Welfare Costs of Travel Reductions within the U.S. due to COVID-19*

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Abstract

Using daily county-level travel data within the U.S., this paper investigates the welfare costs of travel reductions due to COVID-19 for the period between January 20th and September 5th, 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 policy makers can act to mitigate welfare costs of travel reductions without worsening the COVID-19 spread.

JEL Classification: J61, I10, I31, R11, R13

Key Words: COVID-19, Travel Reductions, Welfare Costs, U.S. Counties

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1 Introduction

The coronavirus disease 2019 (COVID-19) has resulted in about 346,050 deaths and more than 20 million cases within the U.S. during 2020. The geographical distribution of these developments suggests heterogeneous effects across U.S. counties; e.g., Los Angeles County of California has experienced about 25,144 deaths during 2020, whereas others such as Dukes County of Massachusetts has experienced zero deaths due to COVID-19.[1] Based on these developments, individuals in the U.S. started traveling less due to health concerns or stay-at-home orders.[2] Although these travel reductions are useful to fight against COVID-19 as indicated by studies 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 and Hensher (2020) and De Vos (2020)).

Within this context, using daily county-level travel data from the U.S., this paper attempts to measure the welfare costs of travel reductions due to the COVID-19 pandemic for the period between January 20th and September 5th, 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, Chernozhukov, Werning, and Whinston (2020), Alvarez, Argente, and Lippi (2020), Jones, Philippon, and Venkateswaran (2020) or Eichenbaum, Rebelo, and Trabandt (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, Fang, Hou, Han, Xu,

[1] These observations are based on U.S. county-level data obtained from The New York Times. The corresponding web page is https://github.com/nytimes/covid-19-data.

[2] This experience has been similar to those observed for different countries or time periods as indicated in studies such as by Bajardi, Poletto, Ramasco, Tizzoni, Colizza, and Vespignani (2011), Wang and Taylor (2016), Charu, Zeger, Gog, Bjørnstad, Kissler, Simonsen, Grenfell, and Viboud (2017) or Fang, Wang, and Yang (2020).

Dong, and Zheng (2020), Holmes, O'Connor, Perry, Tracey, Wessely, Arseneault, Ballard, Christensen, Silver, Everall, 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, Brodeur, and Wright (2020) show that the reduction in economic activity (measured by unemployment) has been larger in U.S. 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 January 20th, 2020, which we consider as the pre-COVID-19 era.

A simple model at the U.S. 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) U.S. 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, Mandal, Mondal, Sadat, Chowdhury, and Mandal (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 January 20th and September 5th, 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 U.S. 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 U.S. counties to the welfare of individuals. As the cost of traveling has increased due to 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 January 20th, 2020 have reached its highest value of about 11% on April 19th, 2020 for the U.S., with a range between 7% and 16% across U.S. counties.

When the heterogeneity across U.S. counties on April 19th, 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 policy makers 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 data set. Section 5 depicts the estimation results and the corresponding welfare implications, both for the U.S. 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 spreads through traveling (e.g., see Germann, Kadau, Longini, and Macken (2006), Chong and Zee (2012), Yang, Wang, Chen, and Wang (2012), Poletto, Tizzoni, and Colizza (2013) and Musselwhite, Avineri, and Susilo (2020)). Especially long-distance travel has been shown to be the main driver behind airborne virus transmissions (e.g., see Camitz and Liljeros (2006) and Epstein, Goedecke, Yu, Morris, Wagener, and Bobashev (2007)), which implies that drastic measures of travel reduction are necessary to prevent the spread of the COVID-19 pandemic (e.g., see Poletto, Gomes, Piontti, Rossi, Bioglio, Chao, Longini Jr, Halloran, Colizza, and Vespignani (2014), Anzai, Kobayashi, Linton, Kinoshita, Hayashi, Suzuki, Yang, Jung, Miyama, Akhmetzhanov, et al. (2020) and Ebrahim, Ahmed, Gozzer, Schlagenhauf, and Memish (2020)). Accordingly, individuals have traveled less during the COVID-19 pandemic due to 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 and 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 policy makers between mitigating the COVID-19 spread and handling the corresponding economic recession (e.g., see Sarkar and Dentinho (2020)). Accordingly, earlier studies in the literature such as by Acemoglu, Chernozhukov, Werning, and Whinston (2020), Alvarez, Argente, and Lippi (2020), Jones, Philippon, and

Venkateswaran (2020), Eichenbaum, Rebelo, and Trabandt (2020) or Kydland and Martínez-García (2020) have focused on the *direct* welfare costs through the potential tension between reducing mortality due 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, Fang, Hou, Han, Xu, Dong, and Zheng (2020), Dam, Mandal, Mondal, Sadat, Chowdhury, and Mandal (2020), Holmes, O'Connor, Perry, Tracey, Wessely, Arseneault, Ballard, Christensen, Silver, Everall, 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, Rao, Kang, Liang, Kruse, Dopfer, Sethi, Reyes, Yandell, and Patz (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 policy makers 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, Liu, Huang, and Zhu (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)). Policy makers 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 and 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, Mandal, Mondal, Sadat, Chowdhury, and Mandal (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 is 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 U.S. county n at time t denoted by T_{nt} is given by the following function:

$$T_{nt} = \left(\sum_i \left(\alpha_{it} \right)^{\frac{1}{\eta}} \left(T_{int} \right)^{\frac{\eta-1}{\eta}} \right)^{\frac{\eta}{\eta-1}} \tag{1}$$

where T_{int} represents travels to the U.S. county i, and α_{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 $\sum_i C_{int} T_{int} = E_{nt}$, 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:

$$T_{int} = \alpha_{it} \left(\frac{C_{int}}{C_{nt}} \right)^{-\eta} T_{nt} \tag{2}$$

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

$$C_{nt} = \left(\sum_i \alpha_{it} \left(C_{int} \right)^{1-\eta} \right)^{\frac{1}{1-\eta}} \tag{3}$$

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:

$$C_{int} = (D_{in})^{\delta_t} \tag{4}$$

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

3.1 Aggregation across the U.S. Counties

The utility of the U.S. individuals at the national level is given by the following function:

$$T_t \equiv \prod_i (T_{it})^{\gamma_{it}} \tag{5}$$

where $\gamma_{it} = \frac{H_{it}}{H_t}$ is the smartphone share of county i in the U.S. (to take into account potential representation issues in U.S. counties), with H_{it} and H_t representing the number of smartphone devices in county i and the U.S., respectively, at time t.

