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Covid Economics **Issue 4, 14 April 2020**

Staying at home: Mobility effects of Covid-19

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We combine GPS data on changes in average distance travelled by individuals at the county level with Covid-19 case data and other demographic information to estimate how individual mobility is affected by local disease prevalence and restriction orders to stay at home. We find that a rise of local infection rate from 0% to 0.003%[4] is associated with a reduction in mobility by 2.31%. An official stay-at-home restriction order corresponds to reducing mobility by 7.87%. Counties with larger shares of population over age 65, lower share of votes for the Republican Party in the 2016 presidential election, and higher population density are more responsive to disease prevalence and restriction orders.

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4 This is the median infection rate (number of confirmed cases divided by county population) across counties with positive number of confirmed cases as of 20 March 2020.

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1 Introduction

In the face of the rapidly growing threat posed by the COVID-19 pandemic, public health experts and economists alike are relying on epidemic models to make predictions and evaluate policies. In the standard SEIR model (e.g. Wang et al. (2020)), the effective reproduction rate R_t measures the actual average number of secondary cases per infected case at time t. It is widely acknowledged that R_t reflects both the nature of the virus (including the basic reproduction rate R_0), as well as the effectiveness of various protective measures taken by individuals and governments in response to available information. In the case of COVID-19, the key policy measure to reduce R_t is a restriction order to stay-at-home. To date, this policy has been promoted by governments across the globe. It is an open question, however, to what extent individuals alter their mobility in response to government orders. It is also little known how they adjust traveling behaviour when perceived risks of COVID-19 increases, but the government has not yet announced a restriction order.

Mobility statistics provide invaluable information as to whether people are actively reducing their exposure to COVID-19 by reducing distances traveled and avoiding social contact, and by how much. In this paper, we use a novel dataset from Unacast, a location data firm. Their dataset includes a measure of daily average changes in distance traveled (Δ_{it}) in every U.S. county. Their measurement of distance travelled is a relative change to a baseline measure of distance travelled based on historical data, so Δ_{it} is an important measure of changing behaviours in response to the COVID-19 pandemic. We use this data to estimate how the average change in distance traveled is related to perceived risk of contracting the disease (Ω_{it}) and restriction orders I_{it}. We also investigate how these relationships depend on demographic characteristics (X_i). The methodology here is similar to that in Auld (2006), where the author estimates elasticities of risky behavior to local prevalence of AIDS, and explored heterogeneity across observable characteristics.

The estimates obtained here contribute to the current discussion in three ways. First, our results provide an estimate of how much human behavior, in our case average distance

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traveled, responds to perceived risks of contracting the disease. Second, the results give us a sense of how important government announcements are in affecting people's behaviour. Lastly, by considering demographics, political attitude and population density, we evaluate whether characteristics of the underlying population play a role in determining the effectiveness of restriction orders and responses to disease prevalence. In particular, since older individuals are at higher risk[2], we would be interested in whether counties with relatively high elderly populations have altered their behavior more than younger counties. There has also been some discussion that political partisanship is an indicator of skepticism in the legitimacy of the COVID-19 outbreak [3]. We also evaluate whether counties with higher population density adjust behavior more due to the fact that the virus is spreading mainly through interpersonal interactions. To summarize, the novel data and careful analysis in this paper contributes to the understanding of mobility changes amid COVID-19 epidemic while focusing on levels of travel distance and raw percentage change without considering confounding factors such as local disease prevalence and population density could paint an incomplete picture.[4]

Another paper in this issue, Painter and Qiu (2020), also investigates how political beliefs affect compliance with COVID-19 restriction orders. They define a social distancing measure using the fraction of mobile users completely staying at home with location data from SafeGraph Inc. Their panel regression results support our finding that counties with a lower share of votes for the Republican Party in the 2016 Presidential Election respond less to restriction orders. They also use party misalignment to argue that faith in the credibility of government officials affects adherence to those policies. Our paper differs from theirs in three ways. First, besides political affiliation, we also demonstrate the importance of other heterogeneities such as age structure and population density. Second, we focus on people's

