Analysis of the Uninsured Population in Maryland: How Was the Uninsured Rate Effected by COVID-19 Pandemic Job Losses and Subsequent Loss of Employer-Sponsored Insurance?

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Abstract

The Maryland Health Benefit Exchange, which operates Maryland's state-based health insurance marketplace, Maryland Health Connection, analyzed the Maryland uninsured population by geography, demographic characteristics, and eligibility for government programs before and after the job losses resulting from the COVID-19 pandemic. This report details the methodology and results of this effort along with the construction of an interactive web dashboard that will enable other researchers, outreach, and marketing to effectively identify and target those most at risk of being uninsured and those experiencing new uninsurance due to the pandemic.

Keywords:

Uninsured, COVID-19 Pandemic, Job Loss, Employer-Sponsored Insurance, Maryland, State-Based Health Insurance Exchange

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Background

A previous analysis[1] of the uninsured population in Maryland was completed in 2019 using the 2018 5-year American Community Survey (ACS) table C27016, "HEALTH INSURANCE COVERAGE STATUS BY RATIO OF INCOME TO POVERTY LEVEL IN THE PAST 12 MONTHS BY AGE", with ArcGIS (U.S. Census Bureau 2018). To increase transparency, accessibility, and reproducibility, the Maryland Health Benefit Exchange's (MHBE's) data analyst created a new data analysis pipeline to allow for flexible analysis of the uninsured population under varying scenarios. The Census Bureau publishes Public Use Microdata Samples (PUMS) each year that are available at the person or household level allowing researchers to create their own tables or extracts of the available census surveys including the ACS. The University of Minnesota publishes census and survey microdata that has been extensively harmonized, cleaned, and annotated for use by researchers via their IPUMS projects and this analysis utilized the IPUMS USA project to generate a data extract from the 2018 5-year ACS dataset (Ruggles, et al. 2020). IPUMS also maintains a library, ipumsr, for RStudio that allowed us to import and edit the data and metadata directly using the R Programming Language (RStudio Team 2020).

Using these data, along with other data detailed below, MHBE analyzed the uninsured population in Maryland. With the onset of the COVID-19 pandemic and subsequent job losses in early 2020, it became clear that the uninsured population would likely be impacted as people lost their employer-sponsored insurance (ESI) when they lost their jobs. Therefore, an additional analysis of the impact of COVID-19 related job losses and subsequent loss of ESI was integrated into this analysis using a modified version of the analysis completed by the Urban Institute for their report "Estimating Low Income Job loss due to COVID-19", which we have made available on GitHub.[2] Once complete, our analyses were compiled into an RMarkdown dashboard[3] and all code and data were added to our repository on GitHub[4] (Allaire, et al. 2020). Some data that was deemed sensitive or private was not included in our repository. Additionally, the IPUMS extract was too large to upload, so we instead provide all the parameters used to generate our extract in our methodology for ease of replication. All other code and public data were uploaded to our repository for reference or use by other interested researchers to replicate or review this analysis.

Methodology

Data and Libraries

Data files were obtained from multiple sources. IPUMS (https://usa.ipums.org) was used to generate the data and data dictionary and definition (DDI) files for the ACS microdata using the parameters as detailed below.

For all data at geographies lower than statewide, we used: 2018 ACS 5yr (sample), Variables [`YEAR, MULTYEAR, SAMPLE, SERIAL, HHWT, CLUSTER, STRATA, COUNTYFIP, STATEFIP, METRO,`

[1] Available at: https://arcg.is/1zPiHf
[2] Available at: https://github.com/Maryland-Health-Benefits-Exchange/covid-neighborhood-job-analysis
[3] Available at: https://bit.ly/UninsAnalysisCOVID
[4] Available at: https://github.com/Maryland-Health-Benefits-Exchange/MD_uninsured_analysis

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`PUMA, GQ, OWNERSHP, OWNERSHPD, PERNUM, PERWT, FAMSIZE, RELATE, RELATED, SEX, AGE, RACE, RACED, HISPAN, HISPAND, BPL, BPLD, CITIZEN, YRIMMIG, HCOVANY, HCOVPRIV, HCOVPUB, HINSEMP, EMPSTAT, EMPSTATD, OCC, EDUC, INCSS, INCWELFR, INCSUPP, VETSTAT, IND, POVERTY, MIGRATE1, MIGRATE1D]`

For statewide data, we used: 2018 ACS 1yr (sample), Variables `[YEAR, SAMPLE, SERIAL, HHWT, CLUSTER, STRATA, COUNTYFIP, STATEFIP, METRO, PUMA, GQ, OWNERSHP, OWNERSHPD, PERNUM, PERWT, FAMSIZE, RELATE, RELATED, SEX, AGE, RACE, RACED, HISPAN, HISPAND, BPL, BPLD, CITIZEN, YRIMMIG, HCOVANY, HCOVPRIV, HCOVPUB, HINSEMP, EMPSTAT, EMPSTATD, OCC, EDUC, INCSS, INCWELFR, INCSUPP, VETSTAT, IND, POVERTY, MIGRATE1, MIGRATE1D]`

We utilized the 5-year data for sub-state geographies because it is a larger sample size (as it is 5 years of data aggregated) and therefore the estimates have a lower margin of error. For the statewide statistics, we utilized two sources: For the pre-COVID statewide estimates, the HI-05 Census Report "Health Insurance Coverage Status and Type of Coverage by State and Age for All Persons: 2019" was used (US Census 2020) and for the post-COVID statewide estimates the most recent 1-year 2018 ACS microdata was used, which is accurate at the state or higher level geography. Both the 1- and 5-year ACS microdata were imported, formatted, and edited into dataframes using the ipumsr library (Ellis and Burk 2020)

The unemployment map created by Ajani Pierce at the Maryland Department of Labor (MD LABOR) was imported using the "`ESRI2sf`" library created by Yongha Hwang, which imports an ArcGIS online map from a URL and transforms it into a shapefile dataframe in R (Pierce 2020), (Hwang 2017). Importing the data directly from the static URL this way allows for the data to update when Mr. Pierce updates his map on ArcGIS Online for Maryland.

The Urban Institute's analysis of COVID-19 related job losses that was modified and utilized for this project pulled Current Employment Statistics (CES) from the Bureau of Labor Statistics (BLS) using their available plain text files and several R libraries listed in the script (Urban Institute 2020). The modification applied are described in section C.

Several additional R libraries were used and are listed in the RMarkdown dashboard and in the R scripts containing the code to build the objects and data that were imported into this project including: acs (Glenn 2019), DT (Xie, Cheng and Tan 2020), flexdashboard (Iannone, Allaire and Borges 2020), ggthemes (Arnold 2019), htmlwidgets (Vaidyanathan, et al. 2020), janitor (Firke 2020), knitr (Y. Xie 2020), labelled (Larmarange 2020), plotly (Sievert 2019), sf (Pebesma 2018), shiny (RStudio 2020), testit (Y. Xie, testit: A Simple Package for Testing R Packages 2020), tidyverse (Wickham, et al. 2019), and tigris (Walker 2020). The RMarkdown Definitive Guide was an invaluable resource that was constantly consulted during this project as well (Xie, Allaire and Grolemund, R Markdown: The Definitive Guide 2020).

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A. 2018/19 Uninsured Statewide Estimates

Because we wanted to represent the most recent available data, all of the statewide estimates used for the 2018/2019 estimates are sourced from the 2019 1-year ACS data, specifically from the Census Bureau's ACS Table HI-05, "Health Insurance Coverage Status and Type of Coverage by State and Age for All Persons: 2019" (US Census 2020). The Uninsured that are Maryland Health Connection Eligible (MHC Eligible) are calculated by subtracting the estimated number of uninsured that are undocumented by the Center for Migration Studies of New York's Data Tool from the total uninsured (Warren 2020).

B. 2018/19 Uninsured Sub-State Estimates

For sub-state estimates, we used the 2018 5-year ACS microdata (Ruggles, et al. 2020). The 5-year files are recommended for sub-state analysis by the Census and other experts due to the larger sample size.

