Master in Economics: Empirical Applications and Policies

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Master thesis

Supported degree: a new network measure

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Content

Visual information

Abstract

Since interaction between people exists at all levels of human activity, understanding how the patterns of interactions shape behavior and performance of network members is a key question across social sciences.

This thesis introduces a new measure of individual network positioning which we denote as supported degree that reflects both local centrality of an individual in her network and the cohesiveness of her network neighborhood. We characterize this measure mathematically, propose an algorithm that allows to measure supported degree from the data and compare the ability of supported degree to explain a series of behavioral socio-economics outcomes *vis-a-vis* standard measures of individual local positioning.

We show that supported degree is a good predictor of a series of individual socio-economics characteristics and explains them as well as the degree, a classic measure of local centrality and considerably better than the clustering coefficient, the standard measure of network cohesion.

Keywords: social networks, degree, clustering coefficient, support, social cohesion.

1. Introduction

In 1735 a Swiss born mathematician Leonard Euler had solved the famous Königsberg problem applying the theory of graphs. His approach has revealed that many problems may be simplified and solved if viewed in their graph representation. This postulate is even more relevant nowadays when the human interactions are more complex and people are more connected worldwide. As a result, graphs or networks are widely employed across many areas: economics, computer science, physics and chemistry, social sciences, biology, mathematics etc.

Formally, a network is a graphical representation of a system that consists of a set of actors and the relationships or ties between them. A network describes the interaction patterns between the participants of the network (people, organizations, countries or societies). An example of a network with 10 participants is shown in Figure 1.

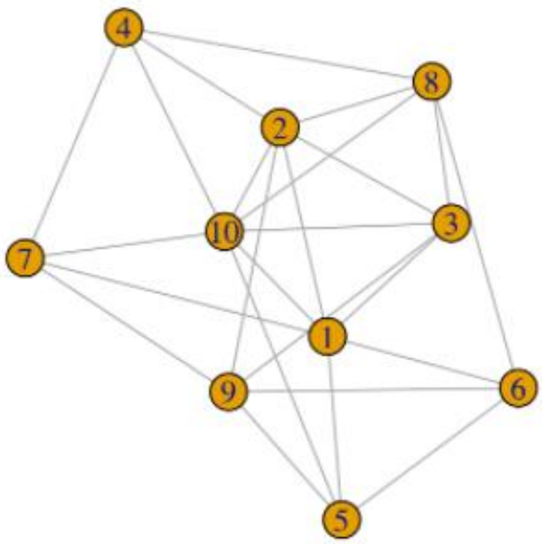

Figure 1 “Example of a network with 10 participants”

The advantage of a network representation is that the structure is simple and visual. A network is basically a map of the pattern of interactions. From the perspective of an analyst, an important feature of the network is that it can serve as an object for network analysis which allows us to determine how network structure interacts with individual behavior of the network participants (Jackson et al., (2017)).

Social-network perspective has shown to be important to shed light in many contexts of economic interest.

For example, social networks are important in transmitting information about job openings and potential employees. Bayer et al., (2005) demonstrate the importance of neighborhood referrals on labor market outcomes such that people that live in the same block have higher probabilities of being employed and work together, which means that referrals can significantly influence one’s wage and labor situation.

Calvo-Armengol and Jackson (2004) show how network connections shape the labor market outcomes. By assigning the importance to the information about the available jobs and its spreading, they prove that an individual with high number of employed friends has more employment prospects in comparison with the individual with less employed friends.

Glaeser, et al., (1996) show that the probability to commit a crime increases when an individual has some friends with criminal records – an individual may fall under bad influence and commit a crime. They also demonstrate that participation of teenagers in crime is influenced by their peers.

Brañas-Garza et al., (2010) detect positive correlation between integration in the social network and individual altruistic attitude.

Goswami and Basu, (2011) explore the influence of individuals' position in the information network and acceptance of new crop in a developing country. They find that farmers that have higher network scores are earlier adopters of cultivation technologies.

In sum, network analysis is an effective tool for explaining many behavioral or socio-economic aspects of network members.

There are four fundamental characteristics of network analysis: degree distributions, homophily patterns, clustering and centrality of the node. They are used at two different levels – macroanalysis and microanalysis. The global level is concentrated on the society-wide issues and includes degree distribution and homophily patterns. The local level focuses on a given individual and includes clustering and measures of centrality.

In this study we concentrate on the local or micro level. Two central notions of the micro level analysis are local centrality and the social cohesion of one's neighborhood.

Local centrality identifies how "important" the position of a given node in her immediate neighborhood is. The most common measure of local centrality is degree - the measure that shows the number of node's connections with its neighbors – and its variants indegree, outdegree, and reciprocal degree that in addition reflect the direction of the connections. Chih-Sheng Hsieh, et al. (2019) find that degree has a positive and significant impact on student's social activities in U.S. high schools such that club participation and sport exercise, which implies that individuals with many friends are more socially active.

In contrast, social cohesion reflects the density of the node's neighborhood in the network, independently of the size of the neighborhood (i.e. degree). The most widely used measure of network cohesion is the clustering cohesion, which reflects to what extent the neighbors of a given node tend to be the neighbors of each other. Kovarik and Van Der Leij (2011) exanimate the correlation between individual's risk aversion and clustering coefficient, showing that individuals with higher clustering are on average more risk-averse.

Apart from these two examples, there are many other that demonstrate significant role of degree and clustering in network analysis (see Jackson et al., 2017).

Although both the degree and the clustering coefficient are two important determinants of human behavior and different socio-economics outcomes, local centrality and social cohesion are two different and independent concepts. This raises the question of whether we can find a network measure that simultaneously reflects both local centrality and cohesion of its neighborhood.

As a first contribution, the thesis proposes a novel measure of individual positioning, supported degree, that combines the ideas of local centrality and social cohesion. Clustering coefficient and degree are too different to be combined directly. Therefore, we focus on network support proposed by Jackson et al. (2013). Support of a link between two individuals reflects the existence of "shared neighbor" for the two linked nodes; the link is supported if they share a common "neighbor".

Although clustering and support are different concepts, they both relate to the presence of triangles (see Section 2). That way, both measure the social cohesion of one's neighborhood. Supported degree measures the number of contacts supported by another third party. Hence, it only reflects the connections embedded in cohesive parts of one's neighborhood. The proposed new measure of individual positioning thus reflects both local centrality and social cohesiveness of the neighborhood.

The second contribution of this thesis is to characterize and explore supported degree. To that aim, we first characterize supported degree theoretically. Second, we propose an algorithm to be able to measure supported degree from empirical networks, using the igraph package in R-studio. Finally, we estimate the influence of supported degree on some individual socio-economics characteristics in a development framework, using data from a number of villages in rural India.

