PENN WHARTON
UNIVERSITY of PENNSYLVANIA
Budget Model

The Diminishing Effect of Physical Encounters on Coronavirus Transmission

Summary: We estimate that the effect of physical encounters on coronavirus transmission has fallen over time, suggesting that people have adapted their behavior in accordance with social distancing best practices. Whether reopenings cause additional outbreaks will depend on the continuation of these behavior changes.

Since April, Penn Wharton Budget Model has been simulating the health and economic effects of policies related to the coronavirus pandemic. Our integrated framework combines several empirical models to project variables like coronavirus deaths and the number of jobs gained or lost under potential policy changes. Our model shows that the magnitude of the relationship between measured physical encounters and coronavirus transmission has fallen over time, suggesting that people have changed their behavior in a way that makes transmission less likely.

Physical Encounters and Transmission: Model

One component of PWBM's coronavirus simulator is the regression model linking physical encounters and the virus's transmission rate, R. This model allows us to translate projections of social distancing under different assumptions about policy and personal behavior into inputs for the epidemiological component of our model. We estimate the following regression:

$$\log R_{i,t} = \alpha_i + \beta \log T_{i,t-10} + \theta \log E_{i,t-10} + \delta W_t + \gamma \log E_{i,t-10} W_t + \varepsilon_{i,t}$$

where:

- $R_{i,t}$ is the instantaneous rate of reproduction for county i at time t. We estimate values using the method outlined in Cori et. al. (2013).[12]
- α_i is a county fixed effect
- $T_{i,t-10}$ is a measure of wet-bulb air temperature, lagged 10 days to account for the time between exposure and a positive test result.[3]
- $E_{i,t-10}$ is an index tracking the number and types of physical encounters by drawing on cell phone location data.[4] The index includes data from Unacast measuring the frequency with which devices come into close contact and the number of trips to nonessential businesses;[5] data from Couture et. al. (2020) measuring the number of distinct devices that visit the same commercial locations;[6] and data from SafeGraph measuring the share of the population staying at home for the entire day.[7]

- W_t is a dummy variable indicating week.

This brief focuses on the estimated effect of the encounter index — in particular, the extent to which it is changing over time. The interaction between $E_{i,t-10}$ and W_t measures this effect. The marginal effect of the encounter index is then:

$$\theta + \gamma W_t$$

We find evidence that in every week, physical proximity is associated with an increase in the reproduction rate of coronavirus. However, we find that the magnitude of this effect has diminished since the beginning of the pandemic.

Physical Encounters and Transmission: Estimated Effect

Figure 1 shows this trend over time, plotting the conditional relationship between encounter index and *R*. In mid-March, a 100 percent increase in the encounter index was associated with an increase in *R* of about 33 percent. In recent weeks, that same doubling of the encounter index leads to an increase in *R* of about 10 percent.

Figure 1. Conditional Relationship Between Encounter Index and R

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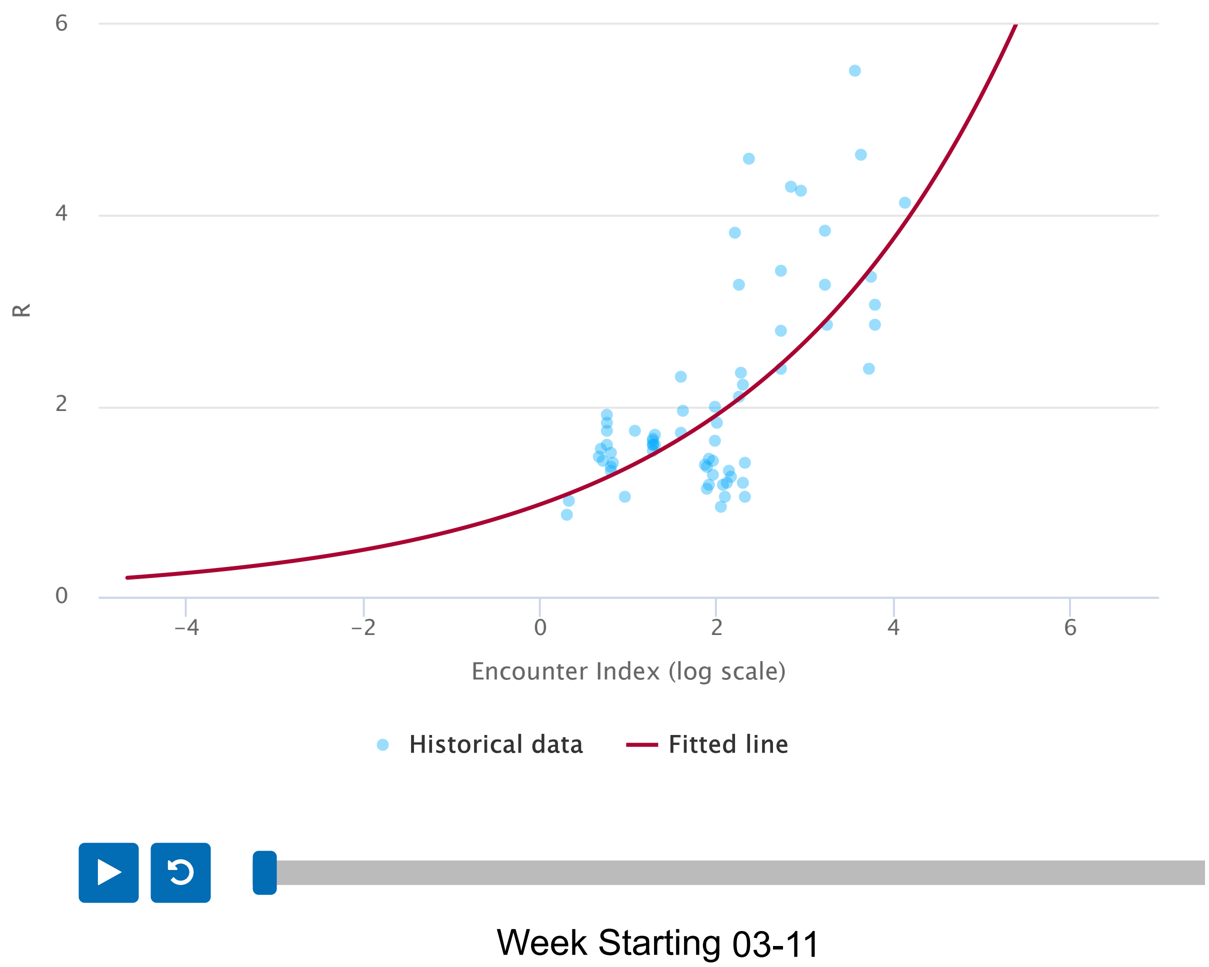

