```
In [1]: import pandas as pd
        import numpy as np
```

```
In [2]: file_path = 'inc_5000.csv'
        inc_5000 = pd.read_csv(file_path)
```

```
In [3]: print(inc_5000.head())
```

```
   rank                                   profile                name  \
0     1      https://www.inc.com/profile/freestar            Freestar
1     2    https://www.inc.com/profile/freightwise         FreightWise
2     3  https://www.inc.com/profile/ceces-veggie  Cece's Veggie Co.
3     4      https://www.inc.com/profile/ladyboss            LadyBoss
4     5        https://www.inc.com/profile/perpay              Perpay

                        url state       revenue    growth_%  \
0       http://freestar.com    AZ  36.9 Million  36680.3882
1  http://freightwisellc.com    TN  33.6 Million  30547.9317
2   http://cecesveggieco.com    TX  24.9 Million  23880.4852
3       http://ladyboss.com    NM  32.4 Million  21849.8925
4         http://perpay.com    PA  22.5 Million  18166.4070

                     industry  workers  previous_workers  founded  \
0      Advertising & Marketing     40.0                 5     2015
1    Logistics & Transportation     39.0                 8     2015
2            Food & Beverage    190.0                10     2015
3  Consumer Products & Services     57.0                 2     2014
4                      Retail     25.0                 6     2014

   yrs_on_list        metro         city
0            1      Phoenix      Phoenix
1            1    Nashville    Brentwood
2            1       Austin       Austin
3            1          NaN  Albuquerque
4            1 Philadelphia Philadelphia
```

```
In [5]: subset_companies = inc_5000['name'].sample(20, random_state=0).tolist()
```

```
In [6]: np.random.seed(0)
        matrix = np.random.choice([0, 1], size=(20, 20), p=[0.7, 0.3])
```

```
In [7]: np.fill_diagonal(matrix, 0)
```

```
In [8]: financial_ties = pd.DataFrame(matrix, index=subset_companies, columns=subset_companies)
```

```
In [9]: financial_ties.to_excel('FinancialTies.xlsx')
```

```
In [10]: print("Financial ties matrix saved to 'FinancialTies.xlsx'")
```

```
Financial ties matrix saved to 'FinancialTies.xlsx'
```

```
In [11]: import pandas as pd
```

```
In [12]: file_path = 'FinancialTies.xlsx'
         financial_ties = pd.read_excel(file_path, index_col=0)
```

```
In [13]: financial_ties.head()
```

Out[13]:

