Injection Drug Users’ Involvement In Drug Economy: Dynamics of Sociometric and Egocentric Social Networks

Cui Yang [scientist],
department of Health, Behavior and Society at the Johns Hopkins Bloomberg School of Public Health in Baltimore, Maryland.

Carl Latkin [professor],
department of Health, Behavior and Society at the Johns Hopkins Bloomberg School of Public Health in Baltimore, Maryland.

Stephen Q. Muth [Director], and
Quintus-Ential Solutions in Colorado Springs, Colorado.

Abby Rudolph [research scientist]
Alcohol, Policy, and Safety Research Center in Calverton, Maryland.

Abstract

The purpose of this analysis was to examine the effect of social network cohesiveness on drug economy involvement, and to test whether this relationship is mediated by drug support network size in a sample of active injection drug users. Involvement in the drug economy was defined by self-report of participation in at least one of the following activities: selling drugs, holding drugs or money for drugs, providing street security for drug sellers, cutting/packaging/cooking drugs, selling or renting drug paraphernalia (e.g., pipes, tools, rigs), and injecting drugs in others’ veins. The sample consists of 273 active injection drug users in Baltimore, Maryland who reported having injected drugs in the last 6 months and were recruited through either street outreach or by their network members. Egocentric drug support networks were assessed through a social network inventory at baseline. Sociometric networks were built upon the linkages by selected matching characteristics, and k-plex rank was used to characterize the level of cohesiveness of the individual to others in the social network. Although no direct effect was observed, structural equation modeling indicated k-plex rank was indirectly associated with drug economy involvement through drug support network size. These findings suggest the effects of large-scale sociometric networks on injectors’ drug economy involvement may occur through their immediate egocentric networks. Future harm reduction programs for injection drug users (IDUs) should consider providing programs coupled with economic opportunities to those drug users within a cohesive network subgroup. Moreover, individuals with a high connectivity to others in their network may be optimal individuals to train for diffusing HIV prevention messages.
1. Introduction

1.1 Background

Drug economy, defined as a range of drug-related behaviors an individual engages in for financial purpose (e.g. selling drugs or drug paraphernalia), offers a source of income in the absence of licit employment opportunities for many marginalized populations, including illicit drug users (Dunlap et al., 2010; Gwadz et al., 2009; Latkin, Davey, & Hua, 2006). Participation in the informal economy was demonstrated by Gwadz and colleagues (2009) to be related to the presence of strong ties to others involved in the informal economy and a perception of the informal economy as a norm (Gwadz et al., 2009). Further, among drug users, information on buying drugs is often obtained through social networks, and drugs are often purchased and used with other users (Latkin et al., 2006). Likewise, drug use among network members may influence one’s participation in the drug economy. For example, a study among Thai methamphetamine drug users reported that having a greater proportion of drug network members who recently stopped using methamphetamine was associated with decreased likelihood of participating in the drug economy (Latimore et al., 2011). These studies collectively suggest the important role that peers play in influencing one’s participation in the drug economy. Because both individual drug use and peer drug use increase one’s connections to those already involved in the drug economy, one’s likelihood of participation in the drug economy is dependent on individual, network, and structural factors. In this analysis, we aim to assess the composition and structure of drug user networks and to identify network features which are indirectly and directly associated with drug economy involvement among a sample of active injection drug users in Baltimore, Maryland.

1.2 Drug economy

Patterns of drug use are influenced by macro and micro economic factors. Since the 1970s, increasing deindustrialization has brought socioeconomic deprivation in urban settings in the United States, characterized by plant closings, massive job losses, and population instability (Bluestone & Harrison, 1988). Urban poverty has been associated with higher rates of illicit drug use and HIV infection, which have disproportionately affected minority groups, such as African Americans (McCord & Freeman, 1990; Wallace, 1990). The costs associated with illicit drugs force drug users, particularly those with severe drug addiction, to engage in drug economy activities (Debeck et al., 2007), and the availability of drugs among individuals in the drug economy may foster drug use.

