Unequal Welfare Costs of Staying at Home

across Socioeconomic and Demographic Groups

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Abstract

Using daily census block group level data from the U.S., this paper investigates the welfare costs of staying at home due to COVID-19 across socioeconomic and demographic groups. The investigation is based on an economic model of which implications suggest that the welfare costs of staying at home increase with the stay-at-home probabilities of individuals. The empirical results provide evidence for significant heterogeneity across census block groups regarding the welfare effects of staying at home. This heterogeneity is further used to obtain measures of welfare changes for different socioeconomic and demographic groups at the national level.

JEL Classification: I14, I31, R11, R13

Key Words: COVID-19, Coronavirus, Staying at Home, Welfare, Demographics

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1   Introduction

Staying at home is considered as one of the most effective ways to fight against COVID-19 (e.g., see Fowler, Hill, Obradovich, and Levin (2020) or Yilmazkuday (2020b)). Accordingly, several layers of government around the world have implemented lockdowns to mitigate the spread of COVID-19. Individuals have also reduced their mobility to protect themselves from COVID-19 in a voluntary way (e.g., see Maloney and Taskin (2020)). Despite its success in reducing the spread of COVID-19, staying at home has resulted in many individuals having economic and psychological problems. Moreover, as individuals belonging to different socioeconomic and demographic groups have access to different employment, consumption or health-related opportunities, they have stayed at home in different amounts of time during COVID-19 (e.g., see Yilmazkuday (2020a)), suggesting that they might have been affected differently from COVID-19.

This paper attempts to measure the welfare implications of staying at home across alternative socioeconomic and demographic groups. The investigation is achieved by using the implications of an economic model, where both direct and indirect welfare effects of COVID-19 are considered as suggested by Farboodi, Jarosch, and Shimer (2020). Specifically, the direct welfare effects are captured by the standard economic measures, namely the amount of consumption versus the amount of labor supplied, whereas the indirect welfare effects are captured by idiosyncratic benefits of being in another location (outside of home) versus the corresponding costs of mobility as in studies such as by Ahlfeldt, Redding, Sturm, and Wolf (2015), Monte, Redding, and Rossi-Hansberg (2018) or Heblich, Redding, and Sturm (2020). In this context, idiosyncratic benefits of being in another location capture the welfare effects of having social interactions as in studies such as by Farboodi, Jarosch, and Shimer (2020), whereas their absence captures the effects of mental distress, anxiety, worry, disinterest, depression, increased risks of suicide, domestic violence, obesity or poor general health

perception as 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), Ravindran and Shah (2020), Flanagan, Beyl, Fearnbach, Altazan, Martin, and Redman (2020), Agüero (2020) or Le and Nguyen (2020). The corresponding costs of mobility capture not only the standard measures of traffic or the opportunity cost of time but also the effects of COVID-19 (e.g., the probability of getting sick) that is essential to measure the welfare effects of COVID-19.

In equilibrium, the model implies that the overall welfare effects of COVID-19 (discussed so far) can be captured by the changes in stay-at-home probabilities of individuals. This implication is used to measure the daily welfare changes in the U.S. at the census block group level. The measurement of mobility is achieved by using SafeGraph cellphone location data for each census block group (220, 115 of them) for the daily period between January 1st and December 31st, 2020. The period between January 1st and February 29th, 2020 is considered as the pre-COVID-19 period, whereas the period between March 1st and December 31st, 2020 is considered as the COVID-19 period. The empirical results show that the median census block group has experienced a welfare loss of about 7.1% during the COVID-19 period. The corresponding nationwide welfare costs of COVID-19 (calculated as the weighted average across census block groups) is as much as 6.4%, with a daily average of about 2.1% during the sample period.

The empirical results also provide evidence for significant heterogeneity across census block groups regarding the welfare effects of staying at home due to COVID-19. This heterogeneity is further used to obtain measures of welfare changes for alternative socioeconomic and demographic groups at the national level, where the American Community Survey data on socioeconomic and demographic characteristics (at the census block group level) are used to aggregate across census block groups. The corresponding results based on race/ethnicity show that the average (across days) welfare costs have been experienced the most by the

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Asian population, followed by the Hispanic population, the white population, the black population, and the native population. The results based on education level suggest that the average (across days) welfare costs have been experienced by the master's degree holders, followed by bachelor's degree holders, doctorate degree holders, elementary school graduates, high school graduates, and middle school graduates. Finally the results also that the average (across days) welfare costs have increased by the income level of individuals.

The results can be explained by individuals belonging to different socioeconomic and demographic groups having access to different employment opportunities. Specifically, the heterogeneity in welfare changes due to COVID-19 based on race/ethnicity can be explained by the Hispanic and black populations not being able to work from home compared to the white or Asian populations. This is consistent with earlier studies such as by Gupta, Montenovo, Nguyen, Rojas, Schmutte, Simon, Weinberg, and Wing (2020) or Yasenov (2020) who have shown that the Hispanic and black populations were not able to work from home. This is reflected in welfare calculations of this paper as the white or Asian populations staying at home more compared to the Hispanic and black populations and thus experiencing higher welfare costs of COVID-19. Similarly, the heterogeneity in welfare changes due to COVID-19 based on education or income levels can also be explained by higher-educated or higher-income individuals being able to work from home as suggested in studies such as by Bick, Blandin, and Mertens (2020) or Dingel and Neiman (2020). This is reflected in welfare calculations of this paper as higher-educated or higher-income individuals staying at home more compared to lower-educated or lower-income individuals and thus having experiencing welfare costs of COVID-19.

There are only a few studies in the corresponding literature that investigate the welfare effects of COVID-19 in the U.S. economy. Among these, Coibion, Gorodnichenko, and Weber (2020) investigate the effects of COVID-19 on consumer spending and macroeconomic expectations across U.S. counties. In another study, Yilmazkuday (2020d) investigates the welfare

implications of COVID-19 by focusing on the trade-off between consumption and COVID-19 cases for U.S. counties. Another study is by Yilmazkuday (2020c) who has investigated the welfare effects of reduced inter-county travel of individuals due to COVID-19 by focusing on the time-varying effects of distance. In comparison to these studies that have mostly considered only direct welfare effects of COVID-19 for U.S. counties, this paper focuses on the welfare effects of staying at home at the census block group level that are further connected to welfare changes for different socioeconomic and demographic groups in the U.S., where both direct and indirect welfare effects of COVID-19 are considered as suggested by Farboodi, Jarosch, and Shimer (2020).

