The (Structural) Gravity of Epidemics

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1 Motivation

Typical epidemiological models (e.g. Ferguson et al., 2020) assume "gravity" interactions of people across space... w/o microfoundation!

Economists have started to incorporate disease transmission into macro models... but with *ad hoc* assumptions about:
economic activity $\Leftrightarrow$ disease transmission.

We combine an SIR model with a bare-bones dynamic model of individual location choice $\Rightarrow$ flows of S, I, R across space obey a **structural gravity equation**.

Applied to data from Great Britain, the model:

1. offers a clear mapping: observed geography $\rightarrow$ disease spread.
2. permits a microfounded analysis of the quarantine trade off.
3. highlights key parameters for such an analysis.

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2 Model

$$S_{n't} = \sum_{n} m^{S}_{nn't} \left(S_{nt-1} - \tilde{I}_{nt-1} \right),$$

$$I_{n't} = \sum_{n} m^{I}_{nn't} \left[(1 - \pi_r - \pi_d) I_{nt-1} + \tilde{I}_{nt-1} \right], \quad \tilde{I}_{nt-1} = \pi_s \frac{I_{nt-1} S_{nt-1}}{L_{nt-1}},$$

$$R_{n't} = \sum_{n'} m^{R}_{nn't} \left(R_{nt-1} + \pi_r I_{nt-1} \right),$$

$$L_{nt} = S_{nt} + I_{nt} + R_{nt},$$

$$I_{n0} = R_{n0} = 0, \quad S_{n0} = L_{n0}, \quad \tilde{I}_{n0} \geq 0.$$

If $\pi_d \simeq 0$, then $m^{S}_{nn't} \simeq m^{I}_{nn't} \simeq m^{R}_{nn't} \equiv m_{nn't}$, where:

$$m_{nn't} = \frac{\left(\tau_{nn't} / v_{n't}\right)^{-\theta}}{\sum_{n'=1}^{N} \left(\tau_{nn't} / v_{n't}\right)^{-\theta}}, \quad v_{nt} = e^{\frac{\beta\gamma}{\theta}} u_n \left[\sum_{n'} \left(\frac{\tau_{nn't+1}}{v_{n't+1}} \right)^{-\theta} \right]^{\frac{\beta}{\theta}}.$$

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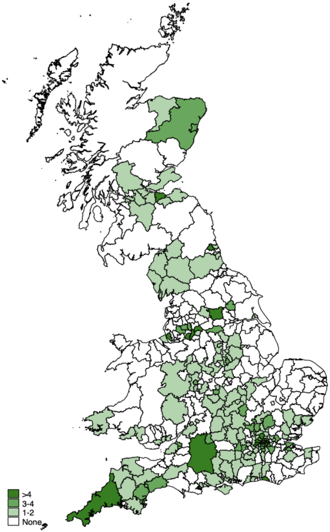
3 Initial Infections



Covid-19 infections (10 March 2020)

England: 324

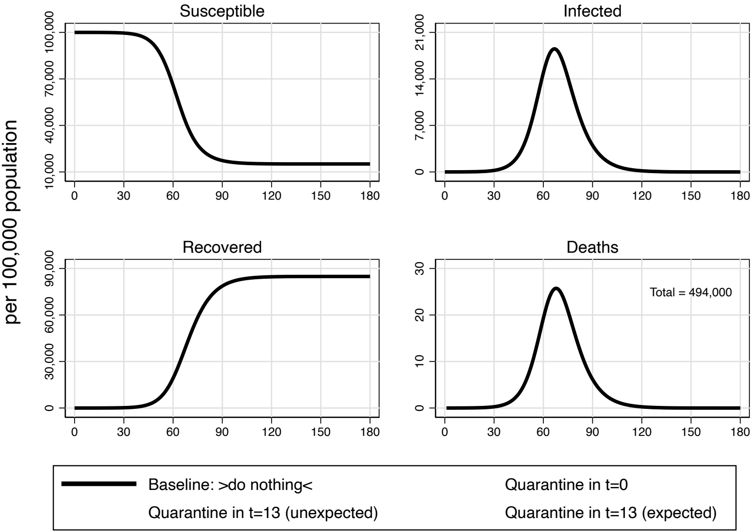
Scotland: 27

Wales: 6

Total: 367

We impose: $I_{n0} =$ reported infections/.30

4 Scenarios


per 100,000 population
Susceptible
10,000
40,000
70,000
100,000
Infected
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14,000
21,000
Recovered
0
30,000
60,000
90,000
Deaths
0
10
20
30
Total = 494,000
0
30
60
90
120
150
180
Baseline: >do nothing<
Quarantine in t=0
Quarantine in t=13 (unexpected)
Quarantine in t=13 (expected)

