Labor Market Monopsony Power among Africa's Manufacturing Sector

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Abstract

This article estimates firm level measure of labor market monopsony power among manufacturing firms from five African countries: Cameroon, Ghana, Kenya, Zambia, and Zimbabwe. A unique employer –employee matched data set is utilized. Parametric estimation of production function is conducted to back out the marginal revenue product of labor, which then is used in combination with the information on wages paid to workers by the firm to construct an empirical measure of monopsony power. The findings thus far suggest the existence of labor market imperfections. Mean estimates of market power suggest that the marginal revenue product of the average worker in somewhere between 1.82 to 3.27 times higher than their wage. The implied supply elasticity of labor facing the average firm ranges from 0.44 to 1.22.

1. Introduction

In the standard competitive model, firms are price takers in the labor market. Since Robinson (1933) first coined the term "monopsony," economist have considered the case where the individual firm faces an upward sloping labor supply curve and thus possess wage setting power. Historically, monopsony power was thought to prevail in isolated labor markets (eg coal mining towns) and considered to be rare in practice. However, more recently, theoretical models have suggested that an individual firm can face an upward sloping labor supply curve due to lack of competitors (oligopsony), differentiation between firms, variation in worker preference, moving costs, costly job search, or efficiency wages (Boal and Ransom 1997; Burdett and Mortensen, 1998; Bhaskar, Manning, and To 2002, Manning 2003; Ashenfelter, Faber, Ransom 2010; Mortensen, 2011). In the "new monopsony" framework, the word monopsony is synonymously used with the following words or phrases: monopsonistic competition, oligopsony, imperfect competition, finite labor-supply elasticity, or upward-sloping labor supply to the firm (Webber, 2015). Estimating the degree of competitiveness in the labor market is pertinent both for theoretical research as well as policy analysis. Evidence of sizeable and prevalent labor market monopsony power would suggest that theoretical models of labor market that assume perfect competition should reevaluate their assumptions. From the public policy perspective, imperfect competition in the labor market has implications for the effect of institutions such as minimum wage on employment (Card and Krueger 1995; Feldman and Scheffler 1982). For example, a common policy prescription for monopsonistic labor market is minimum wage. However, if firms in the same labor market have different degrees of monopsony power, then a market wide minimum wage policy will bring mixed results. In general, anything that makes the firm level labor supply curves flatter will make the labor market more efficient. Despite the relevance of monopsony power in labor markets, economists have not reached a consensus on monopsony power in modern labor markets (see Kuhns (2004) for theoretical critique).

Most of the existing empirical literature examining labor market monopsony power is focused on formal labor markets of advanced economies. Given wage is an important determinant of economic welfare, the significance of labor market monopsony is likely to be even greater in developing countries where most of the world's poor live. The problem facing the poor in developing countries is that there is not enough regular wage employment, as opposed to selfemployment, for those who are willing and capable to perform them (see Fields, 2011). Indeed, employment in the wage sector is a means for getting out of poverty in developing countries. Within the developing country context, we are aware of only one article that investigates labor market monopsony power in the manufacturing sector; finding that over half of the firms in Indonesia have significant market power (Brummund, 2013). With the African high value-added sector, manufacturing being one, widely being considered as the engine for economic growth and employment generation within policy circles (Filmer and Fox, 2014; Brookings Institute, 2017), the dearth in the empirical literature assessing labor market competitiveness within the sector is rather surprising. Evidence of firms behaving monopsonistically in the labor market would suggest that they can play an even greater role in employment generation by behaving more competitively. In this article, we investigate the extent to which manufacturing firms in five sub Saharan African countries – Cameroon, Ghana, Kenya, Zambia, and Zimbabwe – exercise monopsonistic market power in the labor market. We also assess how firm characteristics (firm size, ownership, and location) and average workforce characteristics (education, age, and tenure) are related to the firm level estimate of monopsony power. To our knowledge this is the first estimate of monopsonistic behavior in the labor market by manufacturing firms from sub Saharan Africa.

The empirical measure of monopsony power is constructed by taking the difference between the value of marginal product of labor and wage, relative to wage (Pigou, 1924). This approach of comparing marginal revenue product of labor to wages has been deployed in the past (e.g, Hildebrand and Liu 1957, Thurow 1968, Perskey and Tsang 1975, Scully 1974, Medoff 1976, Zimbalist 1992, Binswanger and Rosenzweig 1986, Udry 1996, Barret, Sherlund, and Adesina 2008). This article utilizes a unique employer-employee matched firm-level panel level dataset to compute the marginal revenue product of labor by estimating a production function. And given the information on wages paid to workers by the firm, we construct the empirical measure of monopsony power. The challenge in the estimation of production function is the endogeneity of labor choice to productivity shocks. This article addresses the endogeneity issue by adopting Blundell and Bond's (1998) parametric System GMM[1] to estimate the production function.

