# DECLARATION OF RUTH GILGENBACH

**IN CONNECTION WITH**
**NATALIA USECHE et al. v. DONALD J. TRUMP et al.**
**Case Number 8:20-cv-02225**
**August 14, 2020**

## I. QUALIFICATIONS

1. My name is Ruth Gilgenbach. I am a partner at Ashenfelter and Ashmore, LLP. I have been with Ashenfelter and Ashmore since 2013, and a partner since 2015. Prior to joining Ashenfelter & Ashmore, I was an economist for the Texas Attorney General. I am also a lecturer in the Economics Department at Rutgers University, a position I have held since 2015. I earned a PhD in Economics from Southern Methodist University in 2012, an MA in Economics from SMU in 2008, and a BA in Economics and Political Science from Agnes Scott College in 2006.

2. As a partner at Ashenfelter & Ashmore, I supervise and oversee many of our major projects. I served as a consulting expert in *Kravitz et al., v U.S. Department of Commerce et al.* I regularly serve as a consulting expert and oversee projects that include calculating and projecting population sizes and demographics at state and local levels. Examples of such cases include *Erick Little et al., v. Washington Metropolitan Area Transit Authority, et al.,* and in connection with *New York State Division of Human Rights v. International Longshoremen's Association, New York Shipping Association, et al.* I have participated in training sessions involving mathematical and statistical issues in congressional redistricting.

3. My time is being billed at the rate of $250 per hour for my work in this matter.

## II. ASSIGNMENT

4. I have been retained by counsel for the Plaintiffs in *Useche et al. v. Trump et al.* This case involves President Donald Trump's recent presidential memorandum instructing the Secretary of Commerce to "exclude from the apportionment base aliens who are not in a lawful

immigration status under the Immigration and Nationality Act."[1] They have asked me to analyze relevant data and provide my expert opinions. In particular, I have been asked the following:

- To estimate the population of every state in the United States as of April 1, 2020.
- To predict the number of congressional representatives each state would be apportioned under the aforementioned population estimates.
- To estimate the number of undocumented immigrants in each state as of April 1, 2020.
- Using those estimates of undocumented immigrants, calculate the effect of removing undocumented immigrants on each state's congressional apportionment.
- To examine the effect of a potential Census undercount on the results of these analyses.
- For each Plaintiff's[2] local area of residence, make a comparison of the estimated percentage of immigrants, non-citizens, individuals of Hispanic origin, and undocumented immigrants as compared to state averages.
- For each Plaintiff's state of residence, make a comparison of the estimated percentage of immigrants, non-citizens, individuals of Hispanic origin, and undocumented immigrants as compared to national averages.

## III. SUMMARY OF CONCLUSIONS

5. I have estimated the population of each state as of April 1, 2020. I have also estimated the number of undocumented immigrants in each state as of that date. I conclude that

[1] https://www.whitehouse.gov/presidential-actions/memorandum-excluding-illegal-aliens-apportionment-base-following-2020-census/. Accessed August 12, 2020.

[2] Throughout this declaration, I use the term "Plaintiff" to refer to the individual plaintiffs rather than the organizational plaintiffs.

removing undocumented immigrants from the population for the purposes of congressional redistricting is highly likely to cause California and Texas to each lose a congressional seat. Other states, including New Jersey, may also lose a congressional seat. These results are robust to alternative treatments of military members abroad, as well as several possible scenarios of Census undercount that are separate and apart from the removal of undocumented immigrants.

6. I conclude that most of the Plaintiffs live in areas with a greater percentage of Hispanics, undocumented immigrants, immigrants in general, and non-citizens as compared to their state of residence as a whole. I also conclude that all of the Plaintiffs live in areas with a greater percentage of Hispanics, undocumented immigrants, immigrants in general, and non-citizens as compared to the United States as a whole.

## IV. DATA

7. In performing the analyses described in this declaration, I have utilized the following sources of data:

- Data from the US Census on population estimates for each state for each year between 2010 and 2019.[3]
- Data from the American Community Survey ("ACS"). The ACS is an ongoing survey that has been conducted by the Census Bureau since 2005. The ACS collects detailed socioeconomic information on an ongoing basis. Because it is an ongoing survey (rather than performed decennially), the ACS provides annual measures of population and demographics for states as well as smaller geographic areas including public-use microdata areas ("PUMAs") and metropolitan statistical areas ("MSAs"). I use one-year ACS estimate files from 2016-2018.

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[3] Nst-est2019-01.xlsx

- Data from the US Census Bureau on the US Armed Forces Overseas and Federal Civilian Employees Overseas Population from the 2010 Census. These data indicate the number of individuals who were serving abroad during the 2010 Census and were tabulated as living in each state for Census purposes.
- Data from the Defense Manpower Data Center ("DMDC") of the Office of the Secretary of Defense on the Number of Military and DoD Appropriated Fund (APF) Civilian Personnel Permanently Assigned, by duty location.[4] These files contain information as of March 31, 2020 and September 30, 2010 on the number of individuals who are based in each State of the United States, as well as counts of the number of individuals who are based in countries abroad.
- Data from the Pew Research Center on estimates of undocumented immigrants in each state.[5] In particular, these data include estimates of the "unauthorized immigrant population" in each state between 2005 and 2017. These data include a rounded point estimate and a rounded 90% confidence interval for that estimate.[6]
- Data from the Pew Research Center on estimates of undocumented immigrants in each of 182 MSAs.[7] These data include rounded point estimates of the number of undocumented immigrants in each MSA in 2007 and 2016, and rounded 90% confidence intervals for each of these estimates. These data also include

[4] DMDC_Website_Location_Report_2003.xlsx, DMDC_Website_Location_Report_1009.xlsx,
[5] These data were collected from the interactive graph at https://www.pewresearch.org/hispanic/interactives/unauthorized-trends/.
[6] *See* https://www.pewresearch.org/hispanic/2018/11/27/unauthorized-immigration-estimate-methodology/ for details on methodology. Accessed August 6, 2020.
[7] FT_2019-03-11_U-S-unauthorized-immigrant-population-estimates-by-metro-area-table.xlsx

estimates of the undocumented immigrant population in 2016 expressed as a share of the total population.

- Data from the Bureau of Economic Analysis ("BEA") estimating the population of each MSA in 2007.[8]

## V. ANALYSIS

A. <u>April 1, 2020 Population Estimates</u>

8. In order to estimate each state's population as of April 1, 2020, I have utilized state population estimates from the US Census for several prior years. The most recent available state population estimates are from July 1, 2019, meaning that in order to estimate each state's population as of April 1, 2020, I need to project three-quarters of one year of population change for each state.

9. I have analyzed two different methods of estimating this population change: (1) Perform a regression analysis of annual population with a model that includes indicator variables for each state and state-specific linear time trends, then use the model coefficients to forecast state populations in 2020 ("regression with linear time trend" model); (2) Perform a regression analysis of annual population with a model that includes indicator variables for each state and state-specific quadratic time trends, then use the model coefficients to forecast state populations in 2020 ("regression with quadratic time trend" model).[9] Regression analysis is a

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[8] Source: Bureau of Economic Analysis. BEA Table: CAINC1 Personal Income Summary: Personal Income, Population, Per Capita Personal Income. Downloaded August 6, 2020 from https://apps.bea.gov/itable/iTable.cfm?ReqID=70&step=1.

[9] Besides the regression-based projection methods I discuss here, there are other potential methods for projecting population forward in time. In particular, one could calculate the average rate of change over a given number of years, and then assume that rate of change will remain constant going forward. However, a regression-based method allows for an estimate of the uncertainty of each projection, which is necessary for verifying that apportionment outcomes are robust to that uncertainty.

standard statistical technique and is commonly used to forecast populations and other data. Additionally, for each of those options, I have used several alternative time ranges.

10. The population projections have a degree of uncertainty associated with them. In order to reflect that uncertainty in my apportionment calculations, I use a method called "bootstrapping." In particular, I randomly draw population figures from a normal distribution centered around my projection estimates, where the standard deviation of the normal distribution is equal to the standard error of those projection estimates. Then, I recalculate the apportionment outcomes using these alternative population estimates. I perform 1,000 iterations of this bootstrap process in order to establish a confidence interval for each state's apportionment outcomes.[10]

11. In order to determine which of these methods provides the most accurate estimate of population change over a one-year period, I have performed a validation exercise where I use data through 2018 to estimate the population in 2019. I then compare this estimate to the official Census population estimate for each state in 2019. I do this for each of the methods described in paragraph 9 above, and summarize these results in Table 1. Table 1 lists, for each method and for the number of years of data included in each analysis, three metrics that help me evaluate the quality of each prediction method. These metrics are:

- The "mean projection error." In order to calculate this metric, I first calculate the difference between a given model's predicted population in each state on July 1, 2019 and the Census's official estimate for July 1, 2019. I then take the mean of this projection error across all states.