The rest of this paper is organized as follows. The next section introduces an economic model for motivational purposes. Section 3 discusses the implications of the model for welfare. Section 4 introduces the data and the empirical methodology. Section 5 depicts the empirical results, whereas Section 6 achieves a corresponding discussion Section 7 concludes. The Appendix contains the technical derivations of certain results in the main text.

2 Model

This section introduces a multi-location shopping model, where both direct and indirect welfare effects of COVID-19 are considered. The direct welfare effects are captured by the amount of consumption versus the amount of labor supplied, whereas the indirect welfare effects are captured by idiosyncratic benefits of being in another location versus the corresponding costs of mobility as in studies such as by Ahlfeldt, Redding, Sturm, and Wolf (2015), Monte, Redding, and Rossi-Hansberg (2018) or Heblich, Redding, and Sturm (2020). In this context, idiosyncratic benefits capture the welfare effects of having social interactions as in studies such as by Farboodi, Jarosch, and Shimer (2020), whereas their absence captures the effects of mental distress, anxiety, worry, disinterest, depression, increased risks of suicide,

domestic violence, obesity or poor general health perception as 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), Ravindran and Shah (2020), Flanagan, Beyl, Fearnbach, Altazan, Martin, and Redman (2020), Agüero (2020) or Le and Nguyen (2020). In the model, the costs of mobility can be considered as not only the standard costs of traffic or the opportunity cost of time but also the negative effects of COVID-19 (e.g., the probability of getting sick). In equilibrium, the fixed number of individuals of any location decide on where to shop based on these direct and indirect welfare effects, where they also consider the prices they face at the shopping location and the wage that they earn. Production is achieved at each shopping location by using labor only.

2.1 Individuals

An individual v living/working in location i and shopping at location n has the following utility function:

$$U_{inv} = \frac{b_{inv} C_{inv}}{\tau_{in} N_{iv}} \tag{1}$$

where b_{inv} is the idiosyncratic benefits of being at location n with respect to being at location i (e.g., being outside of home), C_{inv} is the amount of consumption at shopping location n, $\tau_{in} \geq 1$ represents the costs of shopping at location n due to mobility from i to n (including those related to COVID-19, such as getting the virus) in terms of utility, and N_{iv} is the amount of labor supply. Following studies such as by Ahlfeldt, Redding, Sturm, and Wolf (2015), Monte, Redding, and Rossi-Hansberg (2018) or Heblich, Redding, and Sturm (2020), the idiosyncratic benefit b_{inv} is drawn from an independent Fréchet distribution given by:

$$G_{in}(b) = e^{-B_{in} b^{-\theta}} \tag{2}$$

where the scale parameter $B_{in} > 0$ determines the average benefits of being at location n for any individual living/working in location i, and the shape parameter $\theta > 1$ controls the dispersion of benefits. Having an idiosyncratic benefit b_{inv} implies that individuals make different choices about their shopping locations when faced with the same prices.

The corresponding budget constraint for an individual v living/working in location i and shopping at location n is given by:

$$P_n C_{inv} = W_i N_{iv} \tag{3}$$

where P_n is the price per unit of C_{inv}, and W_i is the wage rate in location i. The maximization of Equation 1 with respect to Equation 3 results in:

$$C_{inv} = \frac{W_i N_{iv}}{P_n} \tag{4}$$

The corresponding indirect utility function for any individual i living/working in location i and shopping at location n is implied as follows:

$$U_{inv} = \frac{b_{inv} W_i}{\tau_{in} P_n} \tag{5}$$

which is a monotonic function of idiosyncratic benefits (b_{inv}'s) that have a Fréchet distribution. It is implied that the indirect utility of an individual living/working in location i from shopping at location n also has a Fréchet distribution as follows:

$$G_{in}(U) = e^{-\Psi_{in} U^{-\theta}} \tag{6}$$

where

$$\Psi_{in} = B_{in} (P_n \tau_{in})^{-\theta} (W_i)^{\theta} \tag{7}$$

Based on this distribution, the expected utility $\overline{U}_i$ of an individual living/working in location i is as follows:

$$\overline{U}_i = \left(\sum_s \Psi_{is} \right)^{\frac{1}{\theta}} \Gamma \left(1 - \frac{1}{\theta} \right) \tag{8}$$

where $\Gamma \left(\cdot \right)$ is the Gamma function. The technical details of this derivation are depicted in the Appendix.

2.2 Production

The unique firm in any location i achieves production Y_i according to the following production function:

$$Y_i = A_i L_i \tag{9}$$

where L_i is the amount of labor used, and A_i represents productivity. Perfectly competitive markets across locations imply the following price for the products sold at location i:

$$P_i = \frac{W_i}{A_i} \tag{10}$$

where prices increase with wages and reduce with productivity.

2.3 Shopping and Mobility

Each individual in any location i decides on where to shop to receive maximum utility. Using the fact that the maximum of Fréchet distributed random variables is also Fréchet distributed, the probability of any individual living/working in location i to shop at location n is as follows:

$$\lambda_{in} = \frac{B_{in} \left(P_n \tau_{in} \right)^{-\theta}}{\sum_s B_{is} \left(P_s \tau_{is} \right)^{-\theta}} \tag{11}$$

for which the corresponding derivation is depicted in the Appendix. It is implied that individuals in location i are more likely to shop at location n, the higher the popularity of shopping location n (measured by the average benefits of shopping at location n, B_{in}), the lower the prices (P_n) at location n, and the lower the costs of shopping at location n due to mobility (τ_{in}). When $i = n$, Equation 11 implies:

$$\lambda_{ii} = \frac{B_{ii} \left(P_i \tau_{ii}\right)^{-\theta}}{\sum_s B_{is} \left(P_s \tau_{is}\right)^{-\theta}} \tag{12}$$

where $B_{ii} = 1$ as the idiosyncratic benefits are defined with respect to the location of living/working. We consider Equation 12 as the probability of staying at home.

3 Implications for Welfare

We are interested in the changes in welfare due to staying at home during the COVID-19 period. We start with measuring the changes in welfare in each location i. We then continue with aggregating across locations based on the socioeconomic and demographic characteristics of locations; this results in having measures of welfare changes for individual groups in different socioeconomic and demographic characteristics at the national level.