A fully annotated R script entitled "`methodology_final.R`" was written for this project. It contains all code and explanations of the code and is available on our GitHub repository. This section will briefly highlight the steps taken in creating this analysis and interested researchers can consult that script for a more in-depth explanation. The IPUMS extract (and indeed all Census microdata samples) are anonymized person-level data, with each record (row) representing a certain number of individuals (the number of individuals that share those characteristics of that row being represented in the `perwt` variable) (Ruggles, et al. 2020). This allows for a person-level analysis of Census data while still protecting the privacy of the respondents.

The Public Use Microdata Area (PUMA) level of geography was chosen because each PUMA contains at least 100,000 individuals, is entirely contained within a state (i.e., does not cross state borders like ZIP codes can), and is geographically contiguous (US Census Bureau 2011). Maps that show county level data were created using crosswalk files available from the Missouri Census Data Center's geocorr application (Missouri Census Data Center 2018). Statewide estimates were aggregated up from PUMA estimates.

First, the two IPUMS data extracts were created on the usa.ipums.org website using the parameters listed in the Data and Libraries section above. Second, the modified Urban Institute analysis was performed on the IPUMS data extracts. More detail on this step can be found in the section C.

The first step taken was to filter the data to include only non-institutionalized persons using the relate variable (i.e.: `filter(relate != 13)`). Next, we generated flag variables to assist in identifying individuals who are likely legally present. Flags were generated for receiving public assistance, having an occupation in the public or military sectors, being employed in an occupation that is likely to require legal status, and lastly a flag variable that takes the other flags and a few other variables and outputs the likely legal migration status for the person record. MHBE utilized a methodology similar to the one used by the Center for Migration Studies of New York (CMSNY) to generate our method of "logical edits" to generate this assumed "`legal`" status variable and they also supplied us with a list of occupations likely to require legal status (Warren 2020). This list is not included the publicly available code. Interested researchers can reach out to CMSNY directly for this list of occupations or they can use their own list

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when replicating this analysis. Several grouping variables were also created including age groupings ("Under 18", "19-34", "35-64" and "65+"), racial/ethnic categories (based on the Census variables race and hispan), and percent of the Federal Poverty Level ("Less than 133% of FPL", "133-138% of FPL", "139-150% of FPL", "151-200% of FPL", "201-250% of FPL", "251-299% of FPL", "300-400% of FPL", and "More than 400% FPL"). These grouping variables allow for easier generation of aggregated plots, tables, and figures.

The `acs_df` dataframe was now ready for actual analysis. To generate the 2018 uninsured estimates, we filtered the data to include only non-institutionalized persons and, for some of the analyses, individuals who are likely legally present. Several summary dataframes were created using different grouping variables including geography (`puma` or `state`) and using the `summarize()` function to aggregate the data up to those geographies using the person weight (`perwt`) variable. For the eligibility table, we created a summary dataframe that broke down the uninsured population by eligibility for Medicaid, subsidized QHP, and unsubsidized QHP as well as those who are not eligible to enroll in Medicaid or the exchange plans. Eligibility was based on the 2018 ACS `fpl` variable, which represents the income as a percent of the federal poverty level, and age. Furthermore, we utilized an analysis of characteristics of the uninsured population done by the Urban Institute to estimate those ineligible for subsidy due to an offer of employer-sponsored insurance (Blumberg, et al. 2018). We also generated dataframes specific to the undocumented population, but they are not utilized in this analysis other than to filter our populations to include only legally present individuals (i.e., `filter(lawful==1)`).

C. Potential COVID Impact 2018/19 – Uninsured Statewide Estimates

We modified the Urban Institute analysis to include all income levels as their analysis originally only looked at low income job losses. Additionally, we altered the script to cover the same time period as the enrollment data we used, which was March 2020 to September 2020. We also limited the analysis to only Maryland, where applicable. From this modified analysis, we obtained percent change in jobs data for each person-level row in our ACS dataset. These percent change in jobs data were used to calculate the number of people who reported having ESI on the 2018 ACS who could now be at risk for losing their ESI due to job loss.

The Urban Institute analysis looks at net job loss and not just unemployment. This was important to isolate jobs lost specifically to COVID-19 rather than the unemployment rate which includes those who were unemployed pre-pandemic. Net change in unemployment rate from February 2020 to July 2020 is 4.3%, which aligns closely with the imputed net job loss from this analysis (4.4%).

We used this modified analysis to generate our dataset from the 1-year 2018 ACS microdata available from IPUMS. This produced a dataframe with the variables listed as well as several additional variables generated during the Urban Institute's analysis (`led_code`, `percent_change_state_imputed`, `random_number`, `disemploy`, `is_employed`, `total_employment`). The variables relevant to our analysis are `led_code` (the CES industry code) and the employment variables that are utilized to generate the percent change in employment.

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Because the modified Urban Institute analysis yielded estimated loss of ESI, but we know that not everyone who loses ESI goes on to become uninsured, we performed two adjustments to the statewide data. First, the pool of people who lost ESI was reduced by 32% to account for individuals who could obtain ESI through their spouse using an estimate from Urban Institute's analysis on COVID-19 related ESI loss (Blumberg, et al. 2018). The pool was further reduced by the net change in Medicaid and QHP enrollment between March and September to yield the final statewide estimates of uninsured individuals.

D. Potential COVID Impact 2018/19 – Uninsured Sub-State and Industry Estimates

The sub-state estimates in this section also used the 5-year 2018 ACS microdata from IPUMS, just like in the previous "2018/19 Uninsured" section. For the sub-state estimates, we used a different approach to estimate the number of individuals that lost ESI but were able to take up their partner's employer-sponsored insurance. The third script, "`household_analysis.R`" contains the code used to perform this analysis. Using a similar approach to that described previously, we deduced the number of people in each PUMA that would switch to their spouse's coverage if they lost ESI. This estimate was obtained using the following logical filters:

1. The head of household (`relate==1`) was employed (`empstat==1`) and had ESI (`hinsemp==2`).
2. The spouse (`relate==2`) was employed (`empstat==1`) and had ESI (`hinsemp==2`).

We then calculated the number of people who lost ESI due to COVID and multiplied that by the probability that their spouse did not lose their job. This value was divided by the total number of people who lost ESI in that PUMA. This dataframe was saved as `acs_df_hh_puma` and used to adjust the PUMA level estimates of uninsured for each post-COVID impact map.

We also obtained county-level net enrollment data from the same publicly available monthly data reports used in the statewide estimates described in section C. This data frame was crosswalked from county to PUMA using the geocorr county to PUMA file and the results were used to further adjust the post-COVID impact maps. Sub-state numbers were then divided into eligibility categories based on income reported at the time of the 2018 ACS (in the form of the `poverty` variable created by IPUMS) and age/age-group as well as a breakdown by race/ethnicity. Further demographic or characteristic based analysis is available upon request from the MHBE Policy Unit.

In addition, we estimated the effects of the COVID-19 related job losses and subsequent loss of Employer-Sponsored Insurance (ESI) on the uninsured population. We generated dataframes summarizing ESI loss by both geography and industry and breaking down the eligibility of those who are uninsured or covered by ESI. ESI loss was determined by calculating the percent change in jobs using the Urban Institute generated variables and methodology, and multiplying the number of individuals with ESI by the percent change in jobs to yield an estimate of the number of individuals who potentially lost ESI coverage. After joining the Job Loss data to ESI data from ACS at the PUMA-industry level, data was further aggregated up to the BLS industry category. BLS industry categories were used (`led_code` variable in `COVID_Uninsured_Analysis`) as they can be considered a parent category of the IPUMS

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"`industry`" variable. Comparing across sub-industries in an area or a small set of areas is likely not going to be very accurate and could be misleading. Lastly, summary dataframes were generated that captured racial and age breakdowns of the uninsured and ESI covered populations.

These dataframes were then saved as R objects (`saveRDS()`) to be imported into the Rmarkdown dashboard to generate the maps and plots. Each leaflet map generated in this project was also saved as HTML a stand-alone file for ease of sharing and distribution on request. This project was designed in such a way as to allow for future modification to meet the needs of the MHBE Policy and Plan Management or Marketing departments, as well as other MHBE stakeholders and departments, and to generate interactive reports and visualizations.

