Networks in Production: Asset Pricing Implications

by Bernard Herskovic

Discussion: Andrea Tamoni

London School of Economics

11th Dec, 2015
Third Economic Networks and Finance Conference, LSE

Outline of the discussion

- Main findings and contributions of the paper.
- Some comments on empirical results.
- Some extensions.
- Conclusions.

Motivation

- Most sectors use the output of other sectors in the economy as intermediate goods. This introduces interlinkages among sectors.
  - Inefficiency in one sector will have implications for productivity in others.
  - Premium on different assets may be explained by the integration of the stock with the economic network and by the relative network position.

The paper in a nutshell

- Theoretically, it develops a network-based pricing model.
  - A theoretical characterization of asset pricing relations in a network context. E.g., how the average return of a stock is related to properties of the entire network?
- Empirically, it evaluates the model's implications for "network factors" (concentration and sparsity) for explaining expected excess returns and return comovement.
  - Sorts firms according to their covariance with network concentration and sparsity.
  - There are substantial (?) systematic differences in average stock returns between firms that have high and low covariances with each of the factors, with the predicted sign from the model.

The paper in a nutshell

- Theoretically, it develops a network-based pricing model.
  - A theoretical characterization of asset pricing relations in a network context. E.g., how the average return of a stock is related to properties of the entire network?
- Empirically, it evaluates the model's implications for "network factors" (concentration and sparsity) for explaining expected excess returns and return comovement.
  - Sorts firms according to their covariance with network concentration and sparsity.
  - There are substantial (?) systematic differences in average stock returns between firms that have high and low covariances with each of the factors, with the predicted sign from the model.

Contributions

- The model is solved in closed form.
- Within the model, we can identify the factors driving asset pricing which operate through the stochastic shocks to the input-output network.
- No fishing for factors in the paper, factors are endogenously determined at equilibrium.
- Two distinct statistical measures of the network structure: concentration and sparsity.

Production Networks - The model

- The paper develops a general equilibrium model of a (multi-sector) dynamic production economy.
  - Based on Long and Plosser (JPE, 1993); Acemoglu, Carvalho, Ozdaglar and Tahbaz-Salehi (Econometrica, 2012).
- Firms operate on an input-output network which changes stochastically over time (in an i.i.d. fashion?).
  - The output of each sector is used by a subset of all sectors as input (intermediate goods) for production.
- A representative household owns the firms and consumes their output.

Timing and production possibilities

- A sequence of one-period production economies linked by an infinitely lived collection of representative households that price the assets in the standard way.
- Each period, firm i draws its vector of productivity coefficients that describes where it will buy its inputs from and in what proportion.
  - This is the $(n \times n)$ matrix $W_t = \{w_{ij,t}\}$.
  - It also draws its TFP which yields a $(n \times 1)$ vector $\varepsilon = (\varepsilon_i)$.

$$Y_{i,t} = \varepsilon_{i,t} I_{i,t}^{\eta} \ ,$$

$$I_{i,t} = \prod_{j=1}^{n} y_{ij,t}^{w_{ij,t}}$$

- This fully describes the production possibilities for that period t, all the asset prices and input costs, and the dividends that will be paid that period.

Competitive Equilibrium

- The infinitely lived representative household maximizes utility.
- All firms maximize profits.
- Asset and goods markets clear.

Equilibrium output shares

- The solution to the system of market clearing conditions determines equilibrium output shares (network centrality), $\delta_t = (\delta_{1,t}, \dots, \delta_{n,t})$:

$$\delta_t = (1-\eta)\left[\mathcal{I} - \eta W_t'\right]^{-1} \alpha \tag{1}$$

  where $\alpha = (\alpha_1, \dots, \alpha_n)$ is the household demand for goods from sector j.
- Sectors' equilibrium output shares represent how important the output of a sector is to all other sectors as a source of input.