	Foster Crown	Denny Cherry & Associates Consulting	Tiempo Development	Averhealth	Legwork Software	Zero Gravity Marketing	MapleMark Bank	Techolution	Escapology	Bellwether Asset Management	FederalConference.com	Nugget	Jaguar Fueling Services	Carroll Organization
Foster Crown	0	1	0	0	0	0	0	1	1	0	1	0	0	1
Denny Cherry & Associates Consulting	1	0	0	1	0	0	0	1	0	0	0	1	0	0
Tiempo Development	0	0	0	0	0	0	0	0	0	0	0	0	1	0
Averhealth	0	0	0	0	0	0	1	0	1	0	1	0	1	0
Legwork Software	0	0	0	0	0	0	0	0	0	1	0	0	0	1

```
In [14]: import numpy as np
```

```
In [15]: num_companies = financial_ties.shape[0]
```

```
In [16]: num_ties = np.sum(financial_ties.values)
```

```
In [17]: density = num_ties / (num_companies * (num_companies - 1))

         num_companies, num_ties, density
```

```
Out[17]: (20, 105, 0.27631578947368424)
```

```
In [18]: from sklearn.metrics import jaccard_score
```

```
In [19]: similarities = pd.DataFrame(index=financial_ties.index, columns=financial_ties.columns)

         for i in financial_ties.index:
             for j in financial_ties.columns:
                 if i != j:
                     similarities.at[i, j] = jaccard_score(financial_ties.loc[i], financial_ties[j])
                 else:
                     similarities.at[i, j] = np.nan

         similarities.head()
```

Out[19]:

	Foster Crown	Denny Cherry & Associates Consulting	Tiempo Development	Averhealth	Legwork Software	Zero Gravity Marketing	MapleMark Bank	Techolution	Escapology	Bellwether Asset Management	FederalConference.com	Nugget	Jaguar Fueling Services	Carroll Organization
Foster Crown	NaN	0.083333	0.2	0.4	0.5	0.444444	0.2	0.111111	0.153846	0.272727	0.090909	0.272727	0.090909	0.083333
Denny Cherry & Associates Consulting	0.1	NaN	0.0	0.222222	0.2	0.25	0.285714	0.166667	0.714286	0.222222	0.285714	0.1	0.285714	0.111111
Tiempo Development	0.166667	0.0	NaN	0.0	0.142857	0.0	0.0	0.0	0.0	0.0	0.0	0.166667	0.0	0.2
Averhealth	0.222222	0.111111	0.285714	NaN	0.2	0.111111	0.125	0.0	0.0	0.1	0.0	0.1	0.125	0.111111
Legwork Software	0.0	0.142857	0.0	0.125	NaN	0.142857	0.166667	0.0	0.25	0.0	0.166667	0.125	0.166667	0.142857

```
In [20]: potential_allies = similarities.unstack().sort_values(ascending=False).dropna()
         potential_allies.head()
```

```
Out[20]: Escapology                           Denny Cherry & Associates Consulting    0.714286
         Carroll Organization                 Harts Servcies                              0.6
