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

Agenda

- Acknowledgements
- Depression Contagion
- London During the pandemic
- What might be next
- Diversity and Economics
- Machine Learning

Acknowledgements: Collaborators and support

Dr. Kim Warren – Strategy Dynamics

Dr. Joana Barros, Dr. Shino Shiode – Birkbeck, University of London

Stephen Barnes, Jennifer Hering Butler, Dr. Richard Larson – MIT

Dr. Jenny Basran, Wade McDonald, Dr. Nathaniel Osgood, – CEPHIL Lab University of Saskatchewan

Dr. Navid Ghaffarzadegan, Glen Lydanne, Dr. Konstantinos Triantis,– Virginia Tech

Andi Orlowski, Dr. Sukhmeet Panesar, Julia Wilkins – UK NHS

Dr. Wayne Wakeland – Portland State University

and dozens of multi disciplinary experts, field professionals, students, and open-source data/research

Depression and Emotional Contagion: Research Examples

About the Author [Podcast: Is Depression Contagious?]

Ellen Hendriksen, PhD

Dr. Ellen Hendriksen was the host of the Savvy Psychologist podcast from 2014 to 2019. She is a clinical psychologist at Boston University's Center for Anxiety and Related Disorders (CARD). She earned her Ph.D. at UCLA and completed her training at Harvard Medical School. Her scientifically-based, zero-judgment approach is regularly featured in *Psychology Today, Scientific American, The Huffington Post*, and many other media outlets. Her debut book, HOW TO BE YOURSELF: Quiet Your Inner Critic and Rise Above Social Anxiety, was published in March 2018.

Front. Psychol., 16 July 2021
Sec. Emotion Science

Emotional Contagion: A Brief Overview and Future Directions

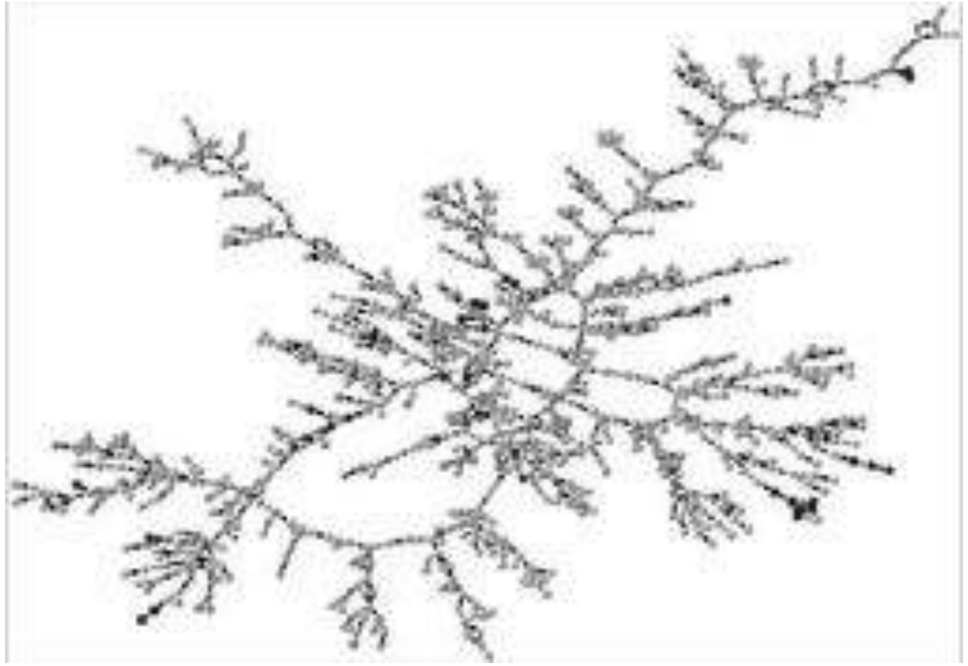
Carolina Herrando* and Efthymios Constantinides

Social interactions can trigger emotional contagion between individuals resulting in behavioral synchrony.

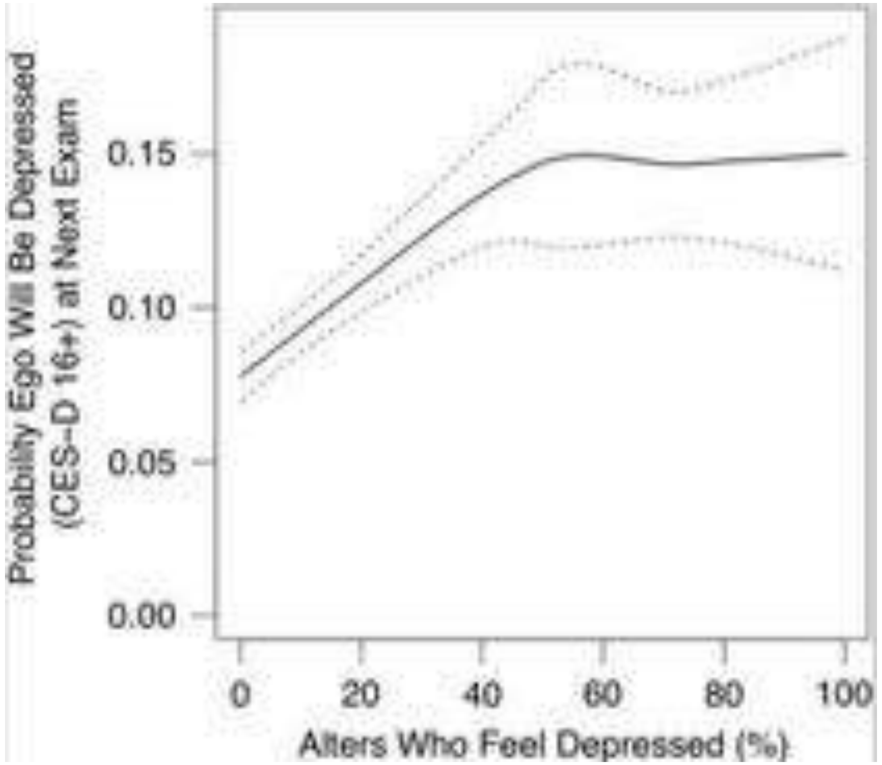
Rosenquist, J., Fowler, J. & Christakis, N. Social network determinants of depression. *Mol Psychiatry* **16,** 273–281 (2011).

Knobloch-Westerwick S, Abdallah JC, Billings AC. The Football Boost? Testing Three Models on Impacts on Sports Spectators' Self-Esteem. *Communication & Sport*. 2020;8(2):236-261

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 80th 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.

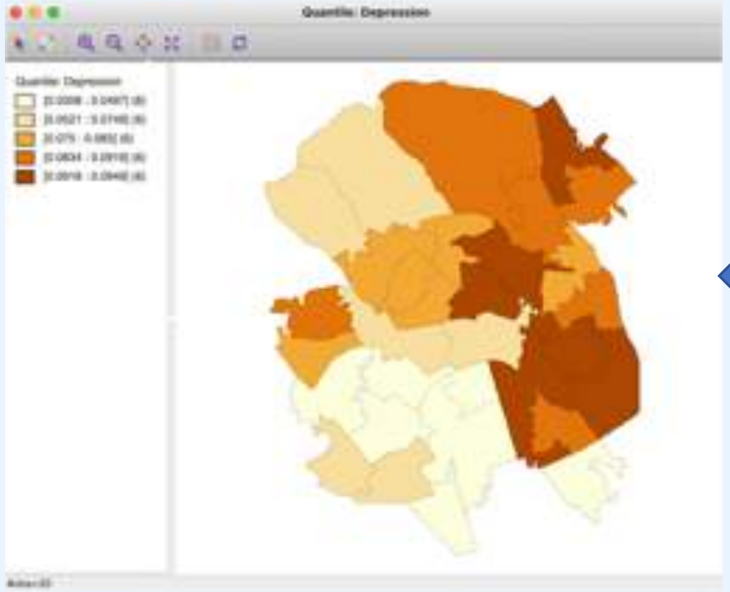
Source: Rosenquist, J. N., Fowler, J. H., & Christakis, N. A. (2011). Social network determinants of depression. *Molecular psychiatry*, *16*(3), 273–281. https://doi.org/10.1038/mp.2010.13

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

Multi-Method Modelling Provides Cross Benchmarks and Rigor

Exploratory Spatial Data Analysis Model (ArcMap or QGIS and GeoDa)



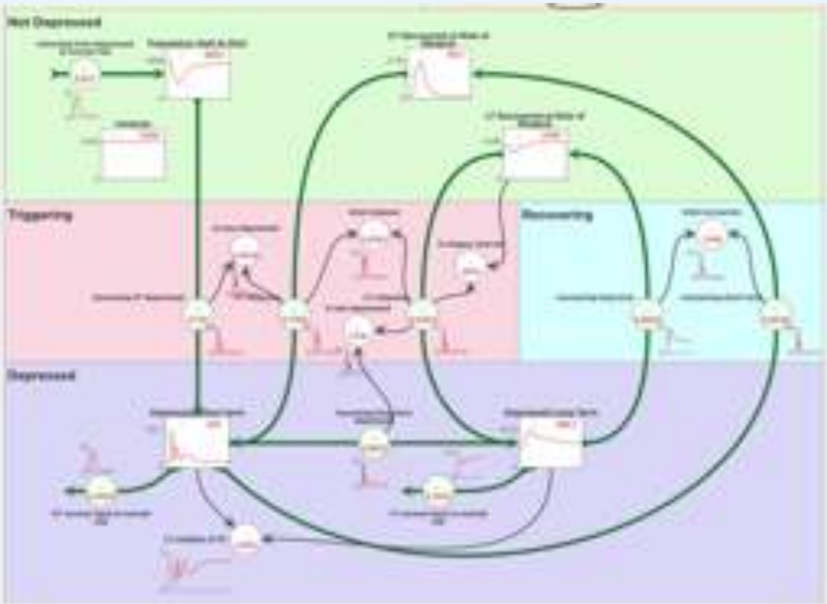
Geospatial exploratory regression identifies local conditions that explain historical depression prevalence. The regression is used as a proxy index of new case vulnerability in each area.

