the higher the increased productivity, and having over-education is associated with the incentive to move to a job that better reflects their education and skills, thus reducing job satisfaction and this would turn to decrease job effort leading to lower productivity (Green and Zhu, 2010). According to Quintini (2011), over-qualification diminishes satisfaction relative to those who are well-matched workers with the same level of qualification, although he found that the effect is insignificant relative to the perfectly matched workers in their jobs.

Educational attainment has a higher premium in the formal sector, as revealed by Kenya's workforce homogenous sequence in the level of technical and those with post-secondary training across the formal and informal sectors. 51 percent of the formal while 40 percent of the informal employees had either a diploma or a certificate as the highest level in training professionally. The earnings mismatch in the formal and informal sector are high and 74 percent of entry working in the formal sector earned between USD 100 to 500 per month, whereas 81 percent in the informal sector earn a monthly income between USD 50 to 250. Consequently, employees in the informal sector, relative to their counterparts in the formal sector, are not only be deprived of the right to earn a competitive wage but that subjects them to employment insecurity, work insecurity as well as social insecurity.

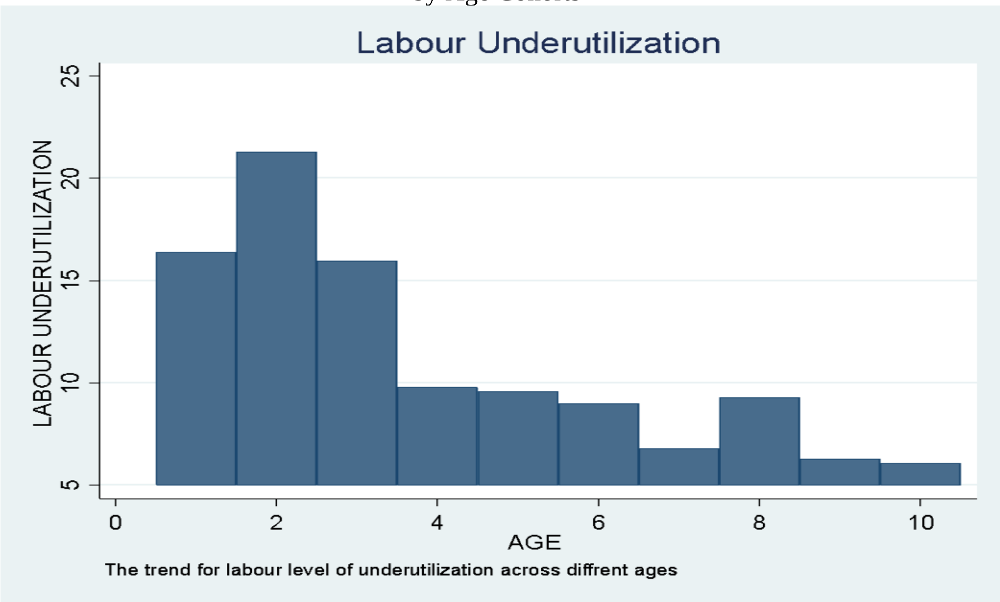
The existence of educational mismatch and in this case over-education, and studies such as United Kingdom(Dolton & Sllies,2003) and the US by Tsai(2010), overeducated workers have lower wage relative to those matched ones with the same educational attainment (Pecoraro, 2016). In the views of Ra, Chin & Liu (2015) wages are normally considered as an indirect measure of productivity and the value addition of human capital to the respective firms since an increase in wages implies higher productivity. Relatively, small wages imply the supplied skills are of no economic value, which may be a result of skills mismatch or does not meet the skills required in the labor market. According to Hartog (2000) and van de Werfhorst and Mijs (2010) return of education for the overeducated was approximately half to two-thirds of the return compared to the well-matched.

Over- and under-skilling, respectively, are examples of skill mismatch (CEDEFOP, 2010). Over-skilled employees tend to usually incur a pay penalty in comparison to those who are well-matched in their employment (Quintini, 2011a; Mavromaras et al., 2009), suggesting that Skill mismatch has a significant influence on income inequality. This is because there is a gap between the range of abilities needed and those that are financially rewarded. Workers that are under-qualified receive a greater salary and must draw on a wider range of their abilities to meet the demands of their jobs (Perry et al., 2014).