The optimization of the social planner results in the following expression:

$$\underbrace{E_{nt}}_{\text{Endowment of County } n} = \underbrace{\gamma_{nt}}_{\text{Share of County } n} \underbrace{\sum_i E_{it}}_{\text{Endowment of the U.S.}} \tag{6}$$

where γ_n is implied as the endowment share of county n as well. The endowment ratio between counties n and i is implied as follows:

$$\frac{E_{nt}}{E_{it}} = \frac{\gamma_{nt}}{\gamma_{it}} \tag{7}$$

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 $T_{nt} = E_{nt}/C_{nt}$ according to the budget constraint. Using Equations 3 and 4, it is implied that:

$$T_{nt} = \frac{E_{nt}}{\left(\sum_i \alpha_{it}\left(\left(D_{in}\right)^{\delta_t}\right)^{1-\eta}\right)^{\frac{1}{1-\eta}}} \tag{8}$$

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

$$T_{nt} = \left(\sum_i \alpha_{int}\left(\frac{\gamma_{it}\left(D_{in}\right)^{\delta_t}}{\gamma_{nt}E_{it}}\right)^{1-\eta}\right)^{\frac{1}{\eta-1}} \tag{9}$$

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:

$$d\left(\log T_{nt}\right) = \underbrace{-\sum_i \lambda_{int} d\left(\log C_{int}\right)}_{\text{Welfare Changes through Travel Costs}} \tag{10}$$

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

$$\lambda_{int} = \frac{C_{int}T_{int}}{\sum_k C_{knt}T_{knt}} = \frac{\left(D_{in}\right)^{\delta_t} T_{int}}{\sum_k \left(D_{kn}\right)^{\delta_t} T_{knt}} \tag{11}$$

Combining Equation 10 with Equation 4 results in:

$$d\left(\log T_{nt}\right) = -d\left(\delta_t\right)\sum_i \lambda_{int}\log D_{in} \tag{12}$$

where welfare changes are connected to changes in time-varying effects of distance measured by δ_t's.

4 Methodology and Data

The log version of Equations 2 and 4 imply the following expression:

$$\underbrace{\log\left(T_{int}\right)}_{\text{Travel}} = \underbrace{\log\alpha_{it}}_{\text{County-Time FE}} - \underbrace{\eta\delta_t \log D_{in}}_{\text{Distance Effects}} + \underbrace{\log\left(\left(C_{nt}\right)^{\eta} T_{nt}\right)}_{\text{County-Time FE}} \tag{13}$$

where $\log\alpha_{it}$'s and $\log\left(\left(C_{nt}\right)^{\eta} T_{nt}\right)$'s are captured by the corresponding (i or n) county-time fixed effects.

Daily data for inter-county and intra-county travel for U.S. counties (2018 of them) are borrowed from Couture, Dingel, Green, Handbury, and Kevin (2020) for the period between January 20th, 2020 and September 5th, 2020.[3] This data set 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 U.S. county (say, county n) on a particular day (say, at time t), the data set provides information on the share of these devices that have pinged in a U.S. county (including county n itself) at least once during the previous 14 days.[4] The distance data between counties have been obtained from the County Distance Database published by

[3] The 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.

[4] Because of the disrepancy between the time of the decision made (i.e., t) versus the time of travel, C_{int} 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.

the National Bureau of Economic Research, where the intra-county distance has been set equal to the one-fourth of the distance to the closest county following Wei (1996).[5]

The estimation is achieved by Pseudo-Poisson Maximum Likelihood (PPML), where potential zero values of travel measures (T_{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 $i = n$).

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 in January 20th, 2020 has decreased to about -1.76 as of April 19th, 2020 and increased back to -1.68 as of September 5th, 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 δ_t's. This requires the knowledge of η 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

[5] The web page is https://data.nber.org/data/county-distance-database.html.

δ_t's are determined, they are also used to calculate the cost shares of λ_{int}'s given in Equation 11.

5.1 Welfare Costs for U.S. Counties

The estimated values of δ_t's and λ_{int}'s are combined with distance measures denoted by D_{in}'s to calculate welfare changes in each U.S. county according to Equation 12. The cumulative welfare changes over time are represented in Figure 2 across all counties, where the initial day of January 20th, 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 April 19th, 2020, when welfare changes were the most. As is evident, the cumulative welfare loss for the median or the average U.S. county has been about 11% as of April 19th, 2020, which is in line with other studies such as by Andersson, Campos-Mercade, Carlsson, Schneider, and Wengström (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 U.S. 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 U.S.

counties. This is further investigated in Figure 3, where the standard deviation (across U.S. counties) of cumulative welfare changes are depicted. As is evident, inequality of welfare costs across U.S. counties takes its highest value on April 19th, 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 April 19th, 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 highest welfare costs (of about 16%) among others.

We further investigate this heterogeneity across U.S. counties as of April 19th, 2020 by using their initial travel patterns, where we measure initial travel patterns by $(1 - T_{nnt})$ 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 U.S.

