Social and Household Networks in Sri Lanka: Does Networking Create a Disparity in Employment Outcomes

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Abstract

This paper estimates the impact of social and household networks on employment outcomes in Sri Lanka. The results indicate that social networks, measured by language choice and locality, improve employment outcomes by 0.01%-0.89%. Additionally, ethnicity and language fluency have significant effects on social networks in Sri Lanka. Household networks, which is measured as the count of employed and unemployed individuals in a household, improve employment outcomes by 0.9%-6.2%. However, when household networks are small, employment may be restricted, an occurrence termed as a networking trap. This networking trap predominantly affects low-income households (82%), thereby, impeding poverty alleviation. This paper suggests a policy mechanism to ease the networking trap for low-income households, which leads to an increase in income and a reduction in poverty.

1.0 Introduction

Networks help identify job opportunities, thereby enhancing employment outcomes. Literature has focused on the influence of networks on employment outcomes. [Montgomery (1991), Reingold (1998), Skoufias et al., (2010), Burns et al., (2010), McDonald (2011), Chua (2011), Toussaint-Comeau (2012), Zaharieva (2015)]. A selection of such literature has focused on employment outcomes based on social networks [Burns et al., (2010) and Skoufias et al., (2010)], with one study focusing on employment outcomes based on household networks (Burns et al., 2010). Each study has shown that social and household networks improve employment outcomes.

However, literature estimating the impact of social and household networks on employment outcomes in Sri Lanka is non-existent. The lack of literature undermines the importance of social and household networks on employment outcomes in Sri Lanka. Individuals in Sri Lanka rely on informal channels of information to identify job opportunities. Therefore, social and household networks may play a crucial role in improving employment outcomes. In fact, household networks may play an even greater role in employment outcomes in Sri Lanka given the relative importance of households as social and cultural institutions. Due to this lack of literature and the relative importance of social and household networks in Sri Lanka, this paper has three objectives.

The first objective is to estimate the effect of social networks on employment outcomes. A standard measure of social networks considers language choice and locality as the primary link in social networks (Bertrand et al., 2000). Studies have used this measure to estimate the effect of social networks on employment outcomes [Burns et al., (2010), Skoufias et al., (2010)]. This paper's measure of social networks follows previous literature. However, it accounts for characteristics specific to Sri Lanka that influences language choice and, thereby, social networks. Ethnicity and language fluency are two characteristics considered to influence language choice and thereby social networks in Sri Lanka.

Ethnicity and language choice are inherently linked; ethnic groups within Sri Lanka have a preferred language choice. For example, the Sinhala populace speaks Sinhalese as a first language, whereas the Sri Lankan and Indian Tamils speak Tamil. This paper accounts for the link between ethnicity and language choice using Burns et al., (2010) methodology.

Fluency in language affects language choice, and, thereby, social networks. Previous studies estimate social networks based on fluency in a single language [Bertrand et al., (2000), Burns et al., (2010) and Skoufias et al., (2010)]. However, in Sri Lanka, most individuals speak a language besides Sinhalese. Thus, individuals can be bi-lingual or tri-lingual and tap into a broader social networking group. This paper accounts for language fluency in the estimation process.

The second objective is to estimate the effect of household networks on employment outcomes. Household networks, measured as the count of employed and unemployed individuals within a household, improve employment outcomes by providing job referrals to household members. Given the social and cultural context of Sri Lanka, households act as social institutions influencing an individual's decision on employment. Therefore, job referrals obtained through a household network plays a significant role. There are two reasons for this. First, household members are likely to give first preference to other household members when sharing information on job opportunities. Second, information shared within a household is considered more trustworthy than information received through other social networks. This suggests that household networks will have a strong influence on employment.

The third objective aims to identify if household networks restrict employment for low-income households. The literature indicates that social networks restrict employment for the urban poor (Reingold, 1998). The rationale for why household networks may restrict employment is based on the size of a household network and limited job opportunities in the labour market. A household with a small network has fewer connections to the labour market; in turn, job referrals to household members remain minimal. Due to fewer referrals, a household with a small network has fewer job opportunities. In contrast, a household with a large network will have many referrals and more job opportunities.