Labor market situation in Kenya

There has been a steady rise in the number of university graduates entering the Kenyan labor market. The overall labor force participation rate was 66.7%, which is an interesting number. At 90.6%, individuals between the ages of 40 and 44 had the greatest percentage, while those between the ages of 15 and 19 had the lowest rate (KNBS, 2019). Labor underutilization is defined in the study as gaps between labor supply and demand, indicating an unfulfilled demand for workers. The labor underutilization rate was 53.70 percent among young people aged 15 to 29 (figure 1) and this represents a sizable fraction of the population. The overall unemployment and underemployment rate was 11.9%.

Figure 1. Unemployment, Time - Related Under Employment and Labour Underutilization by Age Cohorts



Source: KNBS (2019)

According to the OECD (2013), between 30 and 40 percent of the variance in aggregate labour productivity may be attributed to differences in the distribution of skills between countries. In addition, research by Haltiwanger, Hyatt, and McEntarfer (2017) demonstrates that employees with higher levels of education tend to be hired by more successful businesses. Whether or not money has been well spent on education, whether it has been too much or not enough, may be gauged by looking at the levels of overeducation and undereducation. Education has been at the center of development plans in sub-Saharan African countries, making it imperative that policymakers have accurate information on which to base their decisions. Surprisingly, overeducation has been recorded in nations with educational rationing, such as South Africa (Pauw, Oosthuizen, and van der Westhuizen, 2008), possibly due to the opportunity cost of participation. Cross-country research (Caselli 2005; Erosa et al. 2010), for example, shows a sizable income disparity in aggregate labor productivity levels between nations on opposing extremes of the wealth spectrum.

Earnings are directly proportional to an individual's level of education and work experience, according to the human capital theory developed by Becker (1995) and Mincer (1974). On the other hand, Thurow's (1976) job rivalry model places greater emphasis on the demand side of the labor market, suggesting that productivity is attributable to the work itself, as opposed to individuals who possess more productive personal attributes. It is uncertain how transferable the findings from the literature on the correlation between mismatch and productivity are to other nations and, more especially, to the African setting, which has its own set of economic challenges. We also take notice of the fact that many studies on skill mismatch have focused on developed countries and that there have been comparatively few studies on skill mismatch in developing nations, notably in Africa. The paper examines the relationship between mismatch frictions in the labor market and firm productivity in Kenya. The study focuses on examining the effects of qualification frictions within the workplace on firm productivity. Additionally, it aims to evaluate the impact of qualification and skills mismatch on firm productivity.

Literature review

` Human Capital Theory (HCT) posits that in a perfectly competitive market, wages serve as a reflection of the marginal productivity of workers. The skill mismatch is quantified by analyzing its impact on wages, as demonstrated in studies by Mavromaras and McGuinness (2012) and Levels et al. (2014). According to Romer (1989), the accumulation of human capital is identified as the fundamental driver of sustained economic growth. According to Allen and Van der Velden (2001), the optimal allocation in the labor market occurs when there is a match between the skills and capabilities of workers and the skills desired by jobs. The demand for employees with high educational levels is increasing due to the need for general skills and multi-tasking capabilities (Acemoglu, 2002; Bresnahan et al., 2002; Robinson, & Vecchi, 2008). Becker (1964) argued that wages are influenced by a worker's investment in education, in contrast to the findings of Sicherman and Galor (1990). Sicherman and Galor concluded that individuals voluntarily allocate a portion of their working career to firms, even though the direct return on schooling may be lower, because the probability of promotion is higher. Additionally, Sicherman and Galor (1990) observed that promotion involves over-education, which indirectly takes into account the initial investment in human capital.

Duncan and Hoffman (1981) conducted research on the effects of over-education and concluded that, for a given employment, greater levels of education lead to better productivity and salary are fixed, with persons with overkilled producing and earning similarly to those with less schooling in the field in question. Therefore, mismatches include over-education. Freeman (1976) argues that labor market theories have examined salary and skill mismatches, as well as the pattern of projected returns to schooling. Rather than being a function of the nature of the work itself, marginal productivity is determined by factors such as education, training, experience, and abilities (Mincer 1974; Becker 1975). Workers' inability to land jobs commensurate with their education levels is often attributable to a lack of human capital; however, including ability as an explanatory variable in education research has the potential to alter the typical results.

