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Assessing the Impact of Business Closures on COVID-19 Outcomes

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ABSTRACT: In this paper, we present a framework for assessing the effectiveness of different business closure policies, using New York City as a case study. Business closure policies have been widely implemented in an attempt to slow down the pandemic, but it is difficult to measure the contribution of closures of specific industries to virus transmission. Our framework allows us to estimate the impact of specific industry closures on the spread of COVID-19 via their effects on aggregate mobility. We find that early reopening led to a prolonged pandemic and a large case surge in the second wave during 2020, though the reopening allowed the city to regain its economic function as a consumption hub. An alternative policy that extends the lockdown is found to be more cost-effective as it makes future traveling safer and prevents the economy from relapsing into a more stringent policy regime.

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WORKING PAPERS

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I. Introduction

Across the world, national and local governments have implemented business closure policies, with varying degrees of stringency, in response to the COVID-19 pandemic. In comparison to the drastic full lockdown, these closure policies (and the subsequent reopening strategies) have aimed to strike a balance between “lives and livelihoods” or suppressing the spread of COVID-19 while minimizing the cost of restricting economic activities, in terms of both reduced employment and lost consumption opportunities.

This paper evaluates the effectiveness of these closure policies in reducing the transmission of COVID-19, using New York City as a case study. In practice, partial closure policies were specified by ordering specific business types or industries to close (usually in contact-intensive activities), while others remained open. We aim to investigate how these choices over industries affected the evolution of COVID-19 cases and develop a framework for considering alternative policies. Our approach uses New York City, one of the epicenters of the COVID-19 outbreak in the United States, as a case study by exploiting within-city variation in the industry composition of business in each zip code. Detailed high-frequency mobility data produced by SafeGraph allow us to capture the extent to which business closure policies have reduced mobility, which in turn should have slowed the transmission of the virus.

To achieve this, we must overcome several identification challenges. One key obstacle is that we only observe total case counts, rather than the contribution of each industry to spreading infections. To separately identify the effectiveness of each type of business closure policy, we first estimate the response of industry-specific mobility to the introduction of industry level capacity constraints. Then, we further estimate the relationship between aggregate mobility and COVID-19 cases. By combining these two steps, we can assess how effective different business closure policies are at reducing total COVID-19 cases via their effectiveness at curbing mobility.

This approach, however, raises further identification issues. First, business closure policies change in response to the evolution of COVID-19 cases. To address this, we exploit within-city variation in ex-ante industry composition to generate “exogenous” spatial variation in exposure to city-wide closure policies. Second, when estimating the causal impact of mobility on the spread of COVID-19, one may be worried that households respond endogenously to the rise of COVID-19 by reducing their mobility. We resolve this reverse causality issue by using the share of workers in “teleworkable” industries as an instrument for mobility.

The paper has three main findings. First, we find that a more stringent closure policy for a specific industry results in lower mobility associated with that industry. Intuitively, the magnitude of this effect depends on the extent to which the industry provides necessary or luxury goods, the latter being more easily substituted (by, for example, a home activity such as online shopping). Second, we find that this decision to reopen resulted in a 30 percent increase in cases between June 2020 and February 2021 compared to a baseline of no reopening. An alternative lockdown strategy which delays the reopening until August 2020 results in an increase of just 9 percent. Intuitively, a longer lockdown reduces the infection rate further and allows future travelers to commute more safely, mitigating the rise of COVID-19. Finally, when we use the compensating variation to measure the increased consumption benefit from reopening, we find that the delayed reopening strategy is more cost-effective, as allowing greater mobility in a safer environment prevents the economy from relapsing into a more stringent closure policy regime.

This paper connects to several strands of existing literature. In terms of methodology, our work is closely related to papers which use smartphone data to study consumption-oriented travel patterns. In this regard, Redding et al. (2021) and Couture et al. (2020), amongst others, are important references.

Our approach estimates the effect of partial business closures on COVID-19 cases via household mobility. Previous work has investigated the effect of the pandemic and various mitigation measures on mobility. Caselli et al. (2020a), Chen et al. (2020), and Goolsbee and Syverson (2020) find that the effect of lockdown policies on mobility was relatively modest compared to individuals' own efforts to avoid the virus. These papers focus on the early months of the pandemic, where the deterrent effect of the outbreak on mobility may have been stronger and lockdown fatigue may not have been an important factor, whereas we consider a longer series of observations. Using more recent data, Caselli et al. (2020b) find that lockdowns had a large impact on the mobility of women and young people. The second step of our two-step estimation strategy estimates the effect of mobility on COVID-19 cases. In this regard, our work is closely related to Glaeser et al. (2021), which finds that restricting mobility is effective in reducing cases using data across five U.S. cities. Bakker and Goncalves (2021) also find that reduced mobility and more stringent lockdowns are associated with a lower growth rate of COVID-19 deaths, but temperature also plays an important role in suppressing the pandemic. Our paper builds on earlier work by estimating the effect of closures of specific industries on COVID-19 cases, which allows us to consider the effectiveness of different partial lockdown strategies.

Our paper also contributes to the literature assessing the impact of containment policies on economic wellbeing. Deb et al. (2021) explores the effect of containment measures on several high-frequency proxies for economic activity, finding that the most effective containment policies, such as workplace closures and stay-at-home orders, also have the largest economic costs. Argente, Hsieh, and Lee (2020) use data from Seoul to show that public disclosure of information on virus transmission reduces cases and has a much smaller economic cost than a city-wide lockdown. In contrast to these papers, our framework breaks down the impact of lockdown policies into the contributions of specific industry closures, which allows for a more flexible assessment of alternative policies. Similar to these papers, the lack of economic data for recent years prevents from having a direct measure of economic outcomes such as employment or consumption. Instead, we leverage the strength of our model and provide an assessment of the *welfare* cost due to the loss of consumption opportunities during business closures

There is also a theory-driven literature exploring the optimal design of lockdown policies. Jones, Phillippon, and Venkateswaran (2020) present a neoclassical economy with Susceptible-Infected-Recovered (SIR) dynamics and find that, relative to private incentives, the optimal lockdown policy features more frontloading of mitigation efforts. Fajgelbaum et al. (2020) develop a model of virus spread over a commuting network and apply it to Seoul, Daegu, and New York City, finding that spatially targeted lockdowns can be much less costly than uniform lockdowns. Our approach is empirical and does not directly tackle the question of optimal lockdown policies, but our estimation framework can be used to consider the effectiveness of different lockdown strategies and therefore inform discussions on optimal policy. We also provide direct estimates for how sensitive people's consumption-based trips are towards various lockdown policies.

The rest of the paper is organized as follows. In Section II we present the data sources used for this paper and stylized facts about the timeline of the pandemic in NYC. In Section III we present the empirical model used to identify the impact of industry closures on COVID-19 infections. In Section IV, we present the results of the estimation. In Section V, we use the estimates from the previous section to consider several policy counterfactuals. Section VI offers concluding comments.

II. Data and Stylized Facts

In this section, we discuss the data sources and methods used for constructing a set of continuous measures of business closure policies. Then, using these data, we document key facts about policy changes and mobility patterns in NYC.

II.1 Data Sources and Key Variable Construction

Our core dataset for this paper is the SafeGraph mobility data. SafeGraph is a data vendor that collects mobility information from individuals' cellphone-pinned locations, and the company makes the aggregated data available for academic researchers through an annual license. The data available for access contains information on aggregated trip frequencies between a home census block and a destination establishment for each month of 2019, 2020, and 2021. These data have the most comprehensive coverage for the US, but they are also available for some other major cities outside of the US such as London and Toronto. For this paper, we use the monthly trip frequencies generated by residents living inside New York City (NYC) for the entire year of 2020 and two months at the beginning of 2021.

The second core dataset measures the stringency of business closure policies across time for each 2-digit North American Industry Classification System (NAICS) level industry. We collect announcements on business closure policies from local government websites and numerous news sources. We then assign each business type mentioned in the announcement to an industry. Based on this assignment, we form a capacity index, which equals 0 if the industry is ordered to close fully, 1 if it can operate as usual, and a fraction between 0 and 1 if it is subject to a specific capacity constraint (but not full closure). This index can track capacity allowance for each industry on a daily frequency. We then aggregate this index to the monthly level by taking into account the number of days the closure policy was put in place (See Appendix A1 for more details about the construction). For example, if all food stores are allowed to open every day for a particular month at 50 percent capacity, then the food store capacity index for that month will be 0.5; alternatively, if all food stores are completely closed for the first half of the month, then open at 50 percent capacity for the second half of the month, then the index will be 0.25.

Our local COVID-19 cases data come from the New York City Department of Health. The dataset tracks the number of people who tested positive for each zip code on a daily basis.[1] To match the COVID-19 data with the bilateral trip frequencies provided by SafeGraph, we aggregate the number of new cases to the zip code-month level.

