# Welfare Costs of COVID-19: Evidence from U.S. Counties[1]

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**Abtract**

Using daily U.S. county-level data on consumption, employment, mobility and the coronavirus disease 2019 (COVID-19) cases, this paper investigates the welfare costs of COVID-19. The investigation is achieved by using implications of a model, where there is a trade-off between consumption and COVID-19 cases that are both determined by the optimal mobility decision of individuals. The empirical results show evidence for about 11% of an average (across days) reduction of welfare during the sample period between February and December, 2020 for the average county. There is also evidence for heterogeneous welfare costs across U.S. counties and days, where certain counties have experienced welfare reductions up to 46% on average across days and up to 97% in late March, 2020 that are further connected to the socioeconomic characteristics of the U.S. counties.

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# 1 Introduction

The coronavirus disease 2019 (COVID-19) has resulted in not only numerous casualties but also unprecedented reductions in economic activity. Since both COVID-19 cases and economic activity are positively related to mobility of individuals as shown in studies such as by Acemoglu et al. (2020), Alvarez et al. (2020), Jones et al. (2020), Eichenbaum et al. (2020), Kydland and Martinez-Garcia (2020), Yilmazkuday (2020), and Yilmazkuday (2021), individuals and policy makers have faced trade-offs regarding the optimal amount of mobility that people should have. It is implied that investigating the welfare changes due to COVID-19 requires taking into account the mobility of individuals.

Based on this background, this paper investigates the welfare costs of COVID-19 by considering the interaction between COVID-19 cases, economic activity and mobility of individuals. A multi-region model is introduced to motivate the empirical investigation, where individuals optimally decide on their mobility that further determines their current consumption and future COVID-19 cases. The parameters and unknown variables of the model are estimated by using daily U.S. county-level data on consumption, employment, mobility and COVID-19 cases.

The estimation results confirm that economic activity (measured by either consumption or employment) increases with mobility of individuals consistent with earlier studies in the literature such as by Curdia (2020), Maloney and Taskin (2020) or Beland et al. (2020). The estimation results also confirm the positive relationship between mobility and COVID-19 cases as in studies in the literature such as by Fang et al. (2020), Yilmazkuday (2020), and Yilmazkuday (2021). The results are also consistent with earlier studies that have shown positive relationships between mobility and pandemics/epidemics that have led into travel restrictions; e.g., Merler and Ajelli (2010) have suggested preparing for a rapid diffusion of a pandemic influenza because of the high mobility of the population in Europe; Bajardi et al. (2011) have discussed how H1N1 influenza in 2009 has resulted in travel-related controls to contain or slow down its international spread; or Charu et al. (2017) have shown how work commutes have contributed to the spread of influenze in the U.S. during 2002-2010. These results are robust to the consideration of county-specific factors that are constant over time and time-varying nationwide factors that are common across counties.

The implications of the model are further used to investigate welfare costs of COVID-19 and its components based on economic activity and COVID-19 cases. The corresponding model implications suggest evidence for about 11% of an average (across days) reduction of welfare during the sample period between February and December, 2020 for the average U.S. county. These welfare costs are 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, although that paper uses a survey experiment approach different from this paper.

When welfare costs are decomposed into those due to each model component, it is shown that COVID-19 cases contribute the most to welfare reductions in early months of COVID-19, whereas they have similar contributions with consumption/employment starting from about May 2020. Mobility contributes negatively to welfare in a steady way during the sample period, whereas other factors have been more effective in early months of COVID-19. In terms of the contribution of each welfare component as an average across days, increases in COVID-19 cases reduce welfare by about 6.7% for the average county (up to 14.2% across counties), whereas consumption reductions contribute to welfare costs by about 3.7% for the average county (up to 43.2% across counties). The contribution of mobility (with respect to other factors) is much more on average (across days) during the sample period.

The empirical results of this paper also provide evidence for heterogeneous welfare costs across U.S. counties and days, where certain counties have experienced welfare reductions up to 46% on average across days and up to 97% in late March, 2020. The heterogeneity across U.S. counties is further investigated by considering the socioeconomic characteristics of the counties. It is shown that the U.S. counties with higher shares of higher-income or higher-educated individuals have been negatively affected the most out of COVID-19 regarding their welfare, which can be explained by relatively higher consumption reduction of these individuals (in percentage terms). These results are robust to the consideration of alternative data sets as well as alternative parameter values considered in the model.

The rest of this paper is organized as follows. The next section introduces a simple model for motivational purposes. Section 3 introduces the empirical methodology, data, and the estimation results. Section 4 discusses the corresponding welfare implications across counties. Section 5 concludes.

## 2 Model

This section models the welfare of individuals in U.S. counties during COVID-19. The motivation behind this model is to 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 Martinez-Garcia (2020). Accordingly, the utility of individuals is determined by consumption and COVID-19 cases in each county, where both measures depend on the mobility of individuals. The optimal decision of individuals regarding their mobility further determines their optimal consumption and COVID-19 cases in the model.

Since economic activity and COVID-19 developments can depend on several factors other mobility (e.g., overall health system in a county, portion of people who can work from home, nationwide developments such as the declaration of National Emergency on March 13th, 2020 due to COVID-19), county-specific factors that are constant over time and time-varying nationwide factors that are common across counties are also considered as other determinants of economic activity and COVID-19 cases. The implications of the model are further used to calculate welfare changes of individuals over time due to COVID-19. These implications are also used to estimate the unknown parameters and variables of the model, which makes the model consistent with alternative data sets.

## 2.1 Individuals

The utility of individuals $U_{nt}$ in county $n$ at day $t$ is given by the following function:

$$U_{nt} = C_{nt} - \frac{(V_{nt})^{\beta}}{\beta} \tag{1}$$

where $C_{nt}$ represents consumption, and $V_{nt}$ represents (gross) weekly changes in cumulative COVID-19 cases in county $n$ at day $t$.[3] This utility function is similar to earlier studies such as by Gali and Monacelli (2005) or Heathcote et al. (2014), except for replacing disutility from labor supply with COVID-19 cases to focus on the effects of the pandemic through mobility of individuals. Accordingly, following studies such as by Yilmazkuday (2021) who has shown that COVID-19 cases are related to lagged mobility of individuals, $V_{nt}$ is further given by the following expression:

$$V_{nt} = (M_{nt-21})^{\alpha}(F_{nt})^{1-\alpha} \tag{2}$$

where $M_{nt-21}$ represents mobility (measured by time outside home) in county $n$ at day $t-21$ so that the effects of mobility can show up on COVID-19 cases, $0<\alpha<1$ as higher mobility results in higher COVID-19 cases, and $F_{nt}$ represents other county and/or time specific factors.

## 2.2 Production

Production is achieved by using mobility $M_{nt}$ of individuals, subject to productivity $Z_{nt}$. Accordingly, the production $Y_{nt}$ in county $n$ at day $t$ is achieved by using the following production function:

$$Y_{nt} = (M_{nt})^{\gamma}(Z_{nt})^{1-\gamma} \tag{3}$$

where productivity $Z_{nt}$ captures all other production-related factors in county

[3] The potential mismeasurement of COVID-19 cases is partly controlled for by day-fixed effects and county-fixed effects during the empirical investigation below.

$n$ at time $t$, including working from home as discussed in studies such as by Dingel and Neiman (2020). It is important to emphasize that this production function can capture the production of both traded and nontraded goods; e.g., having a haircut requires physically being in a store (and thus mobility), whereas the delivery of a meal or grocery requires mobility of the delivery person.

## 2.3 Equilibrium

The lifetime utility of individuals in county $n$ (given by $\sum_{t=0}^{\infty} U_{nt}$) is maximized using Equation (1) subject to Equations (2) and (3) as well as the market clearing condition that is given by:

$$Y_{nt} = C_{nt} \tag{4}$$

where individuals decide on their mobility (i.e., $M_{nt}$) over time. This dynamic maximization of $\sum_{t=0}^{\infty} U_{nt}$ results in the following optimal relationship between COVID-19 cases and consumption:

$$V_{nt} = \left(\frac{\gamma C_{nt-21}}{\alpha}\right)^{\frac{1}{\beta}} \tag{5}$$

where COVID-19 cases increases with lagged consumption, for example, when $\gamma/\alpha > 0$ and $\beta > 0$. In other words, current consumption based on mobility of individuals due to Equations (3) and (4) determines future COVID-19 cases according to this expression.

## 2.4 Welfare Changes over Time

Welfare in county $n$ at time $t$ is measured by $U_{nt}$. We are interested in welfare changes over time, which we obtain by using the percentage deviations of welfare from its steady state that can be expressed as follows:[4]

$$\underbrace{u_{nt}}_{\text{Welfare Changes}} = \underbrace{\omega_n c_{nt}}_{\text{Due to Consumption}} - \underbrace{\beta(1-\omega_n)v_{nt}}_{\text{Due to COVID-19}} \tag{6}$$

where small-case variables (in the rest of the paper) represent percentage deviations of the corresponding variables from their steady-states, with $\omega_n$ representing the share of consumption in the steady-state welfare in county $n$. Using Equation (5) in terms of percentage deviations, which is:

$$v_{nt} = \frac{c_{nt-21}}{\beta} \tag{7}$$

Equation (6) can be rewritten as follows:

$$\underbrace{u_{nt}}_{\text{Welfare Changes}} = \underbrace{\omega_n c_{nt}}_{\text{Due to Consumption}} - \underbrace{(1-\omega_n)c_{nt-21}}_{\text{Due to COVID-19}} \tag{8}$$

where welfare changes depend on the weighted average of changes in current consumption and changes in lagged consumption (representing COVID-19 cases). We would like to further decompose Equation (6) due to consumption

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[4] Percentage deviations of any variable $X_t$ from its steady state $X$ are expressed as $x_t = \log X_t - \log X$. Percentage deviations of all variables from their steady states are derived by using total derivative of the corresponding equations.

and due to COVID-19 into their components by using the implications of the model.

Specifically, using Equation (3) and (4), we can write the following expression for percentage deviations of consumption from its steady state:

$$\underbrace{c_{nt}}_{\text{Consumption Changes}} = \underbrace{\gamma m_{nt}}_{\text{Due to Mobility}} - \underbrace{(1-\gamma) z_{nt}}_{\text{Due to Other Factors}} \tag{9}$$

where percentage deviations of consumption from its steady state are decomposed into those due to mobility and due to other factors. Similarly, using Equation (2), we can write the following expression for percentage deviations of the COVID-19 measure over time:

$$\underbrace{v_{nt}}_{\text{COVID}-19\text{ Changes}} = \underbrace{\alpha m_{nt-21}}_{\text{Due to Mobility}} - \underbrace{(1-\alpha) f_{nt}}_{\text{Due to Other Factors}} \tag{10}$$

where percentage deviations of the COVID-19 measure from its steady state are decomposed into those due to mobility and due to other factors. Combining Equations (6), (9) and (10), one can further write:

$$\underbrace{u_{nt}}_{\text{Welfare Changes}} = \underbrace{\underbrace{\omega_n \gamma m_{nt}}_{\text{Consumption}} - \underbrace{\beta(1-\omega_n)\alpha m_{nt-21}}_{\text{COVID}-19}}_{\text{Due to Mobility}} - \underbrace{\underbrace{\omega_n (1-\gamma) z_{nt}}_{\text{Consumption}} - \underbrace{\beta(1-\omega_n)(1-\alpha) f_{nt}}_{\text{COVID}-19}}_{\text{Due to Other Factors}} \tag{11}$$

where overall percentage deviations of welfare from its steady state are decomposed into those due to mobility versus other factors as well as into those due to consumption versus COVID-19.

