EXHIBIT M

Governor Murphy Announces "The Road Back: Restoring Economic Health Through Public Health"

04/27/2020

TRENTON – Governor Phil Murphy today announced his vision, "The Road Back: Restoring Economic Health Through Public Health," (http://d31hzlhk6di2h5.cloudfront.net/20200427/db/2d/77/6c/2a8a498ff2edda855c3f456d/The_Road_Back_-_Restoring_Economic_Health_Through_Public_Health.pdf) to restart New Jersey and put the state on the road to recovery. Governor Murphy outlined six key principles and benchmarks to guide the process for restoring New Jersey's economic health by ensuring public health.

"Our priority is to use science, data, and facts to put New Jersey on the road to recovery. In order to restore economic health, we must first promote public health," **said Governor Murphy.** "These key principles and metrics are critical for giving New Jerseyans confidence that we will re-open our state with our public health protocols firmly in place and our health care system prepared. Restarting New Jersey's economy and returning people to work will be done methodically, strategically, and responsibly."

Governor Murphy's stay-at-home Executive Order, which has been in effect since March 21st, will remain in effect in its entirety until further notice. The following six principles and key metrics will guide the process for lifting restrictions and restoring New Jersey's economic health through public health.

Principle 1: Demonstrate Sustained Reductions in New COVID-19 Cases and Hospitalizations

- 14-day trend lines showing appreciable and sustained drop in new COVID-19 cases, hospitalizations, and other metrics reflecting decreasing burden of disease;
- Hospitals stepping down from functioning under crisis standards of care.

Principle 2: Expand Testing Capacity

- At least double current diagnostic testing capacity;
- Prioritize testing for health care workers, essential personnel, and vulnerable populations;
- Create a flexible testing plan accessible to all residents;
- Expand partnerships with institutions of higher education, private-sector labs, and the federal government;
- Ensure that those who test positive are linked to a health care provider.

Principle 3: Implement Robust Contact Tracing

- Recruit and deploy an army of personnel who will identify and follow-up with contacts;
- Leverage technological data and innovative solutions to increase efficiency;
- Coordinate the approach of local and state health officials, which will have a coordinated county/regional component.

Principle 4: Secure Safe Places and Resources for Isolation and Quarantine

- To the greatest extent possible, provide individuals who do test positive in the future with a safe and free place to isolate and protect others from COVID-19;
- Ensure that quarantined contacts are provided supportive services, if needed.

Principle 5: Execute a Responsible Economic Restart

- Create the Governor's Restart and Recovery Commission to advise on the process and recommend responsible and equitable decisions;
- Plan for a methodical and strategic return to work based on level of disease transmission risk and essential classification;
- Continuation of social distancing measures, requirements for face coverings, and work-from-home directions where feasible and appropriate;
- Leverage any available federal funds and programs to support health care, individual, and small business recoveries.

Principle 6: Ensure New Jersey's Resiliency

- Learn from the lessons of COVID-19 and prepare for the possibility of a resurgence;
- Ensure hospitals, health care systems, and other health delivery facilities have inventories of personal protective equipment and ventilators;
- Build our own state personal protective equipment and ventilator stockpile;
- Create a playbook for future administrations for the next pandemic.

For a one-page summary of Governor Murphy's plan to restore New Jersey's economic through public health, click here (http://d31hzlhk6di2h5.cloudfront.net/20200427/db/2d/77/6c/2a8a498ff2edda855c3f456d/The_Road_Back_-_Restoring_Economic_Health_Through_Public_Health.pdf).

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The Road Back: Restoring Economic Health through Public Health

THE ROAD BACK
Restoring Economic Health through Public Health

	Maximum restrictions	STAGE 1	STAGE 2	STAGE 3	New normal
What is happening?	Strict social distancing Non-crucial industries closed	Restrictions relaxed on low-risk activities that may be easier to safeguard	Moderate-risk activities restarted with safeguarding	Higher-contact activities restarting with significant safeguarding	Widespread use of vaccine or life-saving treatment In-person work can resume for all
Which precautions apply across stages?	Work that can be done from home should be done from home Clinically high-risk individuals who can stay at home should do so	Residents and businesses should follow state and federal safeguarding guidelines: Wash hands regularly Respect social distancing Disinfect workplaces Wear masks in public Limit gatherings No mass gatherings			Measures from previous stages may be swiftly reinstated if health conditions deteriorate
Which businesses are open?	Crucial industries with safeguarding and modifications, e.g., emergency healthcare, essential construction with social distancing	Easiest to safeguard work activities with safeguarding and modifications, e.g., non-essential construction with protections, curbside retail	More work activities allowed with safeguarding and modifications, e.g., outdoor dining, limited personal care	Most work activities allowed at physical locations with safeguarding & modifications	
Which social activities are allowed?	• Socialization only with household members, family, caretakers, romantic partner • Only leave home for limited reasons such as essential shopping and exercise	• Outdoor recreation (e.g., hiking) and beach visits allowed with social distancing • Other limited activities may be allowed with significant restrictions, e.g., drive-in activities	• More activities with proper safeguards, capacity limitations, and sanitation protocols may reopen, e.g., libraries and museums	• Higher-density settings may be considered with safeguards, e.g., limited entertainment, bars with limited capacity	

If health metrics develop unfavorably, measures from the maximum restrictions stage or stages 1, 2, 3 may be reinstated

WHAT DRIVES STAGES?

Health indicators: New cases; hospitalizations; use of ICU; use of ventilators

Are childcare and education operating?	• Child care open for children of essential workers • K-12 and higher education engaged in distance learning	• Child care may expand with capacity restrictions • K-12 and higher education engaged in distance learning	• Child care may expand with capacity restrictions • Potential for some in-person learning with modifications in K-12 and higher education • Summer school and summer camps may have limited in-person engagement if health conditions improve	• Child care likely open for most • K-12 and higher education may operate in person with reduced capacity • Day and summer camps likely open for all with safe-guards and modifications
Is public transit available?	• Public transit with enhanced safeguards (e.g., regular vehicle disinfection) encouraged only for essential workers • Service may be modified with off peak travel encouraged • Personal protection measures, e.g., social distancing, face coverings	• Public transit with enhanced safeguards (e.g., regular vehicle disinfection) encouraged only for those who cannot work from home • Service may be modified with off peak travel encouraged • Personal protection measures, e.g., social distancing, face coverings	• Public transit with enhanced safeguards (e.g., regular vehicle disinfection) encouraged only for those who cannot work from home • Service may be modified with off peak travel encouraged • Personal protection measures, e.g., social distancing, face coverings	• Public transit with enhanced safeguards (e.g., regular vehicle disinfection) is no longer discouraged for any passengers • Service may be modified with off peak travel encouraged • Personal protection measures, e.g., social distancing, face coverings
How do I take care of my loved ones and myself?	• I stay at home as much as possible and check in virtually with my loved ones • When I have to go outside, I wear a mask and stay 6ft away from others • I call a doctor in the event of fever, cough, or shortness of breath	• I stay at home as much as possible and check in virtually with my loved ones • When I have to go outside, I wear a mask and stay 6ft away from others • I have access to elective healthcare • I call a doctor in the event of fever, cough, or shortness of breath	• I continue to stay at home for the majority of my time • I engage in small social activities with a limited circle of friends and family • I can engage in some outdoor activities with social distancing • I call a doctor in the event of fever, cough, or shortness of breath	• I follow all safety guidelines posted in public spaces, e.g., I anticipate and respect capacity limits at my local restaurants • I call a doctor in the event of fever, cough, or short-ness of breath