Involvement in the drug economy places drug users at risk of violence and incarceration (Curry & Latkin, 2003b; Sherman & Latkin, 2002b). In a sample of street-involved youths, involvement in the drug trade was associated with homelessness and self-reported police assault (Werb, Kerr, Li, Montaner, & Wood, 2008). A gender difference has been observed with respect to the types of drug economy activities for which men and women are arrested. Male heroin injectors were more likely to get arrested for selling drugs, while steering/touting (publicizing) drugs was associated with female injectors’ arrest (Curry & Latkin, 2003a). Involvement in the drug economy can also increase health-related risk behaviors. Friedman and colleagues found that IDUs involved in the drug economy were more likely to
have HIV and other blood-borne infections as compared to those drug injectors not involved in the drug economy (Friedman et al., 1998). Network characteristics, structure, ties to the drug economy, and social norms about involvement in the drug economy may also influence whether an individual participates in the drug economy. Therefore, it is important to understand the network characteristics, peer connections, and network structure which make drug users more likely to participate in and to inform public health strategies to improve the lives and well-being of drug users.

1.3 Social network analysis (SNA)

Two types of networks are discussed in the literature: risk networks and social networks. Risk networks consist of those engaged in risk behaviors and social networks are comprised of individuals providing social support. There are two fundamental analytic approaches in SNA: egocentric and sociometric. The egocentric approach focuses on respondents’ direct personal ties, usually relying entirely on respondents’ self report of behaviors and attributes for those ties; the sociometric approach describes a larger set of relationships — the entire panoply of linkages among multiple respondents (Wasserman & Faust, 1994). A fundamental difference between egocentric and sociometric analysis is that each respondent’s immediate group is considered independent in egocentric network data analysis, whereas the entire network is considered to be the unit of analysis with sociometric data (Wasserman & Faust, 1994).

Egocentric network characteristics, such as network size and composition, have been linked to a number of drug-related behaviors, including sharing injection equipment (Costenbader, Astone, & Latkin, 2006; Lakon, Ennett, & Norton, 2006; Latkin et al., 1995; Suh, Mandell, Latkin, & Kim, 1997), exchanging sex for money or drugs (Latkin, Hua, & Forman, 2003), overdose (Tobin, Hua, Costenbader, & Latkin, 2007), and entry to drug treatment (Davey, Latkin, Hua, Tobin, & Strathdee, 2007). A few studies have examined the association between egocentric network characteristics and drug economy involvement. In a sample of active IDUs in Baltimore, Sherman and colleagues found that drug users involved in the drug economy were likely to have more daily contact with drug users, as well as to have a greater percentage of drug users in their social networks (Sherman & Latkin, 2002a). Similarly a study among Thai methamphetamine users reported a positive association between the total number of methamphetamine using networks and one’s involvement in the drug economy and an inverse association between the proportion of methamphetamine using networks who recently quit using methamphetamine and one’s involvement in the drug economy (Latimore et al., 2011).

Network structure may also influence one’s likelihood of participating in the drug economy. Behaviors, information, and disease may flow more easily through dense (or more cohesive) networks because there are more paths connecting any two members of a network. (Liljeros, Edling et al., 2003; Wasserman & Faust, 1994). For example, a greater number of connections to drug users may increase one’s likelihood of participating in the drug economy by virtue of the increased number of paths for entry. Networks can also influence drug-related and sex-related risk behaviors through social norms (Davey-Rothwell & Latkin, 2007; De, Cox, Boivin, Platt, & Jolly, 2007; Latkin et al., 2004; Latkin et al., 2006; Shaw et
al., 2007; Tobin et al., 2010; Unger et al., 2006). The perception of involvement in the drug economy as a norm (in networks where drug economy involvement is high) may also increase one’s participation in the drug economy.

Examining group structure provides additional insights over those provided merely by assessing attributes of individuals. To this end, various classes of sociometric network metrics have been developed either to characterize network systems as a whole, or to characterize the significance of the individual node in a network context (Wasserman & Faust, 1994). Network measures of centrality such as betweenness (Freeman, 1979), information centrality (Stephenson & Zelen, 1989), and eigenvector centrality (Bonacich, 1987) are well-suited to such tasks. Previous studies documented that sociometric characteristics are associated with drug equipment sharing, and HIV/STI transmission (Curtis et al., 1995; Friedman et al., 1997; Rothenberg, Hoang, Muth, & Crosby, 2007). For example, Friedman and colleagues found an association between position as core members of an IDU network and drug equipment sharing behaviors and HIV acquisition (Friedman et al., 1997).