3.1 Welfare Changes at the Location Level

The changes in welfare are calculated based on the expected utility given in Equation 8. First, using Equation 7, Equation 8 is rewritten as follows:

$$\overline{U}_i = W_i \left(\sum_s B_{is} \left(P_s \tau_{is}\right)^{-\theta}\right)^{\frac{1}{\theta}} \Gamma\left(1 - \frac{1}{\theta}\right) \tag{13}$$

Second, using Equation 12 results in:

$$\overline{U}_i = \left(\frac{1}{\lambda_{ii}}\right)^{\frac{1}{\theta}} \frac{W_i}{P_i \tau_{ii}} \Gamma\left(1 - \frac{1}{\theta}\right) \tag{14}$$

Third, using Equation 10, this expression can be rewritten as follows:

$$\overline{U}_i = \left(\frac{1}{\lambda_{ii}}\right)^{\frac{1}{\theta}} \frac{A_i}{\tau_{ii}} \Gamma\left(1 - \frac{1}{\theta}\right) \tag{15}$$

Finally, the percentage changes in welfare with respect to the pre-COVID-19 period is obtained as follows:

$$\widehat{\overline{U}}_i = -\frac{1}{\theta} \log\left(\frac{\lambda_{ii}}{\lambda_{ii}^{@}}\right) \tag{16}$$

where $\lambda_{ii}^{@}$ represents the probability of staying at home before the pre-COVID-19 period, and the variables of A_i and τ_{ii} are unchanged during the COVID-19 period. According to this expression, any individual staying more at home during the COVID-19 period has a reduction in welfare $\left(\text{i.e., } \frac{\partial \widehat{\overline{U}}_i}{\partial \lambda_{ii}} < 0\right)$. Therefore, subject to the knowledge of the shape parameter θ, data on stay-at-home probabilities (λ_{ii}'s) before and during COVID-19 are enough to calculate the welfare changes (with respect to the pre-COVID-19 period) at the location level.

3.2 Welfare Changes for Individual Groups at the National Level

The changes in welfare according to Equation 16 are the same for any individual living/working in location i, although these individuals may belong to alternative demographic groups (e.g., people from different ethnicities). It is implied that when an aggregation is achieved across locations for a particular demographic group, the changes in welfare for that demographic group depend on the number of individuals in each demographic group in each location.

Formally, the average welfare changes (across locations) for demographic group g can be calculated as follows:

$$\widehat{\overline{U}^g} = \frac{\sum_i R_i^g \widehat{\overline{U}}_i}{\sum_i R_i^g} = -\frac{1}{\theta} \sum_i \pi_i^g \log\left(\frac{\lambda_{ii}}{\lambda_{ii}^@}\right) \tag{17}$$

where the second equality is due to equation 16, and π_i^g is given by:

$$\pi_i^g = \frac{R_i^g}{\sum_i R_i^g} \tag{18}$$

with R_i^g representing the number of individuals belonging to demographic group G in location i. Hence, π_i^g is the share of individuals belonging to demographic group g who live/work in location i out of all individuals belonging to demographic group g in all locations at the national level.

According to Equation 17, the welfare changes of an average individual belonging to any demographic group g depend on the weighted average of probabilities of staying at home in all locations, where weights are π_i^g's. Therefore, subject to the knowledge of the shape parameter θ, data on stay-at-home probabilities (λ_{ii}'s) before and during COVID-19 as well as the weights of π_i^g's are enough to calculate the welfare changes (with respect to the pre-COVID-19 period) in each socioeconomic and demographic group at the national level.

4   Data and Empirical Methodology

The calculation of welfare changes in Equations 16 and 17 requires data on stay-at-home probabilities (λ_{ii}'s) before and during COVID-19, subject to the knowledge of the shape parameter θ. The calculation of welfare changes in Equation 17 also require data on socioeconomic and demographic characteristics. This section provides details about these data sets.

The investigation is achieved by using daily data at the census block group level $(220, 115$ of them) from the U.S. for the period between January 1st and December 31st, 2020. The period between January 1st and February 29th, 2020 is considered as the pre-COVID-19 period, whereas the period between March 1st and December 31st, 2020 is considered as the COVID-19 period.

The stay-at-home probabilities (λ_{ii}'s) at the census block group level are obtained from SafeGraph cellphone location data.[1] We use the daily median percentage of time spend at home as our measure of λ_{ii} for census block group i over the sample period. Seven-day moving averages of these measures are used to control for weekly seasonality. The corresponding descriptive statistics are given in Table 1 and Figure 1 (over time), where measures of λ_{ii}'s are depicted across census block groups. As is evident, people have stayed at home the most by late March and early April, 2020, when several layers of government implemented stay-at-home orders to fight against COVID-19; the maximum (across days) of the national median percentage of time spend at home is about 94.1% during the sample period. There is also evidence for heterogeneity across census block groups, suggesting that different census block groups have stayed at home for different amounts of time.

The information based on socioeconomic and demographic characteristics to calculate π_i^g's are obtained from the American Community Survey (2018) 5-year estimate on the census block group level.[2] Besides information on total population, we consider three categories, namely race/ethnicity, education level and income level. When the category of race/ethnicity is considered, we use data on the number of individuals who are White, Black, Native, Asian or Hispanic in each census block group that are further used to construct π_i^g's. When the category of education level is considered, we use data on the number of individuals having a degree from an elementary school, a middle school, a high school, a bachelor's program, a

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[1]The web page is https://www.safegraph.com/.
[2]The web page is https://www.census.gov/programs-surveys/acs.

master's program or a doctorate program in each census block group that are further used to construct π_i^g's. When the category of income level is considered, we use data on the number of individuals having an income level less than \$10,000, between \$10,000 and \$50,000, between \$50,000 and \$100,000 and more than \$100,000 in each census block group that are further used to construct π_i^g's.

For each census block group, since the period between January 1st and February 29th, 2020 is considered as the pre-COVID-19 period, $\lambda_{ii}^@$'s in Equations 16 and 17 are calculated as the average (across days) of the median percentage of time spend at home during this period. Similarly, as the period between March 1st and December 31st, 2020 is considered as the COVID-19 period, λ_{ii}'s in Equations 16 and 17 are the daily measures of median percentage of time spend at home during this period. Although the shape parameter θ is nothing more than a scale parameter (as it is the same across socioeconomic and demographic groups) in the calculation of welfare changes in Equations 16 and 17, for the sake of completeness, we borrow its value of $\theta = 3.3$ from Monte, Redding, and Rossi-Hansberg (2018) who have estimated θ using data on bilateral commuting flows in a similar framework.

5   Empirical Results

This section depicts the changes in welfare due to staying at home during the COVID-19 period (represented by the period between March 1st and December 31st, 2020) with respect to the average of the pre-COVID-19 period (represented by the period between January 1st and February 29th, 2020) according to Equations 16 and 17.

