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ABSTRACT

This paper uses a unique large-scale survey administered in April 2020 to assess disparities on several dimensions of wellbeing under rising COVID-19 infections and mitigation restrictions in the US. The survey includes three modules designed to assess different dimensions of well-being in parallel: physical health, mental and social health, and economic and financial security. The survey is unique among early COVID-19 data efforts in that provides insight on diverse dimensions of wellbeing and for subnational geographies. I find dramatic declines in wellbeing from pre-COVID baseline measures across both people and places. Place-level variation is not well explained by local characteristics that either precede or coincide with the pandemic. Analysis by demographic groups also shows large and unequal declines in wellbeing in the COVID era. Hispanic, younger, and lower-earning individuals all faced disproportionately worsening economic conditions, as did those with school-aged children. I conclude that place-based relief policies are unlikely to be efficient relative to support targeted to the neediest individuals. I also find that individual COVID-19 exposure and risk show concerning relationships with employment, protective behavior, and mental health. Those with direct COVID-19 exposure through their households continue working similar hours to others, and those with recent fever symptoms or elevated risk for COVID complications are not reducing their work hours or taking additional precautions, despite negative mental health status changes indicating concern. These findings suggest that some support policies might be directly targeted to households with confirmed infections or heighted risk.

JEL: I1, I15, I18, I31, J1, J15, J38

[1] *Disclaimer:* The *views expressed here are those of the author and do not necessarily represent those of the Federal Reserve Bank of Minneapolis or the Federal Reserve System.*

This paper will be updated as new data are available from the COVID Impact Survey. The latest version of the paper can be found at www.abigailwozniak.com/research-v2.

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1. Introduction

Almost from the beginning of the COVID-19 pandemic in the United States, observers have expressed concern about unequal impacts of recommended mitigation measures. There are good reasons for this. The heavily impacted service sector employs many young, less-educated, and minority workers. At the same time, lower-income, minority, and older individuals are at greater risk from COVID-19 complications due to disproportionate rates of suspected risk factors. These patterns suggest that the burden of mitigating the spread of the virus is unlikely to fall equally on Americans. Geographic disparities are also likely to emerge. Cities and states differ in many ways that can contribute to coronavirus risk as well as the economic and social cost of mitigation.

This paper provides evidence on three dimensions of inequality early in the COVID-19 pandemic. My data allow me to measure multiple dimensions of wellbeing, rather than focusing on a single measure, like employment. I begin with a place-level analysis and ask, which places have experienced the biggest changes in wellbeing since the onset of the epidemic? I also assess what determines place-level disparities. Is there a role for pre-pandemic characteristics, or for local behavior changes during the outbreak? I then turn to individual-level disparities to examine how changes in wellbeing have varied across demographic groups. Finally, I document how direct experiences with COVID-19 relate to outcomes, a contribution that is not possible with other data sources. I look for evidence on whether those with likely or potential COVID-19 exposure are staying home from work or changing their behavior in other ways, and I connect this exposure to other wellbeing indicators.

To answer these questions, I draw on evidence from new data, the COVID Impact Survey (CIS). The survey measures respondents' experience of the pandemic in their daily lives alongside multiple dimensions of wellbeing. The CIS consists of three modules asking about physical health, mental and social health, and economic and financial security. The survey uses a combination of previously fielded questions and new questions developed to assess the unique current context. These allow respondents to report in detail about their behaviors and experiences in the current pandemic. At the same time, the survey collects established measures of physical, mental/social, and financial health. The CIS is administered to a large, probability-based sample that allows estimation of both national statistics and geographically specific estimates for 18 places (a combination of 10 states and 8 metropolitan areas).

To address the first set of questions, I compare COVID-era responses with pre-COVID benchmarks using several items in the CIS that have analogs in other national surveys. These include measures of employment, hours, social connectedness, food security and mental health. I then construct a dataset that allows me to analyze the relationship between aggregate local outcomes on the CIS wellbeing measures alongside place-level characteristics preceding and paralleling the outbreak. I use a similar analysis to study disparate impacts across demographic groups. I compare CIS responses in the COVID era to external benchmarks for select demographic groups. I then run regressions using individual-level data that permit a full set of controls to assess the robustness of these group-level differences.

I report several findings. First, place-level differences from pre-COVID baselines are substantial. Nationally, and for each of the 18 subnational sampled places in the CIS, nearly every measure of wellbeing that I study has deteriorated markedly from a pre-COVID baseline measured prior to the CIS. I find that places differ in the magnitude of the changes they experience, but these differences are not driven by either select pre-COVID place characteristics or by variation across places in the restrictions or behavioral changes implemented locally. This suggests that variation in how places are faring in the current environment is driven more by sectoral linkages that are unevenly distributed across the economy, rather than by specific local policies or behaviors (Osotomehin and Popov 2020; Alstadtsaeter et al. 2020).

The second part of my analysis shows that changes in wellbeing have been uneven across groups as well as places. Some of the early concern about disproportionate negative impacts on communities of color and less advantaged groups is supported by these data, but exceptions are also worth noting. I find disproportionately negative employment and hours impacts on Hispanic respondents and (with more uncertainty) Asian respondents. Black respondents, however, experience negative impacts about on par with those of white respondents. I also find large differences in economic impacts that vary by age and pre-COVID income level. Older, higher earning respondents are much less exposed to negative economic impacts of the current environment. Finally, families with school-aged children are significantly more negatively impacted than other households. Many of these findings parallel those in Montenovo et al (2020), in spite of the fact that they use a different data source (CPS versus CIS) covering a different month of the pandemic (March versus April)

Finally, the CIS allows me to study how direct experiences with COVID-19 relate to outcomes. These findings suggest some cause for concern. First, respondents who have had a COVID diagnosis in their household continue working similar hours to those in households without, despite the fact that at the time of the survey, many diagnoses were likely to be recent. This finding suggests those with COVID in the home may have continued to work regular hours, which may be at odds with an optimal containment strategy.

In support of this view, I find that respondents who report greater underlying risk factors for COVID complications as well as those who report fever symptoms in the last week also continue to work regular hours and are no more likely to separate. These individuals also do not report taking above-average precautions. However, respondents with greater risk or fever symptoms report significantly worse mental health, suggesting they are not unaware of their risk. Taken together, these results are concerning because they suggest individuals at greater risk of infecting others or suffering COVID complications are not altering their work or protective behavior.

An important caveat to all findings reported here is that they are from the first wave of the CIS. Data collection is ongoing, and results may change as more data are collected.

This is the first paper to study employment and wellbeing measures among those with known COVID exposure and symptoms. It therefore adds new knowledge about how COVID exposure, personal risk, and risk to others relate to the massive changes in employment and broader wellbeing that followed the onset of the COVID-19 pandemic. In this respect, this paper is related to others studying behavioral changes using survey data on protective measures taken and cell phone data on changes in movement (Allcott et al. 2020; Cornelson and Miloucheva 2020). However, this paper can assess whether respondents who should be staying home in fact are, and whether this behavior is related to changes in an individual's economic circumstances and other wellbeing indicators.

This paper also adds important detail to the emerging body of survey evidence on the early economic impacts of COVID-related social distancing (Bick and Blandin 2020). Broadly, CIS differs from other survey efforts in two ways. First, the CIS is designed to capture behavioral changes, experience with public restrictions, direct COVID exposure, and physical status in addition to the economic and social

outcomes in other surveys. Second, the CIS allows both national and subnational estimates, something which many early efforts with more limited sample sizes are unable to capture.[2]

This paper also aligns with papers studying the disparate impacts of COVID-19 using other sources. Montenovo et al (2020) uses CPS data to describe disparities in employment declines in the early weeks of the pandemic. By and large, my findings on employment changes by demographic group align with theirs. I then use the additional information in the CIS to examine changes in wellbeing beyond employment, to study employment and wellbeing impacts of a COVID-19 diagnosis (or personal experience through mortality), and to create a place-based analysis of local predictors of the severity of changes in outcomes. Although our methods are substantively different, like Montenovo et al and Lozano Rojas et al (2020) I also conclude that place characteristics – either pre-COVID or COVID-era—are not predictive of the severity of local impacts from the switch to the COVID environment. Alstadtsaeter et al. (2020) find similar demographic and socio-economic disparities in employment impacts early in Denmark's COVID-19 outbreak. Alon et al. (2020) discuss likely disparate impacts by gender, using evidence from pre-COVID era data.