One of the limitations inherent in sociometric network analysis is that many network metrics (e.g. most distance-based centrality measures) apply only within connected “components” – groups where all nodes are reachable by a path of some length. When high connectivity is not assured because of difficulties in identification of alters or a sampling methodology that does not place a premium on recruiting linked persons, it is still possible to use metrics of subgroup formation, such as cliques (Luce & Perry, 1949) and k-plexes (Seidman & Foster, 1978) to rank network members according to the structural complexity of “microstructures” in a network. We used k-plex ranks in the present analysis for its ability to capture the extent of each person’s participation in microstructures, where each member is connected to at least n-k other members within the group (Seidman et al., 1978). As the size of a k-plex increases, so does the sheer number of connections required to maintain the k-plex; in other words, the network cohesion also increases. Since the extent of involvement in these cohesive subgroups is not dependent on which connected component the egos belong to, k-plex rank provides a more robust measure of their network connectivity relative to other sociometric measures (e.g., betweenness, information centrality, or eigenvector centrality).

Despite the differences between egocentric and sociometric network analyses, they are not mutually exclusive. Egocentric network data have been used to build sociometric networks to assess a variety of health-related topics, including smoking cessation, obesity, drug injection behaviors and HIV/STI transmission (Christakis & Fowler, 2007; Christakis & Fowler, 2008; Friedman et al., 1997; Rothenberg et al., 1998). Sociometric network measures are able to assess fundamental social structures that cannot be reduced to individual level factors. It is likely that many behaviors are influenced by direct network contacts, such as family members, friends, or drug-sharing partners, and those can provide proximate potential resources. However, previous studies have rarely utilized both methods of analyses (Gyarmathy & Neaigus, 2006).

A better understanding of how egocentric and sociometric networks interplay to affect risk behaviors may allow for developing more effective interventions (De et al., 2007). The goal
of the current analysis is to model the potential causal pathway between sociometric network features, egocentric, network characteristics, and participation in the drug economy. In this paper, we hypothesized that sociometric network features such as k-plex rank, have direct and indirect effects, mediated through constituent egocentric network characteristics (number providing drug support), to involvement in the drug economy among a sample of active IDUs in Baltimore, Maryland. This hypothesis was tested with structural equation models (SEM) using the latent variable of drug economy involvement. The approach used in this analysis attempts to tie egocentric networks together to assess the larger social network they create, to better understand the social structure of drug economy involvement.

2. Methods
2.1 Data source
The survey data used in this analysis were collected as a part of the SHIELD (Self-Help In Eliminating Life-threatening Diseases) project, a network-oriented experimental pre- and posttest intervention. Index participants were recruited through targeted outreach in high drug use areas. SHIELD study inclusion criteria consisted of: 1) being at least 18 years old, 2) having daily or weekly contact with drug users, 3) willingness to conduct AIDS outreach education, 4) being able to bring in 2 network members for a baseline interview, and 5) not being enrolled in other HIV prevention or network studies. Index participants were asked to bring 2 high-risk members of their networks to the clinic for assessment after the initial interview. Network members were eligible if they were at least 18 years old and were referred by an eligible index participant. Face-to-face and ACASI interviews were conducted to assess their sociodemographic characteristics, HIV related behaviors, and their social networks. There were five waves of data collection from 1997 through 2004. The Johns Hopkins School of Public Health Committee on Human Research approved the study.