[1] Production functions can also be estimated using control function approach. However, those estimators require information on investment or intermediate inputs, which are not available in the dataset employed in this study.

2. Model

We adopt a static model of monopsony power (Pigou, 1924) for a profit maximizing firm. The monopsonistic employer maximizes profits by equating marginal revenue with marginal cost, but marginal cost is greater than wage because of the upward sloping labor supply curve facing the individual employer. The firm chooses employment to maximize profits:

$$\pi = R(L) - W(L)L \quad (1),$$

where π is profits, R is total revenue, W is wages, and L is labor. The first order condition for profit maximization can be written as:

$$R'(L) = W(L) + LW'(L) \quad (2),$$

where $R'(L)$ is the marginal revenue product of labor, and the right-hand side is the marginal cost of labor to the firm, with $W(L)$ being the inverse supply curve. Rearranging the terms in (2) and dividing both sides by $W(L)$, one obtains Pigou's rate of exploitation (E) to be:

$$E = \frac{R'(L) - W(L)}{W(L)} = \frac{LW'(L)}{W(L)} \quad (3).$$

In a perfectly competitive setting, firms will hire labor up to the point where $R'(L) = W(L)$ and Pigou's measure (E) will be zero. Whereas in the presence of monopsonistic behavior, $W'(L)L > 0$, Pigou's measure will be strictly positive. Notice that $\frac{LW'(L)}{W(L)}$ in (3) is the inverse of labor supply elasticity (ϵ). As such, one can succinctly write $E = \epsilon^{-1}$. Note that perfect competition is a limiting case as $\epsilon \rightarrow \infty \; and \; E \rightarrow 0$.

To obtain the above-mentioned measure of market power (E) we need an estimate for marginal revenue product of labor ($R'(L)$). This is achieved by estimating a production function, taking its derivative with respect to the labor input and evaluating it at the firm level of employment and revenue. The roots of this approach can be found in the works of Boal and Ransomb (1997) who lay out much of the theory. While this measure identifies whether firms exercise market power, the source of market power cannot be identified using this technique. As such, we interpret E as suggestive evidence of departure from the perfectly competitive world.

3. Empirical Model of Firm Productivity

We assume each firm's production technology takes the Cobb-Douglas form $Y_{it} = AL_{it}^{\beta_L} K_{it}^{\beta_K}$ where Y_{it} denotes output for firm i at time t such that $i = 1,2,\dots,n$ and $t = 1,2,\dots,T$, L_{it} and K_{it} denote labor and capital, and A is total factor productivity. We estimate the log-transformed specification

$$y_{it} = \beta_L l_{it} + \beta_K k_{it} + \omega_{it} + \mu_i + v_{it} \tag{4}$$

such that lowercase letters denote log-transformed variables. Following previous specifications of firm productivity (e.g., Olley and Pakes 1996), we define ω_{it} to be possibly autoregressive firm-specific productivity shock, μ_i to be a time-invariant firm-specific heterogeneity parameter that may be correlated with l_{it} or k_{it}, and v_{it} is the serially uncorrelated measurement error. The presence of ω_{it} leads to an endogeneity problem; since the Olley and Pakes (1996) method requires an external instrumental variable, a natural alternative is to generate internal instrumental variables using GMM estimators (e.g., Anderson and Hsiao 1982, Arellano and Bond 1991, Arellano and Bover 1995, and Blundell and Bond 1998) based on moment restrictions. Once we estimate the production function, we obtain $R'(L) = \frac{\partial Y}{\partial L} = \beta_L \frac{Y}{L}$, where Y and L are output and labor in their levels. We evaluate $R'(L)$ at the firm level data and plug it into (3) along with firm level wages to obtain Pigou's measure of monopsonistic behavior.

3.1 Parametric System-GMM Identification Strategy

To proceed, consider

$\omega_{it} = \alpha\, \omega_{i,t-1} + e_{it}$ $\qquad\qquad |\alpha| < 1$

$e_{it}, v_{it} \sim MA(0)$

to derive the following dynamic specification of the production function:

$$y_{it} = \alpha y_{it-1} + \beta_L(l_{it} - \alpha l_{it-1}) + \beta_K(k_{it} - \alpha k_{it-1}) + \widetilde{\omega}_{it} + \tilde{\mu}_i + \tilde{v}_{it} \qquad (5),$$

where $\widetilde{\omega}_{it} = \omega_{it} - \alpha\omega_{it-1}$, $\tilde{\mu}_i = (1-\alpha)\mu_i$, and $\tilde{v}_{it} = v_{it} - \alpha v_{it-1}$. (5) can be re-written as:

$$y_{it} = \pi_1 y_{it-1} + \pi_2 l_{it} + \pi_3 l_{it-1} + \pi_4 k_{it} + \pi_5 k_{it-1} + \widetilde{\omega}_{it} + \tilde{\mu}_i + \tilde{v}_{it} \qquad (6).$$