We consider all three decompositions given by Equations (9), (10) and (11), which require information on the variables of $c_{nt}$, $m_{nt}$, $v_{nt}$, $z_{nt}$ and $f_{nt}$ as well as the parameters of $\alpha$, $\beta$, $\gamma$ and $\omega_n$. As we detail in the next section, we have data for $c_{nt}$, $m_{nt}$ and $v_{nt}$; however, we do not have the information on the parameters of $\alpha$, $\beta$, $\gamma$ and $\omega_n$ or the variables of $z_{nt}$'s and $f_{nt}$'s. Accordingly, we estimate $\alpha$, $\beta$ and $\gamma$ as well as $z_{nt}$'s and $f_{nt}$'s by using the implications of the model, whereas we consider alternative values of $\omega_n$'s. In the corresponding robustness checkes, we also discuss the implications of having alternative parameter values for $\alpha$, $\beta$ and $\gamma$.

# 3 Empirical Investigation

The objective of this section is to estimate the parameters of $\alpha$, $\beta$ and $\gamma$ as well as $z_{nt}$'s and $f_{nt}$'s that are essential for the decompositions in Equations (9), (10) and (11). As all estimations are achieved by using panel data sets, the identification is achieved not only through the time dimension but also through the cross-county dimension. The identification is also based on the implications of the model that are taken litereally; accordingly, potential endogeneity issues are taken care of based on the implications of the model. As other factors are approximated by county-fixed effects and day-fixed effects, the estimations are robust to the consideration of any omitted variable bias as well. The corresponding county-level data from the U.S. used in estimations and decompositions are also introduced in this section. Finally, the estimation results are depicted at the end of the section.

### 3.1 Estimation Methodology

We start with the estimation of $\gamma$ (representing the share of mobility in consumption/production) and $z_{nt}$ 's (representing productivity in consumption/production) using data on consumption and mobility considering the stochastic version of Equation (9) as follows:

$$\underbrace{c_{nt}}_{\text{Consumption Data}} = \gamma \times \underbrace{m_{nt}}_{\text{Mobility Data}} \underbrace{- \underbrace{(1-\gamma)z_n}_{\text{County-Fixed Effects}} + \underbrace{(1-\gamma)z_t}_{\text{Day-Fixed Effects}}}_{\text{Other Factors}} + \underbrace{\varepsilon_{nt}^{c}}_{\text{Residuals}} \tag{12}$$

where unknown measures of production-related factors at the county level are approximated by $z_{nt} = z_n + z_t$ for estimation purposes. In this estimation, $z_n$ is a county-$n$ specific production factor that is constant over time (e.g., representing the sectoral decomposition of workers who can work from home in county $n$), and $z_t$ is a day-specific production factor that is common across counties (e.g., capturing the national developments over time regarding working from home, such as using Zoom). Since $Y_{nt} = C_{nt}$ according to the market clearing condition given by (4), we also consider an alternative estimation of $\gamma$ using employment (as a proxy for production) and mobility data as follows:

$$\underbrace{y_{nt}}_{\text{Employment Data}} = \gamma \times \underbrace{m_{nt}}_{\text{Mobility Data}} \underbrace{- \underbrace{(1-\gamma)z_n}_{\text{County-Fixed Effects}} + \underbrace{(1-\gamma)z_t}_{\text{Day-Fixed Effects}}}_{\text{Other Factors}} + \underbrace{\varepsilon_{nt}^{y}}_{\text{Residuals}} \tag{13}$$

which is for robustness purposes. Estimations of the last two equations are also achieved by ordinary least squares (OLS), after which $\gamma$ and $z_{nt}$'s are identified as estimated and fitted values, respectively.

The estimation of $\alpha$ (representing the share of lagged mobility in COVID-19 cases) and $f_{nt}$'s (representing other factors affecting COVID-19 cases) is achieved by using data on COVID-19 cases and mobility, which is achieved by using the stochastic version of Equation (7) as follows:

$$\underbrace{v_{nt}}_{\text{COVID-19 Data}} = \alpha \times \underbrace{m_{nt-21}}_{\text{Mobility Data}} - \underbrace{\underbrace{(1-\alpha) f_n}_{\text{County-Fixed Effects}} + \underbrace{(1-\alpha) f_t}_{\text{Day-Fixed Effects}}}_{\text{Other Factors}} + \underbrace{\varepsilon_{nt}^{v}}_{\text{Residuals}} \qquad (14)$$

where unknown measures of other factors at the county level are approximated by $f_{nt} = f_n + f_t$ for estimation purposes. In particular, $f_n$ represents county-$n$ specific COVID-19 factors that are constant over time (e.g., representing the overall health system or mask-wearing behavior of county $n$), and $f_t$ is a day-specific COVID-19 factor that is common across counties (e.g., capturing nationwide availability of COVID-19 tests or the declaration of National Emergency on March 13th, 2020 due to COVID-19). The estimation is achieved by OLS, after which $\alpha$ and $f_{nt}$'s are identified as estimated and fitted values, respectively.

Finally, for the estimation of $\beta$ (governing the contribution of COVID-19 cases to welfare), we use data on COVID-19 cases and consumption according to the stochastic version of Equation (7) as follows:

$$\underbrace{v_{nt}}_{\text{COVID-19 Data}} = \frac{1}{\beta} \times \underbrace{c_{nt-21}}_{\text{Consumption Data}} + \underbrace{\eta_{nt}}_{\text{Residuals}} \qquad (15)$$

where the inverse of the coefficient in front of $c_{nt-21}$ corresponds to $\beta$. Due to potential endogeneity (based on the implications of the model), this estimation is achieved by using Two-State Least Squares (TSLS), with Equation (12) representing the first stage of this regression. Since $Y_{nt} = C_{nt}$ according to the market clearing condition given by (4), we also consider an alternative estimation of $\beta$ using COVID-19 cases and employment data as follows:

$$\underbrace{v_{nt}}_{\text{COVID}-19\text{ Data}} = \frac{1}{\beta} \times \underbrace{y_{nt-21}}_{\text{Employment Data}} + \underbrace{\theta_{nt}}_{\text{Residuals}} \tag{16}$$

where the inverse of the coefficient in front of $y_{nt-21}$ corresponds to $\beta$. This estimation is also achieved by using TSLS, with Equation (13) representing the first stage of this regression.

## 3.2 Data

Estimations of Equations (12), (13), (14), (15) and (16) require data on consumption, mobility, employment (as a proxy for production), and COVID-19 cases at the U.S. county level over time. We consider daily data for these county-level variables covering the period between February 24th, 2020 and December 6th, 2020. All U.S. county-level daily data have been obtained from Opportunity Insights Economic Tracker (OIET).[5]

Consumption is measured by seasonally adjusted credit/debit card spending relative to the period between January 4 and Junary 31, 2020 in all merchant category codes as seven-day moving average.[6] This data series

[5] The web page is https://tracktherecovery.org/.
[6] OIET obtains this information from Affinity Solutions.

correspond to $c_{nt}$ in the model representing percentage deviations of consumption from its steady state.

Employment (as a proxy for production) is measured by employment level for all workers relative to the period between January 4 and Junary 31, 2020.[7] This data series correspond to $y_{nt}$ in the model representing percentage deviations of employment from its steady state.

Mobility is measured by the time spent outside of residential locations relative to the period between January 3 and February 6, 2020.[8] This data series correspond to $m_{nt}$ in the model representing percentage deviations of mobility from its steady state.

COVID-19 cases are measured by confirmed COVID-19 cases per 100,000 people, seven day moving average.[9] Since $V_{nt}$ represents (gross) weekly changes in cumulative COVID-19 cases, $v_{nt}$ representing percentage deviations of COVID-19 cases from their steady state correspond to weekly percentage changes in cumulative COVID-19 cases.

The corresponding descriptive statistics are given in the Appendix Table A.1, where, for the average U.S. county, the average (across days) reducations are about 7% for consumption, 8% for mobility and employment, whereas increases in COVID-19 cases are about 19%. There is also evidence for heterogeneity across U.S. counties, where all measures have wide ranges. The corresponding changes over time are given in Appendix Figure A.1, where the most significant changes have been experienced mostly during April and May of 2020.

[7] OIET obtains this information from Paychex, Intuit, Earnin and Kronos.
[8] OIET obtains this information from Google.
[9] OIET obtains this information from New York Times COVID-19 repository.

### 3.3 Estimation Results

The estimated parameters of $\gamma$ (representing the share of mobility in consumption/production), $\alpha$ (representing the share of lagged mobility in COVID-19 cases) and $\beta$ (governing the contribution of COVID-19 cases to welfare) are given in Table 1, where fitted values of $z_{nt}$'s and $f_{nt}$'s (subject to the coefficients in front of them) are given in Figure 1 (under the title of "Contribution of Other Factors").

The OLS estimation results of Equation (12) are given in column (1), whereas the OLS estimation results of Equation (13) are given in column (2) of Table 1. As is evident, $\gamma$ is estimated around 0.6 in both estimations, independent of using consumption or employment data. This confirms the implication of the model that consumption increases with mobility, after controlling for other county-specific and day-specific factors. This result is also consistent with earlier studies in the literature such as by Curdia (2020), Maloney and Taskin (2020) or Beland et al. (2020). The corresponding fitted values of $z_{nt}$'s are given in top two panels of Figure 1, where they take their lowest value at around early April according to consumption data and around early May according to employment data.

The OLS estimation results of Equation (14) are given in column (3) of Table 1, where $\alpha$ is estimated around 0.96. This confirms the implication of the model that COVID-19 cases increase with mobility as well, after controlling for other county-specific and day-specific factors. This result is also consistent with earlier studies in the literature such as by Merler and Ajelli (2010) , Bajardi et al. (2011), Charu et al. (2017), Fang et al. (2020), Yilmazkuday (2020), and Yilmazkuday (2021). The corresponding fitted values of $f_{nt}$'s are given in the bottom panel of Figure 1, where they take their highest value at around late March.

The TSLS estimation results of Equation (15) are given in column (4), whereas the TSLS estimation results of Equation (16) are given in column (5) of Table 1. As is evident, $1/\beta$ is estimated around 1.5 in both estimations (corresponding to $\beta$ of around 0.7), independent of using consumption or employment data. This confirms the implication of the model that COVID-19 cases increase with consumption or employment, where consumption or employment is instrumented by mobility, county-fixed effects and time-fixed effects as already depicted in column (1) or (2) of Table 1 as the first-stage of TSLS.

# 4 Implications for Welfare Changes over Time

This section depicts the implications of estimation results for welfare changes over time. We start with the decomposition of each welfare component. We continue with welfare changes across U.S. counties, and finalize with the decomposition of overall welfare. The calculations are based on the consumption share (in the steady-state welfare) of $\omega_n = 0.5$ for all $n$ (implying equal shares of consumption and COVID-19 cases in the steady-state welfare), although we consider alternative values of $\omega_n = 1$ for all $n$ (implying welfare is based on consumption only) and $\omega_n = 0$ for all $n$ (implying welfare is based on COVID-19 cases only) for robustness purposes at the end of this section.

## 4.1 Decomposition of Welfare Components over Time

The decomposition of consumption over time (based on Equation (9)) for the average U.S. county is given in the top panel of Figure 1. As is evident, lowest values of consumption have been experienced during early April, while mobility and other factors have contributed by about the same to changes in consumption in early months of COVID-19. Starting from June, other factors have recovered to their pre-COVID-19 values, whereas the contribution of mobility has remained negative for the whole sample period. Overall, it is implied (due to positive contribution of consumption to welfare) that reduced mobility has contributed negatively to welfare changes through consumption during the sample period.

Similarly, the decomposition of employment over time (again, based on Equation (9)) for the average U.S. county is given in the middle panel of Figure 1, where lowest values of employment have been observed in mid-April. The negative contribution of mobility to employment is observed during the whole sample period, whereas the contribution of other factors have recovered by June. Overall, it is implied (due to positive contribution of consumption to welfare) that reduced mobility has contributed negatively to welfare changes through employment (as a proxy for production) during the sample period.