Theoretical results

- Equilibrium consumption growth:

$$\log \frac{C_{t+1}}{C_t} = \frac{1}{1-\eta}\left[\eta \Delta N^{\mathcal{S}}_{t+1} + (1-\eta)\Delta N^{\mathcal{C}}_{t+1} + \Delta e_{t+1}\right] \qquad (2)$$

- Equilibrium consumption growth depends on:
  - a weighted average of productivity shocks:

$$e_t = \sum_i \delta_{i,t} \log \varepsilon_i, t$$

  - Network concentration which measures the dispersion in sectors' output shares:

$$N^{\mathcal{C}}_t \equiv \sum_{i=1}^{n} \delta_{i,t} \log \delta_{i,t} \ .$$

  - Network sparsity is a measure of the average firm's dispersion over input shares:

$$N^{\mathcal{S}}_t \equiv \sum_i \delta_{i,t} \sum_j w_{ij,t} \log w_{ij,t}$$

Risk exposures and risk prices: Testable implications

- The bulk of variation in the returns can be summarized by two summary descriptions of the (W, ε) pair: the "sparsity" and "concentration" factors.
- Sectors whose cash-flows are high when there are positive shocks to aggregate network concentration carry low average returns.
- Positive exposure to network sparsity is associated with high average returns.

Risk exposures and risk prices: Intuition

- Production is subject to diminishing returns.
- An economy with a high concentration has few large sectors with lower returns to investments.
- High network concentration leads to lower aggregate consumption and higher marginal utility.
- Sparsity: When network sparsity increases, firms reoptimize inputs based on changes in their marginal productivity.
  - Firms gain efficiency from using more inputs with higher marginal product and produce more.
  - When sparsity increases, a firm may use inputs that are relatively more (less) expensive, causing the marginal cost of production to increase (decrease) and its final output to decrease (increase).

Empirical methodology

- For every year t, compute stocks' exposure over a 15-year window from $t-14$ to t.

$$r_t^i = \alpha_i + \beta_{t,N_t^{\mathcal{S}}} \Delta N_t^{\mathcal{S}} + \beta_{t,N_t^{\mathcal{C}}} \Delta N_t^{\mathcal{C}} + Controls + e_t$$

- Valued-weighted portfolios are formed over the subsequent year $t+1$.

Empirical results

Panel A: Sparsity beta-sorted portfolios

	L (1)	(2)	H (3)	H-L (4)	*t*-stat (5)
Average excess returns (%)	5.24	8.61	11.25	6.01	2.26
α_{CAPM}	−3.15	2.29	4.78	7.92	3.11
α_{FF}	−3.21	1.47	3.84	7.04	2.91

Panel B: Concentration beta-sorted portfolios

	L (1)	(2)	H (3)	H-L (4)	*t*-stat (5)
Average excess returns (%)	10.23	8.51	6.19	−4.04	−2.19
α_{CAPM}	2.62	2.43	−1.60	−4.21	−2.26
α_{FF}	2.00	1.64	−2.00	−4.01	−2.12

Figure : One-way sorted portfolios. See Table 1 in the paper.

- Pre-ranking betas and post-ranking betas (see, e.g., Kan and Zhang (1999)).
- Controls for other factors: Profitability and Investment (see, e.g., Hou, Xue, and Zhang (2014); Fama and French (2014)).

Empirical results

Panel A: Sparsity beta-sorted portfolios	L (1)	(2)	H (3)	H-L (4)	*t*-stat (5)
Average excess returns (%)	5.24	8.61	11.25	6.01	2.26
α_{CAPM}	−3.15	2.29	4.78	7.92	3.11
α_{FF}	−3.21	1.47	3.84	7.04	2.91

Panel B: Concentration beta-sorted portfolios	L (1)	(2)	H (3)	H-L (4)	*t*-stat (5)
Average excess returns (%)	10.23	8.51	6.19	−4.04	−2.19
α_{CAPM}	2.62	2.43	−1.60	−4.21	−2.26
α_{FF}	2.00	1.64	−2.00	−4.01	−2.12

Figure : One-way sorted portfolios. See Table 1 in the paper.

- Pre-ranking betas and post-ranking betas (see, e.g., Kan and Zhang (1999)).
- Controls for other factors: Profitability and Investment (see, e.g., Hou, Xue, and Zhang (2014); Fama and French (2014)).

