What Drives the Stock Market Rally Amid COVID-19?

A Learning-Based Explanation

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Background

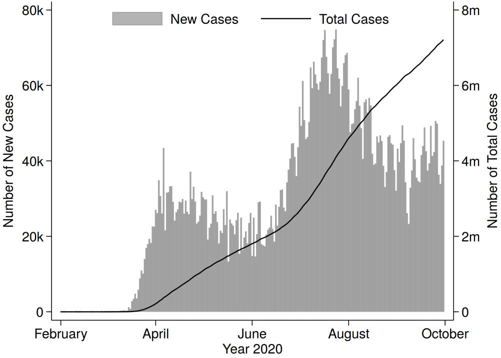
- **COVID-19 pandemic**: a *public health* & *economic* crisis of unprecedented severity
  - From late January through September, number of cases: $1 \nearrow 7\text{m}+$ (deaths $> 200\text{k}$).
  - Nearly 22.2 million jobs were lost; GDP shrank 9.5% in the second quarter of 2020.

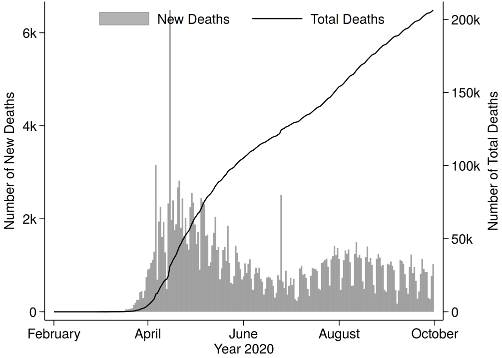
- The behavior of U.S. stock markets during this period is extraordinary:
  - A sharp slump: by late March, S&P 500 plunged $1,200+$ points (that is, $\approx -32\%$).
  - A quick rally: by the end of August, it wiped out all losses, even hitting new highs.

- The market rally since March is widely considered *puzzling*.
  - Pandemic: worsening; both the daily and total cases (deaths) were still on the rise.
  - Economic damages: persist; even by Aug., only half of the lost jobs were regained.

- Q: What is driving the stock market rally during the COVID-19 pandemic?

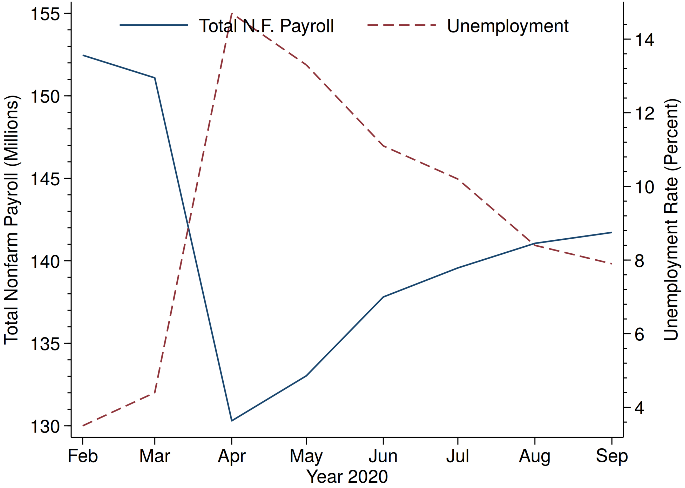
Number of COVID-19 Cases/Deaths





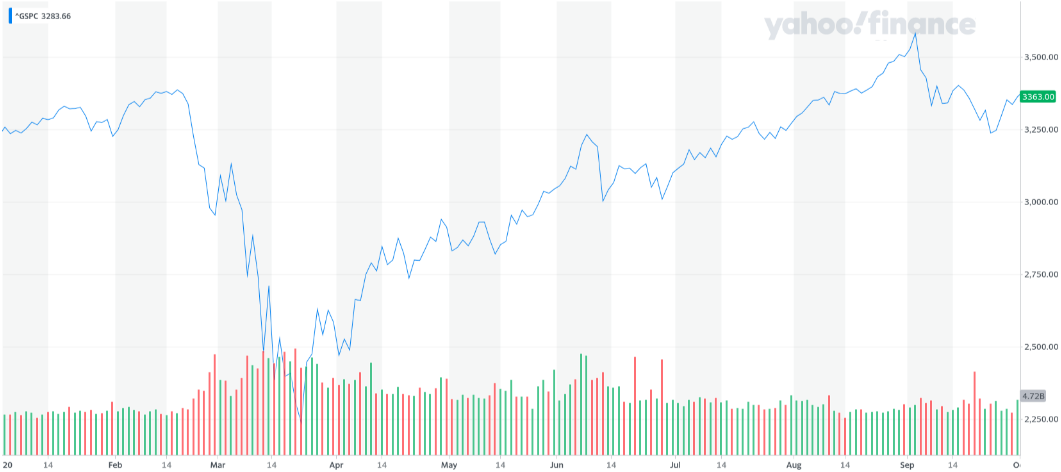
Source: [CDC COVID Data Tracker]