The decomposition of COVID-19 cases over time (based on Equation (10)) for the average U.S. county is also given in the bottom panel of Figure 1, where COVID-19 cases have taken their highest weekly percentage increase during late March. The contribution of mobility has been low but positive and steady during the whole sample period, whereas the contribution of other factors has reduced over time. Overall, it is implied (due to negative contribution of COVID-19 cases to welfare) that mobility has contributed negatively to welfare changes through COVID-19 cases during the sample period.

## 4.2 Welfare Changes across U.S. Counties over Time

Based on the welfare components discussed above, overall welfare changes across U.S. counties over time are given in Figure 2. The top panel represents welfare changes based on consumption data (through Equations (12), (14) and (15)), whereas the bottom panel represents welfare changes based on employment data (through Equations (13), (14) and (15)). As is evident, welfare reductions have been as much as 97% for certain counties during late March, with an average (across counties) of up about 60%. Although some counties have recovered by June, the average county has experienced negative welfare changes for the whole sample period.

When welfare changes are decomposed into those due to consumption versus COVID-19 cases (according to Equation (6)), the results are given in Figure 3. As is evident, consumption has contributed negatively to welfare for the average county during the sample period, while certain counties have experienced reductions in their welfare by close to 50% due to consumption changes. The contribution of COVID-19 cases on welfare has been the most during late March (up to 60%), and it has been highly similar across counties, consistent with having a higher contribution of other factors to COVID-19 cases as depicted in Figure 1. Compared to Figure 3 that is based on consumption data, the results for the average county are similar in Figure 4 where employment data are used, although the heterogeneity across counties regarding the contribution of employment is lower compared to that of consumption in Figure 3.

## 4.3 Decomposition of Overall Welfare over Time

After discussing the heterogeneity across U.S. counties regarding welfare changes, we now turn to the decomposition of welfare into its components for the average county. We start with decomposing welfare changes into those due to consumption versus COVID-19 in the top panel of Figure 5 (according to Equation (6)). As is evident, independent of using consumption versus employment (as a proxy for production) data, the contribution of COVID-19 cases has been much higher in early months of COVID-19, although the contributions of each component have been roughly equalized starting from about May.

When welfare changes are decomposed into those due to mobility versus other factors (according to Equation (11)), the results are given in Figure 6. As is evident, independent of using consumption versus employment data, the contribution of mobility to welfare has been stable and negative during the sample period. The contribution of other factors to welfare has been highly negative in early months of COVID-19, whereas they have recovered to their pre-COVID-19 values by about June.

Finally, we have an overall decomposition of welfare changes into those due to consumption through mobility, consumption through other factors, COVID-19 cases through mobility and COVID-19 cases through other factors. The corresponding results are given in Figure 7, where the negative contribution of COVID-19 cases to welfare through other factors dominates other components in early months of COVID-19. Nevertheless, the negative effects of mobility on welfare dominate other components starting from June.

## 4.4 Summary of Welfare Changes

The results so far are also summarized in Table 2, where, this time, the average values across days of the sample period are depicted for the average, minimum and maximum measures across U.S. counties. When $\omega_n = 0.5$ for all $n$, which is the case in all figures, welfare changes are about $-10.5\%$ ($-13.1\%$) for the average county, which a range between $-45.9\%$ and $18.6\%$ ($-37.5\%$ and $1.8\%$) when consumption (employment) data are used. Contribution of COVID-19 cases to welfare reductions has been higher than that of consumption (or employment). One interesting result is that the contribution of mobility dominates that of other factors for both consumption (or employment) and COVID-19 cases on average across days of the sample period for the average county. Therefore, from a long-run perspective, it is implied that mobility has been the dominant factor reducing welfare.

The county-level average (across days) welfare changes and the contribution of components are also depicted on the U.S. continental maps in the Appendix figures for interested readers (again, for the case of $\omega_n = 0.5$ for all $n$). As is evident in these figures, coastal counties generally seem to have lower welfare costs, whereas landlocked counties generally seem to have higher welfare costs. Contribution of consumption is more heterogeneous across counties compared to the contribution of employment, whereas contributions of COVID-19 cases or mobility are robust to the consideration of consumption versus employment data. Finally, contribution of other factors is also more heterogeneous across counties when consumption data are used compared to using employment data.

### 4.5 Robustness Checks

The results that have been discussed so far are based on $\omega_n = 0.5$ for all $n$ (implying equal shares of consumption and COVID-19 cases in the steady-state welfare), although we consider alternative values of $\omega_n = 1$ for all $n$ (implying welfare is based on consumption only) and $\omega_n = 0$ for all $n$ (implying welfare is based on COVID-19 cases only) for robustness purposes. The corresponding results are given in Table 2, where welfare changes are about $-7.4\%$ and $-13.5\%$ for the average county when $\omega_n = 1$ and $\omega_n = 0$, respectively, when consumption data are used. Similarly, when employment data are used, welfare changes are about $-10.6\%$ and $-15.6\%$ for the average county when $\omega_n = 1$ and $\omega_n = 0$, respectively. Also considering the results for the benchmark case of $\omega_n = 0.5$ in Table 2, it is implied that the results are robust to consideration of alternative $\omega_n$ measures.

Robusness checks can also be achieved for alternative values of $\gamma$ and $\alpha$ as they take values between 0 and 1. In particular, in the special case of $\gamma = 1$, changes in consumption are fully explained by mobility changes, whereas in the special case of $\gamma = 0$, changes in consumption are fully explained by other factors. Similarly, in the special case of $\alpha = 1$, changes in COVID-19 cases are fully explained by mobility changes, whereas in the special case of $\alpha = 0$, changes in COVID-19 cases are fully explained by other factors.

The more interesting robustness check can be achieved by considering alternative values of $\beta$ that partly governs the contribution of COVID-19 cases to welfare changes. The results of this robustness check are given in Table 3, where alternative values of $\beta = 0.5$ and $\beta = 1$ have been considered (by keeping $\omega_n = 0.5$ as in the benchmark case). As is evident, welfare changes are about $-8.6\%$ and $-13.5\%$ for the average county when $\beta = 0.5$ and $\beta = 1$, respectively, when consumption data are used. Similarly, when employment data are used, welfare changes are about $-11.3\%$ and $-17.4\%$ for the average county when $\beta = 0.5$ and $\beta = 1$, respectively. It is implied that the results are robust to consideration of alternative $\beta$ measures.

### 4.6 Understanding Welfare Changes across U.S. Counties

The results that have been discussed so far have suggested significant heterogeneity across U.S. counties regarding the welfare changes amid COVID-19. In this subsection, we attempt to understand the reasons behind this heterogeneity by connecting the county-specific welfare changes to the socioeconomic characteristics of U.S. counties. This is achieved by using univariate regressions (focusing on the correlation), where the dependent variable is the welfare change, and the independent variable is the share of individuals/households belonging to a specific interval based on a certain categorization (e.g., the share of individuals having income less than $10,000).

The results based on the categorization of per capita income are given in Table 4, where it is shown that welfare changes have been significantly positive in U.S. counties with higher shares of lower-income individuals, whereas they have been significantly negative in U.S. counties with higher shares of higher-income individuals.

The results based on the categorization of race/ethnicity are given in Table 5, where it is shown that welfare changes have been significantly positive in U.S. counties with higher shares of white population, while they have been significantly negative in U.S. counties with higher shares of Asian or Hispanic/Latino population; the evidence for black population is mixed.

The results based on the categorization of school attendance are given in Table 6, where it is shown that welfare changes have been significantly negative in U.S. counties with higher shares of college or graduate school attandence, whereas they have been insignificant or significantly positive for others.

Finally, the results based on the categorization of educational attainment are given in Table 7, where it is shown that welfare changes have been significantly negative in U.S. counties with higher shares of more educated people, whereas they have been insignificant or significantly positive for others.

Overall, U.S. counties with higher shares of higher-income or higher-educated individuals have been negatively affected the most out of COVID-19 regarding their welfare, which can be explained by relatively higher consumption reduction of these individuals (in percentage terms).

## 4.7 Discussion of Results

Overall, COVID-19 has resulted in significant welfare costs across U.S. counties during the sample period covering the days between February 24th, 2020 and December 6th, 2020. Although COVID-19 cases due to county-specific and time-varying nationwide factors have contributed the most to the reduction in welfare in early months, COVID-19 cases due to mobility have contributed the most to the reduction in welfare starting from June.

These 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 Martinez-Garcia (2020). In particular, since mobility is positively related to both consumption/employment and COVID-19 cases at the same time according to Equations (6), (9) and (10) of this paper, there is in fact a trade-off between reducing mortality due COVID-19 and stabilizing economic activity as reflected in the corresponding tables and figures.

For sure, this paper has considered welfare changes through consumption/employment and COVID-19 cases, and it does not include any investigation on indirect welfare costs, such as 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). Accordingly, the results of this paper should only be considered as welfare costs based on consumption/employment and COVID-19 cases.

## 5 Concluding Remarks

This paper has investigated the welfare costs of COVID-19 due to reductions in economic activity and increases in COVID-19 cases. A simple model has been introduced for motivational purposes, where the welfare of individuals are connected to the trade-off between economic activity and COVID-19 cases through their mobility. The parameters and unknown variables of the model have been estimated by using daily U.S. county-level data on consumption, employment, mobility and COVID-19 cases. The implications of the model have been combined with these estimation results to investigate the welfare changes across U.S. counties over the sample period covering the days between February 24th, 2020 and December 6th, 2020.

The empirical results have shown evidence for about 11% of an average (across days) reduction of welfare during the sample period between February and December, 2020 for the average U.S. county. There is also evidence for heterogeneous welfare costs across counties and days, where certain counties have experienced welfare reductions up to 46% on average across days and up to 97% in late March, 2020 that are further connected to the socioeconomic characteristics of the U.S. counties.

Regarding the components of welfare over time, COVID-19 cases have contributed the most to welfare reductions in early months of COVID-19, whereas they have similar contributions with consumption/employment starting from about May 2020. Mobility has contributed negatively to welfare in a steady way during the sample period, whereas other factors (representing county-specific effects that are constant over time and time-varying nationwide factors that are common across counties) have been more effective in early months of COVID-19.

In terms of the contribution of each welfare component as an average across days, increases in COVID-19 cases have reduced welfare by about 6.7% for the average county (up to 14.2% across counties), whereas consumption reductions have contributed to welfare costs by about 3.7% for the average county (up to 43.2% across counties). The contribution of mobility with respect to other factors has been much more on average (across days) during the sample period.

The results are not without caveats. Specifically, the model has been introduced to investigate the developments in economic activity through consumption/employment and those in COVID-19 through cases, all depending on the decision variable of mobility. Accordingly, welfare costs of COVID-19 due to other factors such as mental distress, increased rates of suicide or domestic violence cannot be captured by using the implications of our model.

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## Table 1 – Estimation Results

| | Dependent Variable: | | | | |
|---|---|---|---|---|---|
| | Consumption (OLS) | Employment (OLS) | COVID-19 Cases (OLS) | COVID-19 Cases (TSLS) | COVID-19 Cases (TSLS) |
| Coefficient in front of: | (1) | (2) | (3) | (4) | (5) |
| Mobility | 0.607*** | 0.629*** | 0.956*** | | |
| | (0.00920) | (0.00531) | (0.0188) | | |
| Fitted Values of Consumption | | | | 1.446*** | |
| | | | | (0.0343) | |
| Fitted Values of Employment | | | | | 1.552*** |
| | | | | | (0.0447) |
| County-Fixed Effects | YES | YES | YES | YES | YES |
| Day-Fixed Effects | YES | YES | YES | YES | YES |
| Sample Size | 282686 | 169101 | 348065 | 269050 | 162917 |
| R-sq | 0.652 | 0.818 | 0.657 | 0.669 | 0.733 |
| adj. R-sq | 0.650 | 0.817 | 0.655 | 0.667 | 0.731 |

Notes: *** represents significance at the 0.1% level. Standard errors are given in parentheses. Columns (1)-(5) represent the estimation results based on Equations (12)-(16), respectively. Estimation results in columns (1)-(3) are obtained by OLS, whereas those in columns (4) and (5) are obtained by TSLS. Columns (1) and (2) also represent the first-stage of TSLS estimations in columns (4) and (5), respectively.