5.1   Welfare Changes at the Census Block Group Level

Welfare changes at the census block group level according to Equation 16 are summarized in Table 2 and Figure 2 (over time). As is evident, the welfare costs have taken their highest

values in late March and early April, 2020. Welfare changes at the national level have been as low as -6.4%, whereas the 10th and 90th percentiles of welfare changes across census block groups are -10% and -3.1%, respectively.

It is implied that there is a significant heterogeneity across census block groups regarding the welfare changes during the COVID-19 period. As different census block groups have different socioeconomic and demographic characteristics, we will use this heterogeneity to measure welfare changes for alternative individual groups at the national level next.

5.2   Welfare Changes Based on Race/Ethnicity

Welfare changes based on race/ethnicity at the national level according to Equation 17 are summarized in Table 3 and Figure 3 (over time). The highest (across days) welfare costs have been experienced in early May by the Asian population (7.5%), followed by the white population (6.5%), the Hispanic population (6%), the black population (5.6%) and the native population (4.2%).

It is implied that there is a significant heterogeneity based on race/ethnicity regarding the welfare changes during the COVID-19 period. This is also reflected in average (across days) welfare changes with respect to the pre-COVID-19 period, where the Asian population has experienced the highest welfare costs (3.5%), followed by the Hispanic population (2.6%), the white population (2.1%), and the black population (1.5%).

5.3   Welfare Changes Based on Education Level

Welfare changes based on education level at the national level according to Equation 17 are summarized in Table 4 and Figure 4 (over time). When the highest (across days) welfare costs are considered, they mostly increase with the education level. Specifically, the highest (across days) welfare costs have been experienced by doctorate degree holders (7.8%) in early May,

followed by master's degree holders (7.5%), bachelor's degree holders (7.3%), high school graduates (6.5%), elementary school graduates (6%), and middle school graduates (5.9%).

It is implied that there is a significant heterogeneity based on education level regarding the welfare changes during the COVID-19 period. This is also reflected in average (across days) welfare changes with respect to the pre-COVID-19 period, where master's degree holders have experienced the highest welfare costs (3.1%), followed by bachelor's degree holders (3%), doctorate degree holders (2.9%), elementary school graduates (2.4%), high school graduates (2.2%), and middle school graduates (1.7%).

5.4   Welfare Changes Based on Income Level

Welfare changes based on income level at the national level according to Equation 17 are summarized in Table 5 and Figure 5 (over time). When the highest (across days) welfare costs are considered, they mostly increase with the income level. Specifically, the highest (across days) welfare costs have been experienced by the population earning more than $100,000$ a year (7.5%), followed by the population earning between $50,000$ and $100,000$ a year (6.9%), the population earning between $10,000$ and $50,000$ a year (6.2%), and the population earning less than $10,000$ a year (5.5%).

It is implied that there is also a significant heterogeneity based on income level regarding the welfare changes during the COVID-19 period. This is also reflected in average (across days) welfare changes with respect to the pre-COVID-19 period, where by the population earning more than $100,000$ a year has experienced the highest welfare costs (3.5%), followed by the population earning between $50,000$ and $100,000$ a year (2.5%), the population earning between $10,000$ and $50,000$ a year (2%), and the population earning less than $10,000$ a year (1.6%).

6 Discussion of Results

This section discusses the economic intuition behind the empirical results by connecting them to the existing literature.

The heterogeneity in welfare changes due to COVID-19 based on race/ethnicity can be explained by the Hispanic and black populations not being able to work from home compared to the white or Asian populations. In the corresponding literature, this is consistent with earlier studies such as by Gupta, Montenovo, Nguyen, Rojas, Schmutte, Simon, Weinberg, and Wing (2020) or Yasenov (2020) who have shown that the Hispanic and black populations were not able to work from home. This is reflected in welfare calculations of this paper as the white or Asian populations staying at home more compared to the Hispanic and black populations and thus experiencing higher welfare costs of COVID-19.

The heterogeneity in welfare changes due to COVID-19 based on education or income levels can also be explained by higher-educated or higher-income individuals being able to work from home as suggested in studies such as by Bick, Blandin, and Mertens (2020) or Dingel and Neiman (2020). This is reflected in welfare calculations of this paper as higher-educated or higher-income individuals staying at home more compared to lower-educated or lower-income individuals and thus having experiencing welfare costs of COVID-19.

7 Conclusion

This paper has investigated the welfare implications of staying at home across socioeconomic and demographic groups within the U.S. at the census block group level. The daily investigation has been motivated by an economic model, where individuals get utility out of consumption and idiosyncratic benefits of being in another location. The individuals also get disutility out of supplying labor and mobility, where the latter also captures the negative

effects of COVID-19 (e.g., the probability of getting sick). In equilibrium, the model implies that the overall welfare effects of COVID-19 can be captured by the changes in stay-at-home probabilities of individuals, which are used to measure the daily welfare changes in the U.S. at the census block group level.

The empirical results provide evidence for significant heterogeneity across census block groups regarding the welfare effects of staying at home due to COVID-19. This heterogeneity is further used to obtain measures of welfare changes for alternative socioeconomic and demographic groups at the national level, where socioeconomic and demographic characteristics (at the census block group level) are used to aggregate across census block groups. The corresponding results based on race/ethnicity show that the average (across days) welfare costs have been experienced the most by the Asian population, followed by the Hispanic population, the white population, the black population, and the native population. The results based on education level suggest that the average (across days) welfare costs have been experienced by the master's degree holders, followed by bachelor's degree holders, doctorate degree holders, elementary school graduates, high school graduates, and middle school graduates. Finally the results also that the average (across days) welfare costs have increased by the income level of individuals. These results can be connected to individuals belonging to different socioeconomic and demographic groups having access to different employment opportunities.

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8 Appendix

This section contains the technical derivations of certain results in the main text.