Availability of testing and contact tracing capacity per 100,000 residents

Healthcare system resiliency (beds, health workers, PPE)

Ability to effectively safeguard workplaces

Safeguarded child care, education, transit availability

Compliance of individuals and employers

EXHIBIT N

Centers for Disease Control and Prevention

Coronavirus Disease

Deciding to Go Out

Deciding to Go Out

Updated June 15, 2020

What you need to know

- In general, the more closely you interact with others and the longer that interaction, 19 spread.
- If you decide to engage in public activities, continue to protect yourself by practicing
- Keep these items on hand when venturing out: a cloth face covering, tissues, and a h 60% alcohol, if possible.

Understand the potential risks of going out

As communities and businesses are opening, you may be looking for ways to resume som possible. While there is no way to ensure zero risk of infection, it is important to understa adopt different types of prevention measures to protect yourself and to help reduce the s

The risk of an activity depends on many factors, such as:

- Is COVID-19 spreading in your community?
- Will you have a potential close contact with someone who is sick or anyone who is nc may be asymptomatic)?
- Are you at increased risk of severe illness?

- Do you take everyday actions to protect yourself from COVID-19?

CDC cannot provide the specific risk level for every activity in every community. That's wh consider your own personal situation and the risk for you, your family, and your commun

Close contact with other people increases risk

In general, **the more closely you interact with others and the longer that interaction, th spread.** So, think about:

How many *people* will you interact with?

- Interacting with *more people* raises your risk.
- Being in a group with people who aren't social distancing or wearing cloth face cover
- Engaging with new people (e.g., those who don't live with you) also raises your risk.
- Some people have the virus and don't have any symptoms, and it is not yet known h symptoms can transmit the virus to others.

Can you keep 6 feet of *space* between you and others? Will you be outdoors

- The *closer* you are to other people who may be infected, the greater your risk of gett
- Keeping distance from other people is especially important for people who are at hig as older adults and those with underlying medical conditions.
- Indoor spaces are more risky than outdoor spaces where it might be harder to keep ventilation.

What's the length of *time* that you will be interacting with people?

- Spending *more time* with people who may be infected increases your risk of becomi
- Spending more time with people increases *their* risk of becoming infected if there is already be infected.

What makes activities safer

Activities are safer if

- You can maintain at least 6 feet of space between you and others. COVID-19 spreads within 6 feet of each other.
- They are held in outdoor spaces. Indoor spaces with less ventilation where it might b are more risky.
- People are wearing cloth face coverings. Interacting without wearing cloth face cover

Stay home if you are sick

If you have COVID-19, have symptoms consistent with COVID-19, or have been in close co COVID-19, it is important to stay home and away from other people. When you can leave depends on different factors for different situations. Follow CDC's recommendations for y

Consider the risks before you go

Asking these questions can help determine your level of risk.

Is COVID-19 spreading in my community?

Find out by viewing the latest COVID-19 information and a map of states with reported

What are the local orders in my community?

Review updates from your local health department to better understand the situation i local orders are in place in your community. Also find out about school closures, busine home orders in your state.

Will my activity put me in close contact with others?

Practice social distancing because COVID-19 spreads mainly among people who are in

- It's important that you and the people around you wear a cloth face covering whe when it's difficult to stay 6 feet away from others consistently.
- Choose outdoor activities and places where it's easy to stay 6 feet apart, like parks
- Look for physical barriers, like plexiglass screens or modified layouts, that help yo

- Use visual reminders—like signs, chair arrangements, markings on the floor, or ar keep your distance from others.

Am I at risk for severe illness?

Older adults and people of any age who have serious underlying medical conditions mi severe illness from COVID-19. While the risk for severe illness is lower for others, every Some people have no symptoms, others have mild symptoms, and some get severely il

Do I live with someone who is at risk for severe illness?

If you live with older adults or someone with certain underlying medical conditions, the should take extra precautions to minimize risk. Learn more about what you can do if yc family are at higher risk of severe illness from COVID-19.

Do I practice everyday preventive actions?

Continue to protect yourself by practicing everyday preventive actions, like monitoring touching your face with unwashed hands, washing your hands often, social distancing, cloth face covers, and staying home if you are sick.

Will I have to share any items, equipment, or tools with other people?

Choose places where there is limited sharing of items and where any items that are sha and disinfected between uses. You can also choose to visit places that share, post, or a increased cleaning and disinfection to protect others from COVID-19.

Will I need to take public transportation to get to the activity?

Public transit can put you in close contact with others. When using public transportatio how to protect yourself when using transportation

Does my activity require travel to another community?

If I get sick with COVID-19, will I have to miss work or school?

If you are sick with COVID-19, stay home. Also find out about your work or school's tele

Do I know what to do if I get sick?

Know the steps to help prevent the spread of COVID-19 if you are sick.

Be prepared and stay safe

If you decide to engage in public activities, continue to protect yourself by practicing every

Items to have on hand

- A cloth face covering
- Tissues
- Hand sanitizer with at least 60% alcohol, if possible

Get more tips to keep you and others safe when you venture out

- Running Essential Errands
- Doctor Visits and Getting Medicines
- Personal and Social Activities

More Information

Protect Yourself When Using Public Transit

Considerations for Youth and Summer Camps

Considerations for Institutes of Higher Education

Considerations for Youth Sports

Considerations for Schools

Considerations for Restaurants and Bars

Considerations for Pools, Hot Tubs, and Water Playground

Managing Stress and Anxiety

EXHIBIT O

Evidence mounts that outside is safer when it comes to COVID-19

BY PETER SULLIVAN - 05/06/20 05:30 PM EDT

Just In...

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VIEW ALL

Health experts say people are significantly less likely to get the coronavirus while outside, a fact that could add momentum to calls to reopen beaches and parks closed during the COVID-19 pandemic.

Being outside shouldn't be seen as completely safe, health experts say. People should continue to avoid crowds and maintain six feet of distance from others to keep away from the virus.

But experts are increasingly confident in evidence showing that the coronavirus spreads much more readily indoors than outdoors, a finding that could help guide policymakers seeking to figure out ways to end lockdowns that have shuttered much of the nation's economy.