Our empirical results can be summarized as follows. First we find that supported degree is positively correlated with both clustering and degree. However, the correlations are far from one, suggesting that supported degree is different from both of them.
Second, supported degree proves to be a successful predictor of series of socio-economic individual outcomes, such as employment, working outside the village, whether an individual possesses a savings or bank account and election card.
In comparison with the degree and the clustering coefficient, we observe that supported degree explains the socio-economic outcomes under the study as well as the degree and outperforms considerably the clustering coefficient.

The further chapters of the thesis are organized as follows: Section 2 introduces theoretical background for standard network measures and supported degree. Section 3 covers programming aspects of the research. In Section 4 we carry out empirical analysis with the real-life dataset. Finally we summarize the results in conclusion in Section 5.

2. Theoretical backgrounds

In this section we introduce the notation and define formally both the classic network measures and supported degree.

2.1 Notation

Consider a set of nodes (individuals, organizations, countries, etc.) N = {i,j,…n} and set of links among them E = {*ij*, *ik*,*jk*,…}. A graph or network g is the collection of these nodes and links: g = {N,E}. Figure 2 shows an example of a network g, in which N ={i,j,k,n} and E= {*ij*, *ik*,*jk*,*in*}.

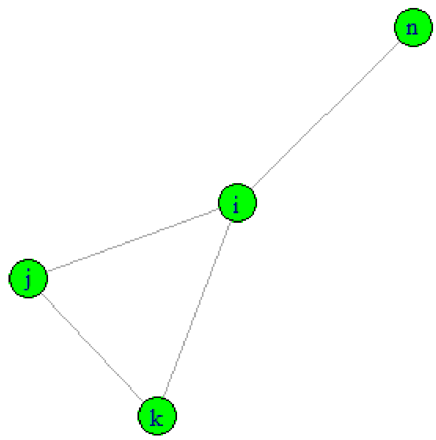

Figure 2: "Hypothetical network *g*"

Network g from Figure 1 can alternatively be presented as an adjacency matrix A.

$$A = \begin{array}{c} \\ i \\ j \\ k \\ n \end{array} \begin{pmatrix} i & j & k & n \\ 0 & 1 & 1 & 1 \\ 1 & 0 & 1 & 0 \\ 1 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 \end{pmatrix}$$

Matrix A

In the matrix every node of g is represented by the row/column by the order and the matrix takes value of 1 if the nodes are neighbors and 0 otherwise. That way if two nodes are linked with each other, it is denoted by writing them together, such as *ij*, *ik* or *in.*

We start with the concept of network centrality. The idea behind all measures of centrality is to identify which node occupies "important "position in a network. The difference between the existing centrality concepts lies in what one considers to be an important position. In this paper, we focus on the local concept of centrality: connectivity. In simple words, connectivity refers to the number of connections that a given node has with its neighbors in the network. In network terminology, connectivity is termed the degree.
Degree of a node is the number of her connections with its neighbors.

We define the *neighborhood* of the node *i* as the set of all vertices adjacent to the node i:

$$N_{i(g)} = \{j \in N | ij \in E\}$$

Degree of the node *i:*

$$d_{i(g)} = | N_{i(g)}|$$

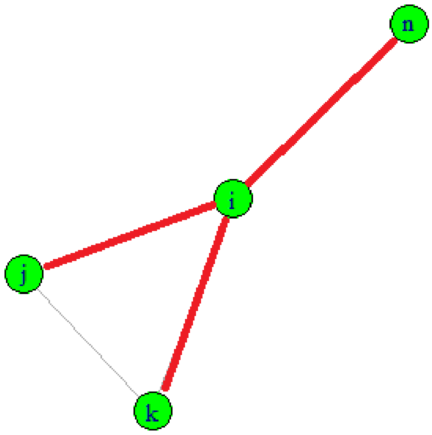

Figure 3: "Degree of the node *i*"

In the figure 3 node *i* has three neighbors and three connections with them, so $d_i(g)$ = 3

The higher the degree of a node (that is the more connections she has), the more locally central she is. Note that degree does not reflect the direction of a connection, but in many applications relationship can be directed. In-degree is the connection directed into a node in a directed graph. Out-degree is the connection directed out of a node in a directed graph. Reciprocal degree is the bidirectional connection of a mutual relationship.

Another widely employed network-related concept –unrelated to centrality- that we address is social embeddedness or cohesion of the neighborhood of a given node. Cohesion it is the measure of network's strength – the more cohesive the network, the more difficult to separate it. In cohesive networks nodes have many ties with others and these ties are widely distributed (rather than routing through one node); Moody and Coleman, (2015).

The concept of cohesion reflects how close the neighborhood of a given node tends to be a clique - a group of nodes where every node is directly connected to every other node.

The most widely applied measure for network cliquishness or social cohesion it is the clustering coefficient that counts the number of connections between neighbors of the node over total number of possible connections between them. In other words, clustering coefficient of a given node quantifies how close its neighbors are to being a clique (complete graph). Mathematically, *clustering coefficient* can be expressed as follow:

$$CC_i(g) = \frac{\sum_{i,k,j} A_{ij} A_{ik} A_{jk}}{d_i(g)(d_i(g) - 1)/2}$$

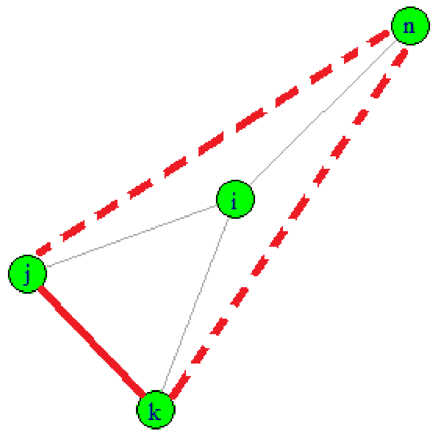

Figure 4: “The clustering coefficient of the node *i*”

As the node *i* has three neighbors: *j*, *k* and *n*, the maximum number of connections that can be established between them is three. However the connection *jk* is the only established connection between the neighbors of *i*. That way $CC_i(g)$ = 1/3

The clustering coefficient shows the number of “triangles” in one’s neighborhood.

Another measures we consider in this chapter – support. It is proposed by Jackson et al. (2012) and measures whether two linked nodes have some third node to which they are both connected. Alternatively it can be called as “common friend” or “shared neighbor”. Mathematically *support* can be shown as following:

$$Support\ ij = \begin{cases} 1\ if\ \exists\ k: ik,\ jk\ \in E \\ 0 \qquad\qquad otherwise \end{cases}$$

where *k* is a “common friend” of *i* and *j*.