Employment Amid COVID-19



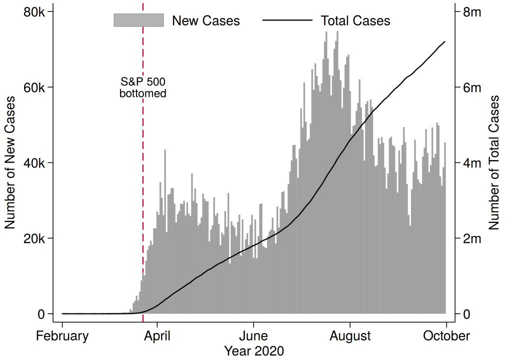
Source: [Bureau of Labor Statistics]

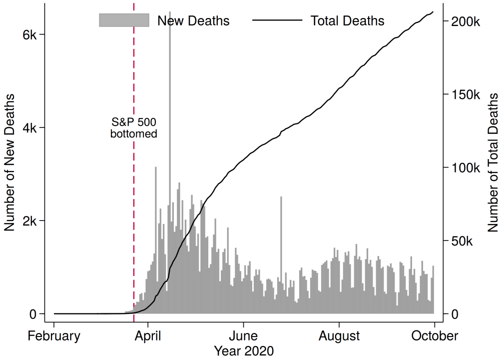
S&P 500 Index



Source: [Yahoo Finance]

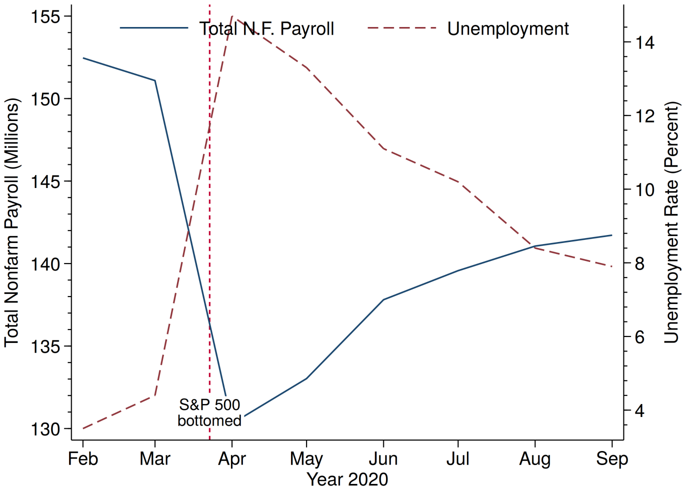
Number of COVID-19 Cases/Deaths





Source: [CDC COVID Data Tracker]

Employment Amid COVID-19



Source: [Bureau of Labor Statistics]()

The Economist: Stockmarket v economy: the impact of COVID-19

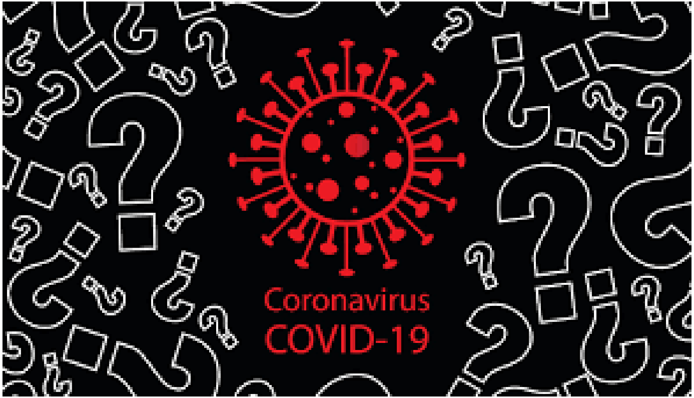
This Paper ...