8.1 Derivation of the Expected Utility

The number of individuals living/working in each location is fixed. Each individual living/working in any location chooses the shopping location that offers the maximum utility. Since the maximum of a sequence of Fréchet distributed random variables is itself Fréchet distributed, the distribution of utility for individuals living/working in location i across all possible shopping locations is as follows:

$$1 - G_i(u) = 1 - \prod_s e^{-\Psi_{is} u^{-\theta}} \tag{19}$$

where the left hand side is the probability that an individual of location i gets a utility higher than u, and the right hand side is one minus the probability that the individual of location i has utility less than u for all possible shopping locations. It is implied that:

$$G_i(u) = e^{-\Psi_i u^{-\theta}} \tag{20}$$

where

$$\Psi_i = \sum_s \Psi_{is} \tag{21}$$

Given this Fréchet distribution for utility in location i, the expected utility $\overline{U}_i$ in location i is implied as:

$$\overline{U}_i = \int\limits_0^\infty \theta \Psi_i u^{-\theta} e^{-\Psi_i u^{-\theta}} du \tag{22}$$

Defining the following change of variables:

$$y = \Psi_i u^{-\theta} \tag{23}$$

and

$$dy = \theta e^{-\Psi_i u^{-(\theta+1)}} \tag{24}$$

the expected utility can be rewritten as follows:

$$\overline{U}_i = \int\limits_0^\infty (\Psi_i)^{\frac{1}{\theta}} y^{-\frac{1}{\theta}} e^{-y} du \tag{25}$$

which is:

$$\overline{U}_i = (\Psi_i)^{\frac{1}{\theta}} \Gamma \left(1 - \frac{1}{\theta} \right) \tag{26}$$

Using $\Psi_i = \sum_s \Psi_{is}$, it is finally implied that:

$$\overline{U}_i = \left(\sum_s \Psi_{is} \right)^{\frac{1}{\theta}} \Gamma \left(1 - \frac{1}{\theta} \right) \tag{27}$$

which is the expression for expected utility in the main text.

8.2   Derivation of Shopping-Location Probabilities

The probability that an individual in location i chooses to shop at location n out of all possible shopping locations is as follows:

$$\lambda_{in} = \Pr\left[u_{in} \geq \max\left\{u_{is}\right\}; \forall s\right] \tag{28}$$

$$= \int_0^\infty \prod_{s \neq n} G_{is}\left(u\right) dG_{in}\left(u\right)$$

$$= \int_0^\infty \prod_s \theta\Psi_{in} u^{-(\theta+1)} e^{-\Psi_{is} u^{-\theta}} du$$

$$= \int_0^\infty \theta\Psi_{in} u^{-(\theta+1)} e^{-\Psi_i u^{-\theta}} du$$

Since we have:

$$\frac{d}{du}\left[-\frac{1}{\Psi_i} e^{-\Psi_i u^{-\theta}}\right] = \theta u^{-(\theta+1)} e^{-\Psi_i u^{-\theta}} \tag{29}$$

it is implied that:

$$\lambda_{in} = \frac{\Psi_{in}}{\Psi_i} = \frac{B_{in}\left(P_n \tau_{in}\right)^{-\theta}\left(W_i\right)^\theta}{\sum_s B_{is}\left(P_n \tau_{is}\right)^{-\theta}\left(W_i\right)^\theta} = \frac{B_{in}\left(P_n \tau_{in}\right)^{-\theta}}{\sum_s B_{is}\left(P_s \tau_{is}\right)^{-\theta}} \tag{30}$$

where the last expression, which is the same as in in the main text, has been obtained after $\left(W_i\right)^\theta$'s have been effectively eliminated.

Table 1 - Percentage of Time Spend at Home

	Maximum	Average	Median
National	94.1%	82.8%	83.1%
Census Block Groups			
10th Percentile	84.9%	69.9%	69.3%
25th Percentile	93.0%	77.9%	76.9%
50th Percentile	98.0%	85.0%	84.6%
75th Percentile	99.6%	90.6%	91.1%
90th Percentile	100.0%	94.5%	95.7%

Notes: National is the weighted average across census block groups, where weights are population levels. Percentiles represent those across census block groups. The maximum, average and median represent those of the period between January 1st and December 31st, 2020.

Table 2 - Welfare Changes across Census Block Groups

	Minimum	Average	Median
National	−6.4%	−2.1%	−2.2%
Census Block Groups			
10th Percentile	−10.0%	−7.4%	−7.5%
25th Percentile	−8.5%	−5.5%	−5.5%
50th Percentile	−7.1%	−3.5%	−3.2%
75th Percentile	−5.3%	−1.2%	−0.8%
90th Percentile	−3.1%	2.1%	2.5%

Notes: Welfare changes are with respect to the period between January 1st and February 29th, 2020. Percentiles represent those across census block groups. The minimum, average and median represent those of the period between March 1st and December 31st, 2020. National is the weighted average across census block groups, where weights are population levels.

Table 3 - Welfare Changes Based on Race/Ethnicity

|	Minimum	Average	Median
National	−6.4%	−2.1%	−2.2%
Race/Ethnicity			
White	−6.5%	−2.1%	−2.2%
Black	−5.6%	−1.5%	−1.6%
Native	−4.2%	0.2%	−0.3%
Asian	−7.5%	−3.5%	−3.9%
Hispanic	−6.0%	−2.6%	−2.5%

Notes: Welfare changes are with respect to the period between January 1st and February 29th, 2020. The minimum, average and median represent those of the period between March 1st and December 31st, 2020. National is the weighted average across census block groups, where weights are population levels.

Table 4 - Welfare Changes Based on Education Level

|	Minimum	Average	Median
National	-6.4%	-2.1%	-2.2%
Education Level			
Elementary School	-6.0%	-2.4%	-2.1%
Middle School	-5.9%	-1.7%	-1.8%
High School	-6.5%	-2.2%	-2.3%
Bachelor's Degree	-7.3%	-3.0%	-3.2%
Master's Degree	-7.5%	-3.1%	-3.3%
Doctorate Degree	-7.8%	-2.9%	-3.3%

Notes: Welfare changes are with respect to the period between January 1st and February 29th, 2020. The minimum, average and median represent those of the period between March 1st and December 31st, 2020. National is the weighted average across census block groups, where weights are population levels.

Table 5 - Welfare Changes Based on Income

	Minimum	Average	Median
National	−6.4%	−2.1%	−2.2%
Income Level			
Less than $10,000	−5.5%	−1.6%	−1.5%
Between $10,000 and $50,000	−6.2%	−2.0%	−1.9%
Between $50,000 and $100,000	−6.9%	−2.5%	−2.7%
More than $100,000	−7.5%	−3.5%	−3.7%

Notes: Welfare changes are with respect to the period between January 1st and February 29th, 2020. The minimum, average and median represent those of the period between March 1st and December 31st, 2020. National is the weighted average across census block groups, where weights are population levels.