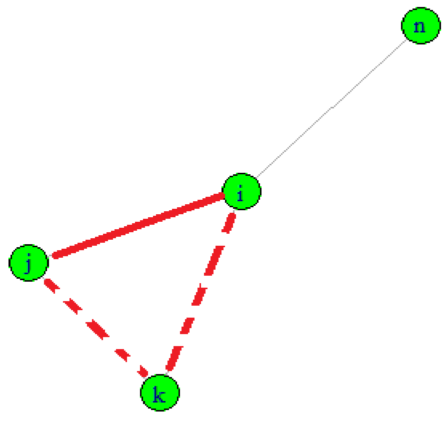

Figure 5: “Support of the link *ij*”

In the figure 5 the link *ij* is considered to be supported if there exists the node *k* and both nodes *i* and *j* are connected to this node. If these conditions are holds, support of the link *ij* equals 1.

As support relates to the existence of “shared neighbor” for two linked nodes, it reveals itself by presence of the triangle.

With increasing the clustering coefficient, the numbers of triangles are necessary created, Jackson (2016), what will case the support to increase as well. That way, it makes sense to assume that the clustering coefficient and support measure social cohesion through the number of triangles.

But despite both clustering coefficient and support relate to the presence of "triangles", they are conceptually different. Firstly, support is property of the link while the clustering coefficient is property of the node. Secondly, for support it is not necessary that neighbors of a given node being a clique, only existence of "common friend" for every connection matters. That way a link can be supported and support equals 1 while clustering coefficient for a given node will be less than 1.

2.2 Supported degree

In the previous chapter, we introduce the local measures of centrality (represented by degree) on the one hand and network cohesion (represented by the clustering coefficient) and support on the other hand. Local centrality reflects one's connectivity while cohesion relate to local density of node's neighbors, two different and independent concepts. Ex ante, there is no reason to expect the neighbors of the node with many connections to either be densely or loosely connected between each other. That is, theoretically, there should be no correlation between one's clustering coefficient and her local centrality.

In this study we propose a new network measure that combines the idea behind both local centrality and network cohesion. Remember that support of a link *ij* represents the existence of "common friend" that is connected to both *i* and *j*. One important aspect of support in social networks is its impact on individual behavior. Jackson et al. (2012) discuss the role of support in providing incentives to favor exchange which makes the connections stronger. Our objective is further exploration of the role of support in the social network.

In the following, we propose a new measure of node's individual positioning called supported degree that reflects the number of node's connections that are supported. The key feature of supported degree is to embrace both local centrality and network embeddedness of a node by adapting the idea of support to reflect a property of the node, rather than a link.

Mathematically, let *supported neighborhood* of node be the following:

$$N_i^S(g) = \{j \in N_i(g) | \exists k: ik, jk \in E\}$$

Then, *supported degree* can be defined as:

$$d_i^s(g) = |N_i^s(g)|$$

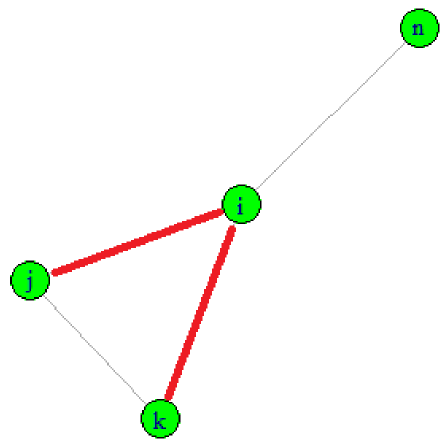

Figure 6: "Supported degree of the node *i*"

In the figure 6, node *i* has two supported links: *ij* and *ik;* link *ik* is supported by existence of the node *k* which is neighbor of both i and *j* and link *ik* is supported by existence of the node *j* which is neighbor of both i and *k*. The link *in* is not supported; there is no “shared neighbor” for nodes *i* and *n*. That way, d_i^s (g) =2

3. Measuring supported degree in networks

Since we propose a new measure, the existing software for the measurement and analysis of network data does not allow one to compute supported degree. Therefore, this section proposes an algorithm that allows researchers and analysts interested in measuring supported degree in the R, a free software environment for statistical computing. In particular, we use the package "igraph" specially designed for computational analysis of network data and the package "expm" that allows us to perform arithmetical operations with matrices.

The main challenge is to program an algorithm that computes the number of supported links of each node in a network even for large network data sets. As a visual example of how the algorithm works we use the hypothetical network g from the figure 2 and its matrix A:

First we introduce the concept of path or the way that connects the nodes with each other. To show it we square the matrix A and obtain:

$$A^2 = \begin{array}{c} \\ i \\ j \\ k \\ n \end{array} \begin{array}{c} \begin{array}{cccc} i & j & k & n \end{array} \\ \begin{pmatrix} 3 & 1 & 1 & 0 \\ 1 & 2 & 1 & 1 \\ 1 & 1 & 2 & 1 \\ 0 & 1 & 1 & 1 \end{pmatrix} \end{array}$$

Matrix A^2

Here we can see how many nodes can achieve any given node if it had two steps. For example node *n* can arrive to any node for two steps, except from the node *i*. In turn, node *i* has 3 possible combination of returning to itself (*i*-*j*,*j*-*i*, *i*-*k*,*k*-*i* and *i*-*n*,*n*-*i*), one path to arrive node *j* (through node *k*) and node *k* (through node *j*) and no path to arrive to node *n*. Paths between nodes *i* – *j*, *i* –*k* and *j*–*k* represent support – we have a "common friend" for every pair of connections *i* – *j*, *i* –*k* and *j*–*k*.

In the next step we combine these two matrixes to obtain the new one. We combine them in the following way: if the interception in the first matrix equals 1 (which means that the nodes are connected) and the interception is greater than zero in the squared matrix (which means that there is a path between two nodes through a "common friend"), the value of interception in the new matrix equals 1, and 0 otherwise. For our example we have the following matrix B:

$$B = \begin{array}{c} \\ i \\ j \\ k \\ n \end{array} \begin{array}{c} \begin{array}{cccc} i & j & k & n \end{array} \\ \begin{pmatrix} 0 & 1 & 1 & 0 \\ 1 & 0 & 1 & 0 \\ 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix} \end{array}$$

Matrix B

Finally, we count the numbers of the positive values in columns or rows of matrix B for every particular node, where every unit accounts for one supported link. In this example, node *i* has two supported links, node *j* has two supported links, node *k* also has two supported links and node *n* has no supported links.

In R studio the algorithm exploits two add-on packages: igraph and expm. Once both packages are loaded into R using the *library ()* command, the following code computes the undirected supported degree of a network x, which should be an igrapgh object:

```
supported_degree <-function(x){
  matrix <- as.matrix(x[])
  matrix_square <- matrix %^% 2
  supported_degree_1 <- colSums(ifelse(matrix_square>0 & matrix==1,1,0))
  return(supported_degree_1)
}
```

In order to assess the speed of the algorithm in larger network data sets, we run it for a network with 4000 network members. The igraph package takes 0.002 seconds to find the degree of all nodes and 1.23 seconds to find the clustering coefficient, while our algorithm needs 46.04 seconds to find the supported degree. This is quite slow relatively speaking. That can be explained by the complexity and numerous operations in the function. Despite that, the function can be optimized for work with big data in perspective.