One possible explanation for this decreasing effect is the changing nature of human interactions over the last few months. Americans are beginning to move around more frequently as the country steadily opens up, but these interactions look different than they did at the start of the pandemic. Mask-wearing is a social expectation if not a requirement by law in many places. Activities like dining and religious services that were previously held indoors have been moved outdoors, where transmission appears to be more difficult. Retail businesses have reoriented their spaces to encourage social distancing, taking measures like installing plexiglass barriers for cashiers and mandating 6 feet of space for customers in line.

Our model shows that lifting restrictions alone will lead to more encounters between people, which in turn has positive economic effects. But whether this increased activity translates into coronavirus transmission will depend largely on whether personal habits change. People may view reopenings as a signal that the pandemic is over and that it's safe to return to normal behavior, or they might continue to exercise caution and strictly adhere to the advice of public health officials. PWBM does not take a stance on this issue, instead allowing users of our interactive tool to view projections under two scenarios. The first scenario ("Baseline") assumes that current social distancing practices are maintained, and that the relationship between encounters and *R* remains at its current level. The second scenario ("Reduced Distancing") assumes that people return to their pre-pandemic behavior over time, thus increasing the magnitude of the relationship between encounters and *R* to its mid-March level.

This analysis was produced by John Ricco, under the direction of Richard Prisinzano. Prepared for the website by Mariko Paulson.

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1. Cori, A., Ferguson, N., Fraser, C. and Simon Cauchemez. *A New Framework and Software to Estimate Time-Varying Reproduction Numbers During Epidemics*, American Journal of Epidemiology, Volume 178, Issue 9, 1 November 2013, Pages 1505–1512, https://doi.org/10.1093/aje/kwt133. ↩

2. County-level case data comes from the New York Times and the Covid Tracking Project. We adjust for changes in testing capacity over time. We first estimate state-specific reporting rates by dividing reported cases by a "true" measure of cases that assumes a 1 percent infection fatality ratio and a 3-week period from symptom onset until death. We then regress this rate on the positivity rate (positive tests / total tests) and fit reporting rate values for each state, applying these to each county within a given state. ↩

3. Evidence shows an incubation period (time from exposure to onset of symptoms) of about 5 days, and we add an additional 5 days to account for both the time from symptom onset to the choice to receive a test and recording a positive result. Our results are robust to similar lag specifications. ↩

4. The index is the first principal component of the measures described above, calculated separately by county. It reflects variation over time that is common to all measures. ↩

5. https://www.unacast.com/covid19/social-distancing-scoreboard ↩

6. Couture, V., Dingel, J., Green,. A and Jessie Handbury. *Device exposure based on PlaceIQ data*, working paper, 14 April 2020. Data retrieved from this repository. ↩

7. SafeGraph is a data company that aggregates anonymized location data from numerous applications in order to provide insights about physical places. To enhance privacy, SafeGraph excludes census block group information if fewer than five devices visited an establishment in a month from a given census block group. Specifically, we use SafeGraph's Social Distancing Metrics. ↩