According to human capital theory, workers with lower levels of education tend to be less productive and consequently receive lower wages compared to workers with similar education levels in the same job. This, in turn, has an impact on the overall productivity of the firm. Green, McIntosh, and Vignoles (1999) found that workers with lower levels of education tend to earn less than their counterparts with similar job roles but higher levels of education. However, these undereducated workers still earn more than their peers who have similar education levels but are not matched to their job. Firms may assign individuals to positions for which they have insufficient education due to a scarcity of labor with the appropriate level of education.

According to Thurow (1975), the job competition model (JCM) suggests that being over-qualified for a job may not result in higher wages. However, having more qualifications can increase the chances of being selected for a job. Additionally, it is important to note that wages are influenced by the specific requirements of a job and are determined by the production processes in place. This relationship between production processes and wage levels has been discussed by Duncan and Hoffman in their 1981 study. According to Thurow's (1975) perspective, educational investment by workers is seen as unproductive. Thurow argues that employees are primarily motivated by job requirements, which they perceive as rewarding. According to McGuinness (2006) and Slonimczyk (2008), workers who possess higher levels of education than what is necessary for a particular job tend to receive higher compensation than what is typically expected for that job. In this scenario, overeducation can be seen as a situation where there is a mismatch between an individual's level of education and the requirements of their job or occupation. From a different perspective, companies might choose to employ workers who are overqualified if the cost of training them is low and they demonstrate higher levels of productivity (Weiss, 1995).

Overeducated workers have been shown to be paid less than their similarly employed peers with similar levels of education, which can have a negative impact on a company's productivity (Chevalier, 2003; Groot and Maassen van den Brink, 2000). Overeducated graduates in the United Kingdom face a 14 percent salary penalty, according to research by Chevalier (2003). Similarly, Leuven and Oosterbeek (2011) draw the conclusion that highly educated workers obtain a salary premium compatible with Human capital theory in comparison to their less educated coworkers, indicating that at least some of their investment in education is worthwhile.

McGowan and Andrews (2015) used two methods to investigate the connection between labor market mismatch and labor productivity. The first method looked at qualification and skill mismatches separately, identifying the factors that contribute to each, and considering the overlap between the types of mismatches. It is consistent with a body of literature that concludes that underqualification and under-skilling cause lower productivity within the affected firms due to the allocative inefficiency associated with skills mismatch in the labor market that a higher level of qualification and skill mismatch leads to lower labor productivity, but this varies across the different types of mismatches. Given the greater potential for reducing mismatches in sectors with higher reallocation, this article fails to evaluate its direct influence on productivity.

Based on the dynamic system-GMM estimator developed by Blundell and Bond (1998), an empirical study conducted by Mahy, Rycx, and Vermeylen (2015) investigating the role of skills mismatch found that overeducation affects firm productivity positively, while undereducation was associated negatively. This went against their theory that highly educated people are less productive because they are dissatisfied with their jobs. Over-education had a favorable and substantial influence on productivity in any business context, however the effect was bigger in companies that employed a higher proportion of highly qualified workers.

Fanti, Guarascio, and Tubiana (2021) found that the capacity to immediately match their skills requirements was crucial to improving company efficiency in Spain by analyzing data from Turkish household surveys conducted between 2004 and 2015. Skills matching was one element that contributed to Italian companies' productivity, but others, like age, size, innovation, internationalization, and recruiting tactics, were also important.

The Labour Force Survey (LFS) (Office of National Statistics, 2017), the Vacancy Survey, the Annual Survey of Hours and Earnings (ASHE), and regional and sectoral productivity measures were all utilized by Turrell, Speigner, Djumalieva, Copple, and Thurgood (2018). They demonstrated that, even in a situation of output-optimizing counterfactual scenario with an unemployment rate near zero, the impacts of mismatch on productivity and production are minor and do not explain the productivity differences in the UK. Consequently, the diversity of the labor market may account for the trend. Specifically, mismatch has been found to be influenced by variations in regional or occupational productivity, market tightness, and matching efficiency in the United Kingdom as a whole.

Using firm- and individual-level data from Statistics Sweden from 1990-2013, Halvarsson and Tingvall (2017) found that overeducation led to productivity improvements in firms that employed mismatched people in terms of productivity, earnings, and output. Reduced productivity can be directly linked to a lack of knowledge. However, the potential dynamic impacts of educational mismatches were not investigated in this work. According to a study conducted by Grunau (2016) with GMM and a sample size of 23,052 establishment-year observations, the percentage of overeducated workers in a given establishment is 6.1%, while the percentage of undereducated workers is 10.0%. The study also found that the GMMS approach had a negative effect on the productivity of establishments with educationally mismatched employees, particularly those with many undereducated workers.