4. Empirical analysis of supported degree

In this section, we empirically test to what extent the notion of supported degree explains certain individual characteristics using large data set from development context and compare its performance to that of centrality measures and the clustering coefficient.

4.1 Data description

For the study we use the data from the deployment of a micro-finance program, Banerjee et al (2013). In this data we have the observations from 75 rural villages from an area of southern India.

The survey was organized as follow: individuals in all the villages were asked to name several people, with whom they have a particular type of relationships, for example borrowing money, asking for help in emergency situation, company to temple and so on. In addition, the individuals were elicited a variety of socio-economic indicators, such that employment, education, health, wealth, etc. We combine both types of data below to assess to what extent different social network measures determine individuals' performance.

In this study we concentrate on the "favor" networks, which reflects whether two individuals exchange either physical favors (borrowing money, lending money, borrowing kerorice, lending kerorice) or intangible favors (advice come, advice go, medical help).

We divide the networks on directed (indicate a one-way relationship) and reciprocal (indicate mutual relationship).
For directed networks we have the following measures:

1. In-degree (connection directed into a node)
2. Out-degree(connection directed out a node)
3. The clustering coefficient
4. Supported degree

The measures for reciprocal networks:

1. Degree_ reciprocal
2. The clustering coefficient_ reciprocal
3. Supported degree_ reciprocal

We have selected five variables from heterogeneous individual's indicators that could be affected by supported degree and the other measures:

1. Employed: – whether the individual worked previous week
2. Work outside the village: – does the individual have to travel outside the village for work
3. Savings – does the individual has a bank or savings account
4. Election card – does the individual have an election card
5. Education – what is the maximum level of education achieved by the individual

We chose these variables because we assume that they may embrace the concepts of both centrality and social cohesion and consequently supported degree demonstrates its effect on them.

Table A-1 (in the Appendix) provides some descriptive statistics for the variables employed in the regression analysis across all the 75 villages in the dataset.

In-degree, out-degree and degree with the highest values are found in the village № 50 (4.666). The lowest value for these variables shows the village № 67 (2.372). Across all the villages the mean value for degree measures is 3.382.

Highest mean value for the clustering coefficient in directed networks demonstrates the village № 37 (0.053) and the lowest shows village № 32 (0.014). In reciprocal networks the mean values are higher: the highest one is found in the in village № 40 (0.261) while the lowest one in the village № 32 (0.075).

Average value for supported degree in directed and reciprocal networks is 1.455. The highest value is found in village № 41 (2.828) and the lowest one in the village № 46 (0.544).

Individual characteristics of the surveyed population are presented as dummy variables and displayed in percentages.

About 87% of surveyed populations in the village № 36 have worked previous week, what is the highest value for employment variable. The lowest value (57%) is found in the village № 6. In average across all villages, 62% of the people are employed.

About 34% of the village population in average has to travel outside the village to work. In the village № 57 its value is the highest (77%), while the lowest percentage is in the village № 41 – only 12% of the population regularly travel outside the village for work.

In average, 39% of total population has bank account or savings. The highest mean value is in the village № 41 where 66% of inhabitants have bank account or savings. The lowest value is in the village № 2 (16%)

In average, 86% of total population in the dataset has the election card. Its percentage is the highest in the village № 5 where in average 97% of people are election card holders. The lowest percentage is in the village № 6 – about 65%.

Average age of population across the villages is 38.9 years. The village № 56 shows the higher average age of inhabitants, 42.3 years while the lowest age is in village № 57 – 35.7 years.

As for level of education, 37% of population have no education, 16% have secondary level school certificate, 5.2% are degree holders or above and 41.8% have other option.

Among total population 55.4% are women. The highest percentage of the women (58.9%) lives in the village № 28. The lowest percentage of women (51.7%) lives in the village № 2.

4.2 Relation between supported degree and other network measures

Since supported degree is a new measure of individual positioning, we first provide a small analysis of how it relates with the classic characteristics in the data. In particular, we correlate it in the table 1 with the clustering coefficient and the degree measures.

Table 1: Correlation of the network measures

	Directed				Reciprocal		
	SD	Clustering	In-degree	Out-degree	SD_rec	Clustering_rec	Degree_ges
SD	1	0.5619099	0.7644533	0.7644533	1	0.4849509	0.7644533
Clustering	0.5619099	1	0.1771755	0.1771755	0.5619099	0.9901101	0.1771755
In-degree	0.7644533	0.1771755	1	1	0.7644533	0.1153162	1
Out-degree	0.7644533	0.1771755	1	1	0.7644533	0.1153162	1
SD_rec	1	0.5619099	0.7644533	0.7644533	1	0.4849509	0.7644533
Clustering _rec	0.4849509	0.9901101	0.1153162	0.1153162	0.4849509	1	0.1153162
Degree _rec	0.7644533	0.1771755	1	1	0.7644533	0.1153162	1

All correlations are significant at $p<0.0001$

Supported degree and supported degree reciprocal have positive correlation with in-degree, out-degree and degree measures, all of them are above 0.76.
Also both supported degree and supported degree reciprocal demonstrate positive correlation with the clustering coefficient and clustering coefficient reciprocal although it is lower than in case of degree: 0.56 for directed networks and 0.48 for reciprocal network.
These correlations suggest that all these variables move to the same direction. At the same time, these numbers are far enough from 1 (perfect positive correlation) which is the evidence that supported degree differs from clustering and degree.

In social networks, the neighbors of a higher degree node are less likely to be linked to each other compared to the neighbors of a lower degree node. It happened when high-degree nodes attracted most of their neighbors via network-based meetings, and each of those neighbors then forms a relatively small number of connections to the node's neighbors. For example, a negative clustering – degree relationship can be found in the prison and the Ham data sets, Jackson, Rogers (2004). However, in our data set supported degree and the clustering coefficient are highly positively correlated. Hence, supported degree measures an aspect of local centrality linked to social cohesion.

4.3 Regression analysis

In this sub-section we introduce regression models that determine relationship between individual’s characteristics and individual’s positioning in the networks and reveal how good supported degree can explain that relationship.
In chapter 4.1 we denote the dependent variables as a set of different socio-economic individual’s characteristics. As the regressors we take the network measures for directed and reciprocal networks. For the better accuracy, we include two control variables in the models: individual’s age and gender. Also, it is important to assess how well every particular model fits the data, that way we address to the goodness of fit. We consider three different measures: log likelihood (negative value where smaller values of the negative log-likelihood indicate the better fit), AIC or Akaike information criterion (lower AIC scores are better for goodness of fit) and R^2 (greater value indicates the better goodness of fit). We compare the model with the best goodness of fit with the other, less fitted models.