The weighted average of the results in Figure 2 are also calculated to have a nationwide measure for the U.S., where weights are based on the daily number of smartphone devices in each county. The corresponding results are given in Figure 5, where the cumulative welfare has decreased over time until April 19th, 2020 after which it has started recovering. As indicated in Table 1, the cumulative reduction in welfare has been about 11% for the U.S. as of April 19th, 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 U.S. counties. Specifically, due to the COVID-19 pandemic, the cumulative welfare has decreased over time until April 19th, 2020 after which it has started recovering. When we investigate the political reasons behind the reduction in welfare specifically on April 19th, 2020, we observe that it is the day when the highest portion of U.S. counties have experienced stay-at-home orders according to the data borrowed from Bognanni, Hanley, Kolliner, and Mitman (2020).[6] In particular, as shown in Figure 6, the portion of U.S. counties that have experienced stay-at-home orders has taken its highest value as of April 19th, 2020, right after which it has started going down. Therefore, travel reduction of individuals can be explained by stay-at-home orders as in studies such as by Gao, Rao, Kang, Liang, Kruse, Dopfer, Sethi, Reyes, Yandell, and Patz (2020). It is implied that the corresponding welfare costs of travel reductions can also be explained by stay-at-home orders and thus policy makers 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, Mandal, Mondal, Sadat, Chowdhury, and Mandal (2020). Accordingly, since the model introduced in this paper

[6] The corresponding data have been obtained from https://github.com/iamlemec/econsir/tree/main/data.

focuses on the welfare of individuals 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, Chernozhukov, Werning, and Whinston (2020), Alvarez, Argente, and Lippi (2020), Jones, Philippon, and Venkateswaran (2020), Eichenbaum, Rebelo, and Trabandt (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, Fang, Hou, Han, Xu, Dong, and Zheng (2020), Holmes, O'Connor, Perry, Tracey, Wessely, Arseneault, Ballard, Christensen, Silver, Everall, 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 policy makers 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 policy makers. 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, Gazzaniga, Bragazzi, and Barberis (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, Liu, Huang, and Zhu (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)).

Policy makers 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 and 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)).[7]

7 Concluding Remarks

This paper has investigated the welfare implications of travel reductions across (and within) U.S. counties amid COVID-19 by using daily inter-county data from smartphones for the period between January 20th, 2020 and September 5th, 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) U.S. 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

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

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 January 20th, 2020 takes its highest value of about 11% on April 19th, 2020 for the U.S., with a range between 7% and 16% across U.S. counties.

When we investigate the political reasons behind the highest cumulative reduction in welfare specifically on April 19th, 2020, we observe that it is the day when the highest portion of U.S. 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) 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.

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.

References

Acemoglu, D., V. Chernozhukov, I. Werning, and M. D. Whinston (2020): "Optimal Targeted Lockdowns in a Multi-Group SIR Model," Working Paper 27102, National Bureau of Economic Research.

Alvarez, F. E., D. Argente, and F. Lippi (2020): "A Simple Planning Problem for COVID-19 Lockdown," Working Paper 26981, National Bureau of Economic Research.

Amditis, A. (2020): "Opinion: mobility in the aftermath of the covid-19 pandemic," *Available at https://www.traffictechnologytoday.com/opinion/opnion-mobility-in-the-aftermath-of-the-covid-19-pandemic.html.*

Anderson, J. E., and E. Van Wincoop (2003): "Gravity with gravitas: A solution to the border puzzle," *American economic review*, 93(1), 170–192.

Andersson, O., P. Campos-Mercade, F. Carlsson, F. Schneider, and E. Wengström (2020): "The Individual Welfare Costs of Stay-At-Home Policies," *Available at SSRN: http://dx.doi.org/10.2139/ssrn.3641781.*

Anzai, A., T. Kobayashi, N. M. Linton, R. Kinoshita, K. Hayashi, A. Suzuki, Y. Yang, S.-m. Jung, T. Miyama, A. R. Akhmetzhanov, et al. (2020): "Assessing the impact of reduced travel on exportation dynamics of novel coronavirus infection (COVID-19)," *Journal of clinical medicine*, 9(2), 601.

Bajardi, P., C. Poletto, J. J. Ramasco, M. Tizzoni, V. Colizza, and A. Vespignani (2011): "Human mobility networks, travel restrictions, and the global spread of 2009 H1N1 pandemic," *PloS one*, 6(1).

Beck, M. J., and D. A. Hensher (2020): "Insights into the impact of COVID-19 on household travel and activities in Australia–The early days of easing restrictions," *Transport policy*, 99, 95–119.

Beland, L.-P., A. Brodeur, and T. Wright (2020): "COVID-19, stay-at-home orders and employment: Evidence from CPS data," *IZA Discussion Paper*.

Bognanni, M., D. Hanley, D. Kolliner, and K. Mitman (2020): "Economics and Epidemics: Evidence from an Estimated Spatial Econ-SIR Model," Discussion paper, IZA Discussion Papers.

Camitz, M., and F. Liljeros (2006): "The effect of travel restrictions on the spread of a moderately contagious disease," *BMC medicine*, 4(1), 1–10.

Cao, W., Z. Fang, G. Hou, M. Han, X. Xu, J. Dong, and J. Zheng (2020): "The psychological impact of the COVID-19 epidemic on college students in China," *Psychiatry research*, p. 112934.

Charu, V., S. Zeger, J. Gog, O. N. Bjørnstad, S. Kissler, L. Simonsen, B. T. Grenfell, and C. Viboud (2017): "Human mobility and the spatial transmission of influenza in the United States," *PLoS computational biology*, 13(2), e1005382.

Chinazzi, M., et al. (2020): "The effect of travel restrictions on the spread of the 2019 novel coronavirus (COVID-19) outbreak," *Science*, 368(6489), 395–400.

Chong, K. C., and B. C. Y. Zee (2012): "Modeling the impact of air, sea, and land travel restrictions supplemented by other interventions on the emergence of a new influenza pandemic virus," *BMC infectious diseases*, 12(1), 1–12.