[10] Within the bootstrapping procedure, besides accounting for the uncertainty that concerns my total state population projections, I also account for the uncertainty that concerns my unauthorized immigrant projections, as well as the uncertainty that concerns my estimates of each state's overseas military population. These additional dimensions of uncertainty will be discussed in turn below.

- The "mean absolute projection error." This is similar to the above, but I calculate the absolute value of the difference between each model's predicted population in each state on July 1, 2019 and the Census's official estimate for July 1, 2019. I then take the mean of this absolute value of the prediction error across all states. This metric is more informative than the simple mean projection error, which allows underestimates in one state to cancel out overestimates in another. Taking the absolute value on the other hand punishes the model equally for any underestimates and any overestimates.
- The "mean proportional projection error." This metric takes each state's absolute projection error and divides by the total state population (from the official Census estimate) to determine the proportional projection error. Then, as before, I take the average across all states.

12. I find that estimating population growth rates over fewer years yields more accurate predictions for 2019 than estimating population growth rates over a longer period. This is not surprising, as estimating population growth rates over a long period will tend to capture long-term trends that may not be valid over a short period of time. I find that that the regression method with quadratic time trends over a four-year period yields the most accurate predictions for 2019, with the smallest mean absolute projection error. This is therefore my preferred method of projecting total population. However, there is some uncertainty about the true population on April 1, 2020, so I will also use the regression method with a linear time trend over a three year period (the second-best performing model in my validation exercise) as a robustness check to ensure that my results are not sensitive to this modeling choice. Table 2 presents the estimated population for each state as of April 1, 2020 using these estimation

methods. The first column is the Census population estimate for each state on July 1, 2010. The second column is the Census Bureau's official estimate of each state's population as of July 1, 2019, the most recent date for which such an estimate has been published. The third column is the predicted population as of April 1, 2020 based on my preferred model: a quadratic regression based on four years of data (2016-2019). The fourth column is based on my second-most-preferred model: a linear regression based on three years of data (2017-2019).

B. Estimate of the Number of Undocumented Immigrants

13. In order to estimate the number of undocumented immigrants in each state, I have reviewed data from the Pew Research Center ("Pew"). The Pew Research Center estimates the number of undocumented immigrants in each state based on a method described by the Department of Homeland Security.[11] This estimation methodology is based on a residual estimation method that compares an estimate of the number of authorized immigrants with an estimate of the total number of immigrants, where the difference between the total immigrant population and the estimated authorized immigrant population provides an estimate of the total undocumented immigrant population. The residual method of estimating the undocumented population has been used in government reports[12] and peer reviewed academic studies.[13] An Executive Order issued in July 2019 by President Trump describes a residual estimation method for estimating the population of undocumented immigrants.[14]

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[11] https://www.pewresearch.org/hispanic/2018/11/27/unauthorized-immigration-estimate-methodology/. Accessed August 10, 2020.

[12] *See, for instance* Baker, Bryan. 2017. "Estimates of the Unauthorized Immigrant Population Residing in the United States: January 2014." Washington, D.C.: U.S. Department of Homeland Security, Office of Immigration Statistics, July. Available at https://www.dhs.gov/sites/default/files/publications/Unauthorized%20Immigrant%20Population%20Estimates%20in%20the%20US%20January%202014_1.pdf. Accessed August 10, 2020.

[13] *See, for instance* Warren, Robert and John Robert Warren. 2013. "Unauthorized Immigration to the United States: Annual Estimates and Components of Change, by State, 1990 to 2010." International Migration Review, February.

[14] "[D]ata identifying citizens will help the Federal Government generate a more reliable count of the unauthorized alien population in the country. Data tabulating both the overall population and the citizen population could be

14. There are several other publicly available potential alternative sources of estimates on the number of undocumented immigrants in each state in the United States. One of these is the Migration Policy Institute, which provides estimates of the number of undocumented immigrants in each state based on data from 2012 to 2016.[15] MPI's estimate of all undocumented immigrants in the US is 11.3 million people, approximately (6%) larger than the 10.7 million estimate provided by Pew in the same year. Another source is the Center for Migration Studies, which publishes estimates of undocumented immigrants in the US in 2010 and 2018. These indicate that there were approximately 10.56 million undocumented immigrants in the US in 2018, a number which is approximately 0.05% larger than the Pew estimate from 2017. I prefer the Pew Research Center's data because it covers more years than the other two sources, which makes it more flexible to use in estimating population trends among undocumented immigrants.

15. The Pew Research Center provides state-level estimates on the number of undocumented immigrants on an annual basis from 2005-2017.[16] The number of undocumented immigrants in the United States has fallen from its peak in 2007: in 2007, Pew estimates that there were 12.2 million undocumented immigrants in the United States; by 2017, they estimate that this number has fallen to 10.5 million, a decrease of approximately 14%.[17] However, this trend was not uniform, with some states seeing large declines in the population of undocumented

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combined with records of aliens lawfully present in the country to generate an estimate of the aggregate number of aliens unlawfully present in each State." https://www.whitehouse.gov/presidential-actions/executive-order-collecting-information-citizenship-status-connection-decennial-census/. Accessed August 13, 2020.

[15] For a description of MPI's methods, *see* Batalova, Jeanne, Sarah Hooker, and Randy Capps with James D. Bachmeier. 2014."DACA at the Two-Year Mark: A National and State Profile of Youth Eligible and Applying for Deferred Action" MPI. August.

[16] Data were manually collected from the graph at https://www.pewresearch.org/hispanic/interactives/unauthorized-trends/

[17] https://www.pewresearch.org/hispanic/interactives/unauthorized-trends/

immigrants (e.g. Oregon) while other states saw increases in the population of undocumented immigrants (e.g. Massachusetts).

16. In order to select a model for estimating the population of undocumented immigrants in each state as of April 1, 2020, I have used data on the estimated population of undocumented immigrants from 2005 to 2017 and performed a similar validation exercise as described above. In particular, I have estimated each state's undocumented population in 2017 (using data through 2014) and compared my 2017 estimate to the Pew Research Center's 2017 estimate.[18] I use the same two candidate methods (regression with a linear time trend and regression with a quadratic time trend) over various lengths of time, and calculate the mean projection error, the mean absolute projection error, and the mean proportional projection error for each method.[19] The results of this analysis are presented in Table 3. I conclude that estimating each state's undocumented population based on a regression model with a linear time trend using 8 years of data is the most accurate method of projecting the population of undocumented immigrants forward.

17. As described above, when computing congressional apportionment, I use a bootstrapping procedure to take into account the uncertainty of the underlying population estimates. In the case of undocumented immigrant populations, I address uncertainty in a manner analogous to my total population projections. In particular, within each bootstrap iteration, I randomly draw undocumented-immigrant population figures from a normal distribution centered on my undocumented-immigrant projection estimates, where the standard deviation of the normal distribution is equal to the standard error of those projection estimates.

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[18] I use data through 2014 to estimate 2017 population in order to approximate the amount of time between the 2017 estimate and April 1, 2020.

[19] See ¶ 11 above for a discussion of these metrics.

18. The number of undocumented immigrants living in each state as of April 1, 2020 is summarized in Table 4. The first column represents the Pew Research Center's estimate of each state's undocumented population in 2007; the second column represents the 2017 estimate. The third column represents each state's undocumented immigrant population based on the linear regression model described above. Note that the first two columns, which present data from the Pew Research Center, present data rounded to the nearest 5,000. The third column is rounded to the nearest 1,000. Additionally, note that the Pew Research Center does not present a time-series of estimates for states with a small number of estimated undocumented immigrants. Throughout the analyses in this report, I have assumed these states have an estimate of 5,000 undocumented immigrants in each year (the midpoint of the 0 – 10,000 range).[20]

C. Apportionment

19. Congressional seats are apportioned in the United States according to the "Method of Equal Proportions" or "Huntington-Hill" method.[21] Each state is guaranteed one seat; further seats are distributed according to that state's proportion of total US population. After each state has received one seat, each state's population is multiplied by the reciprocal geometric mean $\frac{1}{\sqrt{n(n+1)}}$ where $n$ is equal to the number of seats that each state has been allocated so far. Multiplying each state's population by the relevant multiplier yields a value referred to as the "priority value." The next seat goes to the state with the highest priority value. This process is then repeated until all congressional seats are allocated. In order to calculate the seats apportioned to each state, I have written a script which implements this procedure.

[20] I believe that these data are truncated at states with fewer than 10,000 undocumented immigrants based on comparisons with 2016 and 2017 data, which include these states, with estimates of either 10,000, 5,000 or "<5000" undocumented immigrants in each state.

[21] https://www.census.gov/history/www/reference/apportionment/methods_of_apportionment.html#huntington-hill.