Table 2: Employment

	Workflag						
	Directed				**Reciprocal**		
Supported degree	0.0413184*** (1.24e-13) (0.0055401)	-	-	-	-	-	-
Clustering coefficient	-	0.563385* (0.0145) (0.230353)	-	-	-	-	-
In-degree	-	-	0.0462379*** (0) (0.0048423)	-	-	-	-
Out-degree	-	-	-	0.0462379*** (0) (0.0048423)	-	-	-
Supported degree_rec	-	-	-	-	0.0410652*** (1.24e-13) (0.0055401)	-	-
Clustering coefficient_rec	-	-	-	-	-	0.0717565. (0.0935) (0.0427798)	-
Degree_rec	-	-	-	-	-	-	0.0462379*** (0) (0.0048423)
Age	-0.0061742*** (4.35e-12) (0.0008915)	-0.005988*** (1.81e-11) (0.000891)	-0.0065382*** (2.47e-13) (0.0008931)	-0.0065382*** (2.47e-13) (0.0008931)	-0.0061742*** (4.35e-12) (0.0008915)	-0.0059869*** (1.82e-11) (0.0008909)	- 0.0065382*** (2.47e-13) (0.0008931)
Gender	-1.3931562*** (0) (0.0242061)	-1.397446*** (0) (0.024195)	-1.3807854*** (0) (0.0242417)	-1.3807854*** (0) (0.0242417)	-1.3931562*** (0) (0.0242061)	-1.3967364*** (0) (0.0241928)	-1.3807854*** (0) (0.0242417)
Log Likelihood	-9204.389 (-0.2%)	-9229.539 (-0.47%)	-9185.25	-9185.25	--9204.389 (-0.20%)	-9231.126 (-0.49%)	-9185.25
AIC	18417 (+0.2%)	18467 (+0.47%)	18379	18379	18417 (+0.2%)	18470 (+0.49%)	18379
R^2	0.2119259 (-1.07%)	0.2092626 (-2.35%)	0.2141982	0.2141982	0.2119259 (-1.07)	0.2091393 (-2.4%)	0.2141982

First number in brackets is the p-value and the second number in the brackets is the standard error.

Table 2 shows that all the measures of local centrality – supported degree, in-degree, out-degree and degree in both the directed and reciprocal networks exhibit positive and highly significant influence on the probability of employment. The estimate of the clustering coefficient is also positive but only significant at 2% level of significance in directed network and 10% level of significance in the reciprocal graphs.

P-values for degree, in-degree and out-degree are zero. P-values for supported degree are small and very close to zero while the clustering coefficient shows p-values that are significantly higher than of supported degree. Hence, we conclude that supported degree explains employment as well as degree but considerably better than clustering.

Degree, in-degree and out-degree have the best goodness of fit according to the all fit measures. R squared of supported degree is lower by 1.7% and differences in AIC and log likelihood are smaller than 1% in comparison with the values for degree. Despite that, supported degree demonstrates better fit than clustering in both directed and reciprocal networks.

Table 3: Work outside

Work outside							
	Directed				**Reciprocal**		
Supported degree	-0.032384*** (01.53e-07) (0.006170)	-	-	-	-	-	-
Clustering coefficient	-	-0.71874* (0.0133) (0.29040)	-	-	-	-	-
In-degree	-	-	-0.034700*** (1.25e-10) (0.005394)	-	-	-	-
Out-degree	-	-	-	-0.034700*** (1.25e-10) (0.005394)	-	-	-
Supported degree_rec	-	-	-	-	-0.032384*** (1.53e-07) (0.006170)	-	-
Clustering coefficient_rec	-	-	-	-	-	-0.10698. (0.0503) (0.05465)	-
Degree_rec	-	-	-	-	-	-	-0.034700*** (1.25e-10) (0.005394)
Age	-0.019100*** (0) (0.001209)	-0.01939*** (0) (0.00121)	-0.018687*** (0) (0.001211)	-0.018687*** (0) (0.001211)	-0.019100*** (0) (0.001209)	-0.01939*** (0) (0.00121)	-0.018687*** (0) (0.001211)
Gender	-0.589344*** (0) (0.027855)	-0.58685*** (0) (0.02785)	-0.597286*** (0) (0.027914)	-0.597286*** (0) 0.027914	-0.589344*** (0) 0.027855	-0.58544*** (0) (0.02785)	-0.597286*** (0) (0.027914)
Log Likelihood	-6536.169 (-0.1%)	-6547.138 (-0.27%)	-6529.014	-6529.014	-6536.169 (-0.1%)	-6548.294 (-0.29%)	-6529.014
AIC	13080 (+0.1%)	13102 (+0.27%)	13066	13066	13080 (+0.1%)	13105 (+0.29%)	13066
R^2	0.05755879 (-2.3%)	0.05551818 (-6.09%)	0.0589001	0.0589001	0.05755879 (-2.3%)	0.05530514 (-6.5%)	0.0589001

First number in brackets is the p-value and the second number in the brackets is the standard error.

Table 3 shows that all the measures of local centrality – supported degree, in-degree, out-degree and degree in both the directed and reciprocal networks exhibit negative and highly significant influence on the probability to travel outside the village for work. The estimate of the clustering coefficient is also negative but only significant at 2% level of significance in directed networks and 6% level of significance in the reciprocal graphs.

P-values for degree, in-degree, out-degree and supported degree are very small and close to zero, however p-values for degree are even closer to zero than that of supported degree . The clustering coefficient shows p-values that are significantly higher than of supported degree. We conclude that supported degree explains the probability to travel outside the village for work as well as degree but considerably better than clustering.

Degree, in-degree and out-degree have the best goodness of fit according to the all fit measures. R squared of supported degree is lower by 2.3% and deviations in AIC and log likelihood are less than 1%, in comparison with the values for degree. Despite that, supported degree shows better fit than clustering in both directed and reciprocal networks.

