Is Hard and Soft Information Substitutable? Evidence from Lockdown

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Social Isolation during Lockdown



Lockdown made it difficult for social interaction

- Lockdown has changed the way people collect, process, and transmit information. It's much harder to gather soft information, and people try to switch to hard information and the virtual world.
- Is soft information tied to human physical contacts or virtual meetings suffice to produce it?
- Can soft information be quickly replaced by hard information or do the two types require different technologies that cannot be easily adapted?

Hard and Soft Information

Information comes to the financial markets in two ways: hard and soft (Stein, 2002; Petersen, 2004; Liberti and Petersen, 2019).

Soft information

- Example: talking to local firms' managers and employees, informal meetings at bars, cafes, golf course, fitness center etc.
- Feature: qualitative, nonverifiable, unobservable, private

Hard information

- Example: balance sheet data, credit scores,
- Feature: quantitative, verifiable, codifiable, often public
- Soft or hard? Not always clear definition and no precise boundary.

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- In this paper, we define:

Soft information = human-interaction-based information

We study information substitutability by testing the impact of lockdown on proximity investment

Geographic proximity has been argued to facilitate information production and to provide local information advantages.

Coval and Moskowitz (1999, 2001), Gaspar and Massa (2007), Hong, Korniotis and Kumar (2012), Jagannathan, Jiao, and Karolyi (2018), Sulaeman (2014), etc.

- mutual fund managers invest more in companies located closer to their funds and this strategy helps deliver better performance
- Similar results have been found for hedge fund managers

The source of local information advantages however is still not clear.

- Explan 1 proximity facilitates collecting "soft" information
- Explan 2 proximity relates to a better understanding of the local economy and hence the economic perspectives of local firms
- Explan 3 proximity is related to behavioral bias such as familiarity, trust, etc.

Hypotheses

The soft-soft substitutability hypothesis: proximity investment is related to the ability to collect and to understand human-interaction-based soft information in either form, physical or virtual.

• Lockdown induces a shift from physical social interaction to virtual interaction. This will not affect the degree of proximity investment and the relative information advantages.

The soft-hard substitutability hypothesis: proximity investment is primarily based on physical-interaction-based information advantages, which cannot be fully substituted by virtual interactions in lockdown.

• Lockdown hampers information advantages based on human interactions but does not affect the ability to gather and process non-interaction-based hard information. This will increase the relative benefits of distant investing and push fund managers to rebalance portfolios toward distant stocks.

The local information hypothesis: proximity investment is related to non-interaction-based local information such as a better understanding of the local economy and the economic perspectives of local firms.

• Lockdown should not increase the relative benefits of distant investing with respect to local investing.

In this paper

- We exploit a randomized experiment, the pandemic-triggered lockdown that exogenously restrain human interactions
 - address the reflection problem (Manski, 1993,1995)
- We employ the DID method for a short window Jan2019-Jun2020, and utilize the rich cross-sectional variations in lockdown to study the impact of lockdown on proximity investment:

Takeaway:

- $\Rightarrow\,$ It is human interactions that matter, not a general local story.
- ⇒ Either non-interaction-based info or virtual interactions cannot substitute human-interaction-based soft info.

Mutual Fund Data

Sample: U.S. actively-managed open-end equity mutual funds Sample period: January 2019 - June 2020

Source 1: CRSP mutual fund survivor-bias-free dataset

- fund holding data
- fund return, monthly and daily
- fund characteristics

Source 2: MorningStar mutual fund data

- fund management firm's zip code
- fund benchmark index

Source 3: Compustat

- firm's zip code
- firm characteristics (size, bm, lev, roa)

Source 4: IBES analyst data

The Pandemic Lockdown Information

- Type 1: executive order of lockdown Lockdown_{mt} = 1, if fund-located zip-code is in lockdown in month t.
 - 33 states enforced lockdowns in March 2019
 - another 12 states joined the list in April 2019
 - 6 states never issue lockdown orders (Iowa, Arkansas, North Dakota, South Dakota, Wyoming, Nebraska)
- Type 2: real business activity contraction proxied by footprint $Footprint_{mt} = 1$, if fund-located zip code encounters 30% cut in footprint activities in month t compared to those in March 2019.
 - SafeGraph provides foot traffic patterns to 3.6 million commercial points-of-interest from over 45 million mobile devices.
 - The sample is well balanced across USA demographics and geographies, covering roughly 10% of the US population.
 - It describes the number of visits people go to certain places.

