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Social Capital and Employment: Evidence using Kenyan data

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Abstract The contribution of social capital to employment has not been accorded much attention in literature. Filling this gap and supporting employment policy, this study investigates the influence of social capital on employment using cross-sectional household data from Kenya. Social capital supports the symmetric flow of labor information as an innovative tool that allocates and distributes labor market information to individuals within the working-age population (15-64). We apply data from the 2015/16 Kenya Integrated Household Budget Survey to the left-censored Tobit and OLS estimators. By using the Control Function Approach, our results control for both endogeneity and heterogeneity and are empirically robust. The findings indicate that social capital positively and significantly supports employment and may complement human educational capital, which alone may be inadequate in linking individuals to available job opportunities, especially in presence information asymmetry. We further observe that hours worked increase with the prevailing wage rate, males work for longer hours than females in an ordinary week, and relatively younger individuals work for more hours than their somewhat older counterparts.

Keywords: *Social capital, informational symmetry, employment*

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1. Introduction

Information asymmetry among individuals within the working-age population may lead to sub-optimal employment outcomes. Information symmetry ameliorates against failure of the labor market [1,2,3]. Social capital is a resource that could support the flow of information in the labor market by *linking* individuals to available job opportunities and their features and thus *bridging* information gaps in the labor market. Social capital comprises social networks, relationships, trust, and norms that shape the quality and quantity of interactions [4,5,6,7]. Social capital allows people to interact, become familiar, amass trust, and create a social network that supports information exchange [8].

According to the International Labor Organization (ILO), the working-age spans between 15-64 [9]. Adopting this global standard to Kenya as a case study, we note that the country’s working-age population has been growing faster than the growth in total population since the 1990s. The faster growth in the working-age population should be supported with a resource that links individuals to available job opportunities within a network that bridges any information gaps in the labor market. Such information network is important in ensuring the country’s human capital is productively engaged.

In terms of human capital, which measure the capability to work and important in supporting productivity of workers, Kenya ranks 78th globally with a Human Capital Index of 59.48 [10]. This places the country within 2 points adrift of the global average of 62. Kenya’s human capital stock is higher than the average for Africa as a continent (52.97). Kenya’s working-age population is growing faster, but it also possesses higher working capability compared to Africa as a continent. However, a higher working capability may not necessarily lead to higher employment as enshrined in the country’s long-term development blueprint—especially if the highly able workforce can’t access relevant information on job opportunities and their traits seamlessly.

Cognizant that the ability to work has little to do with linking individuals to available job opportunities and bridging information gaps in the labor market, this study strives to examine the link between social capital and employment as a desirable labor market outcome. We’re motivated by the realization that despite social capital presenting an important policy frontier, evidence specific to its linkage with employment across the world is limited.

To the best of our knowledge, few existing studies have examined the link between social capital and employment using Kenya as a case study and applying cross-sectional data to the Control Function Approach to address endogeneity and heterogeneity. Additionally, we’re unaware of previous work that measured employment using the number of hours worked, measured social capital in terms of the total number of days spent in professional networking, and used both Tobit [11] and Ordinary Least Squares (OLS) to ensure robustness.

For instance, whereas Delattre and Sabatier [12] have examined social capital and employment, they have measured social capital as a binary variable indicating whether one uses networks to secure a job and employment in terms of hourly wage. In this study, social capital is a continuous variable and employment is measured in terms of total number of hours worked in a week. Further, whereas their work controls for endogeneity only using switching regression models, this study controls for both endogeneity and heterogeneity using the Control Function Approach. Lastly, whereas their work uses cross-sectional data like the current study, they use France as a case study, while in this study, the focus is given to Kenya. Therefore, this study expands and enriches the existing literature on the link between social capital and employment.

Our findings are consistent with the stylized facts and literature. Notably, we demonstrate that social capital has policy value as it links individuals to available job opportunities and bridges information gaps, supporting employment as a desirable labor market outcome. Lastly, our findings are empirically robust and control potential endogeneity and heterogeneity.

The rest of the study is organized as follows: section 2 reviews relevant literature. Section 3 documents data and presents stylized facts. Section 4 presents the empirical methodology and results, and finally, section 5 offers a conclusion.

2. Literature Review

Existing literature has extensively examined the link between human capital (specifically that obtained from schooling and on-the-job training) and labor market outcomes such as employment. However, the links between social capital (particularly social and professional networking) and employment as a labor market outcome has been accorded peripheral attention. This is so even as it emerges that human capital (capability to work) has little to do with *connecting* or *linking* individuals to job opportunities available in the labor market. Our study makes an original attempt to demonstrate the link between social capital and employment.