Job opportunities are limited within the labour market, and only a few opportunities may match any single individual within a household. Therefore, households through job referrals may unknowingly compete to match household members to a job opportunity. However, given that a household with a larger network can provide more referrals, they are better able to match individuals within a household to a job opportunity. This significantly reduces the availability of job opportunities for households with small networks and makes it more likely for a mismatch in job opportunities. This mismatch in job opportunities creates a restriction on employment for households with small networks.

Due to restricted employment, a household with a small network cannot grow its network to provide better referrals. Furthermore, since household members do not join the workforce, household network sizes remain fixed. Therefore, households with small networks face a cycle of being continuously outcompeted. This occurrence, termed as a networking trap, impedes growth in household income because employment is restricted. This constraint on income may impede poverty alleviation if a vulnerable household income segment falls into a networking trap. This paper assesses the presence of a networking trap through the distribution of household network size across household income.

To summarise, this paper has three objectives. The first objective estimates the effect of social networks on employment outcomes, considering characteristics specific to Sri Lanka, such as ethnicity and language fluency. The second objective estimates the effect of household networks on employment outcomes. The third objective identifies if household networks restrict employment for low-income households.

The findings show that social networks increase employment outcomes by 0.01%-0.89%, and household networks increase employment outcomes by 0.9%-6.2%. The distribution of household network size across household income indicated a skewed distribution; 82% of all low-income households suffered from small networks, implying low-income households fall into a networking trap.

The rest of this paper provides a more detailed explanation for these results across three sections; methodology, results and discussion, and finally, a conclusion.

2.0 Methodology

This section illustrates the methodology and has four subsections. The first subsection covers the measurement and estimation of social networks. The second subsection covers the derivation and interpretation of social networks. The third subsection explains the measurement and estimation of household networks. The fourth subsection considers revisions to the estimation of social networks, where ethnicity and language fluency affect social networks based on the previous discussion.

2.1 Measurement and estimation of social networks

Bertrand et al., (2000) developed an initial measure of social networks. Their paper calculated the social network effect on welfare usage. Literature has also calculated the social network effect on employment outcomes [Burns et al., (2010) and Skoufias et al., (2010)].

Bertrand et al., (2000) states that social networks need two conditions to operate. First, a common language to enable communication among individuals. Second, within a locality, a given number of individuals who speak that language. They argue that individuals share information within a locality across a universal language forming the base of a social network.

Bertrand et al., (2000) states that social networks need to account for quantity and quality. The quantity and quality of a social network require proxy variables. A proxy for the quantity of a social network measures the number of contacts who speak a common language within a locality. A proxy for the quality of a network is a sub-sample of the quantity but with a specific type of information in this case information on employment. Interacting the quality and quantity gives a measure of social networks (1).

(1) $Net_{jk} = \left(CA_{jk}\right) \cdot (\overline{emp}_k)$

As discussed previously, Net_{jk} acts as a measure of social networks. Subscripts j and k represent the area and language group. CA_{jk} measures the quantity of a network by calculating contact availability in area j for language group k. $\overline{emp}_k$ measures the quality of a network as the percentage of employment within a language group k.

Bertrand et al., (2000) uses a unique specification for contact availability (2).[1] Their specification ensures that contact availability remains insensitive to small language groups within a given area.

(2) $CA_{jk} = \left(\frac{C_{jk}/A_j}{L_k/T}\right)$

C_{jk} is the number of people in the area for language group k, A_j is the number of people in area j; L_k is the total number of people in the country for language group k, T is the total number of people in the country. Bertrand et al., (2000) specified many forms and found results to be invariant from one another.

[1] Bertrand et al., (2000) and Burns et al., (2010) use a logged form of equation (2). However, Bertrand et al., (2000) also uses many functional forms of (2) and arrives at similar results. This paper considers a non-logged form of (2).

Mean employment $\overline{emp}_k$ is measured by the language group, taken as a standard deviation from the mean employment in the country- represented in (3).

(3) $\overline{emp}_k = \overline{emp}_k - \overline{emp}$

The literature uses specification following (3). This paper differs in its measurement of mean employment and is specified by (4).