When estimating the causal impact of mobility on COVID-19 outcomes, we instrument for mobility using the ex-ante share of teleworkable workers in each zip code following Glaeser et al. (2020). To construct this instrument, we extract data on the number of residents employed by each 2-digit NAICS industry in each zip code from the American Community Survey. We then weight these worker counts by each industry's

[1]The zip code areas that we refer to here are in fact ZIP Code Tabulation Areas (ZCTAs) compiled by the United States Census Bureau. While the raw zip codes represent mail delivery routes for the United States Postal Service, ZCTAs aggregate these zip codes into larger areas which correspond more closely to human activity and are therefore more suitable for the kind of spatial analysis which we conduct in this paper.

teleworkability using a measure constructed by Dingel and Neiman (2020). Finally, we aggregate across industries to obtain the share of teleworkable workers residing in each zip code.

We restrict the study period to end in Feburary 2021 because the vaccination gradually became available from March 2021 onwards. The availability of the COVID-19 vaccine may have affected households' decisions to travel, causing bias in our estimates in the following sections of the paper. We also restrict the sample to residents living inside NYC instead of using residents living in the broader New York Metro area for two reasons. First, NYC provides consistent reports of COVID-19 cases and deaths on zip code-level over times, which provides the granularity and time frequency we need for identification. Second, the city is a coherent administrative entity and many decisions on industry closures were made on the city level. Therefore, the cost-benefit analysis made based on this sample is policy relevant given the geographical assignment of administrative responsibilities and would also provide the appropriate assessment for the policy impacts on local residents.

II.2 Stylized Facts

Fact 1: Business Closure Policies in NYC
We divide the policies implemented by the New York City government into five policy regimes. Figure 1 plots the months in which these policy regimes start along with the number of new COVID-19 cases over time. On March 22, 2020, the state of New York initiated the first regime by announcing the Pause program, which ordered all businesses to close except those in essential industries. This policy was extended in April 2020. In early June, the local government started preparing for a gradual reopening, which was divided into four phases. In Phases 1 and 2 (which make up the second regime), industries such as finance, wholesale, and retail started to reopen. In July 2020, the third regime began with Phases 3 and 4 of the reopening, allowing restaurants, hotels, and entertainment venues to start reopening. Given the amount of foot traffic and contact associated with these industries, the government often imposed capacity constraints on businesses in these industries as they reopened. However, in mid-November, after witnessing a rise in the number of new cases, the city government announced new restrictions on the industries that were reopened in Phase 3 and 4, beginning the fourth policy regime. Public schools were also ordered to close after being allowed to reopen for a short period in the Fall. These policies remained in place until March 2021 when vaccines became available for residents in NYC.

To capture these nuanced policy changes over time, we construct the capacity constraint index for each 2-digit NAICS industry using policy announcements from the city government website. Figure 2 plots the change in capacity constraints over time.[2] For ease of interpretation, we normalize the index with respect to January 2020. These capacity constraints show that there are large variations in policy stringency across different industries, and each industry has a distinct timeline of closing and reopening. Overall, the most stringent months are March to early June, reflecting the duration of the Pause Program.

Fact 2: Mobility Patterns Over Time
Mobility patterns in NYC also follow the change in lockdown policies closely. Figure 3 shows the percentage change in total mobility with respect to January 2020. As the Pause program began at the end of March, total

[2] We leave out industries that have most of their business types designated as essential by the CDC. These businesses were never closed during 2020, or they were only closed for a short period of time. Their capacity constraints therefore show very little variation over time (See Appendix A2 for graphs).

visits made outside of home experienced their largest decline in April. After that, mobility slowly recovered as the lockdown policies became less stringent over time. Then, mobility declined again as the new restrictions were announced in November 2020.

We notice that for some months when there was no major policy change, mobility still changed slightly. For example, aggregate mobility declined before the Pause program began and increased slightly before the first phase of the reopening. These changes suggest that aggregate mobility patterns are affected not only by the policy choices during that period, but also by people's reactions to the rise and fall of COVID-19 cases. We incorporate these insights into our analysis of mobility decisions.

Fact 3: Mobility Patterns by Industry

Next, we document mobility patterns by industry. Table 1 summarizes the total number of visits generated by NYC residents in January to businesses in each of the 2-digit industries. The most popular destinations in NYC are consumption-based industries such as Accommodation and Food Services, Retail and Arts, and Entertainment and Recreation; these top three industries account for 78 percent of observed mobility in the city. This evidence motivates our focus on consumption related mobility decisions.

SafeGraph data do not allow us to identify whether a person travels to a destination for work purposes or for consumption. It is therefore likely that the recorded patterns include workers as well. Nevertheless, we can show that the mobility pattern we observe at these destination locations is mostly driven by people who are more likely to be consumers. In Column 3 of Table 1, we show that the majority of these visits are made by people who stay for less than 4 hours—a pattern more consistent with consumers than with workers.

III. Empirical Model

Based on the stylized facts documented in the previous section, we outline an empirical model of a household who makes traveling decisions to access different consumption goods/services in different locations. The perceived qualities of the goods/services are affected by the specific lockdown policy put in place, which then affect people's incentives to travel. People who travel outside their home to a specific destination in the city may then be exposed to COVID-19, leading to increase in the number of positive cases detected at their home locations.

III.1 Demand for Consumption Trips

Following Redding et al (2020), we assume that a household living in a neighborhood i consumes a bundle of goods/services locally in the city according to a Cobb-Douglas utility function:

$$\max_{n_{jkt}} \prod_{k\in K} \left(\frac{n_{jkt}}{\alpha_k}\right)^{\alpha_k} B_{ijkt}\,\omega_{ijkt} \qquad (1)$$
$$s.t. \sum_k n_{jkt}p_{jkt} \leq I_{it}^c, \sum_k \alpha_k = 1$$

Where for each type of good/service k and each month t, the household chooses a destination j and the total consumption amount n_{jkt}. The price of each good k in destination j at time t is $p_{j(kt)}$. The total expenditure is subject to the budget constraint I_{it}^c, which is the total income net of tradable goods consumption and housing costs.

B_{jkt} is the observable utility cost of traveling to location j, which we parameterize as

$$B_{ijkt} = exp(\boldsymbol{X_{ijkt}\beta_k}) = exp(\beta_k^p Capacity_{jkt} + \beta_k^c Infection_{jkt} + \beta_k^d Distance_{ij} + \xi_{ijkt}) \quad (2)$$

Where $\boldsymbol{X_{ijkt}}$ is a set of observable characteristics that shape the household's decision to travel to a location j for consumption good k. For the period of the COVID-19 outbreak, we focus on the industry-specific policy $Capacity_{jkt}$ which shapes the quality provided by the destination industry by determining the extent to which the industry will be open. At the same time, the household also cares about the chance of getting infected $Infection_{jkt}$, and the bilateral commuting cost which is proportional to $Distance_{ij}$.

The optimal consumption amount for good/service k is $n_{jkt}^* = \alpha_k I_{it}^c / p_{jkt}$. Substituting this term back to the utility function (1), we can obtain the following indirect utility function.

$$U_{it} = I_{it} \prod_{k \in K} (p_{jkt})^{-\alpha_k} B_{ijkt} \omega_{ijkt} \quad (3)$$

Conditioning on the household living in location i, he/she chooses a destination $j \in J$ to maximize the indirect utility for this consumption good/service. We assume the distribution of the unobservable preference shock ω_{ijkt} follows an independent Fréchet distribution $F(\omega) = \exp(-\omega^{-\epsilon_k})$. Then, the conditional probability of traveling to a location for consumption type k can be written as

$$S_{ijkt|i} = \frac{\left(B_{ijkt} / p_{jkt}^{\alpha_k}\right)^{\epsilon_k}}{\sum_n \left(B_{inkt} / p_{nkt}^{\alpha_k}\right)^{\epsilon_k}} \quad (4)$$

Equation (4) describes the relative demand for good/service k sourced in location j. The household is more likely to commute to location j if the price is relatively cheap, but the quality is high. Aggregating across all locations and industries, we can obtain the expected utility of being able to access a bundle of consumption goods in the city for household living in i.

$$E[U_{it}] = I_{it} \prod_{k \in K} \gamma_k \left[\sum_{k \in K} \left(B_{ijkt} / p_{jkt}^{\alpha_k}\right)^{\epsilon_k} \right]^{1/\epsilon_k} \quad (5)$$

$$\gamma_k = \Gamma\left(\frac{\epsilon_k - 1}{\epsilon_k}\right)$$

In Section IV, we estimate the key parameters $\boldsymbol{\beta_k}$ governing the response of mobility to industry-specific lockdown policies and other local cost shifters. We will calibrate the shape parameter ϵ_k and also the importance of each consumption type to the overall utility α_k following Redding et al. (2020) and Couture et al. (2019).