"Parks, beaches — as long as they're not cheek to jowl, cycling, walking, this is good," said Tom Frieden, the former director of the Centers for Disease Control and Prevention. "Enjoy nature. It's good for us, and it has very low risk of spreading the virus."

Maryland Gov. Larry Hogan (R) on Wednesday said coronavirus figures suggested the state might be able to begin reopening next week. If it does, he said it would include opening state parks and beaches and allowing outdoor gym classes and religious services.

"Studies suggest activities held outdoors as temperatures warm pose lower COVID risk than those done in confined indoor spaces," tweeted Scott Gottlieb, the former Food and Drug Administration commissioner. "As we re-open, states should look to ease rules to allow more recreational, religious, and business activities to occur outside."

Some cities are already considering options that might help local businesses while keeping people safe.

Hartford, Conn., is one of the cities exploring allowing restaurants to expand their outdoor seating options into parking lots or other outdoor spaces.

Vilnius, the capital of Lithuania, has gone further by opening its central square and other outdoor areas to restaurant seating.

"We need creative solutions, and I think things like closing down streets and having some dispersed [seating] from restaurants is a nice creative solution," said Eleanor Murray, a professor at Boston University School of Public Health.

"We can't continue this lockdown indefinitely," she said. "It's just not going to be psychologically or economically feasible."

Gottlieb pointed to a study, which has not yet been peer-reviewed, that examined outbreaks in 320 Chinese cities outside Hubei province, where

the coronavirus is believed to have originated, between Jan. 4 and Feb. 11 and found only one outbreak that occurred outdoors.

Experts warned that people are not completely safe outdoors and that it is important to stay six feet away from people outside.

"You don't want to be in a crowd, regardless of where that crowd is," Murray said.

California Gov. Gavin Newsom (D) ordered beaches in Orange County to close last week after they became packed with people during a heat wave.

Murray said that even outside on the beach, people who do not live together should stay six feet apart and that activities such as beach volleyball should be avoided because multiple people touching the same equipment can spread the virus.

That means playgrounds also are a danger, she said.

"While it's great to have parks and beaches, you probably don't want playground equipment open," Murray said.

The virus is harder to transmit outdoors because the droplets that spread it are more easily disturbed or dispersed outside in the elements than in a closed, confined, indoor setting.

"It definitely spreads more indoors than outdoors," said Roger Shapiro, a professor at Harvard University's T.H. Chan School of Public Health. "The virus droplets disperse so rapidly in the wind that they become a nonfactor if you're not really very close to someone outdoors — let's say within six feet."

As people go outside for their daily exercise and pass by one another, experts offered reassurance that simply passing someone for a split second outdoors presents a low risk.

"The virus can't magically teleport," said Amesh Adalja, a senior scholar at the Johns Hopkins University Center for Health Security. "It needs a cough or sneeze or something, singing, talking, spitting. ... It's not magnetism or something like that."

Adalja said some of the decisions around activities such as sitting closer than six feet away from a friend outside on the grass have to do with how much risk someone is personally willing to accept.

"There's not some kind of black or white answer to all of this stuff," he said. "People are going to have to make a lot of decisions about what risk tolerance they have."

Indoor spaces such as barbershops are certainly higher risk, though. There are more shared surfaces that could transmit the virus, such as the barber's chair. Another danger, especially in the summer, is air conditioning, which can circulate the virus through the air.

"If you're in an indoor space that has the air conditioning blasting ... that air conditioning might be blowing the droplets straight at you," said Murray, the Boston University professor.

Even outdoors, Adalja said people should be mindful of keeping their distance and washing their hands.

"You can go to the beach, you can go to the park, and it can be safe," he said. "It's just you have to be cognizant of the fact that the virus is there."

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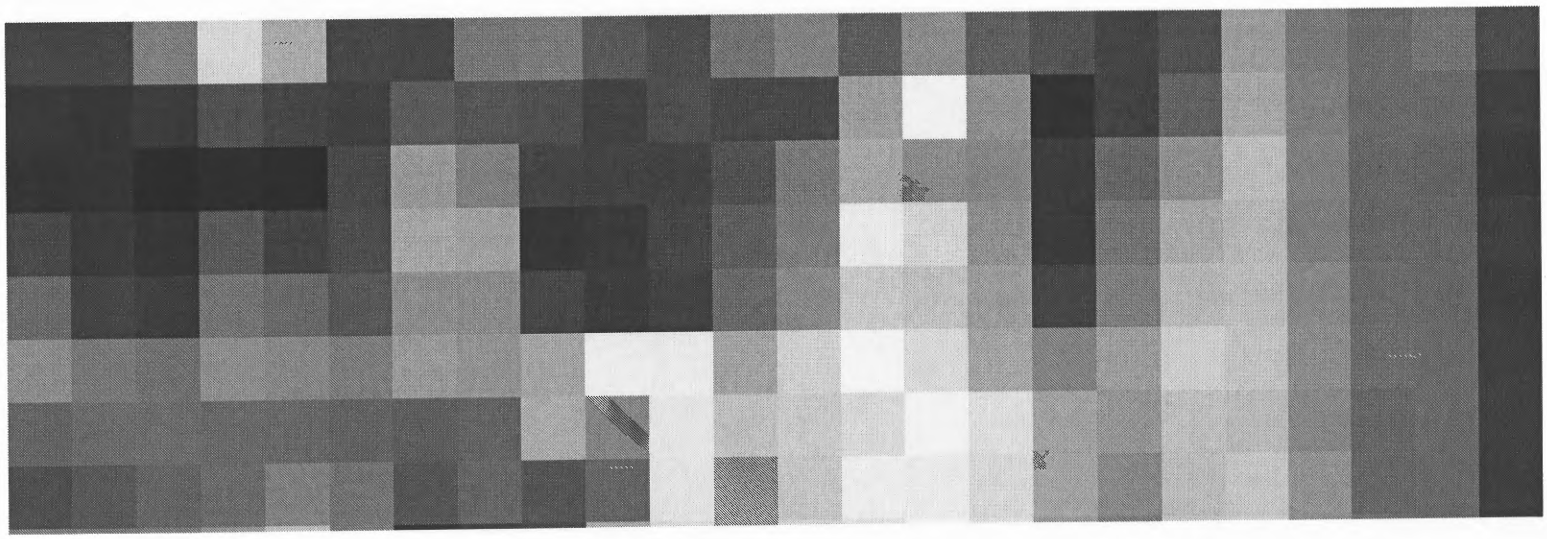
EXHIBIT P

HOME > SCIENCE

You're most likely to catch the coronavirus in a poorly ventilated space. That makes offices very risky.

Aylin Woodward May 6, 2020, 4:46 PM



- Expe[illegible]ecommend increasing air flow in potentially crowded, indo[illegible]s to lower infection risk. But employees might never [illegible]n to office life as it was.

- Visit Business Insider's homepage for more stories.

We are all becoming accustomed to a constant internal monologue about minimizing our risk of coronavirus infection: "Is it safe to go running?" "Should I dash into the pharmacy?" "How close is too close to stand in line?"