Note that (6) does not have a dynamic interpretation. But with a dynamic specification, we can impose and test for non-linear common factor restrictions using standard minimum distance techniques. The parameters to be estimated are $\pi_1 = \alpha$, $\pi_2 = \beta_L$, $\pi_3 = -\alpha\beta_L$, $\pi_4 = \beta_K$, $\pi_5 = -\alpha\beta_K$. This set of parameters imply the following common factor restrictions:

$$\pi_3 = -\pi_1\pi_2 \; ; \pi_5 = -\pi_1\pi_4 \tag{7}$$

We generate internal instrumental variables following the System-GMM approach (Blundell and Bond 1998). Under the linear-in-parameters form (6), the System-GMM method constructs a stacked system of equations based on a differenced y_{it} and y_{it} in levels, using instruments based on both lagged levels and lagged differences of y_{it}. This system approach has been shown to outperform alternative GMM strategies (e.g., Arellano and Bond 1991) such as using only lagged differences for instrumental variables (see discussions in Blundell and Bond 1998). The moment conditions needed to generate the System-GMM instrumental variables are $E[\tilde{\mu}_i] = E[\tilde{v}_{it}] = E[\tilde{v}_{it}\tilde{\mu}_i] = 0$ for all i, t observations, $E[\tilde{v}_{it}\tilde{v}_{is}] = 0$ for all $i, t \neq s$, and $E[y_{i1}\tilde{v}_{it}] = 0$ for all i, t. Moving forward, it is useful to note that in our empirical application $T = 3$; fixing $T = 3$ allows us to conserve notation in setting up our instrumental variable matrix and estimation strategy. For the first (differenced) equation, the outcome is Δy_{i3} for which y_{i1} is a valid instrument. And for the second (levels) equation, the outcome is y_{i3} for which $\Delta y_{i2} = y_{i2} - y_{i1}$ is the valid instrument. Hence, when $T = 3$, the moment conditions imply the following set of System-GMM instrumental variables:

$$Z_i = \begin{bmatrix} y_{i1} & 0 \\ 0 & \Delta y_{i2} \end{bmatrix}. \tag{8}$$

Letting $y = (\Delta y_{i3}, y_{i3})'$ denote the stacked outcome variable and define X to be the corresponding stacked matrix of right-hand-side variables, the parametric System-GMM estimator is:

$$\hat{\pi}_{GMM} = \left[X'Z\hat{A}^{-1}Z'X\right]^{-1} X'Z\hat{A}^{-1}Z'y \tag{9}$$

where $\hat{A}^{-1} = \left[Z'\hat{\Omega}Z\right]^{-1}$is the second-step GMM weighting matrix such that $\hat{\Omega}$ is a first-stage estimate of $\Omega = \tilde{v}'\tilde{v}$ (see, e.g., Arellano and Bond 1991, Blundell and Bond 1998, Roodman 2009). Finally, we can recover back the three structural parameters $\beta = (\alpha, \beta_L, \beta_K)$ from the five reduced form parameters ($\hat{\pi}$) using the standard minimum distance techniques and imposing the common factor restrictions (7). Let *h()* denote the mapping between the structural and reduced from parameters to write the minimization problem as:

$$min_{\beta \in \mathrm{B}}\{\hat{\pi} - h(\beta)\}'\hat{\Xi}^{-1}\{\hat{\pi} - h(\beta)\}, \tag{10}$$

where $\hat{\Xi}$ is an appropriately chosen efficient weighting matrix. Take $\hat{H}$, the Jacobian of *h()*, to obtain the asymptotic variance of the estimates as $AsyVar(\hat{\beta}) = (\hat{H}'[AsyVar(\hat{\pi})]^{-1}\hat{H})^{-1}$.