         Denny Cherry & Associates Consulting Lady M Confections Co.                      0.6
         Jaguar Fueling Services              Escapology                             0.571429
         Denny Cherry & Associates Consulting Jaguar Fueling Services                0.571429
         dtype: object
```

```
In [21]: import networkx as nx
```

```
In [22]: company_a, company_b = potential_allies.index[0]
```

```
In [23]: G = nx.from_pandas_adjacency(financial_ties)
```

```
In [24]: ego_a = nx.ego_graph(G, company_a)
```

```
In [25]: ego_b = nx.ego_graph(G, company_b)
```

```
In [26]: density_a = nx.density(ego_a)
         density_b = nx.density(ego_b)
```

```
In [27]: centrality_a = nx.degree_centrality(ego_a)[company_a]
         centrality_b = nx.degree_centrality(ego_b)[company_b]
```

```
In [28]: betweenness_a = nx.betweenness_centrality(ego_a)[company_a]
         betweenness_b = nx.betweenness_centrality(ego_b)[company_b]
```

```
In [30]: closeness_a = nx.closeness_centrality(ego_a)[company_a]
         closeness_b = nx.closeness_centrality(ego_b)[company_b]
```

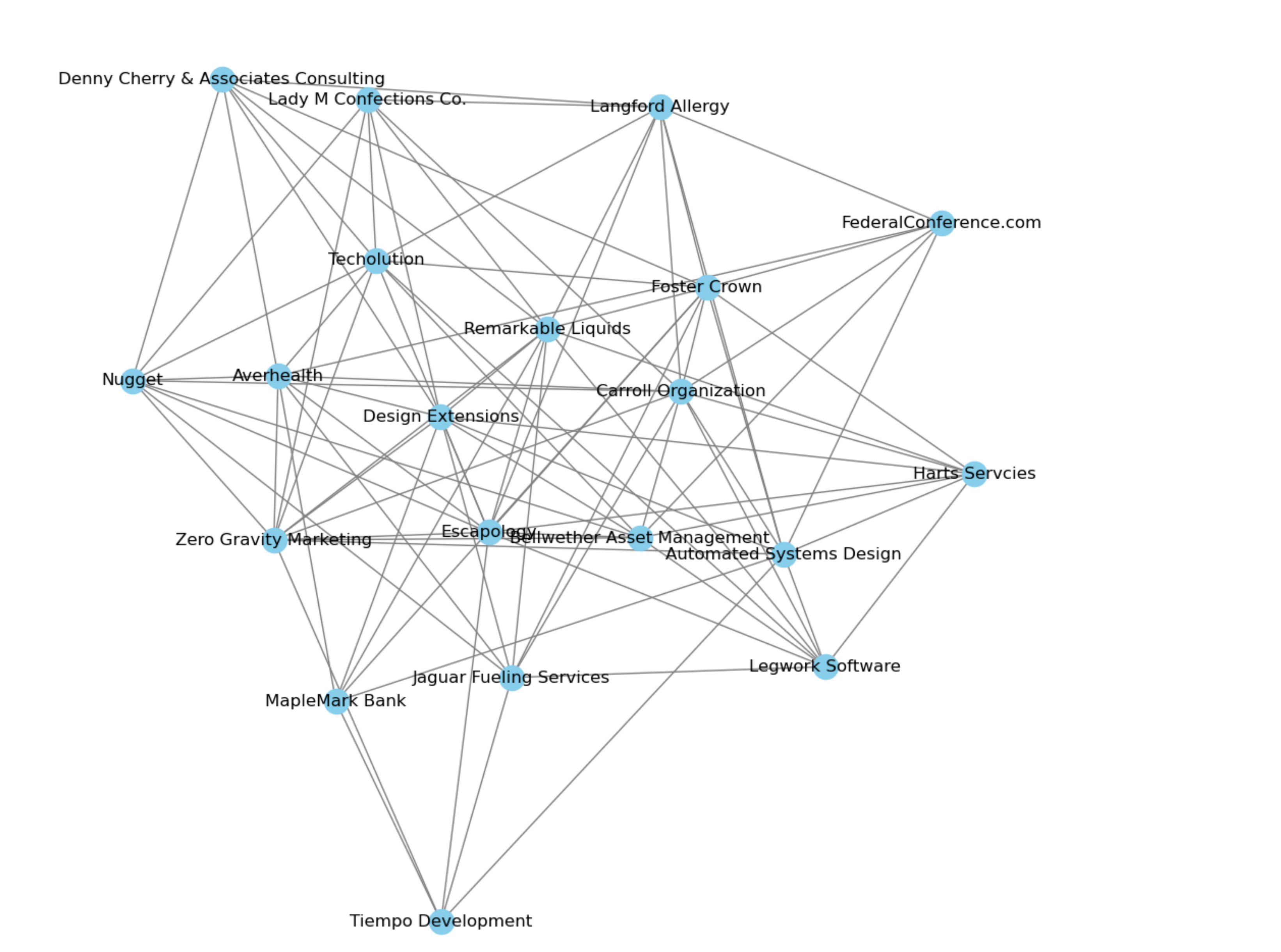
```
In [31]: prestige_a = nx.eigenvector_centrality(ego_a)[company_a]
         prestige_b = nx.eigenvector_centrality(ego_b)[company_b]

         density_a, density_b, centrality_a, centrality_b, betweenness_a, betweenness_b, closeness_a, closeness_b, prestige_a, prestige_b
```

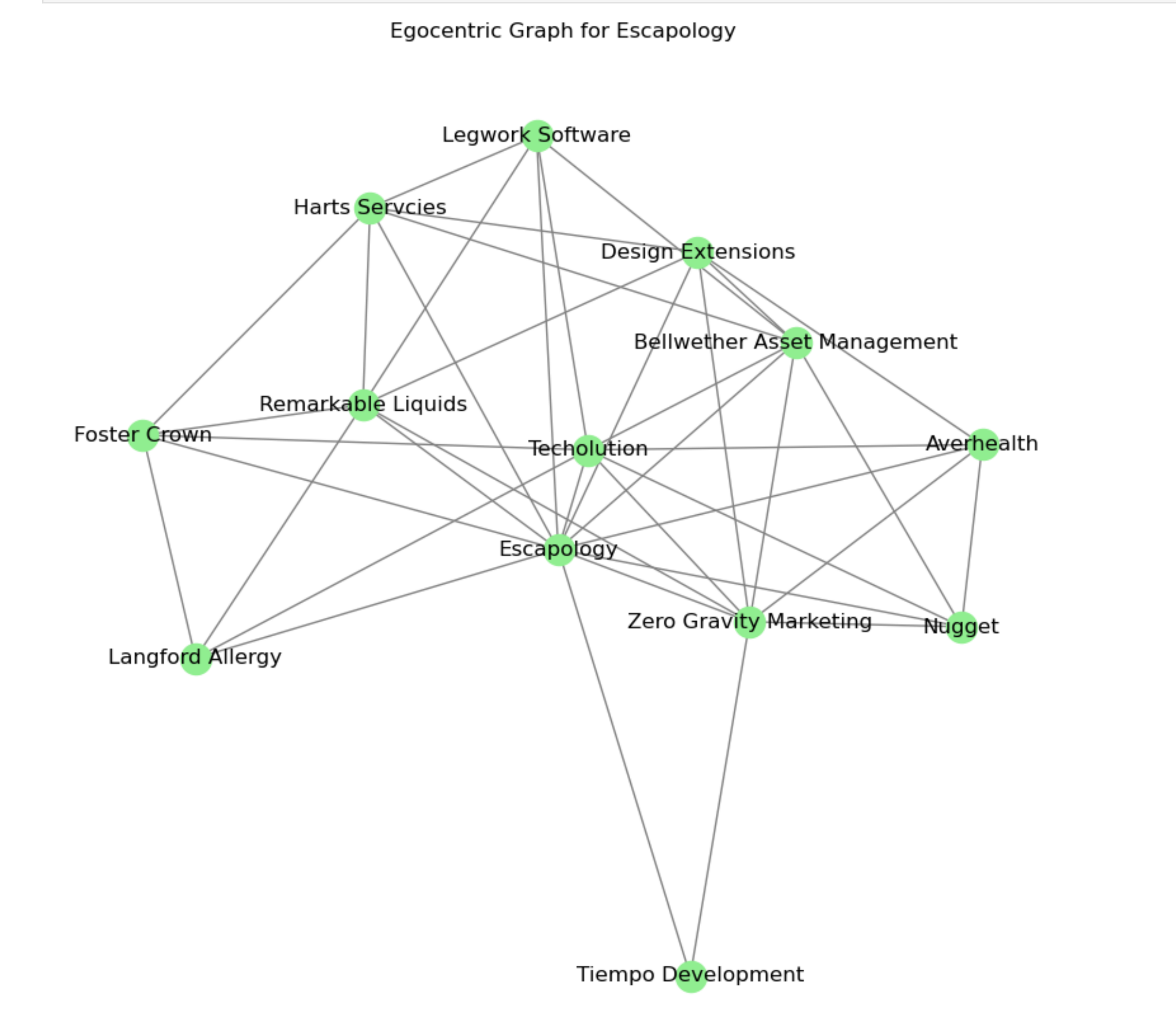
```
Out[31]: (0.5128205128205128,
          0.6071428571428571,
          1.0,
          1.0,
          0.2578282828282828,
          0.2777777777777778,
          1.0,
          1.0,
          0.4441304288861203,
          0.5031549193721591)
```

```
In [32]: import matplotlib.pyplot as plt
```

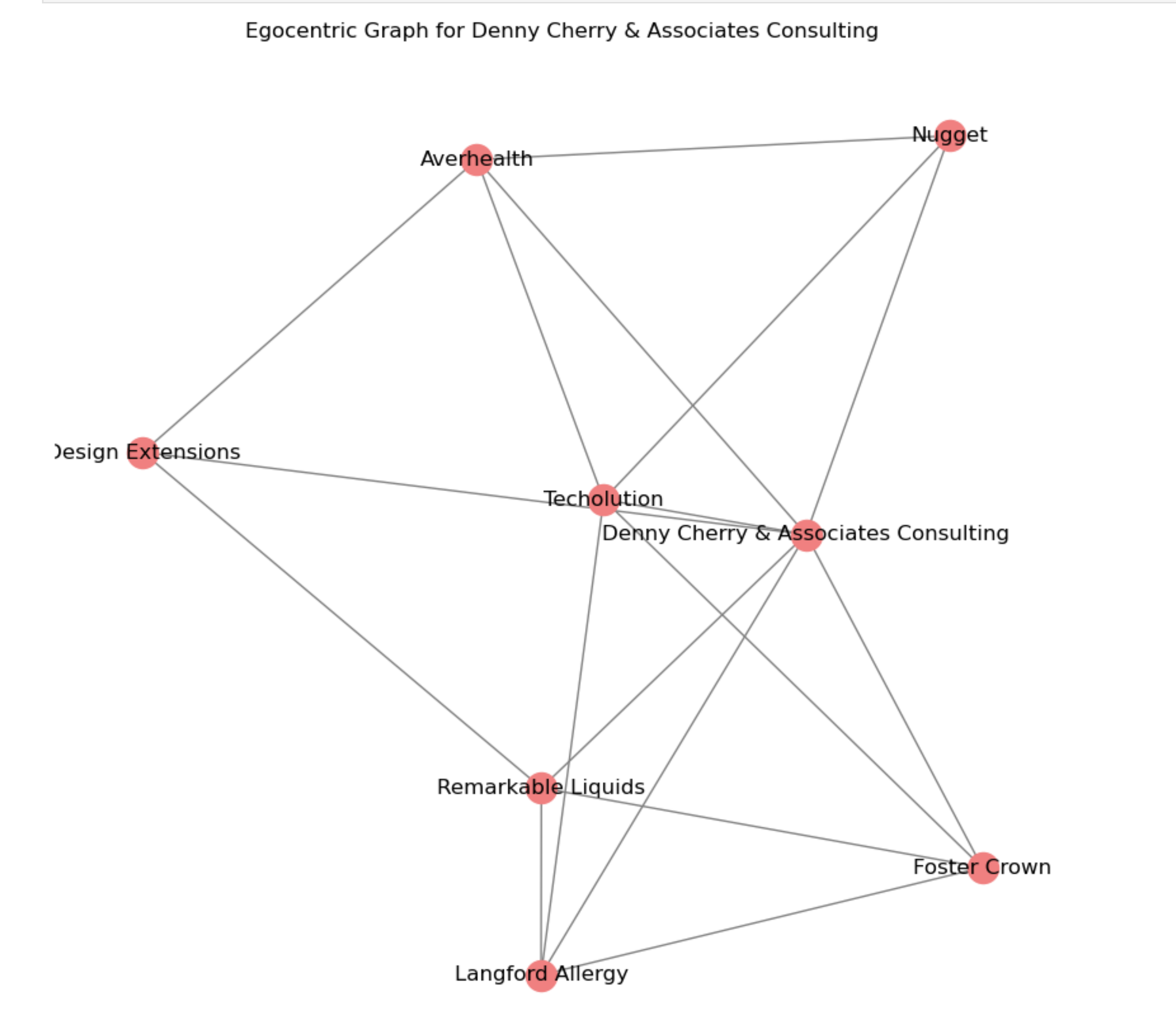
```
In [33]: plt.figure(figsize=(10, 10))
         nx.draw(G, with_labels=True, node_color='skyblue', edge_color='gray')
         plt.title("Financial Ties Network")
         plt.show()
```




```
In [34]: plt.figure(figsize=(8, 8))
         nx.draw(ego_a, with_labels=True, node_color='lightgreen', edge_color='gray')
         plt.title(f"Egocentric Graph for {company_a}")
         plt.show()
```




```
In [35]: plt.figure(figsize=(8, 8))
         nx.draw(ego_b, with_labels=True, node_color='lightcoral', edge_color='gray')
         plt.title(f"Egocentric Graph for {company_b}")
         plt.show()
```




```