We explore a learning-based explanation:

- As a novel virus, COVID-19 has uncertain/unknown epidemiological properties.
  - How (easily) does it spread?
  - How effective are the "lockdown-style" measures?
  - When will a cure (i.e. treatment/vaccine) be available?
  - ... ?

- Also, the economic impact of COVID-19 is up in the air.
  - Direct impact: covid-related illness & deaths; social distancing/lockdown (SDL)
  - The effectiveness of the (unconventional) monetary and fiscal policy responses
    - FFR & Repo & D.W. $\longrightarrow$ Quantitative Easing $\longrightarrow$ Emergency Lending Facilities
    - CARES Act (reliefs to hospitals, businesses, individuals): PPP, "stimulus checks", ...

This Paper ...



Our story:
Agents learn about these epidemiological & economic parameters by observing data, and then make/update their predictions accordingly.

Realizations > Expectations

So Far ...

- We first focus on the learning about the epidemiological parameters.
  - Contagiousness of the virus
  - Effectiveness of SDL policies

Specifically, we

- ... develop an SIRD model that incorporates learning about the *viral transmission*.
  - Examining the spread of COVID-19 through the lens of the model, we find:
    - Early beliefs about the viral contagiousness (SDL effectiveness) are too high (low).
    - Later the relaxation of SDL didn't lead to case-spikes that are as large as expected.
- ... embed the model in a production economy to study the impact on asset prices.
  - The positive "surprises" can generate a market rally similar to what we observed.

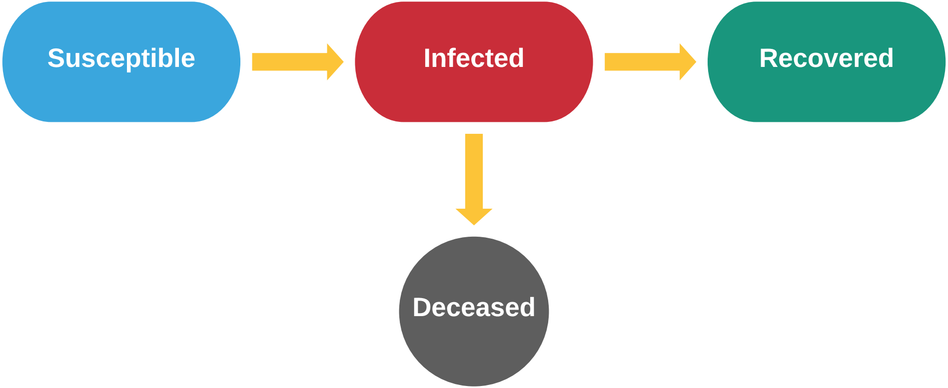
Related Literature

- Asset Markets and COVID-19
  - Cox, Greenwald, and Ludvigson (2020); Caballero and Simsek (2020)
  - Welch (2020); Hong, Wang, and Yang (2020)
  - Acharya, Johnson, Sundaresan, and Zheng (2020)
- Learning in Financial Markets
  - See a survey by Pastor and Veronesi (2009)
  - Many "puzzling" FM phenomena can be explained by param. uncertainty & learning.

Epidemic Modeling

Epidemiological Modeling of A Novel Contagious Disease

- SIRD model: Population = **S**usceptible + **I**nfected + **R**ecovered + **D**eceased
  - The transition rates between compartments determine the course of an epidemic.



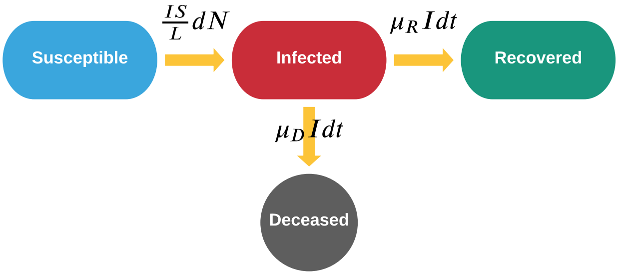
Why SIRD? Some Background on Epidemiological Models