(4) $\overline{emp}_{jk} = \overline{emp}_{jk} - \overline{emp}$

The change from (3) to (4) follows two reasons. First, the networking effect derived through policy shocks, discussed in the next section, is sensitive to the locality. For example, employment policy shocks may differ in an urban and rural setting as information traveling within an urban and rural context is incomparable. Therefore, affecting the social networking effect. Second, spoken language may vary between areas. For example, Tamil spoken between the Northern and Western provinces may differ by dialect. Although miscommunication is unlikely, such variations in language might not match individuals to one another. Therefore, in a social context, information on employment may not pass down from one individual to another, affecting the social networking effect. This paper estimates' mean employment, as shown in (4) to account for such effects.

(5) $emp_{ijk} = \alpha\left(CA_{jk} * \overline{emp}_{jk}\right) + \beta X_i + \gamma_j + \delta_k + \theta CA_{jk} + \epsilon_{ijk}$

(5) gives an econometric specification measuring the social network's effect on employment outcomes estimated through OLS. α measures the social network effect based on the interaction between contact availability CA_{jk} and mean employment $\overline{emp}_{jk}$. γ_j and δ_k specify area and language fixed effects. CA_{jk} acts a control for contact availability but not $\overline{emp}_{jk}$. Language fixed effect accounts for variation in employment by language. X_i represents a set of characteristics. These characteristics are gender, age, the squared effect of age, ethnicity, marital status, years of education, the presence of young dependents in a household, and household size.

This paper utilizes data from the 2013 and 2014 Sri Lanka Labour Force Survey. The sample used in the estimation includes those aged 15 and above. Language groups considered include those fluent in Sinhala, Tamil, and English. However, the initial sample is constrained to those capable of speaking a single language.[2] The area covered in this sample is 52 divisional secretariats (ds) a subset of all ds divisions but covers 24 districts.

Contact availability is estimated using the entire sample. Mean employment is estimated using the employed and unemployed population, helping comply with a standard measurement for employment.[3]

[2] Individuals fluent in a single language were chosen due to the complexity involved in estimating the effect of social networks with individuals fluent in multiple languages.

[3] Individuals who are fluent in all three languages were not discounted from the sample when constructing CA_{jk} and $\overline{emp}_k$ as this would substantially reduce the network size for individuals fluent in a single language.

2.2 Derivation and interpretation of social networks

Bertrand et al., (2000) identifies social networks through α. A positive or negative coefficient indicates the direction of the networking effect, although direct interpretation is not possible in an OLS model. Their approach considers the networking effect through a policy shock. A policy shock focused on improving employment will lead to a percentage increase in employment. A social network will only add on to this positive policy shock, increasing employment outcomes by a further percentage. Thus, social networks only accelerate the transmission of information related to employment opportunities- improving employment outcomes.

(6) $emp_{ijk} = \xi + \alpha\left(CA_{jk} * \overline{emp}_k\right) + \beta X_i + \gamma_j + \delta_k + \theta CA_{jk} + \epsilon_{ijk}$

Their estimation of the networking effect is as follows. With no networking effect- a policy shock will have a one to one scaled effect on employment outcomes. In the presence of a network, a positive policy shock through ξ will lead to an improvement in $\overline{emp}_k$. As employment in language group k increases, information on employment opportunities will be communicated more rapidly across a networking language k. In turn, improving an individual's employment outcomes given he or she speaks language k, this is true only if the networking coefficient remains positive.

To calculate the networking effect. The initial calculation requires averaging (6) and differentiating with respect to ξ. As shown in (7).

(7) $\frac{d\,\overline{emp}_k}{d\xi} = 1 + \alpha\left(\overline{CA}_k * \frac{d\overline{emp}_k}{\mathrm{d}\xi}\right)$

Equating (7) to zero and factoring on the derivative of the policy shock gives (8). Removing the policy effect by subtracting one leaves the estimated social network effect.

(8) $\frac{d\,\overline{emp}_k}{d\xi} = \left[\frac{1}{1-\alpha\overline{CA}_k}\right] - 1$

According to expression (8). Social networks increase employment outcomes for language group k by $\left[\frac{1}{1-\alpha\overline{CA}_k}\right] - 1$ percentage points given a policy shock increases employment outcomes by one percentage point.

2.3 Measurement and estimation of household networks

Burns et al., (2010) estimate household networks on employment outcomes. They consider household networks through the proportion employed within a household. This paper differs in the measurement of household networks on employment outcomes.