Figure 1 - Percentage of Time Spend at Home across Census Block Groups
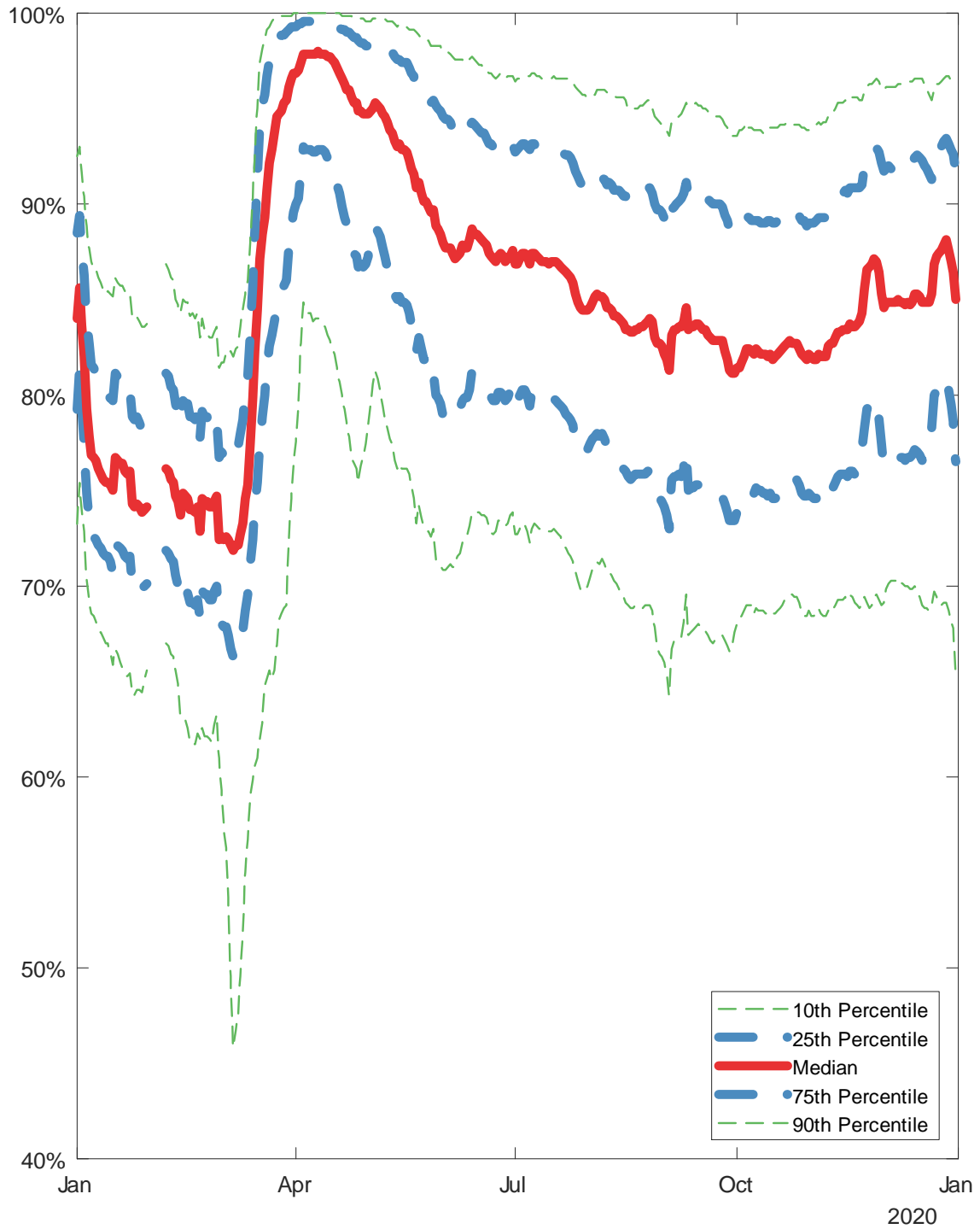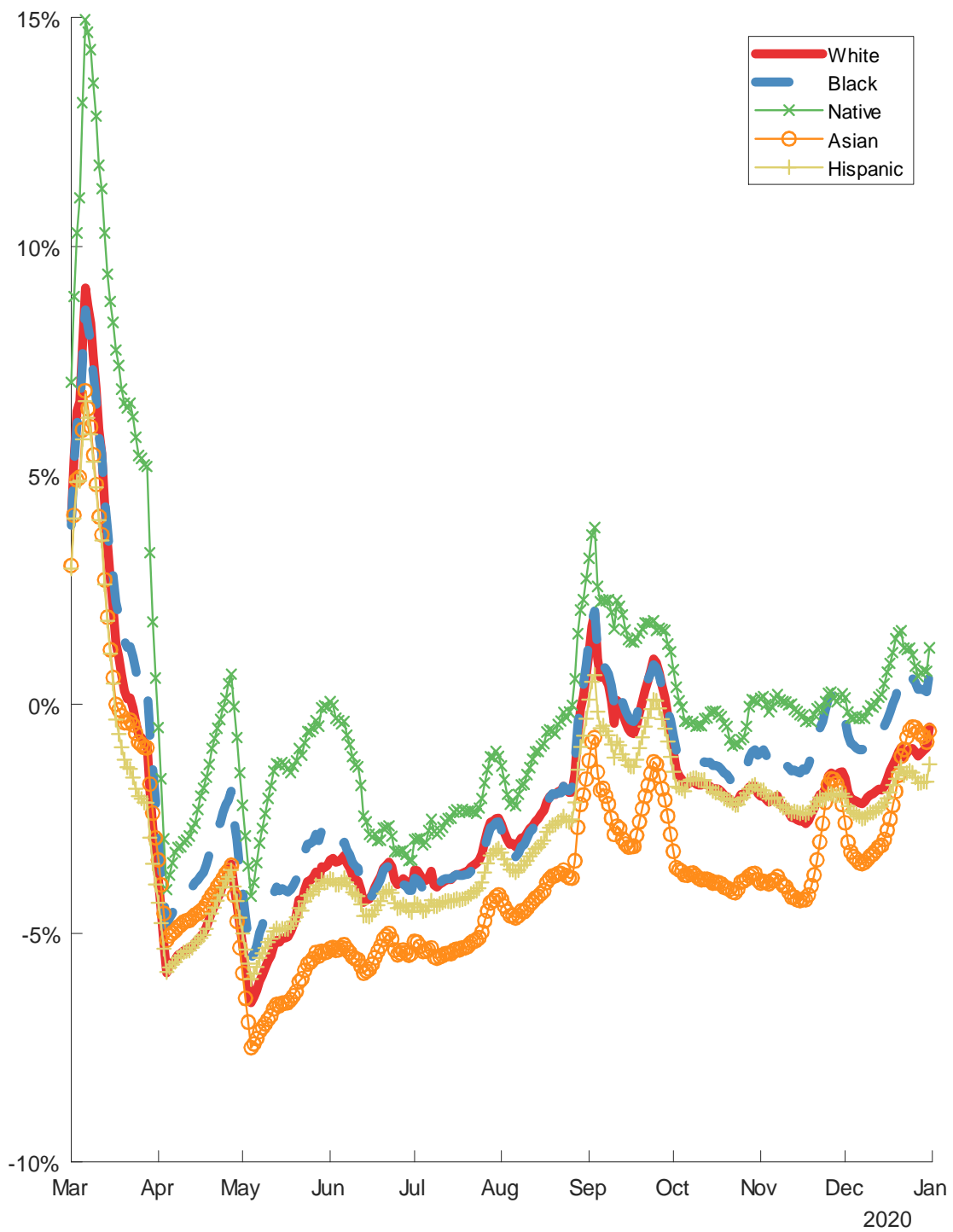

