# Information Difussion, Interdependence and Stock Market Comovement

Hriday Karnani (Master's Thesis Version)
Advisors: Eugenia Andreasen, Alejandro Bernales and Paula Margaretic
April 20, 2024

Universidad de Chile

- ▶ Numerous patterns of comovement have been observed in asset returns.
- ▶ Origins of comov. is relevant: asset pricing, propagation of shocks, risk management, etc.
- ▶ Some explanations and channels have been studied in the literature.
  - ▶ Some theoretical: Calvo and Mendoza [2000], Gorton and Ordoñez [2014]
  - ▶ Some empirical: Barberis et al. [2005], Bekaert et al. [2014], Israelsen [2016]
- ▶ Diffusion of information, agents' learning process' and beliefs are key in determining prices.
  - ▶ learning frictions/biases (e.g. costs to learn, limited attention capacity) can generate correlated beliefs across stocks

**This paper**

Can comovement in stock returns be explained by firm-to-firm *__informational__* linkages?

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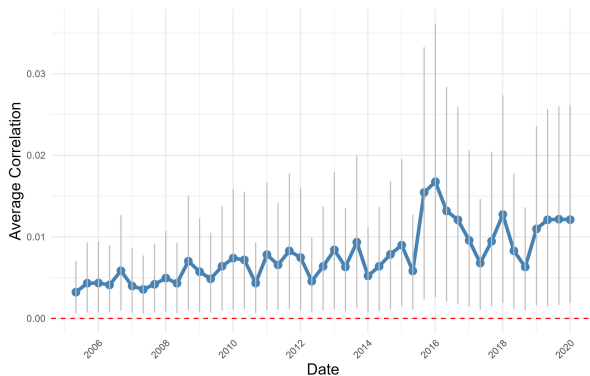


*Idiosyncratic* stock return comovement is positive. Theoretically, the *idios.* comovement should be 0.

- 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?

▶ Investors' form beliefs and trade with the info they receive
  ▶ → their learning process (formation of beliefs) will determine stock returns.
▶ Biases in agents' learning process → correlated agents' beliefs - based on Bernales et al. [2023]
  ▶ two sets of info: common info and idiosyncratic info
  ▶ agents' focus more on new info related to common info → corr. errors in agents' beliefs.

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

- 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], Ozdagli and Weber [2023]

▶ 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 771 US firms', at a monthly freq.

Summary Statistics

# Methodology

▶ 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.
- ▶ $N$ firms, $T$ periods. $r_t$ is a vector of idios. returns at $t \in T$. The model to be estimated is:

$$r_t = \rho \boldsymbol{W}^I_{t-1} r_t + \boldsymbol{X}_{t-1} \beta_i + \mu + \gamma_t + v_t \qquad (2)$$

- ▶ $W^I_{t-1}$ is our $N \times N$ matrix of informational linkages, $\boldsymbol{X}_{t-1}$ contains financial ratios and lagged return and risk as controls, $\boldsymbol{\mu}, \gamma_t$ are firm and time fixed effects, and $v_t$ is an error term.
- ▶ $\rho$ ($|\rho| < 1$) is the avg. intensity with which info. linkages explain the variation on idios. asset returns: intensity of interdependence

Idiosyncratic Returns   S2SLS Details

**Empirical Implementation - Why Spatial Econometric Models?**

▶ We are working with a high dimensional (sparse) matrix of firm-to-firm connections ($771 \times 771$).

▶ 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 ($Wr_t$) 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.

**Table 1:** Informational Linkages and Crisis Behavior

| height | | | | | 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.

▶ 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

**Table 2:** Informational Linkages and Category Learning

| height Groups | Baseline | S&P | Industry | Geog. | Geog. | Common Analy. |
|---|---|---|---|---|---|---|
| | | | Dep. Var.: Monthly Idios. Return | | | |
| 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.