In [36]: interlocking_boards = financial_ties & financial_ties.T
         interlocking_boards = interlocking_boards[interlocking_boards > 0]
         interlocking_boards.dropna(how='all', inplace=True)
         interlocking_boards
```

Out[36]:

	Foster Crown	Denny Cherry & Associates Consulting	Tiempo Development	Averhealth	Legwork Software	Zero Gravity Marketing	MapleMark Bank	Techolution	Escapology	Bellwether Asset Management	FederalConference.com	Nugget	Jaguar Fueling Services
Foster Crown	NaN	1.0	NaN	NaN	NaN	NaN	NaN	1.0	NaN	NaN	NaN	NaN	NaN
Denny Cherry & Associates Consulting	1.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1.0	NaN
Averhealth	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1.0	NaN	NaN	NaN	NaN
Legwork Software	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1.0	NaN	NaN	NaN
Zero Gravity Marketing	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1.0	NaN
Techolution	1.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Escapology	NaN	NaN	NaN	1.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Bellwether Asset Management	NaN	NaN	NaN	NaN	1.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
FederalConference.com	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Nugget	NaN	1.0	NaN	NaN	NaN	1.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Jaguar Fueling Services	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Carroll Organization	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Design Extensions	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1.0
Langford Allergy	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	1.0	NaN	NaN
Remarkable Liquids	NaN	1.0	NaN	NaN	1.0	NaN	NaN	NaN	1.0	NaN	NaN	NaN	1.0
Automated Systems Design	1.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

```
In [37]: no_ties = financial_ties.sum(axis=1) == 0
         no_ties_companies = financial_ties[no_ties].index.tolist()
```

```
In [38]: many_ties = financial_ties.sum(axis=1) > (financial_ties.shape[0] / 2)
         influencers = financial_ties[many_ties].index.tolist()

         no_ties_companies, influencers
```

```
Out[38]: ([], [])
```

```
In [39]: strong_ties = interlocking_boards.index.tolist()
```

```
In [40]: weak_ties = financial_ties.sum(axis=1).sort_values().index[:2].tolist()

         strong_ties, weak_ties
```

```
Out[40]: (['Foster Crown',
           'Denny Cherry & Associates Consulting',
           'Averhealth',
           'Legwork Software',
