Welfare costs of travel reductions within the United States due to COVID-19

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1 Abstract
Using daily county-level travel data within the United States, this paper investigates the welfare costs of travel reductions due to coronavirus disease 2019 (COVID-19) for the period between 20 January and 5 September 2020. Welfare of individuals (related to their travel) is measured by their inter-county and intra-county travel, where travel costs are measured by the corresponding distance measures. Important transport policy implications follow regarding how policymakers can act to mitigate welfare costs of travel reductions without worsening the COVID-19 spread.

KEYWORDS
COVID-19, travel reductions, US counties, welfare costs

JEL CLASSIFICATION
J61; I10; I31; R11; R13

1 | INTRODUCTION
Coronavirus disease 2019 (COVID-19) has resulted in about 346,050 deaths and more than 20 million cases within the United States during 2020. The geographical distribution of these developments suggests heterogeneous effects across US counties; for example, Los Angeles County of California has experienced about 25,144 deaths during 2020, whereas others such as Dukes County of Massachusetts have experienced zero deaths due to COVID-19. Based on these developments, individuals in the United States started traveling less owing to health concerns or stay-at-home orders. Although these travel reductions are useful to fight against COVID-19, as indicated by studies

1These observations are based on US county-level data obtained from The New York Times. The corresponding web page is https://github.com/nytimes/covid-19-data.
2This experience has been similar to those observed for different countries or time periods as indicated in studies such as by Bajardi et al. (2011), Wang and Taylor (2016), Charu et al. (2017), or Fang et al. (2020).
such as by Chinazzi et al. (2020), Kraemer et al. (2020), Yilmazkuday (2020a), and Yilmazkuday (2020b), they also result in welfare losses for individuals who get utility out of traveling for leisure, social, or recreational purposes (e.g., see Beck & Hensher, 2020; De Vos, 2020).

Within this context, using daily county-level travel data from the United States, this paper attempts to measure the welfare costs of travel reductions due to the COVID-19 pandemic for the period between 20 January and 5 September 2020. These travel-related welfare costs may consist of not only direct costs that are based on economic activity, as discussed in studies such as by Acemoglu et al. (2020), Alvarez et al. (2020), Jones et al. (2020), or Eichenbaum et al. (2020), but also indirect costs that are related to mental distress, increased rates of suicide, or domestic violence, as discussed in studies such as by Cao et al. (2020), Holmes et al. (2020), or Taub (2020).

The corresponding literature shows a positive relationship between travel reductions and reduced welfare. Among these, Curdia (2020) shows that the reduction in economic activity (and thus welfare) due to COVID-19 is not only due to people being sick but also due to stay-at-home orders; Maloney and Taskin (2020) show that the reduction in economic activity (and thus welfare) is connected to the voluntary reduction in mobility; or Beland et al. (2020) show that the reduction in economic activity (measured by unemployment) has been larger in US states that have stay-at-home orders. However, these studies have not measured the corresponding welfare implications of travel reductions due to COVID-19. This paper contributes to this developing literature by measuring the welfare effects of travel reductions amid COVID-19, where the reduction in welfare is measured with respect to 20 January 2020, which we consider as the pre-COVID-19 era.

A simple model at the US county level is introduced to measure the welfare of individuals based on their travel behavior. Travel costs are measured as a function of distance across (or within) US counties. This is consistent with earlier studies such as by Beck and Hensher (2020) or De Vos (2020), who discuss utility of individuals from traveling for leisure, social, or recreational purposes as well as studies such as by Dam et al. (2020), who have discussed traveling as having therapeutic effects on mental health. The implications of the model are estimated by using daily data on inter-county and intra-county travel between 20 January and 5 September 2020. The corresponding results show that the negative effects of distance on travel have rapidly increased during the first half of April 2020, after which a gradual recovery has been experienced until June 2020 across US counties.