Depression Contagion Geospatial Agent Based Model (Netlogo)

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

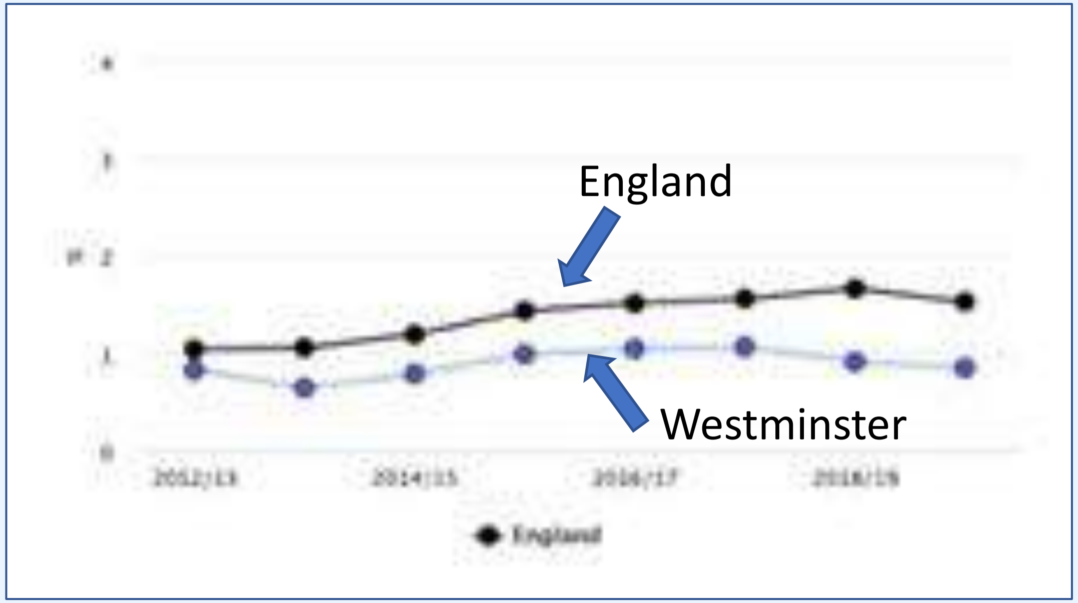
Depression Contagion Epidemiology System Dynamics Model (Silico)



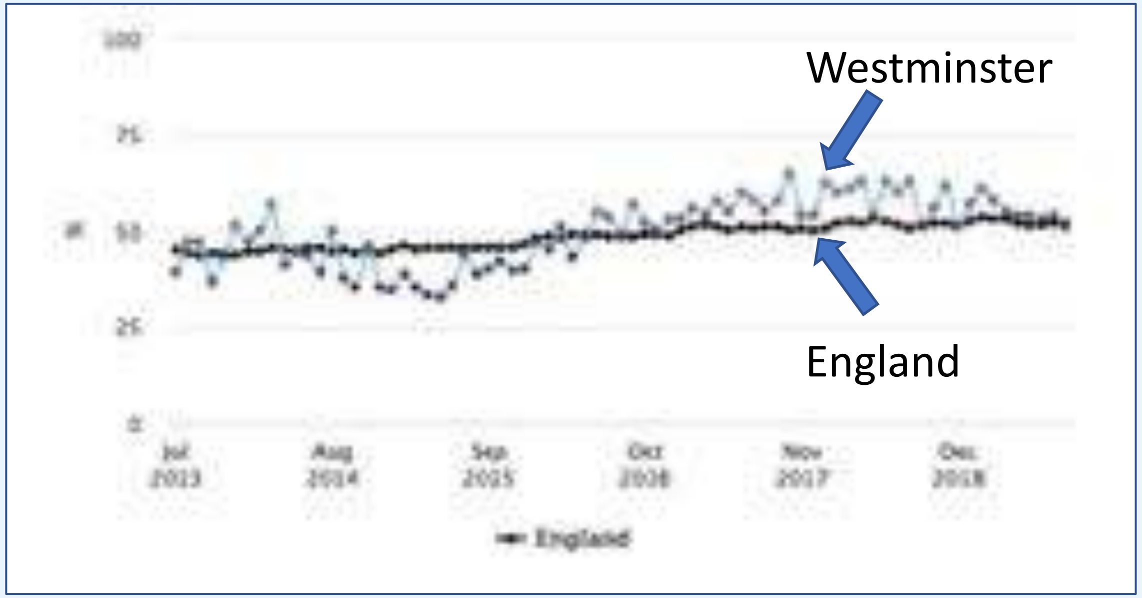
- Estimate relative impact of contagion
- Set up to mimic the evolution of depression capturing the variations of the UCL dataset
- Use the output to benchmark the Agent Based Model against all state variables in Depression Epidemiology
- Estimate future impact of Long Covid

Pre-pandemic: almost stable rate of Depression diagnosis and recovery

Depression: QOF incidence (18+) - new diagnosis



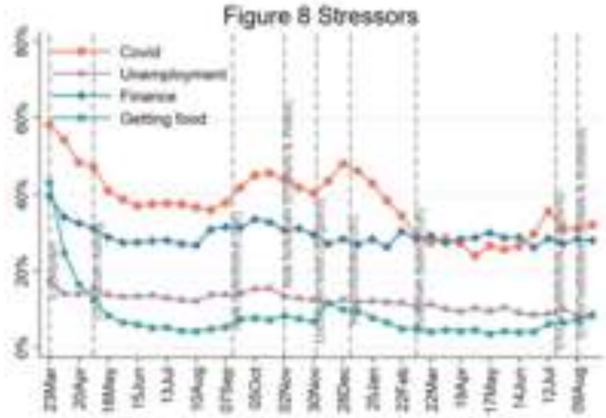
IAPT recovery: % of people who have completed IAPT treatment who are "moving to recovery" (18+ yrs)



Source: Public Health England, Common Mental Health Disorders Trends, NHS Central London (Westminster) CCG, All indicators 2009/10 – 2019/20

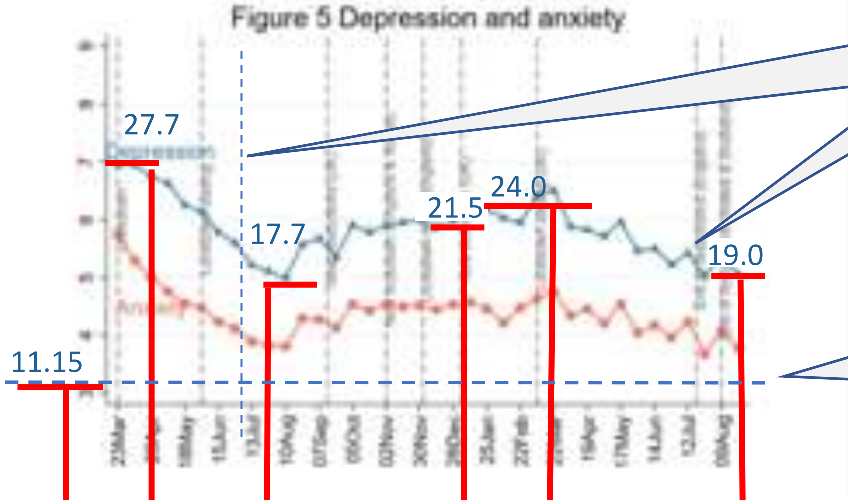
UK surges and collapses of depression: Synthesis of Longitudinal Data

Covid Stressors dominate in peaks but notably 'Getting Food' is early but rapidly dissipating worry



Depression Prevalence Estimates (UCL trends)

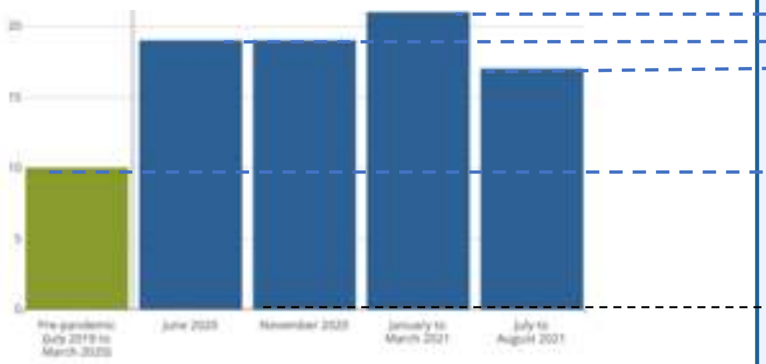
UK Regression estimates 24.0

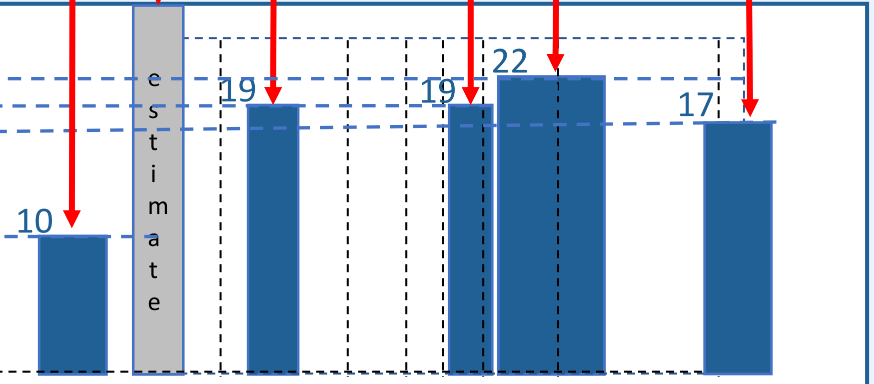


consistent pattern except in July 2020 and August 2021 but just a few weeks earlier it's the same

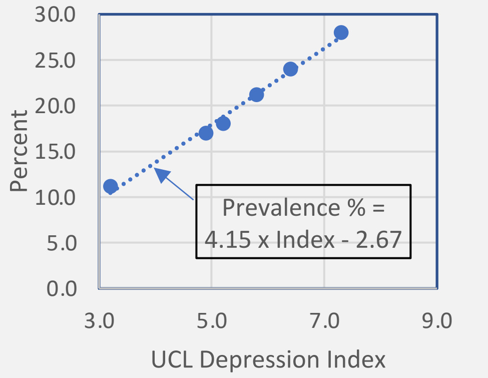
Pre-pandemic Range of UCL index: 2.7 – 3.7 avg = 3.2, corresponds to 11.15% prevalence in Greater London including 36% unreported

Depression Prevalence (ONS)