2. The COVID Impact Survey

The COVID Impact Survey (CIS; Wozniak et al. 2020) was designed to assess a broad spectrum of wellbeing measures at high frequency. It was developed to be a prototype of an ideal survey tool for informing policymakers in the COVID-19 environment. The CIS allows for physical symptom and COVID exposure tracking alongside measurement of mitigation behaviors, experience with restrictions to daily life, and a set of wellbeing indicators encompassing economic security and mental/social health. As such, it has several features that distinguish it from other rapid-response survey efforts around COVID-19.

First, the CIS combines physical health tracking with rapid overall wellbeing assessments. In a the rapidly changing COVID-19 environment, an ideal virus tracking system would also monitor other important measures of population wellbeing. In essence, the CIS asks who is being impacted by what restrictions, and how severe are the impacts, at the same time it tracks physical health. This approach,

[2] The CIS is also closely related to the Household Pulse Survey fielded by the U.S. Census Bureau. Similarities and differences are discussed in the next section.

if deployed on a large scale, would allow survey resources to be used more efficiently and has been proposed as part of large-scale random infection testing in Germany (Bennhold, 18 April 2020; LMU Klinikum 2020).

A second defining feature is that the CIS is designed for large scale, high frequency administration. The survey takes 15-20 minutes to complete in total, and completion rates conditional on beginning the survey were high (Benz, 2020). In principle, a survey of this length could be administered routinely to large numbers of Americans throughout the coronavirus period.

Finally, the CIS is designed to be comparable to several external benchmarks. 12 questions have direct analogs in other nationally representative surveys, and nearly all of those can also be tabulated at the same subnational geographies represented in the survey. Key current outcomes are therefore comparable to indicators from the pre-COVID period. I draw on data from several external surveys to create pre-COVID-19 benchmarks against which to compare the CIS responses. These benchmark surveys are all large, well-known data sets. For the sake of conciseness, a table of benchmark sources and detailed discussion of benchmark construction is provided in the Data Appendix.[3]

The CIS administers questions in three modules: physical health, social and mental health, and economic and financial security. The modules have roughly 5 to 12 items each. Module questions are asked non-sequentially in order to maximize respondent comfort and cooperation. A final demographic module is asked at the end. The CIS is based on the proposed instrument in Wozniak (2020). It was refined with input from experts on the COVID Impact Survey Advisory Panel and the National Opinion Research Center (NORC), which conducted the survey.[4]

NORC recruited respondents through two channels. The first is NORC's AmeriSpeak Panel. Participants in the AmeriSpeak panel are initially recruited through an address-based sample frame. Panel respondents are therefore representative of the 97% of the US population that can be reached through most address-based samples.[5] Roughly 2000 CIS respondents come from the AmeriSpeak Panel.

[3] The Data Appendix is available online at www.abigailwozniak.com/research-v2.

[4] Advisory Panel members are listed here: https://www.covid-impact.org/advisors. The survey was funded by the Data Foundation, with support from the David and Lucile Packard Foundation, the Federal Reserve Bank of Minneapolis, and the Sloan Foundation.

[5] These exclude individuals with PO Box addresses only, some regular addresses excluded from the USPS Delivery Sequence File, and some new construction residents.

These comprise the nationally representative portion of the sample (or the national sample). AmeriSpeaks respondents were compensated according to their participation agreement with the panel. The CIS also includes roughly 6500 respondents from address-based oversamples of 18 subnational areas, which I refer to as "places." These consist of 10 states (CA, CO, FL, LA, MN, MO, MT, NY, OR, TX) and 8 metropolitan statistical areas (Atlanta, Baltimore, Birmingham, Chicago, Cleveland, Columbus, Phoenix, Pittsburgh). Respondents for the subnational oversamples were recruited by postcard invitation and allowed to respond using their choice of a web-based or phone survey. Subnational respondents were offered five dollars for their participation.[6]

Several other survey efforts have been rapidly developed to gauge the impact of the pandemic on the US population. The largest of these is a household pulse survey administered by the US Census Bureau to a large sample (U.S. Census Bureau, 2020). The survey entered the field in April 2020 and will run for 12 weeks. The CIS and Census survey have significant overlap in terms of the questions they ask about financial security and mental health. A number of questions appear on both surveys. However, the CIS also asks questions about direct experience with COVID-19 and the restrictions and behavioral changes it has generated. Specifically, the CIS asks about steps taken to avoid infection, restrictions that impacted respondents' plans, physical symptoms and comorbidities, whether there has been a COVID-19 diagnosis in the household, and whether the respondent has been close to a person who died from COVID-19 respiratory illness since March 1, 2020.[7] The CIS questions about social connectedness also are not part of the Census survey. Essentially, the CIS takes a "wide" approach to surveying about COVID impacts, experiences, and risk while the Census approach goes "deeper" on economic and financial changes, and food and housing security.

Another large survey effort is the result of a partnership between the Delphi Research Group at Carnegie Mellon University and Facebook. This survey administers a COVID symptom checker to very large numbers of Facebook users daily. From this, they generate a signal of COVID spread based on the share of respondents reporting some COVID-like symptoms. This signal is part of broader set of indicators, including a similar survey to Android phone users through a partnership with Google as

[6] For further detail, see Benz (2020), available here: https://www.covid-impact.org/results, along with additional survey and methodological documentation.

[7] The CIS asks whether a close friend or family member has died of COVID-19 or a respiratory illness since March 1, 2020. The question included the broader option due to concerns about deaths at home that may have been undiagnosed and other possible subject confusion about whether COVID-19 was the declared cause of death.

well as doctors' visits and more traditional flu tracking.[8] The CMU-FB survey is essentially one question from the physical health module of the CIS, and it is administered to a sample of Facebook users whose representativeness, even after adjustments, is unknown. By contrast, the CIS has much smaller samples but richer data connected to the same surveillance questions.

Other survey efforts include topical modules added to USC's Understanding America Study panel, COVID-specific Pew surveys, and a large, non-probability internet-based survey (Hollingue et al. 2020a; Hollingue et al. 2020b; Kapteyn 2020; Lazer et al. 2020). A number of questions in the CIS also appear on these surveys. However, the CIS differs from these efforts in ways. First, it allows for subnational estimates. Second, the CIS is designed to be implementable by a national statistical agency. As such, it asks no opinion questions unless these relate to a respondent's subjective evaluation of their own situation.

Finally, several surveys have administered standard employment questions in a timely manner by appending them to existing surveys or deploying them in standing survey panels. These include an ongoing effort to supplement the Federal Reserve Board's Survey of Household Economics and Decisionmaking (SHED). A subset of regular SHED questions, along with some additional COVID-19 specific questions, will be administered to three smaller samples throughout 2020. (Report available on 5/13). Several teams have administered a version of the standard Current Population Survey employment questions at higher frequency than the Bureau of Labor Statistics can field its survey. These include Bick and Blandin (2020) and Coibion, Gorodnichenko and Weber (2020.