[2]See, e.g. the CDC guidelines: https://www.cdc.gov/coronavirus/2019-ncov/need-extra-precautions/people-at-higher-risk.html

[3]e.g. https://www.nytimes.com/interactive/2020/03/21/upshot/coronavirus-public-opinion.html

[4]e.g. https://www.nytimes.com/interactive/2020/04/02/us/coronavirus-social-distancing.html

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reduction in mobility to factors beyond restriction orders, such as confirmed cases in both local and neighboring counties. This is important since as we show in Figure 7, average mobility starts to decrease long before restriction orders were announced. Lastly, we build a model of individual behavior; our estimates aim at providing a benchmark value for individual responses to overall perceived COVID-19 risks that can be used in other studies (e.g. Kaplan et al. (2020)). We view Painter and Qiu (2020) as complementary to our paper.

In the rest of the paper, we outline a simple model in section 2. In section 3 we discuss our novel data source on daily travel patterns and how we have augmented it with COVID-19 data. In section 4 we present our preliminary results and argue that even the simple model provides a solid baseline. We finish with section 5 where we summarize our current progress and outline our plan for current and future work.

2 Simple Model

In this section, we present a simple model that relates an individual's travel decision to perceived disease prevalence. This model provides theoretical motivation for the estimation strategy in Section 4.

Consider an individual that derives utility $U(d) = d^\sigma/\sigma$ from distance traveled (d) with $0 < \sigma < 1$. The cost of traveling each unit of distance is composed of one component that is independent of the epidemic Π, and one component that is the product of a linear perceived risk index of contracting the disease ($\Omega > 0$) and the utility cost of contracting the disease (Z). An individual's utility is given by:

$$\begin{aligned} U(d) &= d^\sigma/\sigma - \Pi d - \Omega Z d \\ &= d^\sigma/\sigma - \Pi\left(1 + \Omega\frac{Z}{\Pi}\right) d \qquad (1) \\ &\approx d^\sigma/\sigma - \Pi e^{\frac{Z}{\Pi}\Omega} d \end{aligned}$$

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The solution of the utility maximization problem is therefore:

$$d^* = \left(\Pi e^{\frac{Z}{\Pi}\Omega}\right)^{\frac{1}{\sigma-1}} \tag{2}$$

As can be seen, when an individual perceives a higher risk level, corresponding to higher Ω, individuals decide to travel less, i.e. by reducing d. We will carefully define Ω later.

If we compare an individual's decision to travel at time t under perceived risk index Ω_t versus some benchmark date t_0 with Ω_0, we get a measure of change in distance traveled:

$$\Delta_t = \frac{d_t^*}{d_0^*} - 1 = e^{\frac{Z}{(\sigma-1)\Pi}(\Omega_t - \Omega_0)} - 1 \equiv e^{\kappa\Omega_t} - 1 \tag{3}$$

since before the outbreak $\Omega_0 = 0$.

Equation (3) is suggestive of a strategy to estimate how the index of perceived risk, Ω, affects the percentage change in distance traveled from date t relative to date 0. We propose to estimate κ via nonlinear least squares, after we consider an appropriate definition of Ω_t below in Section 4.[5]

3 Data

We construct a county-level panel data for the contiguous United States. with dates covering 2/24/2020 to 3/25/2020. Our data includes the following information:

1. Daily confirmed coronavirus cases compiled by The New York Times.[6]

2. Daily changes in average distance traveled relative to the same weekday pre-COVID-19, provided by Unacast. Unacast use GPS signals from mobile devices to calculate

[5]Since change in distance traveled (Δ_t) is large in the data, we do not approximate it by $\log(d_t^*/d_0^*)$.

[6]We also compared this data to case data compiled by the Johns Hopkins University Center for Systems Science and Engineering and found the data to be essentially identical. Our results are robust to both sources.

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average distance traveled by device-holders in each county at a daily frequency.[7]

3. Enacted social-distancing policies (stay-at-home restriction orders) as of 3/28/2020 as compiled by the New York Times.

4. Demographic data is sourced from the MIT Election Data and Science Lab (MEDSL). MEDSL data conveniently matches demographic information from the 2012-2016 5-year ACS, to county-level 2016 Presidential Election Results.