These distance effects are further connected to the welfare of individuals by using the implications of the model. This is achieved by connecting the time-varying effects of distance on travel across (or within) the US counties to the welfare of individuals. As the cost of traveling has increased because of health concerns or stay-at-home orders, it is expected by the model that negative effects of distance on travel have increased during the COVID-19 pandemic. The corresponding results suggest that the cumulative welfare costs of travel reductions with respect to 20 January 2020 have reached their highest value of about 11% on 19 April 2020 for the United States, with a range between 7% and 16% across US counties.

When the heterogeneity across US counties on 19 April 2020 is further investigated, it is shown that initial travel patterns of counties (during the month of January) is correlated with the cumulative welfare costs of travel reductions, suggesting that more-traveling counties in the pre-COVID-19 era have experienced higher welfare costs. As the estimated welfare losses in this paper (due to traveling less for leisure, social, or recreational purposes) are large and significant, there are several implications for policymakers regarding how they can act to mitigate these welfare losses without worsening the COVID-19 spread.

The rest of this paper is organized as follows. The next section introduces the conceptual framework by discussing the developments in the recent literature. Section 3 introduces a simple model for motivating the empirical investigation. Section 4 introduces the empirical methodology and the dataset. Section 5 depicts the estimation results and the corresponding welfare implications, both for the United States at the national level and across counties. Section 6 discusses the policy implications. Section 7 concludes.
2 | CONCEPTUAL FRAMEWORK

It is well known that airborne viruses such as those causing the COVID-19 pandemic spread through traveling (e.g., see Chong & Zee, 2012; Germann et al., 2006; Musselwhite et al., 2020; Poletto et al., 2013; Yang et al., 2012). Especially long-distance travel has been shown to be the main driver behind airborne virus transmissions (e.g., see Camitz & Liljeros, 2006; Epstein et al., 2007), which implies that drastic measures of travel reduction are necessary to prevent the spread of the COVID-19 pandemic (e.g., see Anzai et al., 2020; Ebrahim et al., 2020; Poletto et al., 2014). Accordingly, individuals have traveled less during the COVID-19 pandemic because of either health concerns (through self motivation) or stay-at-home orders (through government restrictions), as indicated by studies such as by Chinazzi et al. (2020), Kraemer et al. (2020), Yilmazkuday (2020a), and Yilmazkuday (2020b). However, as the organization of economic activity in geographic space depends on the travel of individuals and transportation of goods (e.g., see Redding & Turner, 2015), both of which require regional mobility of individuals, economic welfare has been reduced through travel reductions due to the COVID-19 pandemic.

It is implied that there is a trade-off for policymakers between mitigating the COVID-19 spread and handling the corresponding economic recession (e.g., see Sarkar & Dentinho, 2020). Accordingly, earlier studies in the literature such as by Acemoglu et al. (2020), Alvarez et al. (2020), Jones et al. (2020), Eichenbaum et al. (2020), or Kydland and Martínez-García (2020) have focused on the direct welfare costs through the potential tension between reducing mortality due to COVID-19 and stabilizing economic activity. Nevertheless, there may also be indirect welfare costs related to mental distress, increased rates of suicide, or domestic violence amid COVID-19, as discussed in studies such as by Cao et al. (2020), Dam et al. (2020), Holmes et al. (2020), or Taub (2020). Travel reductions due to the COVID-19 pandemic have also resulted in the welfare loss of individuals through their reduced amount of leisure, social interactions, and recreational activities, as discussed in studies such as by Beck and Hensher (2020) or De Vos (2020).

As travel of individuals can be measured by distance traveled, this paper attempts to measure the corresponding welfare loss of individuals using data on reductions in distance traveled due to the COVID-19 pandemic. Since the focus is on the total amount of travel reductions, both direct and indirect welfare costs of travel reductions (as discussed above) are investigated in the following sections. Once the welfare costs of travel reductions are measured, their relationship with the timing of government restrictions is also investigated as in studies such as by Gao et al. (2020).