- **Compartmental models**: a workhorse in the modeling of infectious diseases
  - In these models, the population is divided into *labeled* compartments.
    - e.g. S (susceptible), I (infected), R (recovered), etc.
  - People may progress from one compartment to the next (e.g. S $\rightarrow$ I $\rightarrow$ R).
    - Labels are used as model names; their order indicates the direction of progression.
  - This class of models are widely used to
    1) make predictions about the development of an epidemic.
    2) estimate various epidemiological parameters and measures.
    3) examine the impact of alternative public policies/interventions.
  - Origin: Kermack, McKendrick, and Walker (1927)
  - Widely referred to as **SIR models** (SIR is the most basic one, with many variations)

- The SIRD model adopted in this paper is one of the simplest variations.
  - Suitable for modeling COVID-19 (reinfection risk seems low; no data on asymptomatic)

Epidemiological Modeling of A Novel Contagious Disease

- SIRD model: Population = **S**usceptible + **I**nfected + **R**ecovered + **D**eceased
  - The dynamics of an epidemic is characterized by a system of differential equations.



$$dS = -\frac{IS}{L}dN$$

$$dI = \frac{IS}{L}dN - (\mu_D + \mu_R)Idt$$

$$dR = \mu_R Idt$$

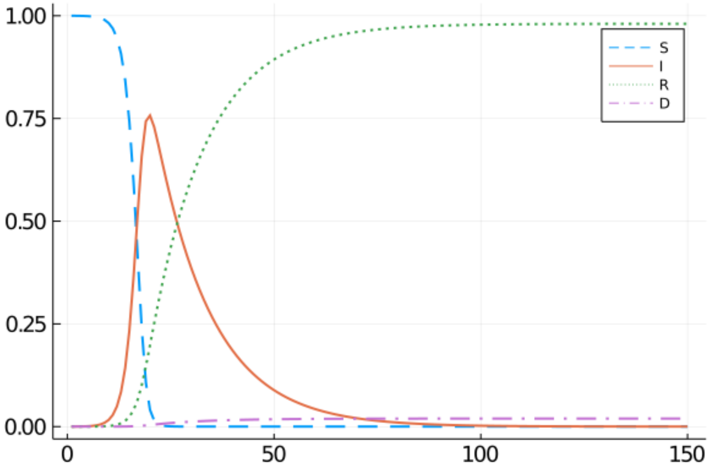
$$dD = \mu_D Idt$$

$$\text{where } L \equiv S + I + R$$

- The viral transmission ($S \to I$) is modeled as a Poisson process with **intensity $\boldsymbol{\lambda_t}$**.
  - Infected individuals (I) bump into others at Poisson rate λ_t, of which $\frac{S}{L}$ are susceptible.

Epidemiological Modeling of A Novel Contagious Disease

- $\boldsymbol{\lambda_t}$: (effective) contact rate; important in determining the prognosis. GIF



- λ_t is unobservable and can be affected by social distancing/lockdown.

Learning About λ_t

- We specify λ_t as

$$\lambda_t = \mathrm{e}^{\rho_0 + \rho_1 \theta_t}$$

  - $\theta_t \in [0, \infty)$ measures the strictness of SDL
  - ρ_0—without SDL; ρ_1—sensitivity to SDL (< 0)
  - Other potential drivers? e.g. mask-wearing

- Agents learn about $\{\rho_0, \rho_1\}$ by observing the changes in
  - infections (I)
  - SDL strictness (θ)

  ... and update their beliefs according to

$$d\hat{\rho}_t = \Sigma_t \; V_t \; (dN_t - \lambda(\hat{\rho}_t)dt)$$

$$d\Sigma_t = -\Sigma_t \; V_t V_t' \Sigma_t \; \lambda(\hat{\rho}_t)dt$$

Learning About λ_t

- We assume that agents update their beliefs via standard Bayesian learning.
  - Non-Gaussian & nonlinear filtering problems $\Longrightarrow$ infinite-dimensional solutions.
- Luckily, Snyder (1972) provides a quasi-optimal low-dimensional filter.
  - It approximates the infinite-dimensional solution that solves the exact problem.
- Nevertheless, the intuition is the same:

$$\underbrace{dI + (\mu_D + \mu_R) I dt}_{Y_t} = \underbrace{\frac{IS}{L}\lambda(\theta_t; \hat{\rho}) dt}_{f(\theta_t;\hat{\rho})} + \underbrace{\frac{IS}{L}(dN - \lambda_t dt)}_{\epsilon_t}$$