3. Geographic Disparities

I begin by examining which places in the CIS sample of states and cities have experienced the biggest changes from the pre-COVID environment. I use a set of five outcomes from the CIS data that are directly comparable to external benchmark data sources. These outcomes capture a broad picture of population wellbeing. Specifically, I compute (i) employment rates; (ii) average hours worked in the

[8] More information about the Delphi Research Group as well as access to their COVIDcast data is available here: https://covidcast.cmu.edu/?sensor=doctor-visits-smoothed_adj_cli&level=county&region=42003&date=20200505&signalType=value.

past week; (iii) an index of social interactions that measures communication with family, friends, neighbors; (iv) an indicator for any food insecurity; and (v) a measure of poor mental health days. For states only, I can also compare a measure of financial security: inability to cover an emergency $400 expense. Details on the construction of these variables from the CIS and their external benchmark sources can be found in the Data Appendix.

Figures 1 and 2 show the gaps between the pre-COVID baseline and CIS measurement for each of these measures. Figure 1 shows results for states and Figure 2 for cities. The figures show that substantial changes (measured on the y-axis) in the five wellbeing measures are widespread across the set of places in the CIS data. The impacts are economically large when compared to the baseline value for each outcome noted at the top or bottom of each bar. Nearly all changes are statistically significant. In general, all places experience substantially reduced employment in the April 2020 survey week as compared to 2019. Among those who continued working, hours worked in the past week also declined markedly. The incidence of food insecurity rose in all places. Comparing state-level responses in the CIS to the SHED, all states saw the share of respondents who could not cover an emergency $400 expense by any means rise relative to baseline. This change was statistically significant in about half the states.

In addition to these marked changes in economic security, cities and states in the CIS sample also saw large changes in mental and social health among their populations. The incidence of poor mental health days rose considerably in all places. (An alternative definition of poor mental health days in the CIS, defined only as experiencing depression, also rose relative to the BRFSS benchmark of self-reported poor mental health days. The change in this alternative measure was statistically significant or nearly so in about half the CIS places.) On the other hand, the index of regular communication with friends, family, and neighbors rose substantially. To get a sense of the magnitude, the mean increase in the index was nearly equal to the span between the minimum and maximum baseline level—0.63 versus 0.7, respectively. All increases were statistically significant.

The data show uniformly large and generally negative changes in measures of wellbeing across all US places in the CIS data. The exception is social connectedness, but here again the changes are large, though tending toward greater connectedness. However, while the direction of these changes is com-

mon across places, Figures 1A and 1B also show meaningful differences in magnitudes. This is particularly true of the changes in economic security. Employment declines ranged from 9 to 20 percentage points; the same range holds within cities and states in the CIS. Hours declines also varied considerably across places. Two places (one city, Phoenix, and one state, Minnesota) saw no change in hours. By contrast, the state (Texas) and city (Birmingham) with the largest declines saw hours decrease by about 20 percent from baseline.

Changes in food security also varied markedly across places. While the place with the smallest rise in food insecurity (Pittsburgh) still experienced a 10 percentage point increase, more than half the places saw increases more than double that. The largest increase in food insecurity, of 29 percentage points, was reported in Phoenix. Changes in the ability to cover an emergency $400 expense can only be compared to baseline data at the state level, but here again there is considerable variation within the generally negative changes.

These changes in economic security, mental health, and social connectedness are of course related to the dramatic changes in private and public behavior that began in March 2020. These changes were likely a response to a combination of public health recommendations, shelter-in-place orders or other restrictions, and general dissemination of information about the spread of COVID-19.

I next examine whether places also differ in the behavioral changes adopted or major restrictions experienced by their residents. Figures 3 and 4 graph the incidence of selected measures of behavioral change or impactful restrictions from the CIS by states and cities, respectively. These measures include the total number of 19 possible COVID-19 avoidance measures respondents reported (mean and median); total number of 18 possible public restrictions that have impacted their plans (mean and median); and the share of respondents impacted by a school closure. The list of avoidance measures and restrictions that could be reported can be found in the Data Appendix. I also include the shares who have had (1) a positive COVID-19 diagnosis in their household and (2) a close friend or family member who died from COVID-19 or a respiratory illness since March 1. These measure direct experience with the effects of the virus.

Figures 3 and 4 tell a different story from the impacts documented in Figures 1 and 2. The behavioral changes and effects of restrictions are widespread, as are negative impacts on wellbeing. However,

places show little variation in behavioral changes and restrictions undertaken by their residents than in the recorded wellbeing impacts. Respondents everywhere report taking a large number of steps to avoid coronavirus. The U.S. average shows respondents taking 8.8 out of 19 possible steps. This number is lower than the local averages in the place-specific subsamples in the CIS, which range from 8.6 to 9.7 steps taken. Respondents also report being affected by a large number of restrictions. The U.S. average is 7.11 impactful restrictions out of 18 possible restrictions. The place-level averages range from 6.7 to 8.7.

The uniformity across places in the extent of behavioral change and impactful restrictions is not simply a function of aggregating individual items to a summary index. Separate indicators for experiencing a work at home restriction or a work closure restriction (not reported) show somewhat more variation across places than the index measure reported in Figures 3 and 4. However, correlation in place level means of these indicators with the summary index are very high. The same is true of specific avoidance steps – for example, the place-level correlation of an indicator for wearing a mask and the summary steps index is 0.84. One exception is the share of the population experiencing a school closure. This restriction measure has somewhat lower correlation with the overall restriction index measure at the place level, of 0.61 compared to 0.77 for the separate work-at-home restriction and 0.83 for the work closure restriction.

By contrast, individuals vary considerably in the specific steps they take and restrictions they experience. Any given restriction is only reported as impactful by about one third of respondents, and correlations of specific steps or specific restrictions with an individual-level summary index is much lower than at the place level. For example, among individuals, wearing a mask has a correlation with total steps taken of 0.37. The correlation between experiencing a work closure restriction and total restrictions experienced is 0.52, and across the specific work and school closure restrictions it is even lower, at 0.25. This implies that while there are substantive differences across people in steps taken and impactful restrictions, the average resident's experience is very similar across places in the CIS data.

Direct COVID-19 experience, either through a diagnosis of someone in the home or through a death, varies much more across places than either behavioral changes or impactful restrictions. This is con-

sistent with the localized nature of severe outbreaks in the U.S. It is important to note that this variation is likely to change as the outbreak progresses. It will be important to monitor variation in direct experience with COVID-19 as new waves of the CIS arrive.

Measures of behavioral changes and impactful restrictions show less variation across places than the changes in wellbeing measures, but it is reasonable to ask if the two are related nevertheless. More broadly, have certain types of places experienced more substantial changes in wellbeing measures than others? In particular, have reductions in wellbeing fallen disproportionately on disadvantaged places?

To assess this, I run place-level regressions of the measured changes from baseline (from Figure 1) on the measures of behavioral change, extent of restrictions, and COVID-19 experience from Figure 2. I also use controls for place characteristics pre-dating COVID-19 from external data sources.

The results are reported in the three panels of Table 1. Because there are only 18 places in the CIS data, place-level analysis can only accommodate a limited number of covariates. To handle this, I break the covariates into four sets and run place-based regressions separately on each set. The results should therefore be interpreted with some caution. However, if there are strong relationships between particular place characteristics and changes in the wellbeing measures during COVID-19, these should show up in the place-based regression analysis. Performing the analysis sequentially using only a small number of covariates each time increases the chance of detecting such relationships in these data.

The top panel of Table 1 shows that places with larger Black and Hispanic population shares experienced lower hours and greater prevalence of food insecurity. Larger Black and Hispanic population shares were also associated with greater social connectedness. This underscores that connectedness measured as frequency of contact is a complicated indicator of wellbeing, since communication may increase if individuals are in distress. Places with more BA degree holders experienced less food insecurity but more individuals reporting poor mental health days. There is no evidence that population characteristics across places predict overall employment shares. Standard errors on these estimates do not allow for conclusions about magnitudes, but with the exception of the changes with Hispanic share, the differences reported in this paragraph are statistically significant.