E. Dashboard

The Rmarkdown dashboard was then created to visualize the summary dataframes in an interactive and intuitive fashion. The raw Rmarkdown code is available by clicking the "Source Code" button in the top right corner of the dashboard header and MHBE endeavored to fully annotate each step taken for readability and reproducibility. In addition to the leaflet maps generated to show the geographic distribution of the uninsured both pre and post COVID-19 related job losses, we also generated demographic breakdowns in the form of bar graphs examining the percent uninsured or ESI covered in each age grouping and racial/ethnic grouping. Lastly, the DT library was used to generate a fully interactive and visually appealing table showing the breakdown by industry of the uninsured, ESI covered, percent change in employment, and estimate of those at risk of losing their ESI coverage. A map of the unemployment insurance claims was also generated from the ArcGIS Online map created by A. Pierce at MD LABOR using leaflet (Pierce 2020). If this dashboard is updated in the future, this report, the dashboard, and the GitHub repository will be updated.

Limitations and Assumptions

Estimated Medicaid and QHP eligibility is based on the reported income at the time of the 2018 ACS and not in the month that coverage was lost. As a result, it is likely that our estimates of individuals who lose ESI and are eligible for Medicaid or QHPs understate those eligible for Medicaid and overstate those eligible for QHPs, since Medicaid eligibility is based on current month income.

The specific occupations likely to require legal status that were used in the logical edits to assign "likely legal status" to person-level records were obtained from the Center for Migration Studies of New York (Warren 2020). This list is not included in the publicly available code. Interested researchers can reach out to CMSNY directly for this list of occupations or they can use their own list when replicating this analysis.

We utilized slightly different datasets to balance using the most recent data, while also doing more granular analysis. At the statewide geography, the 1-year ACS data is both the most recent and reasonably accurate, but at sub-state geographies it is advised by the Census Bureau and IPUMS to use the 5-year ACS file, which has a larger sample size and is therefore more accurate at that level. For statewide statistics in the "2018/19 Uninsured" tab, we utilized the 2019 1-year ACS data, specifically

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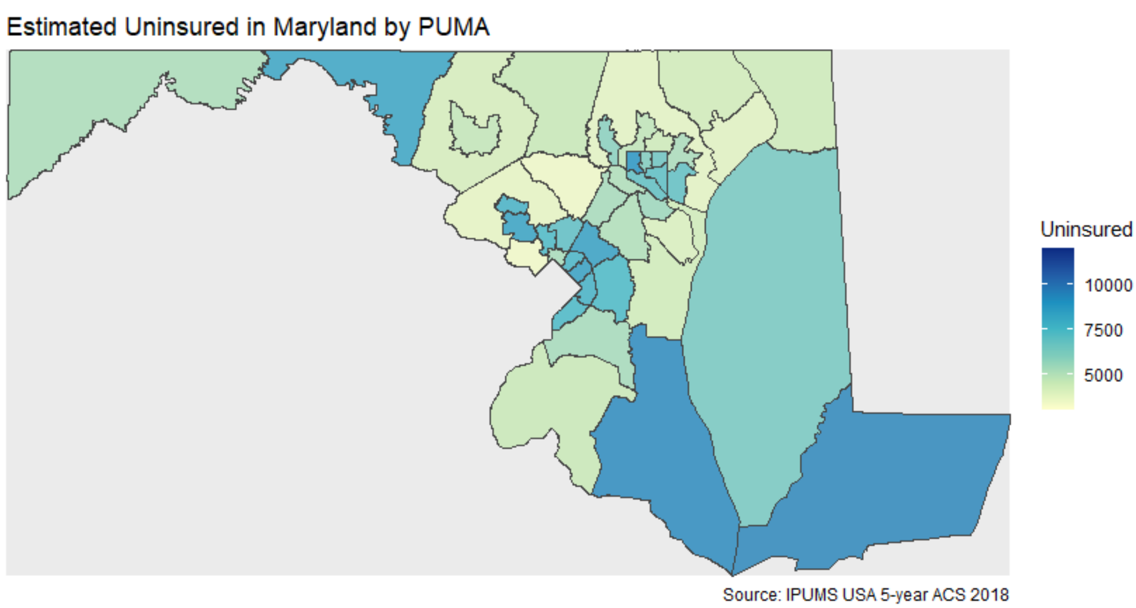
from the Census Bureau's ACS Table HI-05, "Health Insurance Coverage Status and Type of Coverage by State and Age for All Persons: 2019", as described in section A. Maryland's uninsured rate did not increase from 2018 to 2019, so we make the assumption that we can using data from 2019 in comparison to 2018 at the statewide level. For sub-state statistics, we utilized the 5-year ACS microdata file, as described above in section B. For statewide statistics in the "Potential COVID Impact" tab, we utilized the 1-year ACS microdata file for 2018, as described above in section C. For sub-state statistics, we again utilized the 5-year ACS microdata file, as described above in section D. IPUMS has a planned release date of mid-February for the next 5-year ACS microdata file that would include 2019, at which time this analysis will be refreshed with that data[5].

The subpopulation plots (i.e.: "Uninsured by Age & FPL", "Demographic Breakdowns") were not adjusted by the net change in Medicaid and QHP enrollment between March and September due to limitations of substate enrollment data. We intend to update these subpopulation plots, the dashboard, and the methodology when the necessary data is available.

Results:

As described in the methodology, the statewide totals for the 2018/2019 uninsured analysis were taken directly from the Census Bureau's report for 2019, which stated that there were 357,000 total uninsured and that total does comport with the total obtained from the 2018 microdata (352,265) and results in an overall uninsured rate of 6.0% statewide (US Census 2020), (Ruggles, et al. 2020). The estimated number of uninsured who would be eligible for MHC plans was 258,000 and that also aligned with the estimate from the 2018 microdata (251,064). Just over 5.5 million individuals were estimated to hold any type of insurance and 3.7 million were estimated to hold employer-sponsored insurance. Figure 1 below shows



[5] https://forum.ipums.org/t/acs-5-year-2019-data-release/3859

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a static version of the interactive web map available on our dashboard,[6] showing the Public Use Microdata Areas with the highest concentration of MHC eligible uninsured persons.

Figure 1: Estimated Maryland Health Connection eligible uninsured by Public Use Microdata Area.

The highest number of uninsured occurred in certain PUMAs within Prince George's and Montgomery counties, southern Maryland counties, and downtown Baltimore City. Washington County's PUMA also showed a higher concentration of uninsured persons than the surrounding area. This provides a good starting point for where to target resources enrollment outreach, with the added benefit that the analysis allows users to focus on uninsured who are eligible to enroll through MHC.

The potential COVID-19 pandemic impact estimated shows that while all PUMAs across the state are affected, these target areas continue to have a higher concentration of uninsured individuals. Statewide, the COVID-19 impact analysis yields an estimated increase in the uninsured rate to 7.1% with a total of 422,751 uninsured of which 316,961 are eligible for plans through MHC. We estimate that between March and September 2020, an estimated 112,000 Marylanders lost a job that may have provided health insurance and that over 65,000 of those individuals joined the uninsured, with 58,961 of those uninsured individuals estimated to be eligible for plans through MHC. This takes into account the net increase in enrollment through MHC during the same time period, during which MHC launched two new widely available special enrollment periods (SEPs), the COVID SEP and the Easy Enrollment SEP. These

[6] https://bit.ly/UninsAnalysisCOVID

estimates also incorporate as assumptions for the projected number of persons who lost ESI and were able to take up their spouse's insurance through their employer.

