Firm-level Exposures and Stock Returns in the Wake of COVID-19

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November 11, 2020

Introduction

COVID-19 has generated an enormous global shock to economic activity.

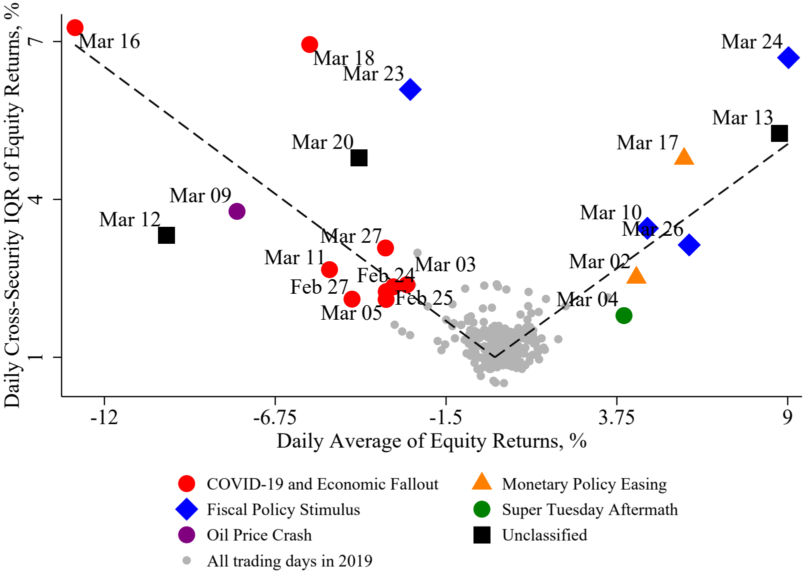
Underneath its aggregate effects lies large heterogeneity, e.g. airline companies vs FAANGs.

This suggests that COVID-19 will drive resource reallocation.

Likely that reallocation will occur at level of firms within industries:

1. Historical evidence (Davis and Haltiwanger 1992)
2. Current surveys (Barrero et. al. 2020)

IQR of Firm-Level Equity Returns on Jump Dates



10-K Risk Factors Discussion

To explain firm-level returns, we use the *Risk Factors* discussion of 10-K regulatory filings.

These texts discuss factors that generate uncertainty in future earnings; exhaustive due to their legal status.

RF corpus for 2,133 companies for the 2010-2016 time period.

Key idea: RF content that explains abnormal returns on jump dates reveals channels through which future earnings react to macro shock.

How to Measure Content of Text Data?

Key empirical challenge is how to extract information from the RF corpus ($>$18K unique terms).

A traditional approach in text mining in economics and finance is dictionary methods. We adopt dictionaries from Baker et. al. (2019).

A newer approach is supervised learning. We use multinomial inverse regression model (Taddy 2013, 2015).

We adopt both methods for analysis:

1. Comparative evaluation in an important concrete setting.
2. Show how elements of *both* approaches can yield good performance in explanatory power and interpretability.

Returns Regressions

Throughout the paper we fit models of the form

$$\mathrm{Abn}_{it} = \sum_{j=1}^{J} \beta_j \,\mathrm{RExp}_i^j + \beta_{J+1}\,\mathrm{Leverage}_i + \beta_{J+2}\,\log(\mathrm{Mcap}_{it}) + \gamma_{s(i)} + \epsilon_{it},$$

- Abn_{it} is the abnormal return of firm i on jump date t (or collection of dates).
- $\mathrm{Leverage}_i$ is leverage.
- Mcap_{it} is market capitalization.
- $\gamma_{s(i)}$ are NAICS2 sector effects.
- RExp_i^j is a text-based measure of the risk exposure(s) of firm i.

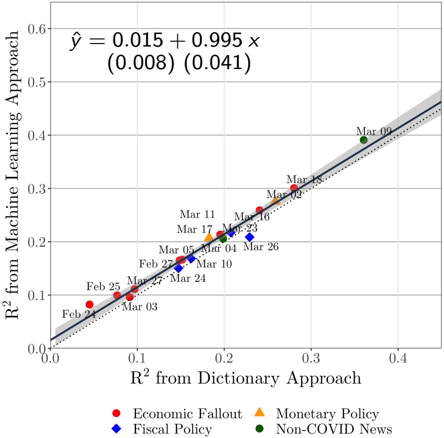
Fitted Returns Model

Jump Classification ⟶ Dependent Variable: Abn_{it}	(1) COVID-19 and Its Fallout		(4) Super Tuesday Election	
Financial Controls				
Log Market Cap	0·53	(7·3)	0·66	(4·8)
Leverage	−0·42	(−3·0)	−0·12	(−0·8)
Observations [Adjusted R^2]	2155	[0.329]	2155	[0.199]