## Table 2 – Decomposition of Welfare Changes

| | $\omega = 0.5$ in All Counties | | | $\omega = 1$ in All Counties | | | $\omega = 0$ in All Counties | | |
|---|---|---|---|---|---|---|---|---|---|
| | Average | Min | Max | Average | Min | Max | Average | Min | Max |
| Based on Consumption Data | | | | | | | | | |
| Welfare Changes | -10.5% | -45.9% | 18.6% | -7.4% | -86.4% | 39.0% | -13.5% | -28.3% | 8.4% |
| Due to Consumption | -3.7% | -43.2% | 19.5% | -7.4% | -86.4% | 39.0% | 0.0% | 0.0% | 0.0% |
| Mobility | -4.0% | -9.9% | -1.5% | -8.1% | -19.8% | -3.0% | 0.0% | 0.0% | 0.0% |
| Other Factors | 0.4% | -40.5% | 22.2% | 0.8% | -81.1% | 44.3% | 0.0% | 0.0% | 0.0% |
| Due to COVID-19 | -6.7% | -14.2% | -0.5% | 0.0% | 0.0% | 0.0% | -13.4% | -28.4% | -1.0% |
| Mobility | -7.4% | -10.8% | -1.3% | 0.0% | 0.0% | 0.0% | -14.7% | -21.6% | -2.6% |
| Other Factors | 0.6% | -6.1% | 9.2% | 0.0% | 0.0% | 0.0% | 1.3% | -12.2% | 18.3% |
| Based on Employment Data | | | | | | | | | |
| Welfare Changes | -13.1% | -37.5% | 1.8% | -10.6% | -31.9% | 8.3% | -15.6% | -78.3% | 5.1% |
| Due to Consumption | -5.3% | -15.9% | 4.1% | -10.6% | -31.9% | 8.3% | 0.0% | 0.0% | 0.0% |
| Mobility | -4.2% | -10.2% | -1.6% | -8.4% | -20.5% | -3.2% | 0.0% | 0.0% | 0.0% |
| Other Factors | -0.3% | -10.7% | 8.6% | -0.6% | -21.4% | 17.2% | 0.0% | 0.0% | 0.0% |
| Due to COVID-19 | -6.3% | -13.2% | -0.5% | 0.0% | 0.0% | 0.0% | -12.5% | -26.4% | -0.9% |
| Mobility | -6.9% | -10.1% | -1.2% | 0.0% | 0.0% | 0.0% | -13.7% | -20.1% | -2.4% |
| Other Factors | 0.6% | -5.7% | 8.5% | 0.0% | 0.0% | 0.0% | 1.2% | -11.4% | 17.1% |

Notes: The welfare changes represent the summary statistics of average, minimum and maximum across U.S. counties. For each county, the corresponding values are obtained by taking the average (across days) of welfare changes over the sample period.

## Table 3 – Robustness for Decomposition of Welfare Changes

| | Estimated $\beta$ | | | $\beta = 0.5$ in All Counties | | | $\beta = 1$ in All Counties | | |
|---|---|---|---|---|---|---|---|---|---|
| | Average | Min | Max | Average | Min | Max | Average | Min | Max |
| Based on Consumption Data | | | | | | | | | |
| Welfare Changes | -10.5% | -45.9% | 18.6% | -8.6% | -45.2% | 18.8% | -13.5% | -47.2% | 18.9% |
| Due to Consumption | -3.7% | -43.2% | 19.5% | -3.7% | -43.2% | 19.5% | -3.7% | -43.2% | 19.5% |
| Mobility | -4.0% | -9.9% | -1.5% | -4.0% | -9.9% | -1.5% | -4.0% | -9.9% | -1.5% |
| Other Factors | 0.4% | -40.5% | 22.2% | 0.4% | -40.5% | 22.2% | 0.4% | -40.5% | 22.2% |
| Due to COVID-19 | -6.7% | -14.2% | -0.5% | -4.9% | -10.3% | -0.4% | -9.7% | -20.5% | -0.7% |
| Mobility | -7.4% | -10.8% | -1.3% | -5.3% | -7.8% | -0.9% | -10.7% | -15.6% | -1.9% |
| Other Factors | 0.6% | -6.1% | 9.2% | 0.5% | -4.4% | 6.6% | 0.9% | -8.8% | 13.2% |
| Based on Employment Data | | | | | | | | | |
| Welfare Changes | -13.1% | -37.5% | 1.8% | -11.3% | -28.7% | 1.8% | -17.4% | -59.1% | 1.9% |
| Due to Consumption | -5.3% | -15.9% | 4.1% | -5.3% | -15.9% | 4.1% | -5.3% | -15.9% | 4.1% |
| Mobility | -4.2% | -10.2% | -1.6% | -4.2% | -10.2% | -1.6% | -4.2% | -10.2% | -1.6% |
| Other Factors | -0.3% | -10.7% | 8.6% | -0.3% | -10.7% | 8.6% | -0.3% | -10.7% | 8.6% |
| Due to COVID-19 | -6.3% | -13.2% | -0.5% | -4.9% | -10.3% | -0.4% | -9.7% | -20.5% | -0.7% |
| Mobility | -6.9% | -10.1% | -1.2% | -5.3% | -7.8% | -0.9% | -10.7% | -15.6% | -1.9% |
| Other Factors | 0.6% | -5.7% | 8.5% | 0.5% | -4.4% | 6.6% | 0.9% | -8.8% | 13.2% |

Notes: The welfare changes represent the summary statistics of average, minimum and maximum across U.S. counties. For each county, the corresponding values are obtained by taking the average (across days) of welfare changes over the sample period. Except for the special cases of $\beta$=0.5 and $\beta$=1, estimated coefficients from Table 1 and $\omega = 0.5$ has been used in these welfare calculations.

## Table 4 – Welfare Changes across U.S. Counties Based on Per Capita Income

| | Welfare Based on Consumption Data | Welfare Based on Employment Data |
|---|---|---|
| Less than $10,000 | 0.485*** | -0.00391 |
| | (0.0650) | (0.0513) |
| $10,000 to $14,999 | 0.858*** | 0.0880 |
| | (0.100) | (0.0772) |
| $15,000 to $24,999 | 0.561*** | 0.103* |
| | (0.0639) | (0.0463) |
| $25,000 to $34,999 | 0.641*** | 0.174** |
| | (0.0818) | (0.0569) |
| $35,000 to $49,999 | 0.605*** | 0.175** |
| | (0.0814) | (0.0535) |
| $50,000 to $74,999 | 0.207* | 0.261*** |
| | (0.0861) | (0.0582) |
| $75,000 to $99,999 | -0.342*** | 0.172* |
| | (0.0934) | (0.0740) |
| $100,000 to $149,999 | -0.386*** | -0.0720* |
| | (0.0469) | (0.0333) |
| $150,000 to $199,999 | -0.630*** | -0.164*** |
| | (0.0684) | (0.0436) |
| $200,000 or more | -0.469*** | -0.101*** |
| | (0.0471) | (0.0275) |

Notes: *, ** and *** represent significance at the 5%, 1% and 0.1% levels. The results are based on univariate regressions with a constant to avoid multicollinearity. Dependent variables are the average (across days) welfare changes in the U.S. counties calculated according to the estimated coefficients in Table 1.

## Table 5 – Welfare Changes across U.S. Counties Based on Race/Ethnicity

| | Welfare Based on Consumption Data | Welfare Based on Employment Data |
|---|---|---|
| Hispanic or Latino | -0.0854*** | -0.0217* |
| | (0.0135) | (0.00908) |
| White | 0.0378*** | 0.0273*** |
| | (0.00965) | (0.00635) |
| Black or African American | 0.0462** | -0.0157 |
| | (0.0142) | (0.0105) |
| American Indian and Alaska Native | -0.00409 | 0.0275 |
| | (0.0423) | (0.0359) |
| Asian | -0.424*** | -0.176*** |
| | (0.0511) | (0.0275) |

Notes: *, ** and *** represent significance at the 5%, 1% and 0.1% levels. The results are based on univariate regressions with a constant to avoid multicollinearity. Dependent variables are the average (across days) welfare changes in the U.S. counties calculated according to the estimated coefficients in Table 1.

## Table 6 – Welfare Changes across U.S. Counties Based on School Attendance

| | Welfare Based on Consumption Data | Welfare Based on Employment Data |
|---|---|---|
| Nursery School, Preschool | -0.212 | -0.0529 |
| | (0.135) | (0.107) |
| Kindergarten | 0.714*** | 0.409** |
| | (0.159) | (0.135) |
| Elementary School | 0.158*** | 0.113*** |
| | (0.0295) | (0.0212) |
| High School | 0.264*** | 0.173*** |
| | (0.0507) | (0.0367) |
| College or Graduate School | -0.0972*** | -0.0639*** |
| | (0.0180) | (0.0127) |

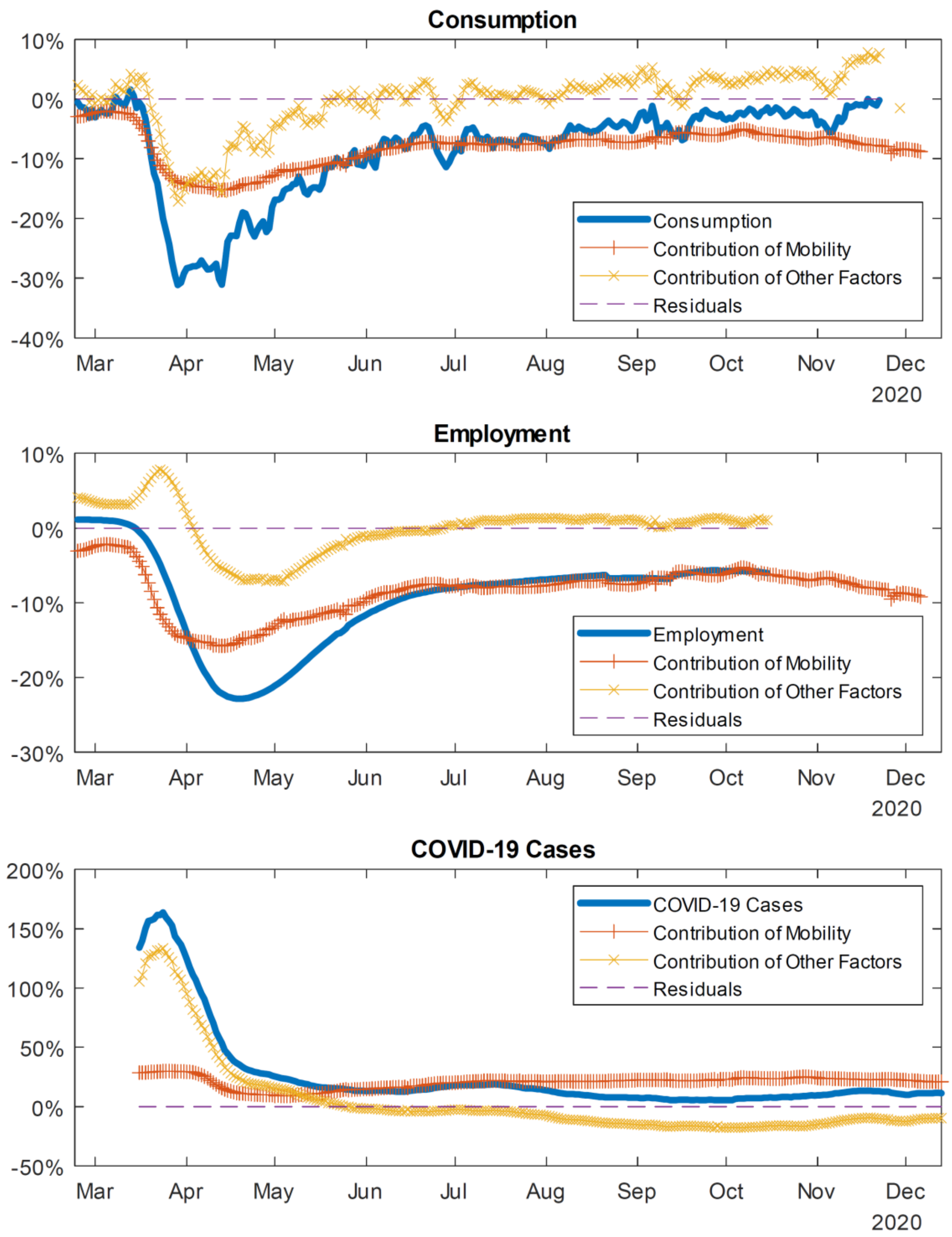
Notes: *, ** and *** represent significance at the 5%, 1% and 0.1% levels. The results are based on univariate regressions with a constant to avoid multicollinearity. Dependent variables are the average (across days) welfare changes in the U.S. counties calculated according to the estimated coefficients in Table 1.