Notes: The descriptive statistics are calculated across census block groups

for each day.
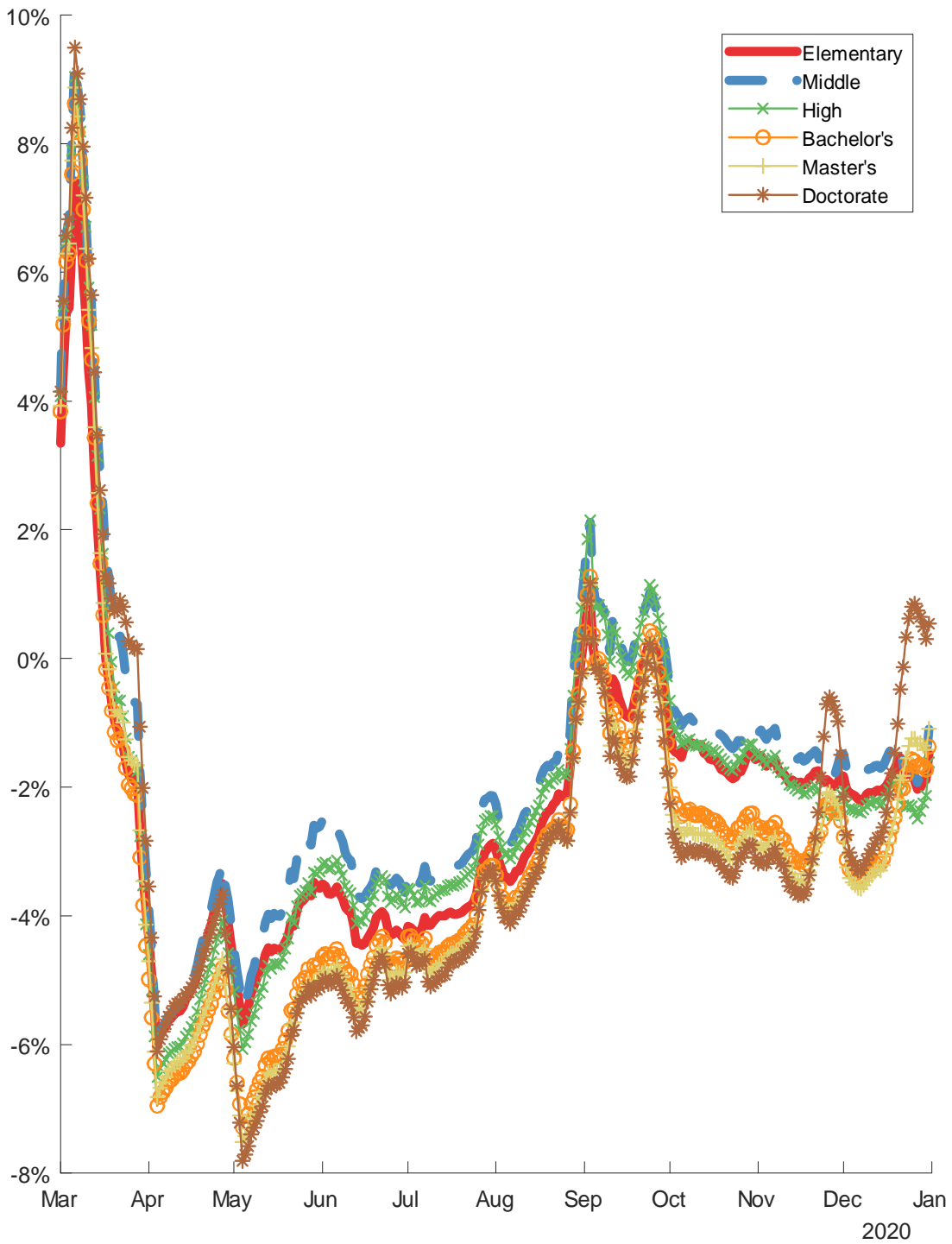
Figure 2 - Welfare Changes at the National Level
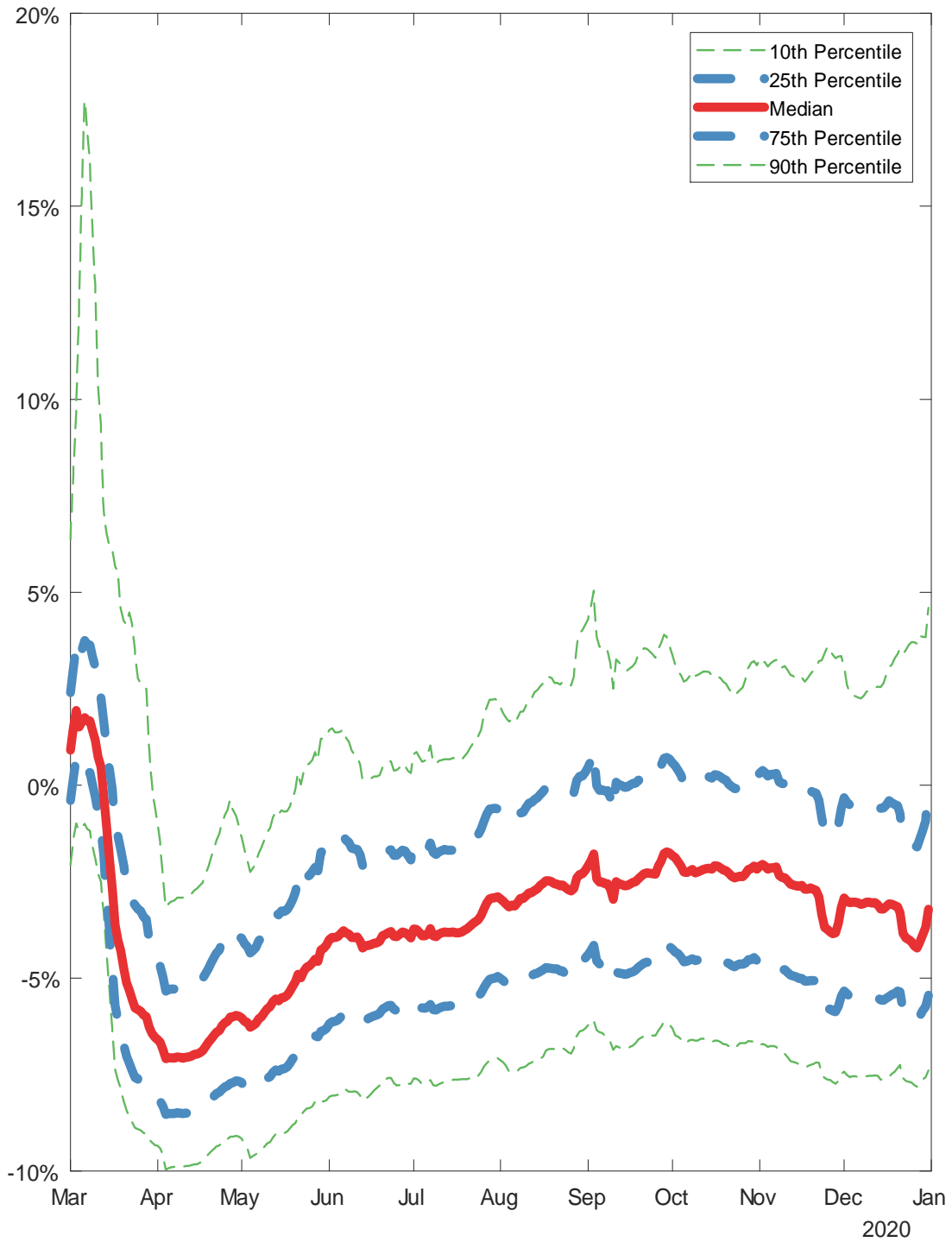
Notes: Welfare changes are with respect to the period between January 1st and February 29th, 2020.