Scientists agree that the virus primarily spreads between people via droplets that fly through the air when an infected person coughs, sneezes, or speaks. Evidence also increasingly shows that the risk of infection is much higher in poorly ventilated, crowded areas.

So while it can be jarring to have a runner invade your 6-foot bubble, that fleeting moment is far less risky than, say, working in an office with hundreds of colleagues.

A recent study about an outbreak in a call center in Seoul, South Korea, revealed that almost half the employees on one floor got infected. Nearly all of them sat in the same section.

That makes the prospect of returning to offices challenging — and scary.

The coronavirus primarily spreads indoors

A man wears a mask to protect himself from the coronavirus while running in front of the San Francisco-Oakland Bay Bridge along the Embarcadero in San Francisco, in April. Jeff Chiu / AP

The more time you spend near someone who has COVID-19, the higher the chance their infectious droplets make it over to your face.

"Even in a healthcare setting, contact is defined by being near someone for a certain amount of time. I would not worry about these fleeting encounters."

Airflow matters, too.

According to William Schaffner, a professor of infectious diseases at Vanderbilt University, coronavirus particles could more easily linger in the air in a small space like an elevator.

"In such a tightly enclosed space without vigorous air movement for a short period of time, I'm afraid you might be exposed," Schaffner previously told Business Insider.

The same goes for hospitals. A study published last week in the journal Nature found that virus particles were most highly concentrated in the air within the 9-square-foot toilet areas in patients' rooms in two hospitals in Wuhan, China. These toilets were not ventilated.

In ventilated ward areas, however, the amount of virus was very low, a difference the authors attributed to proper air circulation.

It's not surprising, then, that most coronavirus transmission occurs indoors.

A crowd of travelers queue up in Cape Town, South Africa, trying to return to the US amid the coronavirus pandemic, March 19, 2020. David Slotnick/Business Insider

A preliminary report from Japanese scientists (which has yet to be peer-reviewed) suggested that the odds an infected person "transmitted COVID-19 in a closed environment was 18.7 times greater compared to an open-air environment." Another pre-print study examined 318 outbreaks in China that involved three or more

"The general principle should be: Outside is better than inside; open is better than closed; fewer is better than more people; and stay away from sick people," Dr. Erich Anderer, a neurosurgeon and founding member of the North Brooklyn Runners group, previously told Insider.

Restaurants, prisons, meat-processing facilities, and nursing homes are all high-risk

The worst coronavirus clusters around the US are all tied to spaces that force people into close quarters for extended periods of time. According to a live-updating New York Times page that tracks outbreaks around the country, all but one of the 12 hardest-hit US locations were prisons, jails, and meat-processing facilities. Multiple nursing homes are also high on the list.

Restaurants, too, can be risky. In a recent research letter in the journal Emerging Infectious Diseases, scientists described how nine people sitting more than 3 feet apart at a restaurant in China got the

Dr. Gabrielle Beger takes a nose-swab sample from Lawrence McGee as she works with a team of University of Washington medical providers conducting testing for the coronavirus at Queen Anne Healthcare facility in Seattle, April 17, 2020. AP Photo/Ted S. Warren

The authors advised restaurants to increase the distance between tables, improve ventilation, and cap how long diners can sit.

The same guidance should probably then apply to office settings as well.

The call-center outbreak in Seoul provided a clear case study of office transmission: Of the center's 811 employees, 97 got sick. Of those 97, all but three sat on the same floor, and 79 were in the same section.

Crystal Cox/Business Insider

"Despite considerable interaction between workers on different floors of building X in the elevators and lobby, spread of COVID-19 was limited almost exclusively to the 11th floor, which indicates that the duration of interaction (or contact) was likely the main facilitator for further spreading," the Korean CDC wrote in its report about the outbreak.

Companies may rethink how they resume office life

pandemic could last up to two years. Waves of COVID-19 infections will likely continue until a majority of the human population becomes immune or a vaccine is developed.

Given that the risk of infection will loom for a long time, employers will be forced to adapt.

"Staggered shifts, enforced flextime, and 24/7 operations may become the norm, along with working remotely," Rachel Morrison, a professor of work psychology at the Auckland University of Technology, wrote in The Conversation.

People work in a crowded office building in London, January 31, 2013. Shutterstock

Some CEOs have already cottoned onto that reality.

Jes Staley, chief executive of Barclays, told reporters on Wednesday that his company is reevaluating how much it needs office space at its London headquarters and branches.

"There will be a long-term adjustment to our location strategy," Staley said, adding, "the notion of putting 7,000 people in the building may be a thing of the past."

Do you have a personal experience with the coronavirus you'd like to share? Or a tip on how your town or community is handling the pandemic? Please email covidtips@businessinsider.com and tell us your story.

Get the latest coronavirus business & economic impact analysis from Business Insider Intelligence on how COVID-19 is affecting industries.

EXHIBIT Q

Are new movies longer than they were 10, 20, 50 year ago?

Crunching data from IMDb.com

Przemysław Follow
Dec 26, 2018 · 14 min read ★

If you like to watch movies and I mean *a lot* of movies, there is a chance that you noticed that movies are getting longer and longer nowadays. When was the last time you went to the cinema and watched blockbuster which was shorter than 120 minutes? More and more movies (thank you Marvel for encouraging this trend!) have also scenes after subtitles, so you wait patiently all the way till the end, even if your bladder is killing you for some time already.

These are the times when you could think "Gosh, movies are getting ridiculously long lately". Are they? I asked myself the same question. I discussed the matter with some fellow movie lovers. They had similar feelings. That wasn't enough for me. I decided to use my data analysis skills to investigate this issue. In this article you can read what I have found out.

Dataset

There is no better place to look for data about movies than IMDb.com. It's the biggest movie website in the world. Developed since 1990 (sic!), its database includes around 5.3 million titles and 9.3 million personalities. That's unbelievable, but it started as the list of actresses with beautiful eyes (for real, check IMDb history on Wikipedia).

IMDb data is available for personal use on the IMDb Datasets page. We don't need detailed database for our study. In our final dataset we only need three columns for each movie:

1. Release year
2. Runtime
3. Number of votes (to filter out niche movies)

Unfortunately, we need to download two datasets and join them later. In *title.basics.tsv.gz* there is a lot of data about every movie, TV show and episode in the database. In *title.ratings.tsv.gz* there is info about number of votes and average rating of items from the database.