Social capital has been measured using friendship networks, social relationships, and ties [4,13,14,15,16,8,17]. Majority of the studies have used cross-sectional data to analyze the relationship between social capital and labor market outcomes such as labor force participation [4,5,18,19,20,21,16,22,23,17], except for [19] who uses panel data. In most of these studies, the dependent variable was binary, which necessitated the use of Logit regression [4,19,8,17], Probit regression [23], and Tobit regression [13].

Other studies have examined social capital and employment regarding how social networks affect wages and incomes and obtained mixed results [12,24,25]. [26] investigated the effect of social networks on wage using the Heckman selection model, which controlled for endogeneity. The findings indicated that social networks raise wages by about 1.53 percent. [27] also examines the role of social capital in determining wages and found that social networks increase wages earned by workers. Whereas existing studies focus on labor market outcomes like employment and the broader labor force participation, few, measure employment in terms of hours worked. Further, although many studies use cross-sectional data and some attempt to control for endogeneity, few, if any, control for both endogeneity and heterogeneity using the Control Function Approach. This study therefore extends the existing literature by introducing a new measure of social capital and employment and applying the Control Function Approach to control for both endogeneity and heterogeneity.

3. Data And Stylised Facts

This study uses cross-sectional data from the 2015/16 Kenya Integrated Household Budget Survey (KIHBS) by the Kenya National Bureau of Statistics (KNBS). The data capture variables measuring social capital and employment. The specific variables are obtained from the Household Information and Household Members' Information Modules. Following [4,5,6], Table 3.1 measures social capital using the total number of days spent in *professional networking* in the last three months.

On the other hand, employment is measured using the number of hours usually worked by an individual per week in the primary job. Since labor supply is a function of the prevailing wage rate, an individual's basic salary in the last one month is considered as a control [28]. Other controls considered education to measure human capital, gender, residence, and age [29,30,31,32]. Finally, since social capital is suspected to be potentially endogenous, the amount of money in Kenyan Shilling spent on transport to participate in professional networking is used as an instrument.

Table 3.1. Measurement And Definition Of Variables

Variable	Definition
Employment	Number of hours worked by an individual per week in the primary job
Social capital	Total number of days spent by an individual in *professional networking* in the last three months
Wage	Amount in Kenyan Shillings earned by an individual as wage and salaries in the last one month
Education	Dummy with 1 if individual has gone to school and 0 if not
Gender	Dummy with 1 if male and 0 if female
Residence	Dummy with 1 if urban and 0 if rural
Age	Individual's age in years (15-64)
Transport cost	Amount in Kenyan Shilling spent on transport to participate in professional networking

Following International Labor Organization (ILO) criterion on the age of the working population, we limit our sample size to individuals within the 15-64 age bracket [9]. By this criterion, our maximum sample size comprises 48,922 individuals. Due to missing values, however, the total observations for some of the other variables may be less than 48,922. Table 3.2 the summary statistics for the used variables at levels. The data reveal that the average number of hours an individual works per week in the main job is about 42.88 (minimum and maximum hours worked are 0 and 168, respectively). Individuals with 0 hours worked per week are deemed to be unemployed, and thus the left-censored Tobit estimator will be used with the lower bound at 0. The average hours worked by individuals per week are within the regular work hours per week in Kenya, which range between 40-52. Individuals within the working-age population (15-64) had spent an average of about .54 days (approximately 12.96 hours) in *professional networking* in the last three months (minimum and maximum number of days being 0 and 60 respectively). About 69.50 percent of individuals within the working-age population had gone to school, 48.90 percent were male, and 71.00 per cent lived in urban areas. The average earnings in basic salary in the last one month were Kenya Shilling 8,618.07 (minimum and maximum earnings in wages and salaries being 0 and 999,999 respectively).

Individuals with a basic salary of 0 are deemed to be unemployed. According to the *Kenya Gazette Supplement No. 1 of January 2019*, the minimum monthly wage in Kenyan urban areas is Kenya Shilling 13,573.00 and Kenya Shilling 7,240.95 in rural areas. Lastly, individuals spend an average of Kenya Shillings 2,060.90 on transport on professional networking (with minimum and the maximum expenditure on transport being Kenya Shilling 0 and 99,999 respectively). The substantial standard deviations are seen in variables like *employment, social capital, basic salary, age,* and *expenditure on transport* point to the potential presence of heterogeneity among individuals within the working-age population. The study employs the Control Function Method [33] to control for heterogeneity.