Based on the trade-off between the COVID-19 spread and welfare costs of travel reductions, the literature has suggested several actions regarding how policymakers can act to mitigate these welfare losses without worsening the COVID-19 spread. These policies may include preparing legal and regulatory frameworks as well as supporting guidelines and contingency plans by transport operators, as suggested by Dickson (1992), Meyer and Belobaba (1982), or Fan et al. (2019). Such policies may also include providing safety for the health and economic conditions of the transport personnel, for example, by supporting smart technologies or providing personal protective equipment (e.g., see Amditis, 2020 or Hirsch, 2020). Policymakers may also simultaneously mitigate the spread of COVID-19 and welfare costs of travel reduction by sharing information not only with the society but also among themselves. This may prevent inconsistent travel policy practices across alternative agencies of government, as suggested by studies such as by Sheehan and Fox (2020). Adjusting operating times of travel or changing the travel mode for mitigating the COVID-19 spread may also help individuals travel more and thus reduce the welfare costs of travel reduction (e.g., see Rubiano & Darido, 2020). Similarly, contract tracers can be hired to detect exposed travelers quickly so that individuals can feel safer to travel (e.g., see Welch, 2020).

In technical terms, based on the literature discussed above, this paper focuses on the part of individual welfare based on their travel. This is motivated by earlier studies such as by Beck and Hensher (2020) or De Vos (2020), who discuss utility of individuals from traveling for leisure, social, or recreational purposes, as well as studies such as by Dam et al. (2020), who have discussed traveling as having therapeutic effects on mental health. Accordingly, the corresponding welfare costs and policy implications should be considered along these lines as, for instance, these welfare changes may not capture the effects of reduced economic activity that are independent of traveling or the health-related effects of COVID-19 due to changes in travel behavior.
3 | MODEL

Motivated by the literature discussed in the previous section, we focus on the part of individual utility obtained from traveling through visiting a variety of locations. Accordingly, the corresponding welfare costs and policy implications below should be considered based on this restriction.

In formal terms, the utility of individuals in the US county $n$ at time $t$ denoted by $T_{nt}$ is given by the following function:

$$T_{nt} = \left( \sum_{i} (\alpha_{it})^q T_{int} \right)^{\frac{1}{q}}$$

where $T_{int}$ represents travels to the US county $i$, and $\alpha_{it}$ represents preferences toward being in county $i$ at time $t$ (e.g., preferences toward being in Miami during the Spring break). The special case of $i = n$ corresponds to intra-county travel for county $n$. For a given budget constraint of $\sum C_{int} T_{int} = E_{nt}$, where $C_{int}$ is the cost of traveling from county $n$ to county $i$, and $E_{nt}$ is the endowment of total income, the optimization results in:

$$T_{nt} = \alpha_{it} \left( \frac{C_{int}}{C_{nt}} \right)^{-q} T_{nt}$$

where $C_{nt}$ is a measure of total cost given by:

$$C_{nt} = \left( \sum_{i} \alpha_{it} (C_{int})^{1-q} \right)^{\frac{1}{1-q}}$$

which also satisfies $C_{nt} T_{nt} = E_{nt}$. For individuals in county $n$ at time $t$, the cost of traveling from county $n$ to county $i$ is further measured by a function of distance across counties as follows:

$$C_{int} = (D_{in})^{\delta_t}$$

where $D_{in}$ represents the distance between counties $i$ and $n$, and $\delta_t$ is the time-varying distance elasticity of travel costs.

3.1 | Aggregation across the US counties

The utility of the US individuals at the national level is given by the following function:

$$T_t = \prod_i (T_{it})^{\gamma_i}$$

where $\gamma_i = \frac{H_i}{H_t}$ is the smartphone share of county $i$ in the United States (to take into account potential representation issues in US counties), with $H_i$ and $H_t$ representing the number of smartphone devices in county $i$ and the United States, respectively, at time $t$.

The optimization of the social planner results in the following expression:
\[
\frac{E_{nt}}{E_{it}} = \frac{\gamma_{nt}}{\gamma_{it}} \sum_j \frac{E_{it}}{E_{jt}}
\]

(6)

where \(\gamma_{nt}\) is implied as the endowment share of county \(n\) as well. The endowment ratio between counties \(n\) and \(i\) is implied as follows:

\[
\frac{E_{nt}}{E_{it}} = \frac{\gamma_{nt}}{\gamma_{it}}
\]

(7)

where the right hand side depends on endowment shares.