## Table 7 – Welfare Changes across U.S. Counties Based on Educational Attainment

| | Welfare Based on Consumption Data | Welfare Based on Employment Data |
|---|---|---|
| Less than 9th Grade | 0.0409 | -0.0360 |
| | (0.0614) | (0.0438) |
| 9th to 12th Grade | 0.455*** | 0.160** |
| | (0.0614) | (0.0488) |
| High School Graduate | 0.237*** | 0.0514** |
| | (0.0246) | (0.0167) |
| Some College | 0.134** | 0.110*** |
| | (0.0505) | (0.0331) |
| Associate's Degree | -0.0127 | 0.0981 |
| | (0.0851) | (0.0597) |
| Bachelor's Degree | -0.318*** | -0.0705*** |
| | (0.0304) | (0.0205) |
| Graduate or Professional Degree | -0.325*** | -0.105*** |
| | (0.0369) | (0.0232) |

Notes: *, ** and *** represent significance at the 5%, 1% and 0.1% levels. The results are based on univariate regressions with a constant to avoid multicollinearity. Dependent variables are the average (across days) welfare changes in the U.S. counties calculated according to the estimated coefficients in Table 1.

## Figure 1 – Estimation Results




Notes: The figures represent the average measures across U.S. counties. The figures based on consumption, employment and COVID-19 cases are obtained by estimating Equations (12), (13) and (14), respectively.

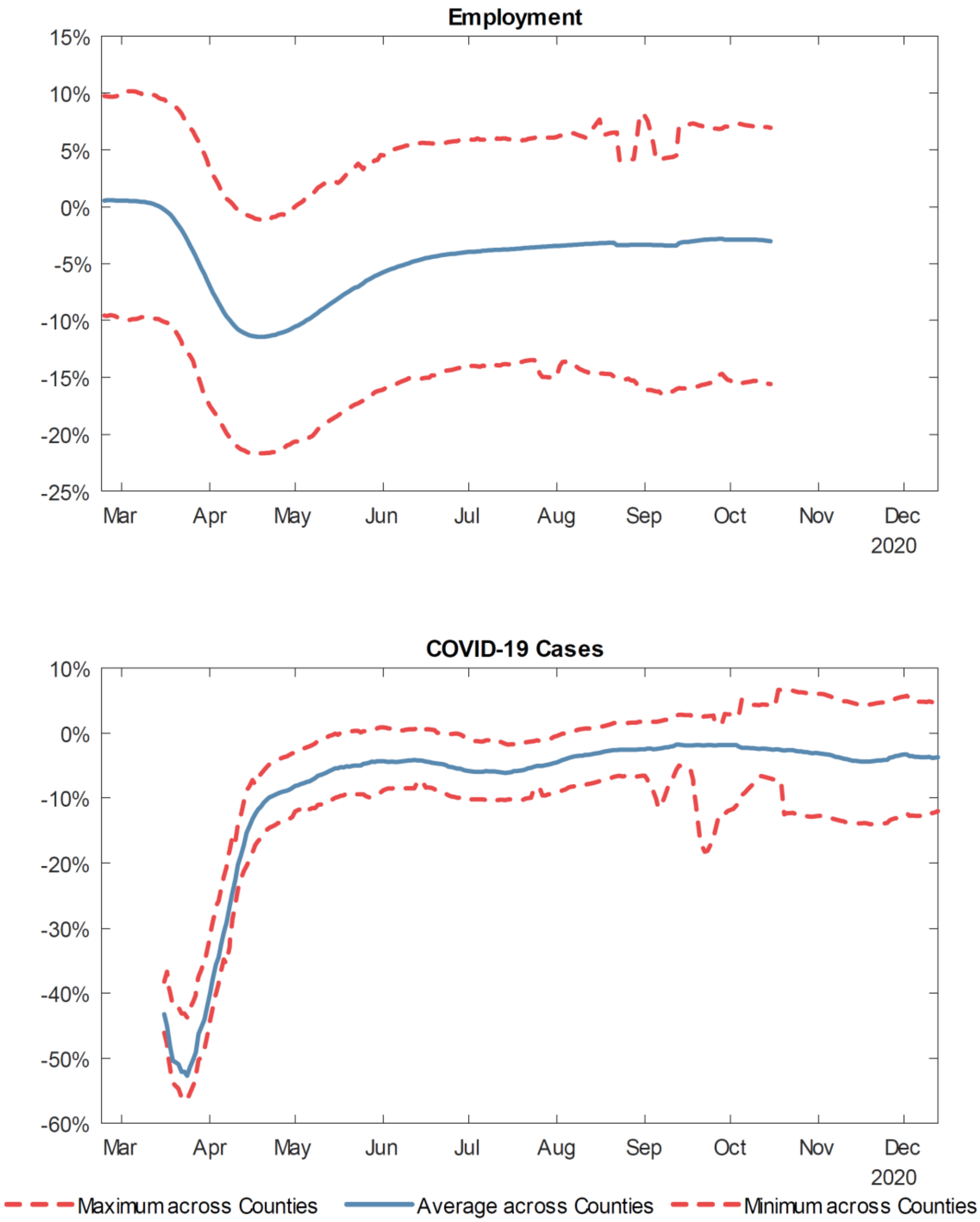
## Figure 2 – Welfare Changes across U.S. Counties


Notes: The figures summarize the distribution of welfare changes across U.S. counties. Welfare changes in each county are calculated according to Equation (8) based on the estimation results.

## Figure 3 – Welfare Changes due to Consumption versus COVID-19 across U.S. Counties

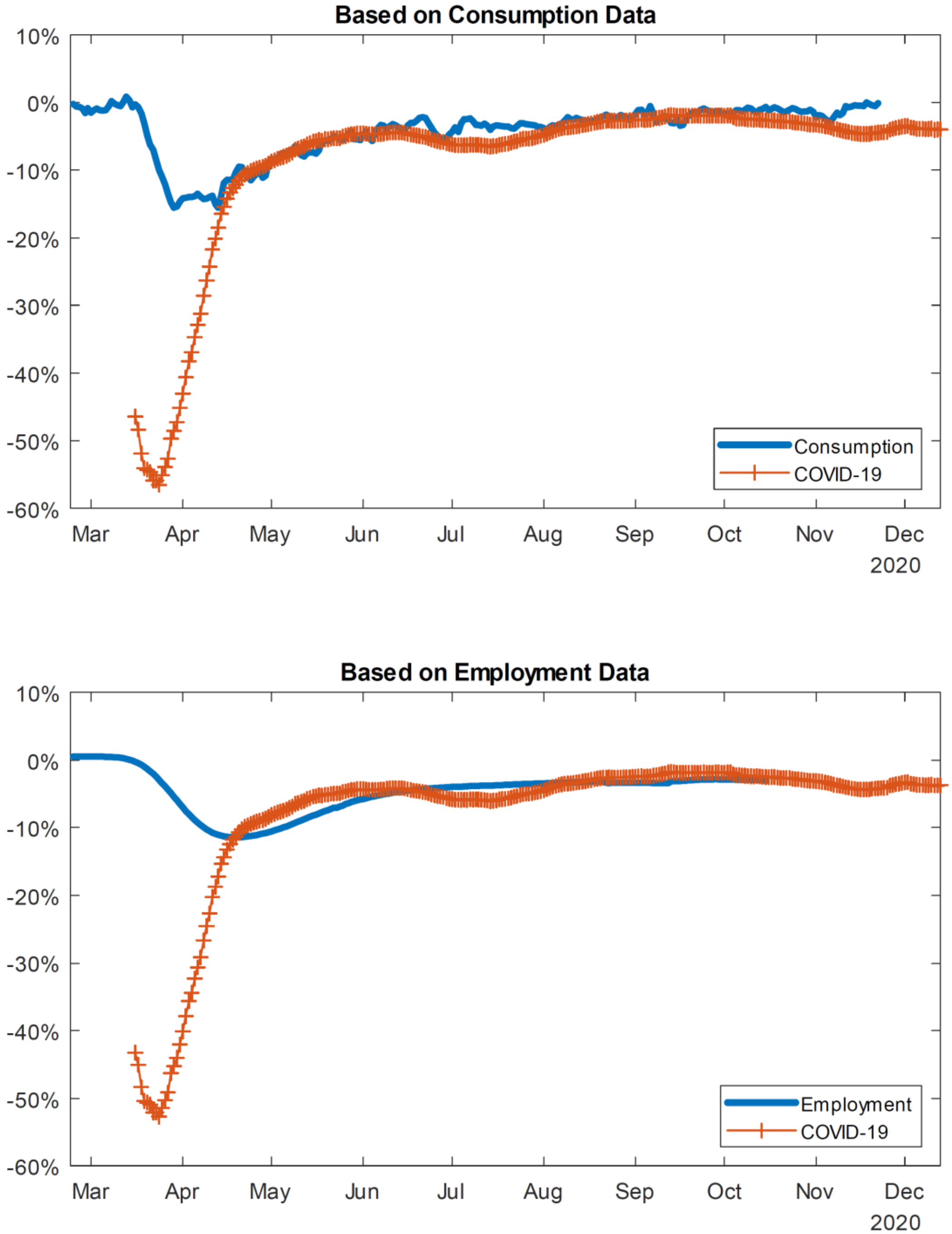

Notes: The figures summarize the distribution of welfare changes across U.S. counties. The decomposition of welfare changes due to consumption versus COVID-19 cases has been achieved according to Equation (11).

# Figure 4 – Welfare Changes due to Employment versus COVID-19 across U.S. Counties



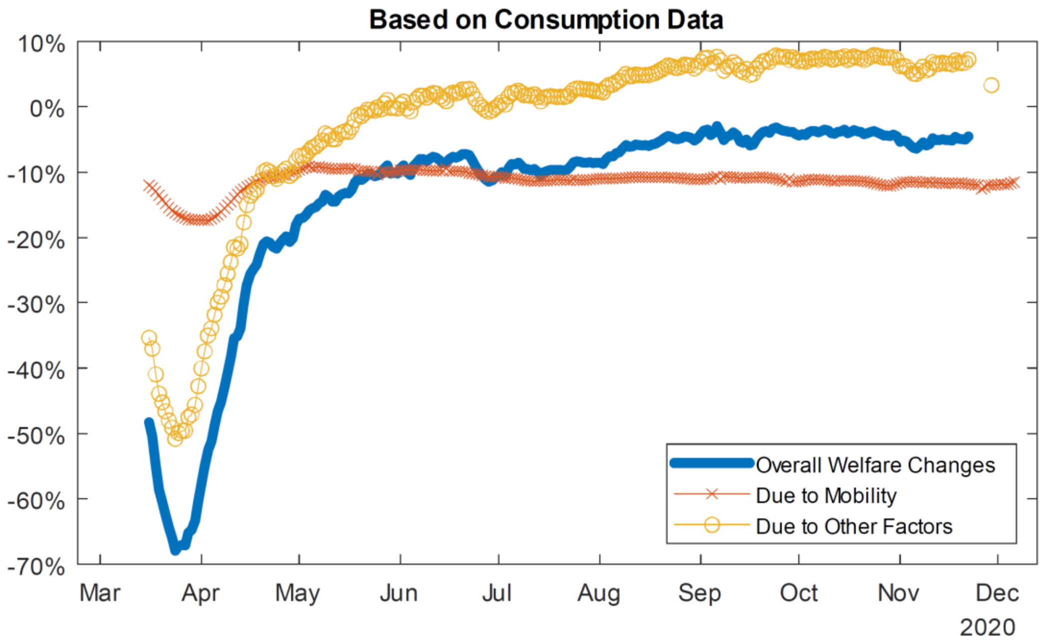

Notes: The figures summarize the distribution of welfare changes across U.S. counties. The decomposition of welfare changes due to employment versus COVID-19 cases has been achieved according to Equation (11).