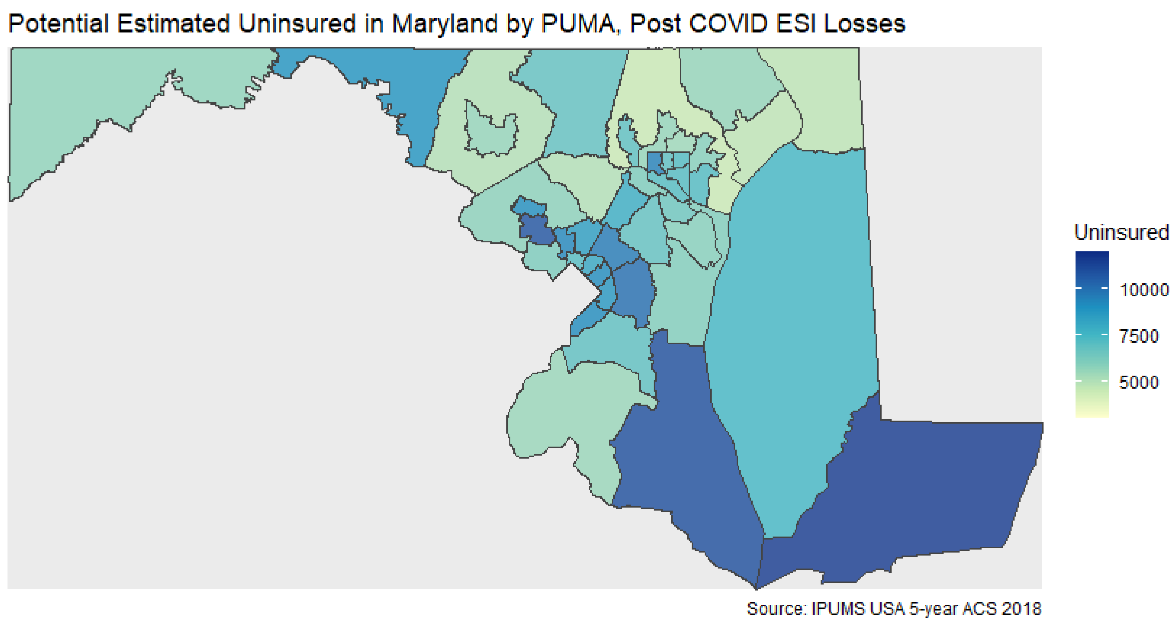

Figure 2: Potential estimated Maryland Health Connection eligible uninsured post COVID-19 pandemic related employer-sponsored insurance losses, by Public Use Microdata Area.

Figure 2 shows the PUMA-level breakdown of the geographic distribution of these estimates, showing that the same general regions are likely still the most affected by the loss of employer-sponsored insurance. Table 1 shows the estimated number of people who were uninsured prior to COVID-19 job losses, the ESI loss experienced, the estimated percentage of those that lost ESI who were able to enroll in spousal coverage, and the estimated post-COVID uninsured total for each PUMA, sorted according to

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the areas that experienced the highest ESI losses. As noted in the methodology, the post-COVID uninsured total also takes into account net enrollment through MHC during this time period.

PUMA	Uninsured	ESI loss	Uptake of spousal insurance	Post-COVID Uninsured
Prince George's County (East)--Bowie City, Kettering, Largo, Mitchellville & Lanham PUMA	7,512	4,737	33%	10,051
Montgomery County (South)--Bethesda, Potomac & North Bethesda PUMA	3,371	4,357	33%	6,127
Howard County (East)--Columbia (East), Ellicott City (Southeast) & Elkridge PUMA	5,315	3,981	36%	7,874
Wicomico, Worcester & Somerset Counties--Salisbury City PUMA	9,475	3,908	35%	11,597
Montgomery County (Central)--Rockville, Gaithersburg Cities & North Potomac PUMA	8,512	3,906	33%	10,831
St. Mary's & Calvert Counties PUMA	9,337	3,394	37%	11,005
Carroll County PUMA	4,544	3,365	36%	6,832
Montgomery County (North & West)--Olney, Damascus, Clarksburg & Darnestown PUMA	3,662	3,292	34%	5,777
Charles County--La Plata Town & Waldorf PUMA	4,492	3,207	34%	5,503
Anne Arundel County (Northwest)--Severn, Odenton, Crofton, Maryland City & Fort Meade PUMA	5,085	3,200	36%	6,847
Prince George's County (Southwest)--Oxon Hill, Hillcrest Heights & Temple Hills PUMA	7,554	3,138	27%	9,173
Prince George's County (South)--Clinton, Fort Washington (South), Rosaryville & Croom PUMA	5,327	3,125	30%	6,910
Anne Arundel County (Central)--Severna Park, Arnold & Lake Shore PUMA	4,059	3,077	36%	5,882
Montgomery County (East Central)--Wheaton, Aspen Hill & Glenmont PUMA	7,488	3,040	34%	9,316
Anne Arundel County (Southeast)--Annapolis City, Parole, Annapolis Neck & Edgewater PUMA	4,319	2,952	36%	5,994
Prince George's County (North)--Laurel, Greenbelt (North & East) Cities & Beltsville PUMA	8,571	2,855	33%	9,689
Montgomery County (Southeast)--Takoma Park City & Silver Spring PUMA	5,265	2,840	42%	7,141
Howard County (West)--Columbia (West) & Ellicott City (Northwest) PUMA	3,428	2,670	36%	4,965
Harford County (North & West)--Bel Air Town, Fallston & Jarrettsville PUMA	4,299	2,621	36%	5,607
Baltimore County--Randallstown (East), Owings Mills, Milford Mill & Reisterstown PUMA	5,933	2,583	38%	6,934
Queen Anne's, Talbot, Caroline, Dorchester & Kent Counties PUMA	6,482	2,545	40%	7,477
Baltimore County--Towson (East & Central), Parkville & Carney PUMA	4,373	2,544	40%	5,433
Montgomery County (East)--Fairland, Calverton, White Oak & Burtonsville PUMA	7,095	2,510	36%	8,567
Montgomery County (West Central)--Germantown & Montgomery Village PUMA	7,812	2,454	38%	9,112
Prince George's County (Central)--Seat Pleasant City, Capitol Heights Town & Landover PUMA	7,834	2,441	37%	8,784
Baltimore City--Sandtown-Winchester, Ashburton & Mount Washington PUMA	9,015	2,416	27%	9,496
Baltimore County--Catonsville, Woodlawn & Arbutus PUMA	5,120	2,381	33%	6,084
Baltimore County--Pikesville (South), Lochearn, Cockeysville & Mays Chapel PUMA	4,730	2,320	39%	5,611
Baltimore City--Guilford, Roland Park & Druid Lake PUMA	6,193	2,295	42%	6,945
Frederick County (Central)--Greater Frederick City PUMA	4,639	2,254	40%	5,597
Baltimore City--Frankford, Belair-Edison & Loch Raven PUMA	6,686	2,194	38%	7,212
Baltimore County (Outer) PUMA	3,773	2,187	37%	4,446
Frederick County (Outside Greater Frederick City) PUMA	4,160	2,179	40%	4,955
Washington County--Hagerstown City PUMA	8,387	2,128	45%	8,895
Baltimore County--Perry Hall, Middle River & Rosedale PUMA	5,233	2,055	39%	5,886
Anne Arundel County (North)--Glen Burnie, Pasadena, Ferndale & Brooklyn Park PUMA	5,536	2,031	38%	6,548
Prince George's County (Northwest)--College Park City & Langley Park PUMA	7,671	2,017	36%	8,180
Prince George's County (Northwest)--New Carrollton & Hyattsville (Southeast) Cities PUMA	8,580	1,993	39%	9,169
Harford County (South & East)--Aberdeen & Havre de Grace Cities PUMA	3,824	1,956	35%	4,696
Baltimore City--Inner Harbor, Canton & Bayview PUMA	7,132	1,836	46%	7,157
Baltimore City--Irvington, Ten Hills & Cherry Hill PUMA	7,037	1,774	41%	7,168
Cecil County PUMA	4,362	1,662	37%	4,721
Baltimore County--Dundalk, Essex & Edgemere PUMA	7,014	1,639	36%	7,215
Allegany & Garrett Counties--Cumberland City PUMA	5,191	1,565	36%	5,698

Due to the nature of the IPUMS microdata that we utilized, we were able to take a much more granular look at demographic and socioeconomic breakdowns of the uninsured population, both prior to and after the COVID-19 pandemic. Figure 3 shows the 2018 uninsured statewide total broken down by age group and income as a percent of the federal poverty level. We observe that as expected, the largest portion of the uninsured individuals by age are between 19 and 34 years old and over 60% of these young adults are potentially eligible for federal premium subsidies or Medicaid based on their income.

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Figure 4 shows the post-COVID ESI loss uninsured, with nearly every subgrouping experiencing some increase. Of note, many of the children who lost parental ESI coverage would be eligible for Maryland's Medicaid and CHIP programs. We do see some potential increase in populations who are most vulnerable to COVID-19 here, namely the 65 years and older subpopulation, but most individuals over 65 will be enrolled in Medicare.