Couture, V., J. I. Dingel, A. Green, J. Handbury, and W. Kevin (2020): "Location exposure index based on PlaceIQ data," *Available at https://github.com/COVIDExposureIndices*.

Curdia, V. (2020): "Mitigating COVID-19 effects with conventional monetary policy," *FRBSF Economic Letter*, 2020(09), 1–05.

Dam, P., S. Mandal, R. Mondal, A. Sadat, S. R. Chowdhury, and A. K. Mandal (2020): "COVID-19: Impact on transport and mental health," *Journal of Transport & Health*.

De Vos, J. (2020): "The effect of COVID-19 and subsequent social distancing on travel behavior," *Transportation Research Interdisciplinary Perspectives*, p. 100121.

Dickson, J. (1992): "Contingency planning for emergencies," *Long Range Planning*, 25(4), 82 – 89.

Ebrahim, S. H., Q. A. Ahmed, E. Gozzer, P. Schlagenhauf, and Z. A. Memish (2020): "Covid-19 and community mitigation strategies in a pandemic," .

Eichenbaum, M. S., S. Rebelo, and M. Trabandt (2020): "The Macroeconomics of Epidemics," Working Paper 26882, National Bureau of Economic Research.

Epstein, J. M., D. M. Goedecke, F. Yu, R. J. Morris, D. K. Wagener, and G. V. Bobashev (2007): "Controlling pandemic flu: the value of international air travel restrictions," *PloS one*, 2(5), e401.

Fan, B., R. Liu, K. Huang, and Y. Zhu (2019): "Embeddedness in cross-agency collaboration and emergency management capability: Evidence from Shanghai's urban contingency plans," *Government Information Quarterly*, 36(4), 101395.

Fang, H., L. Wang, and Y. Yang (2020): "Human Mobility Restrictions and the Spread of the Novel Coronavirus (2019-nCoV) in China," Working Paper 26906, National Bureau of Economic Research.

Gao, S., J. Rao, Y. Kang, Y. Liang, J. Kruse, D. Dopfer, A. K. Sethi, J. F. M. Reyes, B. S. Yandell, and J. A. Patz (2020): "Association of mobile phone location data indications of travel and stay-at-home mandates with covid-19 infection rates in the us," *JAMA network open*, 3(9), e2020485–e2020485.

Germann, T. C., K. Kadau, I. M. Longini, and C. A. Macken (2006): "Mitigation strategies for pandemic influenza in the United States," *Proceedings of the National Academy of Sciences*, 103(15), 5935–5940.

Head, K., and T. Mayer (2014): "Gravity equations: Workhorse, toolkit, and cookbook," in *Handbook of international economics*, vol. 4, pp. 131–195. Elsevier.

Hirsch, C. (2020): "EuropeâĂŹs post-lockdown rules compared," *Available at https://www.politico.eu/article/europe-coronavirus-post-lockdown-rules-compared-face-mask-travel/.*

Holmes, E. A., R. C. O'Connor, V. H. Perry, I. Tracey, S. Wessely, L. Arseneault, C. Ballard, H. Christensen, R. C. Silver, I. Everall, et al. (2020):

"Multidisciplinary research priorities for the COVID-19 pandemic: a call for action for mental health science," *The Lancet Psychiatry*.

JONES, C. J., T. PHILIPPON, AND V. VENKATESWARAN (2020): "Optimal Mitigation Policies in a Pandemic: Social Distancing and Working from Home," Working Paper 26984, National Bureau of Economic Research.

KRAEMER, M. U., ET AL. (2020): "The effect of human mobility and control measures on the COVID-19 epidemic in China," *Science*, 368(6490), 493–497.

KYDLAND, F. E., AND E. MARTÍNEZ-GARCÍA (2020): "Checking the Path Towards Recovery from the COVID-19 Isolation Response," *Available at SSRN 3599525*.

MALONEY, W., AND T. TASKIN (2020): "Determinants of social distancing and economic activity during COVID-19: A global view," .

MARTINI, M., V. GAZZANIGA, N. L. BRAGAZZI, AND I. BARBERIS (2019): "The Spanish Influenza Pandemic: a lesson from history 100 years after 1918," *Journal of preventive medicine and hygiene*, 60(1), E64.

MEYER, M. D., AND P. BELOBABA (1982): "Contingency planning for response to urban transportation system disruptions," *Journal of the American Planning Association*, 48(4), 454–465.

MUSSELWHITE, C., E. AVINERI, AND Y. SUSILO (2020): "Editorial JTH 16–The Coronavirus Disease COVID-19 and implications for transport and health," *Journal of Transport & Health*, 16, 100853.

Poletto, C., M. Gomes, A. P. Piontti, L. Rossi, L. Bioglio, D. L. Chao, I. Longini Jr, M. E. Halloran, V. Colizza, and A. Vespignani (2014): "Assessing the impact of travel restrictions on international spread of the 2014 West African Ebola epidemic," *Eurosurveillance*, 19(42), 20936.

Poletto, C., M. Tizzoni, and V. Colizza (2013): "Human mobility and time spent at destination: impact on spatial epidemic spreading," *Journal of theoretical biology*, 338, 41–58.

Redding, S. J., and M. A. Turner (2015): "Transportation costs and the spatial organization of economic activity," *Handbook of regional and urban economics*, 5, 1339–1398.

Rubiano, L. C., and G. Darido (2020): "Protecting public transport from the coronavirus and from financial collapse," *Available at https://blogs.worldbank.org/transport/protecting-public-transport-coronavirus-and-financial-collapse.*

Sarkar, S., and T. P. Dentinho (2020): "Covid-19 in South Asia: Space Matters," SADF-South Asia Democratic Forum.