Let's start writing our *movies_data.py* script with crunching this huge amount of data and preparing it for further investigation.

```
import pandas as pd

 # Download data from IMDB website
 # Data description https://www.imdb.com/interfaces/
 movies = pd.read_csv
('https://datasets.imdbws.com/title.basics.tsv.gz',
compression='gzip', sep='\t')
 print('"title.basics.tsv.gz" downloaded')
 ratings = pd.read_csv
('https://datasets.imdbws.com/title.ratings.tsv.gz',
compression='gzip', sep='\t')
 print('"title.ratings.tsv.gz" downloaded')
 print(movies.shape)
 print(ratings.shape)

>>>"title.basics.tsv.gz" downloaded
>>>"title.ratings.tsv.gz" downloaded
>>>(5504894, 9)
>>>(900802, 3)
```

So far it looks good. We have two datasets. One has 900k rows and 3 columns, the other has 5.5 million entries and 11 columns. Both datasets have *tconst* variable, which is unique id for every title. We can merge existing data on this column.

```
# Merge data on 'tconst', which is unique id for any title in IMDB
database.
 movies = pd.merge(movies, ratings, on='tconst')
 print(movies.shape)

>>>(900802, 11)
```

In total there are 900k unique titles.

Getting rid of unnecessary data

Now we can investigate our data further. There is a column called *titleType*, which indicates if the title is a movie, TV show, episode, short etc.

```
print(movies['titleType'].unique())

>>>['short' 'movie' 'tvMovie' 'tvSeries' 'tvEpisode' 'tvShort'
'tvMiniSeries' 'tvSpecial' 'video' 'videoGame']
```

There are 11 types of titles. We are interested only in movies, so we will leave in our dataset rows marked as *movie* and *tvMovie*. We could argue if we should consider TV movies, but in the final dataset they contribute for only 5% of all titles and they don't change the results, I checked that.

```
movies = movies[movies['titleType'].isin(['movie', 'tvMovie'])]
print(movies.shape)
```

```
>>>(271427, 11)
```

The number of titles dropped to 271k.

Another thing we should consider are possible genres of the movies. We need to be sure that we consider only feature movies, not documentaries etc. We can check the *genres* column.

```
genres = movies['genres'].unique()
len(genres)

>>>1313
```

There are 1313 unique genres! IMDb has a weird way to build database, because there is only one column for the genre. If a movie is drama, comedy and fantasy at once, it will be written as *Comedy,Drama,Fantasy*. After looking through the array, I could find for example:

- Documentary,News,Sport
- Biography,Drama,History
- Documentary,War
- Animation,Musical,Sci-Fi
- Crime,Documentary,Sport

This column is a mess. Since first draft of this article to publishing it 4 *new genres* were added. Fortunately, we don't need to deal with this. We only want to filter out documentaries. Pandas has a great tool to filter rows containing some string.

```
movies = movies[movies['genres'].str.contains('Documentary') ==
False]
```

Finally we have only the movies we need in our data. Now we can drop all unnecessary columns. As stated before, we only need three columns:

1. *startYear* — represents the release year of a title
2. *runtimeMinutes* — primary runtime of the title, in minutes
3. *numVotes* — number of votes the title has received

```
movies = movies[['startYear', 'runtimeMinutes', 'numVotes']]
```

In the end we need to change data type of those columns to numeric and drop rows with missing values.

```
for column in movies.columns.values.tolist():
    movies[column] = pd.to_numeric(movies[column], errors='coerce')

movies = movies.dropna()
print(movies.shape)

>>>(197552, 3)
```

After this step our number of movies dropped to 197.5k.

Before we continue with further analysis, it is good to check descriptive statistics of our dataset to determine if everything looks all right.

```
print(movies.describe())

>>>startYear runtimeMinutes numVotes
>>>count 197552.000000 197552.000000 1.975520e+05
>>>mean 1988.940932 94.929492 3.643819e+03
>>>std 24.758088 29.967162 3.173653e+04
>>>min 1894.000000 1.000000 5.000000e+00
>>>25% 1973.000000 83.000000 1.700000e+01
>>>50% 1996.000000 92.000000 6.500000e+01
>>>75% 2010.000000 103.000000 3.390000e+02
>>>max 2019.000000 5760.000000 2.029673e+06
```

We can notice that at least one movie is only 1 minute long, which doesn't look right. There are probably some mistakes in the database.

According to the Academy of Motion Picture Arts and Sciences, an original film needs to be 40 minutes or less to qualify as a short film, whereas a feature film is more than 40 minutes. That's a great rule to drop movies which are too short.

```
movies = movies[movies['runtimeMinutes'] > 40]
```

What's more important, we are only interested in popular movies. There are thousands of movies in IMDb database which have only a few dozen votes. They can skew our results. Let's say a popular movie is the one with more than 1000 ratings. We drop all movies which don't apply to this rule (good bye thousands of TV movies and garage productions!).

```
movies = movies[movies['numVotes'] >= 1000]
print(movies.describe())

>>>startYear runtimeMinutes numVotes
>>>count 27951.000000 27951.000000 2.795100e+04
>>>mean 1995.441165 104.993167 2.494047e+04
>>>std 21.236780 22.305108 8.118090e+04
>>>min 1911.000000 43.000000 1.000000e+03
>>>25% 1986.000000 91.000000 1.679000e+03
>>>50% 2003.000000 100.000000 3.440000e+03
```

```
>>>75% 2011.000000 114.000000 1.195000e+04
>>>max 2018.000000 450.000000 2.029673e+06
```

In our final dataset there are 27,951 movies. The shortest one is 43 minutes long and the longest is 450 minutes long (the price of Iron Bladder goes to anyone who can watch it without bathroom break!). The oldest movie(s) is (are) from 1911.

On average every movie in our dataset have almost 25k votes, but the standard deviation is 81k, which probably means that the distribution is skewed right and the mean is overvalued by minority of movies with huge amount of votes (there is at least one movie with over 2 million ratings!). Median looks closer to reality, 50% of movies have 3,440 votes or less.

Now we can save our data to CSV and move to a new script. This one takes a long time to execute. Python needs to download in total over 100MB data and process it few times. If we start over with a new script and smaller dataset, our workflow will be much faster.

```
movies.to_csv('movies.csv', index=False)
print('Success!')

>>>Success!
```

New dataset has the size of 515 KB, less than 1% of the original ones! That's how you get rid of irrelevant data!