           'Zero Gravity Marketing',
           'Techolution',
           'Escapology',
           'Bellwether Asset Management',
           'FederalConference.com',
           'Nugget',
           'Jaguar Fueling Services',
           'Carroll Organization',
           'Design Extensions',
           'Langford Allergy',
           'Remarkable Liquids',
           'Automated Systems Design'],
          ['Tiempo Development', 'MapleMark Bank'])
```

```
In [41]: structural_holes = nx.algorithms.structuralholes.effective_size(G)
         structural_holes = {k: v for k, v in sorted(structural_holes.items(), key=lambda item: item[1], reverse=True)}

         structural_holes
```

```
Out[41]: {'Carroll Organization': 7.5,
          'Escapology': 7.333333333333333,
          'Design Extensions': 7.181818181818182,
          'Foster Crown': 7.0,
          'Remarkable Liquids': 7.0,
          'Automated Systems Design': 6.6,
          'Averhealth': 6.4,
          'Zero Gravity Marketing': 6.2727272727272725,
          'Techolution': 5.8,
          'Jaguar Fueling Services': 5.75,
          'Langford Allergy': 5.222222222222222,
          'Bellwether Asset Management': 5.0,
          'Nugget': 4.777777777777778,
          'Legwork Software': 4.75,
          'Denny Cherry & Associates Consulting': 4.142857142857142,
          'MapleMark Bank': 4.0,
          'Lady M Confections Co.': 3.857142857142857,
          'Tiempo Development': 3.8,
          'Harts Servcies': 3.75,
          'FederalConference.com': 3.3333333333333335}
```

```
In [42]: unreachable = list(nx.isolates(G))
```

```
In [43]: clustering = nx.clustering(G)
         overcrowded = {k: v for k, v in clustering.items() if v > 0.5}

         unreachable, overcrowded
```

```
Out[43]: ([],
          {'FederalConference.com': 0.5333333333333333,
           'Nugget': 0.5277777777777778,
           'Lady M Confections Co.': 0.5238095238095238,
           'Harts Servcies': 0.6071428571428571})
```

```
In [ ]: Positive Impacts

        Enhanced Decision-Making: Informal networks enable quicker and more efficient decision-making by facilitating the
        free flow of information and bypassing bureaucratic hurdles.
        Improved Resource Allocation: Individuals with strong informal ties can access necessary resources more efficiently
        ,leading to better project outcomes.