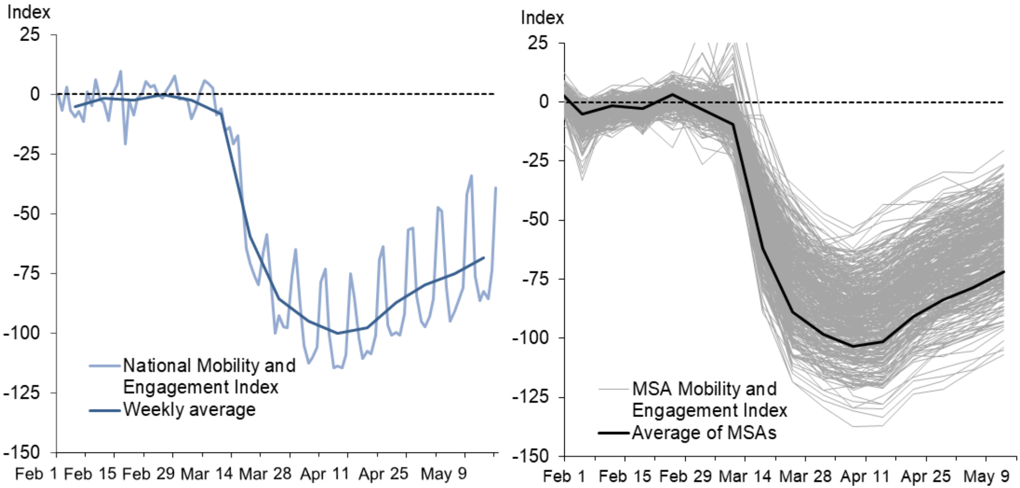
Empirics

- To apply the model to COVID-19, we need two variables:
  - Measure of social distancing
  - Percent of infected population

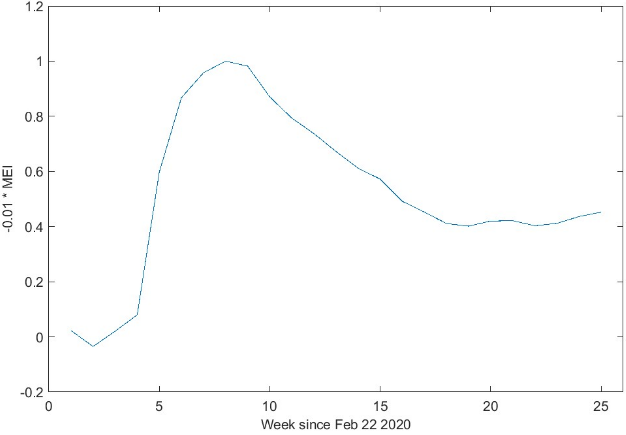
- SDL strictness: Dallas Fed Mobility and Engagement Index (MEI)
  - *SafeGraph*: collected data on a range of spatial behaviors of mobile devices
  - Seven different variables combined via PCA; daily, county-level, de-trend

- Infected population (%): Johns Hopkins data
  - Robustness: impute the number of infections from observed deaths

Chart 1
Mobility and Engagement Bottoms in Late March, Rebounds in Late April



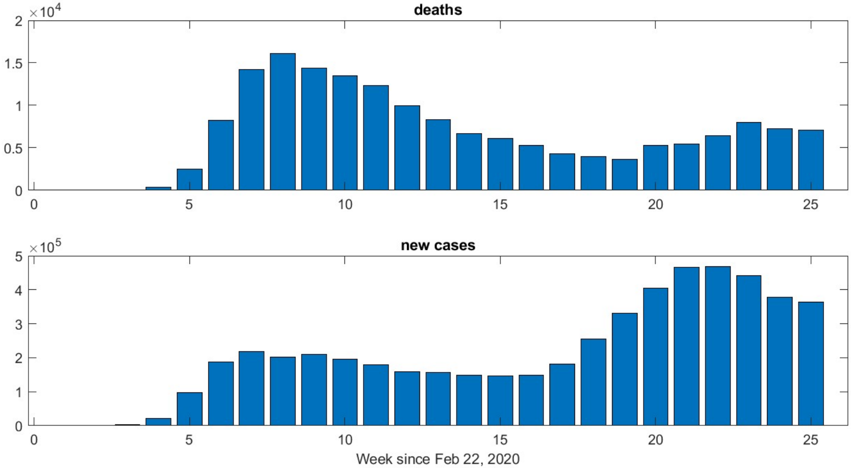
NOTE: MSA is metropolitan statistical area.
SOURCES: SafeGraph; Federal Reserve Bank of Dallas.