Empirical results

Panel A: Sparsity beta-sorted portfolios

	L (1)	(2)	H (3)	H-L (4)	t-stat (5)
Average excess returns (%)	5.24	8.61	11.25	6.01	2.26
α_{CAPM}	−3.15	2.29	4.78	7.92	3.11
α_{FF}	−3.21	1.47	3.84	7.04	2.91

Panel B: Concentration beta-sorted portfolios

	L (1)	(2)	H (3)	H-L (4)	t-stat (5)
Average excess returns (%)	10.23	8.51	6.19	−4.04	−2.19
α_{CAPM}	2.62	2.43	−1.60	−4.21	−2.26
α_{FF}	2.00	1.64	−2.00	−4.01	−2.12

Figure : One-way sorted portfolios. See Table 1 in the paper.

- Does it make sense to run sorting at the firm levels?
- In the model there is perfect competition within each sector in the model, the theoretical model is uninformative about network beta heterogeneity at the *firm level.*

Empirical results - Cont'd

Panel A: returns

	Concentration				
Sparsity	(1)	(2)	(3)	(3)-(1)	t-stat
(1)	10.38	7.95	4.56	−5.82	−1.58
(2)	12.79	7.56	8.54	−4.25	−1.29
(3)	10.95	10.71	15.82	4.87	1.27
(3)-(1)	0.57	2.76	11.26	–	–
t-stat	0.13	0.72	3.00	–	–

Figure : Double sort.

- Pre-ranking betas and post-ranking betas.
- Number of stocks in each portfolios.

Empirical results - Cont'd

Panel A: returns

	Concentration				
Sparsity	(1)	(2)	(3)	(3)-(1)	t-stat
(1)	10.38	7.95	4.56	−5.82	−1.58
(2)	12.79	7.56	8.54	−4.25	−1.29
(3)	10.95	10.71	15.82	4.87	1.27
(3)-(1)	0.57	2.76	11.26	–	–
t-stat	0.13	0.72	3.00	–	–

Figure : Double sort.

- Pre-ranking betas and post-ranking betas.
- Number of stocks in each portfolios.

Empirical results - Cont'd

Panel A: average returns

		Sparsity beta-sorted portfolios					Concentration beta-sorted portfolios				
		(1)	(2)	(3)	(3)-(1)	t-stat	(1)	(2)	(3)	(3)-(1)	t-stat
1.	Benchmark	5.24	8.61	11.25	6.01	2.26	10.23	8.51	6.19	−4.04	−2.19
2.	No level control	5.28	9.23	9.75	4.47	1.90	9.69	8.87	6.18	−3.50	−1.55
3.	All CRSP stocks	5.83	7.94	11.61	5.78	2.17	10.12	8.38	6.29	−3.83	−2.13
4.	Out of Sample	8.42	10.22	8.73	0.31	0.14	10.03	9.93	6.78	−3.25	−1.61
5.	R. TFP from Cons.	5.39	8.35	11.42	6.03	2.09	9.61	8.55	6.19	−3.42	−1.64
6.	No TFP	5.27	8.92	10.76	5.49	1.92	10.47	8.71	5.58	−4.89	−2.51
7.	R. TFP from Cons., $\eta = .35$	5.21	8.89	10.15	4.93	1.94	8.90	8.55	5.80	−3.10	−1.32
8.	R. TFP from TFP, $\eta = .35$	6.46	7.69	11.36	4.90	1.96	8.92	7.53	7.61	−1.32	−0.66
9.	16-year window	4.81	7.47	10.31	5.51	1.92	10.51	6.57	5.17	−5.35	−2.73
10.	17-year window	3.92	7.05	8.83	4.91	1.46	9.67	6.27	3.67	−6.00	−2.52
11.	18-year window	2.46	6.02	7.03	4.57	1.22	7.57	5.24	2.42	−5.15	−2.19
12.	19-year window	−0.52	5.29	8.02	8.54	2.02	6.90	4.36	0.97	−5.93	−2.45
13.	20-year window	0.42	5.69	6.90	6.48	1.73	5.76	4.60	2.17	−3.60	−1.63

Figure : Robustness. See Table J.3 in the paper.