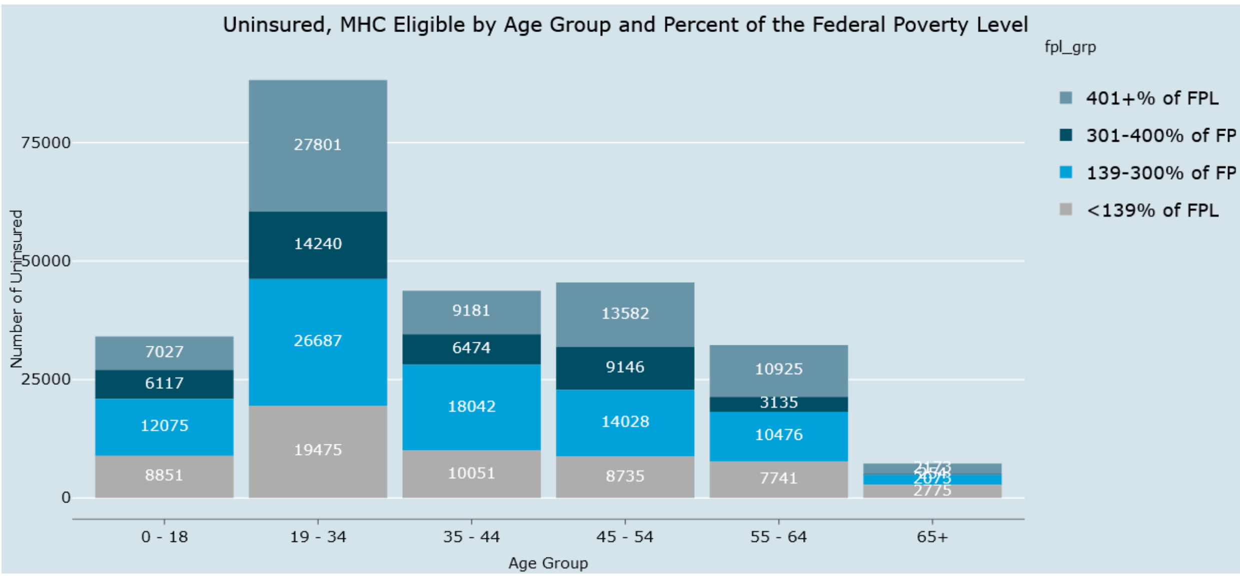

Figure 3: Maryland Health Connection eligible uninsured by age group and income as a percent of the federal poverty level.

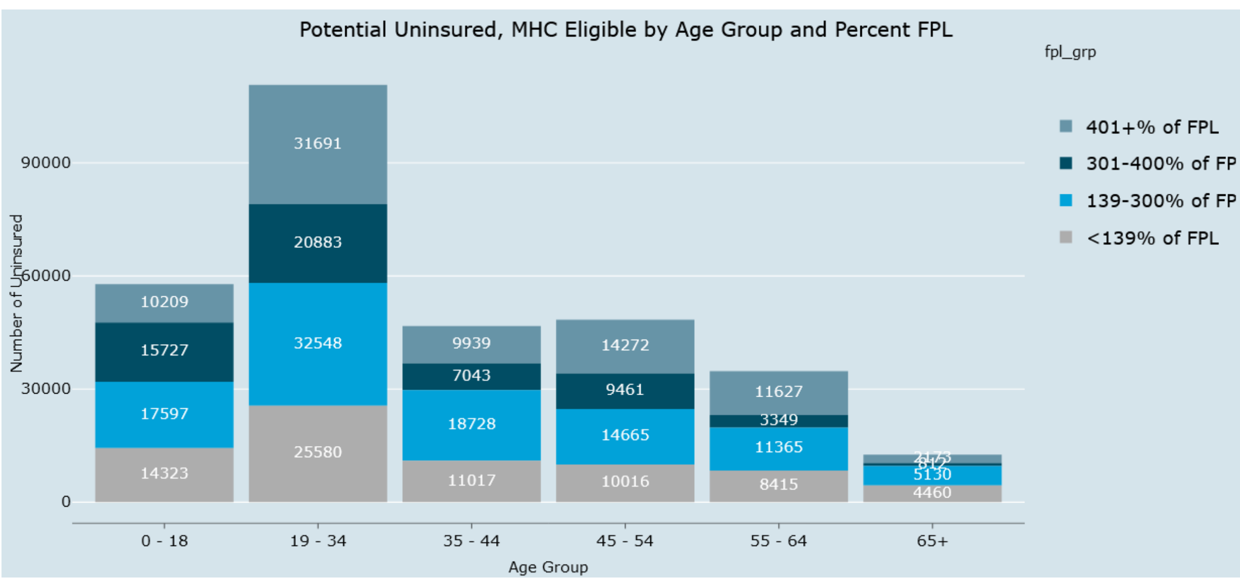

Figure 4: Potential Maryland Health Connection eligible uninsured by age group and income as a percent of the federal poverty level after loss of employer-sponsored insurance due to COVID-19 pandemic job losses.

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Since it is clear that the COVID-19 pandemic is disproportionately affecting communities of color,[7] it is also important to examine the breakdown of uninsured by race and ethnicity and how that may change due to the pandemic ESI losses. Figures 5 shows these breakdowns according to the ACS survey variables RACE and ETHNICITY. Even prior to the pandemic, there were higher rates of uninsurance among many communities of color with Hispanics in particular experiencing more proportional uninsurance than those who identify as white. Figure 6 shows the potential effects of the COVID-19 pandemic on these percentages, where we see an increase across the board but particularly in communities of color. A notably large increase (5.5% to 9%) is projected for the Black community in Maryland, which can be used to inform outreach efforts when attempting to enroll uninsured individuals into plans through MHC. This is particularly important since this community is experiencing higher mortality not just due to COVID-19 but an increased rate of suicides, as noted by researchers at Johns Hopkins and the Office of the Medical Examiner, which they speculate may be due to white communities having more access to relief efforts and the ability to work remotely (Bray, et al. 2020). Outreach efforts can utilize these estimates presented to more effectively target the most vulnerable populations throughout the state.

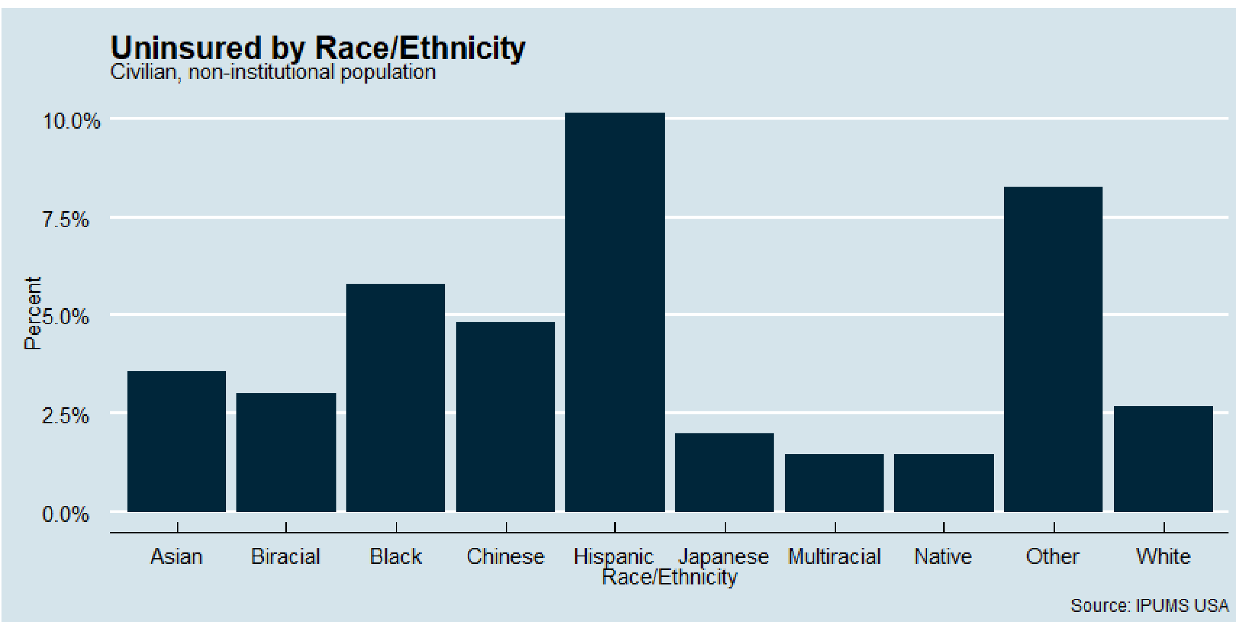

Figure 5: Total estimated Maryland Health Connection eligible uninsured statewide, broken down by race/ethnicity, as a percent of uninsured in each subgrouping.

