Dynamic Networks and Asset Pricing

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joint work with P. Porchia
Motivations

The network origins of factor structure

- Hard to account for firm/sector specific shocks in risk premia. The same way in macro it has been difficult to account for aggregate fluctuation arising from microeconomic shocks.

- Diversification argument in Lucas (1977): firm-specific shocks do not matter in disaggregated (or weakly aggregated) networks. If shocks are independent, aggregate fluctuations would have magnitude proportional to \(1/\sqrt{n}\).

\[
1 \quad 2 \quad 3 \quad \ldots \ldots \quad n
\]

\(Fig\ 1\)

- In asset pricing, the implication is a Two Fund Separation Property.
Motivations
The network origins of factor structure

- Acemoglu et. al. (2012) show that it is not “sparsity” the issue, but symmetry.
- In the following network, firms affect each other symmetrically.
- In fact, firm specific shocks translate into a unique systematic factor in Fig 2.

![Network Diagram](image)

- However, Two Fund Separation Property still emerges.
Motivation
The network origins of factor structure

- In the case of asymmetric networks, idiosyncratic shocks are possibly undiversifiable...
- ... and a complex multi-factor model of asset prices may arise: Consider a ‘Star’ networks with central or noncentral firms.

**Fig 1**: Firm 1 is central. Its shocks give rise to a systematic factor.

**Fig 2**: Shocks to $n$ central firms translate into systematic factors.
Networks of Firms

Connectivity as determinant of the cross-section of returns

We study an economy where:

- Firms’ fundamental cash-flows are connected in a network structure
- A common latent factor affects all cash-flows distributions

We investigate two channels for firm-specific news to affect expectations of other firms’ fundamentals

1) **Direct** (local) linkage: **Asymmetric cash-flow connectivity**.

   - The distribution of future fundamental shocks depends on a persistent ‘distress’ status of other firms
   - The connectivity is dynamic, in the spirit of DSGE models. Shocks to firm-i affect the conditional distribution of fundamentals of firm-j, as opposed to static as in Input-Output models.

2) **Global** linkage: **Incomplete information**.

   - the distribution depends on a common latent factor that is learned cross-sectionally
Policy Decisions in 2008-2009

Policy decisions during the 2008 Credit Crisis to limit excessive propagation of shocks.

- In January 2009, the Federal government used $24.9 billion to rescue two of the Big 3.
  - $17.4 billion for General Motors and Chrysler.
  - $6 billion for GMAC.
  - $1.5 billion for Chrysler Financial.

“The bailout of the auto industry prevented another Great Depression from hitting the Midwest. Without the bailout, GM and Chrysler would have gone under – and that would have sparked widespread failures among suppliers and even a bankruptcy at rival Ford” [Obama’s (2012) speech to the United Auto Workers union]

- Mervyn King called for banks that are too big to fail to be cut down to size. “If some banks are thought to be too big to fail, then, ...”
Our Goals

**Cross-section of Expected Returns**

- Does network connectivity have significant implications for the cross-section of returns?
- Two fund separation fails empirically. What are the properties implied by a network structure?

**Cross-sectional Momentum**

- Momentum is often interpreted as a behavioral result. Can a network structure generate cross-sectional momentum consistent with the data?
- Can cross-sectional momentum be rationalized in an G.E. economy with slow diffusion of information over a specific network structure?
Literature

Economic Networks:

- **Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2011):** Investigate whether aggregate volatility, defined as the standard deviation of log output, vanishes as $n \to \infty$. They use a different (static) notion of connectivity via input-output local connection; no role for incomplete information and learning.

- **Gabaix (2011):** If firm size distribution is power law, aggregate volatility decays at rate less than $\sqrt{n}$. He does not emphasize network origin of fluctuations. Also, **Horvath (1998), Dupor (1999)**

Orchards in Asset Pricing:

- **Santos and Veronesi (2009):** Lucas Orchard, emphasizes cash-flow risk heterogeneity to explain value premium with habit formation. Our network economy accounts for causality in shock propagation, rather than mere comovement, so we can explore the endogenous nature (microfoundation) of cash-flow risk. Also **Cochrane, Longstaff, Santa-Clara (2008); Martin (2010);**

Related Empirical work:

- **Grinblatt and Moskowitz (2007), Cohen and Frazzini (2010); Menzly and Ozbas (2011).** cross-sectional momentum in input-output linkages
The Economy

- A Representative Agent with power utility supports equilibrium.