Sheehan, M. C., and M. A. Fox (2020): "Early Warnings: The Lessons of COVID-19 for Public Health Climate Preparedness," *International Journal of Health Services*, 50(3), 264–270.

Soper, G. A. (1918): "The influenza pneumonia pandemic in the American army camps during September and October, 1918," *Science*, 48(1245), 451–456.

Taub, A. (2020): "A new Covid-19 crisis: Domestic abuse rises worldwide," *The New York Times*, 6.

Wang, Q., and J. E. Taylor (2016): "Patterns and limitations of urban human mobility resilience under the influence of multiple types of natural disaster," *PLoS one*, 11(1).

Wei, S.-J. (1996): "Intra-National versus International Trade: How Stubborn are Nations in Global Integration?," Working Paper 5531, National Bureau of Economic Research.

Welch, C. (2020): "Contact tracing for COVID-19 will be the most complex health investigation ever," *Available at https://www.nationalgeographic.com/science/2020/05/coronavirus-contact-tracing-covid-19-complex-health-investigation/.*

Yang, X.-H., B. Wang, S.-Y. Chen, and W.-L. Wang (2012): "Epidemic dynamics behavior in some bus transport networks," *Physica A: Statistical Mechanics and its Applications*, 391(3), 917–924.

Yilmazkuday, H. (2019): "Estimating the trade elasticity over time," *Economics Letters*, 183, 108579.

——— (2020a): "COVID-19 spread and inter-county travel: Daily evidence from the US," *Transportation Research Interdisciplinary Perspectives*, 8, 100244.

——— (2020b): "Stay-at-home works to fight against COVID-19: international evidence from Google mobility data," *Journal of Human Behavior in the Social Environment, forthcoming.*

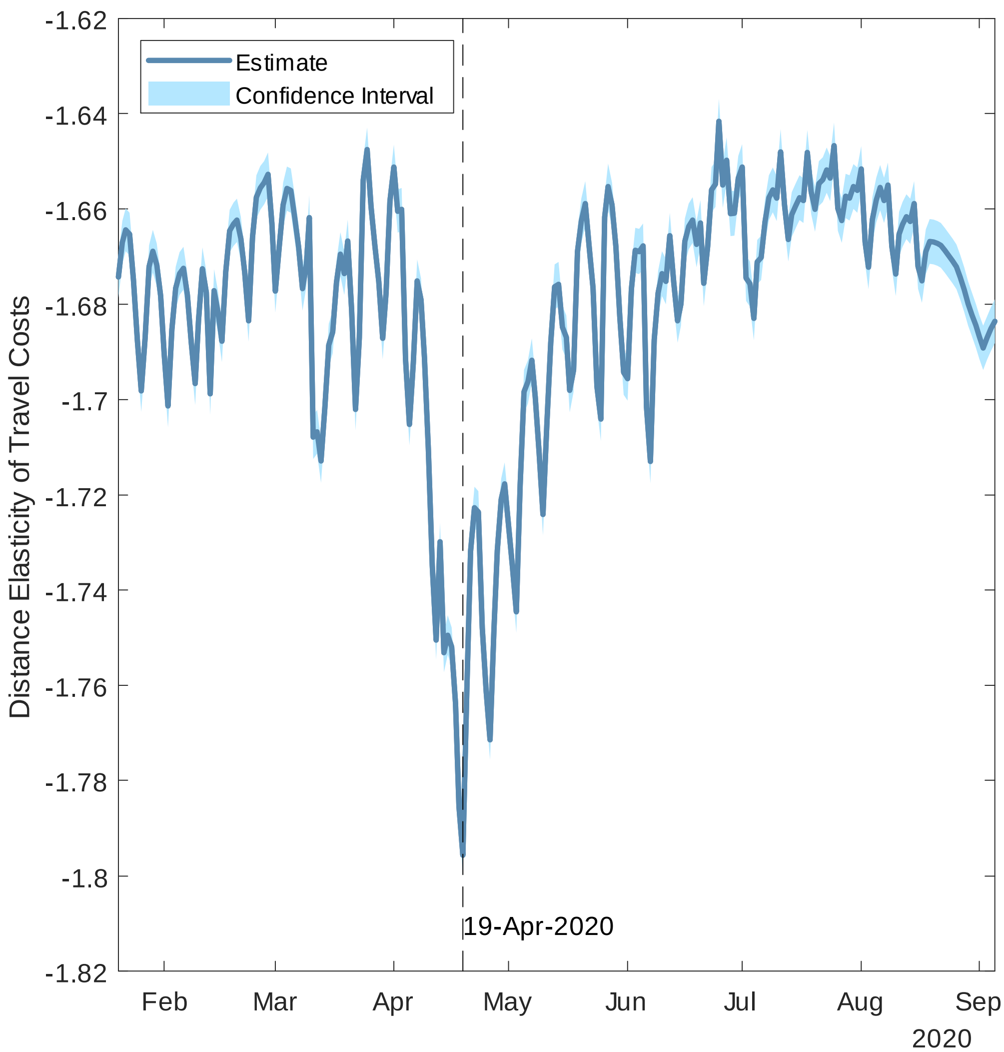
Zhang, J. (2020): "Transport policymaking that accounts for COVID-19 and future public health threats: A PASS approach," *Transport policy*, 99, 405–418.