In total, our data covers 3142 U.S. counties with 94,116 observations. The summary statistics are given in Table 1.

Figure 1 plots the changes in average distance traveled relative to the same weekday pre-COVID-19 on 2/24/2020. The overall light color in the figure indicates that at the beginning of the epidemic when there were very few cases confirmed (see Figure 3), there was not much change in population mobility.

When we turn to a more recent date, 3/23/2020, Figure 2 shows that average distance traveled decreases significantly in most counties across the U.S., with particularly large drop in New York, California, Colorado and Florida. Figure 4 shows that these are also places with relatively large number of reported COVID-19 cases.

Figure 5 and 6 show the share of counties and population that is under a stay-at-home order respectively. Both measures start to grow on 3/19 as national cases surpass 10,000. As of 3/25/2020, more than 30% of the counties and 55% of the national population is under government orders to stay-at-home unless for essential activities.

Figure 7 shows the 10th quantile, median, and 90th quantile of the changes in average distance traveled across counties in our sample. We can see that mobility starts to decrease for median counties at around 3/10, well before the announcements of restriction orders as shown in Figure 5 and 6.

[7]For more information on methods of data collection and aggregation, visit unacast.com and Unacast COVID-19 Social Distancing Scoreboard.

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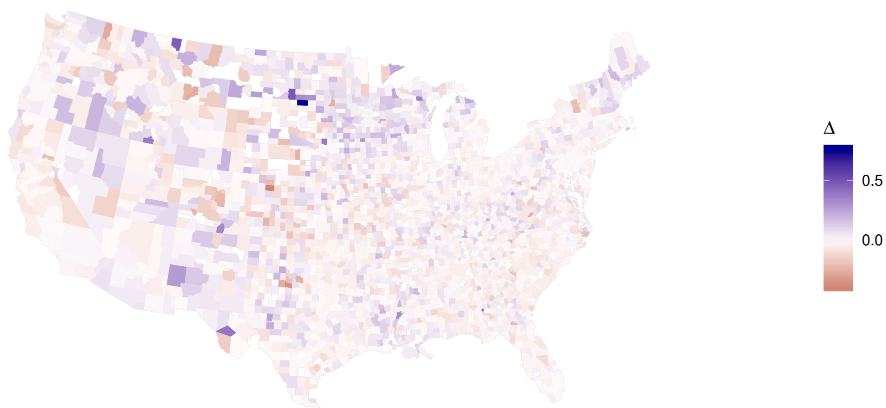

Figure 1: Change in distance traveled relative to the same weekday pre-COVID-19, 2/24/2020

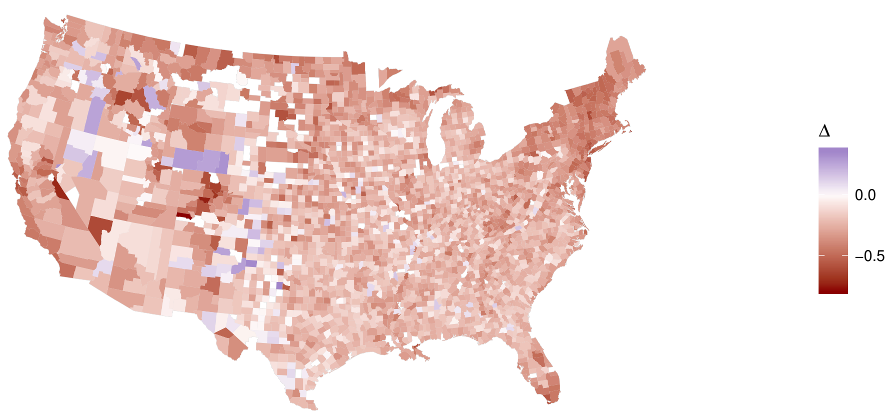

Figure 2: Change in distance traveled relative to the same weekday pre-COVID-19, 3/23/2020