Table 3.2. Descriptive Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
Employment	33777	42.882	20.564	0	168
Social capital	6395	.537	3.417	0	60
Education	42510	.695	.46	0	1
Gender	48922	.489	.5	0	1
Residence	48922	.71	.454	0	1
Wage	33357	8618.072	18290.901	0	999999
Age	48922	31.835	13.269	15	64
Transport cost	7261	2060.898	4354.078	0	99999

4. Empirical Methodology And Results

This section presents the structural Tobit and Ordinary Least Squares (OLS) models used to estimate the effect of social capital on employment. The study further applies the Control Function Approach to control for potential endogeneity between social capital and employment, while controlling for potential heterogeneity [33] among individuals within the working-age population (15-64). The reduced and structural form models are presented in 4.1 and 4.2, respectively.

$$\begin{aligned} &Log\ social\ capital_i = \\ &\beta_0 + \beta_1 Education + \beta_2 Gender + \\ &\beta_3 Residence + \beta_4 Log\ Wage + \\ &\beta_5 Log\ age + \beta_6 Log\ age\ square + \\ &\beta_7 Transport\ Expenditure + \varepsilon \end{aligned} \tag{4.1}$$

$$\begin{aligned} &Log\ employment_i = \\ &\beta_0 + \beta_1 Log\ social\ capital + \\ &\beta_2 Education + \beta_3 Gender + \\ &\beta_4 Residence + \beta_5 Log\ Wage + \\ &\beta_6 Log\ age + \beta_7 Log\ age\ square + \\ &\beta_8 Residuals + \beta_9 Interaction + \mu \end{aligned} \tag{4.2}$$

In 4.1 and 4.2, i represents the i^{th} individual, ε and μ are stochastic error terms controlling for unobservable factors that influence social capital and employment Transport expenditure is the instrument for social capital and appears in the reduced form model (4.1) only. From Table 4.1, expenditure on transport to *professional networking* is a relevant instrument (t=4.31, p<.0). After 4.1 is estimated, *residuals* are obtained. Additionally, the *interaction* between the residuals and social capital is obtained. The *residuals* and *interaction term* are included in 4.2, estimated using both the left-censored Tobit and OLS estimators for robustness. Using the *Shapiro-Wilk test for normality* and normal curve plot for the residuals (Figure 4.1), the study finds that the normality assumption is satisfied (p<.0). The Breusch-Pagan test indicated that inference was efficient (p>.05). A Variance Inflation Factor (VIF) of 4.46 was obtained, and it indicated that multicollinearity was not a major problem because the VIF was below the conventional limit of 10.00 [34].

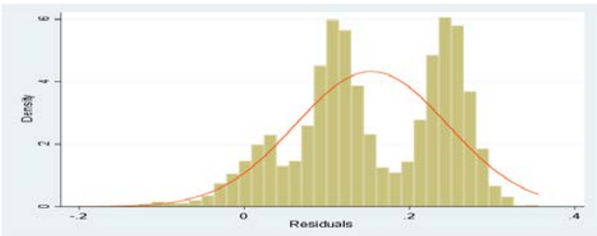

Figure 4.1. Distribution of Residuals

Table 4.2 reports the results from the left-censored Tobit estimator with the censoring done at zero hours of work to exclude individuals with zero hours of work per week which may mean those individuals are unemployed. Whereas the *residuals* are used to control for *endogeneity*, the *interaction term* controls for heterogeneity [35,33]. Whereas the coefficient for the *residuals* was insignificant, that for the *interaction term* was significant. The implication is that heterogeneity was present and was controlled for, but endogeneity was not present [35,33]. According to the findings, social capital significantly influences employment among individuals within the working-age population (15-64). Particularly, if the number of days spent by an individual in professional networking increases by 1 percent, the average number of hours worked in a week increases by about .11 percent. For robustness check, the study also estimates the OLS estimator and finds that social capital significantly influences employment, with the average number of hours worked per week rising by .11 percent if the number of days spent in *professional networking* increase by 1 percent.

In Tables 4.2 and 4.3, we find that the number of hours individuals work per week increases by about .04 per cent on average if an individual's monthly basic salary increases by 1 percent. Labor supply is a positive function of the prevailing wage [28], and as such, a rise in the overall wage rate is likely to motivate workers to work for more hours.

Initially, if an individual's age increases by 1 percent, the total number of hours worked per week increase by about 4.26 percent from both the Tobit and OLS estimators. Beyond some point, however, a 1 per cent increase in an individual's age is associated with about .59 percent decline in the number of hours worked per week. This finding implies that relatively younger individuals are likely to have longer work-weeks than their relatively older counterparts. The reservation wage for individuals nearing retirement age is likely to be higher than that for their relatively younger counterparts [36]. Individuals nearing retirement are likely to spend more time on leisure and less time on work. Although education supports employment [37], it was not significant in our estimation. This may indicate that education alone may not facilitate individuals within the working-age population to find employment especially in information asymmetry on available job opportunities, hiring wage, and non-monetary features of the available job opportunities. Social capital fills this gap by supporting access to information as a resource that links individuals to open job opportunities and accompanying monetary and non-monetary features.