20. In order to test the likely effect of removing undocumented immigrants, I employ the following bootstrap procedure. First, I estimate the population for each state using the method described in Section V.A above. I then calculate the number of congressional seats each state should receive based on this population estimate. I then estimate the number of undocumented immigrants in each state using the procedure described in Section V.B above. I then subtract this estimate of undocumented immigrants from each state's total population figure and then recalculate the number of congressional seats each state will receive under this estimate.

21. Because there is uncertainty both in the population estimate and in the estimate of the size of the undocumented population in each state, I repeat this process a total of 1,000 times, each time replacing the point estimates of my population projections with random draws from normal distributions whose means are equal to those point estimates and whose standard deviations are equal to the standard error of those estimates. This allows me to construct the mean change in congressional seats across 1,000 replications, the median (most likely) outcome, and the $5^{th}$ and $95^{th}$ percentile outcomes, which together yield a 90% confidence interval for the impact of removing undocumented immigrants on congressional apportionment.

22. The top panel of Table 5 presents an analysis based on my preferred method of estimating each state's total population, a regression model with a quadratic time trend estimated over four years. I show results for any state that ever gains or loses a seat in any of the bootstrap replications. The first column presents the number of congressional seats that each state can expect if Census counts are equal to my population estimates and undocumented immigrants *are not* removed from the count. The second column presents the number of congressional seats that each state would receive if Census counts are equal to my population estimates and undocumented immigrants *are* removed from the count. The third column presents the

difference between the first two columns; that is, it presents the expected changes in seats that would result from removing undocumented immigrants from states' populations for apportionment purposes. Columns 1-3 present results based on my estimates of the population of each state and the numbers of undocumented immigrants in each state, and do not account for uncertainty in my population projections. The remaining columns report results from the bootstrap procedure that I use to take that uncertainty into account. Column 4 lists the mean change in seats across all bootstrap replications, which can be roughly interpreted as the net percent of bootstrap replications where the state lost a seat (if negative) or gained a seat (if positive).[22] Column 5 presents the 5$^{th}$ percentile value for changed seats in the bootstrap analysis. Column 6 presents the median value for changed seats in the bootstrap analysis. The final column indicates the 95$^{th}$ percentile value for changed seats in the bootstrap analysis. Together, the 5$^{th}$ and 95$^{th}$ percentile values can be thought of as the 90% confidence interval for congressional seat changes. The median value is the most common outcome for changed seats.

23. The top panel of Table 5 indicates that California and Texas would each be highly likely to lose a congressional seat if undocumented immigrants were removed from congressional apportionment calculations. This can be seen from the fact that the 90% confidence interval for each state is (-1,-1), indicating that at least 90% of bootstrap replications indicate that each state would lose a seat. The median outcome of this analysis is that New Jersey loses a seat, meaning that New Jersey is more likely than not to lose a seat, but I cannot draw this conclusion at the 90% confidence level, as the confidence interval is (-1,0). Minnesota and Ohio

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[22] I say "roughly" because it is possible for a state to gain or lose more than one seat. In that case, that bootstrap replication would enter this analysis with the number of seats gained or lost—for instance, if in a single bootstrap replication, California lost two congressional seats, this would enter as a -2. Also, note that this is a "net" percentage in that it is possible for a state to gain a seat in one bootstrap replication while losing a seat in another, in which case the net effect of those two replications would cancel each other out when calculating the mean.

are each highly likely to gain a congressional seat if undocumented immigrants are removed from population counts for the purposes of congressional apportionment, with a 90% confidence interval of (1,1).

24. The bottom panel of Table 5 is similar to the top panel and can be read in a parallel fashion. The difference between these two panels is that the top panel predicts the total population in each state using a regression model with a quadratic time trend for each state, estimated over four years of data, whereas the bottom panel predicts total population in each state using a regression model with a linear time trend for each state estimated over three years of data. The results of this analysis are similar to those in the top panel: California and Texas are each highly likely to lose a congressional seat, with a confidence interval of (-1,-1). The median outcome of this analysis is that New Jersey loses a seat, meaning that New Jersey is more likely than not to lose a seat, but I cannot draw this conclusion at the 90% confidence level, as the confidence interval is (-1,0). There is a chance that Florida would lose a seat, though the 90% confidence interval of (-1,0) includes Florida neither gaining nor losing a seat. Alabama, Minnesota, and Ohio are each highly likely to gain seats using this projection method, with the 90% confidence interval for seat change at (1,1).

25. The analysis that I have described above does not account for US Military members stationed abroad. In the 2020 Census, active duty military members who are deployed outside the United States while stationed in the United States on Census Day will be counted at their usual residence in the United States. Military members who are stationed outside the United States long-term will be counted in their home state of record in the United States.[23]

[23] *See* https://www.census.gov/library/stories/2020/02/counting-all-military-service-members-and-their-families-in-2020.html at "Special Considerations for Active Duty Military".

26. I have considered two ways to allocate military members abroad in each state's Census count. Both of these methods use data from the following sources:

- Defense Manpower Data Center ("DMDC") data on the number of Americans stationed or deployed abroad as of March 31, 2020.
- DMDC data on the number of Americans stationed or deployed abroad as of September 30, 2010.
- Data from the US Census Bureau on the allocation of U.S. Armed Forces Overseas and Federal Civilian Employees Overseas Population from the 2010 Census.

27. The first step in both analyses is to determine the amount by which the US military presence abroad has changed since 2010. The 2020 DMDC database does not include individuals serving in Afghanistan, Iraq, or Syria, so I have added 24,300 military service people abroad to the total count for 2020.[24] No such adjustment is necessary in 2010. I calculate a ratio of 2020 military service members abroad to 2010 military service members abroad. I will use this "2020 to 2010 military service abroad ratio" in both analyses. I assume that the overall total of US Armed Forces Overseas and Federal Civilian Employees Overseas Population has decreased in the same overall proportion as the 2020 to 2010 military service abroad ratio.

28. I also use data from the 2010 Census on the allocation of U.S. Armed Forces Overseas and Federal Civilian Employees Overseas Population from the 2010 Census. To determine the total number of the overseas population, I apply the 2020 to 2010 military service

[24] Based on press reports, there are approximately 14,000 troops in Afghanistan, approximately 6,000 troops in Iraq, and approximately 4,300 troops in Syria (800 troops joined by additional 3,500). *See* https://www.washingtonpost.com/world/where-us-troops-are-in-the-middle-east-and-could-now-be-a-target-visualized/2020/01/04/1a6233ee-2f3c-11ea-9b60-817cc18cf173_story.html. Accessed August 6, 2020.

ratio to the total Federal Affiliated Overseas (which includes both Armed and Civilian employees) to arrive at total estimates for military population abroad in 2020.

29. For the first version of this analysis, I assume that the total estimated 2020 military population abroad is allocated to the States according to the population of the various states in the domestic "duty state" portion of the DMDC data. I then add this estimated population to each state's population totals before proceeding with the rest of my Apportionment analysis as described above. I describe this as "Military Allocation Method 1."

30. Table 6 describes the results of this analysis. It is parallel to Table 5 and should be read in the same way. The top panel has population estimated using a regression model with a quadratic time trend, adjusting for military members using Military Allocation Method 1. This table indicates that Texas and California are again each highly likely to lose a congressional seat, with a 90% confidence interval of (-1,-1). The median outcome of this analysis is that New Jersey loses a seat, meaning that New Jersey is more likely than not to lose a seat, but I cannot draw this conclusion at the 90% confidence level, as the confidence interval is (-1,0). Minnesota and Ohio are each highly likely to gain a congressional seat, with a confidence interval of (1,1). The bottom panel, based on a regression model with a linear time trend estimated over three years of data shows similar results: Texas and California are highly likely to lose congressional seats, with a confidence interval of (-1,-1). The median outcome of this analysis is that New Jersey loses a seat, meaning that New Jersey is more likely than not to lose a seat, but I cannot draw this conclusion at the 90% confidence level, as the confidence interval is (-1,0). Florida and New York each have a chance of losing a seat. In this analysis, Alabama, Minnesota, and Ohio are each highly likely to gain a seat, with a confidence interval of (1,1).

31. For the second version of this analysis, I assume that the total estimated 2020 military population abroad is allocated to the States in the same proportion that they were allocated during the 2010 Census. I then add this estimated population to each state's population totals before proceeding with the rest of my Apportionment analysis as described above. I describe this as "Military Allocation Method 2."