Table 1 - Welfare Costs (%) of Travel Reductions as of April 19th, 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 U.S.	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

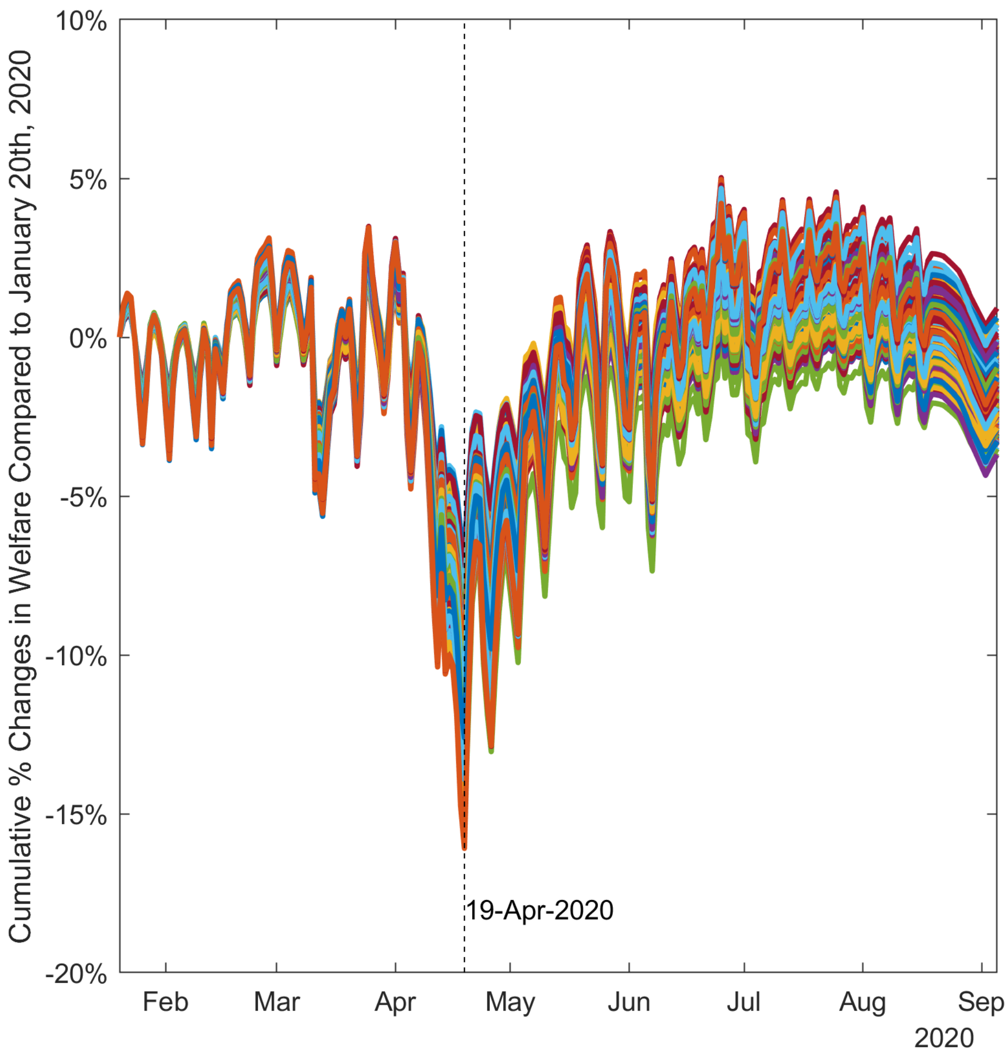
Notes: Welfare costs for the U.S. are the weighted average measures across counties, where the weights are based on the number of smartphone devices in each county.

Figure 1 - Distance Elasticity of Travel



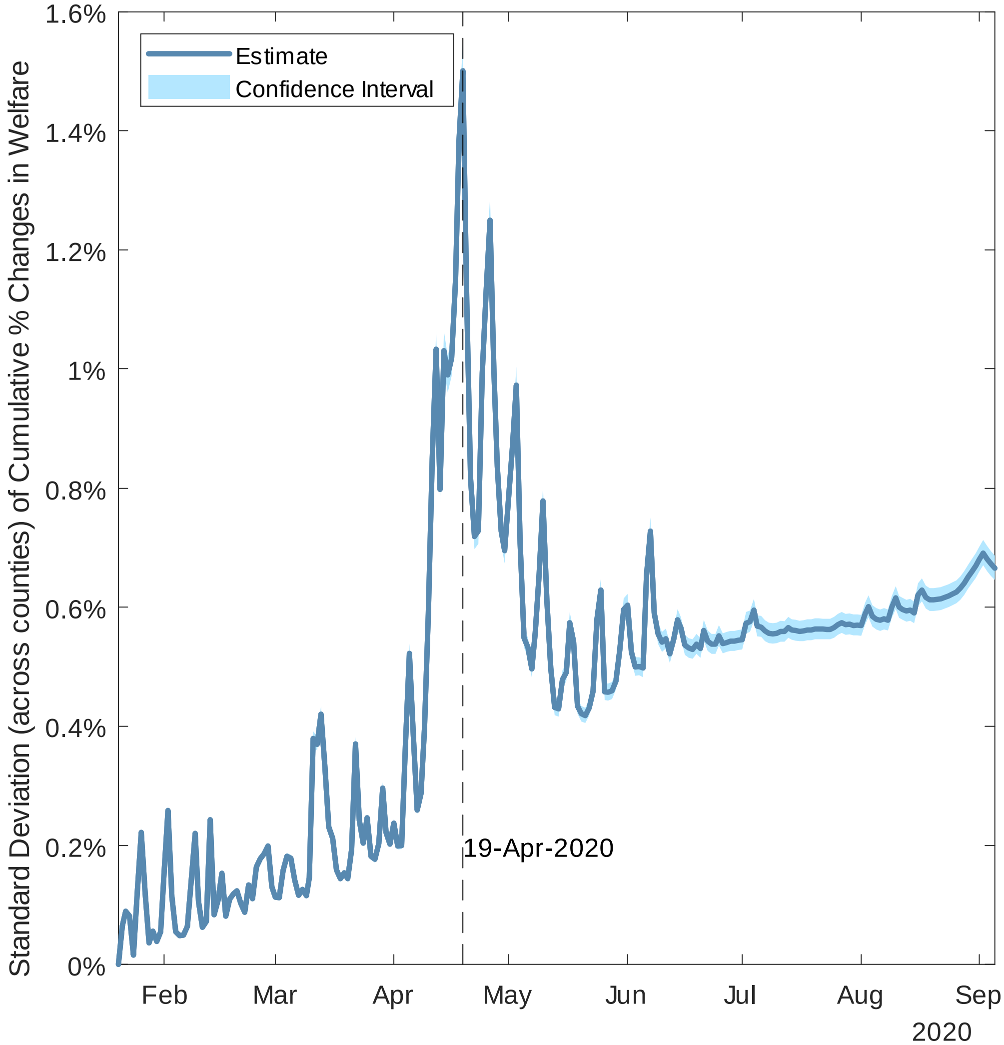
Notes: The shaded area represents the 95% confidence interval.