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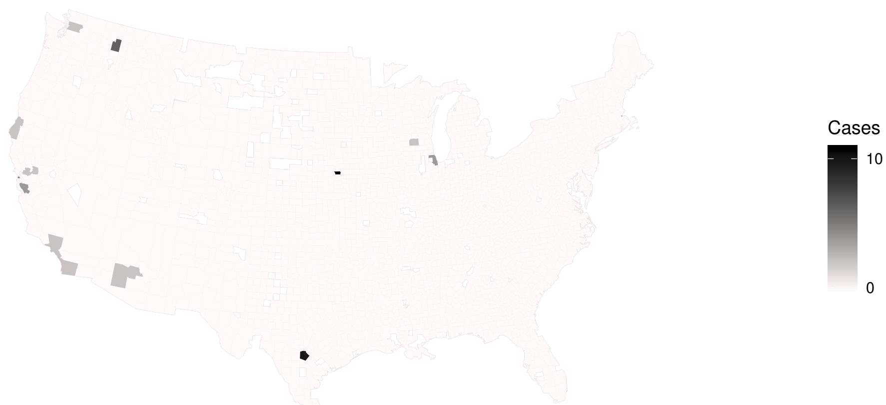

Figure 3: Number of confirmed cases, 2/24/2020

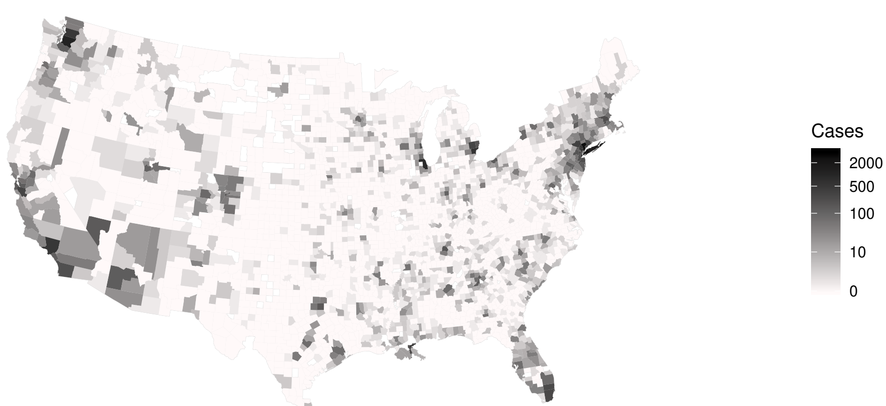

Figure 4: Number of confirmed cases, 3/23/2020

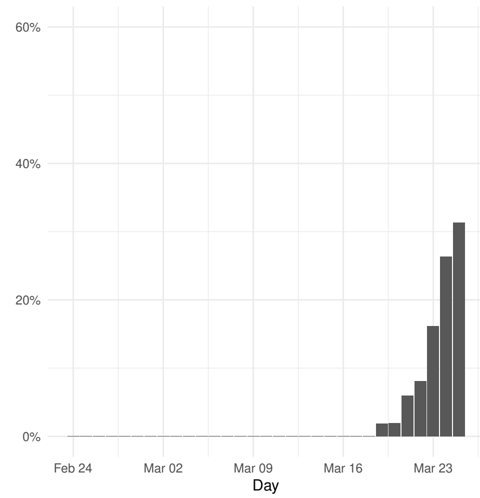

Figure 5: Share of Counties under Stay-at-Home

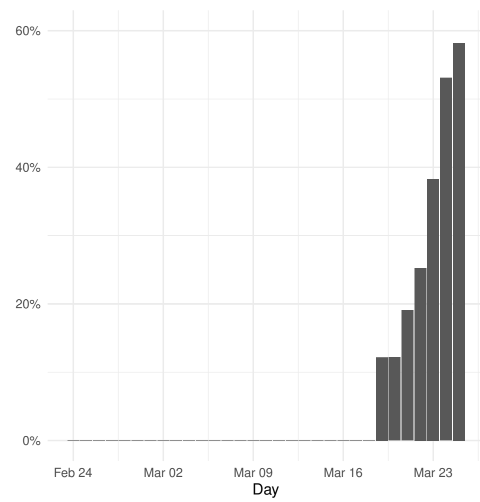

Figure 6: Share of Pop under Stay-at-Home

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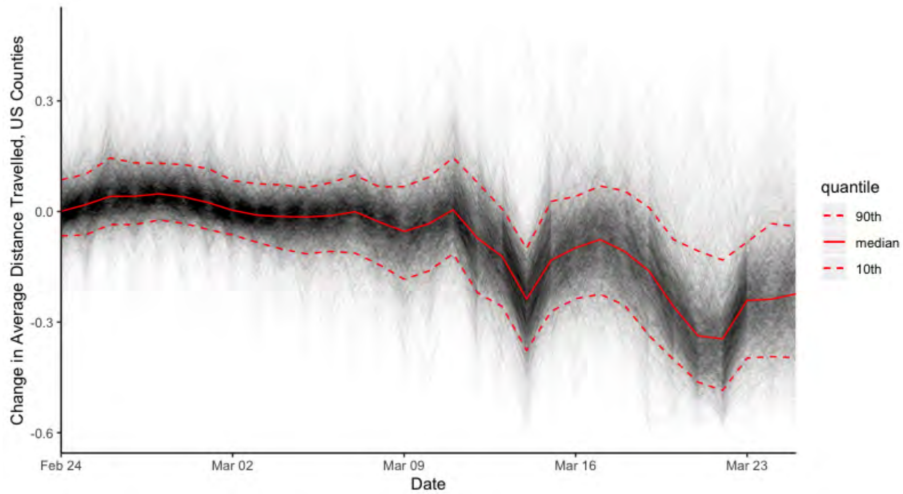

Figure 7: Quantiles of Changes in Average Distance Traveled Across Counties

Table 1: Summary Statistics of Pooled Dataset

Statistic	Mean	St. Dev.	Min	Max
Total Cases	3.004	61.546	0.000	6,154.000
Cases, Share of Pop	0.001%	0.01%	0.00%	0.5%
Neighbor Cases, Weighted	0.005%	0.01%	0.00%	0.2%
Pct Chg in Distance Travelled	−0.079	0.158	−0.879	1.388
Share of Pop Over Age 65	17.502	4.319	3.855	53.106
Share of Republican Votes, 2016	0.629	0.156	0.041	0.916
Population Size, Thousands	104.648	330.248	1.233	10,057.160
Density: Thousands per Sq. Mile	0.268	1.753	0.001	69.468

Note: See Section 4 for formal definition of the *Neighbor Cases* variable.

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4 Empirical Results