3. Measures
3.1 Network configuration
The egocentric network characteristics were assessed at three time points (waves 1, 2, and 4), using the Personal Network Inventory, a modified version of the Arizona Social Support Inventory (Barrera, 1981). This inventory has been shown to have good concurrent and predictive validity and internal consistency (Latkin et al., 1996). The first section of this inventory had nineteen questions designed to generate names of people in respondents’ personal networks, including persons providing or receiving social support, using drugs (injecting or not), or sex partners in the past six months. Characteristics of each nominated network member, such as age, relationship, frequency of contact, duration of relationship and types of drug use were also assessed. The primary egocentric network characteristic in this analysis was the size of each respondent’s drug support network at the baseline, assessed by four name generating questions including: “Who do you do drugs with?”, “Who do you consider your walking partner/running buddy?”, “If you were going through withdrawal, who can/could you usually count on to get you drugs?”, and “Who can/could you usually count on for drugs or the money to get drugs?”
Sociometric networks were built upon the existing information of respondents (egotypes) and nominated individuals (alters) who have been interviewed in all three waves (waves 1, 2 and 4, N=611), 315 (51.6%) of which were index participants and 296 (48.5%) were recruited network members. The sociometric linkages were confirmed by selected matching characteristics, such as first and last name, age, gender, and address. Alters’ full names were only available in wave 4 after the Committee on Human Research approval. As a consequence, matching alters’ identities was better facilitated in wave 4, resulting in a bias against ascertainment of larger network structure for respondents interviewed exclusively in earlier waves. Additionally, respondents interviewed less than three times had fewer chances to provide alters, therefore we restricted analysis to participants interviewed in all three waves, providing a more consistent and less biased sociometric network sample.

Four different levels of matching certainty were applied as “certain,” “probable,” “possible” and “improbable.” Moreover, four broad categories of name generators, equipment, drug, sexual and social were used to elicit identities of alters. Equipment alters were persons with whom the ego shared, borrowed or lent either needles or cookers. Drug alters were persons with whom the ego did drugs. Sex alters were persons with whom the ego had sex in the last 6 months, and social alters included those elicited by questions, such as “Give me the first name, and last name initial of people who you would talk to about things that are very personal and private?” “Is there anybody that you could get together with to have fun or to relax or just hang out with?” In preliminary analyses, twelve networks were examined based on four combinations of linkage attributes (equipment-only, sex-equipment, sex-drug-equipment and all), each under three match certainty assumptions (certain, probable and possible). In the current analysis, we used the network composed of all types of alters under the most conservative (i.e. “certain”) assumption of matching certainty.

K-plex ranks were calculated using UCINet (Borgatti, Everett, & Freeman, 2002) and SAS (SAS Institute, 2011). We enumerated 2-plexes of all sizes with UCINet, and post-processed this information with SAS to create the ranked k-plex score with a scheme similar to one used in a network study of linkages among people and places in a TB investigation (Cook et al., 2007). The network visualization software Pajek was used to create network images (Batagelj & Mrvar, 1998).

3.2 Drug economy

Drug economy involvement was assessed at the baseline. Respondents were asked if they had performed at least one of the following seven roles in the six months prior to the baseline interview: 1) sold drugs; 2) steered customers to or touted (publicized) drugs; 3) held drugs or money for drugs; 4) provided street security for drug sellers including being a “lookout” for police; 5) cut, packaged, or cooked drugs; 6) sold or rented pipes/tools/rigs and 7) “street doctored” (inject into the veins of others).

3.4 Sociodemographic and drug use characteristics

Baseline sociodemographic characteristics examined in this analysis were race/ethnicity (African-American vs. others), gender, age, education (at least high school diploma or GED), relationship status (currently having main partner vs. others), current employment,
monthly income (median split for $1,000 or more), source of income, homelessness, and history of arrest in the past year. Respondents reported on the frequency of injecting heroin, cocaine and speedball (i.e., a combination of heroin and cocaine) in the past 6 months, and daily injectors were operationalized as respondents who have injected heroin, cocaine or speedball at least every day in the past 6 months.

4. Data analysis

The current analysis was limited to SHIELD participants who had injected heroin, cocaine or speedball within the six months prior to the baseline data collection, and been regularly-interviewed in waves 1, 2, and 4, from 1997 through 2003 (N=273).