Looking for the first year to use in the study

Let's create a new script called *movies.py*.

```
import pandas as pd, \
    matplotlib.pyplot as plt, \
    matplotlib.patches as mpatches, \
    matplotlib.lines as mlines, \
    seaborn as sns

movies = pd.read_csv('movies.csv')
```

We should start with thinking about the first year of our studies. Cinematography in the beginning of XX century was still in its infancy. There were not many movies created back then and most of them were just short presentations of new technology and experiments. Let's make a histogram with a number of titles in our dataset from these early years of movie history.

```
plt.hist(movies['startYear'][movies['startYear'] < 1940])
plt.title('Movies count')
plt.xlabel('Year of release')
plt.ylabel('Number of movies')
plt.show()
```

Ok, somewhere around early 1930's number of movies starts to increase. Let's take a closer look at the years before 1930:

```
plt.hist(movies['startYear'][movies['startYear'] < 1930])
plt.title('Movies count')
plt.xlabel('Year of release')
plt.ylabel('Number of movies')
plt.show()
```

These are just histograms with default numbers of bins (10), we just use it to quickly visualize our data. If we want to know the exact number of movies in our dataset, we should instead look at the table (or create histogram with more bins).

```
print(movies['startYear'][movies['startYear'] < 1940].value_counts
().sort_index())

>>>1911.0     1
>>>1913.0     3
>>>1914.0     4
>>>1915.0     3
>>>1916.0     2
>>>1917.0     2
>>>1918.0     5
>>>1919.0    10
>>>1920.0     9
>>>1921.0     9
>>>1922.0     9
>>>1923.0    10
>>>1924.0    15
>>>1925.0    18
>>>1926.0    15
>>>1927.0    22
>>>1928.0    27
>>>1929.0    22
>>>1930.0    22
>>>1931.0    49
>>>1932.0    48
>>>1933.0    51
>>>1934.0    42
>>>1935.0    52
>>>1936.0    68
>>>1937.0    52
>>>1938.0    45
>>>1939.0    73
```

There is only 1 movie from 1911 in our dataset and 1924 is the first year when the number of titles is higher than 10. This is not enough data to create reliable results. We need to decide what year we should start with. I decided to use the same rule of thumb as with popular approach to normal distribution. According to that, minimum sample size to create it is 30. Now we can calculate starting year of our data.

```
start_year = 0  # This will be starting year of the data.
# Create data frame with year as first column and movie count as
second.
movies_per_year = movies['startYear'].value_counts().sort_index()  #
The year is an index, we need it as a column.
movies_per_year_df = pd.DataFrame({'year': movies_per_year.index,
'movie_count': movies_per_year.values})

for i in range(0, len(movies_per_year_df)):
    year = movies_per_year_df.iloc[i, 0]
    movie_count = movies_per_year_df.iloc[i, 1]
    # Check if in a given year there were more than 30 movies.
    if movie_count > 30:
        movies_per_year_df = movies_per_year_df.iloc[i:, :]  # Drop
years before current one in the loop
        # Check whether the rest of years have movie count above 30,
if not, the loop continues.
        # If every year left has movie count above 30, the loop
breaks and we have the answer.
        if sum(movies_per_year_df['movie_count'] < 30) == 0:
            start_year = year
            break

print(start_year)

>>>Name: startYear, dtype: int64
>>>1931.0
```

Our dataset will start from the year 1931. Of course, we could take a quick peek at the table above to determine it, but the goal was to practice loops and conditions to automate the process in case of more complicated data.

```
movies = movies[movies['startYear'] >= 1931]
print(movies.describe())
```

```
>>>startYear runtimeMinutes numVotes
>>>count 27743.000000 27743.000000 2.774300e+04
>>>mean 1995.971380 105.048156 2.507714e+04
>>>std 20.407283 22.103663 8.145749e+04
>>>min 1931.000000 43.000000 1.000000e+03
>>>25% 1986.000000 91.000000 1.684000e+03
>>>50% 2003.000000 100.000000 3.459000e+03
>>>75% 2011.000000 114.000000 1.205400e+04
>>>max 2018.000000 450.000000 2.029673e+06
```

Our final dataset consists of 27,743 titles. What's interesting, the median release year is 2003, which means that 50% of all movies in our dataset were released in 2003 or later. It means that people mostly watch and rate new movies. Median for runtime is 100 minutes and the mean is 105 minutes, which looks right.

Getting to the point

Let's plot distribution of runtimes. We limited it to 40–200 minutes range to improve readability. There are not many titles longer than 200 minutes and 40 minutes is lower band of our data. Every bin corresponds to 10 minute range.

```
plt.hist(movies['runtimeMinutes'], range=(40, 200), bins=16,
ec='black')
plt.title('Movies length')
plt.xlabel('Minutes')
plt.ylabel('Number of movies')
plt.show()
```

The most popular runtime is 90–100 minutes. Vast majority of movies is 80–120 minutes long. This is consistent with our movie-watching intuition.

Let's find an average movie runtime by year. We group dataset by year and get descriptive statistics of every subset.

```
statistics_grouped = movies['runtimeMinutes'].groupby(movies
['startYear']).describe()
```

We can create a plot of this data. Besides average movie runtime we can also create confidence interval based on the standard deviation. We will use simple formulas for that:

```
avg_runtime_by_year = statistics_grouped['mean']  # Mean
avg_runtime_lower_band = statistics_grouped['mean'] -
statistics_grouped['std']  # Lower band of data created using
standard deviation.
avg_runtime_upper_band = statistics_grouped['mean'] +
statistics_grouped['std']  # Upper band of data.
```

Let's create the plot:

```
fig, ax1 = plt.subplots(figsize=(10, 5))
ax1.plot(avg_runtime_by_year, color="blue")
ax1.plot(avg_runtime_lower_band, color="aqua")
ax1.plot(avg_runtime_upper_band, color="aqua")
ax1.fill_between(statistics_grouped.index, avg_runtime_lower_band,
avg_runtime_upper_band, facecolor='aqua')  # Fill space between
bands to create confidence interval.
ax1.set_title('Movies runtime by year')
ax1.set_ylabel('Minutes')
ax1.set_xlabel('Release year')
ax1.set_xlim(1931, 2018)
legend_sd = mpatches.Patch(color='aqua', label='Mean +/- standard
deviation')  # Used mpatches to create rectangular for a legend.
legend_line = mlines.Line2D([], [], color='blue', label='Mean
runtime')
ax1.legend(handles=[legend_line, legend_sd])  # Nice legend with
rectangular and line.
plt.show()```
```

Looks like our intuitive thinking about movies getting longer was wrong. It's true that in the first decades of cinema movies were shorter, they were on average 90 minutes long in early 1930s and reached 100–110 minutes in mid-'50s. Since then there is no trend in our data. Also the confidence interval is fairly consistent with 80–130 minutes runtime.

However, it looks like 2018 can be a beginning of new uptrend, because it's one of two years in movie history when the average runtime was longer than 110 minutes. It's too soon to speculate, especially because 2018 didn't end yet and the number of movies getting at least 1000 votes will increase faster than for other years even in early 2019 (there are 597 titles in our dataset from 2018 and 955 from 2017).