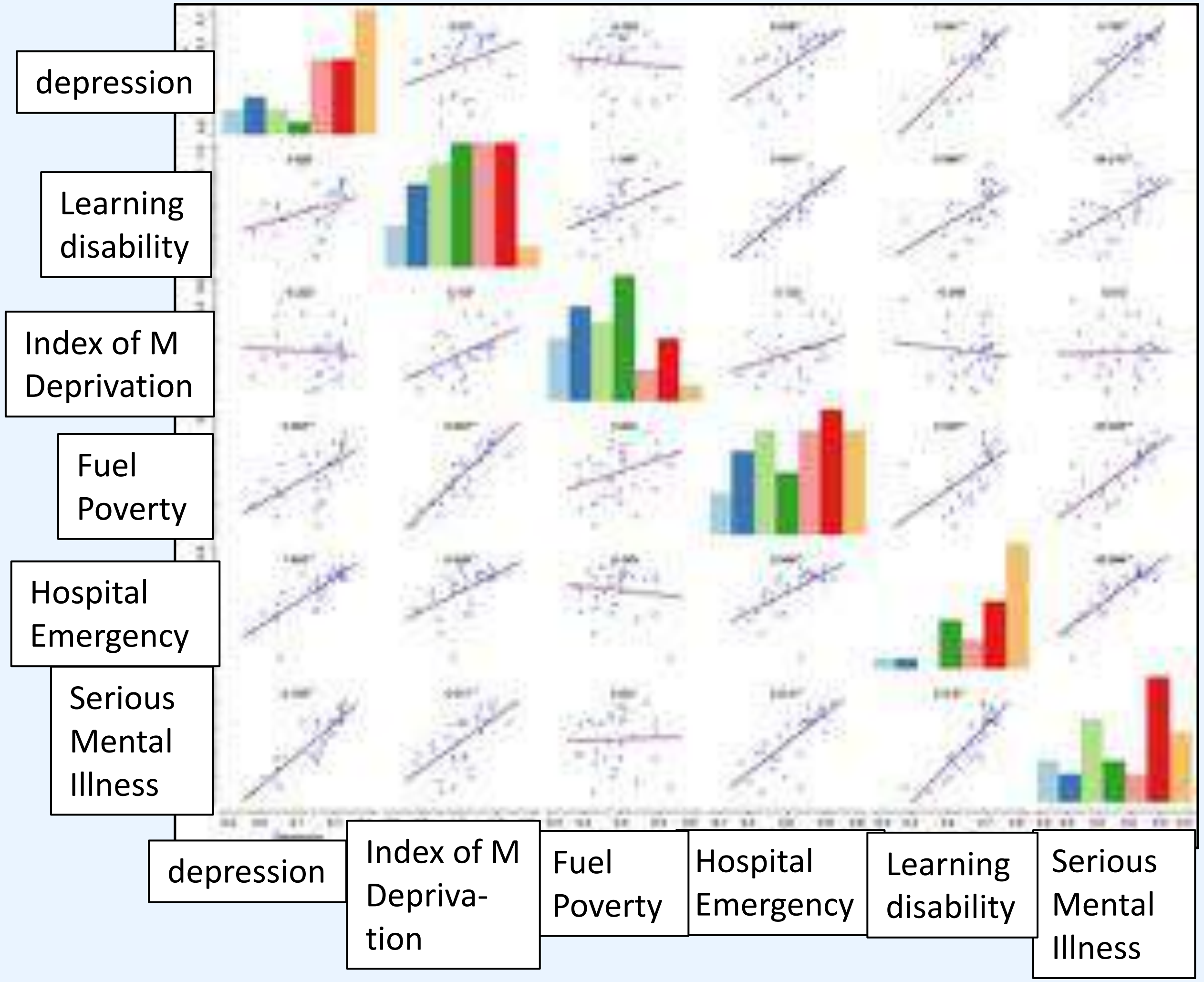


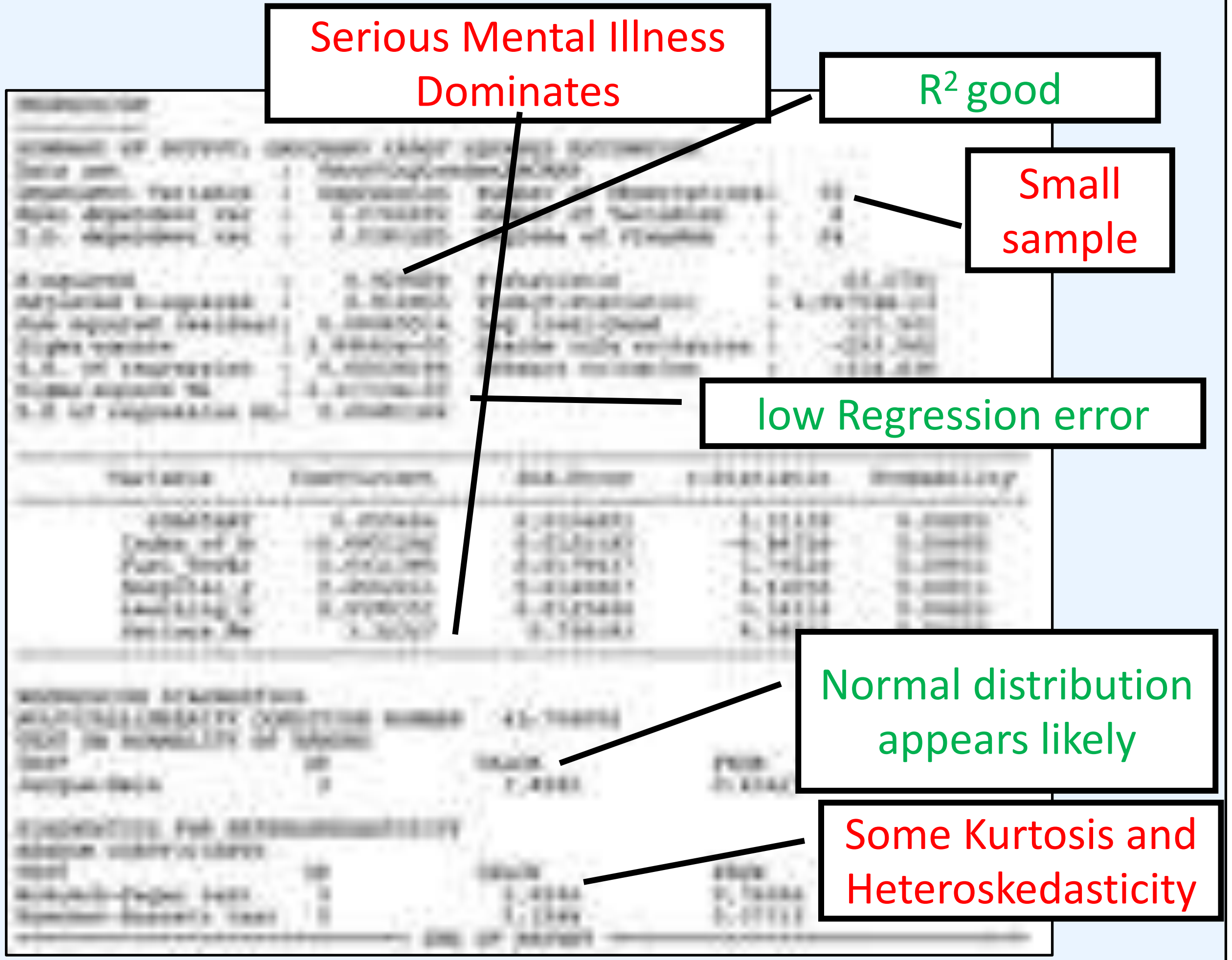
benchmarking ONS data duration on UCL trends timeline



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





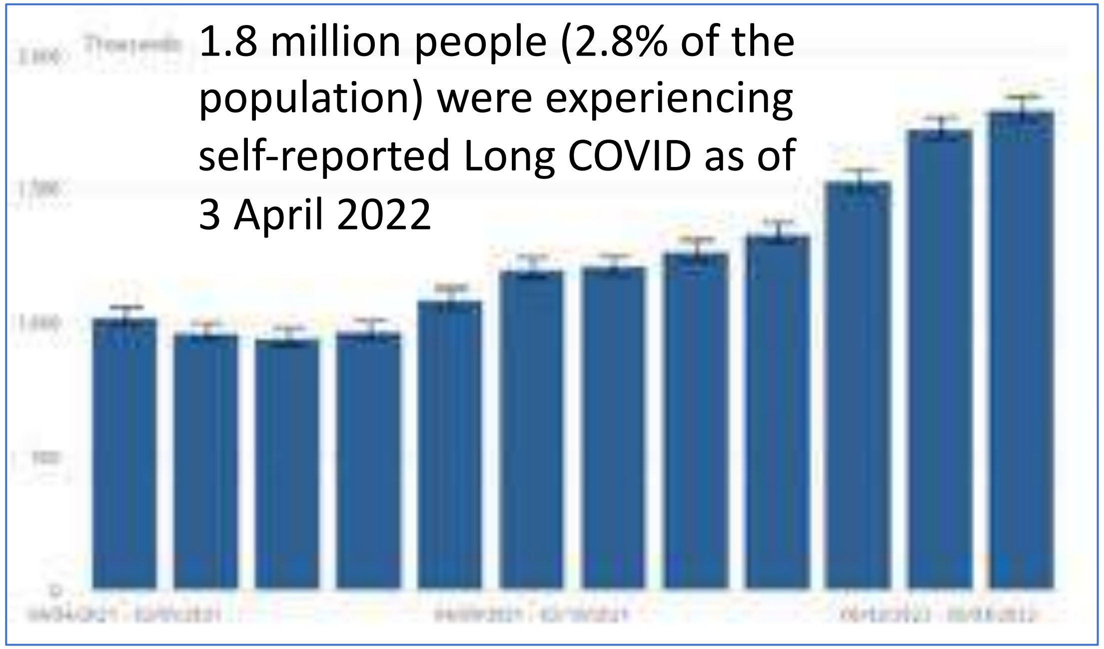
Long COVID Mental Health Outcomes in Saskatchewan, Early Results imply very high levels of Impact from Long Covid on Depression

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

Source: Long COVID longitudinal smartphone study Ongoing Since February 2022 https://www.sasklongcovid.com/

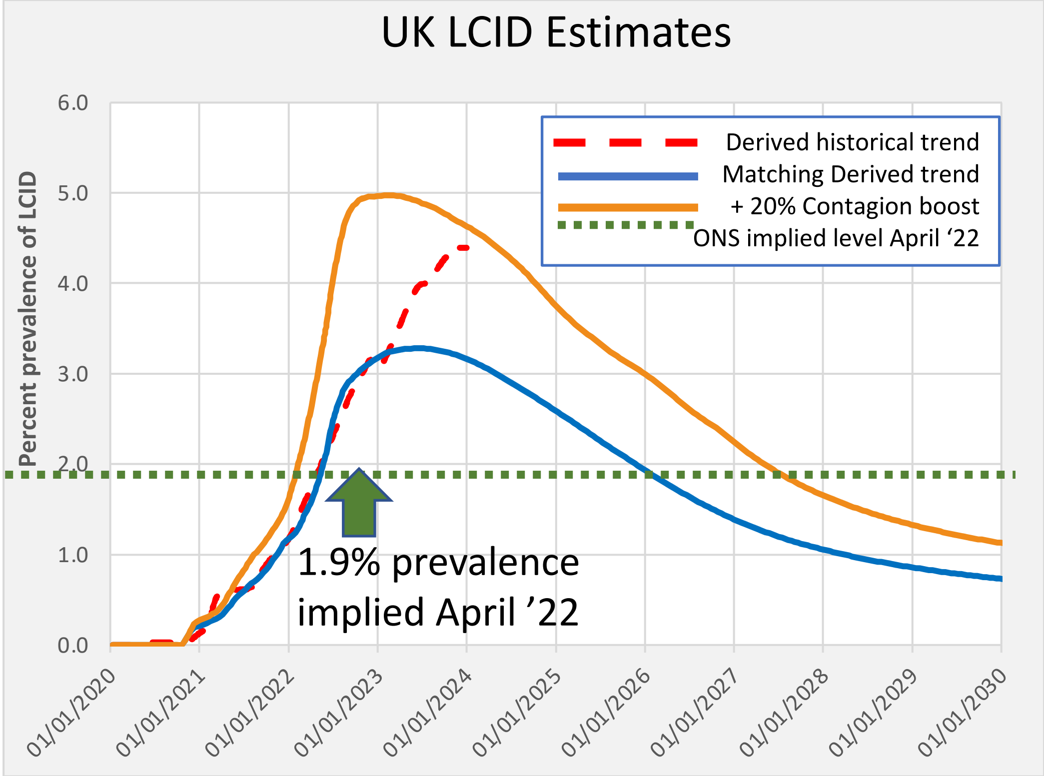
Projected 2-3 x escalation of Long Covid Induced Depression by end '22

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



* 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]()

This narrative of depression epidemiology published by NICE provides key parameters and benchmarks for an SD model

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

The Feared Economic Scenario - UK

2 million (3.1%)
as of 1 May, in UK

1.2 million escalating
to 2+ million

Contagion + Episodic

Covid 19 infection waves

Long Covid Accumulation

Long Covid Induced Depression (LCID)