The construct validity of the drug economy scale was evaluated. First, an exploratory factor analysis (EFA) of the correlation matrix of the original seven items was analyzed with the Mplus program 5.21 (Muthen & Muthen, 2007). As variables for the drug economy were categorical, the mean and variance-adjusted weighted least-squares estimator was used. The factors were correlated under the oblique geomin rotation. Two criteria were used to determine the number of factors to be extracted in the exploratory factor analysis model: 1) the number of eigenvalues greater than one and 2) the scree plot (Netemeyer, Bearden, & Sharma, 2003). Sizes of the loading and cross loadings were examined to determine the quality of the variables measuring the factors. A confirmatory factor analysis (CFA) was then conducted to examine the fit of the factor solution using the items chosen from EFA. Goodness-of-fit was evaluated by five indices: the standardized root mean residual (SRMR) is close to .08 or below, the weighted root-mean-square residual (WRMR), is 1.00 or below, the root-mean-square-error approximation (RMSEA) is close to .06 or below, and the comparative fit index (CFI), and the Tucker-Lewis Index (TLI) values close to .95 or higher(Hu & Bentler, 1999).

A composite score for the drug economy activities was generated by adding dichotomized responses from selected items from EFA and CFA. A binary variable for drug economy involvement was created for the descriptive analysis. Bivariate analyses were conducted to compare characteristics of active IDUs involved in any drug economy activities at the baseline to those not involved at baseline. Tests for significance of differences in proportions were used for categorical variables. For continuous variables, analysis of variance was used for normally distributed variables, and Kruskal–Wallis tests for non-normally distributed variables. Data were analyzed using Stata 10.0 (StataCorp., 2005).

To test the hypothesis that sociometric network characteristics (k-plex rank) are associated with the drug economy involvement directly and indirectly through egocentric network characteristics (number of network members providing drug support), we conducted structural equation modeling (SEM) techniques using Mplus. We tested a model in which k-plex rank had a direct effect on both the number of drug support network members and drug economy involvement, and a model in which k-plex rank had both a direct and an indirect effect on drug economy involvement through the number of drug support network members. Other independent variables (i.e., gender and daily injectors) previously found to be associated with drug economy involvement were included in the model. Given the small
sample size and non-normal distributions of the mediator and outcome, the bootstrap option was used to estimate the standard errors (Shrout & Bolger, 2002). Model fit was evaluated with RMSEA and WRMR.

5. Results

5.1 Drug economy

Among 1,637 participants in the SHIELD baseline, 273 injectors were interviewed at waves 1, 2, and 4. In the EFA of the drug economy scale, two factors with eigenvalues of over 1.00 were identified, and examination of the scree plot confirmed a two-factor solution. Table 1 presents sizes of the loading of the items measuring the factors and model fit indices (SRMR=0.045, RMSEA=0.053, CFI=0.997, TLI=0.991). Item 2 (“steered customers to or touted [publicized] drugs”) had cross-loading on both factors. In accordance with the recommendation that items with cross-loading less than 0.15 difference from its highest factor should be deleted (Worthington & Whittaker, 2006), item 2 was removed from the scale. A two-factor model with latent constructs representing drug-selling activities (sold drugs; held drugs or money for drugs; provided street security for drug sellers including being a “lookout” for police; cut, packaged, or cooked drugs) and injection-related activates (sold or rented pipes/tools/rigs; street doctor or injecting the veins of others) was used for further analyses. Fit indices of CFA indicated good model fit for a two-factor solution of 6 selected items from the EFA (WRMR=0.558, RM-SEA= 0.043, CFI=0.996, TLI=0.993).

The median number of drug economy activities was 1 (mean: 1.38, range 0 – 6). More than half of the sample (54.6%) had at least one drug economy activity in the past 6 months. Table 2 compares the characteristics of IDUs with at least one drug economy activity with those without drug economy activity. Being involved in drug economy activity was associated with hustling and having a friend/family/sexual partners as sources of income, and injecting drugs daily. In addition, larger drug support networks were associated with drug economy involvement.