III.2 Mobility Impact on COVID-19

Equation (4) provides a set of structural equations that link the observed share of the population traveling for consumption type k with a set of location and time-varying fundamentals that shape the mobility cost. Naturally, we can define the mobility (i.e., total number of travelers) for home location i and consumption k at time t as the probability of traveling outside of i multiplied by local population N_i.

$$M_{ijkt} = \sum_{j \neq home} S_{ijkt} \times N_i \qquad (6)$$

The probability that an individual contracts COVID-19 depends crucially on the frequency with which the individual travels and interacts with other individuals who may be infected. First, we define the contact rate at a destination j as the lagged number of infections per capita $R_{jt} = \frac{I_{jt-1}}{N_j}$, where I_{jt-1} is the number of infected people in residential location j, and N_j is the location's total population. We can estimate the relationship between the overall mobility and the number of COVID-19 cases at a residential location by

$$I_{it} = \beta^m \sum_k \sum_{j \neq home} R_{jt} \times M_{ijkt} + \gamma_i + \gamma_t + \epsilon_{it} \qquad (7)$$

Intuitively, this equation tells us that the rate of local COVID-19 infection depends on how mobile the local residents are and how much exposure to other infected people each trip type offers.

IV Estimation and Results

In this section, we discuss how we identify and estimate the model specified in Section III. We also show the key estimation results and discuss the interpretation of the estimates.

IV.1 Estimating Trip Preferences

In the previous section, we outlined a model of household mobility decisions for consumption related trips. This model yields an equation (4) that links the probability of traveling to a location with a set of time-varying location characteristics for a consumption type k. We can log-linearize this equation and normalize it with respect to an outside option. We let staying at home be the outside option $\tilde{j}$, which we assume to have utility normalized to be 1. Thus:

$$lnS_{ij(kt)} - lnS_{i\tilde{j}(kt)} = -\alpha_k \epsilon_k lnp_{ij(kt)} + \epsilon_k (\boldsymbol{X_{ijkt}\beta_k}) + \epsilon_k \xi_{ijkt} \qquad (8)$$

We estimate this mobility model using the following empirical specification:

$$\widetilde{lnS_{ijkt}} = \delta_k^p Capacity_{jkt} + \delta_k^c Capacity_{jkt} \times Covid_{t-1} + \delta_k^d Distance_{ij} + \eta_{it} + \eta_{jk} + v_{ijkt} \qquad (9)$$

Where the dependent variable is the (log) share of population living in location i who choose to travel to a location j for consumption trip k, normalized with respect to the outside option of staying at home. Given that our interest is to estimate the response of mobility to business closure policies, we first consider how the traveling decision may be affected by the availability of that service at the destination in a month t. The variable "$Capacity_{jkt}$" measures the availability of the service as determined by business closure policies. During the COVID-19 outbreak of 2020, people may have responded to the policy differently depending on how much they feared getting infected. We estimate this differential response by interacting the policy variable $Capacity_{jkt}$ with the lagged total COVID-19 cases from the previous month, which summarizes the information people have about the chance of infection. Lastly, we include a bilateral distance measure that captures the transport cost of traveling from home location i to destination j.

We focus on the following non-tradable goods/services categories: (i) Accommodation and Food Services; (ii) Retail Trade; (iii) Arts and Entertainment and Recreation; (iv) Real Estate, Finance, and Information; (v) Personal Care, Repair, and Laundry; (vi) and Religious and Education. We leave out some other service sectors such as Health Care and Administrative Services because the Centers for Disease Control and Prevention (CDC) designated a large share of these sectors as essential, so that local business closure policies barely affected them. It is possible that households voluntarily increased or reduced mobility to these other service sectors during the pandemic, but trips to these places account for only 11 percent of the observed mobility in our sample data, so we believe that leaving them out does not affect our results. For the estimation, we use the ZIP Code Tabulation Areas (ZCTA) as our primary unit of the analysis because this is the finest geographic level at which COVID-19 information is available for New York City.

Endogeneity

The first endogeneity issue which arises when estimating the impact of business closure policies is that these policies are enacted as a response to the severity of the pandemic, which is in turn correlated with mobility patterns. Since mobility data are granular and track bilateral trips for many neighborhoods within the city, we can deal with this endogeneity issue by using a Bartik-style policy shock variable (Goldsmith-Pinkham et al., 2020).

We construct "$Capacity_{jkt}$" by measuring the maximum number of visitors received by an industry at a certain location. This is a combination of the total capacity $Max.Visitors_{jkt_0}$ which we measure as the maximum number of visitors received during January 2020, and the allowed capacity $PolicyAllowance_{kt}$, which measures the proportion of the total capacity allowed according to the business closure policy.

$$Capacity_{jkt} = Max.Visitors_{jkt_0} \times PolicyAllowance_{kt} \qquad (10)$$

Conceptually, we consider the closure policy for industry k as a state- and city-wide shock that affects all locations, while some locations receive more intense "treatment" due to higher ex-ante exposure. We further use time-fixed effects to control for time-varying shocks that induce the government to enact the policy and the destination-fixed effects to isolate unobserved service quality at each location. To be more concrete, consider the example of two locations A and B, where A has a higher ex-ante visitor capacity than B (perhaps due to having more establishments in industry k or naturally having a higher quality of service that attracts more visitors). In this example, a policy constraint which reduces the total capacity to 20 percent would have a larger effect on A than on B.

To estimate equation (9), notice that we don't observe the destination price, lnp_{jt}. We cannot absorb the unobserved price effect directly with destination-time fixed effects since our policy variable also varies on the same level. It might be true that during the pandemic of 2020, there were large (relative) price swings that affected how consumers chose to allocate their expenditures across different goods/services. However, we argue that while there may be shocks that have affected the overall price for an industry (e.g., cost of shopping), they should not change how expensive a consumption good/service is at a location j relative to another location j' over short periods of time. Therefore, the unobserved price effect can be absorbed by the fixed effects $\eta_j + \eta_{it}$.

Results

We display the baseline estimates for equation (9) in Table 2. The elasticities on the policy-induced capacity allowances are positive for all industries, suggesting that people respond to business closures (which lower capacity allowance) by reducing consumption trips to the destination location. Conversely, the coefficient on the capacity-lagged COVID-19 cases interaction term is negative. This suggests that reopening businesses has a weaker effect on mobility when the number of COVID-19 cases is high. Lastly, the coefficients on the bilateral distance are negative, reflecting households' preferences for accessing these consumption goods/services as close to home as possible. These commuting cost elasticities are of a similar magnitude to those found in Redding et al (2020) and Couture et al (2019), which use cell phone mobility data to estimate the gravity equation for consumption-related commuting trips.

Comparing the elasticities on the capacity allowances across industries leads to an interesting observation: the elasticity is smaller (i.e., people respond less to the business closure policy) for industries that provide daily goods/services that are more "necessary" and less "luxury". This suggests that the same level of policy stringency may yield vastly different mobility outcomes for different industries.

This pattern can also be taken as validation for our interpretation of the mobility data as reflecting mostly consumption related trips. However, the concern remains that since the data capture both work trips and consumption trips, the capacity elasticities cannot be purely interpreted as consumer responses to the business closure policies. Although we cannot completely remove the effect of work-related commuting trips from our data, we can still try to assess the robustness of our key estimates by controlling for differential industrial compositions of workers at each home location. Table 3 shows the regression estimates by adding interaction terms for the home zip code's share of workers in each industry.

For example, in Column 2 of Table 3, we add additional controls that interact the three key explanatory variables with the home zip-code's share of workers in retail trade. The insight here is that the mobility data may be more likely to capture work trips to retail trade establishments in neighborhoods where the share of retail workers is higher. By controlling for heterogeneity in worker composition across home locations, we can tease out the capacity elasticities for workers relative to consumers. From the estimates of Table 3, we see that on average workers are slightly more responsive than consumers to the change in capacity constraint, but less responsive to the rise of COVID-19 in the industries Accommodation/Food, Retail Trade, and Personal Care/Repair/Laundry/Religious. Comparing to Table 2, the main estimates for capacity, the capacity-COVID interaction term, and distance are quite robust to adding these additional controls.

IV.2 Calibrating Additional Mobility Parameters (ϵ_k, α_k)

From the optimization problem over different types of consumption goods/services, we know that α_k gives us the expenditure share of type k in the household's total consumption basket: $\alpha_k = n^*_{jk} p_{jkt} / I_{it}$. We calibrate these parameters using consumption data for non-tradable goods from the US Consumer Expenditure Survey of 2020, provided by the U.S. Bureau of Labor Statistics. The calibrated parameters are displayed in Table 4.

Ideally, if we had data on the relative prices across locations for each industry, we could estimate the preference dispersion parameter ϵ_k. However, we do not have price information at such a granular geographic level for each of these industries. We follow the previous literature (Redding et al. 2020, Argente et al. 2020, and Couture et al. 2019) on assessing the consumption driven mobility patterns, and calibrate this set of parameters to be $\epsilon_k = 5$.