On average, hours worked by males were higher (13.50% more) than those worked by their female counterparts. This is explained by gender roles, especially nonmarket activities within households like house cleaning, childbearing, and cooking [38]. Despite being insignificant, the coefficient for a place of residence indicates that the percentage of hours worked by individuals in urban areas is higher (about 0.1% more) than that for individuals in rural areas. In Kenya, rural areas are more likely to suffer from inaccessibility of timely and relevant labor market information compared to urban areas, translating to lower employment rates.

Table 4.1. Reduced Form Regression

Log Social Capital	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Education	.006	.02	0.29	.771	-.033	.045	
Gender	.126	.016	7.94	0	.095	.156	***
Residence	.006	.017	0.38	.705	-.027	.039	
Log Wage	.009	.002	4.14	0	.005	.014	***
Log Age	.943	.478	1.97	.049	.006	1.881	**
Log Age Squared	-.13	.068	-1.92	.055	-.263	.003	*
Log transport cost	.019	.004	4.31	0	.01	.027	***
Constant	-1.817	.836	-2.17	.03	-3.456	-.179	**
Mean dependent var	0.155		SD dependent var		0.533		
R-squared	0.030		Number of obs.		4726		
F-test	20.574		Prob > F		0.000		
Akaike crit. (AIC)	7340.694		Bayesian crit. (BIC)		7392.380		

*** p<.01, ** p<.05, * p<.1

Table 4.2. Structural Form Model Using The Left-Censored Tobit Estimator

Log employment	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Log social capital	.108	.038	2.85	.004	.033	.182	***
Education	.023	.018	1.25	.212	-.013	.058	
Gender	.135	.031	4.37	0	.075	.196	***
Residence	.001	.015	0.05	.958	-.029	.031	
Log wage	.043	.003	14.53	0	.037	.049	***
Log age	4.264	.482	8.84	0	3.318	5.209	***
Log age square	-.598	.068	-8.80	0	-.731	-.465	***
Residuals	-.085	.213	-0.40	.691	-.503	.333	
Interaction	-.421	.169	-2.49	.013	-.752	-.09	**
Constant	-4.229	.848	-4.98	0	-5.892	-2.566	***
Var (e)	.226	.005	.b	.b	.217	.235	
Mean dependent var	3.716		SD dependent var		0.516		
Pseudo r-squared	0.110		Number of obs.		4726		
Chi-square	789.826		Prob > chi2		0.000		
Akaike crit. (AIC)	6413.874		Bayesian crit. (BIC)		6484.943		

*** p<.01, ** p<.05, * p<.1

Table 4.3. Structural Form Model Using The Ols Estimator

Log employment	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Log social capital	.108	.038	2.84	.004	.033	.182	***
Education	.023	.018	1.25	.211	-.013	.058	
Gender	.135	.031	4.36	0	.074	.196	***
Residence	.001	.015	0.05	.958	-.029	.031	
Log wage	.043	.003	14.52	0	.037	.049	***
Log age	4.262	.483	8.83	0	3.316	5.208	***
Log age square	-.597	.068	-8.80	0	-.731	-.464	***
Residuals	-.084	.213	-0.39	.693	-.503	.334	
Interaction	-.421	.169	-2.49	.013	-.753	-.089	**
Constant	-4.226	.849	-4.98	0	-5.89	-2.562	***

Mean dependent var	3.716	SD dependent var	0.516
R-squared	0.154	Number of obs	4726
F-test	95.441	Prob > F	0.000
Akaike crit. (AIC)	6395.004	Bayesian crit. (BIC)	6459.613

*** p<.01, ** p<.05, * p<.1

5. Conclusion

By applying the Control Function Approach to cross-sectional household data from Kenya, we have examined the effect of social capital on employment. We contribute to the existing literature by demonstrating that social capital has policy significance as it promotes information symmetry in the labor market and supports employment.

Our findings have showed that social capital has positive and significant contribution to employment. As a resource, it has a policy value emanating from its capability to curb asymmetry of information in the labor market by *linking* individuals with relevant information on available job opportunities and their features and thus *bridging* information gaps in the labor market. The findings support the available stylized facts and extend the literature on the link between social capital and employment as a labor market outcome. The results are empirically robust and control potential endogeneity and heterogeneity.

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