[7] https://www.cdc.gov/coronavirus/2019-ncov/community/health-equity/race-ethnicity.html

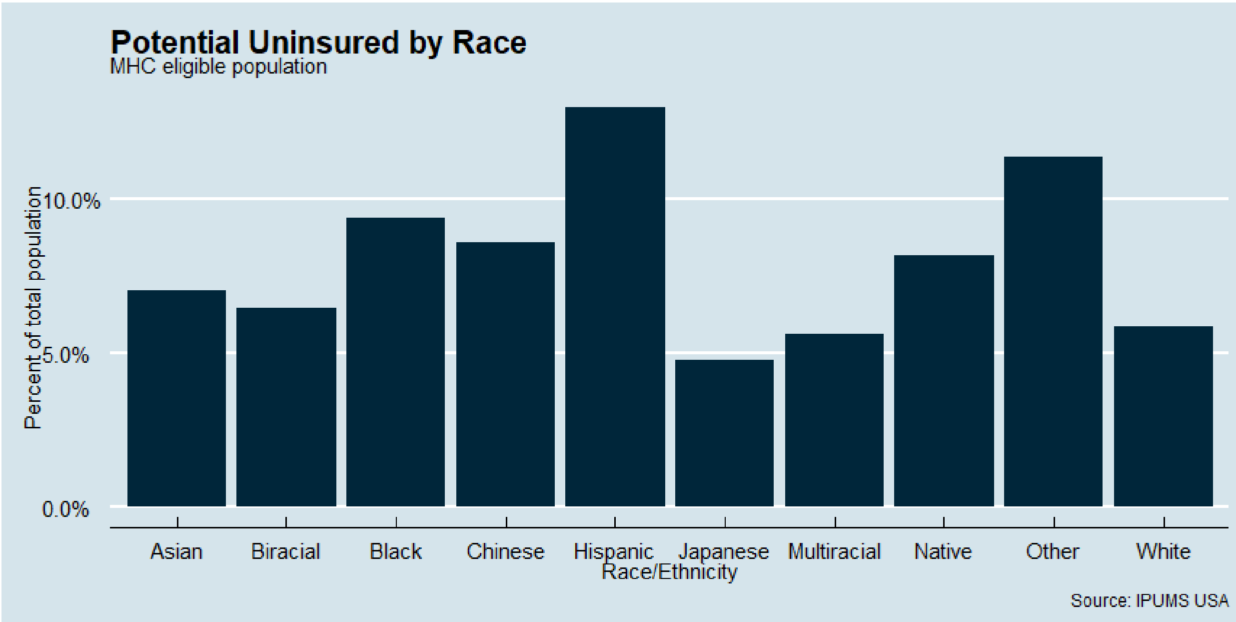

Figure 6: Total potential Maryland Health Connection eligible uninsured statewide, broken down by race/ethnicity.

We also examined the demographics of the young adult (defined here as ages 18 to 34) uninsured population, which we noted earlier is the most likely to be uninsured of any age group. Here we find that the Black community experiences the highest number of uninsured both before and after the pandemic, though the White community in this age bracket experiences the largest potential increase post-pandemic (over 23,000 potential newly uninsured).

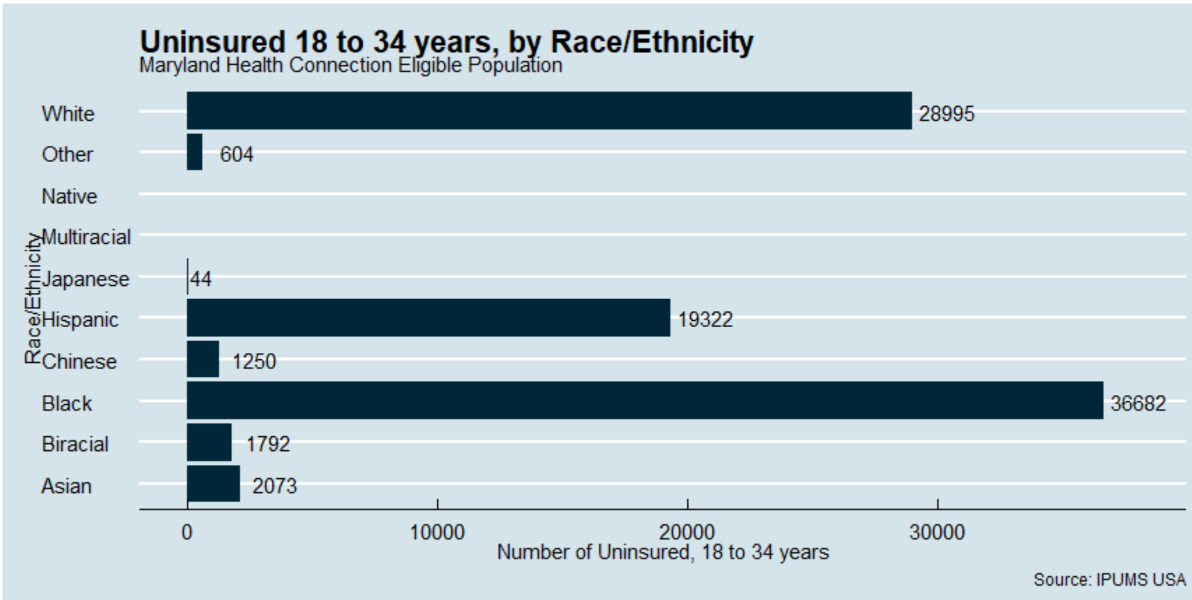

Figure 7: Maryland Health Connection eligible uninsured between 18 and 34 years, broken down by race/ethnicity.

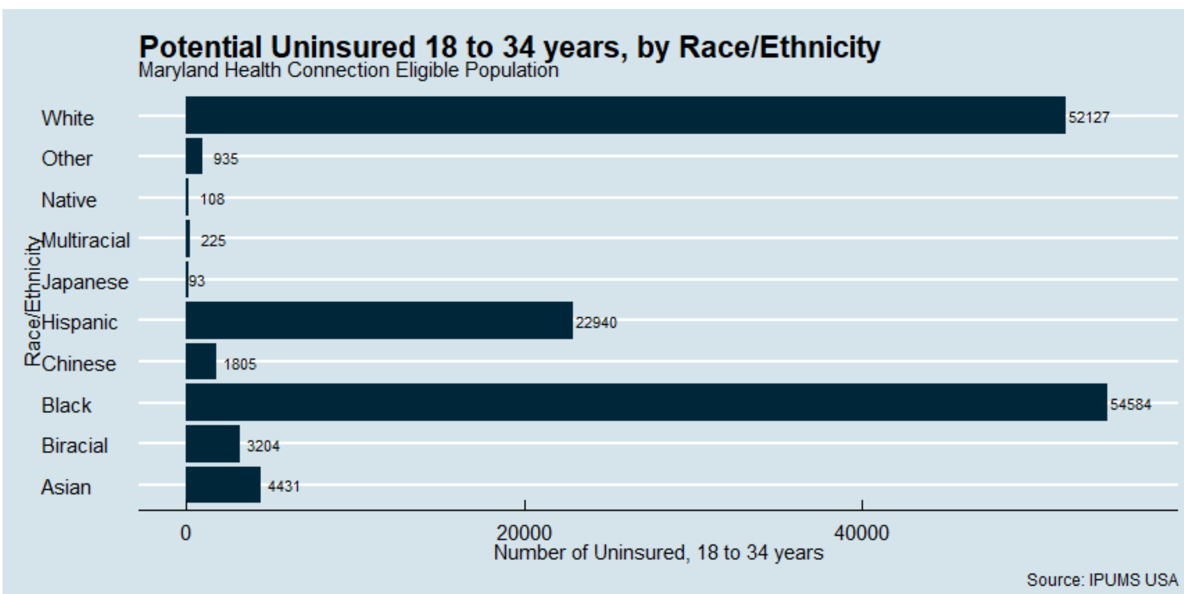

Figure 8: Maryland Health Connection eligible uninsured between 18 and 34 years, broken down by race/ethnicity, post COVID-19 loss of ESI.