- There are $N$ assets, each paying dividends $D_t^i$.

- Market clearing: $C_t = \sum_i D_t^i + L_t$.

- Dividend stream: $D_t^i = Y_t x_t^i$.

  - A common lognormal IID component $Y_t$.
  - A firm specific component $x_t^i$. 
Network

- $x_t^i$ captures a persistent state of distress (or not):
  $$x_t^i = \begin{cases} \bar{x}_t^i & \text{non distress state} \\ \bar{x}_t^i & \text{distress state} \end{cases}$$

- Distress event: $\bar{x}_t^i \Rightarrow x_t^i$ with probability $\lambda_t^i(S_t, H_t)$
- Recovery event: $x_t^i \Rightarrow \bar{x}_t^i$ with probability $\eta_t^i(S_t, H_t)$

- $H_t$: a distress state vector. $S_t$, business cycle two-state Markov chain.

- Network links are embedded in state dependence of distress and recovery shocks:
  - $H_t$: directly changes likelihood of firms’ future shocks according to (all firms’) distress status
  - $S_t$: acts on all intensities and makes network links time-varying
Idiosyncratic Trees

Markov Chain Tree 1

-λ₁ +λ₁
+η₁ -η₁

Markov Chain Tree 2

-λ₂ +λ₂
+η₂ -η₂

Markov Chain Tree 3

-λ₃ +λ₃
+η₃ -η₃
Creating a Network with Direct Connectivity

\[ H(t) = (h,h,h) \]
\[ (l,h,h) \ldots etc \]
Introducing Incomplete Information/Learning

\[ S(t) = \text{High, Low} \]
The Generator of the Network

- The state of the Network \((S_t, H_t)\) has dimension \(2 \times 2^{(N+1)}\).
- The dynamics is described by a the Markov generator \(A^H\), so that
  \[
P \left[ H_{t+\tau}^i = 1 \mid H_{t+\tau}^i = 0 \right] = I_i' \exp(-A^H \tau) I_j
  \]
- With CRRA preferences, SDF \(\xi_t = e^{-\delta t} Y_t^{-\gamma} \left( \sum_{i=1}^{n+1} x_t^i \right)^{-\gamma}\).
- Simple way to introduce dynamics into a global network to study conditional risk premium, not just steady-state.
- It also allow us to introduce incomplete information.
Vertical Integrated Economy

\[ \lambda_2 \text{ very sensitive to state of firm-1 but } \]
\[ \lambda_1 \text{ not sensitive to state of firm-2} \]

\[ \lambda_3 \text{ very sensitive to state of firm-2 but } \]
\[ \lambda_2 \text{ not sensitive to state of firm-3} \]
Panel 1.a: Symmetric Network

Panel 1.c: Vertically Integrated Network

Panel 2: Banking Exogeneity

Banking Exogeneity
Cross-Sectional Learning

- $S_t$ is unobservable, so are true $\lambda$s and $\eta$s
- Bayesianly inferred from dividend shocks.
- $p_t^h$: posterior probability of a boom ($S = 0$).

$$\hat{\lambda}_t^i = E_t[\lambda_t^i] = p_t^h \lambda^i(0, H_t) + (1 - p_t^h) \lambda^i(1, H_t)$$

- A distress event of firm $i$ predicts a more likely distress of $j$: signal for recession state ($S = 1$).