The remaining panels show little evidence of a relationship between place-level characteristics and outcomes. Panel B shows local inequality is unrelated to variation in COVID-era outcomes, as is local median household income. The only exception is that in higher earning places, more respondents report poor mental health – a relationship that mirrors that for BA degree holders in Panel A. Estimates are noisy, but the measures of behavioral changes and restrictions experienced in Panel C show no relationship to employment, hours, social connectedness or mental health. The association between restrictions and food insecurity is significant, but overall the picture is that neither restrictions experienced nor behavioral changes relate to place level outcomes.

The first null result aligns with other analysis showing that – broadly – restrictions in place are poor predictors of economic collapse in the pandemic period. However, the second null result is perhaps surprising, since it is assumed that behavioral changes are driving the economic consequences in the absence of a strong role for formal restrictions. To assess this, I repeated the analysis in Panel C using a narrower measure of behavioral change – an indicator for wearing a mask – that might be expected to detect more true variation in behavioral changes if the signal from the overall index measure is very noisy. But as noted above, the two measures are highly correlated, and the overall results in Panel C are unaffected by changing to the mask indicator.

This leaves two possible explanations for the disparities across places in COVID-era changes in wellbeing. The first is that the CIS measures of behavioral change are simply poor measures of behavioral changes at the local level. However, the second possibility is that behavioral changes at the local level are also poor predictors of local economic impacts of the pandemic. This might be the case if sectoral linkages throughout the economy are pronounced, as explored in Osotimehin and Popov (2020) and Alstadsaedter et al. (2020).

More information will come in as the CIS adds waves, but at this point I conclude there is little evidence that broad place characteristics, local policies, or local behavioral changes determine the impacts that places experience in the pandemic era. Nevertheless, there is substantial variation across places in the impacts on economic and broader wellbeing outcomes in the pandemic. This suggests that policymakers seeking to target relief would do better to focus on groups of individuals most likely to be affected. I turn to this topic in the next section.

4. Demographic Disparities and Individual Behavioral Changes

Another way to study disparities in the impacts of COVID-19 and its associated restrictions is to look at the same changes from baseline by demographic group. Given concerns about inequitable impacts of COVID-19 on health and economic security for lower earning workers and workers of color, it is important to analyze people in addition to places.

For this analysis, I use the national sample component of the CIS.[9] I repeat the construction of changes from baseline used in Figure 1 for several demographic groups. The changes from the pre-COVID external benchmarks for these subpopulations are shown in Figure 5.

The top panels of Figure 5 show that employment and hours declines are widespread across demographic groups. Comparing baseline levels (indicated at the top or bottom of the bar) to the magnitude of the changes (height of the bar) shows these declines are substantial. While all highlighted groups experienced marked employment and hours declines from the pre-COVID baseline, Figure 5 also shows that these impacts varied across groups. Employment declines were largest for younger workers (relative to the oldest group), non-whites (relative to whites), and for individuals with children in the household (relative to those without). In the CIS, men also saw steeper employment declines between baseline and mid-April 2020. The remaining panels show variation across groups that follows a broadly similar pattern.

To assess whether these group-level impacts are robust to controls for group composition, and other individual characteristics, I estimate individual level regressions using a subset of the wellbeing indicators. For this subset, it is possible to make pre-COVID comparisons within the CIS data. These include hours worked, since respondents were also asked about usual weekly hours worked prior to March 1, 2020; employment, since respondents can report loss of employment since March 1 and layoff/furlough in the past week; and the index of social connectedness, since respondents were asked about both the past month and a typical month prior to March 2020. I also use an indicator for seeking or received food aid (through government sources, namely SNAP, or food banks) as a measure of

[9] Weighted analysis of responses from the 18 subnational oversamples is also an option, but this cannot produce nationally representative statistics.

current financial distress. However, an important caveat is that SNAP benefits are disbursed monthly and therefore receipt of this benefit may not be in the seven-day reference window.

These within-individual comparisons allow me to use the CIS microdata to assess impacts of the COVID environment across multiple demographic groups simultaneously. I regress these four within-respondent measures on controls for the demographic groups in Figure 3 and report the results in Table 2. The regressions also include controls for direct COVID experience (COVID diagnosis in the home and COVID/respiratory death among friends or family since March 2020), household type, and density of the respondent's county of residence. Results are robust to excluding various subsets of these covariates.

Several patterns emerge in Table 2. First, older and higher earning respondents are less likely than other groups to report a COVID-era separation (defined as being on layoff or furlough in the last week, or unemployment starting after March 1) and they report an increase in hours. Both groups are also less likely than others to seek food aid in the last week. By contrast, Hispanic respondents and individuals with school-aged children in their household were much more likely to experience a separation and saw significant hours reductions. The incidence of separations was also significantly higher for the "Other" race/ethnicity category, which includes Asians, and this group saw a larger (but not significant) reduction in hours. Dependent variable means at the bottom of the table indicate that all these group differences are large relative to the mean experience. One null result is also noteworthy. Groups reporting larger deteriorations in economic outcomes do not appear to be seeking food aid more intensively. This may be a concern as the pandemic continues.

Table 2 also shows some differences in these wellbeing outcomes for those with direct experience of or exposure to COVID-19. Those with a COVID diagnosis in their home are, by these estimates, less likely to have experienced a job separation since March 1. They may also have increased their use of food aid, but the estimate is marginally significant. Conditional on working, this group also reports stable hours. It will be important to re-examine these findings using subsequent data, but if these results persist into subsequent waves, they are cause for concern. The findings suggest that those with a COVID diagnosis in their home are not reducing their hours worked, even though given the timing of the survey, many infections are likely to be recent. Taken together, these results may imply that

earlier COVID infections occurred disproportionately in households that faced employment instability, with the result that they were reluctant to reduce hours and stay home after a known exposure. Their seeking food aid in higher numbers may be further evidence that such financial instability is binding on these households. The index of social interactions, however, suggests these households have reduced other contacts. The employment, hours, and food security behavior among households with known COVID exposure bears further monitoring as more CIS data come in. Unfortunately, no other source of timely household data will provide these data systematically.[10]

Those who have experienced a likely COVID death among close friends or family report reduced hours but not a greater likelihood of employment separation. This may suggest these respondents had the ability to take some time away from work without suffering a permanent separation. However, these households also report a marginally significant increase in seeking or using food aid. This may imply that COVID deaths – and their loss of family income, informal insurance, or direct personal income – have led to greater financial constraints among individuals experiencing these, at least in the first month of the pandemic in the US.

Table 2 provides a somewhat different picture of disparities in the impacts of COVID-19 than that of Table 1. First, the analysis in Table 1 shows that places with larger black populations saw larger hours reductions alongside greater increases in food insecurity. Table 2 indicates that black respondents are not disproportionately experiencing separations or hours reductions, and there appears to be little evidence of a general increase in food aid receipt or seeking.

These findings might appear contradictory, but considering the data more carefully suggests they are not. Places with a larger share of black residents saw larger hours declines, but the individual level analysis indicates that black residents themselves experienced hours declines that were similar to those of whites. Statistically and economically larger employment and hours declines fell on Hispanics and possibly Asians. To a first approximation, the findings from Table 2 hold up to repeating the individual level analysis using microdata from the 18 subnational oversamples. This exercise will not produce a nationally representative sample, so using the national subsample is preferred. Still, the overlap indicates that the differences across Tables 1 and 2 is not due to the particular subnational population in

[10] The large household pulse survey developed by the Census Bureau in response to the outbreak does not ask about household COVID diagnoses or experience with a close COVID death. This survey was in the field as of this writing.

the place level data. Rather, this suggests that individual characteristics are stronger determinants of heterogeneity in the impacts from the switch to the COVID-19 economy. The insignificant differences between respondents from suburban, rural and urban (the omitted category) counties is additional evidence against broad place-level disparities in COVID-19 impacts.