### 3.2 Welfare gains from traveling

Welfare in county \(n\) at time \(t\) is measured by \(T_{nt}\), which can be written as \(T_{nt} = \frac{E_{nt}}{C_{nt}}\) according to the budget constraint. Using Equations (3) and 4, it is implied that:

\[
T_{nt} = \frac{E_{nt}}{\left(\sum_i \gamma_{int} \left(\frac{D_{int}}{\gamma_{int} E_{int}}\right)^{1-\eta}\right)^{\frac{1}{1-\eta}}}
\]

(8)

Further using the optimization of the world social planner given in Equation 7 results in:

\[
T_{nt} = \left(\sum_i \lambda_{int} \left(\frac{\gamma_{it} (D_{int})^{\eta}}{\gamma_{nt} E_{it}}\right)^{\frac{1}{1-\eta}}\right)^{1-\eta}
\]

(9)

After considering endowments and county shares as given, the welfare effects of a change in travel costs can be measured by taking the total derivative of Equation (9) in its log form as follows:

\[
d\log T_{nt} = -\sum_i \lambda_{int} d\log C_{int}
\]

(10)

where welfare changes through travel costs

where \(\lambda_{int}\) is the cost share of county \(n\) for being in county \(i\) within the overall travel costs:

\[
\lambda_{int} = \frac{C_{int} T_{nt}}{\sum_k C_{knt} T_{knt}} = \frac{(D_{int})^\eta T_{nt}}{\sum_k (D_{int})^\eta T_{knt}}
\]

(11)

Combining Equation (10) with Equation (4) results in:

\[
d\log T_{nt} = -d(\delta) \sum_i \lambda_{int} \log D_{in}
\]

(12)

where welfare changes are connected to changes in time-varying effects of distance measured by \(\delta\)’s.
The log version of Equations (2) and (4) implies the following expression:

$$\log(T_{\text{int}}) = \log(\alpha_{it}) \cdot \log(D_{\text{in}}) + \log(C_{nt}) \cdot \log(T_{nt})$$

where \(\log(\alpha_{it})'s\) and \(\log(C_{nt})'s\) are captured by the corresponding (i or n) county–time fixed effects.

Daily data for inter-county and intra-county travel for US counties (2018 of them) are borrowed from Couture et al. (2020) for the period between 20 January 2020 and 5 September 2020. This dataset has been constructed by using PlaceIQ data that describe smartphone devices ‘pinging’ in a given geographic unit on a given day. Based on this information, once a certain number of smartphone devices are determined to be in a particular US county (say, county n) on a particular day (say, at time t), the dataset provides information on the share of these devices that have pinged in a US county (including county n itself) at least once during the previous 14 days. The distance data between counties have been obtained from the County Distance Database published by the National Bureau of Economic Research, where the intra-county distance has been set equal to one-fourth of the distance to the closest county following Wei (1996).

The estimation is achieved by pseudo-Poisson maximum likelihood (PPML), where potential zero values of travel measures (\(T_{\text{int}}'s\)) are taken into account. The observations in the estimation include both inter-county data (when \(i \neq n\)) and intra-county data (when \(i = n\)).

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**FIGURE 1** Distance elasticity of travel

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3The web page is https://github.com/COVIDExposureIndices. The missing values for certain daily observations starting from the second half of August 2020 have been linearly interpolated for each county.

4Because of the discrepancy between the time of the decision made (i.e., t) versus the time of travel, \(C_{nt}\) in the model can alternatively be thought as the decision of travel made at most 14 days ago under the condition that the individual will be in county n at the end of these 14 days.