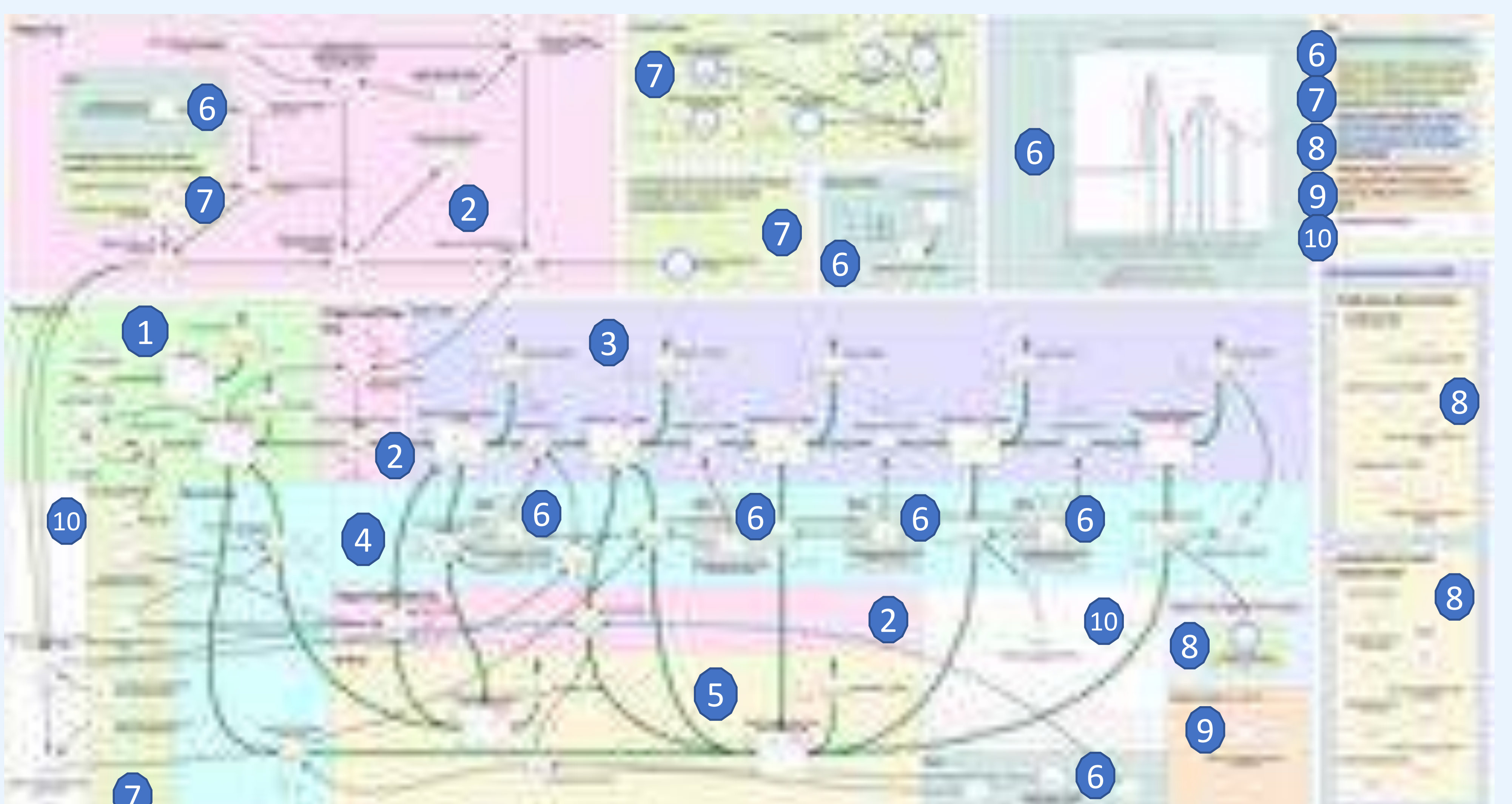
Amplified Depression Prevalence

- Lost Productivity
- Escalation of Healthcare costs
- Early Death
- Lock-in of escalated depression geographic/demographic

60% are depressed
(Saskatchewan Survey)

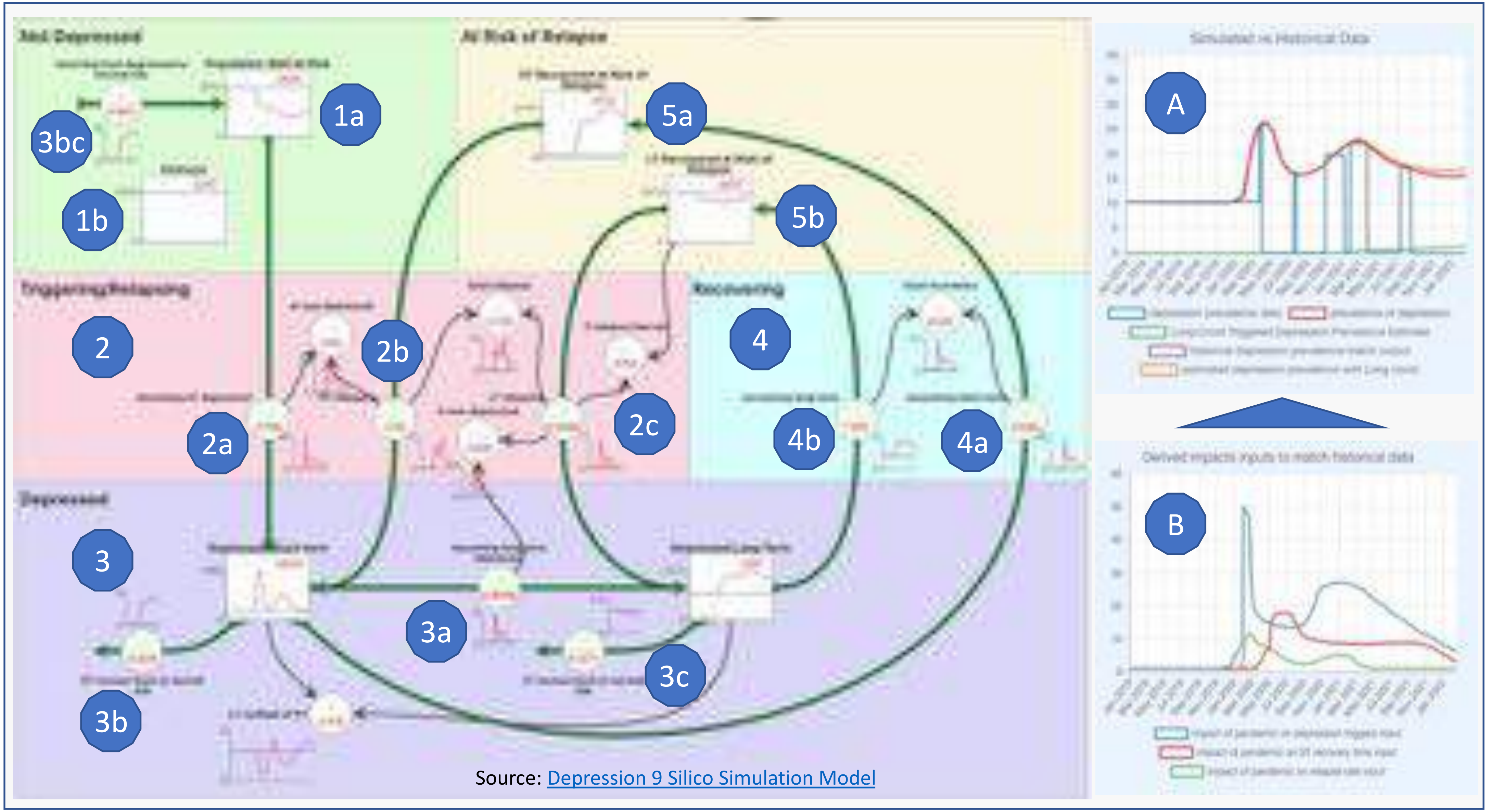
£ 1T total, £15k/capita
£ 330B, £5k/capita from LCID

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

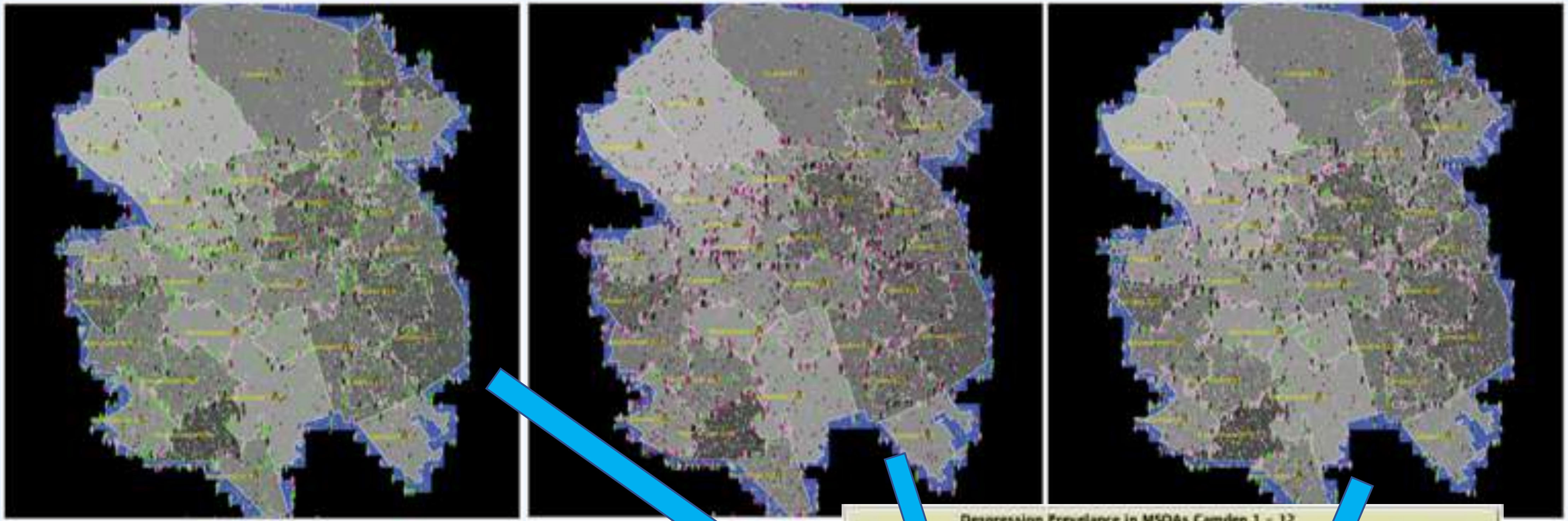
This Summary of the SDDEM reveals surprises and key risks caused by the pandemic



Source: [Depression 9 Silico Simulation Model]

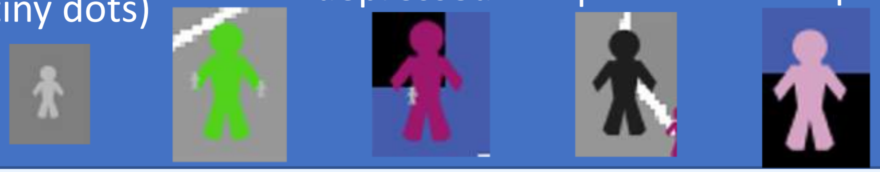
‘Depressed’, ‘At Risk of Relapse’ and Variance significantly higher post pandemic

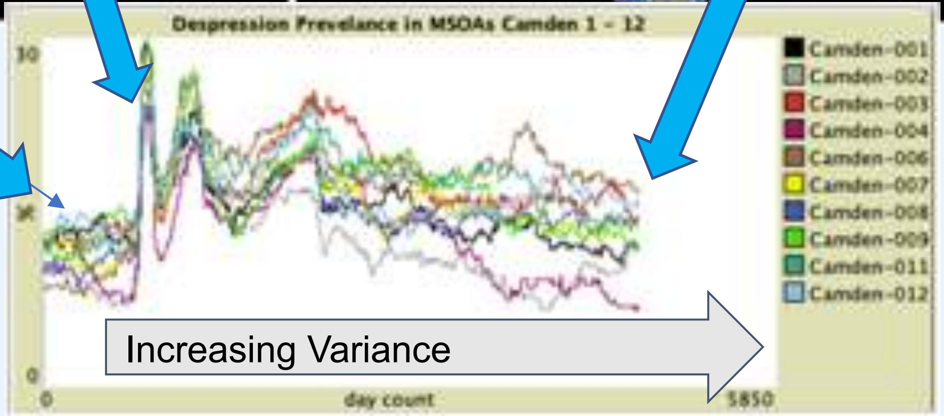
November 2019 Pre-pandemic | May 2020 Lockdown | December 2030 Long-Term Aftermath



Agents move within their areas plus can visit neighbors

Immune (tiny dots) | well | short term depressed | long term depressed | At risk of relapse