Contraction of footprint activities



The aggregate footprint activities across zip codes

Contraction of footprint activities

The histogram of the percentage change of footprint activities



The Evolution of Fund Holding Distance



$$AD_{mt} = \sum_{i} (Weight_{imt}^{Fund} - Weight_{imt}^{Index}) * D_{imt}$$

where D_{im} is the spherical distance between the zip codes of fund *m* and stock *i* $D_{im} = \arccos\{\cos(lat_m)\cos(lat_i)\cos(lon_m - lon_i) + \sin(lat_m)\sin(lat_i)\}R.$

The Impact of Lockdown on Fund Holding Weight

Excess Weight_{imt} = $\alpha + \beta * Lockdown_{mt} + \gamma * D_{im} \times Lockdown_{mt} + Control_{it-1} + \alpha^{FE} + \varepsilon_{imt}$

| Lockdown | -0.0031 | -0.0027 | -0.0029 | -0.0026 |
|---------------------|---------------------|-----------|-----------------------|-----------|
| | (-0.48) | (-0.43) | (-0.46) | (-0.41) |
| D×Lockdown | 0.0064*** | 0.0060** | 0.0052** | 0.0049** |
| | (2.58) | (2.45) | (2.11) | (1.99) |
| Firm Lockdown | () | 0.0294*** | () | 0.0253*** |
| | | (8.12) | | (7.15) |
| Firm RET | | () | 0.0016*** | 0.0016*** |
| | | | (14.78) | (14.69) |
| Firm SIZE | | | 0.0192*** | 0.0194*** |
| | | | (3.44) | (3.47) |
| Firm ROA | | | 0.1348 ^{***} | 0.Ì337*** |
| | | | (7.41) | (7.37) |
| control for fund FI | E, firm FE, time FE | | () | () |
| Obs | 1893661 | 1851887 | 1872119 | 1831606 |
| Adj R ² | 0.570 | 0.572 | 0.570 | 0.572 |
| ., | | | | |

\Rightarrow Fund managers increase investment in distant stocks

Economically, if a stock's issue firm is 100 miles closer to the holding fund than average, funds will reduce the portfolio weight (excess weight) on this stock by 0.18% (0.06%) during lockdown.

What firms do funds in-/de-crease investment in lockdown?



Newly-invested firms are 12.87% farther than divested firms from holding funds

Firms with increasing investment are 24.06% farther than firms with decreasing one Funds in other portfolios ($AD_{-2}, ..., AD_{-5}$) also increase investment in distant stocks, though not as much as funds that used to invest locally (AD_{-1}).

Reliance on Public Information (RPI)

Calculate RPI in spirit of Kacperczyk and Seru (JF, 2007), then check the change of RPI for funds sorted by their pre-lockdown AD.

| A. Fund investing locally (AD_{-1}) | Funds | Mean | STD | 95% Conf | Interval |
|---|------------|--|------------------|------------------|------------------|
| RPI as of March 2020 RPI as of March 2019 Difference (2020-2019) <i>t</i> -statistics <i>p</i> -value (H0:Diff=0, H1:Diff> 0) | 253 253 | 0.0245 0.0182 0.0063 1.7723 0.0388 | 0.0028 0.0023 | 0.0191 0.0137 | 0.0300 0.0228 |
| B. Fund investing far away (AD_5) | Funds | Mean | STD | 95% Conf | Interval |
| RPI as of March 2020 RPI as of March 2019 Difference (2020-2019) <i>t</i> -statistics <i>p</i> -value (H0:Diff=0, H1:Diff>0) | 239 239 | 0.0305 0.0267 0.0038 0.5765 0.2824 | 0.0044 0.0052 | 0.0220 0.0166 | 0.0392 0.0369 |

- Funds investing locally see a significant increase in RPI during lockdown
- Funds investing far away also see an increase of RPI but not significant.