32. Table 7 describes the results of this analysis. It is parallel to Table 5 and should be read in the same way. The top panel has population estimated using a regression model with a quadratic time trend, adjusting for military members using Military Allocation Method 2. This table indicates that Texas and California are again each highly likely to lose a congressional seat, with a 90% confidence interval of (-1,-1). The median outcome of this analysis is that New Jersey loses a seat, meaning that New Jersey is more likely than not to lose a seat, but I cannot draw this conclusion at the 90% confidence level, as the confidence interval is (-1,0). Minnesota and Ohio are each highly likely to gain a congressional seat, with a confidence interval of (1,1). The bottom panel, based on a regression model with a linear time trend estimated over three years of data shows similar results: Texas, and California are highly likely to lose congressional seats, with a confidence interval of (-1,-1). The median outcome of this analysis is that New Jersey loses a seat, meaning that New Jersey is more likely than not to lose a seat, but I cannot draw this conclusion at the 90% confidence level, as the confidence interval is (-1,0). Florida and New York each have a small chance of losing a seat. In this analysis, Alabama, Minnesota, and Ohio are each highly likely to gain a seat, with a confidence interval of (1,1).

33. Tables 5-7 show the same broad pattern: Texas and California are each highly likely to lose a congressional seat; New Jersey is more likely than not to lose a congressional seat; and Minnesota, Ohio, and, in some specifications Alabama, are highly likely to gain a congressional

seat if undocumented immigrants are removed from population counts for purposes of congressional apportionment.

D. Robustness to Potential Undercount

34. Though the Decennial Census is directed by the US Constitution to enumerate each individual living in the United States, it is generally understood that there will likely be some degree of either under- or overcount. For example, the Census Bureau estimated that the 2010 Census had a net overcount of 0.01 percent, amounting to approximately 36,000 people who were overcounted. However, this overall figure obscures differences across populations. For instance, the non-Hispanic white population was estimated to have been overcounted by 0.8 percent, while the Black population was undercounted by 2.1 percent, and the Hispanic population was undercounted by 1.5 percent.[25] In this section I analyze whether my results regarding which states are likely to lose a congressional seat if undocumented immigrants are removed from the total population for the purposes of congressional apportionment are robust to several potential undercount scenarios.

35. The Urban Institute published a research paper estimating potential Census miscounts under three different scenarios: "Low Risk," "Medium Risk," and "High Risk."[26] These scenarios are based on the Census Bureau's reported under- and over-counts by population characteristics in 2010, updated population and demographics for 2020, and additional factors for the 2020 Census including the new internet self-response approach (which may increase response rates of people with home internet but depress response rates of those without),[27]

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[25] *See* https://www.census.gov/newsroom/releases/archives/2010_census/cb12-95.html.
[26] Elliot, Diana, Rob Santos, Steven Martin, Charmaine Runes. "Assessing Miscounts in the 2020 Census." Urban Institute. June 2019. ("Urban Institute Report") https://www.urban.org/sites/default/files/publication/100324/assessing_miscounts_in_the_2020_census.pdf Accessed August 4, 2020.
[27] *See* Urban Institute Report at pp. 5-6.

innovations in the use of administrative records,[28] and potential suppression from the late addition (and subsequent removal) of the question "is this person a citizen of the United States" from the 2020 Census.[29] Further, the ongoing Covid-19 pandemic has complicated the Census Bureau's non-response follow up ("NRFU") operation.[30]

36. The Urban Institute provides national and statewide miscount estimates for three scenarios, "Low Risk," "Medium Risk," and "High Risk." The national undercounts range from 0.27% in the Low Risk scenario up to 1.22% in the High Risk scenario. However, because of demographic differences between states, there are large variations of the degree (and direction) of miscount in each state. For instance, in the Low Risk scenario, the authors estimate a 0.95% undercount for California, but a 0.87% overcount for Maine. Likewise, in the High Risk Scenario, the authors estimate a 1.98% undercount for California but a 0.09% overcount for Vermont.[31]

37. In order to test the robustness of my previous apportionment findings, I repeat the previous apportionment exercise for each of the Military Allocation Methods presented in Tables 6 and 7, allowing for the possibility of varying size undercounts as estimated by the Urban Institute. I again perform a bootstrap replication analysis. In particular, I re-estimate the population using my preferred quadratic time trend method. I then take the following steps in sequence: (i) apply the miscount percentages from either the Low, Medium, or High Risk undercount scenarios published by the Urban Institute to project each state's reported population after undercount (or overcount); (ii) add the relevant estimate of overseas military populations;

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[28] *See* Urban Institute Report at pp. 6-8.
[29] *See* Urban Institute Report at pp. 8-9. The authors argue that "[e]ven if the citizenship question is struck down by the courts [which it ultimately was], there will likely be residual negative affect on the Hispanic/Latinx and immigrant response rates in the 2020 Census." *Ibid.*
[30] *See* https://www.nytimes.com/2020/04/18/us/coronavirus-census.html. Accessed August 4, 2020.
[31] *See* Urban Institute Report at Table 2, pp. 16-17.

and (iii) calculate each state's congressional seat total. I then estimate the number of undocumented immigrants in each state, remove this estimate from the previous population (adjusted for under- or overcount) and recalculate each state's number of congressional seats. As before, I replicate this analysis 1,000 times in order to calculate a confidence interval.

38. Table 8 is based on the top panel of Table 6. Panel A is based on the Low Risk scenario described above. Panel B is based on the Medium Risk Scenario described above. Panel C is based on the High Risk Scenario described above. In all three undercount scenarios, Texas is highly likely to lose a congressional seat, with a confidence interval of (-1,-1). California's most likely outcome is to lose one seat (median outcome of -1); the 90% confidence interval of (-2,0) indicates that California may lose 1 or 2 seats, but may also neither gain nor lose a seat. New Jersey's most likely outcome is to lose a seat, though the confidence interval of (-1,0) means that I cannot say with 90% confidence that New Jersey will lose a seat.

39. Table 9 is based on the top panel of Table 7. Panel A is based on the Low Risk scenario described above. Panel B is based on the Medium Risk Scenario described above. Panel C is based on the High Risk Scenario described above. In all three undercount scenarios, Texas is highly likely to lose a congressional seat, with a confidence interval of (-1,-1). California's most likely outcome is to lose one seat (median outcome of -1); the 90% confidence interval of (-2,0) indicates that California may lose 1 or 2 seats, but may also neither gain nor lose a seat. New Jersey's most likely outcome is to lose a seat, but the confidence interval of (-1,0) means that I cannot say with 90% confidence that New Jersey will lose a seat.

E. Analysis of Demographics of Plaintiffs' Areas of Residence

40. Counsel has asked me whether, assuming that the Presidential Memorandum will cause a disproportionate undercount among undocumented immigrants, immigrants generally,

non-citizens, and/or Hispanics, this will result in a disproportionate undercount in the localities and states in which the Plaintiffs reside relative to the other parts of their states and the nation as a whole. In order to answer this question, I have analyzed each locality and state in which Plaintiffs reside in order to determine the proportion of the population of that state or locality that is comprised of undocumented immigrants, immigrants generally, non-citizens, and/or Hispanics.

41. I understand that each of the Plaintiffs' states of residence uses Census data to draw congressional and state legislative districts of equal size.[32] If there is a disproportionate undercount in the area that a Plaintiff lives relative to the rest of the state, then I would expect the Plaintiff's areas to have a reduced congressional and legislative representation at the state level. I also understand that various federal funding streams are allocated to states and localities based on decennial Census population data, such that a disproportionate undercount in a state relative to the rest of the country or in an area within a state relative to the rest of the state will result in a reduction in federal funding.[33]

42. I have used data from the American Community Survey ("ACS") at the state and public use microdata area ("PUMA") level.[34] To predict each relevant PUMA's population as of April 1, 2020, I have used a regression model with a linear time trend predicted using three years

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[32] "Redistricting and Use of Census Data." Denver, Colorado. National Conference of State Legislatures. Available at https://www.ncsl.org/research/redistricting/redistricting-and-use-of-census-data.aspx. Accessed August 13, 2020.

[33] *See, for instance* Lynch, Karen. 2019. "Social Services Block Grant." Washington, D.C.: Congressional Research Service. Available at https://crsreports.congress.gov/product/pdf/IF/IF10115. Accessed August 13, 2020. *See additionally, for instance* "Fixing America's Surface Transportation Act or 'FAST Act.'" Washington, D.C.: U.S. Department of Transportation, Federal Highway Administration. Available at https://www.fhwa.dot.gov/fastact/factsheets/stbgfs.cfm. Accessed August 13, 2020.

[34] PUMAs are geographic areas designed for statistical use and are intended to allow users to analyze data associated with individual respondents at a sufficiently coarse geographic area so as to maintain respondents' anonymity. PUMAs contain at least 100,000 people and are built from counties and census tracts, and nest into states. *See* https://www.census.gov/programs-surveys/geography/guidance/geo-areas/pumas.html. Accessed August 4, 2020.

of data to forecast population in each relevant state and PUMA in a similar manner as to what I described in Section V.A above. The ACS contains information *inter alia* on individual respondents' ethnicity, citizenship status, and whether or not he or she is an immigrant.