IV.3 Estimating the Impact of Mobility on COVID-19

In this sub-section, we estimate the casual impact of mobility on the severity of COVID-19 outbreaks, using the following equation:

$$I_{it} = \beta^m Mobility_{it} + \gamma_i + \gamma_t + \epsilon_{it} \qquad (11)$$

Equation (5) specifies a linear relationship between the number of infected people (or COVID-19 related deaths) and the observed mobility. We estimate this equation by regressing the (log) number of cases per capita reported in that month on measures of mobility from the same month. We use two mobility measures:

$$MobilityPure_{it} = \sum_k \sum_{j \neq home} M_{ijkt} \qquad (12)$$

$$MobilityContact_{it} = \sum_k \sum_{j \neq home} R_{jt} \times M_{ijkt} \qquad (13)$$

The first measure $MobilityPure_{it}$ considers purely the number of people living in location i who choose to travel to another location. The second measure $MobilityContact$ adds a "weight" for each trip by multiplying the number of travelers with the probability of infection at the destination location. We measure the probability of infection at the destination location using the lagged number of COVID-19 cases per capita at that destination.

Endogeneity

Two endogeneity issues arise when estimating equation (11). First, mobility affects the chance of travelers contracting COVID-19, and the information about local COVID-19 outbreaks may also contain information about generally how severe the pandemic is, deterring people from travelling outside. This raises a reverse causality issue. The second endogeneity concern is that both the mobility and number of COVID-19 cases may be measured with error, further attenuating the estimate of β^m.

We deal with these endogeneity issues using an instrumental variable approach, following Glaeser et al (2020) and Song et al (2021). The instrument we use is the ex-ante share of local workers in teleworkable industries. We use the definition from Dingel and Neiman (2020) who identify a list of teleworkable industries on the 2-digit NAICS sector level. We construct this instrument using American Community Survey 2019 ZCTA tabulation from IPUMS NHGIS, which provides the number of workers in each of 2-digit NAICS sector for each zip code. To obtain intertemporal effects for mobility, we interact the ex-ante share of workers in teleworkable industries with month fixed effects.

Locations with higher shares of workers in teleworkable industries are more likely to reduce mobility voluntarily even in the absence of any business closure policy, so this instrument satisfies the relevance condition. Additionally, conditioning on time fixed-effects and location fixed-effects, the share of these workers would only affect the spread of COVID-19 by switching from working on site to working from home, satisfying exclusion restriction.

Estimation Results

Table 5 Panel A shows the impact of pure mobility on COVID-19 per capita. Log-transformations are used on both sides to simplify the interpretation. Without month fixed-effects, Columns 1 and 2 show that mobility is negatively correlated with the observed COVID-19 per capita, suggesting that these estimates suffer from a reverse causality issue (as people may be more reluctant to go out when the COVID-19 cases are rising). Adding month fixed effects in Column 3 helps alleviating part of the reverse causality issue that arises from people reacting to the city-wide rise in COVID-19 cases and also helps to isolate city-wide policy shocks, as a response to the rise of COVID-19, that would also affect mobility. In Column 4, we use the instrumental variable as described above. The estimate in Column 4 suggests that a one percentage point increase in the number of people traveling leads to 26.3 percent increase in COVID-19 cases per capita at the zip code-month level.

In Panel B of Table 5, we use the second mobility measure that takes into account the likelihood of a traveler contracting COVID-19 in each trip. We interpret the coefficient in Panel B as the “aggregate effect” of mobility on COVID-19, as it reflects those trips to “riskier” locations (with larger COVID-19 outbreaks) not only expose the traveler to the virus but also increase the risk of transmission to other travelers in the future. The estimate in Column 4 suggests that a one percentage point increase in the “aggregate” mobility leads to 9.9 percent increase in COVID-19 per capita.

In Table 6, we repeat the same exercise for COVID-19 related deaths per capita. A one percentage point increase in pure mobility leads to 6.4 percent increase in COVID-19 deaths per capita. Taking into account the probability of contracting COVID-19 in each trip, this effect is 1.1 percent increase.

The “aggregate” mobility allows us to capture more nuanced aspects of how mobility impacts the spread of COVID-19. First, it allows the predicted number of COVID-19 cases in a month to vary depending on the severity of the outbreak in the recent past, effectively introducing a dynamic effect. If the past infection rate is high, then a small increase in the number of travelers on the road would further exacerbate the pandemic outcome. Second, it allows for spatial heterogeneity in the response of COVID-19 cases, as a one percentage point increase in the number of travelers to a consumption amenity rich neighborhood can lead to a worse COVID-19 outbreak than the same increase in neighborhoods that have less access to these consumption options.

V. Assessing the Policy Impact

We are interested in the aggregate impact of partial business closures (or equivalently, partial reopening) on COVID-19 outcomes and consumer welfare. In this section, we use the model and key estimates from Section IV to perform two sets of counterfactual policy simulations to provide quantitative measures of the costs and benefits of different business closure policies.

V.1 Current Policy

NYC implemented the Pause program which ordered all non-essential industries to close in late March 2020. Then, two months later after the first wave had passed, the local government gradually reopened the economy industry by industry. In this sub-section, we assess the aggregate impact of this reopening policy rollout in NYC by comparing it to a counterfactual policy in which the economy does not reopen in June 2020.

Specifically, we reset our policy variable $Capacity_{kjt}$ back to the level we observe in May 2020 and hold it at this level until February 2021, after which the vaccine had become available. Then using our two-step model, we simulate the implied mobility change for each consumption type and the resulting estimates for COVID-19 outcomes. For the simulation, we use results from Table 3 as our robust estimates for how mobility responses to the policy change, and we use the estimates from the IV regression in Panel B of Table 4 for how mobility affects the COVID-19 outcomes.

Columns 1 and 2 of Table 7 summarize the results. Gradual reopening leads to 11.5 percent more travelers for the period June 2020–February 2021 relative to the baseline of no reopening. The increase in mobility due to the gradual reopening policy leads to 97 thousand more COVID-19 cases and 2.9 thousand more deaths during the counterfactual periods.

Figure 4 shows the contribution of each industry to the overall increase in mobility under NYC gradual reopening policy. Retail trade contributes 40 percent of the rise in mobility, as retail was one of the industries that attracted the bulk of observed mobility in the city before the pandemic and was also one of the industries that reopened early with few capacity constraints. On the other hand, the local government was very cautious about reopening Accommodation and Restaurant businesses and put much more stringent capacity allowances on them throughout the year. However, given the popularity of this industry before the pandemic, it still contributed 15 percent of the increase in total mobility.

Figure 5 plots the impact of the policy on COVID-19 cases and deaths month by month, which shows a sharp increase for the winter season. As people start to travel more to access these consumption goods/services, the number of COVID-19 cases rises, which further increases the probability of getting infected for future travelers, resulting in an accelerating outbreak moving into the winter season.

Reopening the economy can be welfare-enhancing as consumers regain access to consumption goods/services on site and customers return to stores. This is one of the motivations for local government to rollout a reopening plan despite ongoing virus transmission. We can produce a measure of these welfare gains using the expected utility in mobility model of Section III.1. Equation (5) (repeated here as equation 14) specifies the expected utility from being able to access a bundle of consumption goods/services in the city for a typical household living in location i at time t.

$$E[U_{it}] = I_{it} \prod_{k \in K} \gamma_k \left[\sum_{k \in K} \left(B_{ijkt} / p_{jkt}^{\alpha_k} \right)^{\epsilon_k} \right]^{1/\epsilon_k} \qquad (14)$$

$$\gamma_k = \Gamma\left(\frac{\epsilon_k - 1}{\epsilon_k}\right)$$

To obtain the compensating variation (i.e., the dollar value of having a certain level of consumption access), we first log-linearize the expected utility. Then, we define the compensating variation by calibrating the total amount of income I_{it} needed to bring the level of (log) utility to zero. Intuitively, compensating variation represents the total amount of transfer required in order to make the household indifferent between having these consumption benefits versus forging them.

To assess the welfare impact of partial reopening, we compare the compensating variation of the actual policy implemented in NYC to the alternative baseline of no reopening after May 2020. Table 7 column 2 shows that allowing consumers to regain access to consumption goods/services, even under some capacity constraints, increases welfare by 2 percent. However, this is at the cost of increasing the number of infected people and COVID-19 related deaths.

V.2 Alternative Policy

Assessing the actual policy rollout gives us some assessment of its costs and benefits, but it is hard to evaluate whether this policy is efficient. In particular, we may be interested in whether imposing a more stringent lockdown for longer, until the infection rate decreases substantially, would yield a more efficient outcome.

To answer this question, we simulate a counterfactual policy regime which delays the reopening for another two months (i.e., shifting the entire reopening schedule back to August 2020). Column 3 of Table 7 shows the simulated results. Delaying the reopening would still increase the number of COVID-19 cases relative to the full lockdown baseline, but it would allow consumers to regain access to consumption goods/services starting from August. We can compare these different policy regimes by considering how costly an additional unit of welfare is in terms of additional COVID-19 cases. With delayed reopening, 1 percent increase in welfare gain relative to the baseline would lead to 20.7 thousand more COVID-19 cases and 409 more deaths. In comparison, NYC gradual reopening had led to doubling of the COVID-19 cases and tripling of deaths for the same amount of welfare gain.

