Information Difussion, Interdependence and Stock Market Comovement

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February 3, 2024

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Introduction

Motivation

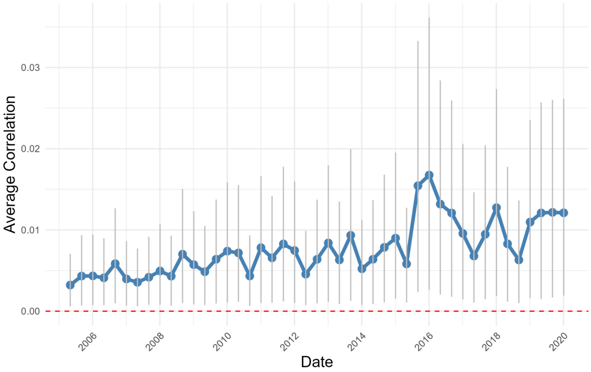
- Numerous patterns of comovement have been observed in asset returns. Some of them explained by fundamentals and common factors, a relevant residual is yet to be explained.
- Some explanations and channels have been studied in the literature.
  - Some theoretical: Calvo and Mendoza [2000], Gorton and Ordoñez [2014], Miller [1977]
  - Some empirical: Barberis et al. [2005], Bekaert et al. [2014], Debarsy et al. [2018], Israelsen [2016]
- Increasing literature studying the effects of information and analysts on markets.
- Understanding the origins of these patterns is relevant for understanding the propagation of shocks, portfolio decisions and risk management, among others.

This paper

We apply a novel measure for informational linkages that helps to explain stock comovement empirically. Based on it, we study the propagation of shocks in the stock market.

Motivation

Figure 1: Avg. Corr. of Idios. Daily Returns



Idiosyncratic stock return comovement is positive. Theoretically, the ***idios.*** comovement should be 0.

This paper

- We apply a novel measure for informational linkages between stocks based on analysts forecast errors and estimate empirically its relevance in explaining stock return comovement.
- The informational channel successfully explains idios. return comovement
  - with diff. effects in periods of higher uncertainty.
  - category-learning amplyfing the effect (S&P, industry, geog. proximity, common analysts).
- We estimate and quantify the propagation of simulated and real world (idios.) shocks.
  - what is the indirect impact of a shock on idios. returns of a stock over ***other*** stocks?
  - how different is the impact of a highly connected stock v/s a less connected one? Systemic risk analysis!
  - how does an unexpected climate event over one state propagates to other states?

The informational channel

- Inverstors learning process and their beliefs will determine stock returns.
- Investors form their beliefs and trade with the information they receive. Following Bernales et al. [2023], agents receive signals of information on idiosyncratic factors and signals on common factors.
- The correlation in agents' beliefs (thus, their investments) is induced by biases in the agents' learning process
  - agents over-weight the precision of new information related to common factors
  - this induces correlated errors in agents' beliefs, which generates what we call the informational channel.

$$\text{new info.} \rightarrow \underbrace{\text{learning process}}_{\text{biased towards common factors}} \rightarrow \underbrace{\text{correlated errors in agents' beliefs}}_{\text{informational linkages}} \rightarrow \text{comov. stock returns}$$

Related Literature

- Stock market comovement:
  - Barberis et al. [2005], Bekaert et al. [2014], Chen et al. [2016], Greenwood [2007], Israelsen [2016], Veldkamp [2006]
- Information Production/Acquisiton, Herding & contagion:
  - Basu [2002], Bernales et al. [2023], Calvo and Mendoza [2000], Chousakos et al. [2023], Cole et al. [Forthcoming], Diether et al. [2002], Forbes and Rigobon [2001], Gorton and Ordoñez [2014], Johnson [2004], Kaminsky and Schmukler [1999], Miller [1977]
- Spatial Econometric Modelling/Applications:
  - Debarsy et al. [2018], Elhorst et al. [2021]

Data

- Combine information from security prices, financial ratios and analyst forecasts. Data from 2000 until 2019.
  - CRSP: Data on securities daily returns.
  - Fama-French Factors: We are interested in explaining the idiosyncratic component of returns.
  - Compustat: Financial ratios as control variables.
  - I/B/E/S: Analysts forecast on Earnings per Share (EPS).
- After some filters, this gives us a total of $\approx$ 770 US firms', at a monthly freq.