Using the Household, Income, and Labour Dynamics in Australia (HILDA) dataset, Mavromaras, McGuinness, O'Leary, Sloane, and Wei (2013) found that mismatch had no appreciable impact on occupational mobility and that there was a significant pay penalty for those who were over-skilled and over-educated. Focusing on the negative impact on male workers' well-being and the elimination of this issue may have benefits for both businesses and employees. Researchers Sandulli, Baker, and López-Sánchez (2014) found that in a sample of Spanish companies with at least one employee and fewer than 250 employees working in services industries in IT firms, efficiency and productivity increased when employees had similar levels of education.

According to Andrews and Cingano (2014), there is evidence in the literature suggesting that skills mismatches have a significant impact on firm productivity. According to Wolbers (2003), the impact of labor market mismatch is influenced by various factors, including gender, educational level, and age. Job tenure in Europe has a negative impact on the likelihood of a job mismatch. Several studies have been conducted on the education mismatch and productivity in different regions such as Europe and the USA. However, there is limited research available on this topic specifically in the African context (Yanikkaya and TAT, 2019; Bassanini and Venn, 2008; Mahy, Rycx, & Vermeylen, 2015). Given the dearth of research in developing countries, which has previously made it difficult to draw general conclusions due to the distinct economic dynamics between developed and developing nations, this study will serve as the basis for developing a policy framework and conducting further research in this field.

Methodology

The Human capital theory proposes that different forms of input (Capital and Labor) may be combined to produce the same output (Y). Our theoretical approach is grounded in Mueller's (1972) life cycle theory and the Human Capital Theory, both of which view education and skill sets as inputs to the production process. During the early phases of growth, when labor market frictions are at their greatest, companies start with no employees and gradually begin employing both the jobless and the employed. The companies' goal during the recruiting process is to increase productivity. Researchers want to know how search and matching frictions affect business output. A basic open-economy model is presented in this research to test the hypothesis that the time and money spent on employing new employees reduces a company's production. The underlying question for researchers is how search and matching frictions impact the firm's productivity. This paper presents a simple open-economy model which hypothesizes that firms incur costs in the hiring process and delayed hiring process, hence affecting productivity.

The model starts by assuming that time is continuous and there exists no aggregate improbability (Bilal et al, 2021). Labor markets follows a Poisson process, where people learn of available jobs through searching. Employed persons contact firms at Poisson rates defined as γ_e while for the unemployed person, it is defined as γ_u. Job matches outcomes is dependent on the effectiveness of the workers and the searching process of the firms, and the entire process exhibits constant returns to scale function. Defining $\underline{s}$ as the exertion by the firms in trying to get employees, and M as the measure of the firms, the rate at which employed and unemployed workers contact potential employers is defined as:

$$\gamma_i = \tilde{\gamma}_i \left(\frac{\underline{s}M}{\tilde{\gamma}_u \mu + \tilde{\gamma}_e (1-\mu)} \right) \quad for\ i = u, e \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 1$$

Where, $\tilde{\gamma}_u$ and $\tilde{\gamma}_e$ are the matching efficiencies of unemployed and employed. Higher values of $\tilde{\gamma}_u$ and $\tilde{\gamma}_e$ implies reduced unemployment rates or high rates of job-to-job transitions, hence a preferred stiff labor market is defined by reduced values of these parameters. A firm in such a rigid labor market makes revenues defined by:

$$y = [(1-\mu)y]^{\frac{1}{\sigma}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 2$$

Where, y is the income produced per employed worker. Generally, matching efficiencies increases firm productivity, through increasing the income generated per worker.

Empirical Model

To explore the link between labor market frictions using education mismatch and firm productivity, we estimate the following firm level model:

$$Prod_i = \alpha_i + \beta_i Mismatch_{i,k} + \beta_i \delta + \varepsilon_i \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 3$$

Where, Prod represents firm productivity, expressed as the value added to the firm per worker, while mismatch refers to the measures of qualification and skill mismatch and their components, such as overqualified, underqualified and over skilled/qualified, and under skilled/qualified. The δ represents other factors included in the model such years of work experience, matched qualifications, and industrial sector.