The strictness of SDL

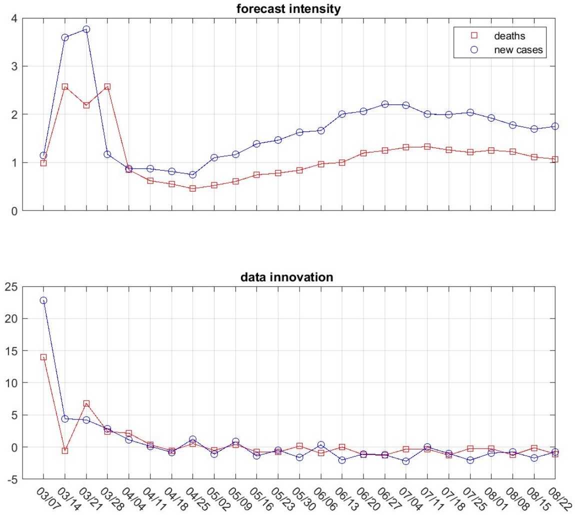
$\propto$

\- Mobility & Engagement



deaths
$\times 10^4$
2
1.5
1
0.5
0
0
5
10
15
20
25
new cases
$\times 10^5$
5
4
3
2
1
0
0
5
10
15
20
25
Week since Feb 22, 2020

Innovations in COVID-19 Infections



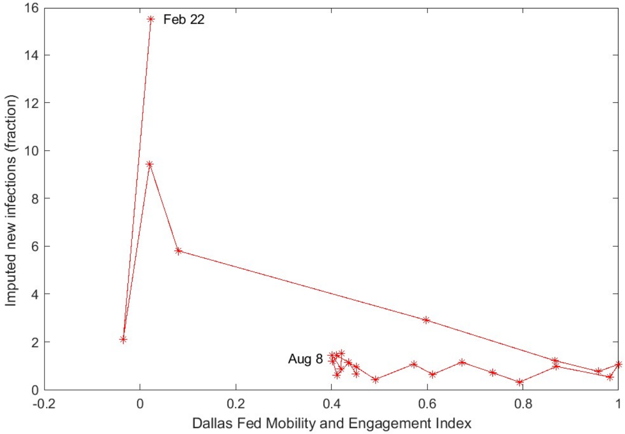
- Upper panel:

  Infection intensity $\hat{\lambda}_t dt$

- Lower panel:

  Innovations $dN - \hat{\lambda}_t dt$

Innovations in COVID-19 Infections



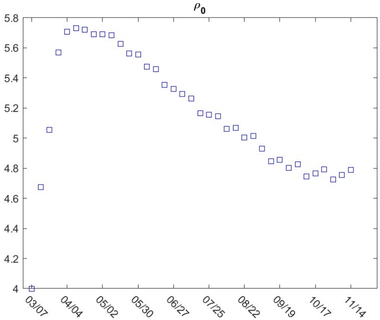
- Y axis:

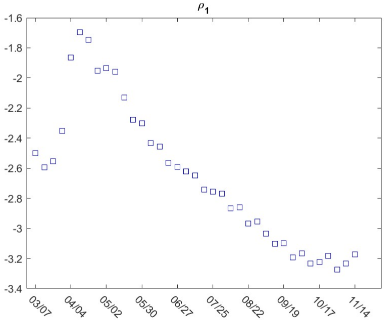
Imputed new infections

- X axis:

Social distancing θ

Innovations in COVID-19 Infections





Innovations in COVID-19 Infections

- Poisson1:

$\lambda(\hat{\rho}) \longrightarrow \widehat{\lambda(\rho)}$

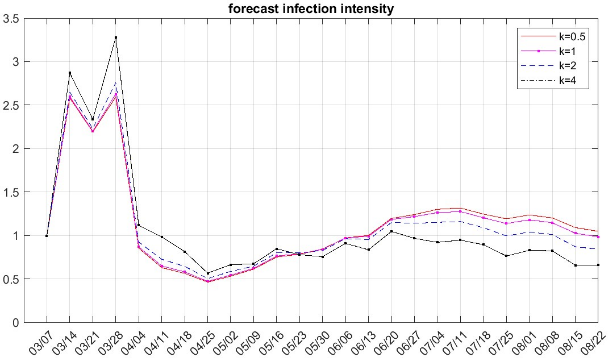
- Poisson2:

$\rho_1 \longrightarrow -e^{\rho_2}$

- Gaussian:

Model changes not levels

Innovations in COVID-19 Infections

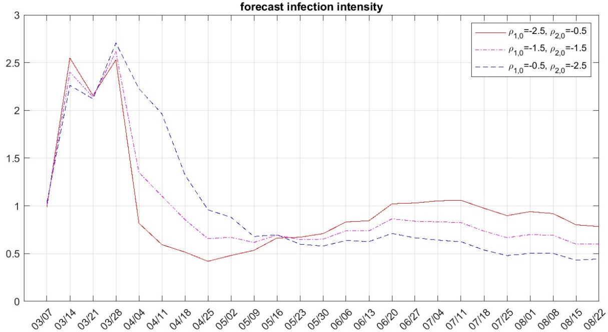


- Time-varying ρ

$d\rho = G\ dW$

- k: fraction of Σ_0

Innovations in COVID-19 Infections



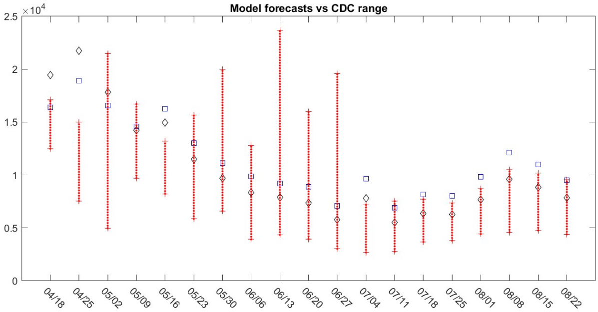
- Mask-wearing

Ipsos: survey self-reported mask use

- Alternative priors

Change timing of the good news

Innovations in COVID-19 Infections



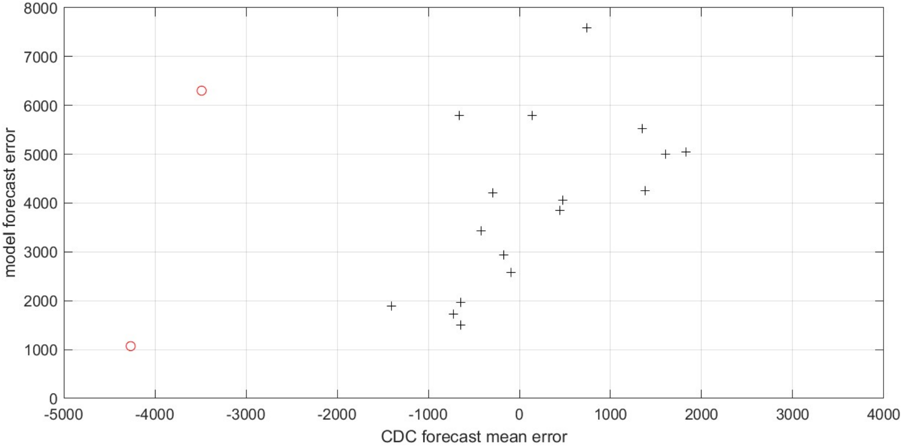
- CDC forecasts

  From researchers; for death count; weekly

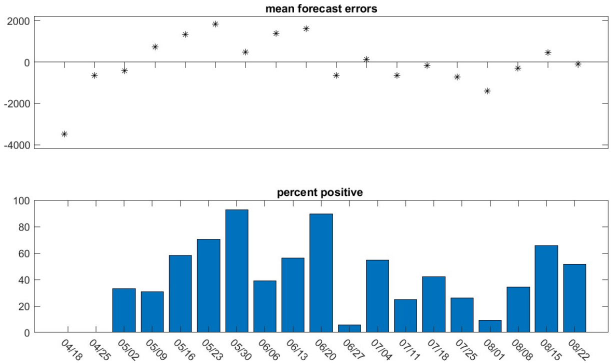
- Square: time-varying ρ

- Diamond: incl. mask-wearing

Innovations in COVID-19 Infections



Innovations in COVID-19 Infections



- Average forecast errors across participants
- Fraction of forecasters positively surprised