43. Table 10 presents, for each Plaintiff, a comparison of demographics between his or her: (a) PUMA, (b) MSA, (c) State and for (d) the country as a whole.[35] The demographics of interest are the percent of the population in each geographic area that are (Panel A) Hispanic, (Panel B) immigrants, and (Panel C) non-citizens of the United States.

44. Panel A of Table 10 presents estimates of the percent of the population that is Hispanic for each Plaintiff's geography. Most Plaintiffs live in areas that have a larger proportion of the population that is Hispanic than the state as a whole.[36] All Plaintiffs live in areas that have a larger proportion of the population that is Hispanic than the nation as a whole.

45. Panel B of Table 10 presents estimates of the percent of the population that are immigrants for each Plaintiff's geography. Most Plaintiffs live in areas that have a larger proportion of the population that are immigrants than the state as a whole.[37] All Plaintiffs live in areas with a greater percentage of the population that are immigrants than the nation as a whole.

46. Panel C of Table 10 presents estimates of the percent of the population that are non-citizens for each Plaintiff's geography. Most Plaintiffs live in areas that have a larger proportion

[35] MSAs can cross state boundaries. Plaintiffs Cohen and Park live in the New York-Newark-Jersey City MSA, which includes portions of New York, New Jersey, and Pennsylvania. Other Plaintiffs reside in MSAs that are contained entirely in one state. In Table 10, I report results for portion of the MSA that are in the same state as the Plaintiff's residence.

[36] Exceptions to this are (1) Dodani, whose PUMA is less Hispanic than California as a whole; (2) Kang, whose PUMA and MSA are less Hispanic than Texas as a whole; and (3) White, whose MSA is less Hispanic than Texas as a whole.

[37] Exceptions to this are (1) Lira whose MSA has a smaller percentage immigrant population than California as a whole and (2) Kang, whose PUMA and MSA have smaller percentage immigrant populations than Texas as a whole.

of the population that are non-citizens than the state as a whole.[38] All Plaintiffs live in areas with a greater percentage of the population that are non-citizens than the nation as a whole.

47. Across Panels A-C, every Plaintiff lives in a state that has a higher percentage of Hispanics, immigrants, *and* non-citizens than the nation as a whole, and all but three Plaintiffs live in PUMAs that have a higher percentage of Hispanics, immigrants, *and* non-citizens than their states as a whole.

48. I also provide a comparison of the percentage of undocumented immigrants, as estimated by the Pew Research Center, for the metropolitan area in which each Plaintiff lives, again as compared to (a) the state as a whole, and (b) the United States as a whole. Pew has provided estimates on the number of undocumented immigrants at the MSA level in 2007 and 2016.[39] The same data also provides 2016 estimates as a proportion of the overall MSA population; since the data does not provide such a proportion for 2007, I calculate the proportion myself using estimates of 2007 MSA population from the Bureau of Economic Analysis. I measure the change in the undocumented immigrant share of each MSA's population from 2007 to 2016, and then I project these estimates forward to April 1, 2020 by assuming that these shares will continue to change at the same rate for the 3.75 years between July 1, 2016 and April 1, 2020. I compare these projections to the April 1, 2020 projection of undocumented immigrants for each state, and for the nation as a whole.

49. The results of this analysis are presented in Table 11. The El Paso, Houston, Las Vegas, Los Angeles, Miami, and New York City MSAs all have greater percentages of the

[38] Exceptions to this are (1) Dodani, whose PUMA has a smaller percentage of non-citizens than California as a whole; (2) Lira, whose MSA has a smaller percentage of non-citizens than California as a whole; (3) Kang, whose PUMA and MSA have a smaller percentage of non-citizens than Texas as a whole; and (4) Ulloa, whose MSA has a smaller percentage of non-citizens than Texas as a whole.

[39] Unlike in the analysis reported in Table 10, I cannot separately identify the portion of each MSA that is in a given state using these data. As such, the MSA data reported in Table 11 are given for the entire MSA.

population that are undocumented immigrants than their respective states. All Plaintiffs live in MSAs that have a greater share of undocumented immigrants as compared to the nation as a whole.

## VI. CONCLUSIONS

50. I have estimated the population of each state as of April 1, 2020. I have also estimated the number of undocumented immigrants in each state as of that date. I conclude that removing undocumented immigrants from the population for the purposes of congressional redistricting is likely to cause California and Texas to each lose a congressional seat. Other states, including New Jersey, may lose a congressional seat. These results are robust to alternative treatments of military members abroad, as well as several possible scenarios of Census undercount that are separate and apart from the removal of undocumented immigrants.

51. I conclude that most of the Plaintiffs live in areas with a greater percentage of Hispanics, undocumented immigrants, immigrants in general, and non-citizens as compared to their state of residence as a whole. I also conclude that all of the Plaintiffs live in areas with a greater percentage of Hispanics, undocumented immigrants, immigrants in general, and non-citizens than the nation as a whole.

52. I reserve the right to amend or supplement my opinions if additional materials or information become available to me. I declare under penalty of perjury that the forgoing is true and correct to the best of my knowledge.

Ruth Gilgenbach

August 14, 2020

Table 1
Comparison of Predictive Power for Select Models Projecting Total Population

| Method for Predicting Total 2019 Population | Years of Data Used | 2019 Mean Projection Error | 2019 Mean Absolute Projection Error | 2019 Mean Proportional Projection Error |
|---|---|---|---|---|
| Regression with Linear Time Trend | 3 | 7,481 | 9,918 | 0.0015 |
| Regression with Linear Time Trend | 4 | 12,352 | 14,693 | 0.0020 |
| Regression with Linear Time Trend | 5 | 15,999 | 19,203 | 0.0024 |
| Regression with Linear Time Trend | 6 | 18,501 | 22,829 | 0.0029 |
| Regression with Linear Time Trend | 7 | 19,471 | 25,689 | 0.0036 |
| Regression with Linear Time Trend | 8 | 20,348 | 29,035 | 0.0045 |
| Regression with Linear Time Trend | 9 | 20,944 | 32,804 | 0.0054 |
| Regression with Quadratic Time Trend | 4 | -2,658 | 7,437 | 0.0015 |
| Regression with Quadratic Time Trend | 5 | 878 | 10,271 | 0.0022 |
| Regression with Quadratic Time Trend | 6 | 4,685 | 11,580 | 0.0023 |
| Regression with Quadratic Time Trend | 7 | 9,152 | 14,306 | 0.0026 |
| Regression with Quadratic Time Trend | 8 | 11,705 | 17,604 | 0.0027 |
| Regression with Quadratic Time Trend | 9 | 13,693 | 19,934 | 0.0027 |

In each row, I present statistics related to the predictive power of various methods for projecting total state population. In every case, I run a statistical regression using annual population data, where the final year of data is always 2018. In the top panel, I use a regression model that fits a separate linear time trend to each individual state, while in the bottom panel I use a regression model that fits a separate quadratic time trend (year & year-squared) to each individual state. Within a given method, I vary the years of data used. For example, in the first row, I use 3 years worth of data; since 2018 is always the last year, this means I use data from 2016 to 2018 inclusive.

For each method, I use the regression coefficients from the relevant method to project 2019 populations. Since 2019 populations are known, I can then compare my population projections to the true value. The difference between these two values I call the "projection error," and I present the mean of this value, the mean of the absolute error of this value, and the mean of "proportional" value of this error, where the proportional value is equal to the absolute error divided by the state population.

Besides regression-based projections, there are other methods for projecting population forward in time. For instance, one could calculate the average rate of change over a given number of years, and then assume that rate of change will remain constant going forward. However, a regression-based method allows for an estimate of the uncertainty of each projection, which is necessary for verifying that apportionment outcomes are robust to that uncertainty.