The baseline regression relies on the OLS estimator which is prone to heteroscedasticity and serial correlation issues, hence it may result in spurious results (Aubert and Crépon, 2003). An additional problem with estimating the OLS is because of potential endogeneity problems. As highlighted by Gautier et al. (2002), endogeneity may occur in the sense that employers might exploit cyclical slumps to improve the skill level of their work force. This assumption is in line with empirical studies such as Cockx and Dejemeppe (2002) and Dolado et al., (2000) who depicted those average years of over-education within firms may increase due to reduced labor productivity.

Bover (1995) and Blundell & Bond (1998) advocated utilizing Generalized Method of Moments (GMM) model estimates to account for the problems in a number of research, including Grunau (2016). To aid in model identification, the GMM estimators employ the use of instrumental variables. However, GMM models have a fundamental weakness in that it is difficult to determine which instruments are most suitable for the endogenous regressors (Chevalier, 2003).

In this regard, we adopted the endogenous switching regression (ESR) by Full specification of Maximum Likelihood model, which controls for both endogeneity and sample selection bias (Kirimi and Olunga, 2013) and Shiferaw et al., (2014). In this model, two separate selection equations are estimated (i.e., firms facing frictions/mismatches and not facing frictions/mismatches):

$$Establishment\ 1 : (Prod_1|R_i = 1) = \alpha_1\delta_i' + E(\mu_i) > -\gamma y0 \ldots\ldots\ldots\ldots\ldots 4$$

$$Estabishment\ 2 : (Prod_0|R_i = 0) = \alpha_0\delta_i' + E(\mu_i) \leq -\gamma y \ldots\ldots\ldots\ldots\ldots 5$$

$Prod_1$ and $Prod_0$ are the firm's productivity while experiencing education and skills mismatches and not experiencing mismatches respectively. δ_i' is a vector of explanatory variables that explain firm's productivity . γ, α_1, and α_0 are parameters to be estimated for the selection outcome with and without mismatches respectively. Three random errors are generated from the estimation method, namely, $\varepsilon_0, \varepsilon_1$ and μ_i.

We generated instrumental variables for all the mismatches (education and skills in order for model to be identified. The variables generated are highly correlated with mismatches, but it is unlikely to influence the outcome variable directly or correlated with the unobserved errors. Based on this, the conditional expectation of the outcome variable is defined as:

$E(Y_i'R_i = 1) = \alpha_1\delta_i' + \delta_{1u}\vartheta_1$ ……………………………………………........6

$E(Y_i'R_i = 0) = \alpha_0\delta_i' + \delta_{0u}\vartheta_0$……………………………………........………7

Where, ϑ_1 and ϑ_0 are the Inverse Millis Ratio generated from the outcome equations. The mean outcome variable resulting from the impact mismatches is estimated as:

$E(Y_i'R_i = 1) - E(Y_i'R_i = 0) = Y_i'(\alpha_1 - \alpha_0) + \delta_{1u}\vartheta_1 - \delta_{0u}\vartheta_0$ 8

The second term on the left-hand side of Eq. (8) is the expected value of impact on the firm's productivity if the firm had not experienced mismatches.

The full specification allowed us to estimate the treatment effect on treated and untreated resulting from mismatches (mismatches being treated). However, in this study, we follow the works of Walstrum (2014) by estimating the marginal treatment effects (MTEs) of mismatches on productivity. Similar approach was used by For instance, Carneiro, Heckman, and Vytlacil (2011) in measurement of the differential returns to education for individuals increased their likelihood of pursuing higher education. The MTE approach enables us tell how much an individual's productivity changes given a small change in the propensity score by an additional change in mismatch. Mismatch (over- education, under-education, and education-skills mismatch) is taken as the treatment while the outcome is productivity. The study used secondary data, cross-sectional data from the Skills toward Employment Productivity (STEP) Household Survey 2016 – 2017 for Kenya, which was obtained from the World Bank database. To measure mismatch, the qualification mismatch is defined in terms of the International Standard Classification of Education (ISCED), where, a benchmark of "appropriate" qualifications required to get the job is created. If the person has a qualification level corresponding to their highest qualification) above (below) this benchmark, they are classified as over-qualified (under-qualified).