Household members either employed/unemployed remain connected to the labour market. Their connection to the labour market gives information on job opportunities, say through referrals, to others within the household searching for employment improving employment outcomes. Therefore, a count of employed/unemployed within a household ($econ\_act_{hi}$) measures a household's network, represented as Net_{hi}. The household networks measure used in this paper ensures information from others and not one's own influences employment outcomes. This correction requires excluding the individuals in question (d_i) from the household network given the individual in question is employed/unemployed; this gives an accurate measure of a household's network effect on employment. Referred to as the effective household network size.

(9) $Net_{hi} = \sum_{i=1}^{n} econ\_act_{hi} - d_i \quad d_i \begin{cases} = 1\ if\ economically\ active \\ = 0\ otherwise \end{cases}$

Based on numbers formed through (9). A categorical variable is formed grouping household networks into categories- ranging from zero to five. A household network size of zero being the smallest and five or above being the largest. The coefficient ϕ_{hi} in (10) captures the household network effect on employment outcomes. The size of a household is used as a control when measuring household networks. This inclusion follows a similar approach to Burns et al., (2010). Their study controls for household size through the proportion employed within a household.

(10) $emp_{ijk} = \alpha\left(CA_{jk} * \overline{emp}_{jk}\right) + \sum_{h=0}^{5} \phi_{hi} Net_{hi} + \beta X_i + \gamma_j + \delta_k + \theta CA_{jk} + \epsilon_{ijk}$

This specification helps identify employment outcomes by household network size. The social network effect α and household networks ϕ_{hi} capture improvements in employment outcomes.

2.4 Revisions to the estimation of social networks

This paper considers the link between ethnicity and language choice. Ethnic groups speak a unique language and cluster spatially to one another. An example is when Tamils and Muslims form small social clusters within a location; such variation in the previous specification of literature goes unaccounted, leading to a biased social network effect on employment. A solution is to measure the quantity and quality of the network by area j, ethnic group e, and language group k. The constructed measure for contact availability and mean employment is now indexed over ethnicity, as shown by equation (11).

11) $emp_{ijek} = \alpha\left(CA_{jek} * \overline{emp}_{jek}\right) + \sum_{h=0}^{5} \phi_{ih} Net_{hi} + \beta X_i + \gamma_j + \delta_k + \theta CA_{jek} + \epsilon_{ijek}$

Communication across multiple languages affects social networks and, thereby, employment outcomes. Accounting for language fluency helps control for communication across multiple language groups, improving the estimate for social network effect on employment. This paper also considers the social networking effect with fluency in multiple languages. Equations (10) and (11) are re-specified as (12) and (13). Equation (12) and (13) account for fluency in multiple languages. Equation (13) accounts for the link between ethnicity and language choice.

(12) $emp_{ijk} = \sum_{k=1}^{3} \alpha_k \left(CA_{jk} * \overline{emp}_{jk}\right) + \sum_{h=0}^{5} \phi_{ih} Net_{hi} + \beta X_i + \gamma_j + \delta_k + \sum_{k=1}^{3} \theta_k\, CA_{jk} + \epsilon_{ijk}$

(13) $emp_{ijek} = \sum_{k=1}^{3} \alpha_k \left(CA_{jek} * \overline{emp}_{jek}\right) + \sum_{h=0}^{5} \phi_{ih} Net_{hi} + \beta X_i + \gamma_j + \delta_k + \sum_{k=1}^{3} \theta_k\, CA_{jek} + \epsilon_{ijek}$

Contact availability CA_{jk} and CA_{jek} in (12) and (13) are constructed based on equation (2). The sample used in the estimation process for (12) and (13) is no longer constrained to individuals fluent in a single language. The proceeding section will discuss results based on the methodology.

3.0 Results and Discussion

This section has four separate sub-sections illustrating objectives set out earlier. The first subsection illustrates preliminary results on social networks and household networks on employment. The second subsection illustrates results based on accounting ethnicity into the social networking effect. The third subsection illustrates results accounting for fluency in multiple languages on social networks. The final subsection illustrates results on household networks on employment and the networking trap.