Additionally, we broke down the total young adult uninsured population by income as a percent of the Federal Poverty Level in a much more granular way, showing that the vast majority of uninsured both prior to and post COVID-19 ESI losses are eligible for subsidized coverage through MHC.

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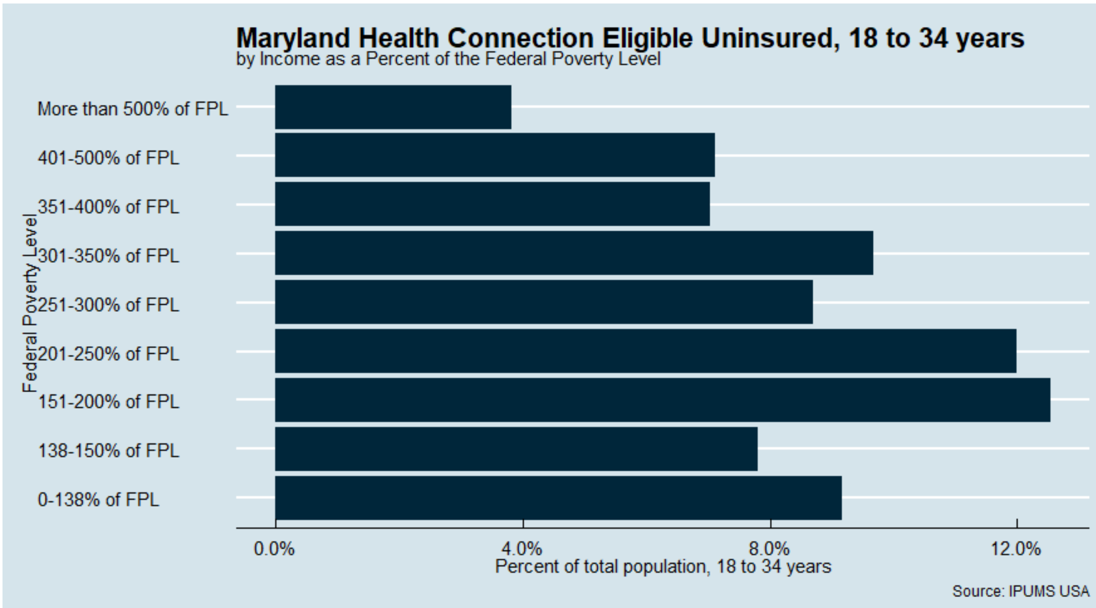

Figure 9: Maryland Health Connection eligible uninsured, ages 18 to 34 years, broken down by income as a percent of the Federal Poverty Level.

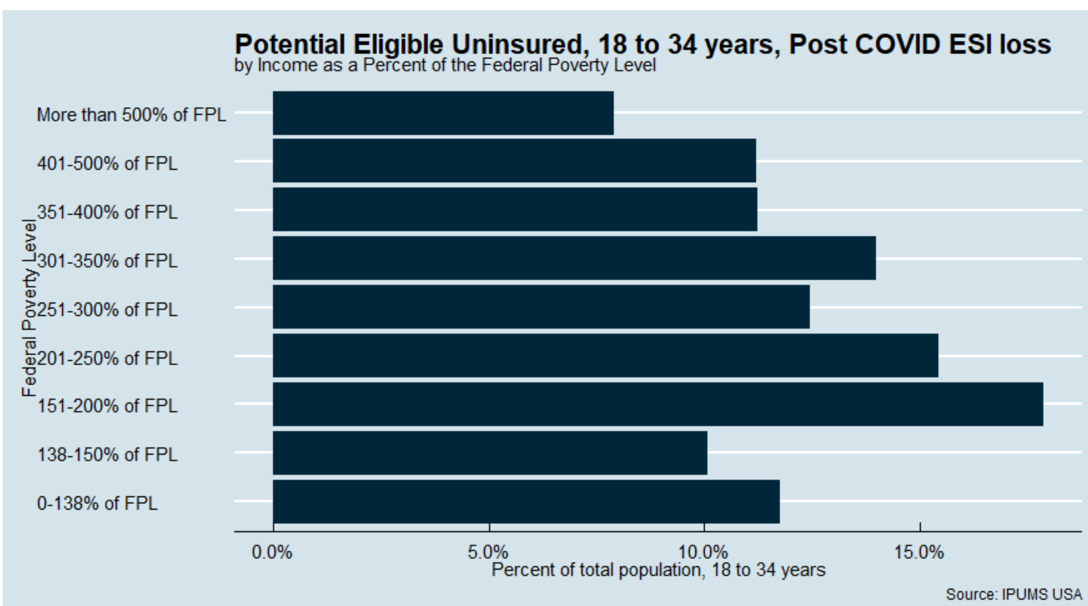

Figure 10: Maryland Health Connection eligible uninsured, ages 18 to 34 years, broken down by income as a percent of the Federal Poverty Level, including newly uninsured due to COVID-19 pandemic related loss of employer-sponsored insurance.

Lastly, we broke down the uninsured population by PUMA and their eligibility for different health insurance, namely, subsidized Qualified Health Plans (QHP) via MHC, Medicaid, and unsubsidized QHP. These tables are included in an appendix at the end of this report. The results for 2018, prior to COVID-

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19 ESI loss, are shown in Table 1 and the post-COVID estimates are shown in Table 2. These data can be used to inform outreach and consumer assistance efforts directed towards these eligibility groups. We have also included a breakdown of the ESI loss by industry at the statewide level in Table 3. All three of these tables are also included in an interactive format on our web dashboard for this project and can be downloaded from there as plain text, csv, Excel, or PDF files.

An estimated 33% of those who lost ESI coverage were able to enroll through the Maryland Health Connection and did not join the ranks of the uninsured based on analysis of the net enrollment gain during the months covered in this analysis (March 2020 to September 2020). Had these individuals not enrolled in MHC via the special enrollment periods, the uninsured would have increased from 6.0% at the end of 2018/2019 to 8.1% post COVID-related job losses. This shows the important role MHC provides as a safety net during economic downturns and periods of instability.

Conclusion

The COVID-19 related job losses and subsequent ESI losses are estimated to have increased the uninsured rate throughout Maryland. However, the increase in uninsured was mitigated by enrollment in plans through Maryland Health Connection. MHBE can use this analysis to target additional outreach or other assistance to demographic groups and geographic areas that estimated to experience the highest uninsured rates or to have experienced disproportionate increases in uninsured rates due to pandemic-related job losses. Populations that are disproportionately likely to be uninsured include young adults, who were already more likely to be uninsured and have experienced much of the job loss during the pandemic, and communities of color, which experience both higher rates of uninsurance and worse COVID-19 outcomes. As the outlook for the pandemic and the economy remain uncertain, MHBE will continue to provide a needed public service in the form of the Maryland Health Connection marketplace and our outreach efforts.

Appendix

Table 1: Maryland Health Connection Eligible uninsured population, broken down by potential eligibility for financial assistance through qualified health plans (QHP) or Medicaid (MA).