Motivated by the model outlined in (3), our baseline regression model is given by:

$$\Delta_{it} = \beta_0 + \beta_1 \exp(\beta_2 \Omega_{it}) + \beta_3 I_{it} + \beta_4 \exp(\beta_2 \Omega_{it}) \times I_{it} + \beta_X I_{it} \times X_i + \rho \Delta_{i,t-1} + \epsilon_{it} \quad (4)$$

where the variables are defined as follows:

Dependent variable (Δ_{it}) Mobility change is measured by the percentage difference in average daily distance in county i at time t, compared to the average in the four weeks before COVID-19 outbreak, by weekday.

Perceived risk index of contracting COVID-19 (Ω_{it}) We assume that individuals' perception of risk is affected by COVID-19 prevalence in both local and neighboring counties, as well as population demographics. We propose using a linear index, Ω_{it}, defined as:

$$\Omega_{it} = C_{i,t-1} + \gamma \sum_{j \neq i} w_{ij} C_{j,t-1} + \gamma_X X + \gamma_{CI} \left[C_{i,t-1}, \sum_{j \neq i} w_{ij} C_{j,t-1} \right] \times X \quad (5)$$

where each term in (5) denotes

1. $C_{i,t-1}$, is total confirmed cases divided by population at county i at time $t-1$. To ease interpretation of coefficients, we then normalize the median prevalence level for counties with positive COVID-19 cases on 3/20/2020 to be one (0.003% - Mecklenburg, North Carolina).