3.1 Preliminary results on social networks and household networks on employment

	Table 1	(1)	(2)	(3)
	network effect	0.090 (0.022)***	0.090 (0.022)***	0.089 (0.022)***
household network size (base size=0)	1		0.001 (0.002)	0.006 (0.002)***
	2		-0.002 (0.004)	0.015 (0.004)***
	3		0.001 (0.004)	0.028 (0.005)***
	4		-0.013 (0.012)	0.025 (0.013)*
	5		0.000 (0.022)	0.043 (0.024)*
	contact availability	-0.080 (0.020)***	-0.080 (0.020)***	-0.078 (0.020)***
	female	-0.022 (0.003)***	-0.022 (0.003)***	-0.025 (0.003)***
	age	0.007 (0.000)***	0.007 (0.000)***	0.007 (0.000)***
	age2	-6.54E-05 (0.000)***	-6.49E-05 (0.000)***	-6.83E-05 (0.000)***
	years education	-0.004 (0.000)***	-0.004 (0.000)***	-0.003 (0.000)***
	young dependents	0.035 (0.003)***	0.035 (0.003)***	0.042 (0.003)***
	constant	0.877 (0.021)***	0.878 (0.023)***	0.877 (0.023)***
	marital status	Yes	Yes	Yes
	ethnicity	Yes	Yes	Yes
	language fixed effect	Yes	Yes	Yes
	ds fixed effects	No	Yes	Yes
	household size	No	No	Yes
	N	40,623	40,623	40,623

Standard errors are clustered at the ds division level and reported in brackets below
***,**,* represent statistical significance at 1%,5% and 10%

Table 1 shows preliminary regression results from equation (5) in column (1). Column (2)-(3) follow equation (10), but column (2) does not have a control for household size. The network coefficient is positive in all columns. This indicates that social networks have some positive contribution to employment outcomes, even with the addition of household networks in columns (2) and (3).

Table 2	Feedback on employment from policy shock via the network effect		
	(1)	(2)	(3)
Sinhala	0.122	0.122	0.120
Tamil	0.364	0.364	0.358
English	0.254	0.253	0.250
Overall	0.180	0.180	0.177

Table 2 shows the estimated change in employment outcomes through social networks. Column (1)-(3) in Table 2 follows the corresponding columns of Table 1 with interpretation limited to column (3). Social networks increase employment outcomes by a %, given a policy shock increases employment outcomes by 1% (Bertrand et al., 2000). However, for simplicity, the social networking effect on employment is directly interpreted. The proceeding section also follows this interpretation of social networks. Results state the social networking effects on employment varies by language, with Tamil being the dominant social networking language (0.358%) followed by English (0.250%) and then Sinhala (0.120%). The overall network effect remains positive (0.193%). [4]

The estimated household network effect in Table 1 of column (2) provides mixed results to column (3) due to the lack of household size as a control. Column (3) provides a more uniform estimate, indicating that employment outcomes are positively related to household network size. Households with a network size ranging from one to five and above have an increased chance of employment- 0.6% to 4.0%. These results are like Burns et al., (2010) but differ in magnitude.

Household size remains an essential variable of control to distinguish the household network effect. This is clear based on the differing results presented in columns (2) and (3) of Table 1 for the household network coefficients.

Overall, the social network effect increases employment outcomes from 0.122%-0.364%, whereas household networks increase employment outcomes from 0.6%-4.0%.

[4] Overall networking effect is calculated as a weighted average of all three networking languages.

3.2 Accounting ethnicity into the social networking effect

The previous results indicate that social networks enhance employment outcomes by 0.122%-0.364. However, previous research does not account for the effect of ethnicity on language choice. This section accounts for the effect of ethnicity on language choice providing results based on equation (11) in the methodology within Table 3.

	Table 3	(1)	(2)	(3)
	network effect	0.159 (0.022)***	0.159 (0.022)***	0.159 (0.021)***
household network size (base size=0)	1		0.001 (0.003)	0.006 (0.002)**
	2		-0.002 (0.004)	0.015 (0.004)***
	3		0.002 (0.004)	0.028 (0.005)***
	4		-0.011 (0.011)	0.027 (0.012)**
	5		0.005 (0.020)	0.049 (0.021)**
	contact availability	-0.181 (0.027)***	-0.181 (0.026)***	-0.179 (0.026)***
	female	-0.023 (0.003)***	-0.023 (0.003)***	-0.026 (0.003)***
	age	0.007 (0.000)***	0.007 (0.000)***	0.007 (0.000)***
	age2	-6.49E-05 (0.000)***	-6.46E-05 (0.000)***	-6.79E-05 (0.000)***
	years education	-0.003 (0.000)***	-0.003 (0.000)***	-0.003 (0.000)***
	young dependents	0.034 (0.003)***	0.034 (0.003)***	0.041 (0.004)***
	constant	0.990 (0.028)***	0.991 (0.029)***	0.989 (0.029)***
	marital status	Yes	Yes	Yes
	ethnicity	Yes	Yes	Yes
	language fixed effect	Yes	Yes	Yes
	ds fixed effects	No	Yes	Yes
	household size	No	No	Yes
	N	40,623	40,623	40,623