Table 2
Overall State Populations

| State | Population 2010 | Population 2019 | Projected Population for April 1st, 2020: Preferred Quadratic Estimate | Projected Population for April 1st, 2020: Alternative Linear Estimate |
|---|---|---|---|---|
| Alabama | 4,785,437 | 4,903,185 | 4,916,289 | 4,913,562 |
| Alaska | 713,910 | 731,545 | 727,492 | 728,326 |
| Arizona | 6,407,172 | 7,278,717 | 7,375,944 | 7,365,620 |
| Arkansas | 2,921,964 | 3,017,804 | 3,022,212 | 3,024,029 |
| California | 37,319,502 | 39,512,223 | 39,496,851 | 39,578,613 |
| Colorado | 5,047,349 | 5,758,736 | 5,811,347 | 5,815,797 |
| Connecticut | 3,579,114 | 3,565,287 | 3,561,661 | 3,563,026 |
| Delaware | 899,593 | 973,764 | 980,328 | 980,179 |
| Florida | 18,845,537 | 21,477,737 | 21,610,075 | 21,678,414 |
| Georgia | 9,711,881 | 10,617,423 | 10,693,811 | 10,694,168 |
| Hawaii | 1,363,963 | 1,415,872 | 1,411,878 | 1,412,830 |
| Idaho | 1,570,746 | 1,787,065 | 1,813,609 | 1,812,453 |
| Illinois | 12,840,503 | 12,671,821 | 12,626,537 | 12,630,942 |
| Indiana | 6,490,432 | 6,732,219 | 6,766,877 | 6,760,138 |
| Iowa | 3,050,745 | 3,155,070 | 3,158,187 | 3,160,243 |
| Kansas | 2,858,190 | 2,913,314 | 2,917,210 | 2,915,152 |
| Kentucky | 4,348,181 | 4,467,673 | 4,469,513 | 4,473,844 |
| Louisiana | 4,544,532 | 4,648,794 | 4,638,878 | 4,640,636 |
| Maine | 1,327,629 | 1,344,212 | 1,348,777 | 1,347,694 |
| Maryland | 5,788,645 | 6,045,680 | 6,048,277 | 6,054,202 |
| Massachusetts | 6,566,307 | 6,892,503 | 6,891,199 | 6,906,934 |
| Michigan | 9,877,510 | 9,986,857 | 9,981,780 | 9,993,373 |
| Minnesota | 5,310,828 | 5,639,632 | 5,661,988 | 5,668,264 |
| Mississippi | 2,970,548 | 2,976,149 | 2,968,574 | 2,971,077 |
| Missouri | 5,995,974 | 6,137,428 | 6,146,971 | 6,148,820 |
| Montana | 990,697 | 1,068,778 | 1,073,037 | 1,074,901 |
| Nebraska | 1,829,542 | 1,934,408 | 1,940,541 | 1,941,476 |
| Nevada | 2,702,405 | 3,080,156 | 3,121,865 | 3,122,270 |
| New Hampshire | 1,316,762 | 1,359,711 | 1,363,645 | 1,363,546 |
| New Jersey | 8,799,446 | 8,882,190 | 8,871,260 | 8,881,662 |
| New Mexico | 2,064,552 | 2,096,829 | 2,100,720 | 2,098,199 |
| New York | 19,399,878 | 19,453,561 | 19,385,603 | 19,405,485 |
| North Carolina | 9,574,323 | 10,488,084 | 10,567,017 | 10,571,680 |
| North Dakota | 674,715 | 762,062 | 766,546 | 764,591 |
| Ohio | 11,539,336 | 11,689,100 | 11,693,629 | 11,700,799 |
| Oklahoma | 3,759,944 | 3,956,971 | 3,972,602 | 3,965,289 |
| Oregon | 3,837,491 | 4,217,737 | 4,236,190 | 4,245,931 |
| Pennsylvania | 12,711,160 | 12,801,989 | 12,805,404 | 12,809,405 |
| Rhode Island | 1,053,959 | 1,059,361 | 1,061,929 | 1,061,001 |
| South Carolina | 4,635,649 | 5,148,714 | 5,197,129 | 5,196,228 |
| South Dakota | 816,166 | 884,659 | 887,012 | 889,059 |
| Tennessee | 6,355,311 | 6,829,174 | 6,871,676 | 6,875,196 |
| Texas | 25,241,971 | 28,995,881 | 29,250,556 | 29,252,972 |
| Utah | 2,775,332 | 3,205,958 | 3,241,731 | 3,245,318 |
| Vermont | 625,879 | 623,989 | 623,308 | 623,920 |
| Virginia | 8,023,699 | 8,535,519 | 8,552,415 | 8,563,071 |
| Washington | 6,742,830 | 7,614,893 | 7,667,114 | 7,688,298 |
| West Virginia | 1,854,239 | 1,792,147 | 1,783,802 | 1,782,731 |
| Wisconsin | 5,690,475 | 5,822,434 | 5,833,246 | 5,834,892 |
| Wyoming | 564,487 | 578,759 | 582,034 | 578,280 |

State populations for 2010 and 2019 are from the Census Bureau (nst-est2019-01.xlsx) and reflect population as of July 1st in those years.

Table 3
Comparison of Predictive Power for Select Models Projecting Undocumented Immigrant Population

| Method for Predicting 2017 Unauthorized Immigrant Population | Years of Data Used | 2017 Mean Projection Error | 2017 Mean Absolute Projection Error | 2017 Mean Proportional Projection Error |
|---|---|---|---|---|
| Regression with Linear Time Trend | 3 | 13,767 | 28,500 | 0.1562 |
| Regression with Linear Time Trend | 4 | 7,130 | 22,410 | 0.1359 |
| Regression with Linear Time Trend | 5 | 9,250 | 20,490 | 0.1204 |
| Regression with Linear Time Trend | 6 | 11,844 | 20,145 | 0.1039 |
| Regression with Linear Time Trend | 7 | 9,507 | 18,564 | 0.0961 |
| Regression with Linear Time Trend | 8 | 4,227 | 17,739 | 0.0866 |
| Regression with Linear Time Trend | 9 | 7,355 | 19,608 | 0.1013 |
| Regression with Linear Time Trend | 10 | 12,045 | 21,525 | 0.1144 |
| Regression with Quadratic Time Trend | 4 | 29,930 | 54,670 | 0.2939 |
| Regression with Quadratic Time Trend | 5 | 8,429 | 43,589 | 0.2751 |
| Regression with Quadratic Time Trend | 6 | 1,252 | 37,031 | 0.2409 |
| Regression with Quadratic Time Trend | 7 | 12,898 | 37,679 | 0.2188 |
| Regression with Quadratic Time Trend | 8 | 25,723 | 41,226 | 0.2126 |
| Regression with Quadratic Time Trend | 9 | 9,485 | 29,108 | 0.1834 |
| Regression with Quadratic Time Trend | 10 | -3,100 | 23,205 | 0.1591 |

In each row, I present statistics related to the predictive power of various methods for projecting states' undocumented immigrant population. In every case, I run a statistical regression using annual population data, where the final year of data is always 2014. In the top panel, I use a regression model that fits a separate linear time trend to each individual state, while in the bottom panel I use a regression model that fits a separate quadratic time trend (year & year-squared) to each individual state. Within a given method, I vary the years of data used. For example, in the first row, I use 3 years worth of data; since 2014 is always the last year, this means I use data from 2012 to 2014 inclusive.

For each method, I use the regression coefficients from the relevant method to project 2017 undocumented immigrant populations. Since 2017 populations are known, I can then compare my population projections to the true value. The difference between these two values I call the "projection error," and I present the mean of this value, the mean of the absolute error of this value, and the mean of "proportional" value of this error, where the proportional value is equal to the absolute error divided by the state population.

Besides regression-based projections, there are other methods for projecting population forward in time. For instance, one could calculate the average rate of change over a given number of years, and then assume that rate of change will remain constant going forward. However, a regression-based method allows for an estimate of the uncertainty of each projection, which is necessary for verifying that apportionment outcomes are robust to that uncertainty.

Table 4
Undocumented Immigrant State Populations

| State | Undocumented Immigrant Population, 2007 | Undocumented Immigrant Population, 2017 | Projected Population for April 1st, 2020 |
|---|---|---|---|
| Alabama | 70,000 | 65,000 | 48,000 |
| Alaska | 10,000 | 10,000 | 10,000 |
| Arizona | 500,000 | 275,000 | 253,000 |
| Arkansas | 70,000 | 65,000 | 62,000 |
| California | 2,800,000 | 2,000,000 | 1,951,000 |
| Colorado | 210,000 | 180,000 | 192,000 |
| Connecticut | 130,000 | 140,000 | 133,000 |
| Delaware | 25,000 | 30,000 | 33,000 |
| Florida | 1,050,000 | 825,000 | 725,000 |
| Georgia | 425,000 | 375,000 | 358,000 |
| Hawaii | 35,000 | 45,000 | 47,000 |
| Idaho | 40,000 | 35,000 | 38,000 |
| Illinois | 550,000 | 425,000 | 377,000 |
| Indiana | 100,000 | 110,000 | 112,000 |
| Iowa | 40,000 | 50,000 | 50,000 |
| Kansas | 70,000 | 75,000 | 71,000 |
| Kentucky | 40,000 | 40,000 | 39,000 |
| Louisiana | 55,000 | 70,000 | 69,000 |
| Maine | 5,000 | 5,000 | 5,000 |
| Maryland | 220,000 | 250,000 | 272,000 |
| Massachusetts | 220,000 | 275,000 | 296,000 |
| Michigan | 140,000 | 110,000 | 108,000 |
| Minnesota | 85,000 | 85,000 | 92,000 |
| Mississippi | 25,000 | 20,000 | 19,000 |
| Missouri | 60,000 | 60,000 | 54,000 |
| Montana | 5,000 | 5,000 | 5,000 |
| Nebraska | 45,000 | 55,000 | 58,000 |
| Nevada | 240,000 | 210,000 | 196,000 |
| New Hampshire | 10,000 | 15,000 | 13,000 |
| New Jersey | 550,000 | 450,000 | 458,000 |
| New Mexico | 85,000 | 55,000 | 49,000 |
| New York | 1,000,000 | 650,000 | 622,000 |
| North Carolina | 325,000 | 325,000 | 313,000 |
| North Dakota | 5,000 | 5,000 | 5,000 |
| Ohio | 90,000 | 95,000 | 88,000 |
| Oklahoma | 95,000 | 90,000 | 89,000 |
| Oregon | 150,000 | 100,000 | 98,000 |
| Pennsylvania | 150,000 | 190,000 | 206,000 |
| Rhode Island | 35,000 | 35,000 | 33,000 |
| South Carolina | 90,000 | 90,000 | 78,000 |
| South Dakota | 5,000 | 5,000 | 5,000 |
| Tennessee | 120,000 | 130,000 | 128,000 |
| Texas | 1,550,000 | 1,600,000 | 1,581,000 |
| Utah | 100,000 | 110,000 | 105,000 |
| Vermont | 5,000 | 5,000 | 5,000 |
| Virginia | 250,000 | 275,000 | 281,000 |
| Washington | 250,000 | 250,000 | 268,000 |
| West Virginia | 5,000 | 5,000 | 5,000 |
| Wisconsin | 85,000 | 75,000 | 78,000 |
| Wyoming | 5,000 | 5,000 | 5,000 |