	Eligible for Financial Assistance				Ineligible for Financial Assistance		
Public Use Microdata Area	Adults - QHP Subsidy Eligible	Adults - Medicaid Eligible	Children - QHP Subsidy or Medicaid	Total Subsidized	Income over 400% FPL	Offer of Employer-Sponsored Insurance **	Total Unsubsidized
Allegany & Garrett Counties--Cumberland City	1,682	2,842	1,015	5,875	1,766	462	2,228
Anne Arundel County (Central)--Severna Park, Arnold & Lake Shore	920	2,025	658	3,782	5,175	361	5,536
Anne Arundel County (North)--Glen Burnie, Pasadena, Ferndale & Brooklyn Park	1,147	2,977	778	5,095	3,734	493	4,227
Anne Arundel County (Northwest)--Severn, Odenton, Crofton, Maryland City & Fort Meade	713	2,403	1,023	4,368	5,720	453	6,173
Anne Arundel County (Southeast)--Annapolis City, Parole, Annapolis Neck & Edgewater	1,187	2,286	559	4,291	4,772	384	5,156
Baltimore City--Frankford, Belair-Edison & Loch Raven	2,364	3,812	1,117	7,601	2,644	595	3,239
Baltimore City--Guilford, Roland Park & Druid Lake	3,017	3,178	891	7,461	2,593	551	3,144
Baltimore City--Inner Harbor, Canton & Bayview	2,932	3,394	1,161	7,653	2,932	635	3,567
Baltimore City--Irvington, Ten Hills & Cherry Hill	2,589	3,894	829	7,621	2,458	626	3,084
Baltimore City--Sandtown-Winchester, Ashburton & Mount Washington	3,645	4,190	1,493	9,565	2,777	802	3,579
Baltimore County--Catonsville, Woodlawn & Arbutus	1,488	2,726	1,150	5,637	3,012	456	3,468
Baltimore County--Dundalk, Essex & Edgemere	1,969	3,707	1,047	6,970	2,687	624	3,311
Baltimore County--Perry Hall, Middle River & Rosedale	1,099	2,661	1,155	5,249	3,369	466	3,835
Baltimore County--Pikesville (South), Lochearn, Cockeysville & Mays Chapel	954	2,717	821	4,744	3,758	421	4,179
Baltimore County--Randallstown (East), Owings Mills, Milford Mill & Reisterstown	1,425	3,623	1,066	6,487	3,642	528	4,170
Baltimore County--Towson (East & Central), Parkville & Carney	1,674	2,386	738	5,193	3,438	389	3,827
Baltimore County (Outer)	998	1,424	482	3,079	4,224	336	4,560
Carroll County	811	2,874	761	4,708	5,103	404	5,507
Cecil County	1,370	2,291	823	4,641	2,364	388	2,752
Charles County--La Plata Town & Waldorf	829	2,603	967	4,630	4,775	400	5,175
Frederick County (Central)--Greater Frederick City	936	2,894	906	4,918	3,516	413	3,929
Frederick County (Outside Greater Frederick City)	1,039	1,979	756	3,929	3,853	370	4,223
Harford County (North & West)--Bel Air Town, Fallston & Jarrettsville	927	2,306	631	4,120	4,272	383	4,655
Harford County (South & East)--Aberdeen & Havre de Grace Cities	1,028	2,167	644	3,991	2,874	340	3,214
Howard County (East)--Columbia (East), Ellicott City (Southeast) & Elkridge	1,030	2,245	879	4,393	6,485	473	6,958
Howard County (West)--Columbia (West) & Ellicott City (Northwest)	229	1,504	485	2,347	5,277	305	5,582
Montgomery County (Central)--Rockville, Gaithersburg Cities & North Potomac	1,452	4,009	1,997	8,058	6,410	758	7,168
Montgomery County (East Central)--Wheaton, Aspen Hill & Glenmont	1,541	4,051	989	6,919	5,257	666	5,923
Montgomery County (East)--Fairland, Calverton, White Oak & Burtonsville	1,468	3,527	1,365	6,586	4,569	631	5,200
Montgomery County (North & West)--Olney, Damascus, Clarksburg & Darnestown	369	1,300	417	2,308	6,390	326	6,716
Montgomery County (South)--Bethesda, Potomac & North Bethesda	685	1,268	477	2,601	7,328	300	7,628
Montgomery County (Southeast)--Takoma Park City & Silver Spring	1,243	2,984	504	5,031	5,106	469	5,575
Montgomery County (West Central)--Germantown & Montgomery Village	1,400	4,292	1,007	6,944	4,966	695	5,661
Prince George's County (Central)--Seat Pleasant City, Capitol Heights Town & Landover	1,582	4,460	1,149	7,458	4,223	697	4,920
Prince George's County (East)--Bowie City, Kettering, Largo, Mitchellville & Lanham	1,173	3,060	1,126	5,730	8,902	669	9,571
Prince George's County (North)--Laurel, Greenbelt (North & East) Cities & Beltsville	1,405	4,431	1,597	7,805	5,070	763	5,833
Prince George's County (Northwest)--College Park City & Langley Park	2,543	3,867	1,039	8,019	2,572	683	3,255
Prince George's County (Northwest)--New Carrollton & Hyattsville (Southeast) Cities	1,602	4,633	1,459	8,052	3,643	764	4,407
Prince George's County (South)--Clinton, Fort Washington (South), Rosaryville & Croom	869	2,133	725	3,969	5,894	474	6,368
Prince George's County (Southwest)--Oxon Hill, Hillcrest Heights & Temple Hills	1,289	4,299	948	6,829	5,081	672	5,753
Queen Anne's, Talbot, Caroline, Dorchester & Kent Counties	1,295	4,024	1,059	6,706	4,053	577	4,630
St. Mary's & Calvert Counties	1,568	4,075	2,536	8,596	6,147	831	6,978
Washington County--Hagerstown City	1,992	4,711	1,391	8,591	3,665	746	4,411
Wicomico, Worcester & Somerset Counties--Salisbury City	3,011	4,741	1,563	9,991	5,461	843	6,304

Table 2: Uninsured population post-COVID ESI loss, broken down by possible eligibility for Qualified Health Plans (QHP) or Medicaid (MA).

Geography	Subsidy Eligible				Subsidy Ineligible		
Public Use Microdata Area	Adults - QHP Subsidy Eligible	Adults - Medicaid Eligible	Children - QHP Subsidy or Medicaid Eligible	Total Subsidized	Income over 400% FPL	Offer of Employer-Sponsored Insurance	Total Unsubsidized
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Washington County--Hagerstown City	1,992	4,711	1,391	8,591	3,665	746	4,411
Wicomico, Worcester & Somerset Counties--Salisbury City	3,011	4,741	1,563	9,991	5,461	843	6,304
Total	64,489	136,973	44,183	258,541	191,957	23,622	215,579

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Table 3: Estimated percent of jobs lost due to COVID-19 pandemic (based on analysis completed by Urban Institute) and resulting estimate of people who lost ESI by industry.

Industry (Bureau of Labor Statistics)	Total Pop	Insured	Uninsured	ESI	Employed Before	Net Unemployed After	Percent Change	Lost ESI
Accomodation and Food Services	240,795	216,288	24,507	125,189	176,181	37,449	-21%	26,610
Administrative and Support and Waste Management and Remediation Services	149,856	132,575	17,281	85,910	118,090	10,266	-9%	7,468
Agriculture, Forestry, Fishing, and Hunting	17,512	16,137	1,375	8,449	12,992	-24	0%	0
Arts, Entertainment, and Recreation	91,341	86,296	5,045	61,396	65,135	19,537	-30%	18,416
Construction	213,617	189,094	24,523	137,124	184,093	5	0%	4
Educational Services	363,359	355,073	8,286	295,364	298,873	14,978	-5%	14,802
Finance and Insurance	130,096	127,724	2,372	109,555	115,432	362	0%	343
Health Care and Social Assistance	497,738	477,767	19,971	347,066	426,137	26,807	-6%	21,833
Information	67,191	64,605	2,586	54,608	57,620	5,030	-9%	4,767
Management of Companies and Enterprises	4,664	4,664	0	3,379	4,409	677	-15%	519
Manufacturing	26,442	25,019	1,423	18,016	21,803	3,954	-18%	3,268
Mining, Quarrying, and Oil and Gas Extractions	2,546	2,374	172	1,565	2,371	-49	2%	0
Other Services	203,028	188,530	14,498	127,697	167,006	15,595	-9%	11,924
Professional, Scientific, and Technical Services	370,159	360,647	9,512	301,222	323,348	1,751	-1%	1,631
Public Administration	412,743	406,543	6,200	345,631	361,650	6,424	-2%	6,140
Real Estate and Rental and Leasing	68,419	64,636	3,783	45,443	57,334	2,461	-4%	1,951
Retail Trade	354,821	328,328	26,493	210,834	277,236	-397	0%	0
Transportation and Warehousing	147,443	138,226	9,217	99,008	122,421	5,120	-4%	4,141
Utilities	22,465	22,409	56	20,050	18,213	-1,581	9%	0
Wholesale Trade	54,507	50,820	3,687	38,327	46,092	768	-2%	639
All Industries Statewide	**3,438,742**	**3,257,755**	**180,987**	**2,435,833**	**2,856,436**	**149,133**	**-6%**	**124,456**

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