Summary Statistics

Methodology

The informational linkage - Metric

- We analyze if EPS forecast errors (proxy for beliefs) are correlated across stocks. On a monthly basis, we calculate the EPS one year ahead forecast error of analysts for firm i as follows:

$$NMRSE_{i,t}^{EPS} = \sqrt{\frac{1}{K}\sum_{k=1}^{K}\left(\frac{E\hat{P}S_{k,i,t+1} - EPS_{i,t+1}}{EPS_{i,t+1}}\right)^2} \tag{1}$$

- Where k is the analyst index, $E\hat{P}S_{k,i,t+1}$ is the k analyst forecast for firm i at period $t+1$, $EPS_{i,t+1}$ is the realized value. $NMRSE$ denotes the Normalized Mean Root Squared Error.
- Based on the $NMRSE_{i,t}^{EPS}$ by firm, we extract common factors and keep the residual.
- Finally, we **estimate the correlations of residualized beliefs between securities** and keep those relevant connections.
  - This gives origin to an $N \times N$ matrix of informational linkages.

Common Factors | Relevant Connections

Empirical implementation - Spatial Autoregression

- Spatial-Two-Stage-Least-Squares (S2SLS) methodology.
- Consider N firms over T periods. Denote by r_t the matrix of idiosyncratic returns at period $t \in T$. The model to be estimated is:

$$\mathrm{r}_t = \rho \mathrm{W}^I_{t-1}\mathrm{r}_t + \mathrm{X}_{t-1}\beta_i + \boldsymbol{\mu} + \gamma_t + \mathrm{v}_t \tag{2}$$

- Where $\boldsymbol{\mu}, \gamma_t$ are firm and time fixed effects, W^I_{t-1} is our matrix of informational linkages that varies each year, X_{t-1} is a matrix that contains financial ratios and lagged return and risk as controls, and v_t is an error term.
- We want to understand the variation on asset returns that can be explained by informational linkages, which is captured by ρ.

Idiosyncratic Returns S2SLS Details

Empirical Implementation - Why Spatial Econometric Models?

- We are working with a high dimensional (sparse) matrix of firm-to-firm connections (771×771).
- Spatial econometric models enable us to analyze the spillover mechanisms from multiple sources of transmission of shocks across firms in a single model.
- Past literature has effectively implemented spatial econometric models without necessarily using geographical connections.
- An alternative methodology would be Global VAR (GVAR) models.
  - Main difference with spatial econometric models is that the latter focuses on potentially sparse levels of connections, which is important in our context.
  - Also, GVARs are typically used in lower dimensions, it estimates unit-specific coefficients.
- Following Elhorst et al. [2021], Spatial Models are particularly useful in our context, since our treatment ($W\mathrm{r}_t$) is endogenous, we include control variables and we have $N > T$.

Results - Informational Channel Relevance

Do learning biases change in periods with higher uncertainty?

- Does the learning process change in periods of higher uncertainty?
  - Information production [Gorton and Ordoñez, 2014]:
    - Producing information is costly, not optimal to produce at every period.
    - When high negative shocks arise, there are more incentives to processing information correctly.
    - Thus, informational linkages intensity would decrease.
  - Herding and contagion theories [Calvo and Mendoza, 2000]:
    - Investors follow the 'market' instead of making their own assessments of fundamentals, 'market' portfolios embodied relevant information.
    - The cost of acquiring information can be higher than the potential gains over 'market' portfolios.
    - Investors have less incentive to gather good news in a bull market, incentives to verify good news increasing in a bear market.
    - Hence, good rumors generate more herding behavior and thus possibly over-reaction in good times.
- Most empirical studies focus on crisis periods to study these theories. At the best of our knowledge, we are one of the first to use a time period that includes 'normal' and periods with high uncertainty.