Distress for $i \implies (p_t^h \downarrow) \implies (\hat{\lambda}_t^j, \uparrow, \hat{\eta}_t^j \downarrow)$
Learning: Updating Mechanism

\[ dp_s^h = \left[ k_l + k_h \right] \left[ \frac{k_l}{k_l + k_h} - p_s^h \right] ds + p_s^h (1 - p_s^h) \left[ (1 - H_s^i) \frac{\lambda^i(1) - \lambda^i(0)}{\hat{\lambda}_s^i} dH_s^i \right. \]

\[ - H_s^i \frac{\eta^i(0) - \eta^i(1)}{\hat{\eta}_s^i} dH_s^i \] + same term for all remaining firms

\[ \text{distress of firm } i \]

\[ \text{recovery of firm } i \]

- \( dH_s^i = 1 (-1) \), for a distress (recovery) of sector \( i \).
- Size of updating depends on
  1. Prior uncertainty
  2. Covariance \( (dH_s^i, dS) \sim \lambda^i(1) - \lambda^i(0) \)
- Intuition: signal is more informative, a distress to firm \( i \) is more likely systematic if intensity is sensitive to business cycle.
Learning Effects in a Connected Two-sectors Economy

The effects on expected aggregate consumption are enhanced by incomplete information via $S_t$ in a connected network.
Cross-Section of risk premia and P/D ratios

**Proposition 1**: Closed-form expressions for

- **P/D ratios**:

\[
P_i^i(H_t)/D_t = p_t^h P_0^i(H_t)/D_t + (1 - p_t^h) P_1^i(H_t)/D_t
\]

\[
P_u^i(H_t)/D_t = A^{-1} C^i \quad u = 0, 1
\]

Similar to stochastic Gordon growth formula where the P/D ratio depends on the global characteristics of the network: \( A^{-1} C^i \)

- **Risk premia**:

\[
\mu_t^i = \gamma \sigma^2_Y + \mu_\lambda^i + \mu_\eta^i
\]

\[
\mu_\lambda^i = \sum_{j=1}^{n+1} (1 - H_t^j) \lambda^j(H_t) \left[ 1 - \theta^j \hat{R}^i(H_t^{-j}) \right]
\]

\[
\hat{R}^i(H_t^{-j}) = \frac{P_i^i(H_t^{-j})}{P_i^i(H_t)}, \quad \hat{R}^i(H_t^{+j}) = \frac{P_i^i(H_t^{+j})}{P_i^i(H_t)}
\]

Weighted average of risk-adjusted returns on security \( i \) in case of distress of some firm, with the likelihoods of distress as weights
The separate effects of the two channels

Case 1: Full Information + No Connectivity

Distress for \( i \)
\[ \downarrow \]
\[ C_t \downarrow \quad \text{but} \quad E[\Delta C_t] \uparrow \]
\[ \downarrow \]
smaller hedging demand for securities

A recovery is eventually foreseen

Less desire to save and postpone cons.

- If there is only one firm, the P/D ratio drops and risk premium increases.
- But in a N-firm disconnected network, as \( N \to \infty \) the shock is diversified away.

\[ \Rightarrow \text{Effect on cross-section of P/D ratios only if firm dividend share is large enough as } N \to \infty. \]
Case 2: Full Information + Connectivity

Distress for $i$

$\lambda^j \uparrow \quad E[\Delta D^j_t] \downarrow$

Hedging demand for countercyclical securities may arise

- Effect of these “Central” firms depend on their connectivity.
- If $\lambda(H_t)$ is large, their ability to spread distress imply that they are procyclical, thus high correlation marginal utility.
- For these firms P/D ratio drops the most .... and Risk premium is the ex-ante the highest.
- If $\lambda(H_t)$ is low, firm- are less procyclical, and their P/D ratio relatively higher in the cross-section.
Case 3: Incomplete Information + Connectivity

Distress for $i$

\[
\begin{align*}
\hat{\lambda}^j &\uparrow \quad E[\Delta D_t^j] &\downarrow \\
\end{align*}
\]

Cross-sectional learning.
Perceived contagion

Hedging demand of countercyclical securities may raise

- Shocks to firm-$i$ are used to update posterior about $S_t$
- Thus, even if $\lambda^i(H)$ is small, the sensitivity of $\lambda$ to $S_t$ can cause large posterior update.
- Those firms with $\lambda^j(1) \gg \lambda^j(0)$, have largest covariance with SDF, thus lower P/D and highest risk premium
- Those firms with $\lambda^j(1) \approx \lambda^j(0)$ are used as hedging tools.