4. Data

We use the Regional Program for Enterprise Development (RPED) database that is made available by the Center for the Study of African Economics at the University of Oxford[2]. This dataset originates from initiatives by the World Bank and multilateral donors which funded many surveys in African countries during the 1990s. While a number of studies analyze these surveys (e.g, Bigsten et al., 1999, a, b; Bigsten et al., 2000; Teal, 2000; Soderbom and Teal, 2001, a, b; Velde and Morrissey, 2003; Strobl and Thornton, 2004), none address the research question raised in this article. The dataset consists of three years of employer-employee matched panel data for manufacturing firms from five African countries: Cameroon, Ghana, Kenya, Zambia, and Zimbabwe. The data is from the 1993- 1995 for all countries, except for Ghana, where survey was conducted over 1992-1994. Workers in the manufacturing establishments were interviewed in parallel with the firm level survey, making it possible to match worker characteristics with firm level characteristics. Similarity of data collected on manufacturing firms across countries makes an international comparison possible. At the firm level, data on output, input, and details of work force was collected. The variables used to estimate production function include output in terms of value added (US PPP dollars), total number of employees in the firm, and physical capital defined as the replacement value of plant and equipment (US PPP dollars). There also information in the dataset about the sector (food, furniture, textile, metal), location (whether the firm is in the capital city) and ownership (whether there is some state or foreign ownership). For production function estimation, we use a balanced panel of those firms for which observations exist in all three survey years. This is the minimum number of time period necessary to address the endogeneity of input choice using the econometric framework. As noted in Bigsten et al. (2000), high inflation in Zambia during 1990s may cause PPP exchange rate used to convert Zambian currency into US dollars to be misleading. As such, we are cautious about comparing the results from Zambia with other countries. Mean and standard deviation of the variables used to estimate the production function are reported in Table 1.

[2] Available directly from CSAE website: http://www.csae.ox.ac.uk/

Within each firm, workers were interviewed and information about their earnings and other characteristics were collected. The earnings variable utilized in this article is the average earnings per worker with allowances added to the basic wage rate. While the information on allowances was not collected for Kenya and Zambia during the first round of survey, the earnings data is scaled up by the ratio of wages to allowance in later years to make the data comparable across survey rounds. For Zimbabwe, the information of individual workers is available only for the first two rounds. Information monthly earnings were not available for all firms. Table 2 reports mean and standard deviation of earnings for all observations for which data is available.

5. Results

Table 2 reports the parametric System GMM estimates for the Cobb-Douglas production function. These estimates are based on the two-step estimator with heteroskedastic-consistent asymptotic standard errors with finite sample correction as proposed by Windmeijer (2005). The Hansen test for the validity of the instruments could not be rejected[3], and this result is consistent across countries. The coefficient of the lagged dependent variable is statistically significant for Cameroon and Zambia. In Zimbabwe, the coefficient of the lagged dependent is negative but statistically insignificant. The coefficient of labor is positive for all countries, and is statistically significant for Cameroon, Ghana, and Zimbabwe. The coefficient of lagged labor and that of capital are imprecisely estimated in all countries. The coefficient of lagged capital is significant only for Kenya.

The minimum distance test for the common factor restrictions could not be rejected, and this result is consistent across countries. Furthermore, the Wald test of constant returns to scale for the restricted model could not be rejected for any country. Our structural parameter estimate for the lagged dependent variable was highly statistically significant and positive for Cameroon, Ghana, and Kenya, insignificant for Zambia, and negative and significant for Zimbabwe. In all countries $|\alpha| < 1$. The technology parameter for labor is found to be positive and statistically significant for all countries. There are significant differences in the labor productivity among the five countries. For example, estimate of β_L is 0.292 for Zambia, 0.481 for Ghana, 0.618 for Kenya,

[3] The one-step estimator was also implemented. The Sargan test for the validity of the instruments was rejected only for Cameroon with a p-value of 0.084

0.701 for Cameroon, and 0.871 for Zimbabwe. These estimates suggest that a 10% increase in labor will cause somewhere between 2.92 % - 8.71% increase value added, *ceteris paribus*. The technology parameter for capital, while positive for all countries, is imprecisely estimated[4].

5.1 Market Power Estimates

Estimates of the empirical measure of labor market monopsony power are reported in Table 3. In addition to the mean estimates, the table reports the 25th, 50th, and 75th percentile of the market power distribution. For all countries, the mean market power estimate is greater than the median, suggesting a right skew of the market power distribution. The estimated mean E is 1.892 for Cameroon, 0.815 for Ghana, 2.274 for Kenya, -0.25 for Zambia[5], and 1.557 for Zimbabwe. These estimates suggest that the marginal revenue product of labor is 2.892 times the wage in Cameroon, 1.815 times the wage in Ghana, 3.274 times the wage in Kenya, 0.75 times wage in Zambia, and 2.557 times wage in Zimbabwe on average in the sample. The implies labor supply elasticity ($\epsilon = E^{-1}$) facing the average firm is 0.528 for Cameroon, 1.226 for Ghana, 0.439 for Kenya, and 0.642 for Zimbabwe. In all countries except for Zambia we find evidence for an upward sloping labor supply curve facing the average firm. It is worth noting that only in Ghana the average firm faces an elastic labor supply curve. These labor supply elasticities facing the average firm is far from being considered perfectly elastic, as would need to be cause for the assumption of perfect competition to hold.