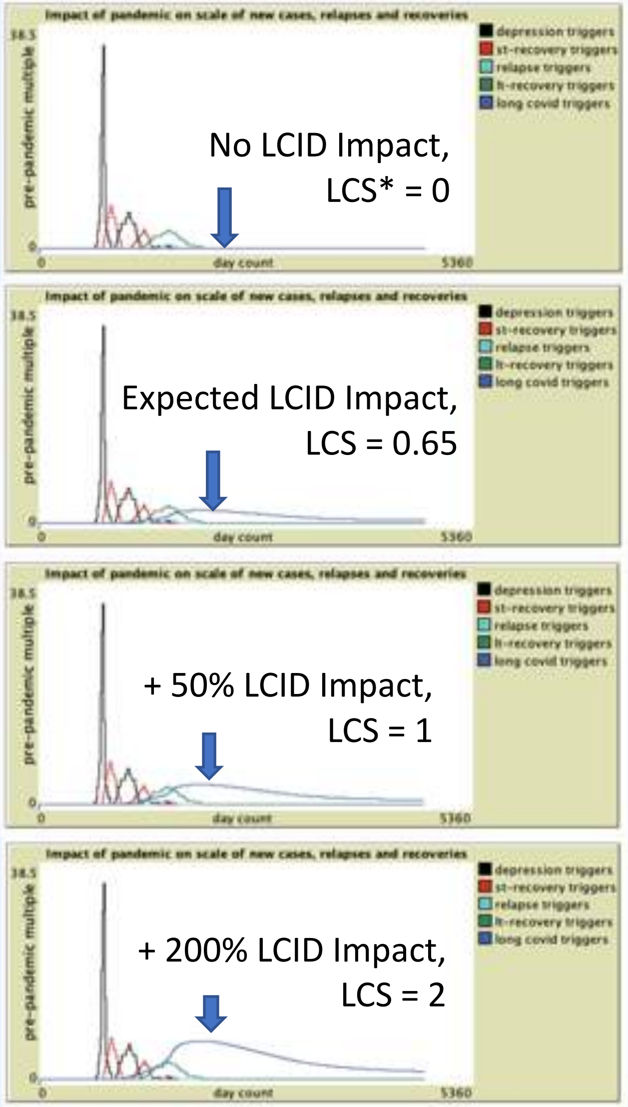




Source: Depression_Shock_six_dclasses31.nlogo

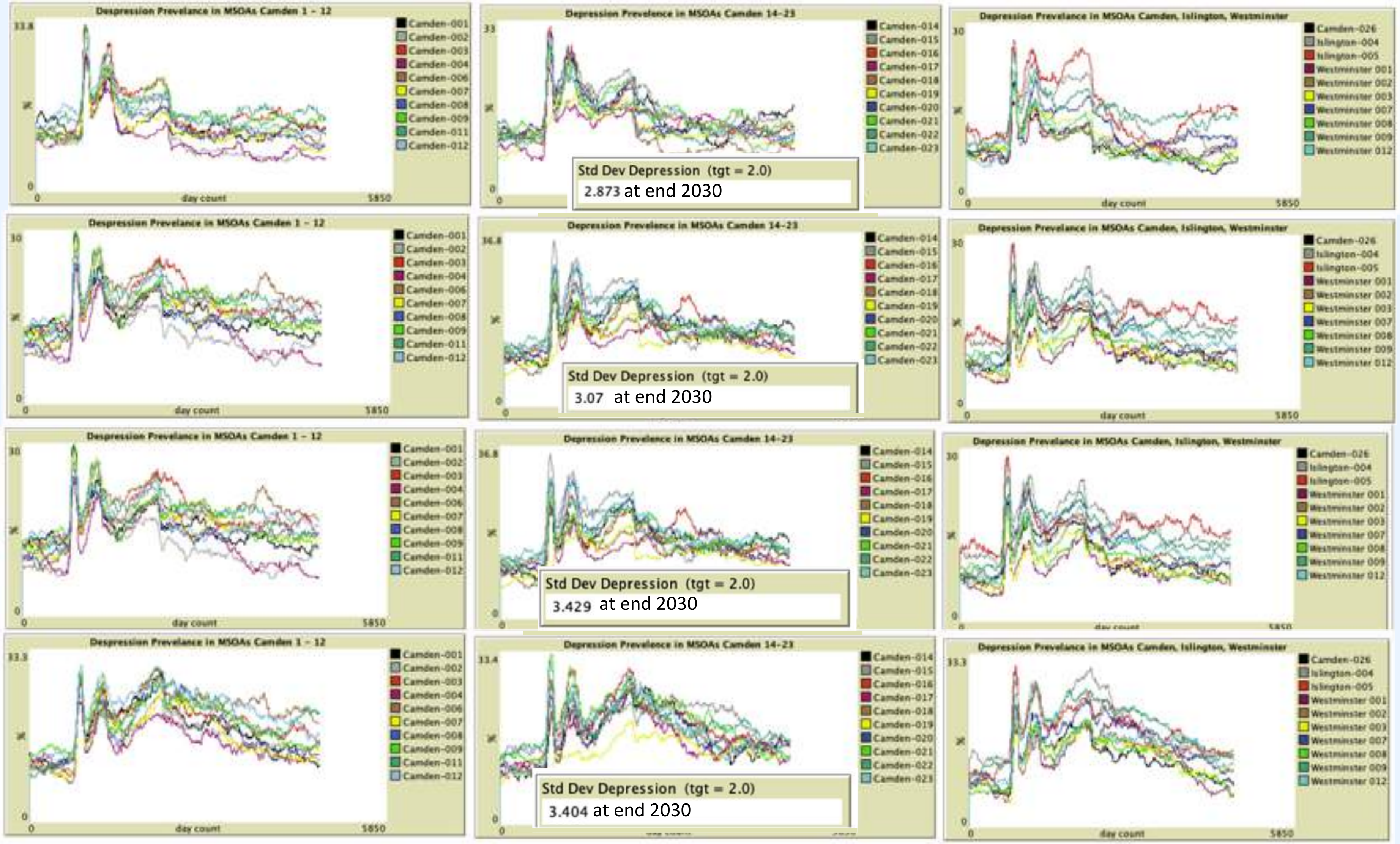
LCID is Uncertain. Increased LCID -> higher Depression Prevalence and Variance

Scenario Inputs



Source: Depression_Shock_six_dclasses31.nlogo

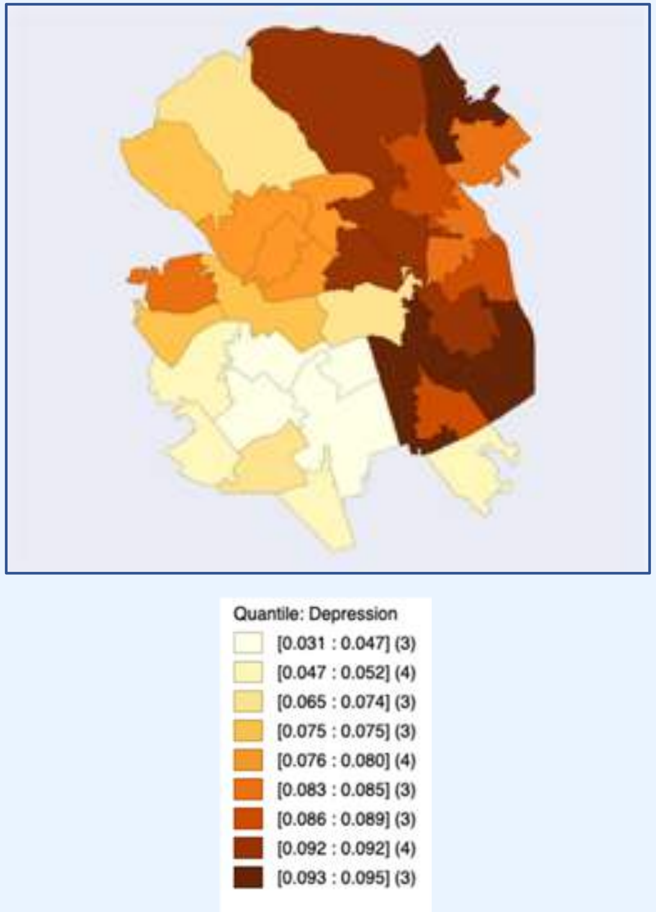
Depression Prevalence 2018 – 2030



* LCS = Long Covid Sensitivity parameter in section 2 of ABM Dashboard

Risk Heat Maps, varying LCID produces very different hot-spot locations

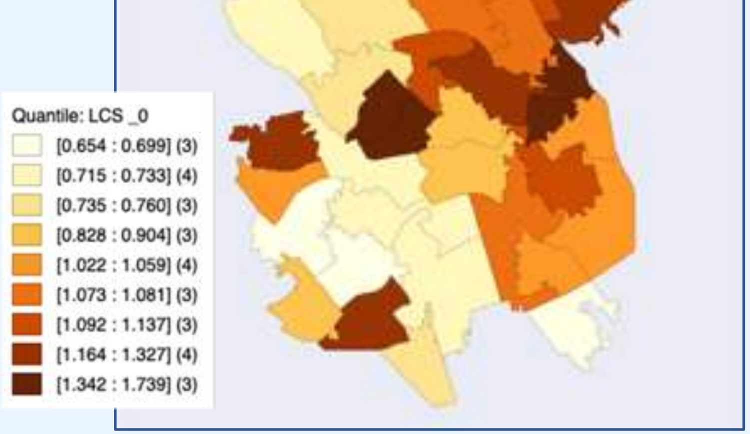
Before:
Pre-Pandemic Depression 2019



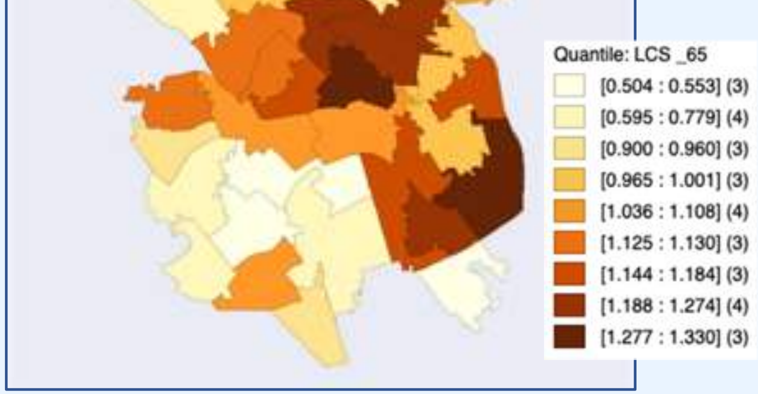
Sources: Depression_Shock_six_dclasses31.nlogo
GeoDa Analysis, House of Commons Library
* LCS = Long Covid Sensitivity parameter in section 2 of ABM Dashboard