The Cross-section of P/D ratio and RP are structurally linked to $\lambda(S, H)$, degree of exogeneity
Formalizing the link
Assume centrality of Firm 1 is the only distinctive feature

**Proposition 3 [Centrality and Risk Premia].** Consider a ‘Star’ network economy; Assume distress of Firm 1, the central firm, increases the other distress intensities by a factor $k$. There exists a $k^*$, dependent on firm characteristics, such that if $k > k^*$, as $n$ gets arbitrarily large Firm 1 has a higher risk premium than any noncentral Firm $N$, conditional on any present state $H_t$ where both firms 1 and $N$ are not in distress.
For small connectivity levels, firms that are more endogenous have also more volatile cash-flows as they absorb shocks from many other firms (example: “Inverse-Star network”); this does not imply, however, that they are riskier since these shocks may not propagate, i.e. they are diversifiable.

However, for $k$ large enough, fundamental risks of Firm 1 translates into a systematic risk factor.

Aggregate consumption is systematically worse during Firm 1’s distress than during others’.

This needs to be compensated ex-ante in a larger risk premium.
Failure of two-fund separation

Proposition 4. Consider a sequence of economies indexed by the total number of firms, \( n \), with asymptotically homogeneous dividends. As \( n \to \infty \):

- If the network is symmetric, two fund-separation holds: assets' risk-premia have an exact one-factor representation.
- If the network is asymmetrically connected, two fund separation does not hold; In the ‘Star’ form (with one central firm) three fund-separation holds.
- Impossibility to diversity away shocks of central firms.
An indicator of network centrality
A reduced-form indicator of exogeneity in networks for asset pricing

Goal:

• Proposing a simple reduced-form indicator of firm exogeneity in the network
• Univariate, easy to construct and test empirically

\[
DC_{ij}^\tau = \frac{P[H_t^j = 1, H_t^i = 1] - P[H_{t+\tau}^i = 1]P[H_t^i = 1]}{\sqrt{P[H_{t+\tau}^j = 1]P[H_t^i = 1](1 - P[H_{t+\tau}^i = 1]) (1 - P[H_t^i = 1])}}
\]

• Captures firm i’s ability to transfer its distress state to j within \( \tau \) periods.
• Unconditional correlation between the events that i is in distress at time t and that j is in distress \( \tau \) periods afterwards.
An indicator of network centrality

Aggregate across firms \( j \) to obtain **Dynamic centrality** of firm \( i \):

\[
\overline{DC}_{T}^{i} = \sum_{j=1,j\neq i}^{n} (DC_{T}^{ij} - DC_{T}^{ji})
\]

- Net ability to transfer distress of firm \( i \), distinguish between:
  - Incoming \((j \rightarrow i)\): \( DC_{T}^{ji} \).
  - Outgoing \((i \rightarrow j)\): \( DC_{T}^{ij} \).

Larger \( \overline{DC}_{T}^{i} \) at all horizons \( \tau \)

- Larger active connectivity (centrality)

\[\implies\] It should be associated to larger expected returns
Empirical Analysis

**Part A.** Example of network at *industry*-level using NIPA Input-Output tables:

1. Analyze characteristics (if it exists) of a network structure
2. Existence of link between network positioning and risk premia?

**Part B.** Go one step deeper to *firm*-level:

1. Create sorted portfolios on firm exogeneity
2. Fundamentals: Earnings and Customer-Supplier relationships; No price-information used for network identification
3. Run Fama-French (1992) analysis controlling for network structure

**Part C.** Networks and Cross-Momentum:

1. Can network structure be a rational explanation for cross-momentum?
Example: Network Structure at Industry Level
Nine Industry (4 SIC codes);
Within these, consider all NYSE, Nasdaq, Amex listed firms; 1963-2007 with Compustat accounting data.

Local connectivity. Source NIPA Tables by BEA, “Industry-by-industry requirements” (production required from another industry per dollar of delivery of final use”

Global connectivity. Source Earnings for $x_t^i$ and Gdp for $S_t$
• “FIRE” (i.e. finance, insurance and real estate) is actually not Central.