Tables 1 and 2 also at first appear to differ in what they imply regarding food security and social connectedness. Figures 1 and 2, and Table 1, show large increases in measured food insecurity over external baselines, but in Table 2, there is little evidence of significant increases in seeking food aid. The two actually measure different concepts. Disturbingly, Table 1 suggests that the risk of not being able to purchase adequate food (Table 1) is out of line with food aid access (Table 2). This is important to monitor as the pandemic progresses.

Finally, Tables 1 and 2 also differ in the picture they suggest about social connectedness. In this case, the comparison in Table 1 is likely more accurate since it is not subject to recall bias or bias induced by comparing with the current reference point. Table 1 reports identical measures from comparable samples taken before and after COVID-19, and these likely generate a more accurate comparison than asking respondents to do the comparison themselves retrospectively.

The results in Table 2 suggest those with a COVID infection in the home are, if anything, less likely to separate from their employer or reduce hours. I next examine whether individuals at higher risk for spreading the virus or suffering a severe infection are withdrawing from work or taking other containment steps. In Table 3, I report results from similar regressions to those in Table 2, this time substituting measures that capture risk of spreading the virus or from contracting it. Risk of spreading the virus is measured with a self-reported scale covering fever symptoms in the last 7 days.[11] Risk of contracting the virus is measured as an indicator for having two or more risk factors for COVID complications identified by the CDC. Additional controls are the same as those in Table 2.

Table 3 shows that respondents with two or more underlying health issues that put them at higher risk for COVID complications are less likely to be employed. However, this is unlikely to be a response

[11] This is positively correlated with a measured temperature above 99 F in the CIS sample (correlation of 0.25). Subjective fever reports are treated as similarly informative to triage temperature in a set of clinical decision guidelines for influenza testing in U.S. emergency departments (Dugas and Rothman, 2015).

to current risk. Subsequent columns show that those with greater risk were no more likely to separate or reduce hours in April 2020 than other respondents. These individuals do not report taking additional protective steps to avoid the virus either. Perhaps even more concerningly, individuals who report fever symptoms in the last seven days show a similar pattern. Employment and hours are not differentially reduced for these respondents, even though a recent fever should lead to reduced hours, or possibly even employment, if sick workers are staying home. Those with self-reported fever also report no additional avoidance steps taken. The final column in Table 3 shows that mental health, however, is affected by these risk measures. The CES-D index of depression, hopelessness, anxiety, and loneliness increases significantly with both risk measures. This suggests that respondents are not unaware of the risks they face (or pose). The fact that other behavior does not respond to these risks is cause for some concern and merits ongoing monitoring.

5. Conclusion

I use a new survey data resource, the COVID Impact Survey (CIS), to study impacts of the COVID-19 environment on a broad set of wellbeing measures. The CIS also allows me to examine how individuals with heightened risk of spreading or suffering complications from COVID-19 are altering their behavior.

I report several findings. First, although places differ in the magnitude of changes they've experienced since the onset of the pandemic, these differences are not driven by pre-COVID place characteristics or by variation across places in the restrictions or behavioral changes implemented. This suggests that variation in how places are faring in the current environment is driven more by changes specific to their individual residents. These in turn seem likely to be driven by sectoral linkages that are unevenly distributed across the economy but affect some individuals more than others, rather than by specific local policies or behavior. Concern about disproportionate negative impacts on communities of color and less advantaged groups is supported by these data, but there are also exceptions. I find disproportionately negative employment and hours impacts on Hispanic respondents and (with more uncertainty) Asian respondents. Black respondents, however, experience negative impacts about on par with those of white respondents. I also find large differences in economic impacts that vary by age and pre-COVID income level. Older, higher earning respondents are much less exposed to negative economic

impacts of the current environment. Finally, families with school-aged children are significantly more negatively impacted than other households.

I conclude that place-based relief policies are unlikely to be an efficient means of targeting support during the pandemic and subsequent recovery. Instead, relief might be more efficiently delivered by targeting individuals for outreach by pre-COVID earnings, family structure, and possibly other characteristics like industry of pre-COVID employment, race/ethnicity, and age.

My findings also suggest that policymakers should consider targeting support to those directly affected by COVID-19, both for ex post transfers after recovery and for incentive payments to engage in self-quarantine and other mitigating behaviors while infected. My findings suggest that individuals with clear COVID exposure or related symptoms are not engaging in significant self-quarantine despite suggestive evidence that these symptoms concern them.

An important caveat to the findings reported here is that they are from the first wave of the CIS. Data collection is ongoing, and results may change as more data are collected.

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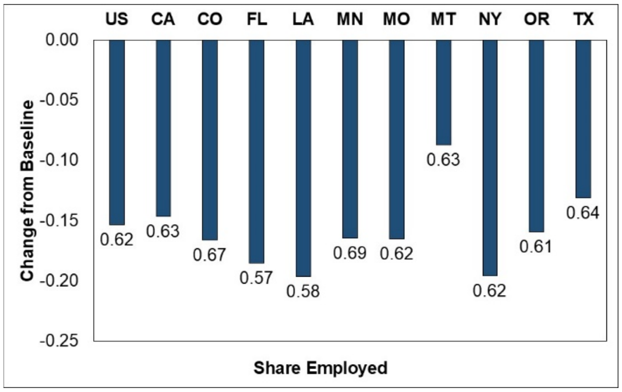
Figures



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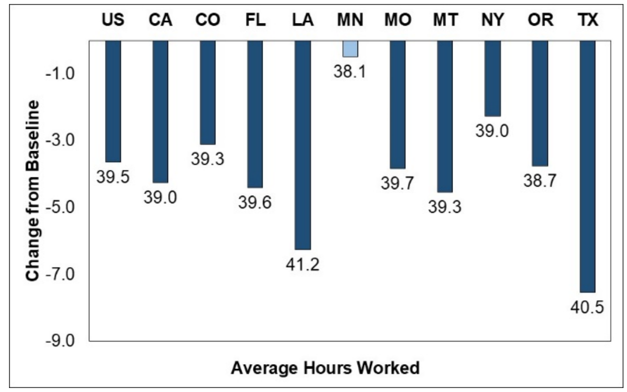

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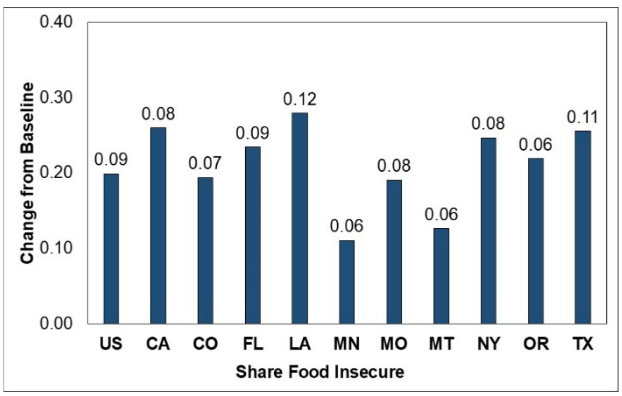

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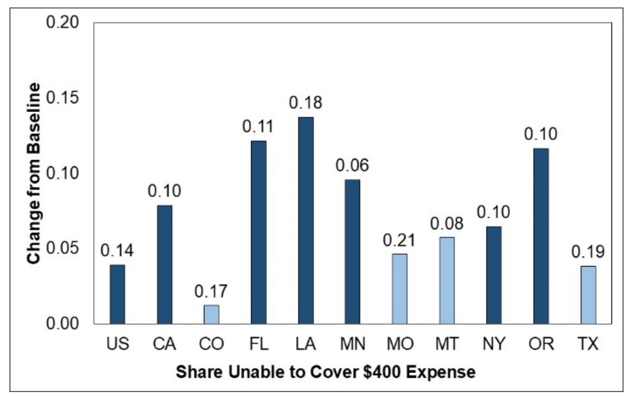