5The web page is https://data.nber.org/data/county-distance-database.html.
5 | EMPIRICAL RESULTS

The distance elasticity of travel $-\eta_\delta t$ estimates are given in Figure 1. As is evident, the estimate of around $-1.67$ on 20 January 2020 has decreased to about $-1.76$ as of 19 April 2020 and increased back to $-1.68$ as of 5 September 2020. It is suggested that the negative effects of distance on travel were most effective during the month of April, when several layers of government implemented stay-at-home orders (to be discussed more, below). The 95% confidence interval highly supports these estimates. Figure 1 also suggests that the negative effects of distance on travel have increased rapidly during the first half of April 2020, whereas the corresponding recovery has been more gradual as the distance elasticity of travel $-\eta_\delta t$ estimates have recovered until June 2020.

In order to use the estimated values of $-\eta_\delta t$’s in Figure 1 for welfare calculations based on Equation (12), they have to be converted into the distance elasticity of travel costs denoted by $\delta t$’s. This requires the knowledge of $\eta$ representing the elasticity of substitution across destination counties. Following international trade studies such as by Anderson and Van Wincoop (2003), Head and Mayer (2014), or Yilmazkuday (2019), we consider $\eta = 5$ in our welfare calculations, although this scale factor can easily be changed for robustness purposes. Once $\delta t$’s are determined, they are also used to calculate the cost shares of $\lambda_{int}$’s given in Equation (11).

5.1 | Welfare costs for US counties

The estimated values of $\delta t$’s and $\lambda_{int}$’s are combined with distance measures denoted by $D_{in}$’s to calculate welfare changes in each US county according to Equation (12). The cumulative welfare changes over time are represented in Figure 2 across all counties, where the initial day of 20 January 2020 is set equal to zero for comparison purposes.

As is evident, all counties have experienced reductions in their welfare due to traveling less during the month of April, when several layers of government implemented stay-at-home orders. Figure 2 also suggests that the welfare reductions have been rapid during the first half of April 2020, whereas the corresponding recovery has been more gradual as it has taken time until June 2020.

The results in Figures 2 are further summarized in Table 1 in percentage terms for 19 April 2020, when welfare changes were the most. As is evident, the cumulative welfare loss for the median or the average US county has been about 11% as of 19 April 2020, which is in line with other studies such as by Andersson et al. (2020) who have shown that welfare cost of a stay-at-home policy is about 9% for Sweden.

5.2 | Inequality of welfare costs across US counties

Although all counties have experienced reductions in their welfare due to travel reductions, the results in Figure 2 show that there are significant differences in magnitudes across US counties. This is further investigated in Figure 3, where the standard deviation (across US counties) of cumulative welfare changes is depicted. As is evident, inequality of welfare costs across US counties takes its highest value on 19 April 2020. This is also reflected in Table 1, where welfare costs due to travel reductions are shown to range between 7% and 16% as of 19 April 2020, with a standard deviation of about 1.5%. Table 1 also shows that counties such as Uinta County, WY, or McKinley County, NM, have experienced the highest welfare costs (of about 16%) among others.

We further investigate this heterogeneity across US counties as of 19 April 2020 by using their initial travel patterns, where we measure initial travel patterns by $\left(1 - T_{int}\right)$ for county $n$ by taking the average across days during the month of January 2020. The relationship between county-specific welfare costs and initial travel patterns of counties is shown in Figure 4, where there is a negative correlation between them. It is implied that counties where people have traveled more in the pre-COVID-19 era have experienced higher welfare costs of travel reductions during April 2020.
5.3 Welfare costs for the United States

The weighted average of the results in Figure 2 is also calculated to have a nationwide measure for the United States, where weights are based on the daily number of smartphone devices in each county. The corresponding

**FIGURE 2** Cumulative welfare changes across counties

| Welfare costs (%) of travel reductions as of 19 April 2020 |
|----------------------------------------------------------|
| Welfare costs                                      | Estimate | Lower bound | Upper bound |
| Median across counties                               | 10.823   | 10.817       | 10.830      |
| Average across counties                              | 11.025   | 11.018       | 11.032      |
| Minimum across counties                              | 6.634    | 6.630        | 6.639       |
| Maximum across counties                              | 16.089   | 16.078       | 16.100      |
| Standard deviation across counties                    | 1.501    | 1.456        | 1.549       |
| For the United States                                | 10.575   | 10.569       | 10.582      |