• “Wholesaler and Trade” is the most Central, this includes “Motor Vehicle and Motor Vehicle Parts and Supplies Merchant Wholesalers” and “Professional, Scientific, and Technical Services”
Table VII – The first panel reports the dynamic centrality measures of 9 US industrial sectors obtained from the estimation of Section V.b, both with and without weighting (see the main text). It also reports model-implied expected monthly returns and average historical returns. The second panel reports a Fama-McBeth regression of simulated returns on sample returns: we generate 1000 samples of 540 monthly returns each (the sample size); for each sample we regress cross-sectionally model sector returns on empirical returns at each point in time, and then report time averages of coefficients. We repeat the procedure on each sample, and average the coefficients across samples. Standard errors are computed across time and samples. Regression coefficients can be estimated with arbitrary accuracy by increasing the number of samples, due to the stationarity of returns. The last panel reports average returns and t-statistics of a portfolio long the sectors with largest dynamic centrality and short those with the smallest, using both the weighted and the unweighted centrality measure.

<table>
<thead>
<tr>
<th>Sector</th>
<th>Expected Return data</th>
<th>Expected Return model</th>
<th>$\bar{DC}_i^{1\text{month}}$-unweighted</th>
</tr>
</thead>
<tbody>
<tr>
<td>1- Mining</td>
<td>0.0079</td>
<td>0.0086</td>
<td>-0.0196</td>
</tr>
<tr>
<td>2- Utilities</td>
<td>0.0066</td>
<td>0.0030</td>
<td>0.0199</td>
</tr>
<tr>
<td>3- Construction</td>
<td>0.0058</td>
<td>0.00059</td>
<td>-0.0439</td>
</tr>
<tr>
<td>4- Manufacturing</td>
<td>0.0056</td>
<td>0.00054</td>
<td>-0.0474</td>
</tr>
<tr>
<td>5- Wholesale Trade</td>
<td>0.0083</td>
<td>0.00080</td>
<td>0.0254</td>
</tr>
<tr>
<td>6- Retail</td>
<td>0.0053</td>
<td>0.0028</td>
<td>-0.0329</td>
</tr>
<tr>
<td>7- Transportation</td>
<td>0.0053</td>
<td>0.00054</td>
<td>0.0081</td>
</tr>
<tr>
<td>8- Arts &amp; Entertainment</td>
<td>0.0054</td>
<td>0.00065</td>
<td>0.0295</td>
</tr>
<tr>
<td>9- FIRE</td>
<td>0.0073</td>
<td>0.00043</td>
<td>0.0073</td>
</tr>
<tr>
<td>10- Others</td>
<td></td>
<td></td>
<td>0.0536</td>
</tr>
</tbody>
</table>

Dynamic Centrality Test: Long-Short Portfolio

buy 4,3,6 - sell 8,5,2

Data E[R]: 0.0036 t-stat: 1.14
Model E[R]: 0.00047
The Cross-Section of Expected Returns
Empirical Analysis - A Fama-French Style Analysis

- Use all US listed firms (1963 - 2008) to form $10 \times 10$ beta-size sorted portfolios to populate network (as in Fama and French (1992)).

- **Two forms of information:**
  - For *direct* linkages, use customer/sales data from Regulation SFAS 131, as firms are required to report major customers that account for > 10% of sales. We follow Cohen and Frazzini and use $(\text{Supplier sales from } i \text{ to } j / \text{Total market value})$.
  - Parametrize $\lambda(H)$ as linear function in % sales-dependence.
  - For *global* linkages in $S(t)$, use earnings data (EPSX).

- Estimate network using structural ML (Brand and Santa-Clara).

- Compute $\overline{DC}_{i}^{1m}$, then each stock is matched with the $\overline{DC}_{i}^{1m}$ of its portfolio (as in FF(1992) for Beta).
Portfolios Characteristics
beta, size, BE/ME

- As in FF(1992): Use Pre-sort Beta (July t-1, June t) for portfolio construction, then Post-sort Beta (July t, June t+1)

- Betas have a wide range of variation: 0.6-2.3; Negatively correlated with size; Betas are U-shaped in BE/ME;

- Average returns strongly decreasing in size; Increasing in BE/ME

- No clear increasing pattern beta-average returns, at least until the 6th decile (CAPM failure).
Portfolios Characteristics: Dynamic Centrality

- For each of the 4×4 portfolio, compute $DC$.