Table 4: Savings and bank account

Savings and bank account							
	Directed				**Reciprocal**		
Supported degree	0.0617368*** (0) (0.0048593)	-	-	-	-	-	-
Clustering coefficient	-	0.3464310 (0.103) (0.2126572)	-	-	-	-	-
In-degree	-	-	0.0779886*** (0) (0.0042828)	-	-	-	-
Out-degree	-	-	-	0.0779886*** (0) (0.0042828)	-	-	-
Supported degree_rec	-	-	-	-	0.0617368*** (0) (0.0048593)	-	-
Clustering coefficient_rec	-	-	-	-	-	0.0258576 (0.515) (0.0396837)	-
Degree_rec	-	-	-	-	-	-	0.0779886*** (0) (0.0042828)
Age	0.0039637*** (1.14e-06) (0.0008145)	0.0042556*** (1.56e-07) (0.0008113)	0.0032723*** (6.52e-05) (0.0008195)	0.0032723*** (6.52e-05) (0.0008195)	0.0039637*** (1.14e-06) (0.0008145)	0.0042504*** (1.61e-07) (0.0008113)	0.0032723*** (6.52e-05) (0.0008195)
Gender	0.1315725*** (2.79e-10) (0.0208517)	0.1203491*** (7.03e-09) (0.0207853)	0.1586592*** (4.30e-14) (0.0210097)	0.1586592*** (30e-14) (0.0210097)	0.1315725*** (2.94e-10) (0.0208517)	0.1209847*** (5.89e-09) (0.0207886)	0.1586592*** (4.30e-14) (0.0210097)
Log Likelihood	-11279.68 (-0.79%)	-11359.89 (-1.5%)	-11190.14	-11190.14	-11279.68 (-0.7%)	-11360.99 (-1.5%)	-11190.14
AIC	22567 (+0.79%)	22728 (+1.5%)	22388	22388	22567 (+0.7%)	22730 (+1.5%)	22388
R^2	0.01230254 (-85.7%)	0.002837104 (-700.6%)	0.0228558	0.0228558	0.01230254 (-85.7%)	0.002709035 (-743.6%)	0.0228558

First number in brackets is the p-value and the second number in the brackets is the standard error.

Table 4 shows that all the measures of local centrality – supported degree, in-degree, out-degree and degree in both the directed and reciprocal networks exhibit positive and highly significant influence on the probability to have savings or bank account. The estimate of the clustering coefficient is also positive but not significant at 10% level of significance none in the directed neither in the reciprocal networks.

P-values for degree, in-degree, out-degree and supported degree equal to zero. P-values for clustering are much higher; however estimate of clustering is not significant for savings. We conclude that supported degree explains the probability to have savings or bank account as well as degree.

Degree, in-degree and out-degree have the best goodness of fit according to the all fit measures. R squared of supported degree is lower by 85.7% however the deviations in AIC and log likelihood are not that big: less than 1% in comparison with the values for degree. Despite that, supported degree shows better fit than clustering in both directed and reciprocal networks.

Table 5: Election card

	Election card						
	Directed				**Reciprocal**		
Supported degree	0.053456*** (7.54e-13) (0.007456)	-	-	-	-	-	-
Clustering coefficient	-	0.144734 (0.609) (0.282783)	-	-	-	-	-
In-degree	-	-	0.071401*** (0) (0.006709)	-	-	-	-
Out-degree	-	-	-	0.071401*** (0) (0.006709)	-	-	-
Supported degree_rec	-	-	-	-	0.053456*** (7.54e-13) (0.007456)	-	-
Clustering coefficient_rec	-	-	-	-	-	-0.006249 (0.905) (0.052209)	-
Degree_rec	-	-	-	-	-	-	0.071401*** (0) (0.006709)
Age	0.057413*** (0) (0.001511)	0.058095*** (0) (0.001514)	0.056268*** (0) (0.001510)	0.056268*** (0) (0.001510)	0.057413*** (0) (0.001511)	0.058091*** (0) (0.001514)	0.056268*** (0) (0.001510)
Gender	-0.251361*** (0) (0.029966)	-0.253026*** (0) (0.029915)	-0.236496*** (3.71e-15) (0.030072)	-0.236496*** (3.71e-15) (0.030072)	-0.251361*** (0) (0.029966)	-0.252499*** (0) (0.029917)	-0.236496*** (3.71e-15) (0.030072)
Log Likelihood	-5418.282 (-0.06%)	-5444.525 (-1.09%)	-5385.277	-5385.277	-5418.282 (-0.06%)	-5444.648 (-1.09%)	-5385.277
AIC	10845 (+0.06%)	10897 (+1.09%)	10779	10779	10845 (+0.06%)	10897 (+1.09%)	10779
R^2	0.2267564 (-1.4%)	0.2242743 (-2.5%)	0.2300657	0.2300657	0.2267564 (-1.4%)	0.2242567 (-0.259%)	0.2300657

First number in brackets is the p-value and the second number in the brackets is the standard error.

Table 5 shows that all the measures of local centrality – supported degree, in-degree, out-degree and degree in both the directed and reciprocal networks exhibit positive and highly significant influence on the probability to have an election card. The estimate of the clustering coefficient is also positive but not significant at 10% level of significance none in the directed neither in the reciprocal networks.

P-values for degree, in-degree, and out-degree are zero while p-values for supported are very small and close to zero. The difference between them is minor. P-values for clustering are much higher; however estimate of clustering is not significant for the probability to have an election card. Hence, we conclude that supported degree explains the probability to have an election card as well as degree.

Degree, in-degree and out-degree have the best goodness of fit according to the all fit measures. R squared of supported degree is lower by 1.4% in comparison with the values for degree and deviations in AIC and log likelihood are less than 1%. Again, supported degree shows better fit than clustering in both directed and reciprocal networks.

Table 6: Level of education

Education							
	Directed				**Reciprocal**		
Supported degree	0.014738 (0.371) (0.016471)	-	-	-	-	-	-
Clustering coefficient	-	-0.023010 (0.975) (0.725389)	-	-	-	-	-
In-degree	-	-	0.04209** (0.00296) (0.01416)	-	-	-	-
Out-degree	-	-	-	0.04209** (0.00296) (0.01416)	-	-	-
Supported degree_rec	-	-	-	-	0.014738 (0.371) (0.016471)	-	-
Clustering coefficient_rec	-	-	-	-	-	0.079013 (0.559) (0.135217)	-
Degree_rec	-	-	-	-	-	-	0.04209** (0.00296) (0.01416)
Age	-0.169562 (0) (0.002765)	-0.169486 (0) (0.002764)	-0.17005 (0) (0.00277)	-0.17005 (0) (0.00277)	-0.169562 (0) (0.002765)	-0.169469 (0) (0.002764)	-0.17005 (0) (0.00277)
Gender	-2.508178 (0) (0.070612)	-2.510317 (0) (0.070612)	-2.49106 (0) (0.07085)	-2.49106 (0) (0.07085)	-2.508178 (0) (0.070612)	-2.512017 (0) (0.070624)	-2.49106 (0) (0.07085)
Log Likelihood	-48961.91 (0%)	-48962.31 (0%)	-48957.9	-48957.9	-48961.91 (0%)	-48962.14 (0%)	-48957.9
AIC	97933.83	97934.63	97925.79	97925.79	97933.83	97934.29	97925.79
R^2	0.192 (-1.03%)	0.192 (-1.03%)	0.1924	0.1924	0.192 (-1.03%)	0.192 (-1.03%)	0.1924

Table 6 shows that in-degree, out-degree and degree in both the directed and reciprocal networks exhibit positive and significant influence on the level of individual education. The estimate of supported degree is positive but not significant at 10% level of significance likewise the clustering coefficient.