- Table 1 shows that there is evidence of interdependence between stock returns.
    - robust to including different sets of controls
- Coefficient do not have a direct interpretation, more on the next section.
    - interpretation: avg. intensity of interdependence (due to info. links)
- Is this evidence of stock market comovement as an aggregate?
    - the avg. intensity of info. links is way above 0, kind of...
- We find evidence that on periods of higher uncertainty, informational interdependence decreases, consistent with information production and some herding theories.
- Table 2 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]:

$$r_t = (I_N - \rho W_{t-1}^I)^{-1}(X_{t-1}\beta_i + \boldsymbol{\mu} + \gamma_t + v_t) \tag{3}$$

▶ Then

$$\frac{\partial r_t}{\partial v_t} = (I_N - \rho W_{t-1}^I)^{-1}v_t \tag{4}$$

▶ 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 $\rho < 1$, $(I_N - \rho W_{t-1}^I r_t)^{-1}$ can be written as: $(I_N + \rho W_{t-1}^I + \rho^2 W_{t-1}^{I}{}^2 + ...)$. 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.

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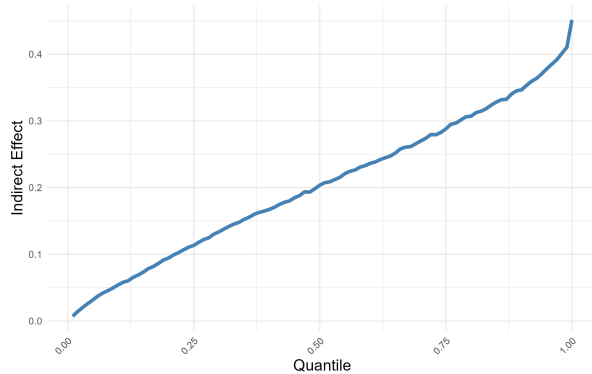
▶ Counterfactuals: What would happen if a regulator helps to have a world where analysts learning process is not biased (thus, $\rho = 0$)?
  ▶ How does stock comovement changes?
  ▶ How does the diversification of a portfolio change?
▶ Real world applications:
  ▶ How does an unexpected climate event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

# Conclusion

► 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?

# References

Nicholas Barberis, Andrei Shleifer, and Jeffrey Wurgler. Comovement. *Journal of Financial Economics*, 75(2):283–317, 2005. ISSN 0304-405X. doi: https://doi.org/10.1016/j.jfineco.2004.04.003. URL https://www.sciencedirect.com/science/article/pii/S0304405X04001308.

Ritu Basu. Financial contagion and investor "learning": An empirical investigation. *IMF Working Paper*, (No. 2002/218), 2002.

Geert Bekaert, Michael Ehrmann, Marcel Fratzscher, and Arnaud Mehl. The global crisis and equity market contagion. *The Journal of Finance*, 69(6): 2597–2649, 2014. ISSN 00221082, 15406261. URL http://www.jstor.org/stable/43611077.

Alejandro Bernales, Hriday Karnani, and Paula Margaretic. Informational economic transmission between countries: Learning, common factors, and category thinking. *Unpublisehd mimeo.*, 2023.

Guillermo A. Calvo and Enrique G. Mendoza. Rational contagion and the globalization of securities markets. *Journal of International Economics*, 51 (1):79–113, 2000. ISSN 0022-1996. doi: https://doi.org/10.1016/S0022-1996(99)00038-0. URL https://www.sciencedirect.com/science/article/pii/S0022199699000380.

Honghui Chen, Vijay Singal, and Robert F. Whitelaw. Comovement revisited. *Journal of Financial Economics*, 121(3):624–644, 2016. ISSN 0304-405X. doi: https://doi.org/10.1016/j.jfineco.2016.05.007. URL https://www.sciencedirect.com/science/article/pii/S0304405X16300988.

Kyriakos Chousakos, Gary Gorton, and Guillermo Ordoñez. Information dynamics and macro fluctuations. *American Economic Journal: Macroeconomics*, 15(4):372–400, October 2023. doi: 10.1257/mac.20210101. URL https://www.aeaweb.org/articles?id=10.1257/mac.20210101.

Harold Cole, Daniel Neuhann, and Guillermo Ordoñez. Information spillovers and sovereign debt: Theory meets the eurozone crisis. *Review of Economic Studies*, Forthcoming.