6. Conclusion (tentative)

This article estimates labor market monopsony power for manufacturing firms from five African countries. Some tentative conclusions are as follows: 1) For Cameroon, Ghana, Kenya, and Zimbabwe there is suggestive empirical evidence for the existence of labor market imperfections. 2) The mean estimates of market power suggest that the marginal revenue product of the average worker in Cameroon, Ghana, Kenya, and Zimbabwe are somewhere between 2.27 to 3.327 times

[4] We note that the estimated technology parameter for capital is very small in all countries. This is indicative of measurement error associated with the measure of physical capital. We abstract away from this issue because the research question in hand does not rely on this coefficient.

[5] Since the marginal revenue product of labor is constrained to be positive, the minimum possible value for E is "-1"

higher than their wage 3) the implied labor supply elasticity facing the average firm range from 0.43 to 1.22

If we are to assume that job creation is one of the primary concerns of policy makers and development partners of Africa, then incorporating antitrust policies within the broader discourse of development policy agenda might be a step towards the right direction. While we do not go as far as to recommend specific policies, it does seem that institutions such as minimum wage and unions possess the potential to raise employment and wages. At the very least, this research suggests that there is room for more efficient functioning of the labor market.

Table 1: Mean and Standard Deviation of Variables used in the Estimation of Production Function

Variable	Cameroon	Ghana	Kenya	Zambia	Zimbabwe
Output (Value Added US PPP $)	1786811 (4263929)	279543.6 (989006.4)	2501116 (6229119)	540947.5 (1415561)	5643880 (1.76e+07)
Labor	84.46 (200.55)	35.98 (65.47)	84.95 (156.40)	92.2 (322.41)	302.93 (485.95)
Capital (US PPP $)	2131147 (4448946)	387047.6 (1421018)	2193286 (4274473)	1771212 (4922358)	8748069 (3.23e+07)
CapCity	0.65 (0.478)	0.479 (.500)	0.628 (0.484)	0.466 (0.501)	0.522 (0.500)
AnyFor	0.35 (0.478)	0.156 (0.363)	0.185 (0.389)	0.133 (0.341)	0.247 (0.432)
AnyStat	0.066 (0.250)	0.031 (0.174)	0.014 (0.118)	0.033 (0.180)	0.055 (0.228)
N (each firm is observed over all 3 waves)	60	96	70	30	109

Table 2: Mean and Standard Deviation of Workforce Earnings

Variable	Cameroon	Ghana	Kenya	Zambia	Zimbabwe
Monthly Wages (US PPP $)	388.839 (292.078)	154.912 (118.641)	418.105 (347.909)	270.689 (537.809)	429.872 (358.051)
N	120	239	199	82	175

Table 2: Production function estimates with log (value added) as the dependent variable

	Cameroon (1)	Ghana (2)	Kenya (3)	Zambia (4)	Zimbabwe (5)	Pooled (6)
y_{t-1}	0.378* (0.222)	0.314 (0.297)	0.098 (0.195)	0.376* (0.198)	-0.127 (0.125)	0.199* (0.103)
l_t	0.594** (0.294)	0.483* (0.275)	0.606 (0.374)	0.487 (0.328)	0.798*** (0.190)	0.668*** (0.195)
l_{t-1}	-0.005 (0.508)	-0.093 (.277)	-0.115 (0.428)	-0.053 (.122)	0.396 (0.246)	0.034 (0.133)
k_t	0.229 (0.161)	0.124 (0.147)	0.314 (0.268)	-0.069 (0.215)	0.098 (0.172)	0.209* (0.122)
k_{t-1}	0.101 (0.117)	0.109 (0.091)	0.317* (0.173)	-0.052 (0.147)	0.094 (.069)	0.148** (0.069)
Hansen	0.264	0.749	0.809	0.546	0.853	0.841
N	60	96	70	30	109	365
GMM parameter estimates imposing the common factor restrictions						
y_{t-1}	0.546*** (0.128)	0.568*** (0.183)	0.201*** (0.049)	0.297 (0.182)	-0.215*** (.058)	0.386*** (0.055)
l_t	0.701*** (0.265)	0.481* (0.259)	0.618* (0.315)	0.292* (0.172)	0.871*** (0.162)	0.579*** (0.146)
k_t	0.149 (0.144)	0.099 (.143)	0.253 (0.236)	.043 (.065)	0.141 (0.154)	0.157* (0.087)
Comfac	0.535	0.544	0.848	0.531	0.727	0.089
CRS	0.957	0.910	0.972	0.905	0.998	0.972

Note: The standard errors are based on two-step heteroskedastic-robust estimator with finite sample correction proposed by Windmeijer (2005).
'*': significant at the 10% level; '**': significant at the 5% level; '***': significant at the 1% level.
The levels equation includes dummy variables for time, industry, ownership, and location.
The Hansen test is for validity of the over-identifying restriction. p-values are reported
Comfac is the minimum distance test of the non-linear common factor restrictions. p-values are reported.
CRS is a Wald test of the constant returns to scale hypothesis in the restricted model. p-values are reported.