Figure 1 presents the visualization of the entire network of sex, equipment, drug, and social connections (N=273 respondents), while Figure 2 provides a close-up of the eleven components that contain higher-order microstructure (N=62 respondents). Respondents are visualized as open squares (males) and circles (females), proportional to their reported number of drug economy activities (see Legend). Non-respondent alters are the smallest (closed) squares and circles depicted in the figures. The respondents depicted in Figure 2 (the upper left quadrant of Figure 1) have higher k-plex rank scores than the balance of the respondents, due to greater involvement in network microstructures of higher complexity. Generally, respondents with higher k-plex rank are positioned closer to the upper left in both figures. The three respondents with highest k-plex rank are indicated with arrows in the Figure 2.

5.2 Structural equation model

The model specified a pathway from k-plex rank through the drug support network and to two measures of drug economy, fitting the data well (RMSEA=0.000, WRMR=0.574).
Standardized path coefficients were presented to facilitate comparisons among the coefficients. Figure 3 presents the complete model with standardized path coefficients. The factor correlation for drug-selling and injection-related activities was 0.58 (p<.001). There was no significant direct effect from k-plex rank to either of the two measures of drug economy. K-plex rank had significant indirect effects on both drug selling ($\beta=0.076$) and injection-related activities ($\beta=0.081$). Females were less likely to be involved in drug selling activities, while daily injectors were more likely to get involved in both drug selling and injection-related activities. For the drug support network, the $R^2$ (variance explained) was 0.18; for drug-selling activities, the $R^2$ was 0.13, and for injection-related activities, the $R^2$ was 0.14. The final model provided support for the hypothesis that k-plex rank was indirectly associated with the drug economy activities through the presence of more drug support networks.

6. Discussion

Using structural equation modeling, we examined the relationships among sociometric network characteristics, egocentric network composition and the drug economy involvement. Although no direct effects were observed, k-plex rank was indirectly associated with two measures of drug economy involvement through the size of their drug support network. IDUs in highly connected social-drug-sex-equipment networks may have frequent direct access to drug support networks, leading to the increased likelihood of being involved in the drug economy to sustain their drug addiction. The current findings may also suggest that one’s most immediate networks – i.e. those named in a network inventory, are likely to have a larger influence on one’s participation in the drug economy than those who are more loosely connected to him/her.

This analysis has several limitations. Due to the study design, the sequence of causal pathway cannot be established from k-plex rank to drug economy involvement through the drug support network. An alternative explanation is that through the drug economy, IDUs frequently interact with other drug users, which may lead to increasing cohesiveness of the risk networks. Additionally, generalizability of the findings is restricted due to the sampling strategy and analytical strategy. Identity-matching of alters was based on the completeness of various combinations of selected matching characteristics, with full name of alters unavailable until wave 4. Any incompleteness of information undoubtedly led to missed matches and consequent underassessment of network complexity. Sociometric networks were built upon the existing information of respondents (egos) and nominated individuals (alters) who have been interviewed in all three waves. Those participants who lost to follow-up were more likely to be arrested or involved in the drug economy. In addition, the face-to-face assessment of high risk behaviors, such as drug economy involvement, may have the potential for heightened social desirability response bias. Finally, sociometric networks were comprised of networks listed at three different time points, whereas drug support networks were listed only at baseline. However, we expect the social network was relatively stable.

The present study findings provide a better understanding of the interplay between network structure, network composition and drug-related outcomes. Although egocentric networks are easier and less costly to investigate, they describe network characteristics only from the
perspective of the ego in isolation. Despite the disconnected nature of the network sample, the current study demonstrates the utility of constructing sociometric networks, providing additional context from interactions among groups of persons – an improvement over the traditional assessment of social network. The data support the hypothesis that the effects of sociometric networks on individuals may occur through their immediate egocentric networks (Friedman & Aral, 2001). Moreover, without demonstrable linkages between all network components, it is imperative to assess appropriate network metrics that apply across components, such as those involving microstructural complexity.

Both network structure and composition can be used to assess the adoption of risk-reduction messages, norms, and social support in a cohesive network, identifying subgroups at potentially higher risk, locating targets for prevention and disrupting chains of disease transmission. Future harm-reduction interventions could be targeted in a network-informed manner, for instance, prioritizing programs with job creation and training to those drug users holding positive roles within their network subgroups. Moreover, such individuals who happen to be adjacent to dense risk microstructures might be given priority for training in disseminating risk-reduction messages and mobilizing normative pressures against high-risk behaviors.