To deepen our understanding of how delaying reopening is a more cost-efficient policy alternative, Figure 6 and 7 outlines various outcomes overtime. As shown in Figure 6, delaying reopening shifts the reopening behind for two months, which leads to a large reduction in the total number of people traveling outside for the two months in the summer (June and July) of 2020. The reduced mobility leads to fewer COVID-19 cases early in the summer, which subsequently makes traveling safer in the future periods, leading to a compounding dynamic effect on the mitigation of COVID-19.

In Figure 8, we show that the neighborhoods that benefit most from a delayed reopening are places like the Central Manhattan, the West side of Brooklyn, and the Flushing Chinatown area in Queens. These are also places that are very rich in consumption amenities and have high residential populations (see Appendix Figure A2.2). Intuitively, as people tend to consume non-tradable goods/services close to their home locations, they are also more likely to contract the virus from and pass it on to people in nearby neighborhoods, exacerbating the infection rates in places which are rich in consumption amenities.

V.3 Discussion on Spillover Effects

In this study, we focus on mobility decisions of residents who live inside New York city given the availability of COVID-19 data on zip code level within the city. One issue which naturally arises is that this sample does not allow us to account for spillover effects arising from trips between NYC and areas which neighbor NYC. As a result, we do not account for the possible welfare impact (positive or negative) of NYC's closure policy on the residents of surrounding areas. As demonstrated by, for example, Fajgelbaum et al. (2020), a fully optimal lockdown policy would extend to a wider geographical area (such as the New York Metropolitan Area) to account for these flows in and out of cities. However, in practice, this would require strict cooperation between multiple local governments and may not be feasible, especially when swift implementation is important. We therefore consider the effect of NYC's lockdown policies on NYC residents to be a more salient measurement issue.

VI. Conclusion

In this paper, we demonstrated a framework for estimating the impact of business closure policies on COVID-19 transmission. This framework combined a model of the contribution of different consumption activities to aggregate mobility with an analysis of the relationship between aggregate mobility and total COVID-19 cases.

When applied to the experience of New York City in 2020, our framework suggests that the reopening policy initiated in June 2020 resulted in a 30 percent increase in cases compared to a counterfactual in which the closure of May 2020 is extended until February 2021. We compared this to an alternative policy of delaying the reopening by two months and showed that this reduces cases significantly compared to the actual policy. In addition, if we use the compensating variation to measure the additional consumption benefit generated by reopening, we find that the delayed reopening is less costly in terms of additional cases per unit of additional welfare. This is due to the dynamics of virus transmission, whereby a large reduction in cases early in the outbreak reduces the probability of contracting the virus in later months.

In light of discussions about the appropriate reopening sequence, an interesting result is that restaurants and schools do not account for a very large share of foot traffic increase in New York, even though they were frequently used as a lever for tightening or loosening the lockdown policy. Retail and personal care services instead account for much larger share of mobility. Using the granular geographical component of the mobility data, we also found significant geographical variation in the impact of business closures, suggesting that targeting zip codes with dense consumption amenities more intensively may have been a more effective approach.

Going forward, a more complete characterization of the costs and benefits of business closure policies would take into account the disruptive effect on local businesses and employment when these economic data become publicly available. For the readers' references, some recent studies have used indirect measurement such as google search trend for unemployment benefits (Kong and Prinz, 2020), confidential data of credit card spending (Relihan et.al., 2020), and employment records collected from private software (Kurmann et.al., 2020) to provide early evidence for the economic costs of lockdown policies. It would also be instructive to extend our analysis to other cities and countries and check the robustness of our findings.

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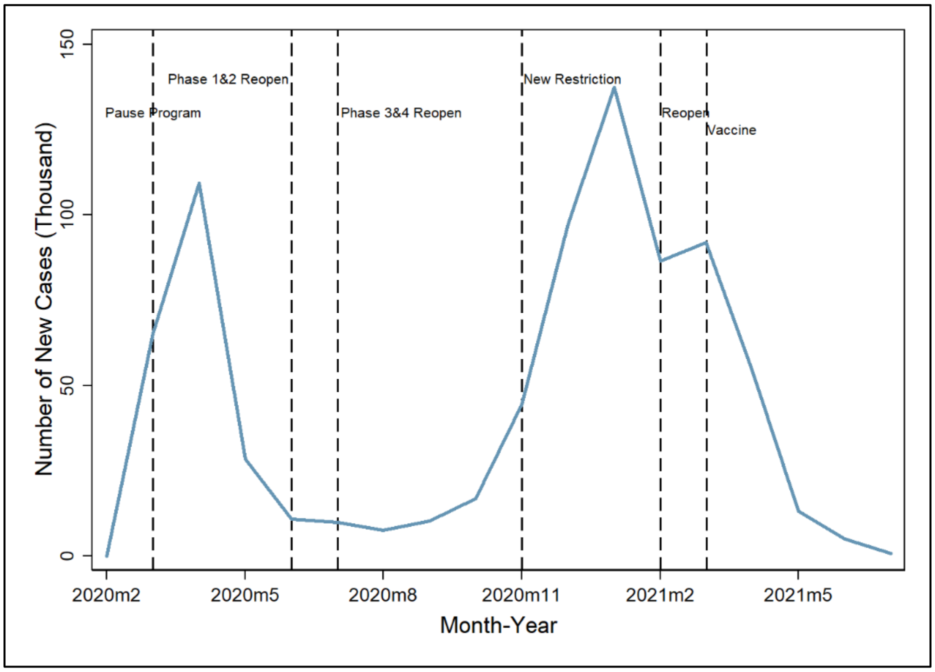
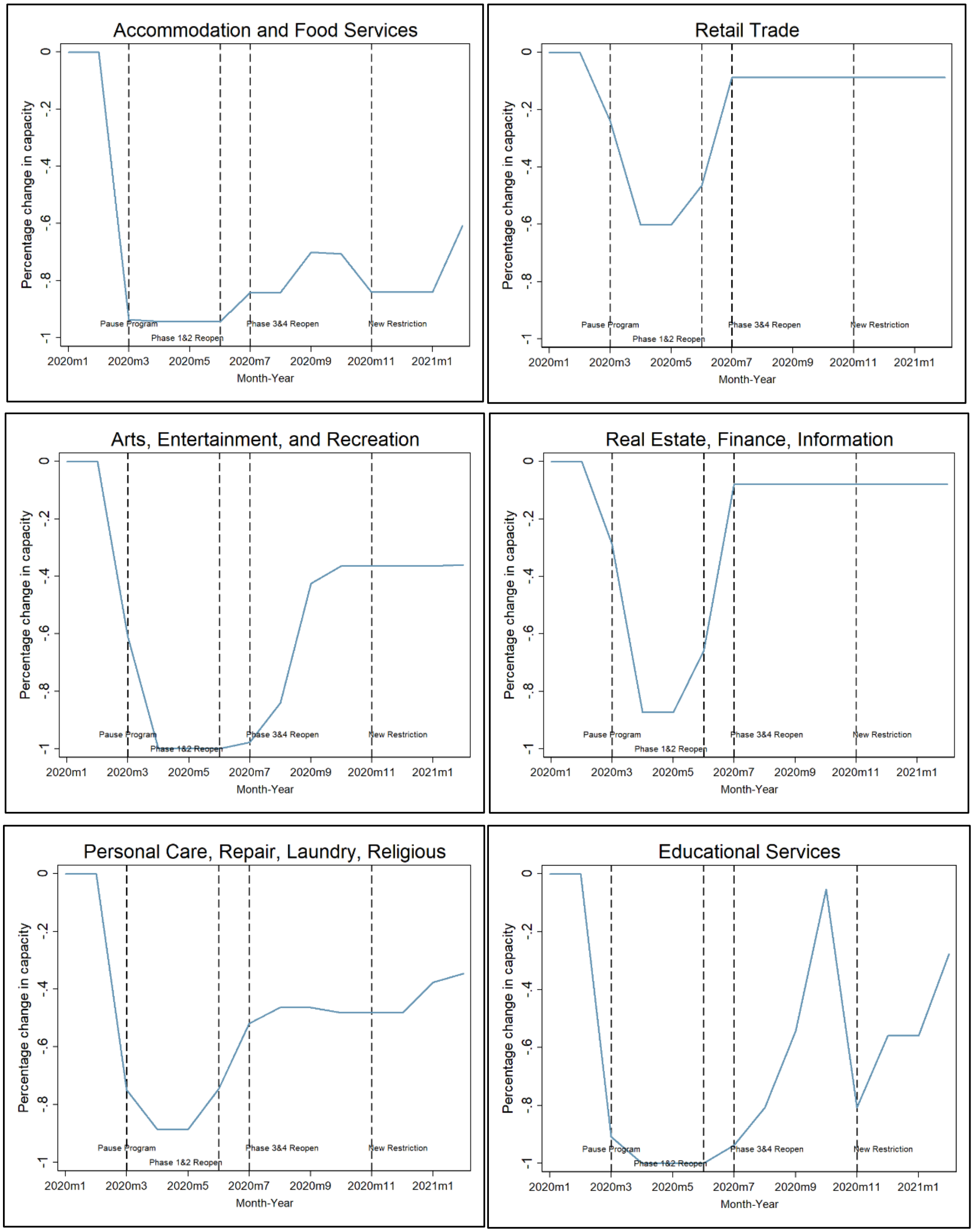
Figures