Counties with highest welfare costs

- Uinta County, WY: 16.089, 16.078, 16.100
- McKinley County, NM: 16.085, 16.073, 16.096
- Sweetwater, WY: 16.043, 16.032, 16.054
- Mankato, MN: 15.876, 15.865, 15.887
- Navajo County, AZ: 15.842, 15.831, 15.853
- La Paz County, AZ: 15.815, 15.804, 15.825
- Siskiyou County, CA: 15.598, 15.589, 15.608
- Elko County, NV: 15.586, 15.575, 15.597
- Elmore, ID: 15.536, 15.525, 15.546
- Lincoln, NE: 15.525, 15.515, 15.536

Notes: Welfare costs for the United States are the weighted average measures across counties, where the weights are based on the number of smartphone devices in each county.

Notes: Each line represents a U.S. county. In total, 2018 counties are represented.

WELFARE COSTS OF TRAVEL REDUCTIONS
results are given in Figure 5, where the cumulative welfare has decreased over time until 19 April 2020, after which it has started recovering. As indicated in Table 1, the cumulative reduction in welfare has been about 11% for the United States as of 19 April 2020, which is in line with the cross-county measures of median and average.

6 | DISCUSSION OF RESULTS AND POLICY IMPLICATIONS

This section connects the empirical results of this paper to the existing literature and discusses the corresponding policy implications.

Overall, travel reductions due to health concerns, social distancing, lockdowns, or stay-at-home orders have resulted in significant welfare losses across US counties. Specifically, due to the COVID-19 pandemic, the cumulative welfare has decreased over time until 19 April 2020, after which it has started recovering. When we investigate the political reasons behind the reduction in welfare specifically on 19 April 2020, we observe that it is the day when the highest portion of US counties experienced stay-at-home orders according to the data borrowed from Bognanni et al. (2020). In particular, as shown in Figure 6, the portion of US counties that have experienced stay-at-home orders has taken its highest value as of 19 April 2020, right after which it started going down. Therefore, travel reduction of individuals can be explained by stay-at-home orders, as in studies such as by Gao et al. (2020). It is implied that the corresponding welfare costs of travel reductions can also be explained by stay-at-home orders, and thus, policymakers should take into account the magnitude of these welfare costs while deciding on their policy actions.

As discussed in the corresponding literature, these welfare losses can be not only due to the reduced amount of leisure, social interactions, and recreational activities, as in studies such as by Beck and Hensher (2020), or De Vos (2020), but also due to the lack of having therapeutic effects of traveling on mental health, as in studies such as by Dam et al. (2020). Accordingly, since the model introduced in this paper focuses on the welfare of individuals

\[ \text{FIGURE 3} \quad \text{Inequality of welfare changes across US counties} \]
FIGURE 4  Initial travel versus welfare changes on 19 April 2020

Notes: Each circle represents a county. In total, 2018 counties are represented.

FIGURE 5  Cumulative welfare changes for the United States

Notes: Welfare costs for the U.S. are the weighted average measures across counties, where the weights are based on the number of smartphone devices in each county. The shaded area represents the 90% confidence interval.
Based on their travel, the results consist of implications for both direct and indirect welfare costs. Regarding direct welfare costs, the results shed light on the potential tension between reducing mortality due COVID-19 and stabilizing economic activity, as discussed in earlier studies such as by Acemoglu et al. (2020), Alvarez et al. (2020), Jones et al. (2020), Eichenbaum et al. (2020), or Kydland and Martínez-García (2020). Regarding indirect welfare costs, the results shed light on the discussion related to mental distress, increased rates of suicide, or domestic violence amid COVID-19, as discussed in studies such as by Cao et al. (2020), Holmes et al. (2020), or Taub (2020).