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**References**


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Figure 1.
SHIELD study network of recent heroin and crack injectors, Baltimore Maryland, USA (N=273).
Figure 2.
Eleven components of the SHIELD study network, showing respondents with higher k-plex rank (N=62).
Figure 3.
Structural equation model.
Notes
Root mean Square Error of Approximation (RMSEA) Estimate 0.000
Weighted Root Mean Square Residual (WRMR) Value 0.569
Indirect effects of k-plex rank
K-plex rank → drug support network → drug selling activities=0.076**
K-plex rank → drug support network → injection-related activities=0.081**
Direct effects of k-plex rank
K-plex rank → drug selling activities=0.077 (NS)
K-plex rank → injection-related activities=-0.016 (NS)
NS p>.05 (z test), * p<.05 (z test), **p<.01 (z test), ***p<.001(z test)
Table 1
Exploratory factor analysis (EFA) of drug economy sale.

<table>
<thead>
<tr>
<th>Items</th>
<th>Factor 1</th>
<th>Factor 2</th>
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</thead>
<tbody>
<tr>
<td>1) Sold drugs</td>
<td>0.902</td>
<td>0.000</td>
</tr>
<tr>
<td>2) Steered customers to or touted (publicized) drugs</td>
<td>0.513</td>
<td>0.511</td>
</tr>
<tr>
<td>3) Held drugs or money for drugs</td>
<td>0.848</td>
<td>0.161</td>
</tr>
<tr>
<td>4) Provided street security for drug sellers which includes being a “lookout” for police</td>
<td>0.636</td>
<td>0.350</td>
</tr>
<tr>
<td>5) Cut, packaged, or cooked drugs</td>
<td>0.951</td>
<td>−0.231</td>
</tr>
<tr>
<td>6) Sold or rented pipes/tools/rigs</td>
<td>−0.008</td>
<td>0.726</td>
</tr>
<tr>
<td>7) Street doctor or hitting veins on others</td>
<td>0.058</td>
<td>0.667</td>
</tr>
</tbody>
</table>

Model fit indices

<p>| | |</p>
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<th></th>
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<tr>
<td>SRMR</td>
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</tr>
<tr>
<td>RMSEA</td>
<td>0.053</td>
</tr>
<tr>
<td>CFI</td>
<td>0.997</td>
</tr>
<tr>
<td>TLI</td>
<td>0.991</td>
</tr>
</tbody>
</table>
### Table 2

Sociodemographics, drug use behaviors, personal network and sociometric network characteristics of active IDUs, SHIELD Study (N=273).

