The Value of Anticipating Surges and Collapses of Depression in Local Areas in the aftermath of the Pandemic

Abbreviated update and review prepared for System Dynamics Conference
Parallel Session 194 - Microeconomics
By Maurice Glucksman, The Localisation Modelling Group
20 July 2022 (updated with latest model links 31 August 2022)

Note Low Resolution version for upload limited to 2Mb renders many exhibits illegible
For High Resolution version and additional materials please write to: mglucksman@alum.mit.edu
• Acknowledgements
• Depression Contagion
• London During the pandemic
• What might be next
• Diversity and Economics
• Machine Learning
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Depression and Emotional Contagion: Research Examples


Depression Contagion Quantification: Framingham Heart Study

Depression Clusters in the Framingham Social Network. This graph shows the largest component of friends, spouses and siblings at exam 7 (centered on the year 2000). There are 957 individuals shown. Each node represents a subject and its shape denotes gender (circles are male, squares are female). Lines between nodes indicate relationship (red for siblings, black for friends and spouses). Node color denotes the percentile score of the mean level of depression in ego and all directly connected (distance 1) alters, with yellow being below the 10th percentile, shades of green being the 80th to 95th percentile, and blue being above the 95th percentile (the most depressed).

Depressed Alters in the Framingham Social Network. This plot shows that the probability of being depressed (CES-D score of 16 or greater) in exams 6 and 7 is positively associated with the fraction of their friends and family in the previous exam who are depressed. Blue line shows smoothed relationship based on bivariate LOESS regression, and dotted lines indicate 95% confidence intervals. CES-D, Center for Epidemiological Studies Depression Scale.

The Study area is 30 MSOA Regions in central London UK with diverse levels of depression and diverse demographics, economic prosperity, other local conditions.

Sources: House of Commons Library, Constituency data: health conditions, 2019/20; Cambridgeshire Insight Open Data – Middle Super Output Areas Boundaries (December 2001); data consolidated into VeryTinyLondonARCMAP shape file and associated database files created in ARCMAP.
Depression Contagion Epidemiology

System Dynamics Model (Silico)

Depression Contagion Geospatial Agent Based Model (Netlogo)

Geospatial exploratory regression identifies local conditions that explain historical depression prevalence. The regression is used as a proxy index of new case vulnerability in each area.

Depression triggered by agent interaction
• with changing Local area Conditions
• By contagion from contact with other agents in home and neighboring areas
• Mapped to System Dynamics disease states transitions between short-term and long-term depression and recoveries

• Estimate relative impact of contagion
• Set up to mimic the evolution of depression capturing the variations of the UCL dataset
• Use the output to benchmark the Agent Based Model against all state variables in Depression Epidemiology
• Estimate future impact of Long Covid

Multi-Method Modelling Provides Cross Benchmarks and Rigor
Pre-pandemic: almost stable rate of Depression diagnosis and recovery

Depression: QOF incidence (18+) - new diagnosis

IAPT recovery: % of people who have completed IAPT treatment who are "moving to recovery" (18+ yrs)

UK surges and collapses of depression: Synthesis of Longitudinal Data

Covid Stressors dominate in peaks but notably ‘Getting Food’ is early but rapidly dissipating worry.

Depression Prevalence (ONS)

Depression Prevalence Estimates (UCL trends)

UK Regression estimates 24.0

consistent pattern except in July 2020 and August 2021 but just a few weeks earlier it’s the same

Pre-pandemic Range of UCL index: 2.7 – 3.7 avg = 3.2, corresponds to 11.15% prevalence in Greater London including 36% unreported

Depression Prevalence Estimate

Sources: Office for National Statistics – Opinions and Lifestyle Survey, Coronavirus and depression in adults, Great Britain: July to August 2021; 2020 UCL COVID-19 Social Study UCL Release 38 page 15,22
GeoDa Regression results mixed but are used as a depression trigger in the absence of a better option from exploratory regression.
Long COVID Mental Health Outcomes in Saskatchewan, Early Results imply very high levels of Impact from Long Covid on Depression

<table>
<thead>
<tr>
<th></th>
<th>Self-Identified Long COVID n=208</th>
<th>COVID but no Long COVID n=42</th>
<th>No COVID n=178</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Has experience in the past 18 months:</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Anxiety</td>
<td>73.3%</td>
<td>38.1%</td>
<td>44.8%</td>
</tr>
<tr>
<td>Depression</td>
<td>61.8%</td>
<td>33.3%</td>
<td>31.4%</td>
</tr>
<tr>
<td>Mood changes</td>
<td>63.6%</td>
<td>26.1%</td>
<td>22.4%</td>
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<tr>
<td>Headaches</td>
<td>80.2%</td>
<td>69.0%</td>
<td>52.0%</td>
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<tr>
<td>Sleep issues</td>
<td>74.9%</td>
<td>42.9%</td>
<td>40.8%</td>
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<tr>
<td>Brain fog</td>
<td>83.5%</td>
<td>33.3%</td>
<td>21.3%</td>
</tr>
<tr>
<td>Memory or concentration issues</td>
<td>84.1%</td>
<td>35.7%</td>
<td>31.7%</td>
</tr>
<tr>
<td>Fatigue</td>
<td>91.1%</td>
<td>59.5%</td>
<td>46.6%</td>
</tr>
</tbody>
</table>