Figure 2 - Cumulative Welfare Changes across Counties



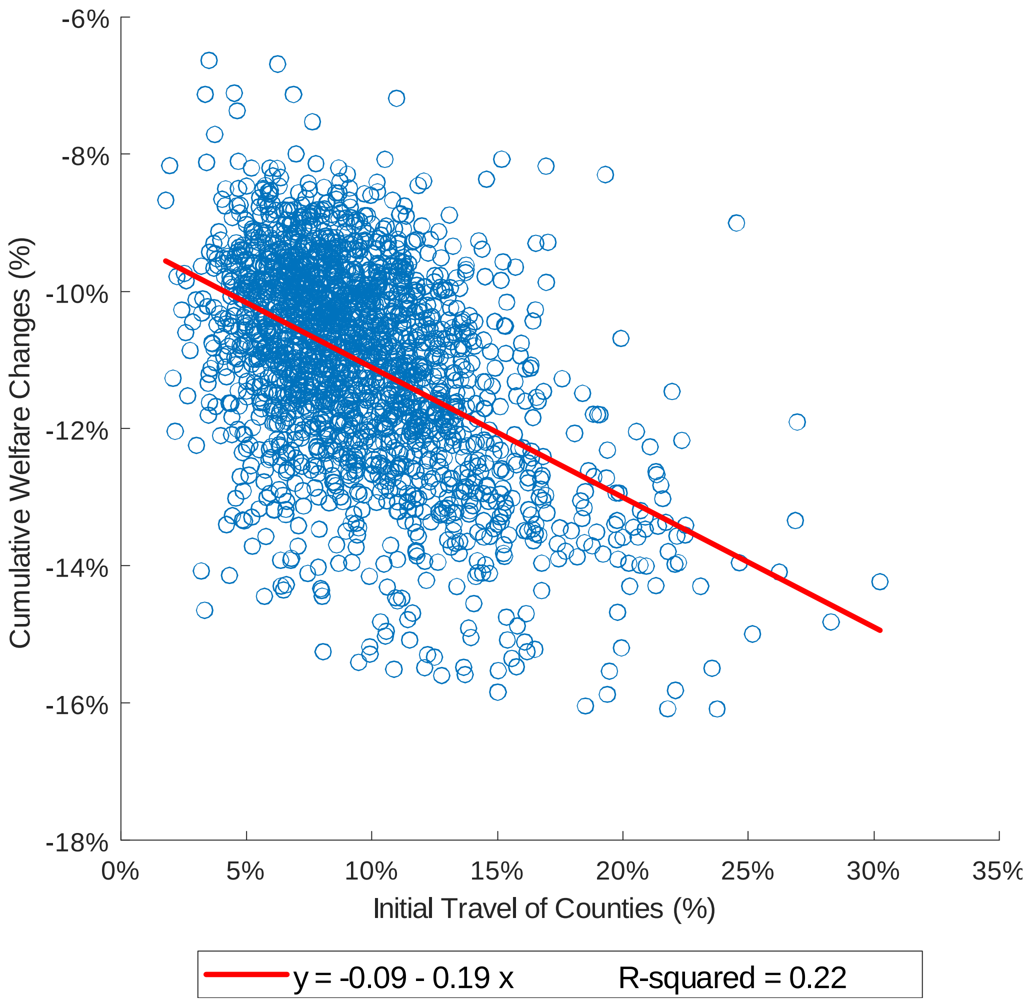
Notes: Each line represents a U.S. county. In total, 2018 counties are represented.