After: Multiple of Average Depression at end 2030

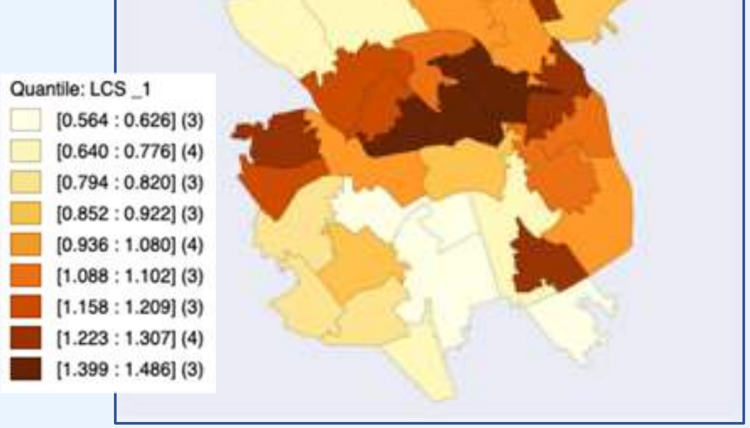
No LCID
Impact
LCS* = 0



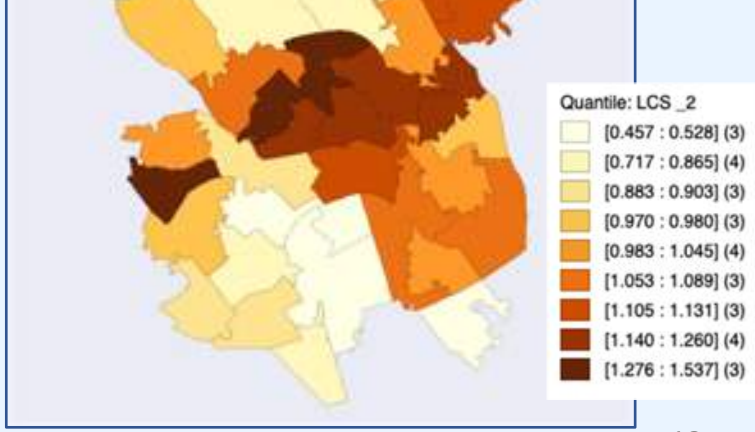
Expected LCID
Impact
LCS =
0.65



+ 50% LCID
Impact
LCS = 1



+ 200% LCID
Impact
LCS = 2



Counter-Intuitive outcome: Medium Vulnerability areas are worst impacted

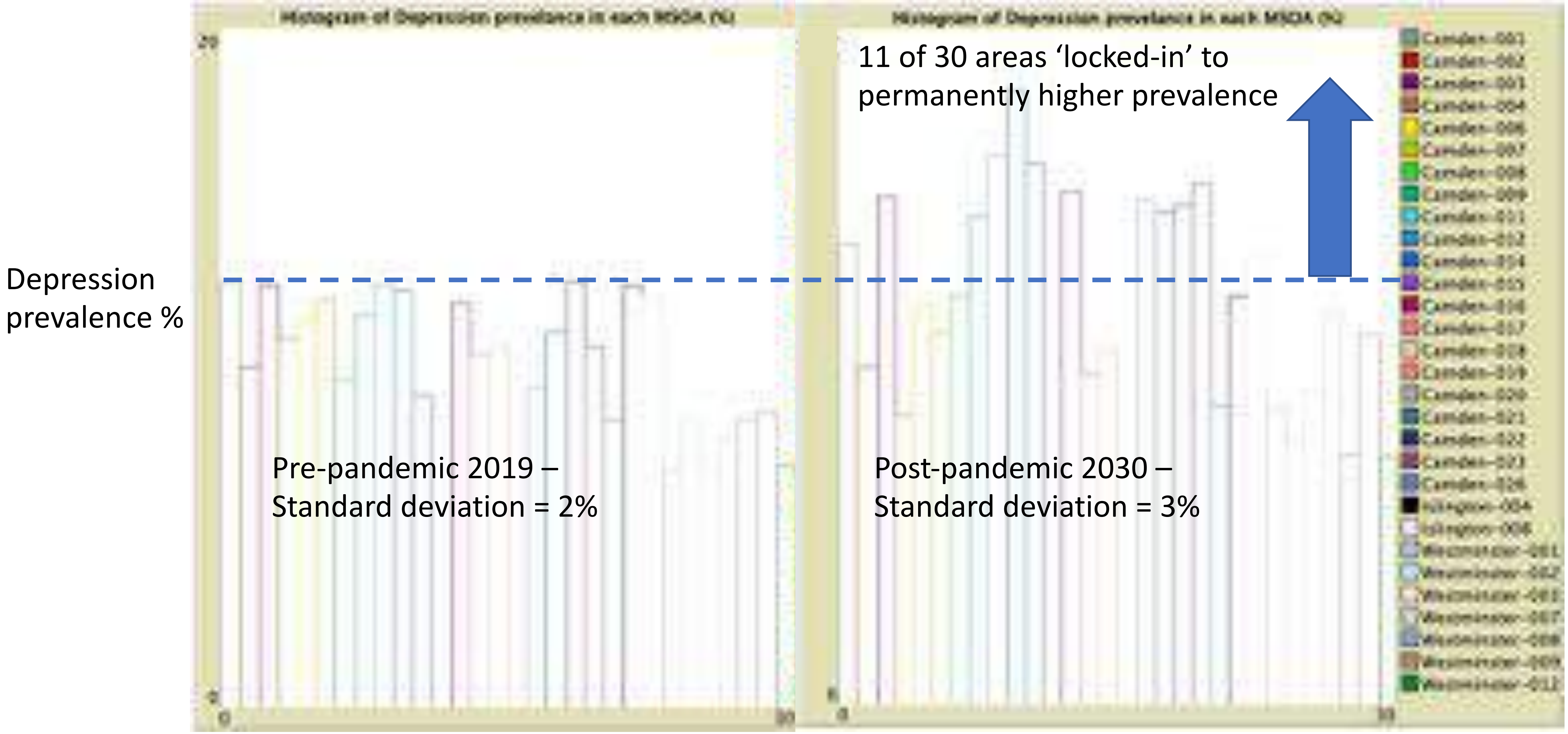
		ORDINAL RANK				
Area Ordered by increasing Regression Trigger	Starting Depression Prevalence %	Area Depression Trigger from Exploratory Regression	Multiple of Average Depression at end 2030 Long Covid Sensitivity (LCS) Scenario Input			
			LCS = 0	LCS = 0.48	LCS = 1	LCS = 2
Westminster 001	12.83	0.0383	0.733	[illegible]	0.626	[illegible]
Westminster 003	11.53	0.0414	0.699	[illegible]	0.990	0.717
Westminster 002	10.59	0.0419	0.842	0.779	0.813	0.980
Westminster 008	11.75	0.0454	0.713	0.700	0.581	[illegible]
Camden 026	9.86	0.0473	0.654	0.537	0.564	0.528
Westminster 012	10.67	0.0535	0.760	0.980	0.640	0.803
Westminster 007	13.04	0.0597	0.619	0.640	0.794	0.893
Camden 004	11.82	0.0664	0.736	0.595	0.737	0.972
Westminster 009	8.33	0.0674	1.327	1.108	0.839	0.909
Camden 019	10.53	0.0689	0.849	1.052	0.852	1.105
Camden 017	9.52	0.0692	0.735	1.036	1.087	0.883
Camden 008	11.83	0.0724	0.748	1.130	1.118	1.089
Camden 002	12.50	0.0728	0.735	0.968	0.647	0.843
Camden 014	11.47	0.0775	[illegible]	1.164	1.486	1.162
Camden 020	8.20	0.0786	1.028	0.917	1.163	1.276
Camden 011	12.50	0.0819	1.359	1.125	1.209	[illegible]
Camden 006	11.88	0.0825	1.137	1.274	1.095	1.457
Camden 012	9.05	0.0835	0.904	1.330	1.448	1.218
Camden 009	8.96	0.0842	1.342	1.051	1.223	1.140
Camden 001	12.28	0.0858	1.061	0.900	1.067	0.784
Camden 016	6.74	0.0870	1.164	1.121	1.264	0.983
Camden 007	13.88	0.0875	1.296	1.220	1.399	1.260
Camden 023	7.47	0.0878	1.059	1.188	1.307	1.045
Islington 004	7.86	0.0880	1.092	1.280	1.302	1.128
Camden 018	9.64	0.0886	1.127	0.965	1.088	1.027
Camden 015	8.05	0.0912	1.040	1.184	1.102	0.970
Camden 021	10.14	0.0932	1.073	1.144	0.776	1.068
Islington 008	12.84	0.0939	1.290	1.094	0.921	1.131
Camden 003	11.89	0.0951	1.080	1.248	0.936	1.045
Camden 032	10.16	0.0952	1.022	1.277	1.011	1.053
Average Prevalence	10.51		10.81	12.49	12.84	13.72
Standard Deviation	2.00		2.83	3.07	3.42	3.40

Sources: Depression_Shock_six_dclasses31.nlogo GeoDa Analysis, House of Commons Library

Legend	
0.50	Reduction
1.00	Neutral
2.00	Increase

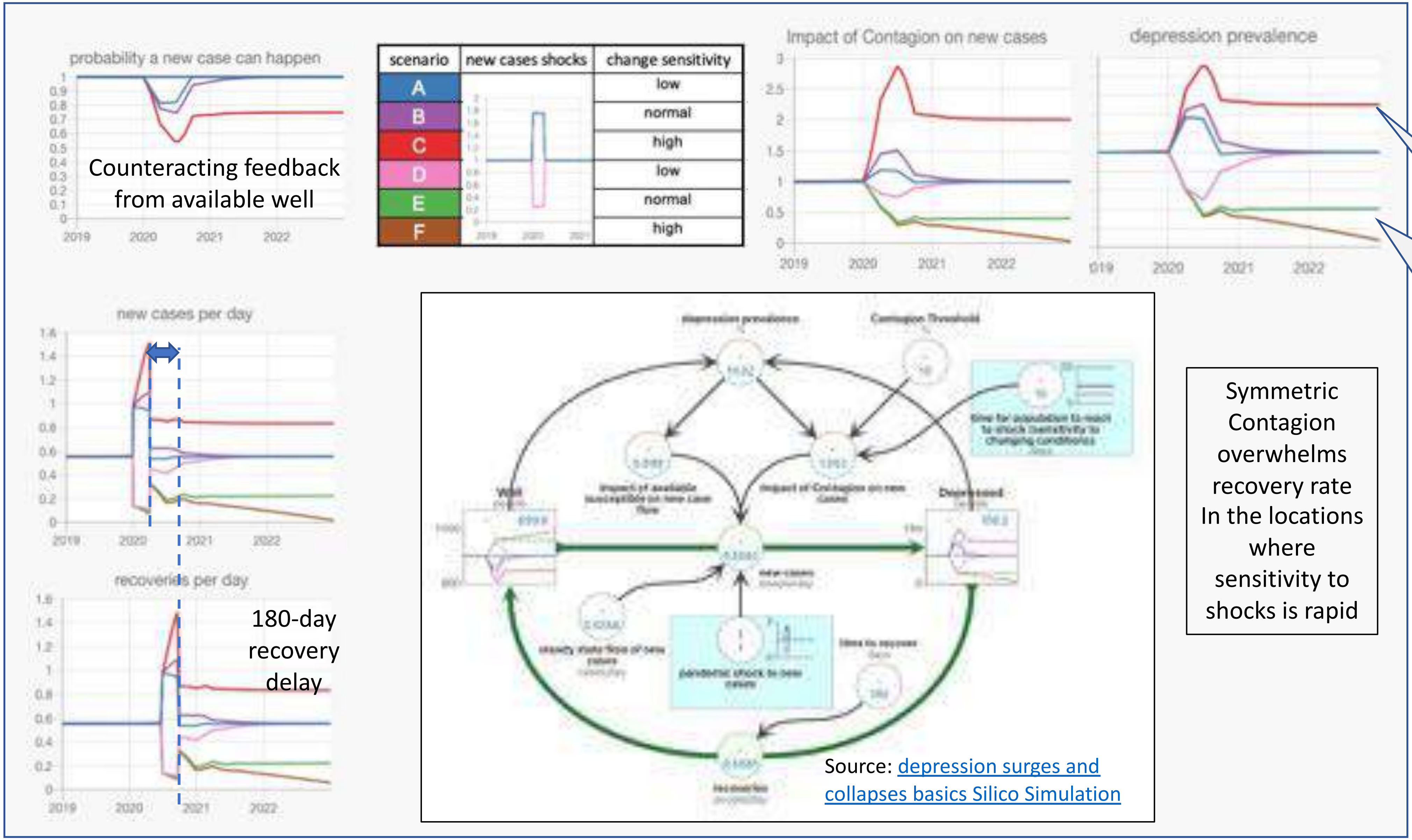
- The Multiple of average Depression creates clear patterns in the results
- Middle to high regression trigger (RT) areas are more at risk than areas at extremes
- Low RT areas are better off
- High RT areas appear more stable
- LCS 2 appears less risky than LCS 1 scenario
- Sustained increase in depression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

Most areas return to pre-pandemic levels but 1/3 are permanently ‘locked-in’