Undocumented immigrant populations for 2007 and 2009 are from the Pew Research Center's interactive graph at https://www.pewresearch.org/hispanic/interactives/unauthorized-trends/. Pew provides estimates that are rounded to the nearest 5,000. My projections are rounded to the nearest 1,000.

Table 5

Panel A: Using Preferred Quadratic Model to Project Total State Population

| State | Congressional Seats Using Estimated Total Population [1] | Congressional Seats Removing Undocumented Immigrants [2] | Seats Gained or Lost [3] | Bootstrap Mean Change in Seats [4] | Bootstrap 5th Percentile [5] | Bootstrap Median Change in Seats [6] | Bootstrap 95th Percentile [7] |
|---|---|---|---|---|---|---|---|
| Texas | 39 | 38 | -1 | -0.98 | -1 | -1 | -1 |
| California | 52 | 51 | -1 | -0.98 | -1 | -1 | -1 |
| New Jersey | 12 | 11 | -1 | -0.67 | -1 | -1 | 0 |
| New York | 26 | 26 | 0 | 0.00 | 0 | 0 | 0 |
| Alabama | 7 | 7 | 0 | 0.12 | 0 | 0 | 1 |
| Michigan | 13 | 13 | 0 | 0.13 | 0 | 0 | 1 |
| Montana | 2 | 2 | 0 | 0.32 | 0 | 0 | 1 |
| Florida | 28 | 29 | 1 | 0.06 | -1 | 0 | 1 |
| Minnesota | 7 | 8 | 1 | 1.00 | 1 | 1 | 1 |
| Ohio | 15 | 16 | 1 | 1.00 | 1 | 1 | 1 |

Panel B: Using Alternative Linear Model to Project Total State Population

| State | Congressional Seats Using Estimated Total Population [1] | Congressional Seats Removing Undocumented Immigrants [2] | Seats Gained or Lost [3] | Bootstrap Mean Change in Seats [4] | Bootstrap 5th Percentile [5] | Bootstrap Median Change in Seats [6] | Bootstrap 95th Percentile [7] |
|---|---|---|---|---|---|---|---|
| Texas | 39 | 38 | -1 | -1.00 | -1 | -1 | -1 |
| California | 52 | 51 | -1 | -0.98 | -1 | -1 | -1 |
| New Jersey | 12 | 11 | -1 | -0.82 | -1 | -1 | 0 |
| Florida | 29 | 29 | 0 | -0.22 | -1 | 0 | 0 |
| New York | 26 | 26 | 0 | -0.02 | 0 | 0 | 0 |
| Michigan | 13 | 13 | 0 | 0.04 | 0 | 0 | 0 |
| Alabama | 6 | 7 | 1 | 1.00 | 1 | 1 | 1 |
| Minnesota | 7 | 8 | 1 | 1.00 | 1 | 1 | 1 |
| Ohio | 15 | 16 | 1 | 1.00 | 1 | 1 | 1 |

Column [1] uses my projections of state populations (as of April 1, 2020) to estimate congressional apportionment. This column ignores uncertainty in the population projections; that is, it performs the apportionment calculation on the population estimates as if they were known with certainty.

Column [2] calculates what congressional apportionment would be if undocumented immigrants were removed from the state population totals. That is, I subtract my estimates of undocumented immigrant populations from my estimates of state total populations and then perform the apportionment calculation on the resulting adjusted population. As in Column [1], the point estimates (for both total population and undocumented immigrant population) are treated as if they are known with certainty.

Column [3] is equal to the difference Colum [1] – Column[2]. A negative number indicates that a state loses a seat when undocumented immigrants are removed from population totals, while a positive number indicates that a state gains a seat.

Columns [4]–[7] are based on my bootstrapped analysis. That analysis accounts for the uncertainty of my population projections by defining, for each state and for both the total population projection and the undocumented immigrant population projection, a normal distribution that is centered on the corresponding estimate and whose standard deviation is equal to the standard error of that estimates. I then repeat my analysis 1000 times, in each case making random draws from those normal distributions and using those figures in the apportionment calculation.

Column [4] is the mean value of "seats gained or lost" across all the bootstrap iterations. Column [5] is the is fifth percentile of "seats gained or lost" across all the bootstrap iterations. Likewise, Column [6] is the median (or 50th percentile) of "seats gained or lost" and Column [7] is the 95th percentile. Taken together, columns [5] and [7] can be thought of us a 90% confidence interval for seats gained or lost due to removing undocumented immigrants for purposes of congressional apportionment.

Table 6
Apportionment Analysis Using Military Allocation Method 1

Panel A: Using Preferred Quadratic Model to Project Total State Population

| State | Congressional Seats Using Estimated Total Population [1] | Congressional Seats Removing Undocumented Immigrants [2] | Seats Gained or Lost [3] | Bootstrap Mean Change in Seats [4] | Bootstrap 5th Percentile [5] | Bootstrap Median Change in Seats [6] | Bootstrap 95th Percentile [7] |
|---|---|---|---|---|---|---|---|
| Texas | 39 | 38 | -1 | -0.98 | -1 | -1 | -1 |
| California | 52 | 51 | -1 | -0.97 | -1 | -1 | -1 |
| New Jersey | 12 | 11 | -1 | -0.71 | -1 | -1 | 0 |
| New York | 26 | 26 | 0 | -0.01 | 0 | 0 | 0 |
| Rhode Island | 1 | 1 | 0 | 0.01 | 0 | 0 | 0 |
| Michigan | 13 | 13 | 0 | 0.05 | 0 | 0 | 0 |
| Montana | 2 | 2 | 0 | 0.22 | 0 | 0 | 1 |
| Florida | 28 | 29 | 1 | 0.38 | -1 | 0 | 1 |
| Minnesota | 7 | 8 | 1 | 1.00 | 1 | 1 | 1 |
| Ohio | 15 | 16 | 1 | 1.00 | 1 | 1 | 1 |

Panel B: Using Alternative Linear Model to Project Total State Population

| State | Congressional Seats Using Estimated Total Population [1] | Congressional Seats Removing Undocumented Immigrants [2] | Seats Gained or Lost [3] | Bootstrap Mean Change in Seats [4] | Bootstrap 5th Percentile [5] | Bootstrap Median Change in Seats [6] | Bootstrap 95th Percentile [7] |
|---|---|---|---|---|---|---|---|
| Texas | 39 | 38 | -1 | -1.00 | -1 | -1 | -1 |
| California | 52 | 51 | -1 | -0.97 | -1 | -1 | -1 |
| New Jersey | 12 | 11 | -1 | -0.84 | -1 | -1 | 0 |
| Florida | 29 | 29 | 0 | -0.17 | -1 | 0 | 0 |
| New York | 26 | 26 | 0 | -0.03 | 0 | 0 | 0 |
| Michigan | 13 | 13 | 0 | 0.01 | 0 | 0 | 0 |
| Alabama | 6 | 7 | 1 | 0.99 | 1 | 1 | 1 |
| Minnesota | 7 | 8 | 1 | 1.00 | 1 | 1 | 1 |
| Ohio | 15 | 16 | 1 | 1.00 | 1 | 1 | 1 |

Military Allocation Method 1 assumes that the total estimated 2020 military population abroad is allocated to the States according to the relative population of the various states in the domestic duty-state portion of the DMDC data.