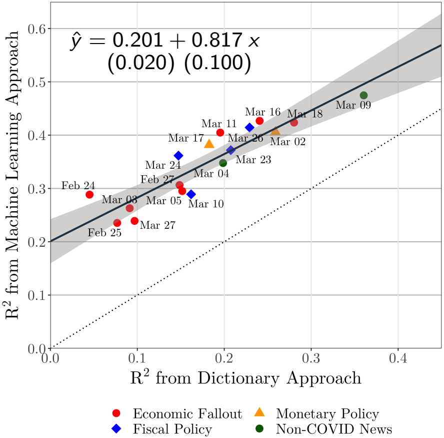
Significant exposures for pandemic fallout include *intellectual property matters*, *healthcare policy*, *taxes*, and *entitlement and welfare programs*.

Significant exposures for Super Tuesday include *real estate markets*; *commodity markets*; and *financial regulation*.

Adjusted R^2 with Different Term Sets

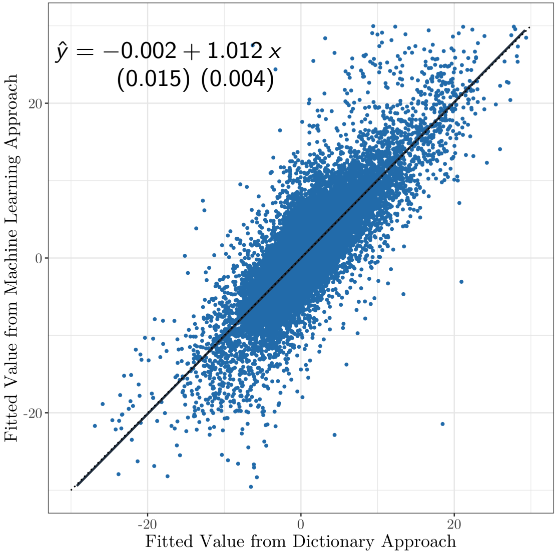


(a) Restricted Feature Space in MNIR

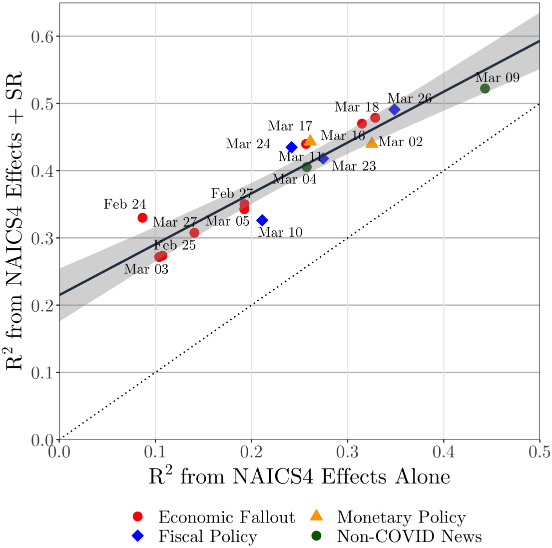


(b) Full Feature Space in MNIR

Predicted Returns from Both Methods



NAICS4 in Forward Regression



Interpreting the Additional Information Content

The results above suggest that MNIR refines the information extracted from dictionaries, but says nothing about why.

There are thousands of estimated coefficients to organize and interpret.

We address this challenge for pandemic fallout days (also Super Tuesday).

Some suggestive evidence comes from terms with high loadings:

1. wheat, ecommerce, games, alcohol, clinical trials
2. oil, restaurants, hotels, airline industry.

Exposures to large companies also predicts returns:

1. Intel, Salesforce
2. Boeing, Phillips

Firms with Large Residual Shrinkage

NETFLIX: World's leading internet television network with streaming memberships in over 190 countries.

Influential terms: dvd; streaming; subscribers; titles; studios.

NOVAVAX: Late-stage biotechnology company focused on the discovery, development and commercialization of vaccines to prevent serious infectious diseases.

Influential terms: vaccine; influenza; clinical trials; candidates; collaborators.

PLAINS ALL AMER PIPELNE: Provider of midstream energy infrastructure and logistics services for crude oil, natural gas liquids, natural gas and refined products.

Influential terms: crude; ngl; barrels per day; pipeline; pipelines.

Algorithm for Constructing Targeted Risk Factors

Begin with a set of *seed words* that we choose to build targeted exposures around (45 in total).

Associate to each seed word all terms in the RF corpus that:

1. Have an MNIR coefficient with same sign and sufficiently high absolute value.
2. Lie sufficiently close in the embedding space.