We can wonder what part of our dataset was considered when creating confidence interval. It's easy to check that. We need to find a number of movies longer (shorter) than lower (upper) band of the confidence interval and divide it by the number of all movies from given year.

```
percentage_of_included_movies = []
for year in statistics_grouped.index:
    movies_from_year = movies[movies['startYear'] == year]
    avg_runtime_low = avg_runtime_lower_band[int(year)]
    avg_runtime_up = avg_runtime_upper_band[int(year)]
    movies_included = movies_from_year[movies_from_year
['runtimeMinutes'] > avg_runtime_low][movies_from_year
['runtimeMinutes'] < avg_runtime_up]
    percentage_of_included_movies.append(len(movies_included)/len
(movies_from_year))
```

Now we can add new column to our *statistics_grouped* data frame:

```
statistics_grouped['included_movies_perc'] =
percentage_of_included_movies
print(statistics_grouped['included_movies_perc'].describe())
```

```
>>>count 88.000000
>>>mean 0.782741
>>>std 0.058665
>>>min 0.619718
>>>25% 0.745369
>>>50% 0.786273
>>>75% 0.817378
>>>max 0.928571
>>>Name: included_movies_perc, dtype: float64
```

On average 78% of movies from every year fit into the confidence interval. We can add extra line to our previous plot showing this proportion by year.

```
# Main plot
fig, ax1 = plt.subplots(figsize=(10, 5))
ax1.plot(avg_runtime_by_year, color="blue")
ax1.plot(avg_runtime_lower_band, color="aqua")
ax1.plot(avg_runtime_upper_band, color="aqua")
ax1.fill_between(statistics_grouped.index, avg_runtime_lower_band,
```

```
avg_runtime_upper_band, facecolor='aqua')
ax1.set_title('Movies runtime by year')
ax1.set_ylabel('Minutes')
ax1.set_xlabel('Release year')
ax1.set_xlim(1931, 2018)
# Plot with proportions
ax2 = ax1.twinx()
ax2.plot(statistics_grouped['included_movies_perc'], color='olive')
ax2.set_ylabel('Proportion')
plt.axhline(y=0.70, color='red', linestyle='dashed')  # Add line at
0.70
legend_sd = mpatches.Patch(color='aqua', label='Mean +/- standard
deviation')
legend_line = mlines.Line2D([], [], color='blue', label='Mean
runtime')
legend_line_2 = mlines.Line2D([], [], color='olive',
label='Proportion included in CI')
dashed_line = mlines.Line2D([], [], color='red', label='Proportion =
0.7', linestyle='dashed')
ax1.legend(handles=[legend_line, legend_sd, legend_line_2,
dashed_line])
plt.show()
```

The plot looks a little messy, but the message is clear. Since late '40s our confidence interval contained more than 70% of titles every year.

Let's create another plot, this time with median and interquartile range and check the results. We are mostly interested in the confidence interval, which will now contain 50% movies. 25% of the shortest titles and 25% of the longest ones will be outside the blue area.

```
# Data
avg_runtime_by_year = statistics_grouped['50%']
avg_runtime_lower_band = statistics_grouped['25%']
avg_runtime_upper_band = statistics_grouped['75%']

# Plot
fig, ax1 = plt.subplots(figsize=(10, 5))
ax1.plot(avg_runtime_by_year, color="blue")
ax1.plot(avg_runtime_lower_band, color="aqua")
ax1.plot(avg_runtime_upper_band, color="aqua")
```

```
ax1.fill_between(statistics_grouped.index, avg_runtime_lower_band,
avg_runtime_upper_band, facecolor='aqua')
ax1.set_title('Movies runtime by year')
ax1.set_ylabel('Minutes')
ax1.set_xlabel('Release year')
ax1.set_xlim(1931, 2018)
legend_sd = mpatches.Patch(color='aqua', label='Interquartile
range')
legend_line = mlines.Line2D([], [], color='blue', label='Median
runtime')
ax1.legend(handles=[legend_line, legend_sd])
plt.show()
```

Here we also cannot see any clear pattern. However, the jump in recent 2 –3 years is quite high. Still, it doesn't mean this is the start of new trend, but we should check that sentiment in the future. We can also notice, that the median is on average lower than the mean. It fluctuates around 100 minutes, about 5 minutes shorter than the mean. It makes sense, because mean is affected by a small percentage of long movies and median is just the central value from every year.

OK, so now we know that movies *in general* are not getting longer. Maybe our intuition wasn't wrong and it only happens with the most popular movies, the biggest blockbusters. We can create few more plots and every time consider smaller sample of most popular movies from every year.

Let's take a look only at movies since 1960, so we can have a closer look at data most interesting for us. Maybe if we take only 50 most popular movies from every year, there will be some trend visible.

```
movies_since_1960 = movies[movies['startYear'] >= 1960]
```

Because we want to check few different values, we can create a function to return statistics about *n* most popular movies from every year. We can use it later.

```
def top_n_movies(data, n):
    top_n_movies_per_year = data.groupby('startYear').head(n)
    stats = top_n_movies_per_year['runtimeMinutes'].groupby(
        top_n_movies_per_year['startYear']).describe()
    return stats
```

Now we can get the data needed and create our plot.

```
statistics_grouped_50 = top_n_movies(movies_since_1960, 50)
# Data
avg_runtime_by_year = statistics_grouped_50['mean']
avg_runtime_lower_band = statistics_grouped_50['mean'] -
statistics_grouped_50['std']
avg_runtime_upper_band = statistics_grouped_50['mean'] +
statistics_grouped_50['std']

# Plot
fig, ax1 = plt.subplots(figsize=(10, 5))
ax1.plot(avg_runtime_by_year, color="blue")
ax1.plot(avg_runtime_lower_band, color="aqua")
ax1.plot(avg_runtime_upper_band, color="aqua")
ax1.fill_between(statistics_grouped_50.index,
avg_runtime_lower_band, avg_runtime_upper_band, facecolor='aqua')
ax1.set_title('Runtime of 50 most popular movies by year')
ax1.set_ylabel('Minutes')
ax1.set_xlabel('Release year')
ax1.set_xlim(1960, 2018)
legend_sd = mpatches.Patch(color='aqua', label='Mean +/- standard
deviation')
legend_line = mlines.Line2D([], [], color='blue', label='Mean
runtime')
ax1.legend(handles=[legend_line, legend_sd])
plt.show()
```

There is still no visible trend. What's more, when we consider smaller amount of more popular movies, even the peak from 2017–2018 disappears.

What if we take a look at 30 most popular movies? Or 10? We can create new plot with means for different values. This time we will drop confidence intervals. Our *top_n_movies* function will be useful to do that.

```
mean_10 = top_n_movies(movies_since_1960, 10)['mean']
mean_30 = top_n_movies(movies_since_1960, 30)['mean']
mean_50 = top_n_movies(movies_since_1960, 50)['mean']
mean_100 = top_n_movies(movies_since_1960, 100)['mean']
mean_all = top_n_movies(movies_since_1960, len(movies_since_1960))
['mean']

# Chart
fig, ax = plt.subplots(figsize=(10, 5))
ax.plot(mean_10, color='black')
ax.plot(mean_30, color='blue')
ax.plot(mean_50, color='red')
ax.plot(mean_100, color='green')
ax.plot(mean_all, color='purple')
ax.set_title('Movies runtime by year')
ax.set_ylabel('Minutes')
ax.set_xlabel('Release year')
ax.set_xlim(1960, 2018)
ax.legend(labels=['10 most popular movies',
                  '30 most popular movies',
                  '50 most popular movies',
                  '100 most popular movies',
                  'All popular movies'])
plt.show()
```

No matter what number of most popular movies we take, there is no sign of trend. When we consider less movies from every year, there is more volatility on the chart, which is in pair with our statistical intuition — smaller sample leads to higher volatility.