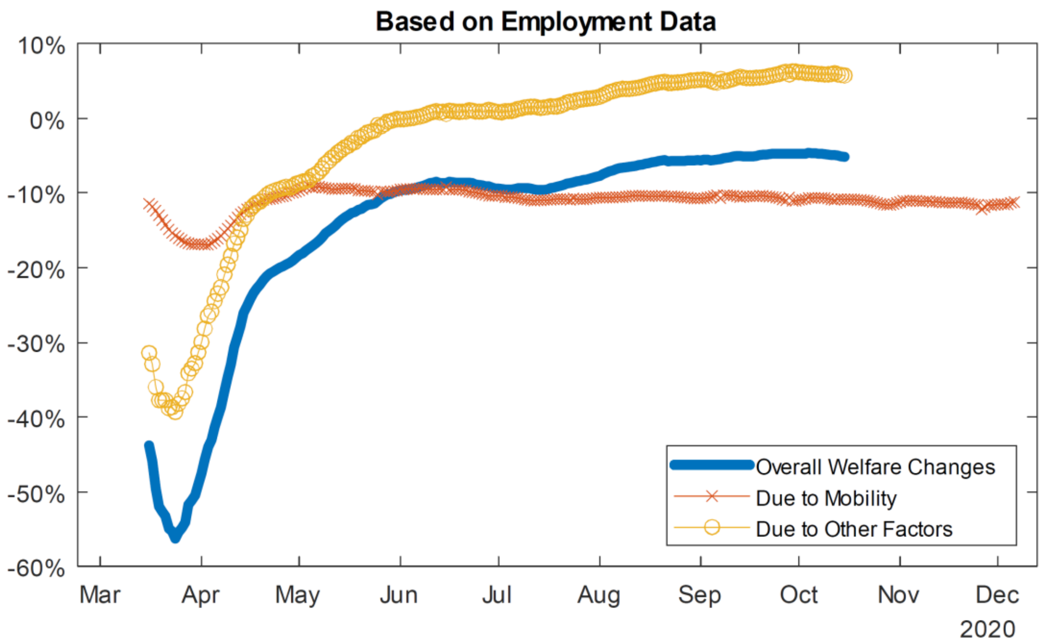
## Figure 5 – Welfare Changes due to Consumption or Employment versus COVID-19




Notes: The figures represent the average measures across U.S. counties. The decomposition of welfare changes due to consumption/employment versus COVID-19 cases has been achieved according to Equation (11).

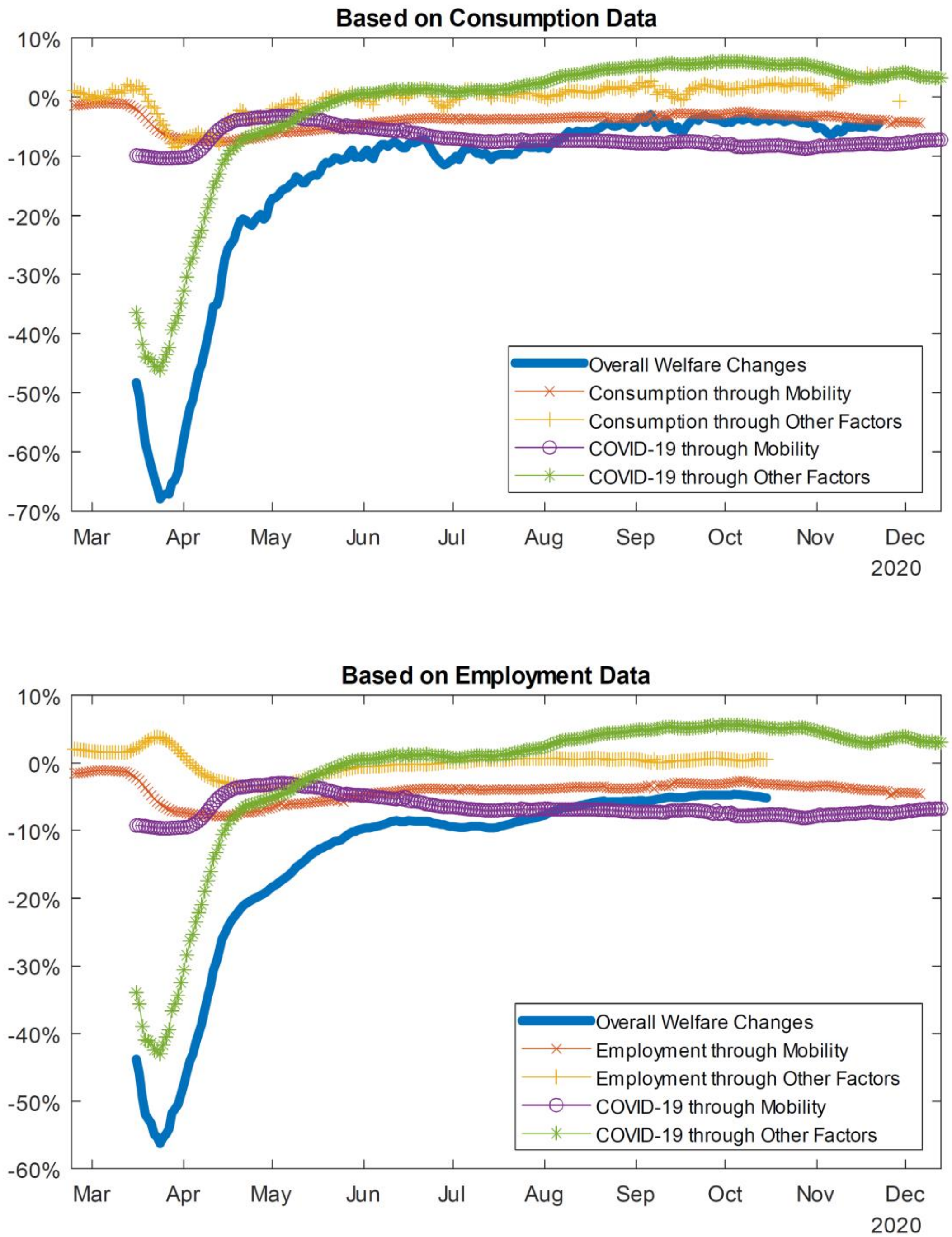
## Figure 6 – Welfare Changes due to Mobility versus Other Factors




Notes: The figures represent the average across U.S. counties. The decomposition of welfare changes due to mobility versus other factors has been achieved according to Equation (11).

# Figure 7 – Decomposition of Welfare Changes




Notes: The figures represent the average across U.S. counties. The decomposition of welfare changes has been achieved according to Equation (11).

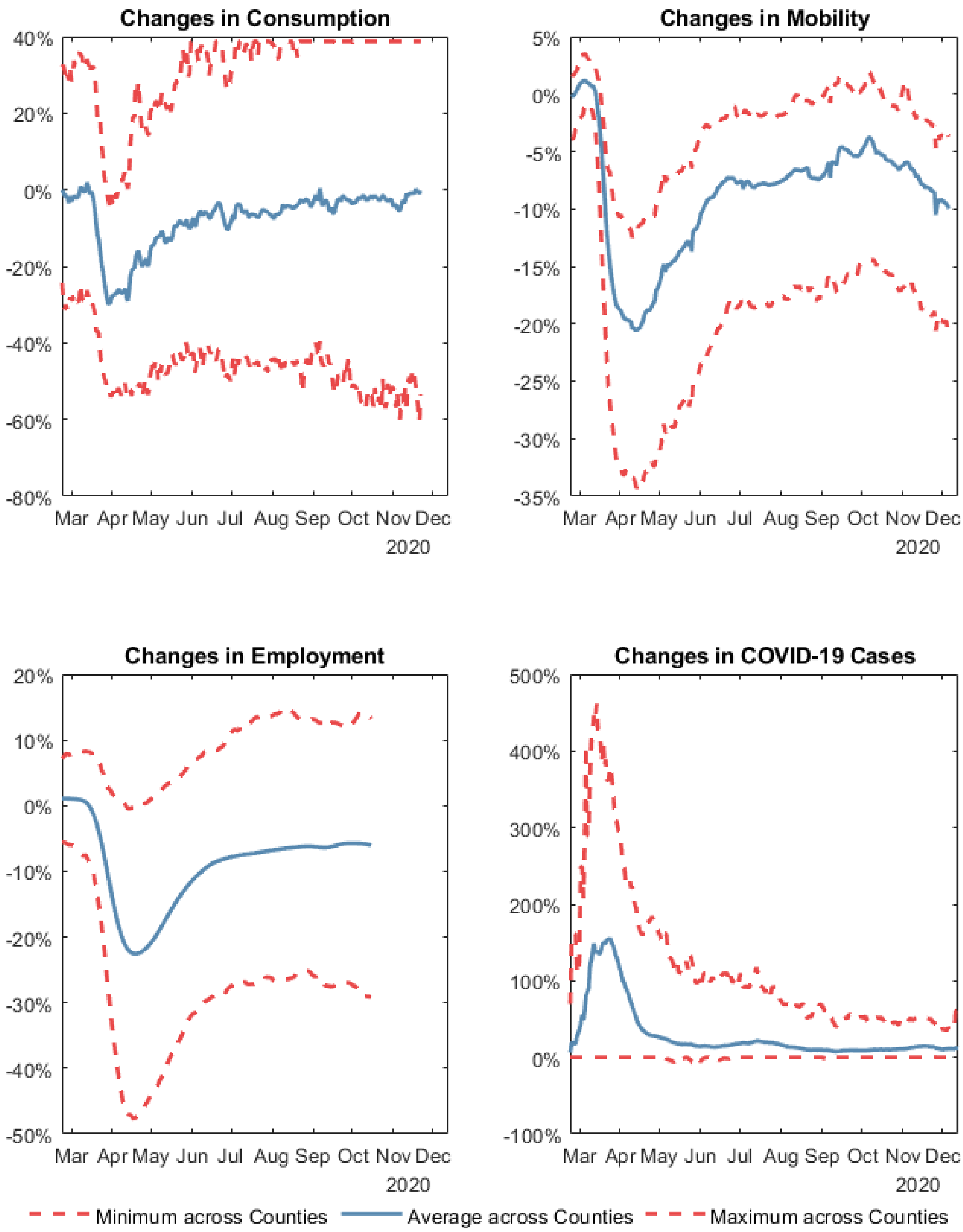
# Appendix Tables and Figures

## Table A.1 – Descriptive Statistics across U.S. Counties

| | Changes in: | | | |
|---|---|---|---|---|
| | Consumption | Mobility | Employment | COVID-19 Cases |
| Average | -6.60% | -7.72% | -7.74% | 18.66% |
| Minimum | -71.50% | -26.18% | -26.70% | 0.00% |
| 25th Percentile | -12.34% | -9.53% | -10.71% | 16.62% |
| Median | -6.62% | -7.21% | -7.62% | 18.59% |
| 75th Percentile | -0.63% | -5.46% | -4.59% | 20.61% |
| Maximum | 26.51% | 2.46% | 10.29% | 59.15% |