As the estimated welfare losses in this paper (due to traveling less for leisure, social, or recreational purposes) are large and significant, there are several implications for policymakers regarding how they can act to mitigate these welfare losses without worsening the COVID-19 spread. In this respect, policy recommendations proposed by Zhang (2020) can be helpful for policymakers. Among these, governments may learn from historical experiences and policy actions during earlier pandemics, such as the Spanish Flu pandemic, as discussed in Soper (1918) or Martini et al. (2019), so that they can consider alternative travel policies that have worked in the past and that are also in line with mitigating the spread of COVID-19. These policies may include preparing legal and regulatory frameworks as well as supporting guidelines and contingency plans by transport operators, as suggested by Dickson (1992), Meyer and Belobaba (1982), or Fan et al. (2019). Such policies may also include providing safety for the health and economic conditions of the transport personnel, for example, by supporting smart technologies or providing personal protective equipment (e.g., see Amditis, 2020 or Hirsch, 2020).

Policymakers may also simultaneously mitigate the spread of COVID-19 and welfare costs of travel reduction by sharing information not only with the society but also among themselves. This may prevent inconsistent travel policy practices across alternative agencies of government, as suggested by studies such as by Sheehan and Fox (2020). Adjusting operating times of travel or changing the travel mode for mitigating the COVID-19 spread may also help individuals travel more and thus reduce the welfare costs of travel reduction (e.g., see Rubiano & Darido, 2020). Similarly, contract tracers can be hired to detect exposed travelers quickly so that individuals can feel safer traveling (e.g., see Welch, 2020).7

Notes: The line represents the percentage of U.S. counties with stay-at-home orders.

FIGURE 6 Percentage of US counties with stay-at-home orders

7Highly useful other policy recommendations to simultaneously mitigate the spread of COVID-19 and welfare costs of travel reduction can be found in Zhang (2020).
CONCLUDING REMARKS

This paper has investigated the welfare implications of travel reductions across (and within) US counties amid COVID-19 by using daily inter-county data from smartphones for the period between 20 January 2020 and 5 September 2020. A simple model has been introduced for motivational purposes, where the focus is on the welfare of individuals based on their travel. Travel costs have been measured by the corresponding effects of distance across (or within) US counties.

The estimation results based on the implications of the model have shown that the negative effects of distance on travel have rapidly increased during the first half of April 2020, after which a gradual recovery has been experienced until June 2020. These negative effects have further been connected to the welfare costs of travel reductions by using the implications of the model. The corresponding results have suggested that the cumulative welfare cost of travel reductions with respect to 20 January 2020 takes its highest value of about 11% on 19 April 2020 for the United States, with a range between 7% and 16% across US counties.

When we investigate the political reasons behind the highest cumulative reduction in welfare specifically on 19 April 2020, we observe that it is the day when the highest portion of US counties have experienced stay-at-home orders. When the heterogeneity across counties has further been investigated, it has been shown that initial travel patterns of counties (during the month of January) are correlated with the cumulative welfare costs of travel reductions, suggesting that more-traveling counties in the pre-COVID-19 era have experienced higher welfare costs.

There are several important transport policy implications for governments. Following studies such as by Zhang (2020), these may include learning from historical experiences and transport policy actions during earlier pandemics, preparing legal and regulatory frameworks as well as supporting guidelines and contingency plans for traveling, providing safety for the health and economic conditions of the transport personnel, sharing information not only with the public but also among different layers of government, adjusting operating times or the travel mode, or hiring contract tracers to detect exposed travelers quickly. Considering these policy recommendations would not only mitigate the spread of COVID-19 but also let individuals travel with fewer concerns, which is essential to reduce the severity of the welfare costs of travel reductions estimated in this paper.

ACKNOWLEDGMENTS

The author(s) would like to thank the editor, Tomaz Ponce Dentinho, and two anonymous referees for their helpful comments and suggestions. The usual disclaimer applies.

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How to cite this article: Yilmazkuday, H. (2021). Welfare costs of travel reductions within the United States due to COVID-19. Regional Science Policy & Practice, 13(S1), 18–31. https://doi.org/10.1111/rsp3.12440