Source: Long COVID longitudinal smartphone study Ongoing Since February 2022 [https://www.sasklongcovid.com/](https://www.sasklongcovid.com/)
Projected 2-3 x escalation of Long Covid Induced Depression by end ‘22

New reports of Long Covid have increased 70% since August 2021*

1.8 million people (2.8% of the population) were experiencing self-reported Long COVID as of 3 April 2022

* Estimated number of people living in private households with self-reported long COVID of any duration, UK: four-week periods ending 2 May 2021 to 3 April 2022

Projected cases of Long Covid Induced Depression (LCID) matches ONS data and Implies 3.3% – 5% prevalence at end 2022

Sources: Office for National Statistics – Coronavirus (COVID-19) Infection Survey (CIS), Depression 8 Silico Simulation Model, Taquet et al. The Lancet 2021, LG Inform
With treatment, episodes of depression last about 3–6 months — more than 50% of people experiencing a major depressive episode recover within 6 months, and nearly 75% within a year. Longer-term, the proportion of people who recover drops to approximately 60% at 2 years, 40% at 4 years, and 30% at 6 years.

The likelihood of recurrence is high — this risk increases with every episode.

Approximately 80% of people who receive psychiatric care for an episode of major depression have at least one more episode and a median of four episodes in a lifetime.

Up to 27% of people do not recover and go on to develop a chronic depressive illness.

The outcome is less favourable with older age of onset.

The prognosis is worse for people with:
- Psychotic features.
- Prominent anxiety.
- Personality disorders.
- Severe symptoms.

Persistent depression develops in at least 10% of people with depression.

Persistent subthreshold depressive symptoms progress to the full criteria for depression in about 70% of people.

Source: National Institute for Health and Care Excellence
Covid 19 infection waves → Long Covid Accumulation → Long Covid Induced Depression (LCID) → 60% are depressed (Saskatchewan Survey) → 2 million (3.1%) as of 1 May, in UK → 1.2 million escalating to 2+ million → £1T total, £15k/capita £330B, £5k/capita from LCID → Amplified Depression Prevalence
- Lost Productivity
- Escalation of Healthcare costs
- Early Death
- Lock-in of escalated depression geographic/demographic

Contagion + Episodic

The Feared Economic Scenario - UK
SD Depression Epidemiology Model (SDDEM) is set up to mimic the NICE narrative and UK data yields key ratios for the Agent Based Model (section 8)

Source: Depression 9 Silico Simulation Model
This Summary of the SDDEM reveals surprises and key risks caused by the pandemic.
‘Depressed’, ‘At Risk of Relapse’ and Variance significantly higher post pandemic

Source: Depression Shock six dclasses31.nlogo
LCID is Uncertain. Increased LCID -> higher Depression Prevalence and Variance

Scenario Inputs

- No LCID Impact, LCS* = 0
- Expected LCID Impact, LCS = 0.65
- + 50% LCID Impact, LCS = 1
- + 200% LCID Impact, LCS = 2

Source: Depression_Shock_six_dclasses31.nlogo

Depression Prevalence 2018 – 2030

* LCS = Long Covid Sensitivity parameter in section 2 of ABM Dashboard
Risk Heat Maps, varying LCID produces very different hot-spot locations

Before: Pre-Pandemic Depression 2019

After: Multiple of Average Depression at end 2030

No LCID Impact LCS* = 0

Expected LCID Impact LCS = 0.65

+ 50% LCID Impact LCS = 1

+ 200% LCID Impact LCS = 2

Sources: Depression_Shock_six_dclasses31.nlogo GeoDa Analysis, House of Commons Library
* LCS = Long Covid Sensitivity parameter in section 2 of ABM Dashboard
Counter-Intuitive outcome: Medium Vulnerability areas are worst impacted

- The Multiple of average Depression creates clear patterns in the results
- Middle to high regression trigger (RT) areas are more at risk than areas at extremes
- Low RT areas are better off
- High RT areas appear more stable
- LCS 2 appears less risky than LCS 1 scenario
- Sustained increase in depression and volatility with increased LCID especially in Medium Vulnerably areas

Sources: Depression_Shock_six_dclasses31.nlogo GeoDa Analysis, House of Commons Library
Most areas return to pre-pandemic levels but 1/3 are permanently ‘locked-in’