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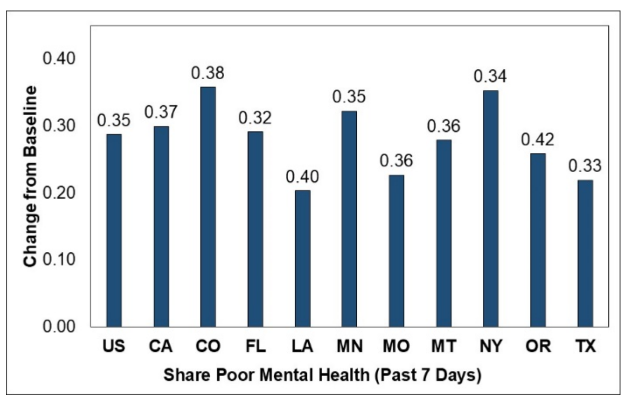

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Figure 1. Changes in Wellbeing Indicators from Pre-COVID Baseline (state level). Source: CIS and various baseline sources. Pre-COVID baseline sources are listed in the Data Appendix. Baseline levels are given at the top (or bottom) of each bar. Y-axis indicates change from pre-COVID baseline measured in the CIS. Unless lightly shaded, all changes are statistically significant at the 5% level.

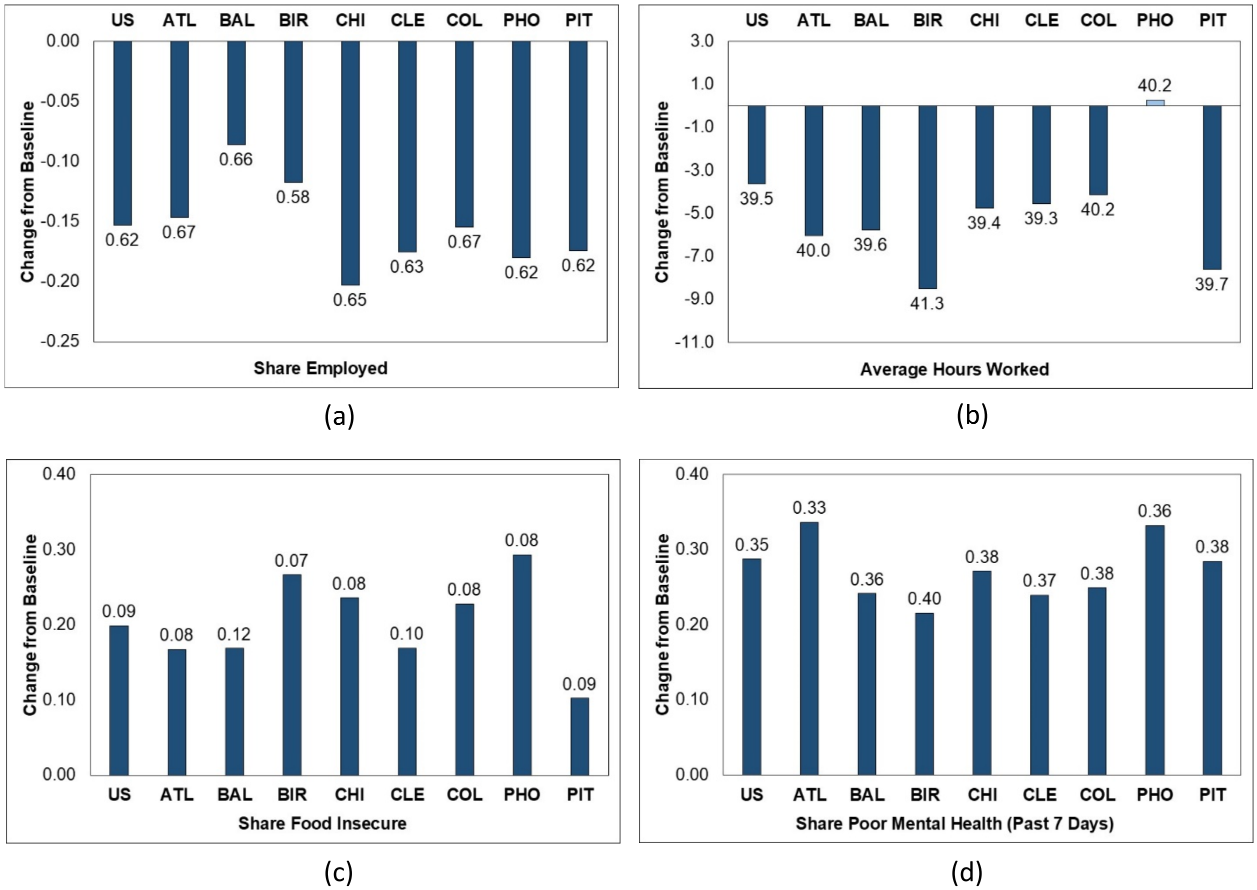
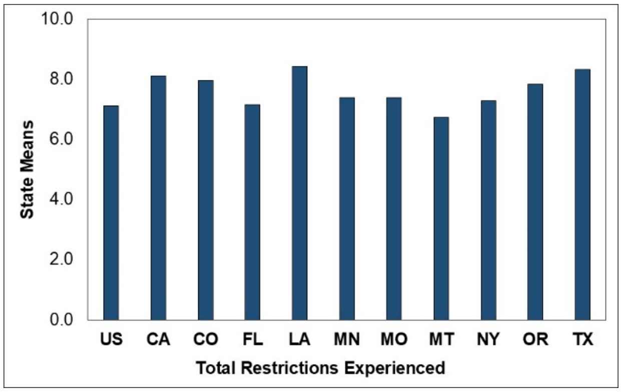


Figure 2. Changes in Wellbeing Indicators from Pre-COVID Baseline (state level). Source: CIS and various baseline sources. Pre-COVID baseline sources are listed in the Data Appendix. Baseline levels are given at the top (or bottom) of each bar. Y-axis indicates change from pre-COVID baseline measured in the CIS. Unless lightly shaded, all changes are statistically significant at the 5% level. Ability to cover $400 expense omitted because baseline comparisons cannot be constructed at the MSA-level.



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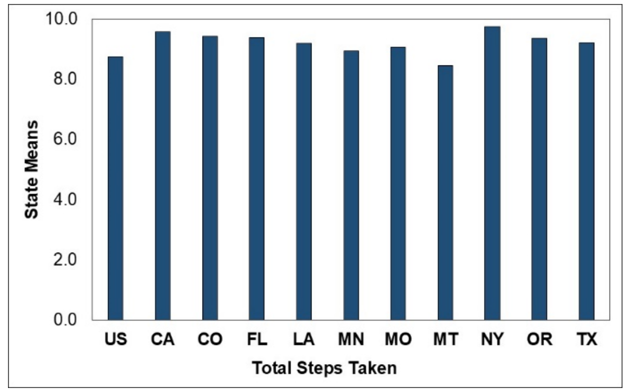

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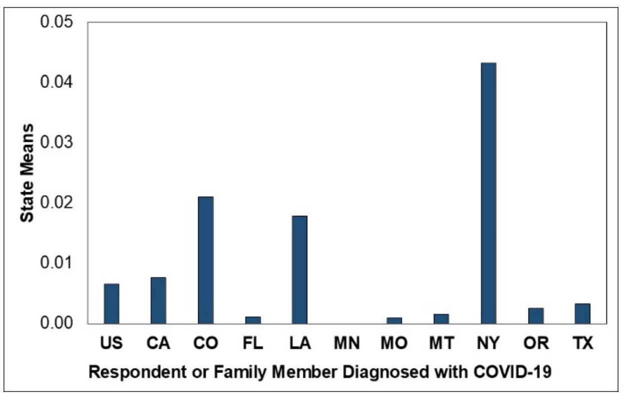