<table>
<thead>
<tr>
<th></th>
<th>Total (n=273)</th>
<th>No drug economy role (n=124)</th>
<th>At least one drug economy role (n=149)</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Age</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>≤42</td>
<td>159 (58)</td>
<td>69 (56)</td>
<td>90 (60)</td>
<td>0.43</td>
</tr>
<tr>
<td>&gt;42</td>
<td>114 (42)</td>
<td>55 (44)</td>
<td>59 (40)</td>
<td></td>
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<tr>
<td><strong>Race</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Other</td>
<td>14 (5)</td>
<td>4 (3)</td>
<td>10 (7)</td>
<td>0.19</td>
</tr>
<tr>
<td>African American</td>
<td>259 (95)</td>
<td>120 (97)</td>
<td>139 (93)</td>
<td></td>
</tr>
<tr>
<td><strong>Gender</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>175 (64)</td>
<td>76 (61)</td>
<td>99 (66)</td>
<td>0.38</td>
</tr>
<tr>
<td>Female</td>
<td>98 (36)</td>
<td>48 (39)</td>
<td>50 (34)</td>
<td></td>
</tr>
<tr>
<td><strong>Education</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Less than high school</td>
<td>139 (51)</td>
<td>66 (53)</td>
<td>73 (49)</td>
<td>0.49</td>
</tr>
<tr>
<td>At least high school graduate</td>
<td>134 (49)</td>
<td>58 (47)</td>
<td>76 (51)</td>
<td></td>
</tr>
<tr>
<td><strong>Currently having main partner</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>98 (36)</td>
<td>40 (32)</td>
<td>58 (39)</td>
<td>0.25</td>
</tr>
<tr>
<td>Yes</td>
<td>175 (64)</td>
<td>84 (68)</td>
<td>91 (61)</td>
<td></td>
</tr>
<tr>
<td><strong>Current employment</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unemployed</td>
<td>236 (86)</td>
<td>104 (84)</td>
<td>132 (89)</td>
<td>0.26</td>
</tr>
<tr>
<td>Employed</td>
<td>37 (14)</td>
<td>20 (16)</td>
<td>17 (11)</td>
<td></td>
</tr>
<tr>
<td><strong>Monthly income</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>≥$1,000</td>
<td>20 (7)</td>
<td>14 (9)</td>
<td>6 (5)</td>
<td>0.15</td>
</tr>
<tr>
<td>&lt;$1,000</td>
<td>253 (93)</td>
<td>135 (91)</td>
<td>118 (95)</td>
<td></td>
</tr>
<tr>
<td><strong>Source of income</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Salaries or wages</td>
<td>47 (17)</td>
<td>24 (19)</td>
<td>23 (15)</td>
<td>0.39</td>
</tr>
<tr>
<td>Welfare/public assistance</td>
<td>93 (34)</td>
<td>38 (31)</td>
<td>55 (37)</td>
<td>0.28</td>
</tr>
<tr>
<td>Food stamps</td>
<td>141 (52)</td>
<td>63 (51)</td>
<td>78 (52)</td>
<td>0.80</td>
</tr>
<tr>
<td>Social security</td>
<td>57 (21)</td>
<td>30 (24)</td>
<td>27 (18)</td>
<td>0.22</td>
</tr>
<tr>
<td>Hustling/legal or illegal</td>
<td>119 (44)</td>
<td>41 (33)</td>
<td>78 (52)</td>
<td>0.001</td>
</tr>
<tr>
<td>Friends/family/sexual partner</td>
<td>159 (58)</td>
<td>61 (49)</td>
<td>98 (66)</td>
<td>0.006</td>
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<tr>
<td><strong>Homeless</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>230 (85)</td>
<td>105 (85)</td>
<td>125 (84)</td>
<td>0.96</td>
</tr>
<tr>
<td>Yes</td>
<td>42 (15)</td>
<td>19 (15)</td>
<td>23 (16)</td>
<td></td>
</tr>
<tr>
<td><strong>Incarcerated</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>226 (83)</td>
<td>107 (86)</td>
<td>119 (80)</td>
<td>0.16</td>
</tr>
<tr>
<td>Yes</td>
<td>47 (17)</td>
<td>17 (14)</td>
<td>30 (20)</td>
<td></td>
</tr>
<tr>
<td><strong>Daily injectors</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>104 (38)</td>
<td>57 (46)</td>
<td>47 (32)</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
<td>Total (n=273)</td>
<td>No drug economy role (n=124)</td>
<td>At least one drug economy role (n=149)</td>
<td>p</td>
</tr>
<tr>
<td>---------------------------------------------</td>
<td>---------------</td>
<td>------------------------------</td>
<td>----------------------------------------</td>
<td>--------</td>
</tr>
<tr>
<td>Yes</td>
<td>170 (62)</td>
<td>68 (54)</td>
<td>102 (68)</td>
<td></td>
</tr>
<tr>
<td>Size of drug support network: Mean (SD)</td>
<td>4.9 (2.8)</td>
<td>4.2 (2.3)</td>
<td>5.4 (3.1)</td>
<td>&lt;.001</td>
</tr>
<tr>
<td>k-plex rank: Mean (SD)</td>
<td>156.5 (102.1)</td>
<td>154.1 (108.8)</td>
<td>158.5 (96.4)</td>
<td>0.72</td>
</tr>
</tbody>
</table>