Figure 1. Policy Timeline in NYC



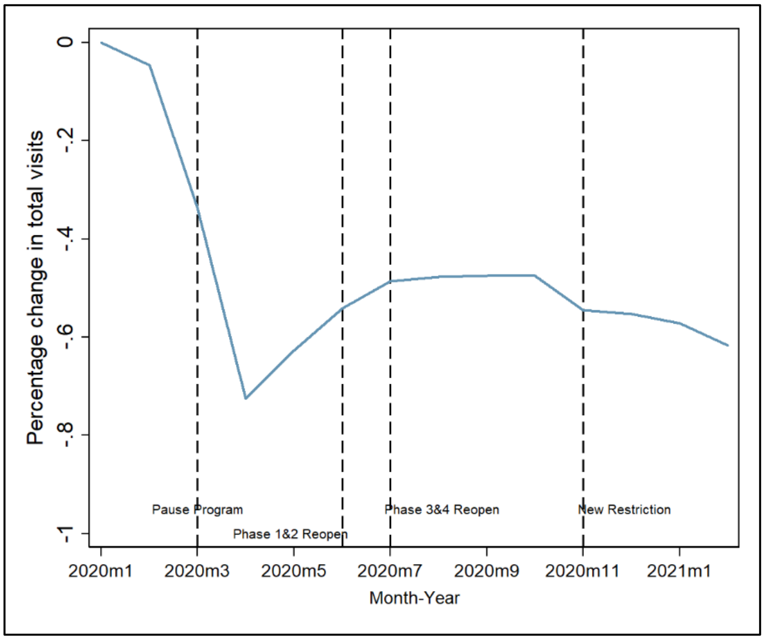
Note: This graph plots monthly number of new COVID-19 cases for NYC. The dash lines indicate the key policy regimes for business closures and reopening implemented by the city government.

Figure 2. Capacity Constraint Across Different Industries



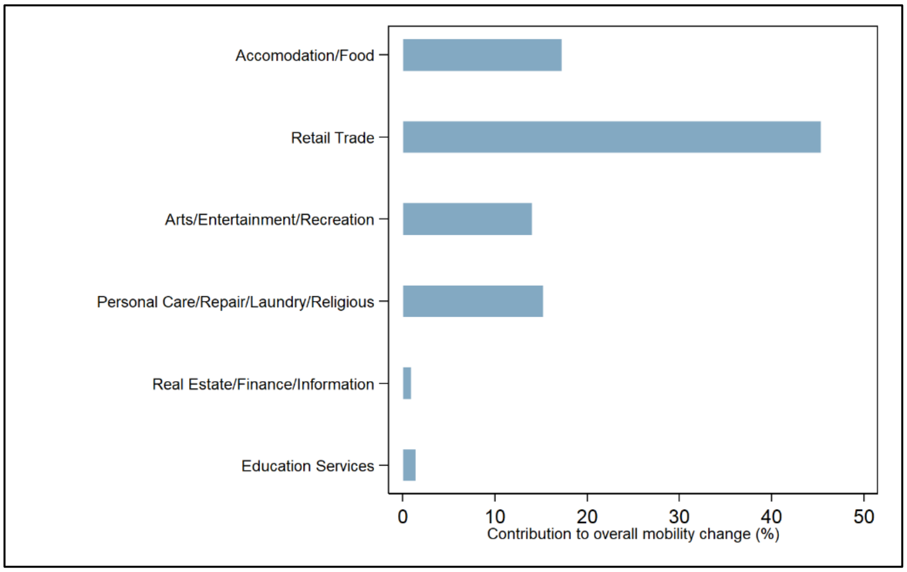
Note: The figure plots capacity constraint over time for each of 2-digit NAICS industries. The constraint is normalized with respect to its initial level observed in January 2020. We exclude industries such as Health Care, Transportation, Construction, Manufacturing, etc., as they are mostly classified as essential industries and are barely affected by NYC business closure policies.

Figure 3. Change in Aggregate Mobility



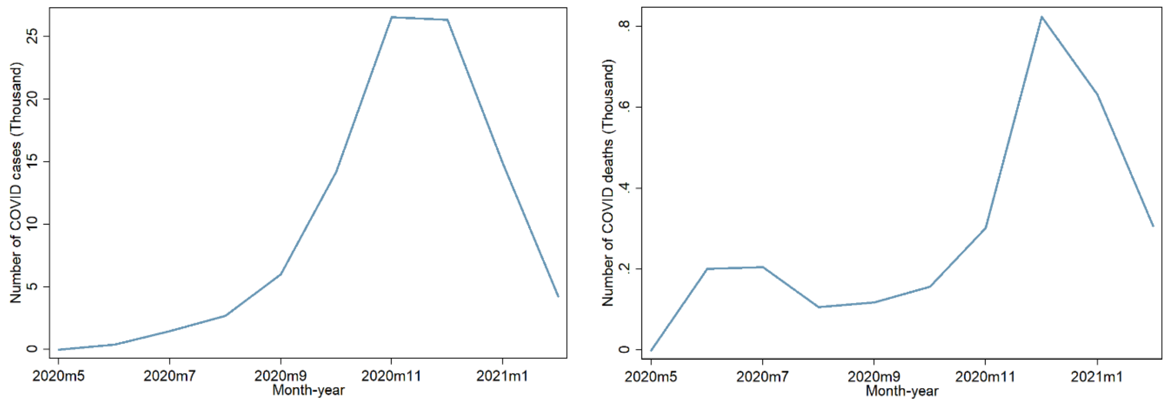
Note: this figure shows percentage change in aggregate mobility in NYC, relative to January 2020. The aggregate mobility is measured by total number of trips residents in NYC made outside of home in each month.

Figure 4. Industry Contribution to Overall Change in Mobility with Gradual Reopening



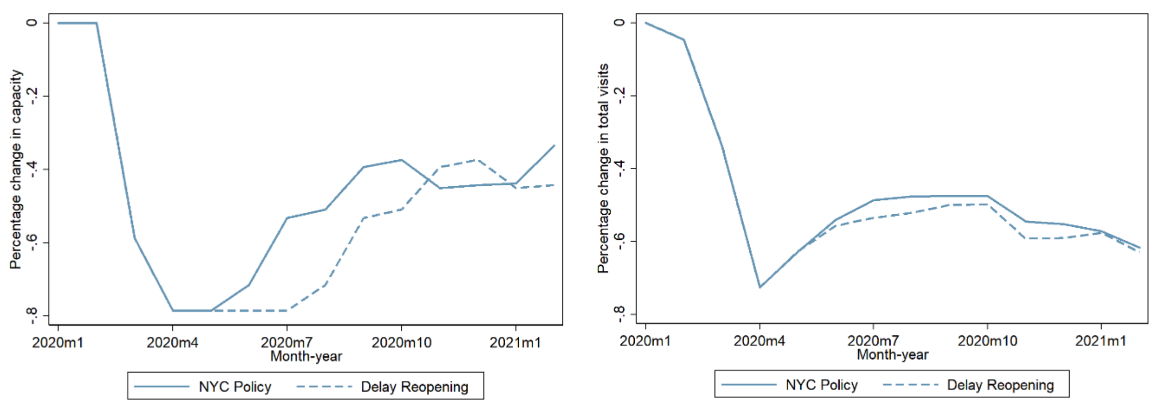
Note: the bar chart plots each industry's contribution to the overall change in total mobility. The change in total mobility is measured by the difference between the mobility under the actual policy rollout in NYC and the baseline of no gradual reopening since May 2020 for the rest of the year.