### Panel 1. 1-month dynamic centrality of beta-size sorted portfolios

<table>
<thead>
<tr>
<th>ME-</th>
<th>$\beta - 1$</th>
<th>$\beta - 2$</th>
<th>$\beta - 3$</th>
<th>$\beta - 4$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.3734</td>
<td>0.2558</td>
<td>0.2649</td>
<td>0.1277</td>
</tr>
<tr>
<td>2</td>
<td>-0.0527</td>
<td>-0.4749</td>
<td>-0.1994</td>
<td>-0.1402</td>
</tr>
<tr>
<td>3</td>
<td>0.0220</td>
<td>-0.1676</td>
<td>-0.4067</td>
<td>0.1786</td>
</tr>
<tr>
<td>4</td>
<td>0.0444</td>
<td>-0.0153</td>
<td>0.1384</td>
<td>0.0515</td>
</tr>
</tbody>
</table>

- Beta is not a good proxy for Dynamic Centrality
- Size is not monotone in Dynamic Centrality
- The Fama-French factor are unlikely to subsume $DC$
Portfolios-level Results

- Construct a Long-Short portfolio based on quintile $DC$.

**Panel 2. Dynamic centrality sorted portfolios**

*a) Average monthly returns, July 1963-June 2008*

<table>
<thead>
<tr>
<th>$\bar{DC}^\tau$-quintile</th>
<th>1-st</th>
<th>5-th</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.0113</td>
<td>0.0322</td>
</tr>
</tbody>
</table>

*b) Long-short portfolio returns:*

$$R_{ls}^t = \alpha + \beta(R^m_t - r_t) + \beta_{hml}HML_t + \beta_{smb}SMB_t + \epsilon_t$$

<table>
<thead>
<tr>
<th></th>
<th>$\alpha$</th>
<th>$\beta$</th>
<th>$\beta_{hml}$</th>
<th>$\beta_{smb}$</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0.020</td>
<td>-0.117</td>
<td>0.120</td>
<td>0.486</td>
<td>11.2%</td>
</tr>
<tr>
<td></td>
<td>(10.78)</td>
<td>(-2.55)</td>
<td>(1.75)</td>
<td>(8.13)</td>
<td></td>
</tr>
</tbody>
</table>

1 month dynamic centrality measures of beta-size sorted portfolios. Average monthly returns of 5 value-weighted portfolios, formed after sorting stocks according to their (beta-size sorted) portfolio’s dynamic centrality. Monthly returns ($R_{ls}^t$) of a portfolio long the last and short the first quartile of the centrality distribution are regressed (from July 1963 to June 2007) on an intercept, the market excess return, the HML and SMB factors.
### Individual-firm Fama-McBeth Test

- Run second-stage Fama-French at individual firm level;
- Associate to each firm its portfolio $DC$, as FF(1992) do for betas

<table>
<thead>
<tr>
<th>Factors</th>
<th>Column 1</th>
<th>Column 2</th>
<th>Column 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta$</td>
<td>0.003</td>
<td>0.012</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.04)</td>
<td>(4.24)</td>
<td></td>
</tr>
<tr>
<td>$\log(ME)$</td>
<td>−0.0044</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(−8.79)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$BE/ME$</td>
<td>0.0031</td>
<td>0.0031</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(6.835)</td>
<td>(6.90)</td>
<td></td>
</tr>
<tr>
<td>$DC^{1m.}$</td>
<td>0.0167</td>
<td>0.024</td>
<td>0.048</td>
</tr>
<tr>
<td></td>
<td>(7.33)</td>
<td>(8.77)</td>
<td>(11.27)</td>
</tr>
</tbody>
</table>

- Network centrality emerges as an important characteristics.
- After controlling for $DC$, Beta is significant.
- Robust to specifications: B/M, Size do not subsume its significance.
## Errors-in-variables adjustment

*Monte-Carlo slopes and t-statistics of Fama-McBeth regressions adjusted for error-in-variables, July 1963-June 2008*