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

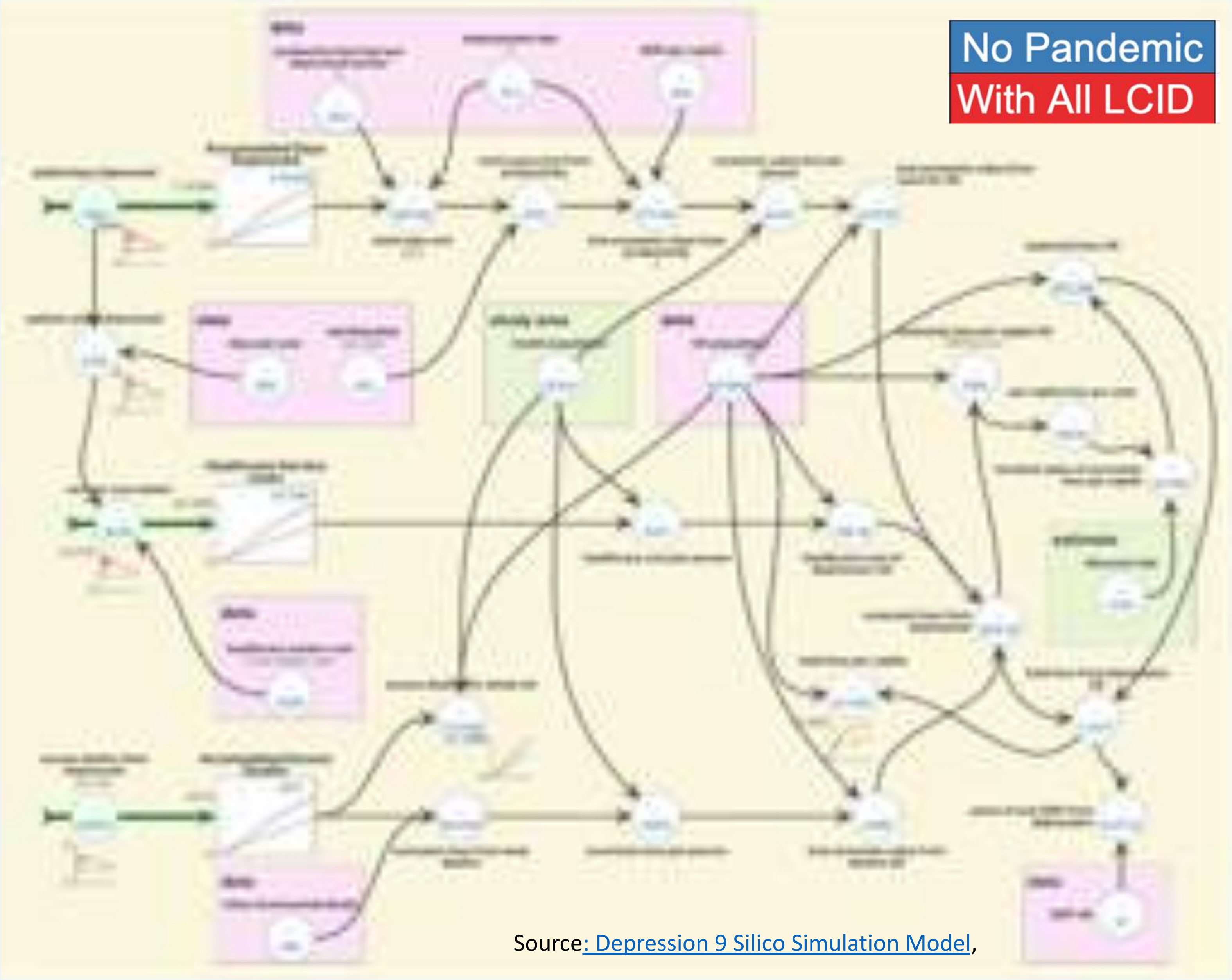


scenario	new cases shocks	change sensitivity
A		low
B		normal
C		high
D		low
E		normal
F		high

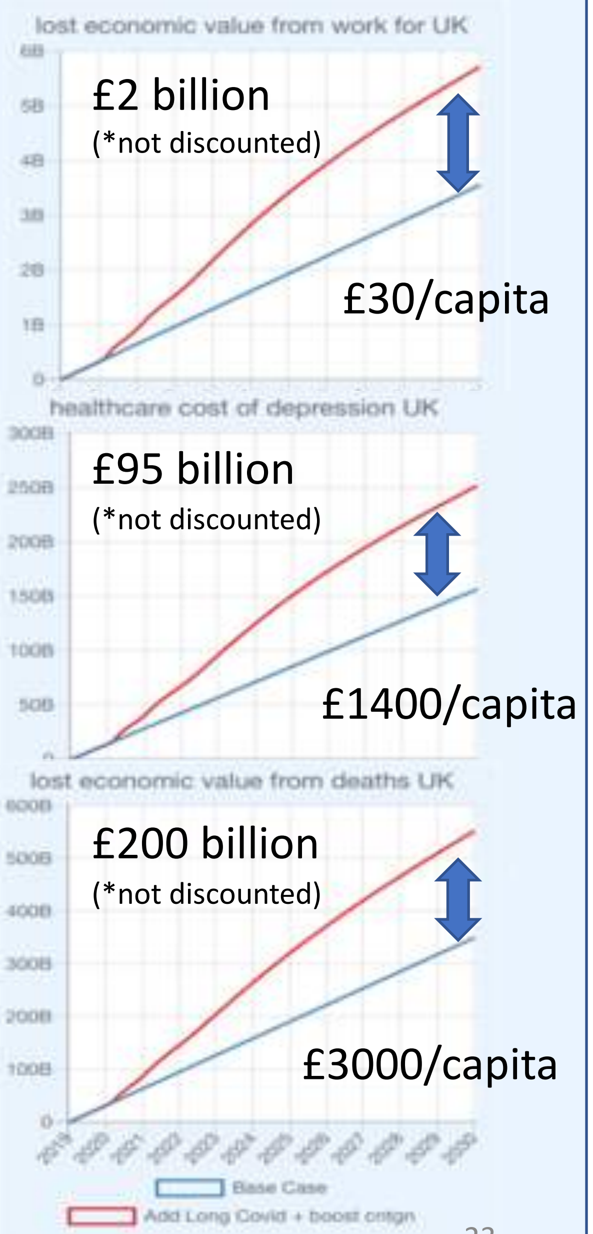
Source: [depression surges and collapses basics Silico Simulation]

3 out of 6 cases are a permanent change to depression prevalence

UK Accumulated Cost* of Depression: employment, health services, mortality

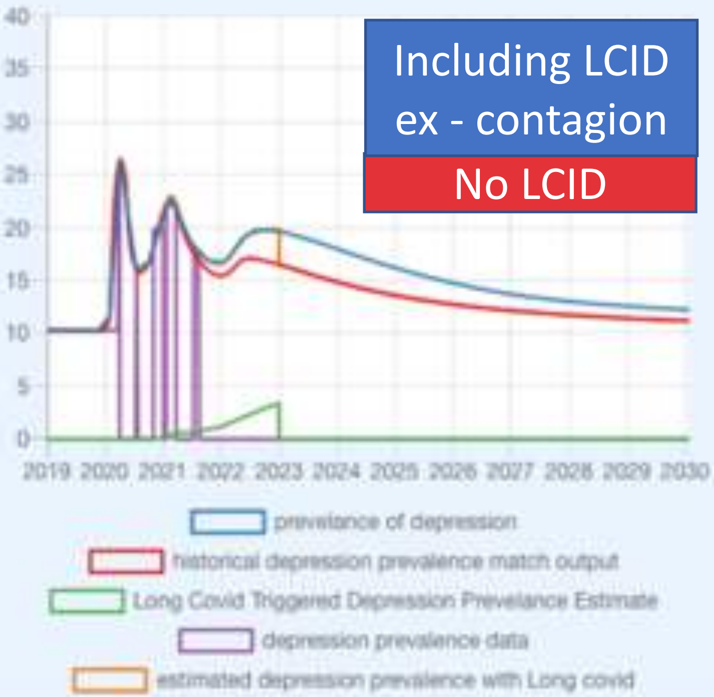


Source: Depression 9 Silico Simulation Model,



Projected UK Depression Prevalence, Economic Impact with and without LCID

UK Depression Prevalence %
Scenarios vs Historical data

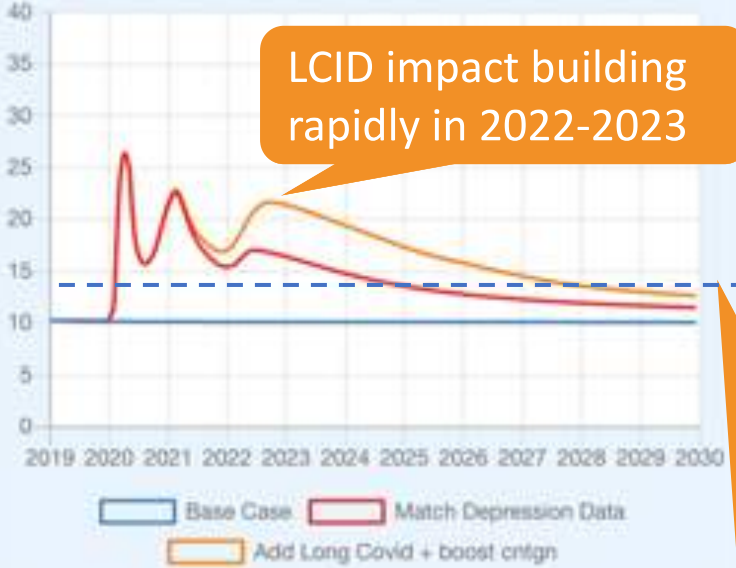


Including LCID ex - contagion

No LCID

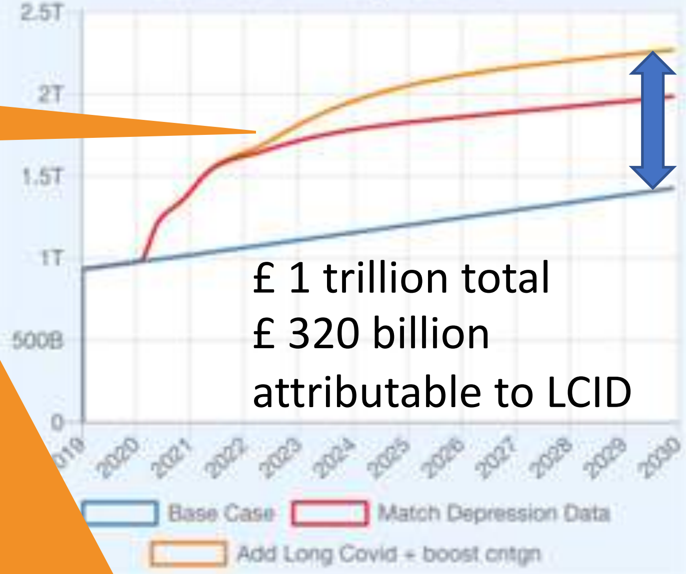
Source: [Depression 9 Silico Simulation Model,]()

UK Depression Prevalence %
Including LCID



LCID impact building rapidly in 2022-2023

Economic loss* from excess depression



£ 1 trillion total
£ 320 billion attributable to LCID

No Pandemic

Pandeimic, no LCID

With LCID

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

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

Saskatchewan, Canada

Modelling and Data Infrastructure is Geographically and Demographically Diverse and Detailed