        Career Advancement: Employees who actively engage in informal networks can advance their careers more rapidly
        through mentorship and early access to opportunities.
        Faster Information Dissemination: Informal networks ensure that critical information, especially tacit knowledge,
        is shared promptly among employees.
        Increased Innovation: Collaboration across informal networks fosters creativity and innovation, leading to the
        development of new ideas and solutions.
        Effective Conflict Resolution: Informal networks provide an avenue for resolving conflicts quickly and amicably,
        improving workplace harmony.

        Negative Impacts

        Undermining Formal Authority: Strong informal networks can challenge formal authority and decision-making processes,
        leading to potential conflicts.
        Perceptions of Favoritism: Unequal access to resources through informal networks can create perceptions of favoritism
        and inequity.
        Exclusivity and Resentment: Employees outside influential informal networks may feel excluded and resentful,
        affecting organizational cohesion.
        Risk of Misinformation: Informal channels may sometimes spread inaccurate or incomplete information, leading to
        misunderstandings.
        Fragmented Efforts: Innovation driven by informal networks may not always align with formal organizational goals,
        leading to fragmented efforts.

        Conclusion
        Informal networks are a double-edged sword in organizational contexts. While they enhance efficiency, innovation,
        and employee satisfaction, they also pose risks to formal authority and inclusivity. Organizations that recognize
        and strategically manage informal networks can harness their benefits while mitigating potential downsides,
        leading to a more dynamic and resilient power structure. Properly leveraging informal networks can result in a
        more agile, innovative, and harmonious organization, while failing to do so can create challenges in maintaining
        formal authority and equity.

        References

        mysar ahmad bhat. (2019). Inc 5000 Companies. Kaggle.com. https://www.kaggle.com/datasets/mysarahmadbhat/inc-5000-companies

        Krackhardt, D., & Hanson, J. R. (1993, July 1). Informal Networks: The Company Behind the Chart. Harvard Business Review. https://hbr.org/1993/07/informal-netwo
```