Nicolas Debarsy, Cyrille Dossougoin, Cem Ertur, and Jean-Yves Gnabo. Measuring sovereign risk spillovers and assessing the role of transmission channels: A spatial econometrics approach. *Journal of Economic Dynamics and Control*, 87:21–45, 2018. ISSN 0165-1889. doi: https://doi.org/10.1016/j.jedc.2017.11.005. URL https://www.sciencedirect.com/science/article/pii/S0165188917302385.

Karl B. Diether, Christopher J. Malloy, and Anna Scherbina. Differences of opinion and the cross section of stock returns. *The Journal of Finance*, 57 (5):2113–2141, 2002. ISSN 00221082, 15406261. URL http://www.jstor.org/stable/3094506.

J. Paul Elhorst, Marco Gross, and Eugen Tereanu. Cross-sectional dependence and spillovers in space and time: Where spatial econometrics and global var models meet. *Journal of Economic Surveys*, 35(1):192–226, 2021. doi: https://doi.org/10.1111/joes.12391. URL https://onlinelibrary.wiley.com/doi/abs/10.1111/joes.12391.

Kristin Forbes and Roberto Rigobon. *Measuring Contagion: Conceptual and Empirical Issues*, pages 43–66. Springer US, Boston, MA, 2001. ISBN 978-1-4757-3314-3. doi: 10.1007/978-1-4757-3314-3_3. URL https://doi.org/10.1007/978-1-4757-3314-3_3.

Gary Gorton and Guillermo Ordoñez. Collateral crises. *American Economic Review*, 104(2):343–78, February 2014. doi: 10.1257/aer.104.2.343. URL https://www.aeaweb.org/articles?id=10.1257/aer.104.2.343.

Robin Greenwood. Excess Comovement of Stock Returns: Evidence from Cross-Sectional Variation in Nikkei 225 Weights. *The Review of Financial Studies*, 21(3):1153–1186, 10 2007. ISSN 0893-9454. doi: 10.1093/rfs/hhm052. URL https://doi.org/10.1093/rfs/hhm052.

Ryan D. Israelsen. Does common analyst coverage explain excess comovement? *The Journal of Financial and Quantitative Analysis*, 51(4):1193–1229, 2016. ISSN 00221090, 17566916. URL http://www.jstor.org/stable/44157611.

Timothy C. Johnson. Forecast dispersion and the cross section of expected returns. *The Journal of Finance*, 59(5):1957–1978, 2004. ISSN 00221082,

# Appendix

**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).

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

- Where $f_t$ are unobserved common factors and $\lambda_i$ 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.

## 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 $t \in \{1, 2, \ldots, T\}$

► 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.

## 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: $r_t^{Monthly} = \prod_{t \in T}(1 + r_t^{Daily}) - 1$. 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:

$$H_n = \left\{ \left( W_t' \otimes I_T \right) X_{i,t-1} \right\}_{t \in T}$$

which allows the estimation of the following parameters

$$\widehat{\theta} = \begin{bmatrix} \widehat{\rho} \\ \widehat{\beta} \end{bmatrix} = \left[ Z'QH_n \left( H_n'QH_n \right)^{-1} H_n'QZ \right]^{-1} Z'QH_n \left( H_n'QH_n \right)^{-1} H_n'Qy,$$

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,

$$Q = \left( I_N - N^{-1} J_N \right) \otimes \left( I_T - T^{-1} J_T \right),$$

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

$$se(\widehat{\theta}) = \widehat{\sigma}^2 \left[ Z'QH_n \left( H_n'QH_n \right)^{-1} H_n'QZ \right]^{-1}$$

with

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

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.

$$y_t = \rho_1 W_t^I y_t + \rho_2 W_t^I * \text{Geog} * y_t + X_{t-1}\beta_i + \boldsymbol{\mu} + \gamma_t + v_t \tag{7}$$

▶ 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.

$$y_t = \rho_1 W_t^I y_t + \rho_2 W_t^I * \text{Geog} * \text{Industry} * y_t + X_{t-1}\beta_i + \boldsymbol{\mu} + \gamma_t + v_t \tag{8}$$

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