Figure 3 - Inequality of Welfare Changes across U.S. Counties



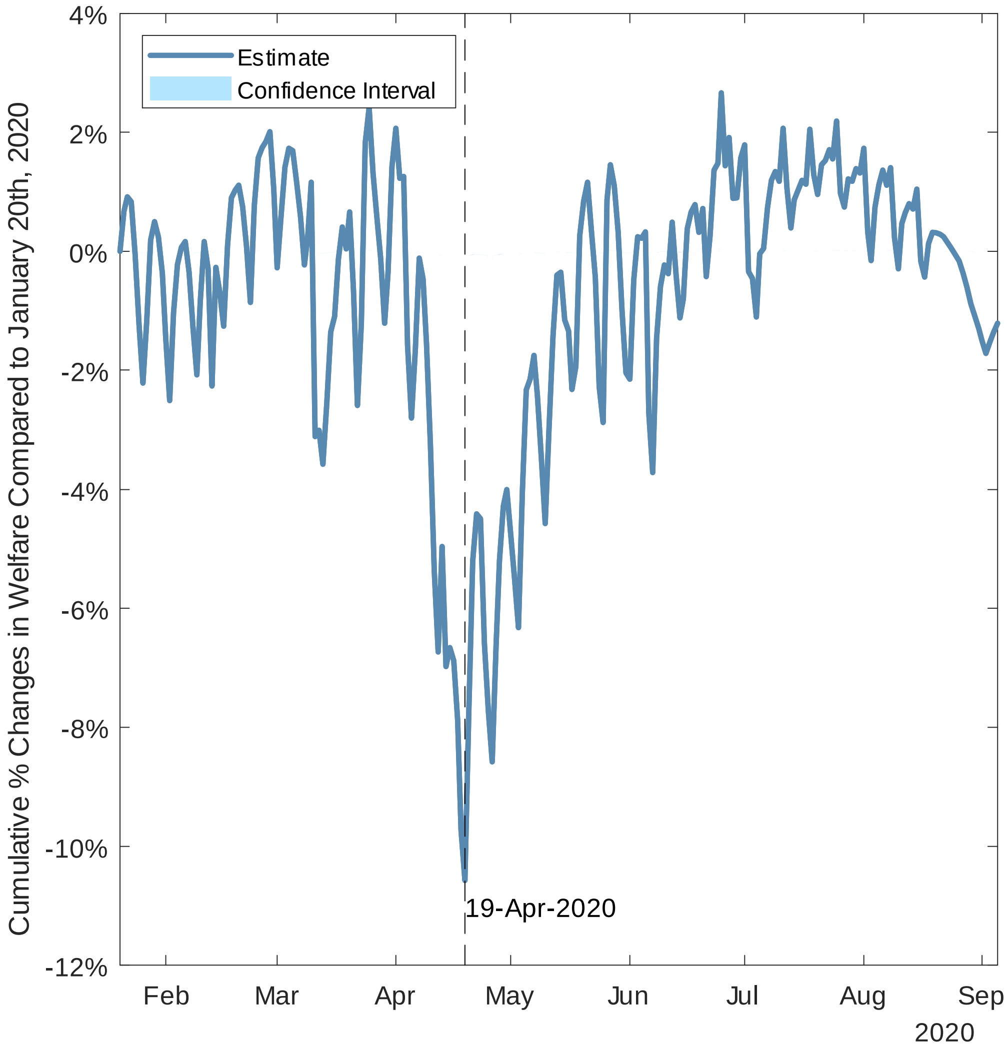
Notes: The shaded area represents the 95% confidence interval.

Figure 4 - Initial Travel versus Welfare Changes on April 19th, 2020



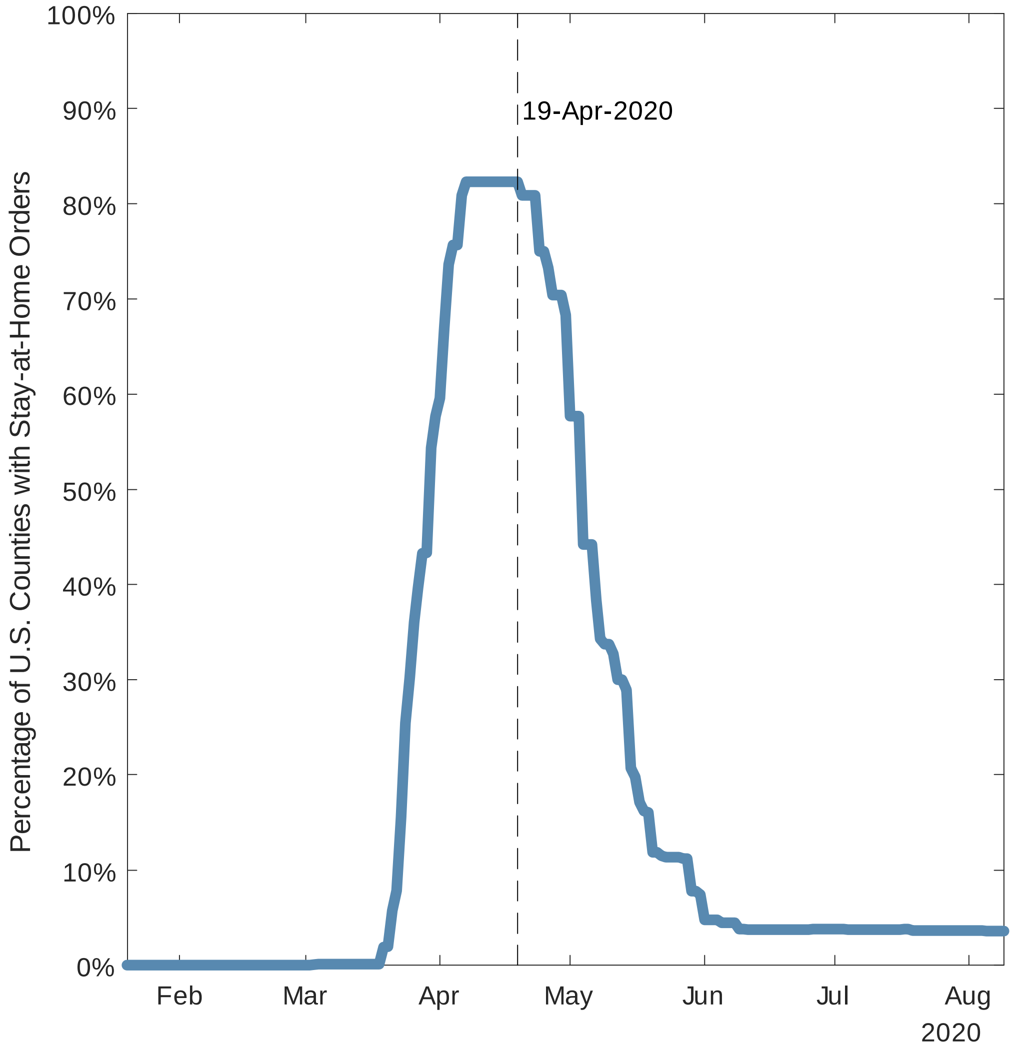
Notes: Each circle represents a county. In total, 2018 counties are represented.

Figure 5 - Cumulative Welfare Changes for the U.S.



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 95% confidence interval.

Figure 6 - Percentage of U.S. Counties with Stay-at-Home Orders



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