Table 1. Definition and measurement of variables

Variable	Definition and Measurement
Firm Productivity	This is defined as the ratio of sales in the latest fiscal year to the number of permanent full-time employees.
Over education	A binary variable, defined as 1 if a person has a qualification level corresponding to their highest qualification (ISCED) above the benchmark, and 0 otherwise
Under Education	A binary variable, defined as 1 if a person has a qualification level corresponding to their highest qualification (ISCED) below the

	benchmark, and 0 otherwise
Education & Skills Mismatch	A binary variable, defined as 1 if a person has a qualification level corresponding to their highest qualification (ISCED) in addition to having skills and vocational training above or below the benchmark, and 0 otherwise
Firm Size	This is a binary variable defined as 1 if the firm is large and 0 if Small. A firm was considered large if it has more than 5 permanently employed workers and zero otherwise
Working Experience	This is a binary measurement. An individual was considered experienced if they had more than 3 years working experience, otherwise less experienced.

Empirical findings and discussion

The data provided includes information on both the demand and supply in the labor market. The demand side focuses on factors like firm productivity and firm size, while the supply side considers labor market frictions such as over-education, under-education, and education and skills mismatch. Working experience is included as a control variable in the analysis. In aggregate, just 3 percent of the graduating cohort possessed the designation of being experienced, as defined by a requisite minimum of 3 years of professional work experience. A total of 54.8 percent of the employees were found to possess higher educational qualifications than required for their current positions, while 25.1 percent were observed to have lower educational qualifications. Additionally, 11.9 percent of the employees were identified as experiencing a discrepancy between their educational background and the skills required for their roles (table 2). Overall, the firms that were interviewed demonstrated a productivity rate of 11 percent.

Table 2. Descriptive Statistics

Variable	Mean	SD	Skewness	Kurtosis
Firm Productivity	11.3799	1.4070	-0.9671	2.9203
Firm Size	0.1644	0.3706	1.8114	4.2811
Working Experience	0.0336	0.1803	5.1730	27.7600
Over Education	0.5488	0.4977	-0.1961	1.0385
Under Education	0.2509	0.4336	1.1492	2.3206
Education & Skills Mismatch	0.1186	0.3234	2.3586	6.5632

Semi-Parametric ESR Model results- treatment effect of mismatches on productivity

To mitigate the concerns related to endogeneity, we employed the endogenous switching regression model to estimate the impact of mismatches on productivity across various measures. Subsequently, we computed the treatment effects. Heckman and Vytlacil (2005) introduced the notion of policy-relevant treatment effects, which refers to the average effect on the outcome of interest resulting from a transition from the baseline policy to an alternative policy.

Table 3 displays the estimations of the Local Average Treatment effects, specifically examining the variations in these effects across various levels of firm productivity. Based on the findings, it can be observed that the Marginal Policy-Relevant Treatment Effect for over-education exhibited a positive trend, whereas, for under-education and education & skills mismatches, it demonstrated a negative trend. These findings suggest that an excessive level of education among employees led to a significant increase in firm productivity, amounting to 33.2 percent. Conversely, a lack of education and skills, as well as mismatches between education and skills, resulted in a decrease in firm productivity, with reductions of 0.9 percent and 19.3 percent, respectively. The findings align with the conclusions made by Vandeplas and Thum-Thysen (2019), who reported a rising trend in skills shortages and overqualification within the European Union. They also highlighted the negative correlation between job mismatches and productivity in labor markets, as well as the positive relationship between skills supply and productivity. According to research conducted by Mahy, Rycx, and Vermeylen (2015), there is a notable and positive correlation between the level of education required for a job and firm productivity. Specifically, an increase in the level of over-education, where employees possess qualifications exceeding the requirements of their positions, has been found to enhance firm productivity. Conversely, a decrease in the level of education, resulting in undereducation among employees, has been found to diminish firm productivity.

Table 3. Semi-Parametric ESR Model results- treatment effect

	Over Education	**Under Education**	**Education & Skills Mismatch**
	Firm Productivity	Firm Productivity	Firm Productivity
Average Treatment Effect	-12.25^{***}	5.772^{***}	40.82^{***}
	(5.090)	(0.892)	(4.745)
Treatment on the Treated	-26.33	-7.375^{***}	-40.11^{***}
	(28.48)	(0.502)	(3.609)
Treatment on the Untreated	84.85^{**}	10.17^{***}	51.73^{***}
	(27.91)	(1.317)	(5.836)
Local Average Treatment Effect/ IV	38.26^{***}	-3.910^{***}	-8.680^{***}
	(6.109)	(0.140)	(0.857)
Marginal Policy-Relevant Treatment Effect	33.22^{***}	-0.894^{**}	-19.32^{***}
	(4.322)	(0.328)	(1.625)
Observations	3894	3894	3894

Over-education, under-education, and education-and-skills mismatches all have decreasing estimated Marginal Treatment Effects (MTEs) (see Figures 2, 3, and 4). Figure 2 implies that people are more likely to boost production through greater marginal productivity when their degrees of over-education rise. Figure 3 shows that marginal productivity and the propensity to boost productivity both decline as people's levels of education fall below the norm. Finally, figure 4 demonstrates that the marginal production associated with an education and skills mismatch falls as the extent of mismatch grows. As a result, people are less likely to make efforts to boost productivity under these conditions.