Government of Saskatchewan
Ministry of Health

"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

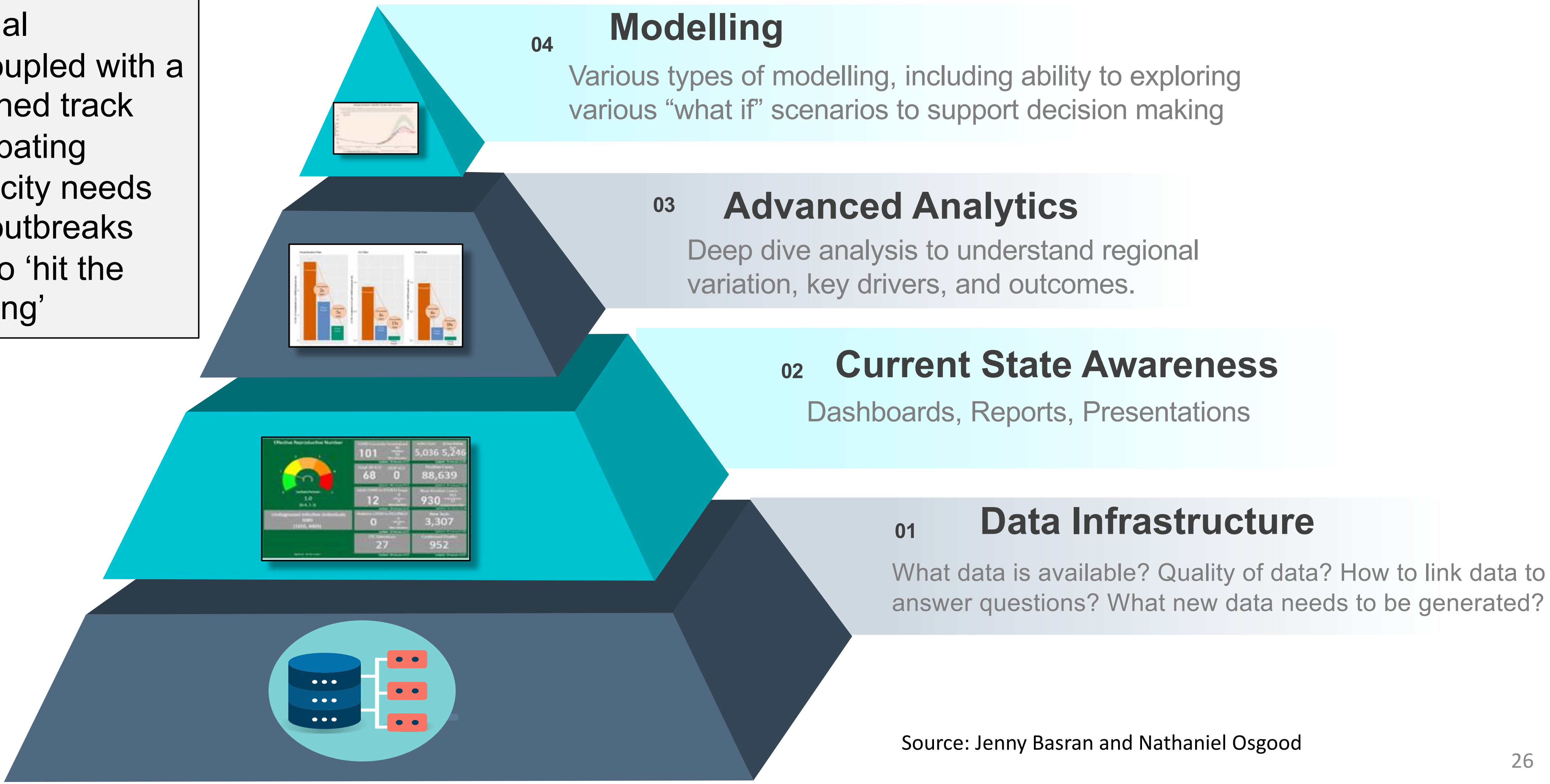
"The reality is that managing demands of care for all patients during a global pandemic has been extremely challenging. Modelling provides a level of pandemic situational awareness that is mission critical to prepare for pandemic waves. Ongoing refinement of this capacity has provided increasingly accurate 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

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'

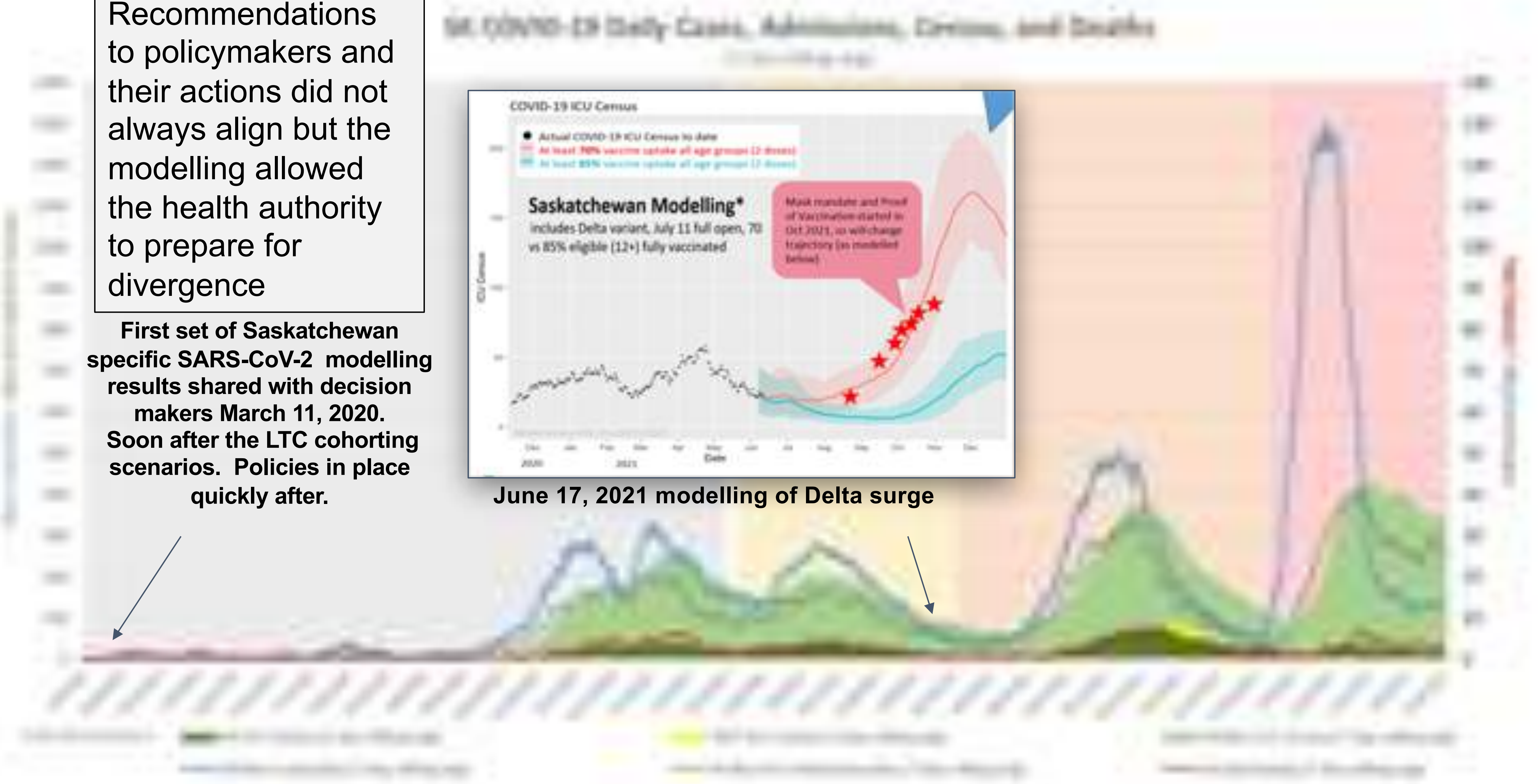


Source: Jenny Basran and Nathaniel Osgood

Progression of COVID-19 in Saskatchewan

Analytics and Modelling Allowed SHA to prepare in advance

Saskatchewan Health Authority
Digital Health Analytics



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

First set of Saskatchewan specific SARS-CoV-2 modelling results shared with decision makers March 11, 2020. Soon after the LTC cohorting scenarios. Policies in place quickly after.

June 17, 2021 modelling of Delta surge

Source: Jenny Basran and Nathaniel Osgood

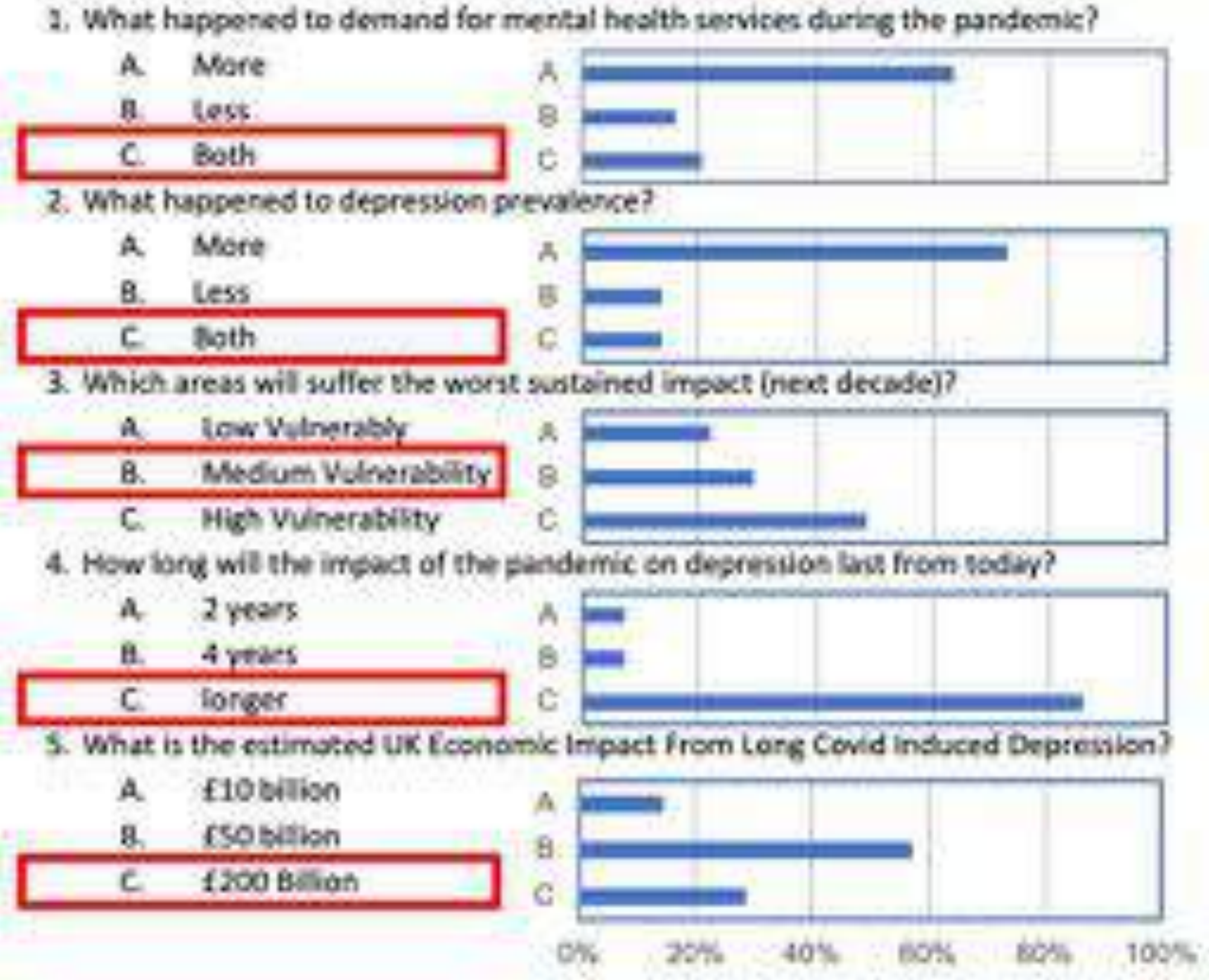
Impact of machine learning

- 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

Survey Results, Pandemic Impact of Depression is not well understood

Data/Modeling Findings | Live Survey Results | Survey vs. Analysis Insights



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

Observations

- 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

Questions: mglucksman@alum.mit.edu