In case same term assigned to multiple seeds, assign to seed with highest semantic similarity.

Manually remove terms that have ambiguous meaning.

Examples for Pandemic Fallout Days

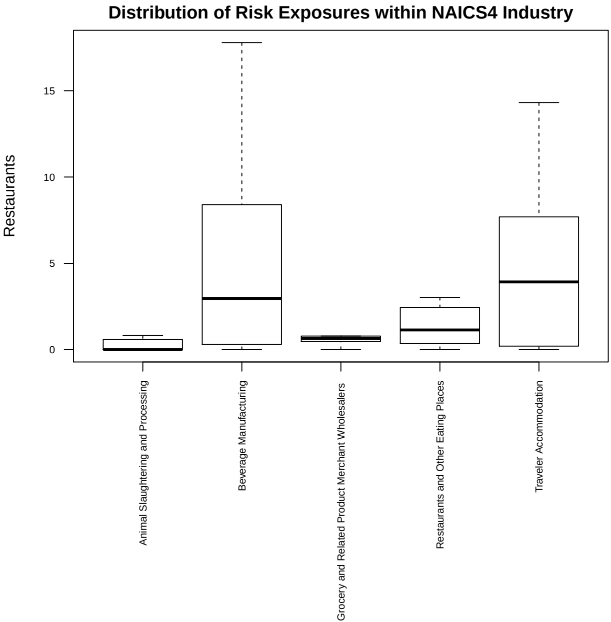
Raw Metals and Minerals: {tantalum*, **tin**, tungsten, conflict minerals, democratic republic of congo, minerals, ~~adjoining countries~~, **zinc**, precious metals, such minerals, oxide, **platinum**, ~~requirements for companies~~, ~~sheet~~}

Web-Based Services: {cloud*, saas, cloud computing, web, hosted, server, internet, premise, ~~ip~~, ~~desktop~~, virtual, data center, networking, messaging, browser, mobility, wireless networks, hosting, subscription, network security, wireless, telephony, data centers, centric, bandwidth}

Gambling: {gaming*, casino, slot, horse, native}

Oil and Gas: {**oil***, ngls, ngl, oils, liquids, **natural gas**, **petroleum**, hydrocarbon, hydrocarbons, marcellus shale, exploration}

Distribution of Risk Across Sectors



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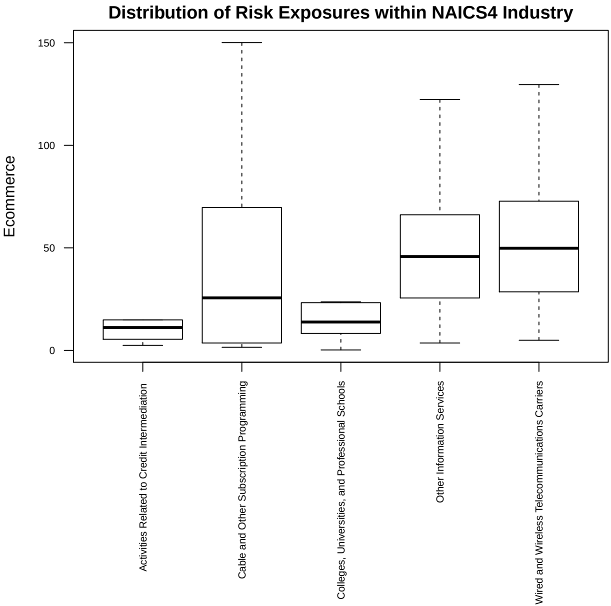

Returns Regressions with Targeted Factors

Adjusted R^2	Pandemic Fallout Days	Super Tuesday
Baseline	0.329	0.199
Targeted Factors	0.41	0.242
Full SR	0.501	0.349

Interpreting Pandemic Fallout

Negative Factors	Positive Factors
Retail Card Payments	Ecommerce
Restaurants	Foodstuffs
Gambling Travel	Video Games
Oil and Gas	Raw Metals and Minerals Electronic Components Web-based Services
Mortgages	Deposits/Banking Investment Management

Interpreting Super Tuesday

Negative Factors	Positive Factors
Fracking Power Generation	Health Insurance Drugs Govt Healthcare
Hotels	REIT Rental Market Waste
Financial Contracting Financial Regulation Investment Management	

Conclusion

10-Ks provide a rich source of information for analyzing the firm-level impacts of aggregate shocks.

The main empirical challenge is to extract information that explains reactions well while also remaining interpretable.

We show how supervised learning combined with human judgment can achieve these twin goals.

General purpose technology: can be used for other macro shocks, and other firm-level outcomes.