Figure 5. Impact of Gradual Reopening on COVID-19 Cases and Deaths



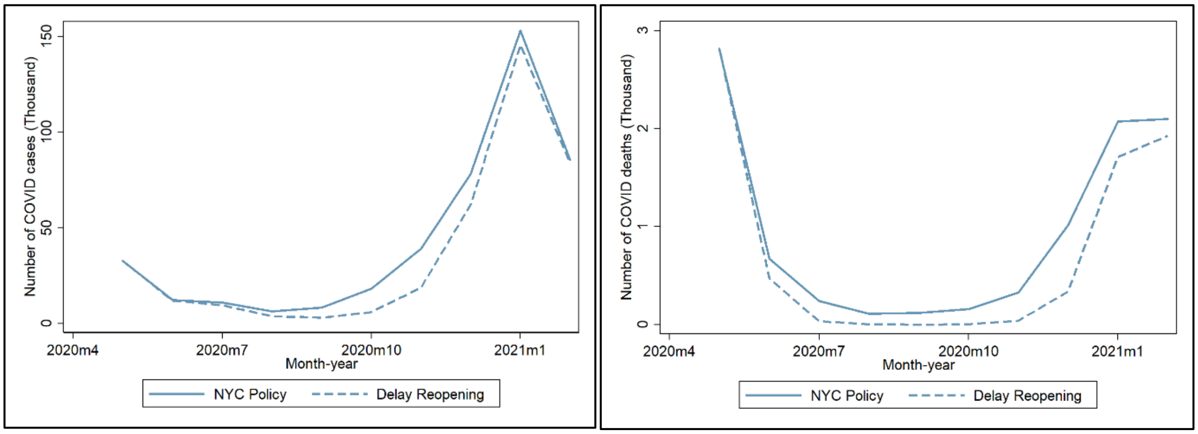
Note: this figure plots the difference between the actual number of COVID-19 cases (deaths) and the implied COVID-19 cases (deaths) under the baseline of no gradual reopening since May 2020.

Figure 6. Delayed Reopening Policy and Mobility



Note: The left figure compares aggregate capacity under the actual NYC policy to the alternative policy of delaying reopening for two months. The right figure compares mobility under the actual NYC policy to delaying reopening. Both series are normalized with respect to their levels observed in January 2020. The dash line plots the simulated number of travelers when the reopening schedule is delayed until August 2020.

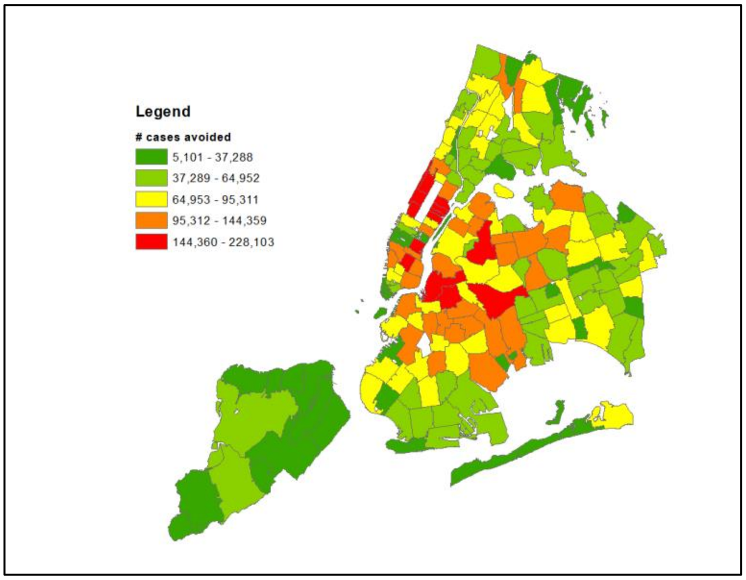
Figure 7. Impact of Delayed Reopening on COVID-19 Cases and Deaths



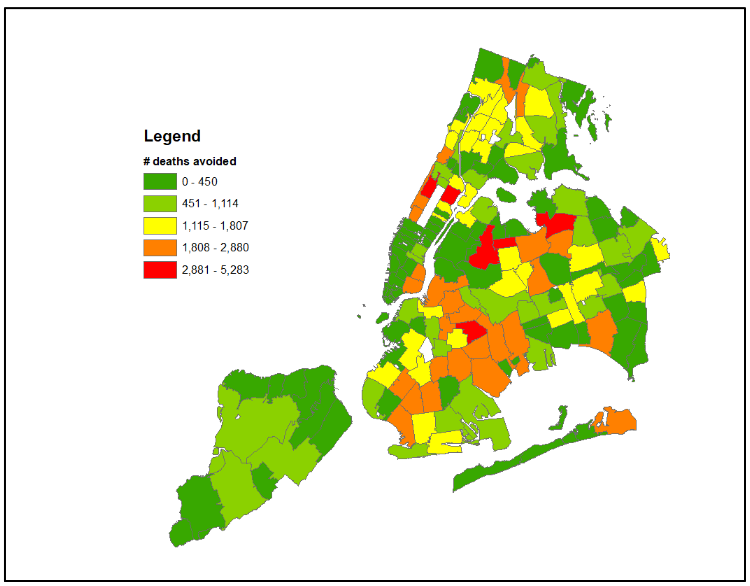
Note: this figure compares number of COVID-19 cases (deaths) under the actual NYC policy to the alternative policy of delaying reopening for another two months. The solid line plots the actual number of COVID-19 cases (deaths) on monthly level from May 2020 to February 2021. The dash line plots the simulated number of COVID-19 cases (deaths) when the reopening is delayed until August 2020.

Figure 8. Neighborhood Heterogeneity

Panel A. Number of Cases Avoided



Panel B. Number of Deaths Avoided



Note: These maps show heterogenous impacts of delaying reopening for another two months on different zip codes. Panel A shows the implied COVID-19 case reduction per 1 percentage decline in consumer welfare (due to reduction in access to consumption goods/services). Panel B shows the implied COVID-19 deaths reduction per 1 percentage decline in consumer welfare. Warmer color indicates the neighborhood benefits more from delaying reopening.

Tables

Table 1. Travel Pattern by Industry

Industry	Total travelers (million)	Industry share	Share staying < 4 hours
Accommodation and Food Services	4.051	0.402	0.866
Retail Trade	2.668	0.265	0.875
Arts, Entertainment, Recreation	1.139	0.113	0.873
Real Estate, Finance, Information	0.481	0.048	0.772
Personal Care, Repair, Laundry, Religious	0.385	0.038	0.658
Educational Services	0.345	0.034	0.892
Other Industries	1.016	0.101	0.825
Total	10.083		

Note: Data is from SafeGraph. The table summarizes visit frequencies at industry destination for January 2020. This tabulation includes only travelers residing inside NYC.

Table 2. Trip Preference by Industry

	Accommodation, Food Services	Retail Trade	Arts, Entertainment, Recreation	Personal Care, Repair, Laundry, Religious	Real Estate, Finance, Information	Educational Services
	(1)	(2)	(3)	(4)	(5)	(6)
Capacity	0.009***	0.021***	0.037***	0.043***	0.074***	0.125***
	(0.001)	(0.002)	(0.003)	(0.004)	(0.016)	(0.020)
Capacity x CovidCOVID-19	-0.000	-0.001***	-0.002***	-0.005***	-0.004***	-0.010***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)
Distance	-1.561***	-1.635***	-1.584***	-1.598***	-1.324***	-1.443***
	(0.025)	(0.028)	(0.030)	(0.036)	(0.051)	(0.033)
Observations	433,664	433,664	433,664	433,136	428,912	430,672
R-squared	0.705	0.659	0.579	0.432	0.473	0.407
Home-Month FE	Y	Y	Y	Y	Y	Y
Destination FE	Y	Y	Y	Y	Y	Y

Note: Each regression is run on a home-destination-month triplet. The dependent variable is (log) relative share of population going to a destination in a month conditioning on living in a home location. Each column corresponds to a 2-digit NACIS industry for nontradable consumption goods/services. The columns are ranked by the magnitude of coefficient on Capacity from smallest to the largest. Standard errors clustered by destination zip code.
***** p<0.01, ** p<0.05, * p<0.1*

Table 3. Trip Preference by Industry with Worker Heterogeneity

	Accommodation, Food Services	Retail Trade	Arts, Entertainment, Recreation	Personal Care, Repair, Laundry, Religious	Real Estate, Finance, Information	Educational Services
	(1)	(2)	(3)	(4)	(5)	(6)
Capacity	0.009***	0.019***	0.037***	0.049***	0.082***	0.107***
	(0.001)	(0.002)	(0.004)	(0.008)	(0.015)	(0.035)
Capacity x CovidCOVID-19	-0.001***	-0.002***	-0.001***	-0.007***	-0.003***	-0.009***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)
Distance	-1.433***	-1.069***	-1.923***	-0.941***	-1.784***	-1.259***
	(0.036)	(0.045)	(0.039)	(0.073)	(0.073)	(0.061)
Industry Worker Share x						
Capacity	0.010***	0.022	-0.007	-0.122	-0.032	0.193
	(0.004)	(0.019)	(0.048)	(0.179)	(0.023)	(0.212)
Capacity x CovidCOVID-19	0.007***	0.011***	-0.031***	0.036**	-0.006***	-0.012
	(0.001)	(0.001)	(0.006)	(0.015)	(0.002)	(0.018)
Distance	-1.841***	-6.538***	11.278***	-13.242***	1.754***	-1.999***
	(0.301)	(0.466)	(0.829)	(1.086)	(0.156)	(0.465)
Observations	433,664	433,664	433,664	433,136	428,912	430,672
R-squared	0.707	0.664	0.584	0.438	0.486	0.408
Home-Month FE	Y	Y	Y	Y	Y	Y
Destination FE	Y	Y	Y	Y	Y	Y