Results - Crisis Behavior

Table 1: Informational Linkages and Crisis Behavior

	Dep. Var.: Monthly Idios. Return							
	Baseline	GFC	VIXQ75	VIXQ90	Unc. PolQ75	Unc. PolQ90	S&P Ret.Q25	S&P Ret.Q10
W	0.74	0.72	0.71	0.73	0.69	0.72	0.73	0.75
	30.29	27.67	26.43	27.7	25.16	27	27.06	28.07
W*Crisis		-0.24						
		-3.08						
W*VIX			-0.15	-0.35				
			-2.9	-4.99				
W*Unc Policy					-0.16	-0.49		
					-3.38	-8.09		
W*S&P Ret							-0.2	-0.56
							-4.31	-9.29
Observations	138780	138780	138780	138780	138780	138780	138780	138780
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
log-Lik								

Notes: The Dep. Var. is the residualized monthly return of stocks after accounting Fama-French 6-Factor model. Each estimation controls for Market-Book, Cash-Assets, Ebitda-Assets, Log(Sales), Return and Risk (all lagged) with firm-specific coefficients, besides stock and monthly FE. Each column includes an interaction for crises periods. The second column, Global Financial Crisis (GFC) considers 2007m7-2009m3. VIXQ75 considers periods where the VIX index distribution was in its upper 25%, same for VIXQ90, but with the upper 10%. Unc. Pol. uses the Uncertainty Policy Index. S&P Ret uses periods where the monthly return of the S&P index was in its lower 25% and 10% values. T-stats are below each coefficient.

Category Learning

- Investors might think in terms of categories. If two companies are in the same group, investments might flow in similar ways to both companies.
- The informational channel has different effects in securities that share groups, such as:
  - Companies in S&P 500
  - Companies in the same industry
  - Companies Geog. Connected
  - Companies with common analyst coverage
  - We show that, even after controlling for each of these groups, the informational channel is still relevant.

Geographical Connections Common Analyst Coverage

Results - Category Learning

Table 2: Informational Linkages and Category Learning

	Dep. Var.: Monthly Idios. Return					
Groups	Baseline	S&P	Industry	Geog.	Geog.	Common Analy.
W	0.74	0.48	0.35	0.64	0.6	0.63
	30.29	18.27	13.4	25.86	24.54	23.41
W*SP		0.76				
		13.40				
W*Industry			0.85			
			16.14			
W*GeogThres				9.12		
				3.7		
W*GeogState					12.89	
					4.67	
$W_{ComAnaly}$						0.75
						28.07
$W*W_{ComAnaly}$						6.11
						1.05
Observations	138780	138780	138780	138780	138780	138780
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Stock-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
log-Lik						

Notes: The Dep. Var. is the residualized monthly return of stocks after accounting Fama-French 6-Factor model. Each estimation controls for Market-Book, Cash-Assets, Ebitda-Assets, Log(Sales), Return and Risk (all lagged) with firm-specific coefficients, besides stock and monthly FE. Each column includes an interaction for pair of firms that belong to a group. The second column interacts the W matrix keeping only pair of firms that have ever been part of the S&P 500 index. The third column keeps connections between pairs of firms that are in the same industry. The fourth column keeps connections between stoctks hat are at most 100km. distanced (between their headquarters). The fifth column keeps connections that are in the same state. The sixth column builds a matrix of common analyst coverage (see the Appendix) and then interacts our base W with the common analyst W. T-stats are below each coefficient.

Interpretation

- The Table in slide 12 shows that there is interdependence between stock returns.
- Coefficient do not have a direct interpretation, more on the next section.
- We find evidence that on periods of higher uncertainty, informational interdependence decreases, consistent with information production and some herding theories.
- The Table in slide 14 shows evidence that category learning is observed and amplifies the effect of the informational channel.