2. $\sum_{j \neq i} w_{ij} C_{j,t-1}$, a weighted average of confirmed cases at neighboring counties measured at time $t-1$. For simplicity, we let weight be proportional to the inverse of distance between county centroids with $\sum_{j \neq i} w_{ij} = 1$.We adopted the same normalization as in $C_{i,t-1}$.

3. X_i, County-level demographics include age structure (share of population over 65), political attitude (share of the population that voted Republican in the 2016

Presidential Election), and population density (thousand people per square mile).

In this baseline model, we interpret Ω_{it} as a linear approximation perceived risk.

Restriction orders (I_{it}) Restriction order I_{it} is a dummy variable that takes the value of one if an order to stay-at-home is in effect in county i at date t; zero otherwise.

In (4), we allow individuals' response to perceived risk to differ depending on whether the government have announced restriction or not. We also consider the possibility that responses to a restriction order might vary based on demographic characteristics. In (5), perceived risk index Ω_{it} is affected by both local and neighborhood COVID-19 confirmed cases, as well as underlying population characteristics. We also include an interaction term to study how population characteristics affect individuals' perceived risks as the disease become more widespread. Note that the coefficient in front of $C_{i,t-1}$ in Equation (5) is normalized to 1, since the overall scale of the γ's cannot be separately identified from β_2 in Equation 4.

Our main results are shown in Table 2. The top-half of the table shows estimates of the parameters in Equation (4) while the bottom-half shows coefficients in the perceived risk equation (5). In subscripts of coefficients, we use $\{P, O, D\}$ to represent the share of population that voted Republican in the 2016 Presidential Election, share of population with age over 65, and population density (in thousands of people per square mile) respectively. Subscripts $\{L, N\}$ refer to the interaction terms of population characteristics with local confirmed cases $C_{i,t-1}$ and neighborhood confirmed cases $\sum_{j \neq i} w_{ij} C_{j,t-1}$.

We start the interpretation of the main results from the top. The positive value of $\hat{\beta}_1$ combined with negative $\hat{\beta}_2$ implies that an increase in perceived risk index Ω_{it} reduces leads to a decrease in Δ_{it}.

To get a sense of the magnitude of the effect of restriction orders on mobility, we consider the case where the government announces a stay-at-home order in a county with median demographic characteristics $(\bar{P}, \bar{O}, \bar{D})$ and our median estimate of perceived risk index, $\bar{\hat{\Omega}}$.

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Table 2: Main Results

	Δ	
	Estimate	SE
β_0	-0.1222^{***}	(0.0011)
β_1	0.1349^{***}	(0.0031)
β_2	-1.5616^{***}	(0.2554)
β_3	-0.0685^{***}	(0.0106)
β_4	-0.0890^{*}	(0.0439)
β_{PI}	0.1810^{***}	(0.0141)
β_{DI}	-0.0025^{***}	(0.0006)
β_{OI}	-0.0034^{***}	(0.0005)
ρ	0.5141^{***}	(0.0029)
$\boldsymbol{\Omega}$		
γ	0.2132^{*}	(0.0952)
Political Affiliation		
γ_P	-0.0056	(0.0180)
γ_{PC}	-1.1557^{***}	(0.1118)
γ_{PN}	-0.4063^{***}	(0.1267)
Population Density		
γ_D	0.0034	(0.0029)
γ_{DC}	-0.0959^{*}	(0.0430)
γ_{DN}	0.5541^{***}	(0.1153)
At Risk Share		
γ_O	0.0033^{***}	(0.0008)
γ_{OC}	-0.0069	(0.0094)
γ_{ON}	0.0439^{***}	(0.0076)

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Num. Obs = 91080

Based on our estimates from Table 2, we find that the restriction order would reduce mobility by 7.87% for a county with characteristics $\bar{P}$, $\bar{O}$, $\bar{D}$, and perceived risk index $\bar{\hat{\Omega}}$.