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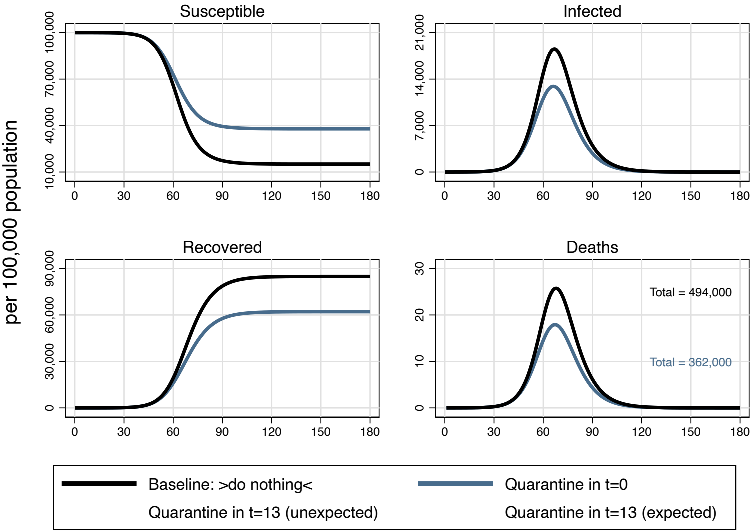
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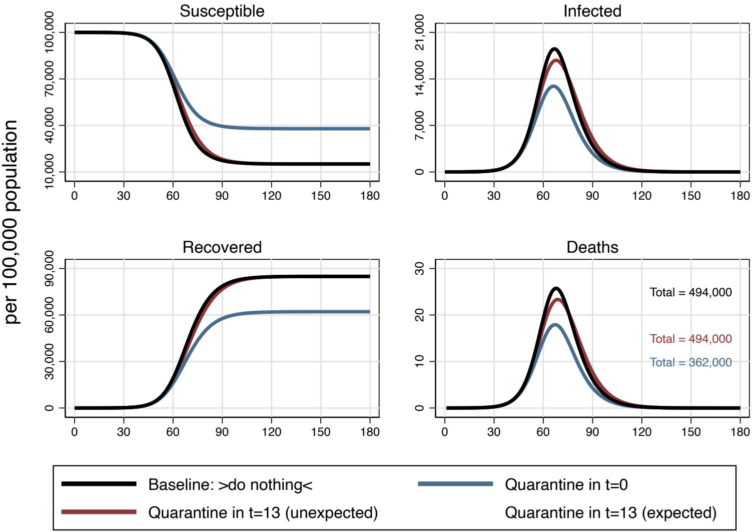
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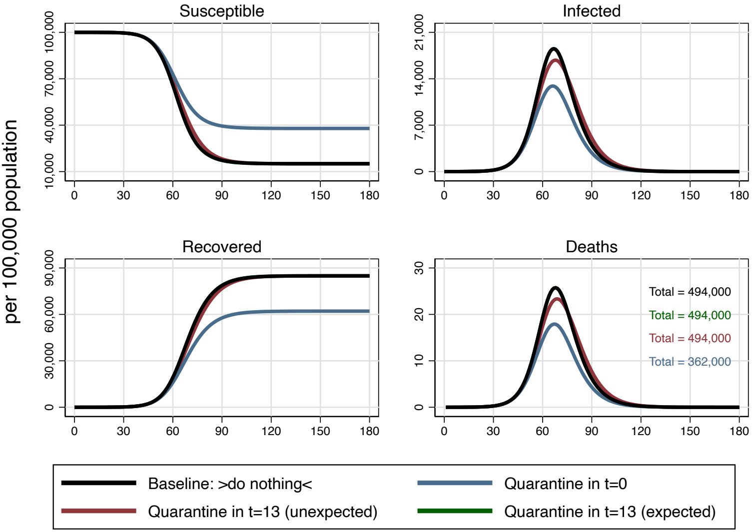
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5 Welfare and Conclusion

- Key parameters: "mobility elasticity" (θ); "value of life" (u_N).
- For any reasonable value of these parameters:
  1. Quarantine in $t = 0 \succ$ "Do nothing"
  2. Unexpected quarantine in $t = 13 \succ$ "Do nothing"
  3. Expected quarantine in $t = 13 \prec$ "Do nothing"
- The model could be generalised (heterogeneity, production side, disease properties, etc.)...
- ...used to assess other interventions (e.g. localised lockdowns)...
- ...and applied in other contexts (e.g. border closures).

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