Applications - Quantifying the Propagation of Shocks

Indirect Impacts of Shocks

- Our baseline model allows us to identify the direct and indirect impacts of a shock over one stock. The model can be written as[1]:

$$\mathrm{r}_t = (I_N - \rho \mathrm{W}^{I}_{t-1})^{-1}(\mathrm{X}_{t-1}\beta_i + \boldsymbol{\mu} + \gamma_t + \mathrm{v}_t) \tag{3}$$

- Then

$$\frac{\partial \mathrm{r}_t}{\partial \mathrm{v}_t} = (I_N - \rho \mathrm{W}^{I}_{t-1})^{-1}\mathrm{v}_t \tag{4}$$

- Note that the resulting derivative will give us an $N \times N$ matrix. The diagonal of the matrix has the direct effects of a shock over each firm. The non-diagonal elements will include the indirect effects of the shock.

[1] If $\rho < 1$, $(I_N - \rho \mathrm{W}^{I}_{t-1}\mathrm{r}_t)^{-1}$ can be written as: $(I_N + \rho W^{I}_{t-1} + \rho^2 {W^{I}_{t-1}}^2 + \dots)$. The first element includes the direct effect, the second one the impact over direct "neighbours", the third one the impact over second-order "neighbours", and so on.

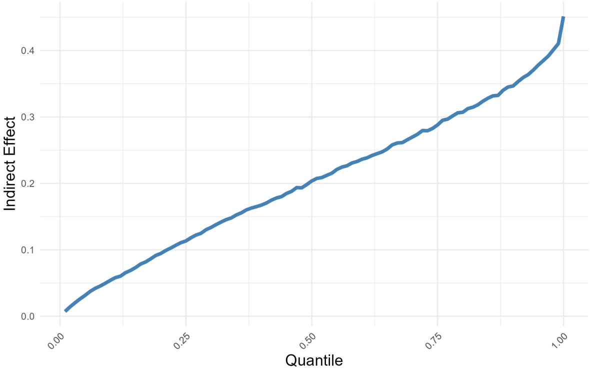
Indirect Impacts of Shocks

	Avg. Indirect Impact of a Shock to:		
	All firms	More connected	Least connected
Impact	0.205	0.464	0.010
Std. Dev.	(0.001)	(0.002)	(0.000)

Table 3: Indirect impact of a 1 sd shock to errors

- 1sd of errors = 7.37%
- On avg., a shock over one firm has an aggregate indirect impact of 20.5%.
- Extension: what is the effect if we take out more connected firms? Too big to fail?

Figure 2: Indirect Impacts of a 1sd shock (7.37%) by Quantiles of Centrality



Extensions to be done...

- Counterfactuals: What would happen if a regulator helps to have a world where analysts learning process is not biased (thus, $\rho = 0$)?
    - How does stock comovement changes?
    - How does the diversification of a portfolio change?
- Real world applications:
    - How does an unexpected climate event over one state impacts stocks of the rest of the states?

Conclusion

Conclusion

- We show empirically that stock return comovement might arise due to analysts' learning biases, shedding lights on a long-standing puzzle in finance.
- Category-thinking is observed and amplifies the effect of informational linkages.
- Learning biases change during periods of uncertainty, there's more at stake.
- Simulated and real world applications to study the propagation of shocks across stocks and portfolio decisions.
  - we study the impact of highly connected stocks on propagating shocks, insights on systemic risk
  - propagation of climate events
  - counterfactuals: if learning biases didn't exist, what about portfolio choice and stock market comovement?