Pre-pandemic 2019 –
Standard deviation = 2%

Post-pandemic 2030 –
Standard deviation = 3%

Source: Depression_Shock_six_dclasses31cleanCCMExp.nlogo
Two-stock model embeds contagion and vulnerability to illustrate how a short-term shock to new cases can induce ‘lock-in’ past a threshold

Counteracting feedback from available well

<table>
<thead>
<tr>
<th>scenario</th>
<th>new cases shocks</th>
<th>change sensitivity</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td></td>
<td>low</td>
</tr>
<tr>
<td>B</td>
<td></td>
<td>normal</td>
</tr>
<tr>
<td>C</td>
<td></td>
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<td>E</td>
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<tr>
<td>F</td>
<td></td>
<td>high</td>
</tr>
</tbody>
</table>

Symmetric Contagion overwhelms recovery rate. In the locations where sensitivity to shocks is rapid, 3 out of 6 cases are a permanent change to depression prevalence.

Source: depression surges and collapses basics Silico Simulation
UK Accumulated Cost* of Depression: employment, health services, mortality

Source: Depression 9 Silico Simulation Model,
Projected UK Depression Prevalence, Economic Impact with and without LCID

UK Depression Prevalence %
Scenarios vs Historical data

Source: Depression 9 Silico Simulation Model,

No Pandemic
Pandemic, no LCID
With LCID

Economic loss* from excess depression

£ 1 trillion total
£ 320 billion attributable to LCID

ABM implies sustained depression prevalence up to 14%: Economic loss could exceed £320 billion

*Economic loss is discounted at 4% and includes terminal value

LCID impact building rapidly in 2022-2023

£ 320 billion

Source: $1 trillion total

- Economic loss is discounted at 4%
- Includes terminal value
“If asked what is one of the most important components of our pandemic response, I would say it was the modelling”

Andrew Will, CEO, Saskatchewan Health Authority

“The reality is that managing demands of care for all patients during a global pandemic has been extremely challenging. Modelling provides a level of pandemic situational awareness that is mission critical to prepare for pandemic waves. Ongoing refinement of this capacity has provided increasingly accurate forecasting allowing more measured and strategic use of system resources to provide best possible care for all patients (COVID and non-COVID)”

Dr. John Froh, Deputy Chief Medical Officer - Pandemic; Chief of Operations-Emergency Operations Centre, Saskatchewan Health Authority

Source: Jenny Basran and Nathaniel Osgood
Advanced Analytics & Modelling Structure

01 Data Infrastructure
What data is available? Quality of data? How to link data to answer questions? What new data needs to be generated?

02 Current State Awareness
Dashboards, Reports, Presentations

03 Advanced Analytics
Deep dive analysis to understand regional variation, key drivers, and outcomes.

04 Modelling
Various types of modelling, including ability to exploring various “what if” scenarios to support decision making

Infrastructure and Organizational Capability coupled with a well-established track record anticipating service capacity needs for disease outbreaks was crucial to ‘hit the ground running’

Source: Jenny Basran and Nathaniel Osgood
Progression of COVID-19 in Saskatchewan
Analytics and Modelling Allowed SHA to prepare in advance

Recommendations to policymakers and their actions did not always align but the modelling allowed the health authority to prepare for divergence.


June 17, 2021 modelling of Delta surge

Source: Jenny Basran and Nathaniel Osgood
Impact of machine learning

- In context of a good theory
- With preparation and practice between analysts and policymakers
- A well constructed information architecture
- In fast moving situation (like the pandemic)

Structurally guided (by well founded epidemiology) Machine Learning was indispensable for delivering robust policy recommendations that had a chance of timely action
64% of surveyed believe impact will only greater demand everywhere but data and simulations shows both are happening

73% believe prevalence will be greater everywhere but model implies both due to stochastic contagion induced lock-in

Surprising diversity of views: 50% believe High vulnerability = high risk; modeling says medium vulnerability are highest risk

85% of surveyed agree with the modelling: the impact will be long term. Simulations imply > 10 years

71% of surveyed believe the impact of Long Covid Induced Depression is <= £50 Billion but modelling implies £200 billion

Source: Survey of 44 participants in NHS ML Monday - Machine Learning and Mental Health – Basran, Osgood, Glucksman 4 April 2022
• Locked-in post-pandemic depression epidemic could happen in groups/locations
• How far along is this? could be 18 months to act
• Key take aways:
  - Hybrid modelling has been crucial to understanding
  - Prescriptive policy actions will require more work especially with Machine Learning
  - Complementary information architecture is indispensable
  - That won’t be enough, the bridge to impact it requires effective communications. Saskatchewan shows what can work
  - Policymakers and Decisionmakers Trust is needed

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