Epidemic in An Economy

Economic Settings

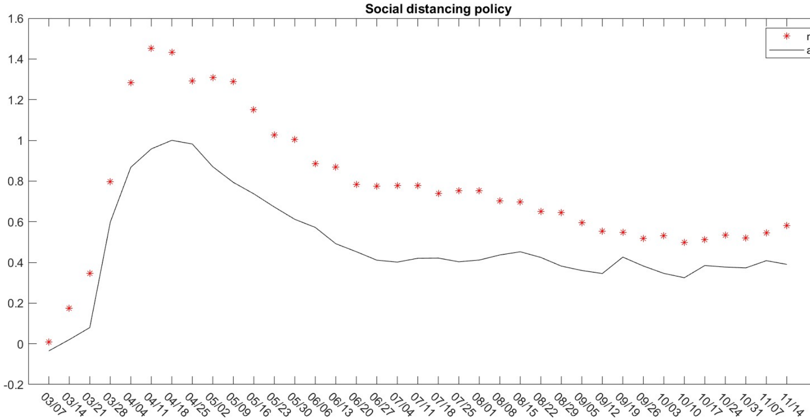
- Aggregate production: $Y = A(S + R)\mathrm{e}^{-\theta}(1 + \theta)$
  - Output is determined given the path of the epidemic and SDL.
- Stock market: a claim to the aggregate output

$$S_t = \mathbb{E}\left[\int_t^{\infty} e^{-\delta(\tau - t)} \frac{M_\tau}{M_t} Y_\tau \; d\tau \;\middle|\; i_t, s_t, L_t; \hat{\rho}_t, \Sigma_t\right]$$

  - Full information vs. uncertain & subject to learning
- Representative agent with power utility: $u(C) = \frac{C^{1-\gamma}}{1-\gamma}$

$$V_0 = \max_{\theta_t} \mathbb{E}\left[\int_0^{\infty} \mathrm{e}^{-\delta t} u(Y(\theta_t, i_t, s_t, L_t)) \; dt\right]$$

  - The policy for θ: endogenously determined vs. exogenously set



Social distancing policy
model
actual
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
-0.2
03/07
03/14
03/21
03/28
04/04
04/11
04/18
04/25
05/02
05/09
05/16
05/23
05/30
06/06
06/13
06/20
06/27
07/04
07/11
07/18
07/25
08/01
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08/15
08/22
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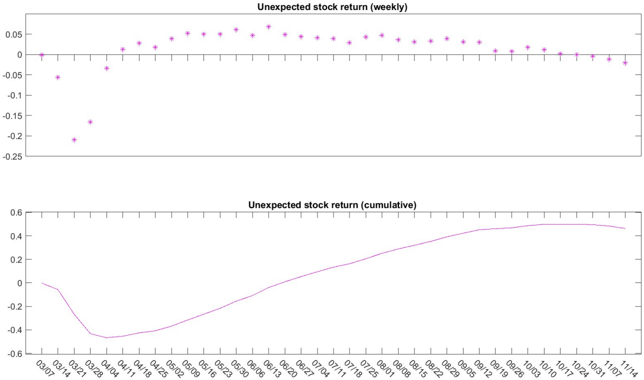
10/31
11/07
11/14



Unexpected stock return:

$$\left[\frac{S^+}{S} - 1\right] \; (dN - \hat{\lambda} dt)$$

Conclusion

- We provide a learning-based perspective to the "puzzling" stock market rally.
- We find a series of positive surprises about the epidemic during summer.
- We show in our model that these good news can generate a similar market rally.
- This paper highlights that investors may not have completely lost their rationality.
  - A learning-based theory can go a long way in rationalizing this striking market rally.

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