Note: Each regression is run on a home-destination-month triplet. The dependent variable is (log) relative share of population going to a destination in a month conditioning on living in a home location. Each column corresponds to a 2-digit NACIS industry for nontradable consumption goods/services. The columns are ranked by the magnitude of coefficient on Capacity from smallest to the largest. Standard errors clustered by destination zip code.
**** p<0.01, ** p<0.05, * p<0.1*

Table 4. Expenditure Share

Industry	Expenditure Share
Arts, Entertainment, and Recreation	0.08
Accommodation and Food	0.14
Education	0.07
Retail Trade	0.42
Real Estate, Finance and Information	0.19
Personal Care, Repair, Laundry, Religious	0.10

Table 5. Mobility and COVID-19 Cases

	(1)	(2)	(3)	(4)
Dep. Var.	Log(COVID-19 per capita)			
Panel A				
Log(Mobility)	-0.022**	-0.508***	0.186***	0.263***
	(0.010)	(0.030)	(0.022)	(0.040)
Observations	2,288	2,288	2,288	2,288
spec	OLS	OLS	OLS	IV
Zip code FE	N	Y	Y	Y
Month FE	N	N	Y	Y
Panel B				
Log(Mobility wt contact rate)	0.049***	0.049***	0.127***	0.099***
	(0.001)	(0.001)	(0.010)	(0.009)
Observations	2,288	2,288	2,288	2,288
spec	OLS	OLS	OLS	IV
Zip code FE	N	Y	Y	Y
Month FE	N	N	Y	Y

Note: Each regression runs on a home location-month panel. Panel A uses pure mobility as the key independent variable. Panel B uses mobility weighted by the infection rate at destination location as the key independent variable. Column 1 has no fixed-effect. Column 2 adds home zip code fixed-effect. Column 3 adds month fixed-effect. Column 4 uses telecommunicable worker share as the instrument for mobility. Standard errors clustered by home zip code.
**** p<0.01, ** p<0.05, * p<0.1*

Table 6. Mobility and COVID-19 Deaths

	(1)	(2)	(3)	(4)
Dep. Var.	Log(Covid-19 death per capita)			
Panel A				
Log(Mobility)	-0.002	-0.057***	0.028***	0.064***
	(0.001)	(0.004)	(0.005)	(0.008)
Observations	2,288	2,288	2,288	2,288
spec	OLS	OLS	OLS	IV
Zip code FE	N	Y	Y	Y
Month FE	N	N	Y	Y
Panel B				
Log(Mobility wt contact rate)	0.002***	0.002***	0.009***	0.011***
	(0.000)	(0.000)	(0.001)	(0.001)
Observations	2,288	2,288	2,288	2,288
spec	OLS	OLS	OLS	IV
Zip code FE	N	Y	Y	Y
Month FE	N	N	Y	Y

Note: Each regression runs on a home location-month panel. Panel A uses pure mobility as the key independent variable. Panel B uses mobility weighted by the infection rate at destination location as the key independent variable. Column 1 has no fixed-effect. Column 2 adds home zip code fixed-effect. Column 3 adds month fixed-effect. Column 4 uses telecommunicable worker share as the instrument for mobility. Standard errors clustered by home zip code.
*** p<0.01, ** p<0.05, * p<0.1

Table 7. Policy Impact Summary

	Baseline	**NYC Policy**	**Alternative Policy**
	May 2020 lockdown until Feb 2021	Partial reopening (NYC case)	Delay reopening until August,2020
COVID-19 Cases	316,481	413,186	345,380
COVID-19 Deaths	3,959	6,813	4,530
Change in travelers (%)	-	11.501	7.173
Change in welfare (%)	-	1.997	1.396
Change COVID-19 Cases per % welfare	-	48,425	20,701
Change COVID-19 Deaths per % welfare	-	1,429	409

Annex I. Data Construction

In this section, we explain in detail how each location-industry's capacity constraint is constructed.

1. Forming the Capacity Index for each 4-digit NAICS industry

1.1 Collect the policy announcements from local government websites and news article.

1.2 Assign businesses mentioned in the announcement to a 4-digit NAICS industry.

1.3 The capacity index equals to 1 if the 4-digit industry is allowed to fully open, equals to 0 if the industry is ordered to be fully closed, equals to a fraction number if the industry is ordered to open at some capacity (e.g., restaurant is only allowed to open at 15 percent capacity, then the index would be coded as 0.15). We construct this index for each day since March 1st and for each industry.

1.4 To aggregate the daily index to monthly level, we weight the index by the number of days the closure policy was effective during that month.

2. Zip Code Level Industry Capacity Constraint

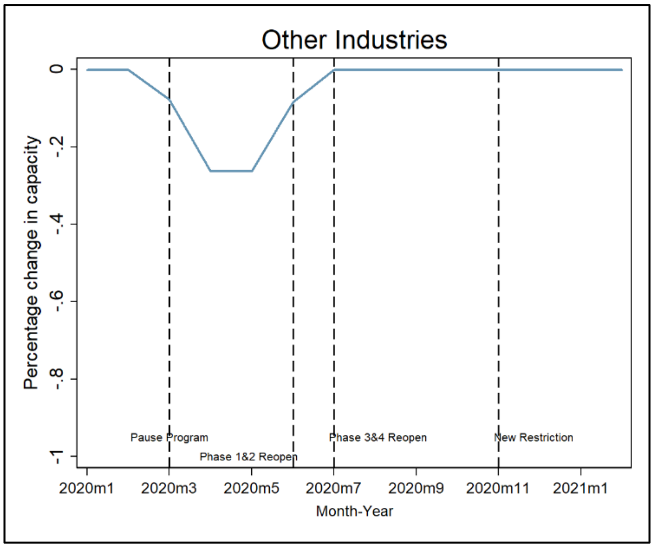
2.1 We take the observed total number of visitors at each business establishment in January 2020 from SafeGraph data as the maximum capacity that each establishment is able to serve for a given month.

2.2 We multiply the maximum capacity for each establishment with its 4-digit industry capacity index. This allows us to compute a maximum capacity allowance at establishment level.

2.3 We further aggregate these capacity allowances to zip code-industry level. For the purpose of this analysis, we aggregate them up to 2-digit industry sector level.

Annex II. Additional Figures

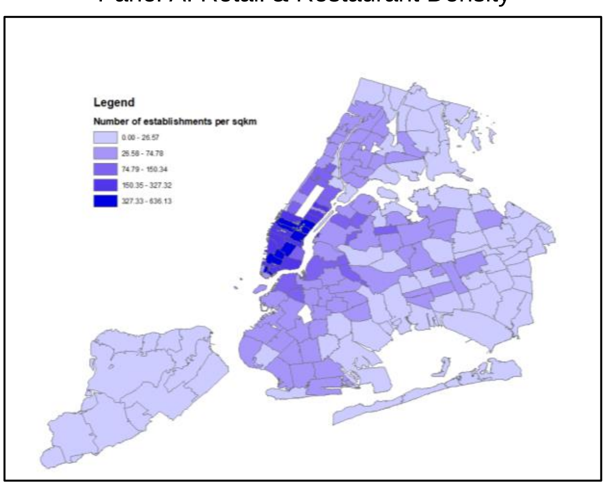
Figure A2.1. Capacity Constraint for Other Industries



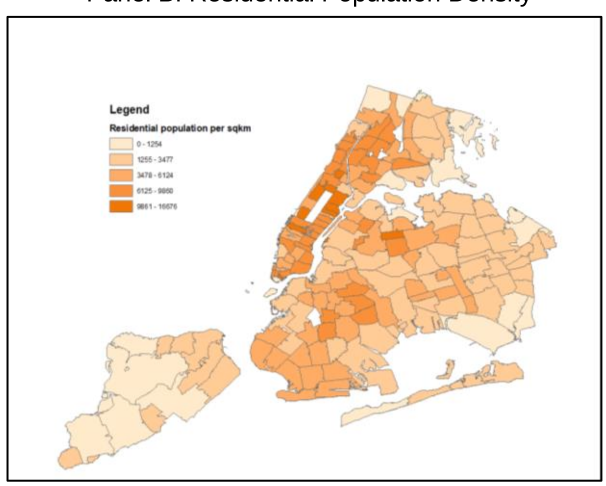
Note: This figure plots the capacity constraint for all the other industries that are excluded from Figure 2. This includes Health Care and Social Assistance, Transportation, Utilities, Manufacturing, Construction, Public Administration, Delivery and Warehousing Professional, Scientific, and Technical Services, Wholesale Trade, Manufacturing, Administrative and Support and Waste Management and Remediation Services, Management of Companies and Enterprises, Agriculture, Forestry, Fishing and Hunting.

Figure A2.2. Local Amenities and Population Density

Panel A: Retail & Restaurant Density



Panel B: Residential Population Density



PUBLICATIONS

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