To be sure that more popular movies are not longer, let's create a table with mean from all n-most popular movies of the year — mean of means.

```
total_mean = pd.Series()
mean_list = [mean_10, mean_30, mean_50, mean_100, mean_all]
index_list = ['top_10', 'top_30', 'top_50', 'top_100', 'all']
for i in range(0, 5):
    mean_n = pd.Series([mean_list[i].mean()], index=[index_list[i]])
    total_mean = total_mean.append(mean_n)

print(total_mean)
```

```
>>>top_10 103.716949
>>>top_30 106.461017
>>>top_50 106.330508
>>>top_100 106.327119
>>>all 105.893473
>>>dtype: float64
```

The difference between mean runtimes are marginal, they oscillate around 106 minutes with one exception of top 10 movies from every year, where the average is 103,7 minutes. As we said earlier, the sample here is small and volatile, so it doesn't mean that most popular movies are in fact shorter than average.

We looked at the movie runtimes year after year. Let's create one last plot. This time we will generalize and create a new dataset with the decade movies were released instead of a year. Thanks to that we will have smaller number of groups and we can create a boxplots for them.

```
movies_by_decade = movies.copy()
movies_by_decade['startYear'] = ((movies_by_decade['startYear'] //
10) * 10).astype('int64')
sns.boxplot(x="startYear", y="runtimeMinutes",
data=movies_by_decade, color='lightskyblue', showfliers=False)
plt.ylim(40,180)
plt.title('Movies runtime by decade')
plt.xlabel('Decade')
plt.ylabel('Minutes')
plt.show()
```

There is a big jump between 1930's and 1940's, then a smaller one after 1950's and since then the differences are marginal.

In conclusion, our intuition was wrong. There is no trend in the movies runtime. The differences are too small to be noticed. We can say that for the last 60 years movies on average have the same length. No matter what criteria we take into account, the result is the same. Thanks for the read! Now we can go back to watching movies!

EXHIBIT R

The New York Times

Opinion

Is It Safer to Visit a Coffee Shop or a Gym?

By Katherine Baicker, Oeindrila Dube, Sendhil Mullainathan, Devin Pope and Gus Wezerek May 6, 2020

As states begin to reopen, Americans are looking at any trip outside through the lens of contagion. Is it safe to go back to Starbucks? What about the gym? Nail salons are out of the question, right?

The country faces an ugly trade-off. Keep the economy closed and prolong the economic misery. Or open up the economy and risk a resurgence of Covid-19, undoing the gains earned through weeks of social isolation.

We believe there's another option.

Using anonymized cellphone location data from April 2019, we can measure how crowded businesses get. Each bubble on the chart represents a business, like Walmart or Waffle House. Larger bubbles have more locations and customers.

Fast-food restaurants tend to be small and busy, with a high number of weekly visits per square foot.

Gyms
have fewer visitors per square foot, but visitors linger, increasing the chance they'll interact and spread the virus.

Sit-down restaurants and bars should take extra care when reopening. These venues draw large crowds with long average stays.

Some businesses, like some people, are “super-spreaders.” Through the lens of contagion, a yoga class, a busy corner store or a crowded neighborhood bar may look a lot like a wet market in China.

Cellphone data can’t tell us everything. For example, businesses in low-income neighborhoods with fewer smartphones may appear to have less foot traffic. We looked into this, and to date, we have not found any appreciable bias in the measures we are using.

The anonymized location pings also don't give us any insight into how customers interacted or how many surfaces they touched. And it's tricky to determine whether people were inside a building or moving around outdoors, where air can move freely, and infection risk may be lower.

To overcome some of these limitations, we asked people to rate, on a scale of 1 to 10, how often they interacted with people or touched shared surfaces at various businesses, as well as how much activity in different sectors occurs indoors.

These numbers help us flag risky industries, like beauty and nail salons, that our other metrics didn't. These businesses should be particularly attentive to maintaining social-distancing measures.

The variation in risk between different types of businesses was surprising. People spend twice as much time at electronics stores as they do at lawn and garden stores. A display of new phones and gadgets is an invitation to mill around; you don't linger over fertilizer. Similarly, we found that people spend nearly three times as much time searching through the racks at a Salvation Army as they do scanning the shelves at a Dollar General.

Another reason for differences is how concentrated people are: The same number of customers spaced out evenly over the day poses less risk than if they all arrive in a few short windows of time.

Even within a sector, there is tremendous variation. Consider two similar restaurants: Denny's and the Original Pancake House. Both serve a similar number of customers every week, who stay for a similar length of time. But customers at the Original Pancake House are far more concentrated (at breakfast, of course), producing a far higher risk of customers getting crowded into the same space at the same time.

The existence of super-spreader businesses might seem like bad news. In fact, it means that most of the disease-spreading risk generated by the economy is concentrated in a small portion of it – which means that we can resume a lot of economic activity with minimal risk.

Many governors are considering contagion risk as a factor in determining which businesses to reopen first. Gov. Gavin Newsom of California, for example, has called for reopening "low risk" stores such as those selling toys, books, sporting goods and flowers. Indeed, in our data, florists are among the lowest risk. But toy stores, bookstores and sporting goods stores are in the top

quartile of risk. Curbside pickup, as Governor Newsom suggested, could mitigate these risks, but that would be true for many other sectors, too.

But these data alone cannot tell us which businesses to open first, and we can't simplify all these different metrics into a "yes" or "no" decision on any single business. Common sense and local knowledge are just as important. And we should ensure that policies based on these data do not have a disparate impact on people who are already more heavily hit by Covid-19.

Researchers have already begun using these data. But to make policy, we must work with models from epidemiology. The ultimate health consequences of any contagion-risk measure depend on health system capacity, available treatments and disease prevalence – all of which will change over time and across areas.

Second, we must account for economic factors. Reopening certain businesses will create or diminish demand for others, and post-Covid consumer behavior with a partially open economy may look quite different from before.

Finally, this data comes from standard operations, but American companies are already modifying "business as usual." They can continue to limit the number of people in stores, modify how employees work and change how customers shop.

Our research provides a baseline to spur further ingenuity and adaptation. With the right mix of numbers and on-the-ground knowledge, we can develop policies to minimize both the spread of the virus and the economic hardship of the pandemic.

Notes: The first chart includes businesses with at least 200 establishments in the data, and the second chart includes sectors with at least 300 establishments in the data. Bubbles are scaled relative to the product of a business or sector's average weekly visits and its total number of establishments.

Sources: Cellphone location data and geofence files used to calculate establishment sizes were provided by Safegraph and Veraset. Business classifications come from the North American Industry Classification System.

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