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Appendix

Summary Statistics

Table 4: Summary Statistics

	Min.	p25	p50	p75	Max.	Mean	St.Dev.	Obs.
Idios. Return	-18.53%	-4.24%	-0.22%	3.83%	20.46%	-0.04%	8.76%	136,980
Log(Sales)	11.28	13.72	14.81	15.93	18.37	15	1.7	136,807
Cash-Assets	0.00	0.02	0.07	0.18	1.02	0.25	2.2	136721
Ebitda-Assets	-0.41	0.27	0.72	1.74	149.36	23	332	136,704
Debt-Assets	0.12	0.42	0.58	0.74	0.93	0.57	0.22	136,819
Market-Book	0.62	1.36	2.16	3.52	12.99	3.6	15	136,712
Analys. EPS Forecast Errors	0.02	0.07	0.16	0.39	6.18	0.52	1.1	118,954

Notes: Idios. Returns is the residualized monthly returns of stocks after applying a Fama-French 6 Factor Model to excess returns (return-risk free rate). Analys. EPS Forecasts Errors are estimated following Eq. 1. Every variable is winsorized at the 2% of each tail to estimation being driven by outliers.

Back

The informational linkage - Considering Common Factors

- Linkages observed in the previous step might be showing common factors. We follow Bailey, Holly & Pesaran (2016) two-stage methodology to correct for cross-sectional dependence by de-factoring the forecast error.
- First step: Test Cross-Sectional Dependence (CSD). If the degree of CSD is high (over 0.5), defactor until this measure is weakly CSD (below 0.5).

$$MRSE_{i,t}^{EPS} = \alpha_i + \lambda_i \mathrm{f}_t + \varepsilon_{i,t}^{DFact} \tag{5}$$

- Where f_t are unobserved common factors and λ_i are loadings. Our baseline model uses 1 common factor (where de-factored observations are weakly CSD). But we have tested with variations of this number.
- The de-factored observations, $\varepsilon_{i,t}^{DFact}$, are kept to construct our informational linkage matrix.

Back

The informational linkage - Keeping relevant connections

- We define $\hat{\epsilon}_{i,j}$ as the sample estimate of the de-factored pairwise correlation of the EPS forecast error between any two firms i and j over $t \in \{1, 2, \dots, T\}$
- In order to keep relevant connections, we follow Bailey, Holly and Pesaran (2016) methodology and apply a multiple testing procedure:

$$w_{i,j}^{I} = I\left(\hat{\epsilon}_{i,j} > T^{-1/2} c_p(n_{ij})\right) \tag{6}$$

- where $c_p(n_{ij}) = \Phi^{-1}\left(1 - \frac{p}{2f(n_{ij})}\right)$, p is the size of the test, which is set to $p = 0.01$, $\Phi^{-1}(.)$ is the inverse cumulative standard normal distribution and $f(n_{ij})$ is a function linearly increasing in n_{ij}, the number of firm pairs, that is $n_{ij} = N \times (N-1)$.
- Intuition: An element w_{ij}^{I} of the matrix of informational linkages W^{I} is non-zero when the informational link between countries i and j is sufficiently strong, that is, when it is statistically different from zero.
- We allow for different degrees of intensity of the link based on $\hat{\epsilon}_{i,j}$, multiplying w_{ij}^{I} by $\hat{\epsilon}_{i,j}$ and row-normalizing.

Back

Keeping idiosyncratic returns

- Stock returns might comove due to common factors. We want to explain the idiosyncratic component of stock return comovement. To keep the idios. component, we:
  - Compute the excess return of each asset by subtracting the effective return by a risk-free instrument at a daily basis.
  - Keep idiosyncratic returns by de-factoring the assets excess returns with typical common factors used in finance. We use CAPM's & Fama and French's factor models to de-factor asset returns. These idiosyncratic excess returns are denoted by r_t
  - Aggregate daily observations at a monthly frequency: $\mathrm{r}_t^{Monthly} = \prod_{t \in T}(1 + \mathrm{r}_t^{Daily}) - 1$. Where T is the number of days in each month.
- Theoretically, idios. returns should not comove. We show that they **do** comove and this can be explained by Infor. Linkages.