The coefficients from interacting restriction order with population demographics tell an interesting story. We illustrate this point with the hypothetical county with characteristics $(\bar{P}, \bar{O}, \bar{D})$ and perceived risk index $\bar{\hat{\Omega}}$) as before. If we perturb the characteristics $\{P, O, D\}$ one at a time by increasing each in turn by one standard deviation of that characteristic, how would the effect of the restriction order change? Recall that this baseline effect is a 7.87% decrease. The estimates suggest that the effect of a restriction order would be of smaller magnitude, going to a 5.05% decrease with a 15.6 percentage point increase in the share of the population that voted Republican in the 2016 Presidential Election; the effects would be stronger when the share of the population over age 65 increases by 4.3 percentage points, with the effect size of a 9.33% decrease. Lastly, when population density increases by 1000 people per square mile, we would expect the effect of a restriction order to be stronger, an 8.30% decrease. These results suggests that the effects of restriction order are highly heterogeneous depending on the underlying population, with the direction of the effect being consistently negative, as expected.

The coefficient of the interaction between Ω and I, β_4, is negative with an absolute value smaller than β_1. This implies that an increase in perceived risk index of contracting the disease Ω still decreases mobility when restriction order is announced, but with a smaller impact.

Now we turn to the bottom half of Table 2 to interpret the estimates of coefficients in Equation (5) determining perceived risks. Parameter γ measures the relative importance of cases in neighboring counties relative to local cases. The estimate $\hat{\gamma}$ shows that an increase in COVID-19 confirmed cases in neighboring counties would indeed raise the perceived risk locally, but individuals discount that increase at rate 0.2. This implies that spillover of risks across regions are potentially important, but the magnitude is not very large in the data relative to local cases.

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To study the magnitude of these estimates, we consider again the county with median characteristics $\{\bar{P}, \bar{O}, \bar{D}\}$. If the county starts out with zero confirmed cases locally, and with neighboring confirmed cases at the sample median, suppose there is a unit increase[8] in local cases. How much would individuals reduce traveling without government imposing any restriction order? By combining estimates of parameters, our results suggest that the mobility reduction is 2.31%. These estimates suggests that decreases in mobility could take place well before the official announcement of restriction orders, which is in line with the findings in Figure 7 and evidence from OpenTable reservations in Kaplan et al. (2020).

The direct effects of demographic characteristics, and their interactions with confirmed cases, on perceived risk, shown in the bottom half of Table 2, lead to a very similar conclusion to the one we reached on the their effects on restriction order. Counties with a lower share of the population that voted Republican in the 2016 Presidential Election, higher share of elderly population, and higher population density have higher perceived risk in levels, and are more responsive to increases of disease prevalence.

5 Discussion and Conclusion

In this paper, we combine a novel GPS location dataset with COVID-19 cases and population characteristics at the county level to estimate the effects of disease prevalence and restriction orders on individual mobility. We find that population mobility reacts strongly to changes in perceived disease prevalence and government stay-at-home announcements: a rise of local infection rate from 0% to 0.003% reduces mobility by 2.31%, and a government restriction order to stay-at-home reduces mobility by 7.87%. Additionally, we find that these effects of information on individual behaviour depends on characteristics of the underlying population. In particular, counties with larger shares of population over age 65, lower share of population voted Republican in the 2016 Presidential Election, and higher population density are more

[8]Due to the normalization, we could interpret the unit increase as a shift to the median prevalence level in counties with confirmed cases as of 3/20/2020, i.e. Mecklenburg, NC.

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responsive to disease prevalence and restriction orders.

There are a couple of important limitations to our work in its current iteration. First, our perceived risk index Ω_{it} does not line up with the exact interpretation of Ω in the model; to be specific, we are providing a linear approximation to Ω, a strictly positive quantity. Our model fits the data well, as $\hat{\Omega}_{it}$ is positive in over 99.9% of cases. Future work could include a submodel for Ω so that we can directly interpret the estimated quantities as perceived risk. Second, we have not yet included a model of endogeneity. Presumably, travel decisions and perceived risk are simultaneously determined. We have begun to study how to incorporate this into an extended model. Lastly, we plan to include more demographic controls such as industry composition and share of workers in essential jobs. These could affect the substitutability between on-site work and work-from-home, hence affecting changes in mobility. and these will be included in future versions of the project being continuously updated on SSRN.

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