Table 3: Summary of Pigou's Measure of Market Power, *E*

		Percentiles		
	Mean	25th	50th	75th
Cameroon	1.892	-0.182	0.736	3.156
Ghana	0.815	-0.591	-0.122	0.800
Kenya	2.274	-0.261	0.329	1.954
Zambia	-0.250	-0.806	-0.612	-0.126
Zimbabwe	1.557	0.062	0.613	1.941

Figure 1: Kernel Density of E for Cameroon

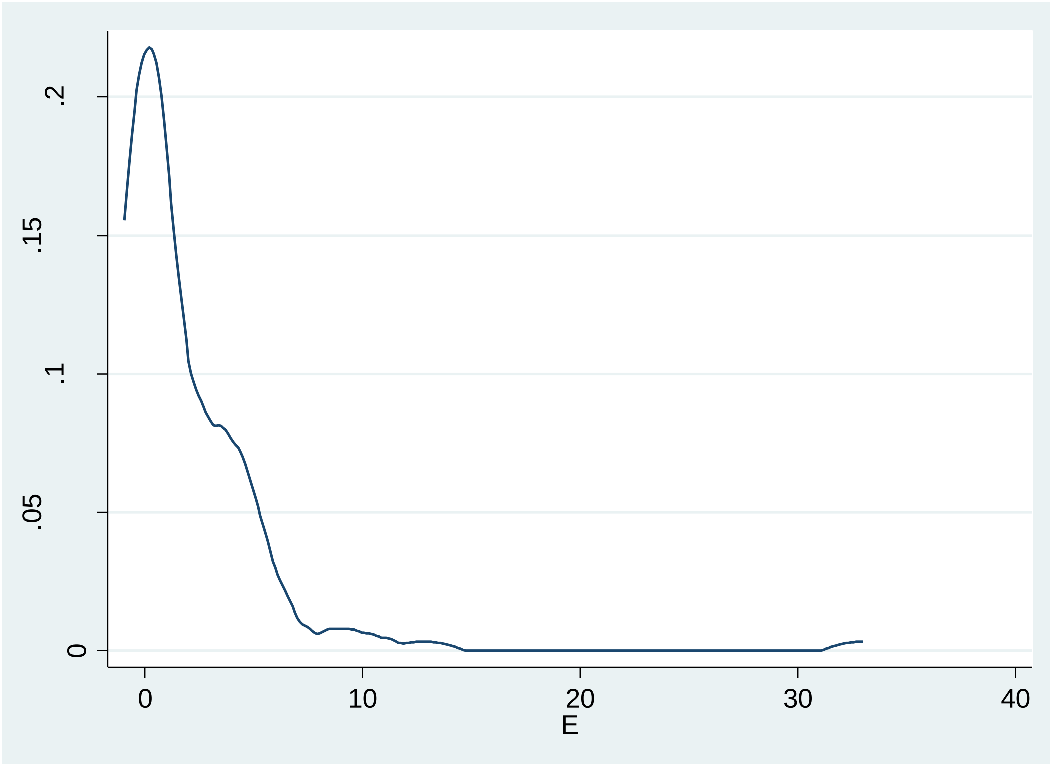


Figure 2: Kernel Density of E for Ghana

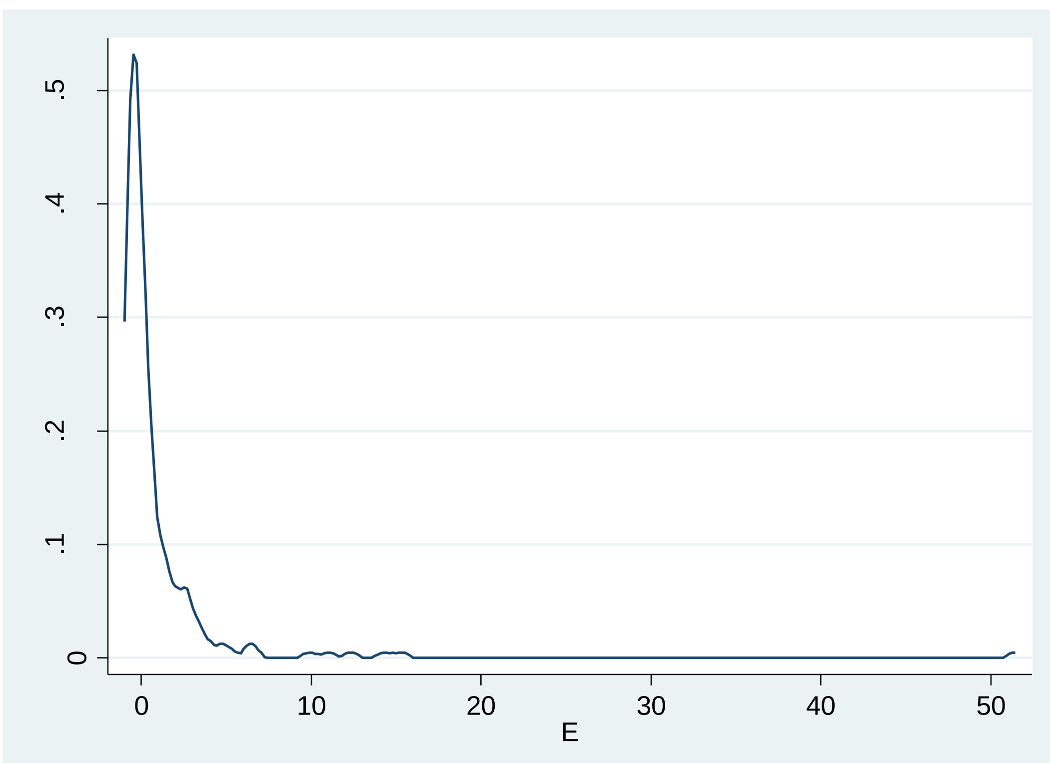


Figure 3: Kernel Density of E for Kenya