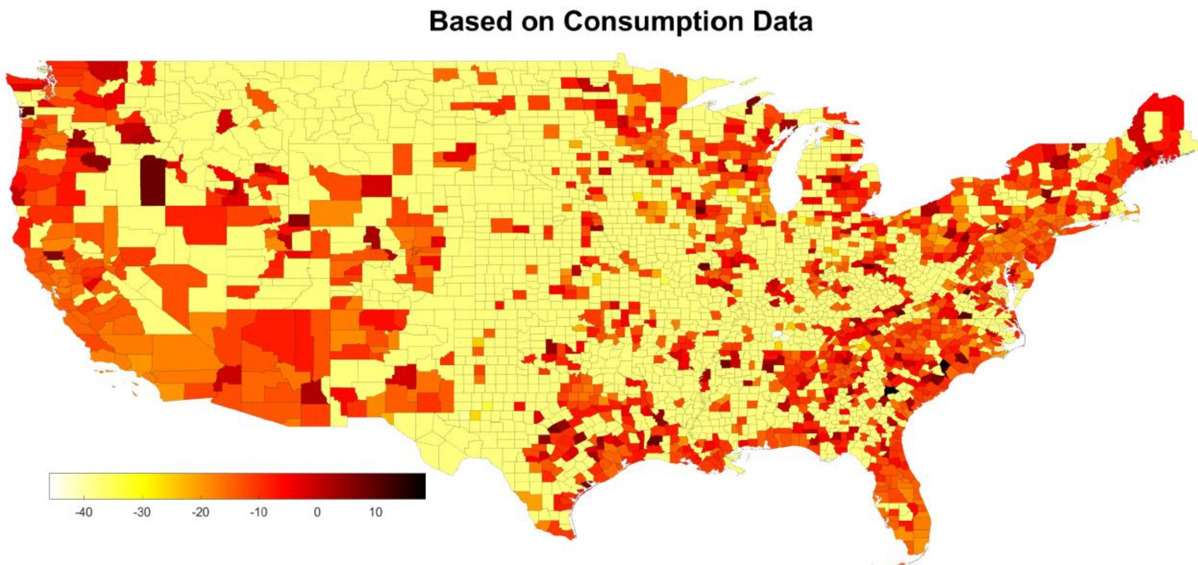
Notes: The values represent the summary statistics across U.S. counties. For each county, the corresponding values are obtained by taking the average (across days) of changes over the sample period.

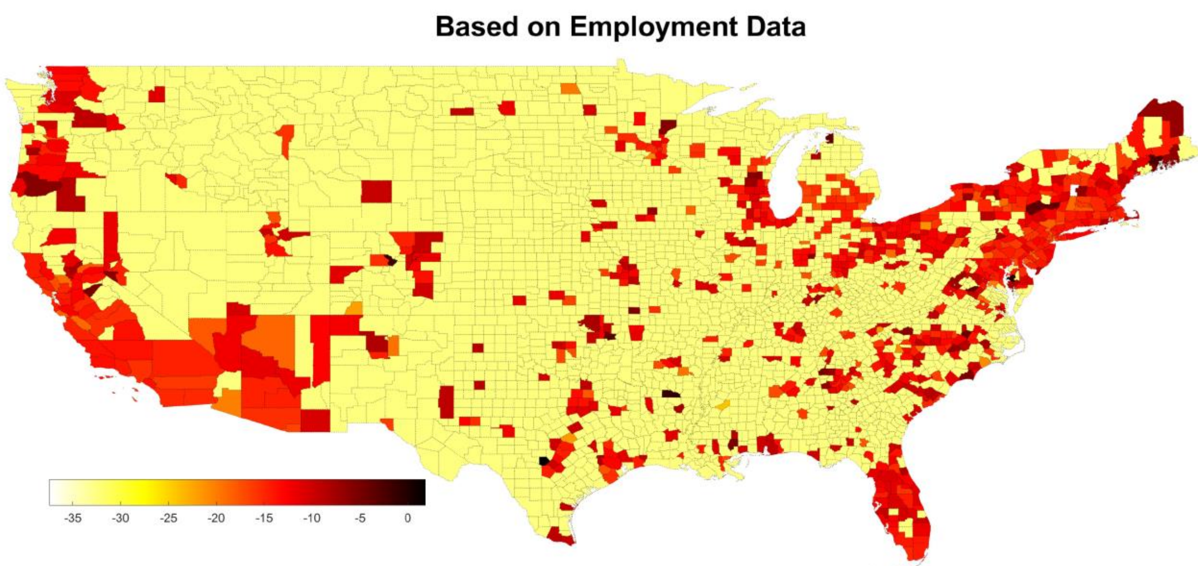
## Figure A.1 – Descriptive Statistics across U.S. Counties




Notes: The values represent % changes over time. The lines in figures represent the minimum, average and maximum across U.S. counties for each day.

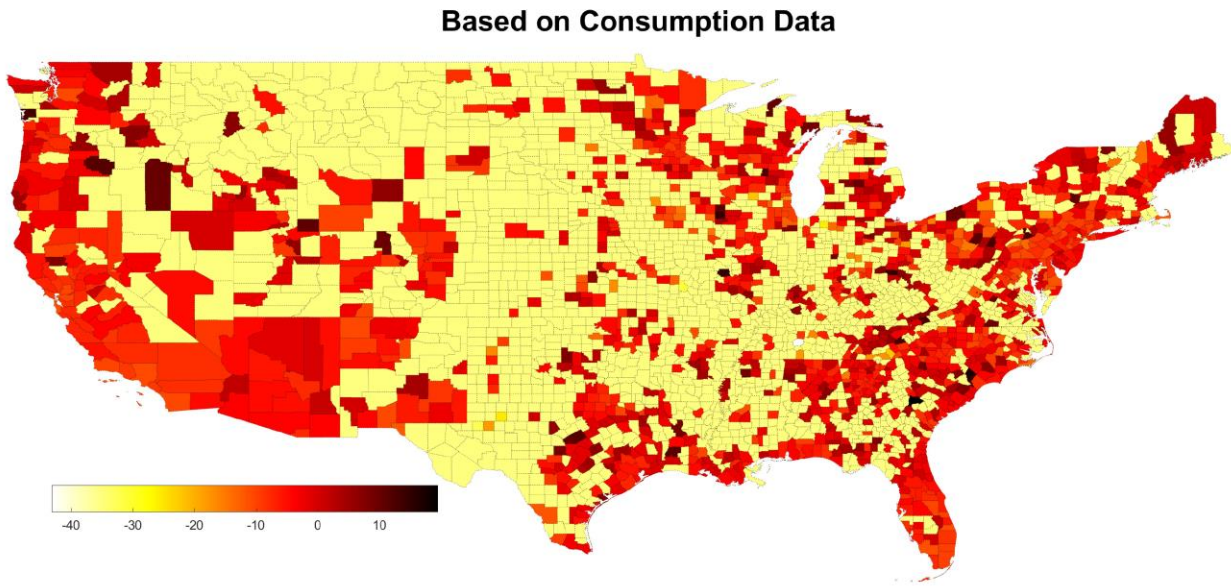
## Figure A.2 – Welfare Changes across U.S. Counties

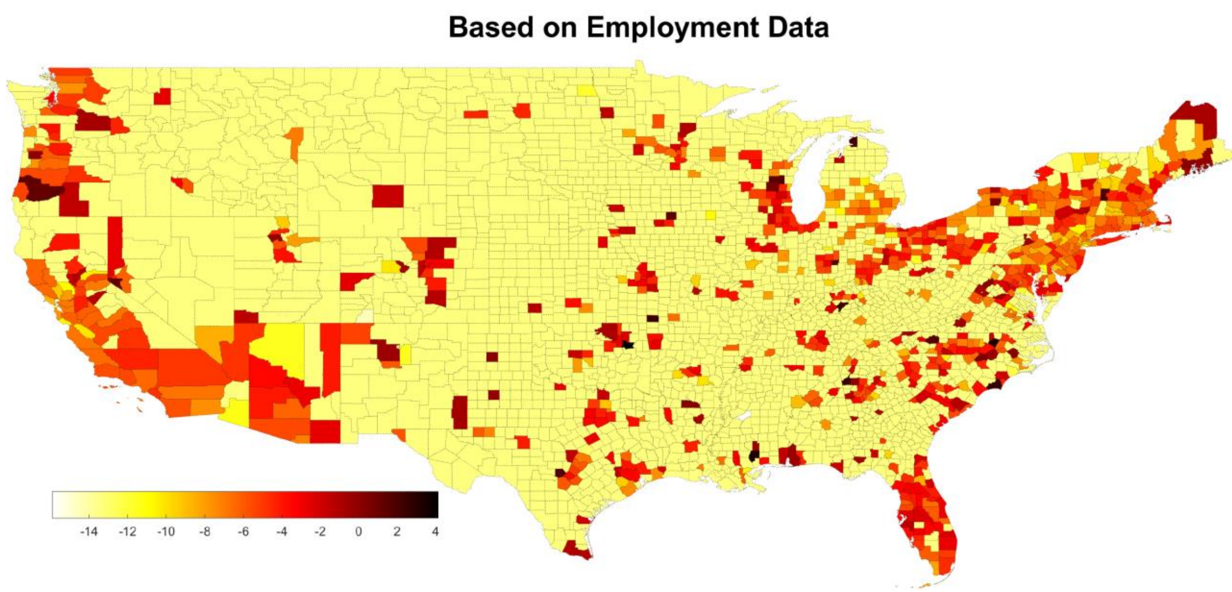



Notes: The values represent average % welfare changes across days.

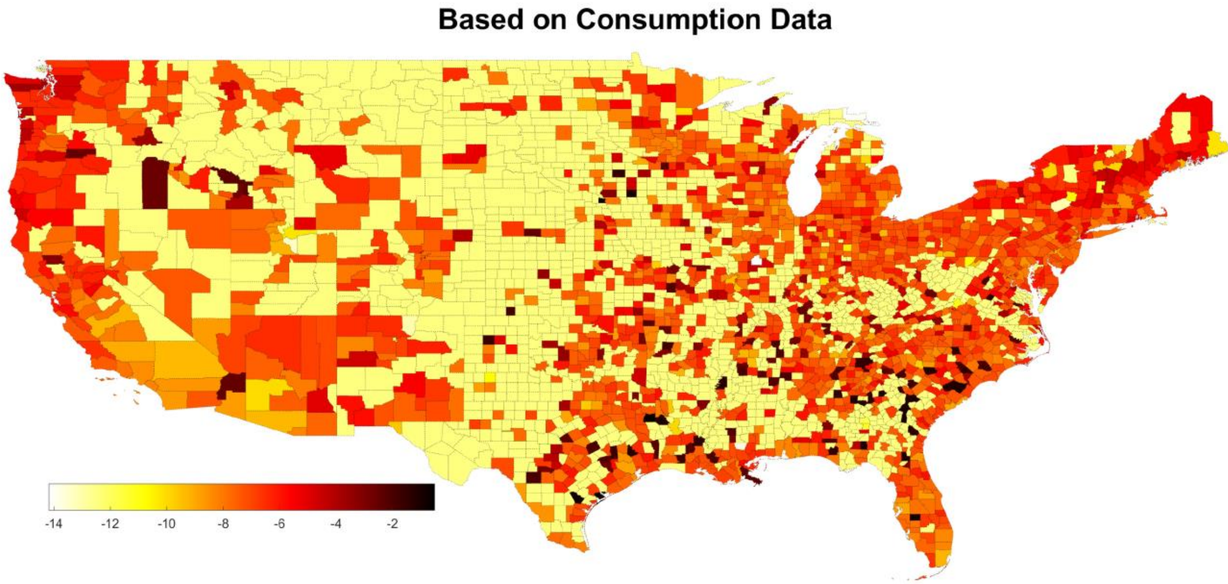
## Figure A.3 - Contribution of Consumption/Employment