Understanding network betas

- Equilibrium dividend growth vary across sectors and this heterogeneity depends exclusively on the differences in sectors' output shares:
$$\Delta d_{i,t+1} = \Delta \log \delta_{i,t+1} + \Delta \log z_{t+1}$$
- "Ultimately, network betas depend on how *sectoral dividends growth* depend on the network factors"?

$$\begin{aligned} r_{i,t} - E_{t-1}\left[r_{i,t}\right] &= (E_t - E_{t-1})\left(\sum_{j=0}^{\infty} \kappa_{i,1}^{j} \Delta d_{i,t+j}\right) \\ &- (E_t - E_{t-1})\left(\sum_{j=1}^{\infty} \kappa_{i,1}^{j} \Delta r_{i,t+j}\right) \\ &= \eta_{d,t} - \eta_{r,t} \end{aligned}$$

and

$$\beta_{i,N_t^j} = \frac{Cov\left(\eta_{d,t} - \eta_{r,t}, \Delta N_t^j\right)}{Var\left(N_t^j\right)} = \beta_{i,d,N_t^j} - \beta_{i,r,N_t^j} \quad \text{for } j = \mathcal{S}, \mathcal{C}$$

Industries and network betas

- The model assumes there is perfect competition within each sector in the model, so the theoretical model is uninformative about network beta heterogeneity at the firm level.
- However, the model helps to understand why and how sectors have different exposures to sparsity and concentration innovations.
- The model help pricing industry-sorted portfolios (see Table I.1 in the paper).
- Control for:
  - Within-industry variable (e.g. Goodman and Peavy (1983), Cohen and Polk (1998)).
  - Across-industry variables (e.g., industry momentum by Moskowitz and Grinblatt (1999)).
  - Customer momentum, Cohen and Frazzini (2008).
  - Centrality of a particular industry, Ahern (2012).

Further comments

- Why not doing asset pricing tests within a GMM framework by using directly consumption computed from network factors

$$\log \frac{C_{t+1}}{C_t} = \frac{1}{1-\eta}\left[\eta \Delta N^{\mathcal{S}}_{t+1} + (1-\eta)\Delta N^{\mathcal{C}}_{t+1} + \Delta e_{t+1}\right]$$

- What if stock prices respond with a delay to the network shocks? Can you track subsequent stock returns of firm exposed to concentration and sparsity?
- Can you price other sets of stocks? Are "value" firms characterized in part by their integration with the economic network?

Further comments

- Why not doing asset pricing tests within a GMM framework by using directly consumption computed from network factors

$$\log \frac{C_{t+1}}{C_t} = \frac{1}{1-\eta} \left[\eta \Delta N^{\mathcal{S}}_{t+1} + (1-\eta) \Delta N^{\mathcal{C}}_{t+1} + \Delta e_{t+1} \right]$$

- What if stock prices respond with a delay to the network shocks? Can you track subsequent stock returns of firm exposed to concentration and sparsity?
- Can you price other sets of stocks? Are "value" firms characterized in part by their integration with the economic network?

Further comments - cont'd

- We must be able to empirically quantify the network.
- The paper uses a common approach that relies on firm-level customer-supplier sales data based on SEC filings and available in Compustat (e.g. Kelly et al. (2013), Cohen and Frazzini (2008)).
  - This approach has the benefit that it treats the network as observable, which vastly simplifies the econometric analysis.
  - But it has the important shortcoming that customer-supplier sales numbers are a very coarse quantification of the production linkages between firms.
  - Other relationships (e.g. networks of competition or trade credit relationships) may also be important to inter-firm production dependence
  - Why not acknowledging the inherent non-observability of inter-firm linkages and using techniques to estimate the latent network?

Conclusions

- Nice and important paper!
- It identifies the sources of systematic risk that arise in an economy where firms are connected through customer-supplier relationships.
- Empirical evidence for those risk prices in the cross-section of stock returns asks for more investigation.