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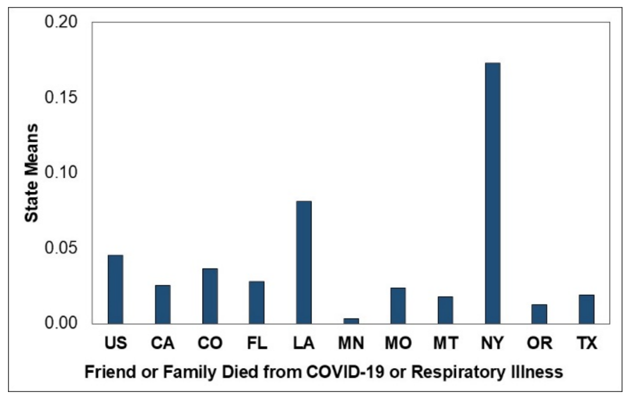

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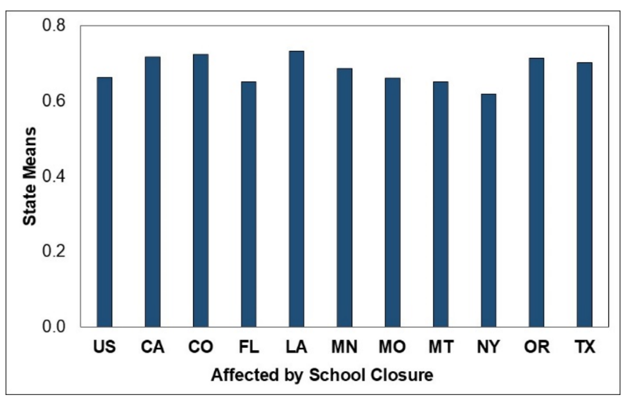

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Figure 3. Behavioral Changes, Experiences with Restrictions, and COIVD-19 Proximity (state level). Source: CIS. Y-axis shows mean by state or national subsample.

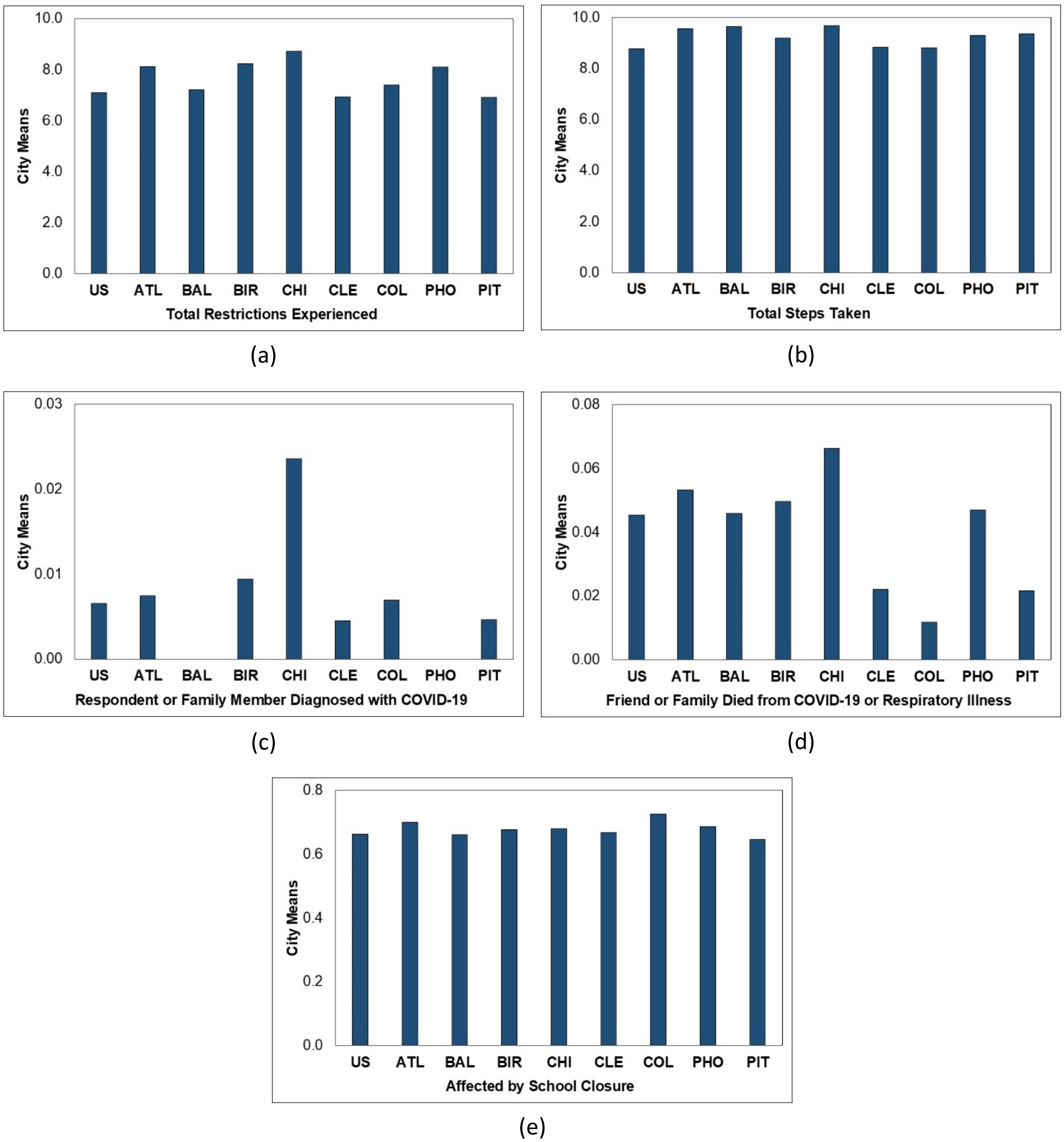

Figure 4. Behavioral Changes, Experiences with Restrictions, and COIVD-19 Proximity (MSA level). Source: CIS. Y-axis shows mean by state or national subsample.