P-values for degree, in-degree, and out-degree are close to zero. P-values for supported degree and clustering are greater and none of them are significant. Hence, we conclude that supported degree explains the level of individual education worse than degree in this model.

Degree, in-degree and out-degree have the best goodness of fit. Deviation between R squared of supported degree and degree is 1.3% and deviations in log likelihood and AIC are extremely small and close to zero.

Summarizing the regression results it can be noted that all the degree measures are highly significant at less than 0.1% in all models and demonstrate the best goodness of fit according to all three criteria considered.

Similarly, supported degree performs almost as well as the classic degree measures: it is highly significant at less than 0.1% level of significance in 4 out of 5 estimated regression models. An exception is the education regression model where supported degree is not significant at any reasonable significance. Since the clustering coefficient also fails to predict education outcomes, this suggests that social cohesion is not an important predictor of performance at school.

Supported degree shows a slightly worse goodness of fit in comparisons with degree, but AIC and log likelihoods are only 1% "worse" while R^2 only 2.3% lower except for the model of savings and bank account where the R^2 is 85.7% lower. This suggests that social cohesion might not be an important aspect of having a bank account.

The clustering coefficient is significant at 5% in the directed networks and 10% in the reciprocal networks. Significance is shown in 2 regression models from 5. Clustering demonstrates the worst goodness of fit in all regression models.

We can interpret the obtained results as follow:

- Classic degree measures and supported degree perform overly similarly in the regression exercises. All of them proved to be important determinants of real-life socio-economic outcomes of the network participants.
- Supported degree clearly outperforms the clustering coefficient while explaining the socio-economic outcomes.

5. Conclusions

Our motivation for the thesis is to introduce a new measure that would combine two different and independent network concepts: local centrality and social cohesion. As these two concepts are different from each other, we combine them using the notion of support to introduce supported degree.

As we propose a novel measure, the existing software does not allow computing supported degree. We therefore, program an algorithm in R-studio using the igraph package, which allows us to measure it from data or theoretical networks. This algorithm can be useful for everybody who is interested in researching the role of supported degree in the networks.

In the empirical part we apply supported degree to real-life data and compare its performance to that of the other classic measures of local centrality and cohesion: the degree and the clustering coefficient. Correlational analysis corroborates that supported degree reflects but at the same time differs from degree and clustering. Then, we estimate how well supported degree explains a series of socio-economic indicators of people in rural India, using regression method. Two main conclusions are:

- Supported degree is significant at 0.1% level in most performed regressions. Hence, it is an important determinant of well-being and behavior.
- In explaining socio-economic characteristics, supported degree is as successful as degree (in terms of the estimates, p-values, AIC, Log likelihood and R^2) and more successful than the clustering coefficient.

This notwithstanding, this thesis should only be considered as a starting point of a wider research project targeting the role of supported degree in the social networks and the local network measures in general. Naturally, further research is needed to uncover the full explanatory potential of supported degree. In particular, there are prospects for researching the supported degree in other contexts, using other dependent variables and datasets.

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7. Appendix

Table A-1: Mean values of our network measures and individual characteristics across the villages.