Back

Spatial Two-Stage Least Squares (S2SLS) Details

We follow and adapt Kelejian and Prucha (1998)'s S2SLS procedure. We consider the following instruments:

$$\mathrm{H}_{\mathbf{n}} = \left\{ \left(\mathrm{W}_t' \otimes \mathrm{I}_{\mathbf{T}} \right) \mathrm{X}_{i,t-\mathbf{1}} \right\}_{t \in \mathbf{T}}$$

which allows the estimation of the following parameters

$$\widehat{\theta} = \left[\begin{array}{c} \widehat{\rho} \\ \widehat{\beta} \end{array} \right] = \left[\mathrm{Z}'\mathrm{Q}\mathrm{H}_{\mathbf{n}} \left(\mathrm{H}_{\mathbf{n}}'\mathrm{Q}\mathrm{H}_{\mathbf{n}} \right)^{-\mathbf{1}} \mathrm{H}_{\mathbf{n}}'\mathrm{Q}\mathrm{Z} \right]^{-\mathbf{1}} \mathrm{Z}'\mathrm{Q}\mathrm{H}_{\mathbf{n}} \left(\mathrm{H}_{\mathbf{n}}'\mathrm{Q}\mathrm{H}_{\mathbf{n}} \right)^{-\mathbf{1}} \mathrm{H}_{\mathbf{n}}'\mathrm{Q}\mathrm{y},$$

where Z denotes the matrix of all LHS variables (including the spatial lags of the dependent variables) and Q is a matrix that sweeps all fixed effects and the intercept, that is,

$$\mathrm{Q} = \left(\mathrm{I}_{\mathbf{N}} - \mathrm{N}^{-\mathbf{1}} \mathrm{J}_{\mathbf{N}} \right) \otimes \left(\mathrm{I}_{\mathbf{T}} - \mathrm{T}^{-\mathbf{1}} \mathrm{J}_{\mathbf{T}} \right),$$

with J a square matrix of ones. The standard errors can be obtained as

$$\mathrm{se}(\widehat{\theta}) = \widehat{\sigma}^{\mathbf{2}} \left[\mathrm{Z}'\mathrm{Q}\mathrm{H}_{\mathbf{n}} \left(\mathrm{H}_{\mathbf{n}}'\mathrm{Q}\mathrm{H}_{\mathbf{n}} \right)^{-\mathbf{1}} \mathrm{H}_{\mathbf{n}}'\mathrm{Q}\mathrm{Z} \right]^{-\mathbf{1}}$$

with

$$\hat{\sigma}^{\mathbf{2}} = \frac{\hat{\mathrm{v}}'\mathrm{Q}\hat{\mathrm{v}}}{(N-1)(T-1) - (k+T)}$$

Back

Geographical Connections

- Investors can associate with a higher magnitude companies that are in a similar geographic context.
- We use two measures of geographical closeness:
  1. State: Securities in the same state.
  2. Thres: Threshold. Keep companies connections that are below the fifth percentile ($\approx 100km$) of the distribution of geographical distances.
- We have tested with different thresholds.

$$\mathrm{y}_t = \rho_1 \mathrm{W}_t^I \mathrm{y}_t + \rho_2 \mathrm{W}_t^I * \mathrm{Geog} * \mathrm{y}_t + \mathrm{X}_{t-1}\beta_i + \boldsymbol{\mu} + \gamma_t + \mathrm{v}_t \tag{7}$$

- Further, we interact the previous estimation with an Industry dummy. Thus, estimating how relevant the informational channel is for companies that are informationally linked, geographically close to each other and that are in the same industry.

$$\mathrm{y}_t = \rho_1 \mathrm{W}_t^I \mathrm{y}_t + \rho_2 \mathrm{W}_t^I * \mathrm{Geog} * \mathrm{Industry} * \mathrm{y}_t + \mathrm{X}_{t-1}\beta_i + \boldsymbol{\mu} + \gamma_t + \mathrm{v}_t \tag{8}$$

Back

Common Analyst Coverage

- Some papers have shown that common analyst coverage can explain stock return comovement.
- As a measure of common analyst coverage, we consider that two firms are connected (by common analysts) if they have shared at least one common analyst over 2 out of the 5 years from which W_t is constructed.

Back