Figure 2. Estimated MTE for Over- Education

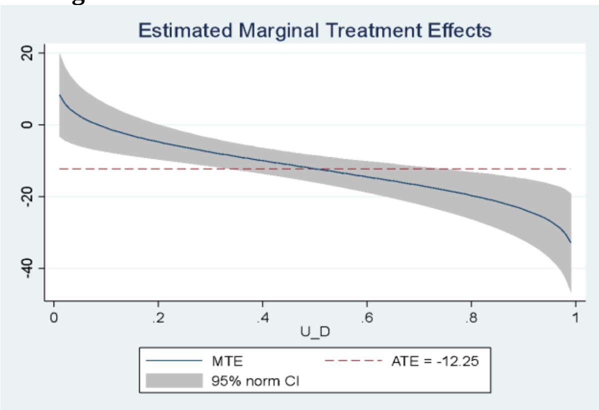


Figure 3. Estimated MTE for Under- Education

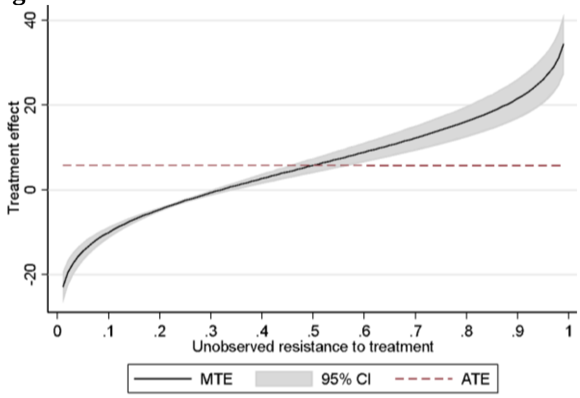
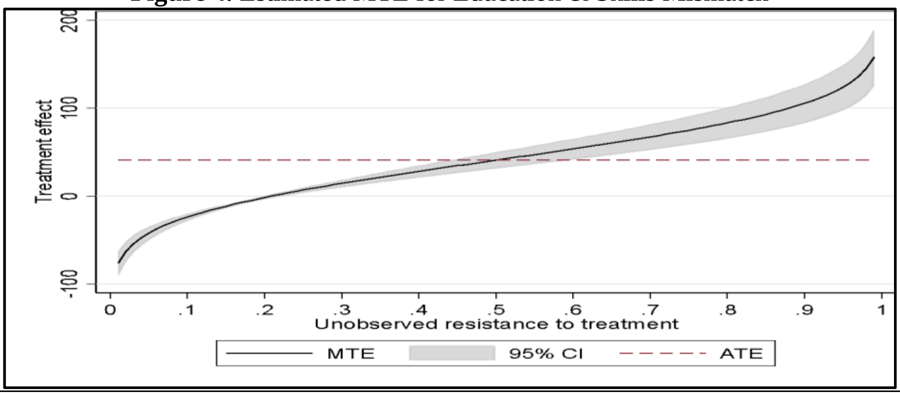


Figure 4. Estimated MTE for Education & Skills Mismatch



Conclusion

This study aimed to estimate the treatment effects of productivity frictions on firm productivity. The concept of the Marginal Policy-Relevant is significant in the realm of policy analysis and decision-making. The observed treatment effect on overeducation demonstrated a significant positive correlation with the enhancement of firm productivity. The phenomenon of education and skills mismatch has been found to be closely linked to a decrease in firm productivity, and the impact of this association is of considerable importance. Additionally, it is worth noting that the impact of undereducation on firm productivity is considerably lower compared to the effects of overeducation and education and skills mismatch. Bassanini and Venn (2008) reached a similar conclusion, stating that labor market policies have a substantial influence on productivity levels and growth rates, independent of their effects on employment. It is important to acknowledge that our study is not comprehensive and that there exist additional variables that influence fluctuations in firm productivity, such as financial frictions and socio-economic factors.

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