Implications on Fund Performance

 $\textit{Ret}_{\textit{mt}} = \alpha + \beta * \textit{Lockdown}_{\textit{mt}} + \gamma * \textit{AD}_{\textit{m}}^{\textit{Mar2019}} \times \textit{Lockdown}_{\textit{mt}} + \textit{Z}_{\textit{m}} + \textit{Z}_{\textit{t}} + \varepsilon_{\textit{mt}}$

| | (1) Fund Ret | (2) Excess Ret | | (3) Fund Ret | (4) Excess Ret |
|---------------------|-----------------|-------------------|--------------------|-----------------|-------------------|
| | | Excess Ret | - | | Excess fiel |
| Lockdown | -0.2781 | -0.0925 | Footprint | -2.6229*** | -1.1899*** |
| | (-0.44) | (-0.19) | | (-5.86) | (-3.58) |
| $AD{	imes}Lockdown$ | 0.0016*** | 0.0006*** | AD×Footprint | 0.0020*** | 0.0009*** |
| | (4.25) | (2.60) | | (4.97) | (3.43) |
| Fund Dummy | Y | Y | Fund Dummy | Y | Y |
| Time Dummy | Y | Y | Time Dummy | Y | Y |
| Cluster (FF) | Y | Y | Cluster (FF) | Y | Y |
| Obs | 14897 | 14885 | Obs | 15949 | 15935 |
| Adj R ² | 0.886 | 0.112 | Adj R ² | 0.885 | 0.105 |

 \Rightarrow 1- σ increase in the pre-pandemic average fund holding distance helps elevate fund raw (excess) return by 0.94% (0.42%) during lockdown.

α and $\beta {\rm s}$ before and during Lockdown

Step 1: calculate $\{\alpha_{mt}, \beta_{mt}\}$ using daily fund returns for fund-*m* in month *t* Step 2: $\alpha_{mt} = a + b * Footprint_{mt} + \gamma * AD_m^{Mar2019} \times Footprint_{mt} + FE + \varepsilon_{mt}$

| | α | β^{MktRF} | β^{SMB} | β^{HML} | β^{RMW} | β^{CMA} |
|--------------------|-----------|-----------------|-------------------------|---------------|---------------|-------------------------|
| Footprint | -6.389*** | 1.992 | 2.947 | 1.179 | -4.578* | 6.910* |
| | (-4.43) | (1.33) | (1.53) | (0.57) | (-1.69) | (1.60) |
| AD×Footprint | 0.005*** | -0.002 | -0.003* [*] ** | 0.001 | 0.002 | -0.010* [*] ** |
| | (4.31) | (-1.38) | (-2.16) | (0.65) | (0.88) | (-3.40) |
| Fund Dummy | Ύ | Ύ | Ύ | ŶΎ | ŶÝ | ŶÝ |
| Time Dummy | Y | Y | Y | Y | Y | Y |
| Cluster (Fund) | Y | Y | Y | Y | Y | Y |
| Obs | 15550 | 15550 | 15550 | 15550 | 15550 | 15550 |
| Adj R ² | 0.092 | 0.514 | 0.818 | 0.679 | 0.250 | 0.395 |
| | Fund | s investing | locally (AD_1) |) Funds | investing fa | ar away(AD_5) |
| | 0010 | | | - | | o == |

| Alpha in March 2019 | 1.47 | -0.57 |
|---------------------|-------|-------|
| Alpha in March 2020 | -3.08 | 0.18 |
| Difference | 4.55 | -0.75 |
| t-statistics | 4.03 | -0.87 |
| <i>p</i> -value | 0.00 | 0.39 |

The Local (non-interaction-based) Information Hypothesis

 H_1 : Proximity investment is related to non-integration-based local information such as a better understanding of the local economy and the economic perspectives of local firms.

Research design: redo the experiment for paired funds which are

- adjacent in geography (local)
- being affected differently by lockdown (diff social interaction)



Can you spot the county divide? Duval county vs St John's county, Florida

Performance for Paired Funds

| | | J | , | 01 | |
|--------------------|--------------------|-------------------|--------------------|-----------------------|----------------------|
| | (1) Fund Ret | (2) Excess Ret | | (3) Fund Ret | (4) Excess Ret |
| Lockdown | -1.4647 (-1.64) | 0.8443 (1.28) | Footprint | -3.1718*** (-5.26) | -0.9957** (-2.21) |
| AD×Lockdown | 0.0029*** | 0.0007** | AD×Footprint | 0.0027*** | 0.0008*** |
| | (8.27) | (2.49) | | (6.80) | (2.66) |
| Suffer Dummy | -0.0138 | -0.0173 | Suffer Dummy | -0.0040 | -0.0091 |
| | (-0.81) | (-1.29) | | (-0.23) | (-0.71) |
| Fund Dummy | Y | Y | Fund Dummy | Y | Y |
| Time Dummy | Y | Y | Time Dummy | Y | Y |
| Cluster (Fund) | Y | Y | Cluster (Fund) | Y | Y |
| Obs | 771255 | 770462 | Obs | 771255 | 770462 |
| Adj R ² | 0.900 | 0.212 | Adj R ² | 0.898 | 0.205 |

Panel A. Paired funds with adjacency< 100miles and activity gap> 20%

 \Rightarrow Results remain the same, rejecting the non-interaction-based local information hypothesis.