Village	In-deg	Out-deg	Clust	SD	Deg_rec	Clust_rec	SD_rec	Employment	Work outside	Savings	Election card	Age	Gender
1	3.428	3.428	0.037	1.467	3.428	0.189	1.467	0.669	0.147	0.206	0.901	40.9	0.536
2	2.876	2.876	0.033	1.32	2.876	0.17	1.32	0.571	0.439	0.162	0.911	37.8	0.517
3	3.234	3.234	0.034	1.489	3.234	0.174	1.489	0.623	0.372	0.263	0.901	39.4	0.544
4	3.21	3.21	0.042	1.609	3.21	0.213	1.609	0.632	0.382	0.214	0.871	38.8	0.558
5	3	3	0.047	1.5	3	0.249	1.5	0.609	0.23	0.213	0.969	41.6	0.542
6	2.618	2.618	0.02	0.709	2.618	0.107	0.709	0.572	0.428	0.463	0.654	37.4	0.581
7	3.372	3.372	0.043	1.767	3.372	0.228	1.767	0.494	0.423	0.575	0.883	40	0.546
8	3.394	3.394	0.024	1.376	3.394	0.116	1.376	0.477	0.423	0.385	0.954	39.2	0.55
9	2.696	2.696	0.021	0.761	2.696	0.114	0.761	0.489	0.3	0.315	0.935	40.9	0.546
10	2.421	2.421	0.022	0.778	2.421	0.118	0.778	0.4	0.236	0.41	0.873	41.5	0.547
11	3.098	3.098	0.019	0.943	3.098	0.098	0.943	0.464	0.454	0.33	0.915	41.7	0.57
12	2.912	2.912	0.027	1.046	2.912	0.141	1.046	0.589	0.426	0.43	0.897	38.8	0.564
14	3.013	3.013	0.028	1.48	3.013	0.137	1.48	0.606	0.483	0.433	0.852	38.7	0.56
15	3.103	3.103	0.016	1.037	3.103	0.079	1.037	0.58	0.414	0.386	0.924	38.3	0.537
16	3.415	3.415	0.034	1.55	3.415	0.171	1.55	0.561	0.303	0.241	0.876	38.1	0.55
17	3.27	3.27	0.027	1.35	3.27	0.138	1.35	0.545	0.376	0.49	0.91	38.9	0.57
18	2.781	2.781	0.027	1.035	2.781	0.145	1.035	0.531	0.245	0.447	0.929	39.4	0.552
19	3.333	3.333	0.024	1.267	3.333	0.119	1.267	0.637	0.27	0.308	0.897	36.7	0.551
20	3.32	3.32	0.021	1.207	3.32	0.106	1.207	0.748	0.193	0.339	0.918	37.3	0.559
21	2.666	2.666	0.023	0.952	2.666	0.121	0.952	0.642	0.348	0.338	0.89	37.2	0.533
23	3.371	3.371	0.032	1.514	3.371	0.159	1.514	0.528	0.29	0.382	0.903	40.3	0.55
24	3.146	3.146	0.026	1.364	3.146	0.126	1.364	0.601	0.283	0.341	0.89	40.4	0.573
25	2.717	2.717	0.019	0.73	2.717	0.102	0.73	0.582	0.372	0.246	0.815	38	0.572
26	2.966	2.966	0.038	1.476	2.966	0.195	1.476	0.684	0.49	0.375	0.852	38.8	0.557
27	2.62	2.62	0.015	0.712	2.62	0.079	0.712	0.563	0.357	0.229	0.781	39.4	0.557
28	2.643	2.643	0.015	0.708	2.643	0.08	0.708	0.678	0.205	0.303	0.807	39.3	0.589
29	3.445	3.445	0.027	1.544	3.445	0.137	1.544	0.679	0.412	0.333	0.861	38.9	0.547
30	3.235	3.235	0.036	1.588	3.235	0.178	1.588	0.605	0.368	0.405	0.811	37.5	0.576
31	3.31	3.31	0.033	1.42	3.31	0.172	1.42	0.66	0.439	0.265	0.69	36.3	0.525
32	2.916	2.916	0.014	0.617	2.916	0.075	0.617	0.667	0.427	0.378	0.84	39.1	0.558
33	3.004	3.004	0.023	1.123	3.004	0.118	1.123	0.703	0.259	0.273	0.885	40.9	0.552
34	3.226	3.226	0.039	1.679	3.226	0.198	1.679	0.674	0.385	0.408	0.751	37.6	0.58
35	3.824	3.824	0.045	2.12	3.824	0.23	2.12	0.583	0.349	0.518	0.819	39	0.55
36	4.423	4.423	0.035	2.245	4.423	0.169	2.245	0.863	0.229	0.433	0.89	39	0.542
37	4.242	4.242	0.053	2.787	4.242	0.256	2.787	0.78	0.145	0.318	0.878	38.7	0.53
38	2.78	2.78	0.016	0.626	2.78	0.087	0.626	0.653	0.344	0.269	0.846	38.4	0.543
39	3.194	3.194	0.024	1.081	3.194	0.127	1.081	0.627	0.245	0.645	0.875	38.7	0.581
40	4.165	4.165	0.052	2.496	4.165	0.261	2.496	0.669	0.28	0.635	0.849	38.2	0.556
41	4.541	4.541	0.045	2.828	4.541	0.212	2.828	0.64	0.12	0.662	0.895	37.3	0.535
42	3.844	3.844	0.037	1.961	3.844	0.184	1.961	0.577	0.302	0.509	0.873	40.8	0.543
43	4.511	4.511	0.038	2.281	4.511	0.18	2.281	0.581	0.121	0.515	0.832	41.1	0.55
44	4.426	4.426	0.039	2.348	4.426	0.19	2.348	0.604	0.211	0.577	0.883	40.3	0.55
45	2.509	2.509	0.018	0.714	2.509	0.096	0.714	0.653	0.412	0.304	0.813	37.3	0.566
46	2.458	2.458	0.015	0.544	2.458	0.081	0.544	0.551	0.558	0.462	0.849	38.8	0.551
47	2.875	2.875	0.023	1.012	2.875	0.114	1.012	0.631	0.366	0.381	0.875	39.7	0.568
48	3.179	3.179	0.021	0.995	3.179	0.108	0.995	0.585	0.409	0.589	0.861	38.6	0.552
49	4.054	4.054	0.031	1.739	4.054	0.15	1.739	0.679	0.192	0.375	0.934	39.4	0.532
50	4.666	4.666	0.041	2.398	4.666	0.195	2.398	0.662	0.138	0.379	0.873	40.7	0.544
51	4.394	4.394	0.039	2.226	4.394	0.193	2.226	0.673	0.192	0.343	0.857	39.2	0.543
52	4.268	4.268	0.03	1.837	4.268	0.149	1.837	0.663	0.19	0.415	0.949	39.7	0.531
53	4.058	4.058	0.033	1.894	4.058	0.158	1.894	0.576	0.275	0.358	0.888	39	0.552
54	3.854	3.854	0.028	1.596	3.854	0.139	1.596	0.604	0.2	0.451	0.838	40.9	0.532
55	3.949	3.949	0.037	2.057	3.949	0.18	2.057	0.655	0.333	0.44	0.87	40.2	0.541
56	3.445	3.445	0.036	1.729	3.445	0.178	1.729	0.614	0.197	0.459	0.939	42.3	0.56
57	2.888	2.888	0.021	0.897	2.888	0.107	0.897	0.688	0.776	0.311	0.666	35.7	0.559
58	2.801	2.801	0.022	0.867	2.801	0.114	0.867	0.627	0.343	0.433	0.816	40.2	0.547

59	2.916	2.916	0.023	1.114	2.916	0.115	1.114	0.572	0.427	0.39	0.851	38.2	0.559
60	3.661	3.661	0.02	1.254	3.661	0.1	1.254	0.692	0.297	0.351	0.811	37.5	0.549
61	4.167	4.167	0.047	2.464	4.167	0.234	2.464	0.707	0.229	0.574	0.877	38.8	0.554
62	3.586	3.586	0.03	1.487	3.586	0.151	1.487	0.71	0.145	0.367	0.867	39.1	0.545
63	2.905	2.905	0.028	1.305	2.905	0.145	1.305	0.652	0.225	0.368	0.894	40	0.557
64	3.503	3.503	0.029	1.537	3.503	0.146	1.537	0.697	0.253	0.421	0.918	40	0.547
65	3.976	3.976	0.032	1.917	3.976	0.156	1.917	0.568	0.314	0.348	0.9	38.7	0.571
66	2.857	2.857	0.024	0.994	2.857	0.127	0.994	0.613	0.448	0.539	0.825	37.1	0.571
67	2.372	2.372	0.017	0.666	2.372	0.085	0.666	0.562	0.523	0.484	0.77	38.7	0.584
68	3.085	3.085	0.028	1.073	3.085	0.15	1.073	0.603	0.404	0.469	0.896	37.9	0.554
69	4.427	4.427	0.037	2.29	4.427	0.175	2.29	0.663	0.465	0.322	0.859	39.4	0.554
70	4.034	4.034	0.02	1.278	4.034	0.094	1.278	0.772	0.522	0.394	0.815	37.5	0.557
71	3.637	3.637	0.034	1.563	3.637	0.174	1.563	0.57	0.688	0.506	0.852	35.7	0.546
72	3.243	3.243	0.024	1.176	3.243	0.122	1.176	0.642	0.725	0.453	0.836	38.7	0.584
73	3.732	3.732	0.034	1.907	3.732	0.171	1.907	0.64	0.553	0.456	0.801	36.8	0.534
74	3.689	3.689	0.04	2.041	3.689	0.198	2.041	0.652	0.293	0.321	0.849	39.3	0.564
75	3.314	3.314	0.036	1.428	3.314	0.185	1.428	0.614	0.317	0.428	0.809	39.4	0.58
76	3.568	3.568	0.03	1.539	3.568	0.147	1.539	0.702	0.328	0.382	0.855	40.5	0.553
77	3.941	3.941	0.031	1.697	3.941	0.152	1.697	0.703	0.38	0.244	0.86	39.2	0.546
Mean	3.382	3.382	0.0297	1.455	3.382	0.1498	1.455	0.6244	0.341	0.3931	0.86	38.9	0.554