Standard errors are clustered at the ds division level and reported in brackets below
***,**,* represent statistical significance at 1%,5% and 10%

The networking effect remains positive in each column of Table 3. However, the network coefficient has increased in size from Table 1 to Table 3. Indicating that ethnicity influences language choice and thereby, the social network effect on employment outcomes.

Table 4	Feedback on employment from policy shock via the network effect		
	(1)	(2)	(3)
Sinhala	0.256	0.256	0.255
Tamil	1.324	1.322	1.317
English	1.366	1.364	1.359
Overall	0.651	0.650	0.648

Table 4 shows the estimated change in employment outcomes through social networks. Column (1)-(3) in Table 4 follow corresponding columns of Table 3. Interpretation is limited to column (3). Results differ from Table 2. English is the dominant social networking language (1.359%), followed by Tamil (1.317%) and Sinhala (0.255%). The overall social networking effect improves employment outcomes by 0.648%, which is higher than the overall effect given in column (3) of Table 2. Results indicate that ethnicity influences social networking outcomes on employment. Implying that language choice alone does not determine social networks, and other factors contribute to the social network effect on employment.

3.3 Accounting for fluency in multiple languages on social networks

	Table 5	(1)	(2)
	Sinhala network effect	0.294 (0.052)***	0.355 (0.040)***
	Tamil network effect	0.022 (0.012)*	0.079 (0.010)***
	English network effect	0.012 (0.016)	0.019 (0.006)***
household network size (base size=0)	1	0.008 (0.002)***	0.009 (0.002)***
	2	0.016 (0.004)***	0.018 (0.004)***
	3	0.025 (0.005)***	0.028 (0.005)***
	4	0.026 (0.012)**	0.028 (0.012)**
	5	0.057 (0.019)***	0.062 (0.019)***
	Sinhala contact availability	-0.183 (0.036)***	-0.192 (0.024)***
	Tamil contact availability	-0.024 (0.011)**	-0.081 (0.010)***
	English contact availability	-0.002 (0.008)	-0.007 (0.004)*
	female	-0.027 (0.002)***	-0.027 (0.002)***
	age	0.008 (0.000)***	0.008 (0.000)***
	age2	-7.84E-05 (0.000)***	-7.76E-05 (0.000)***
	years education	-0.003 (0.000)***	-0.003 (0.000)***
	young dependents	0.044 (0.003)***	0.043 (0.003)***
	constant	0.781 (0.014)***	0.789 (0.015)***
	Controls	Yes	Yes
	N	51,626	51,626

Standard errors are clustered at the ds division level and reported in brackets below
***,**,* represent statistical significance at 1%,5% and 10%

Table 5 presents regression estimates for equation (12) and (13) in columns (1) and (2), respectively. Regression estimates in column (1) and (2) indicate the network coefficient by language. Sinhala is significantly larger, followed by Tamil and English. The English network coefficient is significant in column (2) but not in column (1). All language-based network coefficients are larger in column (2) than column (1) due to accounting variation in ethnicity. All language-based network coefficients are positive. Indicating the presence of a positive social network effect on employment outcomes.

Language fluency helps information travel across social networks through various combinations leading to seven unique network language combinations. Therefore, the effect varies depending on the language combination. Table 6 presents the estimated results for social networking effects on employment outcomes.

	Table 6	(1)	(2)
Networking Languages	Sinhala only	0.40	0.57
	Tamil only	0.01	0.07
	English only	0.00	0.01
	Sinhala and Tamil	0.43	0.74
	Sinhala and English	0.41	0.89
	Tamil and English	0.02	0.08
	All languages	0.37	0.41
	Overall	0.32	0.40

Individuals fluent in a single language have the smallest social networking effect. Fluency in Sinhala alone leads to the highest improvement in employment outcomes (0.57%) for a single language networking effect. Bilingual speakers receive a higher employment outcome from social networks. Given they speak a combination with Sinhala. For example, those speak Sinhala and Tamil (0.74%) or Sinhala and English (0.89%) rather than Tamil and English (0.08%). Therefore, the social networking effect on employment is highest for bilingual speakers. These results are not unremarkable but are in line with common assumptions. A large majority of individuals communicate using Sinhala and evident from the substantial networking effect from individuals speaking Sinhala alone. Fluency in a second language gives access to an extensive network of people, leading to a higher degree of networking ability, improving their employment outcomes.