<table>
<thead>
<tr>
<th></th>
<th>$\beta$</th>
<th>$\overline{DC}^{1m}$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>avg slope</strong></td>
<td>0.0033</td>
<td>0.0157</td>
</tr>
<tr>
<td><strong>median slope</strong></td>
<td>0.0032</td>
<td>0.0159</td>
</tr>
<tr>
<td><strong>mode slope</strong></td>
<td>0.0033</td>
<td>0.0161</td>
</tr>
<tr>
<td><strong>slope std.</strong></td>
<td>0.0017</td>
<td>0.0033</td>
</tr>
<tr>
<td><strong>slope 5%(95%)-ile</strong></td>
<td>0.00012 (0.0058)</td>
<td>0.0098 (0.0206)</td>
</tr>
<tr>
<td><strong>avg t-stat</strong></td>
<td>1.1451</td>
<td>6.875</td>
</tr>
<tr>
<td><strong>median t-stat</strong></td>
<td>1.205</td>
<td>7.00</td>
</tr>
<tr>
<td><strong>mode t-stat</strong></td>
<td>1.283</td>
<td>7.107</td>
</tr>
<tr>
<td><strong>t-stat std.</strong></td>
<td>0.575</td>
<td>0.752</td>
</tr>
<tr>
<td><strong>t-stat 5%(95%)-ile</strong></td>
<td>0.050 (1.93)</td>
<td>5.39 (7.78)</td>
</tr>
</tbody>
</table>

*Table:* Summary statistics of the simulated distribution of (time-series) average slopes and t-statistics of the second stage Fama-McBeth regressions.
Cross-Momentum
Cross-Sectional Momentum and Networks

- (Time-Series) Momentum appears as a recurrent regularity in the data. Often interpreted in the context of “(behavioral) sentiment theories of initial under-reaction and delayed over-reaction” (Moskowitz, Ooi, Pedersen (2012)).

- However, a stream of the literature links predictability to the gradual diffusion of information, due to some informational frictions (Hong and Stein, 1999).

- (Cross-section) Test delayed response of the price of some stocks given new informative signals on other stocks. Joint hypothesis: (a) informational frictions; (b) network structure (as pursued by Cohen and Frazzini (2010), Menzly and Ozbas (2011)).

- Idea: use our previously estimated network to test if the same network can give rise to cross-momentum on stocks that are most likely subject to information frictions.
Regression Design

- Use the network based on the beta-size sorted portfolios.
- For each portfolio $i$, find the set of 4 portfolios $\Omega_i$ with the highest $DC_{ji}^{1m}$
- Construct a signal $S_{t-1}^i$, given by the average performance of individual stocks in portfolios $\Omega_i$
- Interact the signal with a proxy of financial friction: Match dataset with I/B/E/S to measure analyst coverage.

\[
\chi_{t,i,cove,dc} = S_{t-1}^i \mathbf{1}(l_t^i = cove) \mathbf{1}(i \in \Theta_{dc}); \quad cove = h, l \quad dc = 1, 2, 3, \ldots 4
\]

then run regression

\[
r_t^i = a_t + \gamma_t \chi_{t,i,cove,dc} + \beta_t Controls_t + \varepsilon_t
\]

*Controls* = Short-term Reversal; Medium-term Continuation
Cross-momentum

<table>
<thead>
<tr>
<th>DC^{1m}\text{-quartile}</th>
<th>Analyst Coverage</th>
<th>Cross-momentum Factors</th>
<th>Slopes</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>l</td>
<td>x^{i,l,1}</td>
<td>0.245</td>
</tr>
<tr>
<td></td>
<td>h</td>
<td>x^{i,h,1}</td>
<td>0.078</td>
</tr>
<tr>
<td>...</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>l</td>
<td>x^{i,l,4}</td>
<td>-17.14</td>
</tr>
<tr>
<td></td>
<td>h</td>
<td>x^{i,h,4}</td>
<td>-5.87</td>
</tr>
</tbody>
</table>

- Evidence of cross-momentum for (a) Low Coverage; (b) Low DC firms
- Evidence seems to support a friction-based story in the context of a network structure.