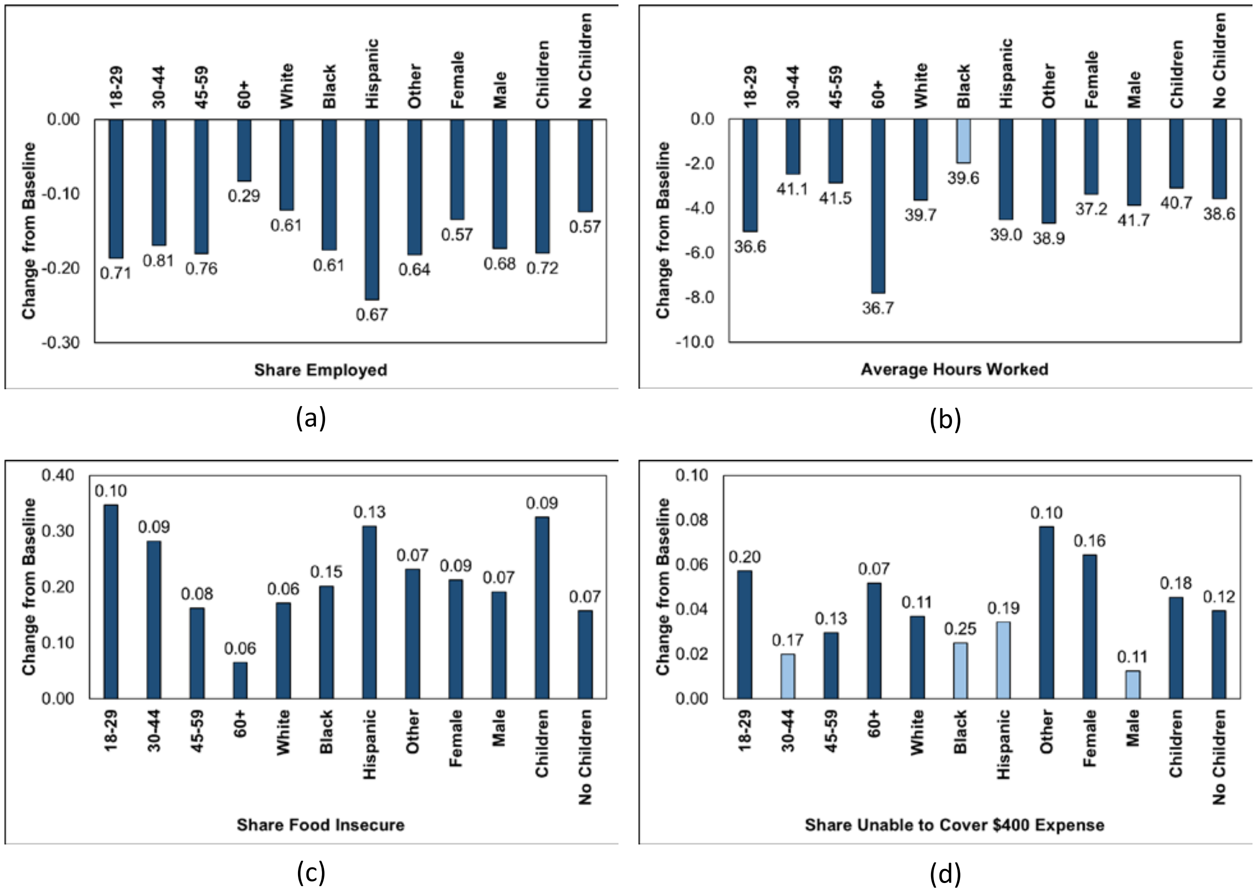

Figure 5. Changes in Wellbeing Indicators from Pre-COVID Baseline for Select Demographic Groups. Source: CIS and various baseline sources. Pre-COVID baseline sources are listed in the Data Appendix. Baseline levels are given at the top (or bottom) of each bar. Y-axis indicates change from pre-COVID baseline measured in the CIS. Unless lightly shaded, all changes are statistically significant at the 5% level.

Table 1. Changes in Wellbeing Outcomes and Place Characteristics

	Employed share	Mean hours last week	Food insecure share	Mean social connected.	Share w. some poor mental health days
PANEL A.					
Share Black	0.03	-12.188	0.199	0.961	-0.152
	(0.11)	(4.327)**	(0.107)*	(0.486)*	(0.105)
Share Hispanic	0.103	-7.162	0.295	1.033	-0.057
	(0.121)	(10.67)	(0.176)	(0.508)*	(0.189)
Share w. BA	0.201	3.235	-0.472	0.943	0.497
	(0.245)	(5.663)	(0.177)**	(0.873)	(0.243)*
Share Foreign Born	-0.299	15.991	0.035	-0.333	0.284
	(0.204)	(13.386)	(0.261)	(0.842)	(0.284)
PANEL B.					
80:20 Inequality	-0.024	-1.366	0.046	-0.1	-0.012
	(0.016)	(1.551)	(0.029)	(0.084)	(0.031)
Log median HH income	0.03	4.289	-0.026	0.457	0.19
	(0.075)	(3.293)	(0.073)	(0.306)	(0.091)*
PANEL C.					
Behavior index	-0.023	0.433	0.001	0.242	0.072
	(0.043)	(1.875)	(0.031)	(0.126)*	(0.046)
Restriction index	-0.009	-0.953	0.072	-0.052	-0.031
	(0.027)	(1.753)	(0.027)**	(0.136)	(0.029)
Any school restriction	0.039	9.788	-0.212	2.423	0.178
	(0.328)	(21.368)	(0.446)	(1.799)	(0.483)

Notes: Data are 18 place-level observations constructed from weighted CIS microdata and baseline data. Each column-panel is one linear regression containing covariates shown in the panel. Constant terms are unreported. Dependent variables indicated in the column headings. Robust standard errors in parentheses. Since all places have roughly equal sample sizes, regressions are unweighted. ** indicates significance at the 5% level; * at the 10% level.

Table 2. Changes in Wellbeing Outcomes and Individual Characteristics

	Layoff, furlough, or unemp. since 3/1	Change in hours	Sought, received food aid in past week	Change in social connected.
Black (NH)	-0.03	-0.27	0.01	0.17
	(0.03)	(1.69)	(0.01)	(0.13)
Hispanic	0.09	-5.43	-0.01	0.13
	(0.03)***	(2.13)**	(0.02)	(0.15)
Other (NH)	0.08	-2.25	0.01	0.01
	(0.04)**	(2.02)	(0.02)	(0.11)
Female	-0.01	0.93	-0.01	-0.03
	(0.02)	(1.17)	(0.01)	(0.08)
Age 30-44	-0.06	-0.08	-0.02	0.17
	(0.03)*	(2.07)	(0.02)	(0.16)
Age 45-59	0.00	-2.25	-0.04	0.02
	(0.03)	(2.2)	(0.02)**	(0.14)
Age 60+	-0.12	5.01	-0.05	0.04
	(0.04)***	(1.85)***	(0.02)**	(0.13)
Income $40k-75k	-0.02	0.14	-0.04	-0.07
	(0.03)	(1.46)	(0.01)**	(0.1)
Income $75k+	-0.07	3.4	-0.07	-0.07
	(0.03)**	(1.51)**	(0.01)***	(0.11)
Two adult only HH	0.05	-1.33	-0.03	-0.13
	(0.03)*	(1.45)	(0.02)**	(0.09)
Kids, none school age	-0.03	0.25	-0.04	-0.16
	(0.06)	(3.00)	(0.03)	(0.2)
Kids, some school age	0.08	-4.11	0.00	-0.19
	(0.03)***	(1.74)**	(0.01)	(0.13)
Other HH type	-0.04	-0.36	-0.03	-0.15
	(0.04)	(1.84)	(0.02)	(0.11)
COVID diagnosis in home	-0.44	1.88	0.05	-0.52
	(0.09)***	(3.24)	(0.03)*	(0.29)*
COVID death in friends, fam	0.07	-5.44	0.03	-0.07
	(0.05)	(3.15)*	(0.02)*	(0.21)
Suburban county	-0.08	1.92	0.02	-0.13
	(0.04)*	(2.3)	(0.02)	(0.15)
Rural county	-0.02	0.85	0.02	0.14
	(0.04)	(2.1)	(0.02)	(0.12)
Constant	-	-10.38	-	0.11
		(2.68)***		(0.16)
Dependent variable mean	0.14	-9.30	0.06	0.11
N	2045	1854	2088	2016

Notes: Data is CIS microdata, Wave 1 only. Columns 1 and 3 report marginal effects from probit estimation (and therefore constant terms are unreported); 2 and 4 report coefficients from linear regression. All analyses are weighted and all variables are categorical. Omitted categories: white non-Hispanic; male; income under $40,000 per year; urban county; one adult only household. *** indicates significance at the 1% level; * at the 5% level; * at the 10% level.

Table 3. Work, Behavior, and Mental Health when COVID Symptoms, Risk Present

	Employed last 7 days	Layoff, furlough, or unemp. since 3/1	Hours worked last 7 days	Behavior Index	CES-D Index
Any self-reported fever symp.	0.06	0.01	-1.33	0.22	1.92
	(0.05)	(0.03)	(2.24)	(0.39)	(0.35)***
2 or more risk factors	-0.15	0.01	1.48	0.03	0.69
	(0.04)***	(0.03)	(1.75)	(0.25)	(0.24)***
Additional controls	Y	Y	Y	Y	Y
N	2166	2128	883	2164	2179

Notes: Source: CIS. Additional controls are identical to those in Table 2, but exclude COVID diagnosis in the home or experience with a COVID death.