However, results deviate from the norm when an individual speaks all three languages. Fluency in all three languages improves employment outcomes (0.41%), but less than those fluent in two languages. However, this is also smaller than individuals capable of speaking a single language. Individuals fluent in all three languages account for 3.2% of the entire sample. This questions the measured contact availability and the estimated networking effect of not being representative of the population fluent in the three languages. The overall social networking effect on employment outcome in column (2) of Table 6 amounts to 0.4%.

3.4 Household networks on employment and the networking trap

Results indicate that household networks improve employment outcomes by 0.9% to 6.2%- refer to Table 7.[5] Note these results consider a household with a network size of zero to be the base, and as the network size grows from zero to five, corresponding improvements in employment follow from 0.9%-6.2%. Interpretation follows a household network size increase from zero to one employment outcomes improves by 0.9%, and from zero to five, employment outcomes increase by 6.2%. Indicating employment is dependent on household network size. These findings collaborate with the introduction where household network size affects the referral of job opportunities and thereby employment.

Table 7		Pr(Employment)
household network size	1	0.9%
	2	1.8%
	3	2.8%
	4	2.8%
	5	6.2%

A household with a network size of one or below, identified as a small network, has a lower employment outcome. Whereas, a household with a network size above one, identified as a large network, has a higher employment outcome. In turn, households with smaller networks face a disadvantage in capturing employment opportunities due to their lower employment outcomes. An explanation for lower employment outcomes for households with smaller networks is dependent on their household network size. Households with smaller networks have fewer connections to the labour market; in turn, job referrals to household members remain minimal. Due to fewer referrals, households with smaller networks are less likely to match job opportunities to potential household members, thereby lowering employment outcomes. Households with larger networks may provide numerous referrals leading to a higher employment outcome.

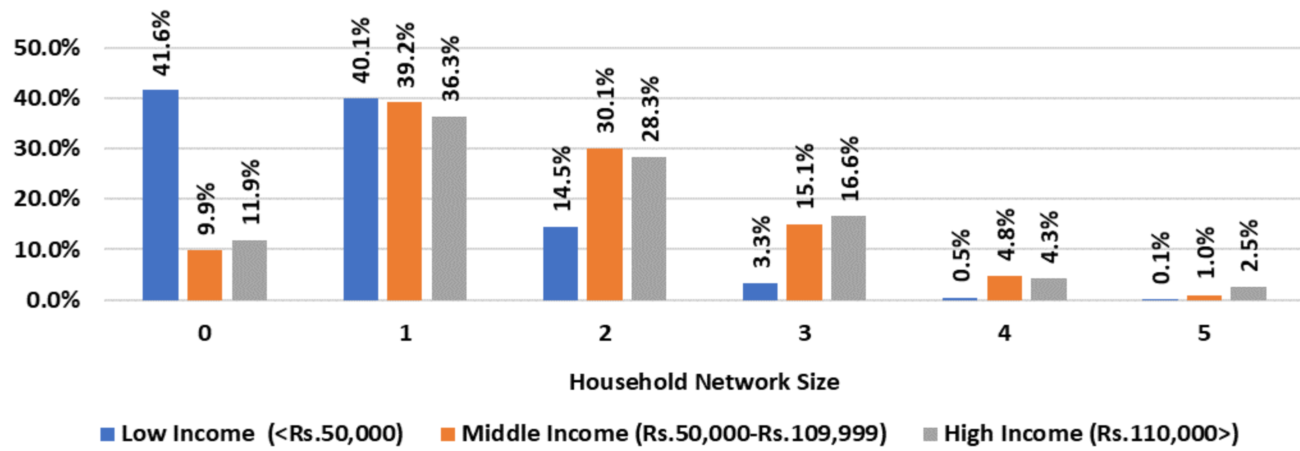
This disparity in employment outcome by household network size creates a point of concern. Within the labour market, job opportunities are limited, and only a few opportunities may match any single individual within a household. Therefore, households may utilize their household networks to provide job referrals and may unknowingly compete to match household members to their ideal job placement. Households with larger networks may provide numerous referrals, capturing a vast segment of these job opportunities. The remaining job opportunities provided by households with smaller networks may be mismatched, thereby restricting employment.