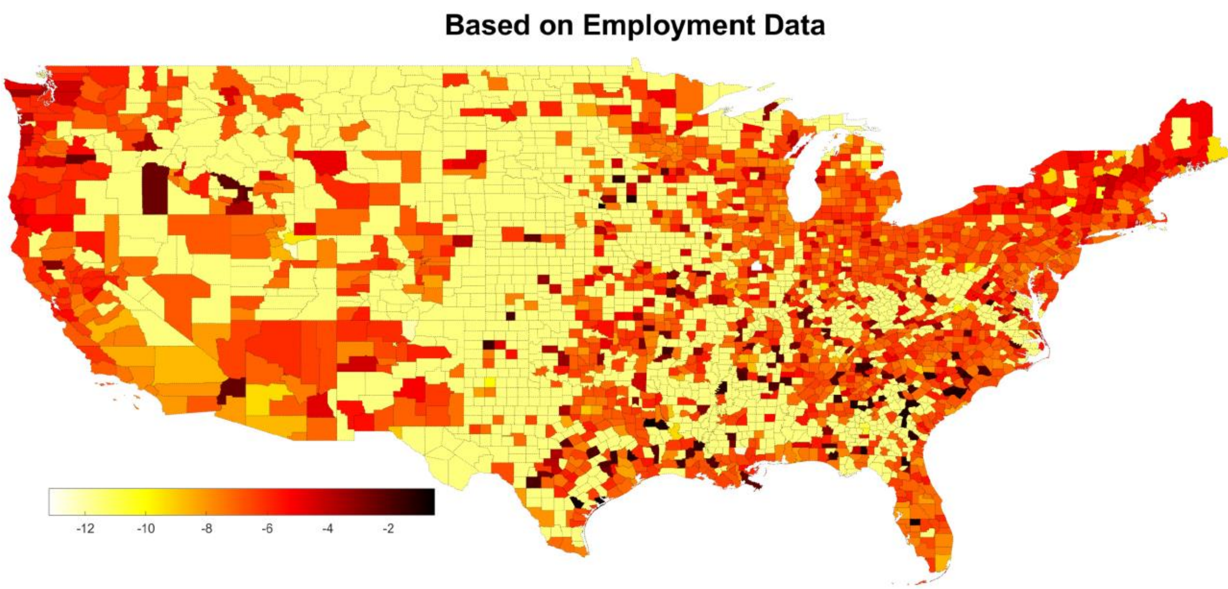



Notes: The values represent average % welfare changes across days.

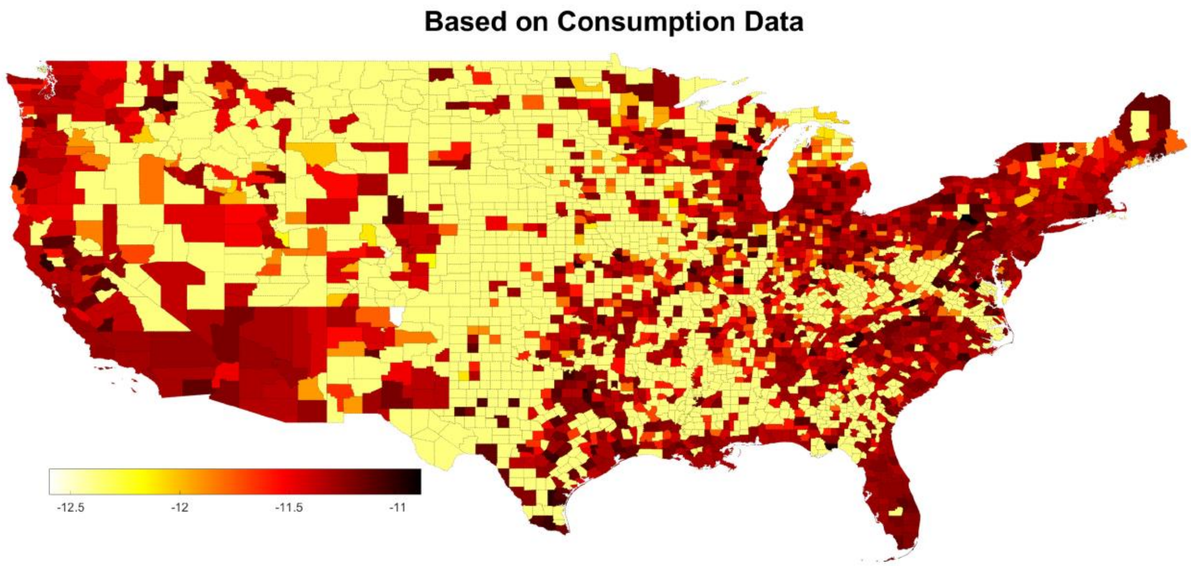
# Figure A.4 - Contribution of COVID-19 Cases

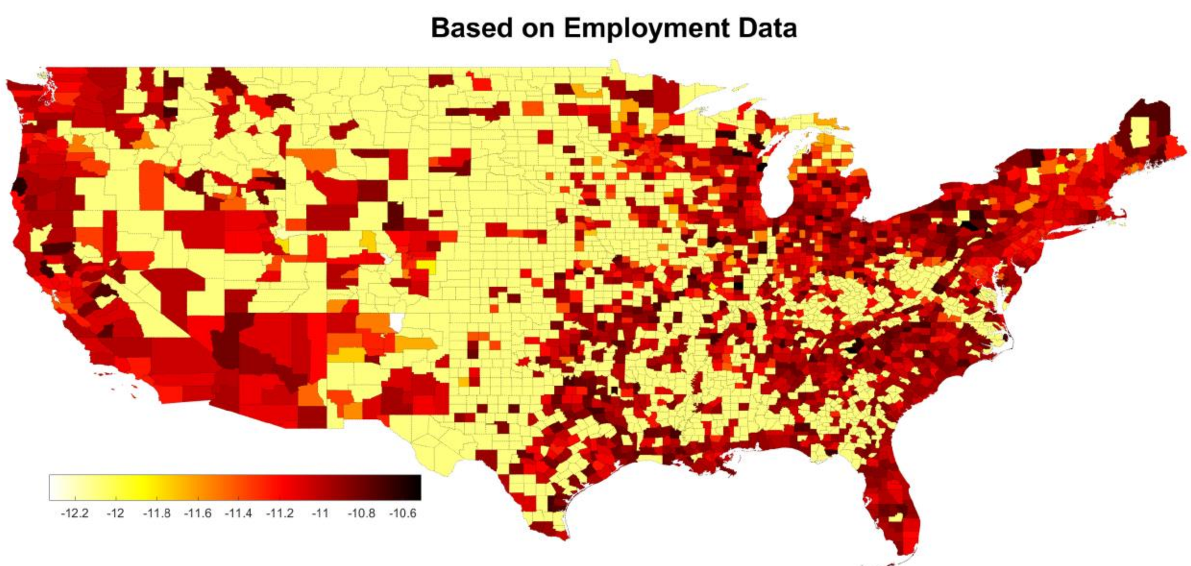



Notes: The values represent average % welfare changes across days.

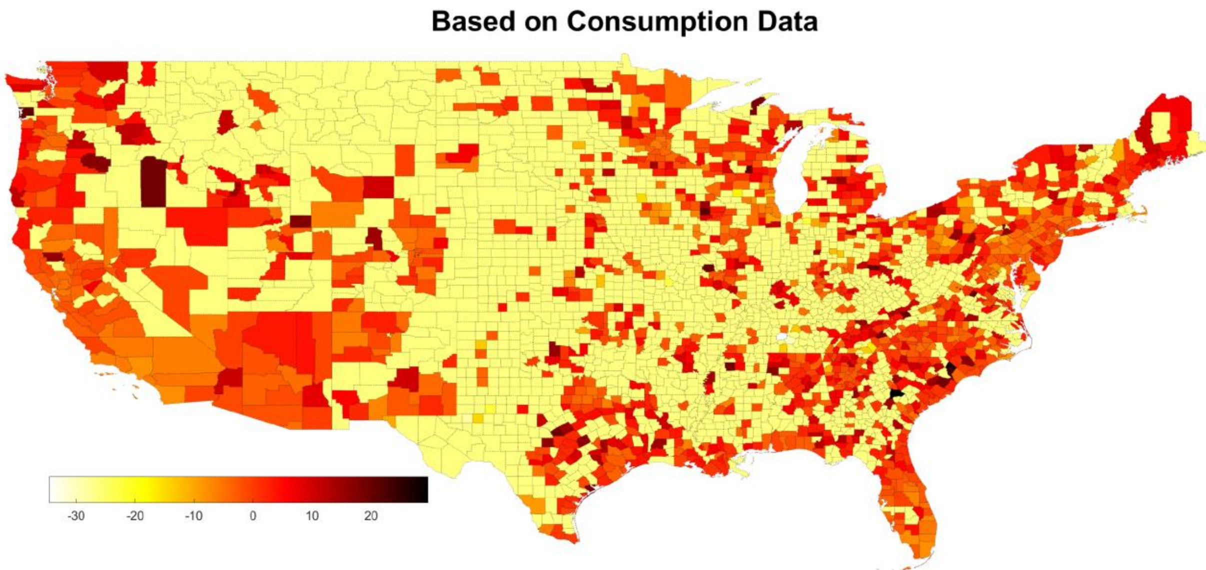
## Figure A.5 - Contribution of Mobility

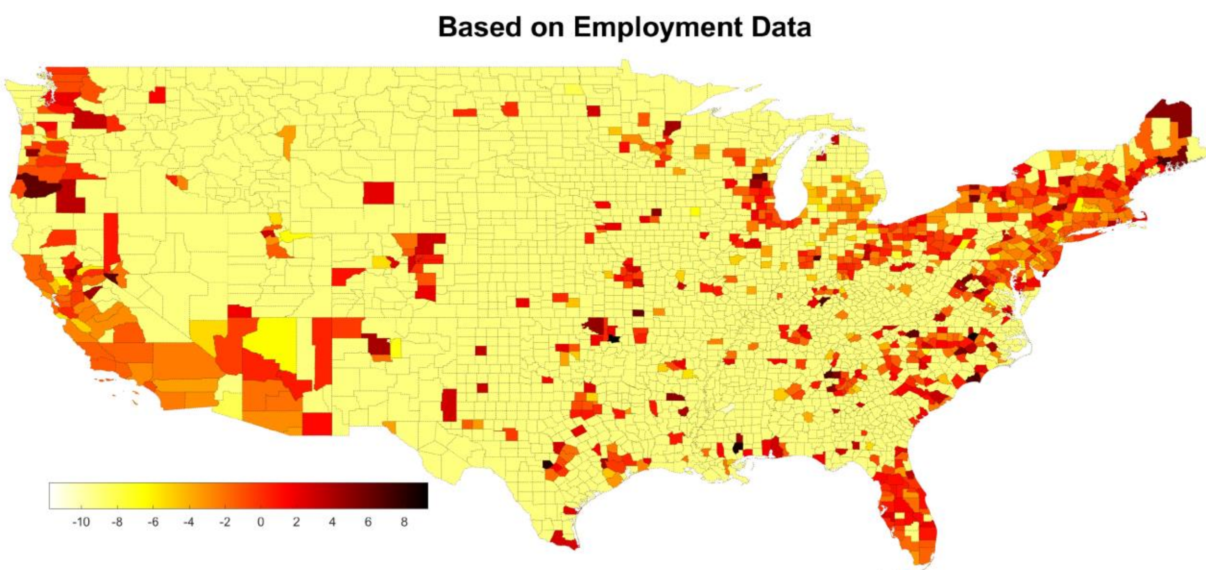



Notes: The values represent average % welfare changes across days.

# Figure A.6 - Contribution of Other Factors




Notes: The values represent average % welfare changes across days.