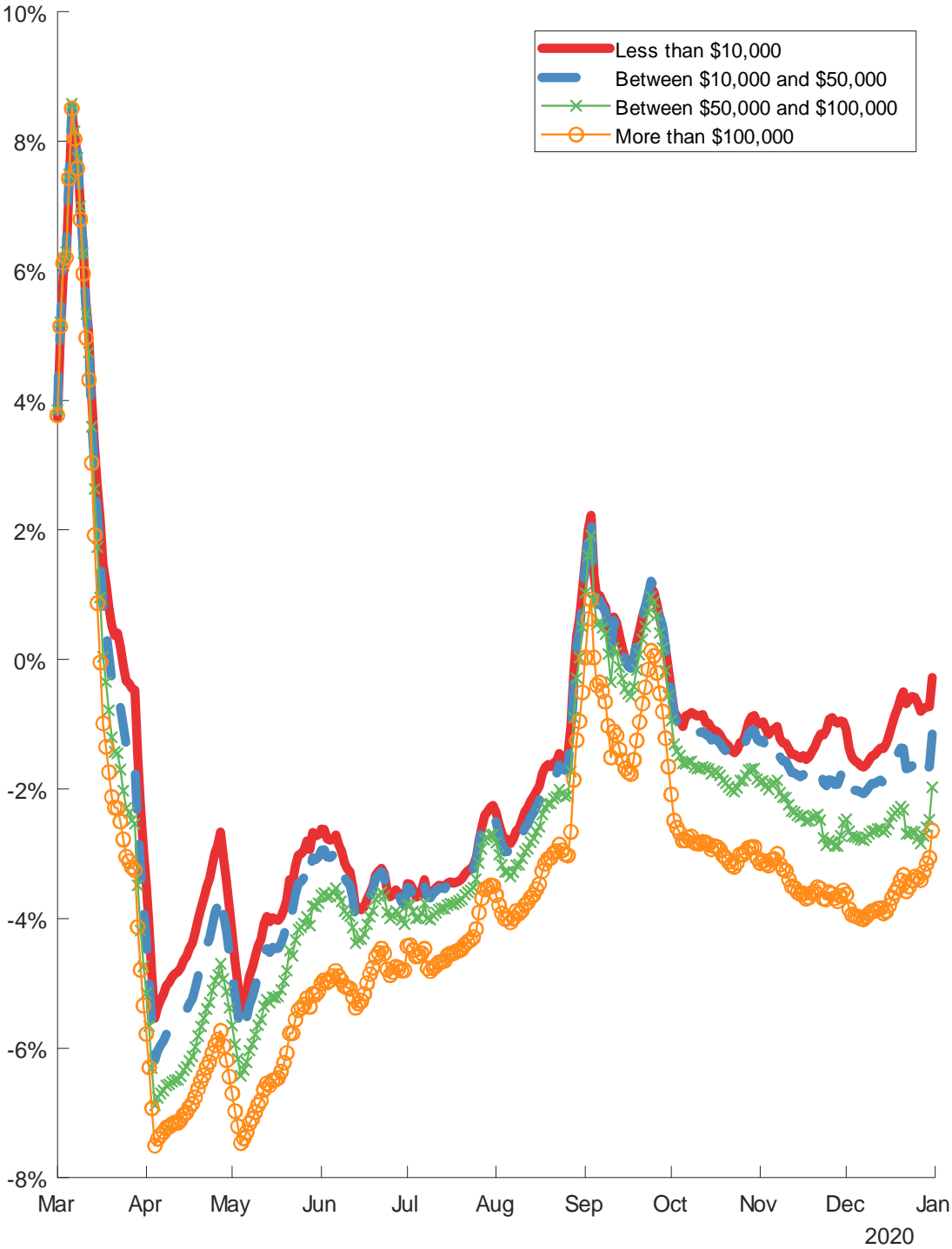Figure 3 - Welfare Changes Based on Race/Ethnicity

Notes: Welfare changes are with respect to the period between January 1st and
February 29th, 2020.

Figure 4 - Welfare Changes Based on Education Level

Notes: Welfare changes are with respect to the period between January 1st and February 29th, 2020.

Figure 5 - Welfare Changes Based on Income Level

Notes: Welfare changes are with respect to the period between January 1st and February 29th, 2020.