This restriction on employment remains fixed for households with smaller networks. Households with smaller networks cannot grow their network, as household members cannot join the workforce, leading to a fixed household network size. In turn, households with smaller networks may be continuously outcompeted due to a fixed network size by households with larger networks. Thereby the restriction on employment is fixed- an occurrence termed as a networking trap

[5] Table 7 results are based on Table 5 column (2).

Figure 1 examines the distribution of household network size across household income segments categorized as low, middle, and high- income households.

Figure 1: Distribution of Households by Income vs. Network Size (2014 LFS)



Based on Figure 1, the majority (82%) of low-income households possess small networks and fall into the networking trap.[6] The networking trap is indicated by the skewed network size distribution for low-income households.

This networking trap creates a vicious cycle for low-income households as limited job placement restricts growth in household income. However, the most adverse effect is felt by low-income households that remain at or below the poverty line. Thus, a networking trap for low-income households restricts growth in household income and impedes poverty alleviation.

[6] One area of concern is that household networks are influenced by household income. A controlled result is presented in Table 8 of the Appendix with household income as a control. Results remain similar to Table 5.

4.0 Conclusion

This paper identifies the impact of social and household networks on employment outcomes in Sri Lanka. The results state that social networks contribute to a 0.01%-0.89% increase in employment outcomes. Furthermore, the results show that ethnicity and fluency in language affect this measurement.

Household networks improved employment outcomes by 0.9%-6.2% and dependent on household network size. However, one concern highlighted is the possibility of household networks restricting employment for low-income households. Results indicated that 82% of all low-income households suffered from small networks, creating a networking trap, that restricted employment for low-income households. This networking trap deterred growth in household income and restricted poverty alleviation for the most vulnerable low-income households.

One approach to ease the networking trap for low-income households is to provide job opportunities, such that their network grows to match middle- and high-income households. Low-income households can then effectively compete for job opportunities, enabling growth in household income and low-income households out of poverty.

Providing job opportunities to low-income households may help ease the networking trap. However, if the allocation of such job opportunities is incorrect, the networking trap may remain. An effective allocation of jobs can occur through a simple targeting mechanism. Low-income households with a network size below two have the lowest employment outcome. Providing job opportunities to low-income households to jump-start their network will be effective as they can then compete against households with larger networks, and in the future, identify job opportunities to grow their network further. However, this allocation will be ineffective if job referral, through a renewed household network, is deferred by household members, or if a household lacks participant to take up such referrals. Leading to household network size remaining fixed beyond the initial job allocation. As such, at least two or more people within a household must be willing to engage in the workforce. In summary, for an initial job allocation to ease the networking trap, a household must have a network size below two and have at least two people willing to engage in the workforce. These conditions give space for an effective targeting mechanism, known as the 2x2 principle, where an initial job allocation may ease the networking trap for low-income households. [7]

In summary, social networks act as a small factor enhancing employment outcomes, dependent on ethnicity and language fluency. Household networks lead to more substantial improvements in employment outcomes. However, household networks form a networking trap restricting income growth for most low-income households in Sri Lanka. A policy such as the 2x2 principal will help overcome the networking trap for low-income households in Sri Lanka.

[7] I would like to thank Dr. Nishan de Mel on providing important insight to this policy.

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Appendix

	Table 8	
	sinhala network effect	0.352 (0.039)***
	tamil network effect	0.074 (0.009)***
	english network effect	0.020 (0.004)***
household network size (base size=0)	1	0.007 (0.002)***
	2	0.012 (0.004)**
	3	0.020 (0.004)***
	4	0.021 (0.012)
	5	0.042 (0.017)***
	sinhala contact availability	-0.203 (0.023)***
	tamil contact availability	-0.074 (0.009)***
	english contact availability	-0.008 (0.004)**
	household income	0.000 (0.000)***
	constant	0.764 (0.010)***
	controls	Yes
	N	55,406