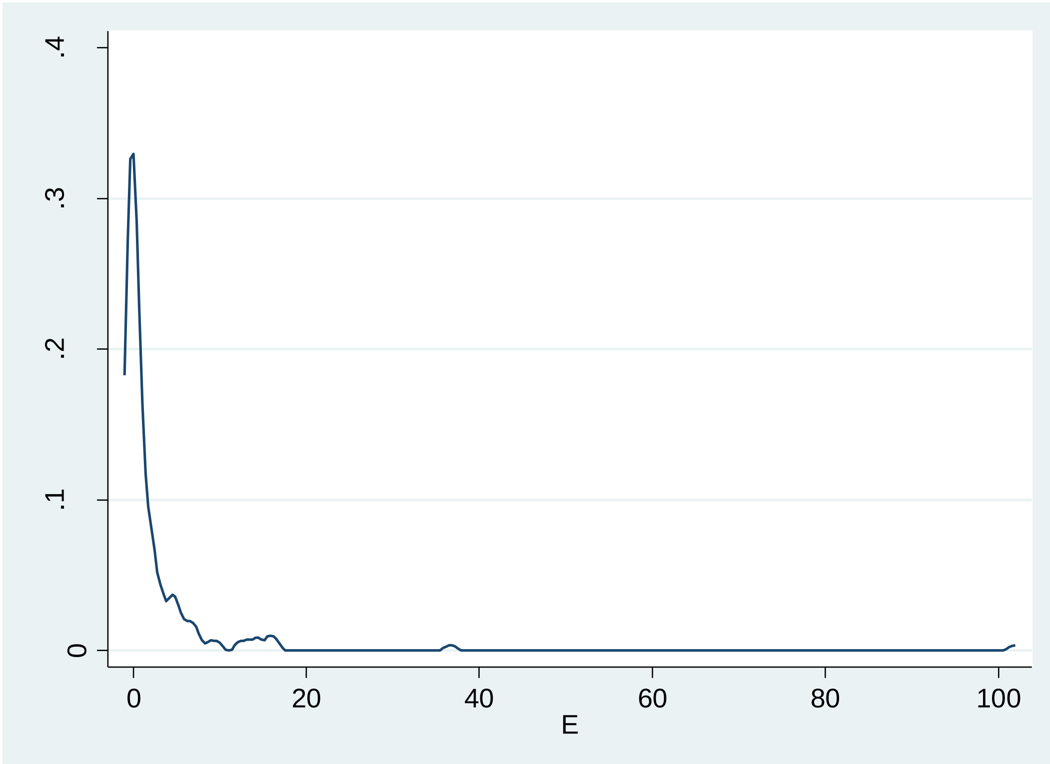


Figure 4: Kernel Density of E for Zambia

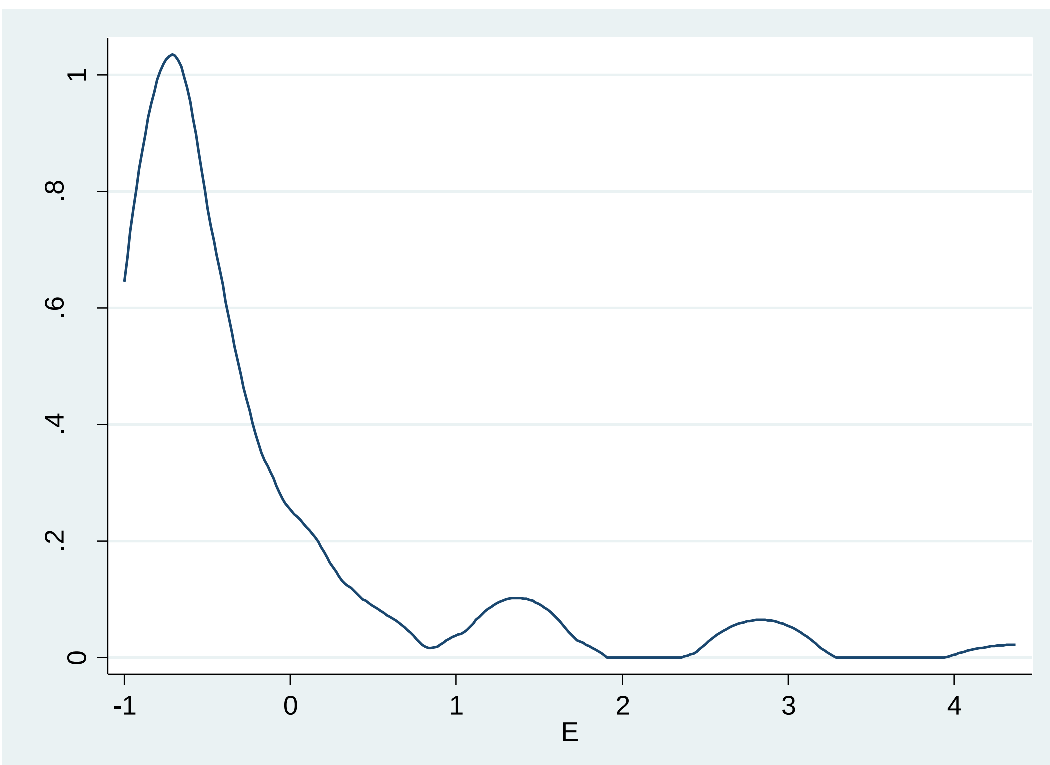
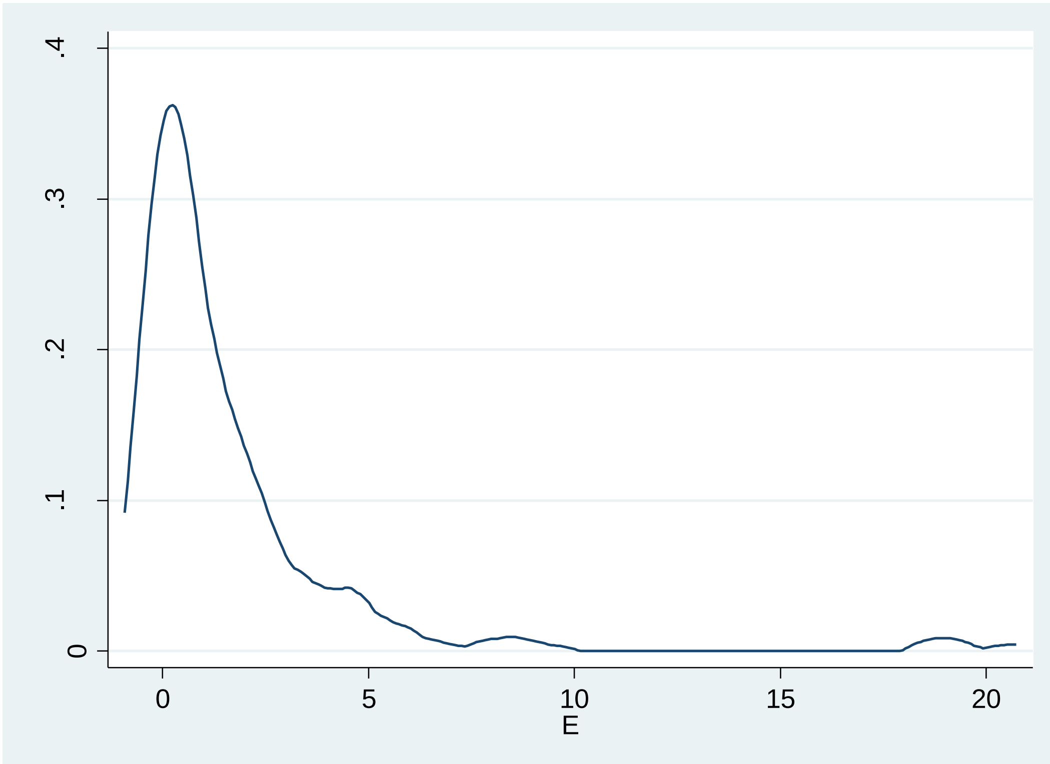


Figure 5: Kernel Density of E for Zimbabwe



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