Performance for Paired Funds

| | , , , , , , , , , , , , , , , , , , , | | | | | |
|----------------------------------|--|-------------------------------|----------------------------------|----------------------|-----------------------|--|
| | (1) Fund Ret | (2) Excess Ret | | (3) Fund Ret | (4) Excess Ret | |
| Lockdown | -0.7351 (-0.47) | -0.3173 (-0.34) | Footprint | -2.9034** (-2.11) | -2.9882*** (-3.81) | |
| AD×Lockdown | 0.0011 [*] (1.75) | 0.0006 [*] (1.69) | $AD{\times}Footprint$ | 0.0012* (1.79) | 0.0011*** (2.71) | |
| Suffer Dummy | -0.0092 (-0.05) | -0.0500 (-0.41) | Suffer Dummy | -0.0081 (-0.04) | -0.0535 (-0.44) | |
| Fund Dummy | Ύ | Ύ | Fund Dummy | Ύ | Ύ | |
| Time Dummy | Y | Y | Time Dummy | Y | Y | |
| Cluster (Fund) | Y | Y | Cluster (Fund) | Y | Y | |
| Obs Adj <i>R</i> ² | 82841 0.901 | 82826 0.240 | Obs Adj <i>R</i> ² | 82841 0.902 | 82826 0.256 | |

Panel B. Paired funds with adjacency< 20miles and activity gap> 20\%

 \Rightarrow Results remain the same, rejecting the non-interaction-based local information hypothesis.

Where does soft information come from?

Design A: repeat the analysis by checking diff. types of footprint activities

 $\textit{ExRet}_{\textit{mt}} = \alpha + \beta * \textit{Activity}_{\textit{kmt}}^{\textit{channel}} + \gamma * \textit{AD}_{\textit{m}}^{\textit{Mar2019}} \times \textit{Activity}_{\textit{kmt}}^{\textit{channel}} + \textit{Z}_{\textit{m}} + \textit{Z}_{t} + \varepsilon_{\textit{mt}}$

where $Activity_{kmt}^{channel} = -\log(\text{Footprint Activity in Channel } k)$.

- Channels we test include all business defined by the first 2-digit NAICS codes, and a refined category by the 4-/5-digit NAICS codes.
- Our findings favor a "human channel", reduction of interactions in cafe, restaurants, drinking places, fitness center, and bookstore have the most salient impact on fund performance during lockdown.

Where does soft information come from?

Design B: repeat the analysis for subsamples when funds are divided by characteristics that may affect social interaction

- The impact of lockdown on fund performance is more salient for funds using sub-advisors a less centralized managing structure relies more on soft information.
- The impact of lockdown on fund performance is less salient for funds managed by fewer managers (≤ 2) – a smaller management team is less likely to collect soft information.

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Nothing can replace "human touch"!

The virtual world based on Zoom/Skype/Team will cannot fully substitute physical interactions to collect and transmit soft information. It takes time to adapt to the virtual world, thus fund managers temporarily first refer to hard information.





International

Feb 18th 2021 edition >

You've lost that lovin' feeling

The pandemic made the world realise the importance of human contact

Touch is the only sense crucial to humans' survival



- According to National Academy of Sciences, social isolation has been linked to a 50% increased risk of dementia, a 29% increased risk of heart disease and a 32% increased risk of stroke.
- Well, social isolation is also linked to less soft information processed or transmitted, and hence increased risk for strategies relying on soft information such as proximity investment.

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- Well, social isolation is also linked to less soft information processed or transmitted, and hence increased risk for strategies relying on soft information such as proximity investment.
- We can do little to promote soft information transmission in COVID

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- But we can at least do one thing to reduce the risk of physical and emotional harm from inadequate social contact
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Now and here. Thank you for attending today's talk!

- Well, social isolation is also linked to less soft information processed or transmitted, and hence increased risk for strategies relying on soft information such as proximity investment.
- We can do little to promote soft information transmission in COVID

THANK YOU!

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