Column [1] uses my projections of state populations (as of April 1, 2020) and my estimates of the relevant overseas military populations (using Allocation Method 1) to estimate congressional apportionment. This column ignores uncertainty in the population projections and the overseas military estimates; that is, it performs the apportionment calculation on these estimates as if they were known with certainty.

Column [2] calculates what congressional apportionment would be if undocumented immigrants were removed from the state population totals. That is, I subtract my estimates of undocumented immigrant populations from my estimates of state total populations (including overseas military) and then perform the apportionment calculation on the resulting adjusted population. As in Column [1], the point estimates (for total population, undocumented immigrant population, and overseas military population) are treated as if they are known with certainty.

Column [3] is equal to the difference Colum [1] – Column[2]. A negative number indicates that a state loses a seat when undocumented immigrants are removed from population totals, while a positive number indicates that a state gains a seat.

Columns [4]–[7] are based on my bootstrapped analysis. That analysis accounts for the uncertainty of my population projections by defining, for each state and for each population projection (state total, undocumented immigrant, and overseas military), a normal distribution that is centered on the corresponding estimate and whose standard deviation is equal to the standard error of that estimates. I then repeat my analysis 1000 times, in each case making random draws from those normal distributions and using those figures in the apportionment calculation.

Column [4] is the mean value of "seats gained or lost" across all the bootstrap iterations. Column [5] is the is fifth percentile of "seats gained or lost" across all the bootstrap iterations. Likewise, Column [6] is the median (or 50th percentile) of "seats gained or lost" and Column [7] is the 95th percentile. Taken together, columns [5] and [7] can be thought of us a 90% confidence interval for seats gained or lost due to removing undocumented immigrants for purposes of congressional apportionment.

Table 7
Apportionment Analysis Using Military Allocation Method 2

Panel A: Using Preferred Quadratic Model to Project Total State Population

| State | Congressional Seats Using Estimated Total Population | Congressional Seats Removing Undocumented Immigrants | Seats Gained or Lost | Bootstrap Mean Change in Seats | Bootstrap 5th Percentile | Bootstrap Median Change in Seats | Bootstrap 95th Percentile |
|---|---|---|---|---|---|---|---|
| | [1] | [2] | [3] | [4] | [5] | [6] | [7] |
| California | 52 | 51 | -1 | -0.98 | -1 | -1 | -1 |
| Texas | 39 | 38 | -1 | -0.97 | -1 | -1 | -1 |
| New Jersey | 12 | 11 | -1 | -0.81 | -1 | -1 | 0 |
| New York | 26 | 26 | 0 | -0.01 | 0 | 0 | 0 |
| Rhode Island | 1 | 1 | 0 | 0.00 | 0 | 0 | 0 |
| Michigan | 13 | 13 | 0 | 0.06 | 0 | 0 | 1 |
| Alabama | 7 | 7 | 0 | 0.10 | 0 | 0 | 1 |
| Montana | 2 | 2 | 0 | 0.31 | 0 | 0 | 1 |
| Florida | 28 | 29 | 1 | 0.30 | -1 | 0 | 1 |
| Minnesota | 7 | 8 | 1 | 1.00 | 1 | 1 | 1 |
| Ohio | 15 | 16 | 1 | 1.00 | 1 | 1 | 1 |

Panel B: Using Alternative Linear Model to Project Total State Population

| State | Congressional Seats Using Estimated Total Population | Congressional Seats Removing Undocumented Immigrants | Seats Gained or Lost | Bootstrap Mean Change in Seats | Bootstrap 5th Percentile | Bootstrap Median Change in Seats | Bootstrap 95th Percentile |
|---|---|---|---|---|---|---|---|
| | [1] | [2] | [3] | [4] | [5] | [6] | [7] |
| Texas | 39 | 38 | -1 | -1.00 | -1 | -1 | -1 |
| California | 52 | 51 | -1 | -0.99 | -1 | -1 | -1 |
| New Jersey | 12 | 11 | -1 | -0.91 | -1 | -1 | 0 |
| Florida | 29 | 29 | 0 | -0.10 | -1 | 0 | 0 |
| New York | 26 | 26 | 0 | -0.02 | 0 | 0 | 0 |
| Michigan | 13 | 13 | 0 | 0.01 | 0 | 0 | 0 |
| Alabama | 6 | 7 | 1 | 1.00 | 1 | 1 | 1 |
| Minnesota | 7 | 8 | 1 | 1.00 | 1 | 1 | 1 |
| Ohio | 15 | 16 | 1 | 1.00 | 1 | 1 | 1 |

Military Allocation Method 2 assumes that the total estimated 2020 military population abroad is allocated to the States in the same proportion that they were allocated during the 2010 census.
Column [1] uses my projections of state populations (as of April 1, 2020) and my estimates of the relevant overseas military populations (using Allocation Method 2) to estimate congressional apportionment. This column ignores uncertainty in the population projections and the overseas military estimates; that is, it performs the apportionment calculation on these estimates as if they were known with certainty.

Column [2] calculates what congressional apportionment would be if undocumented immigrants were removed from the state population totals. That is, I subtract my estimates of undocumented immigrant populations from my estimates of state total populations (including overseas military) and then perform the apportionment calculation on the resulting adjusted population. As in Column [1], the point estimates (for total population, undocumented immigrant population, and overseas military population) are treated as if they are known with certainty.

Column [3] is equal to the difference Colum [1] – Column[2]. A negative number indicates that a state loses a seat when undocumented immigrants are removed from population totals, while a positive number indicates that a state gains a seat.

Columns [4]–[7] are based on my bootstrapped analysis. That analysis accounts for the uncertainty of my population projections by defining, for each state and for each population projection (state total, undocumented immigrant, and overseas military), a normal distribution that is centered on the corresponding estimate and whose standard deviation is equal to the standard error of that estimates. I then repeat my analysis 1000 times, in each case making random draws from those normal distributions and using those figures in the apportionment calculation.

Column [4] is the mean value of "seats gained or lost" across all the bootstrap iterations. Column [5] is the is fifth percentile of "seats gained or lost" across all the bootstrap iterations. Likewise, Column [6] is the median (or 50th percentile) of "seats gained or lost" and Column [7] is the 95th percentile. Taken together, columns [5] and [7] can be thought of us a 90% confidence interval for seats gained or lost due to removing undocumented immigrants for purposes of congressional apportionment.

Table 8
Apportionment Analysis for Undercount Scenarios, Using Military Allocation Method 1

Panel A: Low Undercount Scenario

| State | Congressional Seats Using Estimated Total Population | Congressional Seats Removing Undocumented Immigrants | Seats Gained or Lost | Bootstrap Mean Change in Seats | Bootstrap 5th Percentile | Bootstrap Median Change in Seats | Bootstrap 95th Percentile |
|---|---|---|---|---|---|---|---|
| | [1] | [2] | [3] | [4] | [5] | [6] | [7] |
| California | 52 | 51 | -1 | -1.20 | -2 | -1 | 0 |
| New Jersey | 12 | 11 | -1 | -0.86 | -1 | -1 | 0 |
| Texas | 38 | 38 | 0 | -0.98 | -1 | -1 | -1 |
| New York | 25 | 25 | 0 | 0.00 | 0 | 0 | 0 |
| Florida | 28 | 28 | 0 | 0.06 | 0 | 0 | 1 |
| Rhode Island | 1 | 1 | 0 | 0.17 | -1 | 0 | 1 |
| Idaho | 2 | 2 | 0 | 0.80 | 0 | 1 | 1 |
| Michigan | 13 | 14 | 1 | 1.00 | 1 | 1 | 1 |
| West Virginia | 2 | 3 | 1 | 1.00 | 1 | 1 | 1 |

Panel B: Medium Undercount Scenario

| State | Congressional Seats Using Estimated Total Population | Congressional Seats Removing Undocumented Immigrants | Seats Gained or Lost | Bootstrap Mean Change in Seats | Bootstrap 5th Percentile | Bootstrap Median Change in Seats | Bootstrap 95th Percentile |
|---|---|---|---|---|---|---|---|
| | [1] | [2] | [3] | [4] | [5] | [6] | [7] |
| California | 52 | 51 | -1 | -1.12 | -2 | -1 | 0 |
| Texas | 38 | 37 | -1 | -1.00 | -1 | -1 | -1 |
| New Jersey | 12 | 11 | -1 | -0.90 | -1 | -1 | 0 |
| Florida | 28 | 28 | 0 | 0.03 | 0 | 0 | 0 |
| Rhode Island | 1 | 1 | 0 | 0.15 | -1 | 0 | 1 |
| Idaho | 2 | 2 | 0 | 0.81 | 0 | 1 | 1 |
| New York | 25 | 26 | 1 | 0.04 | 0 | 0 | 0 |
| Michigan | 13 | 14 | 1 | 1.00 | 1 | 1 | 1 |
| West Virginia | 2 | 3 | 1 | 1.00 | 1 | 1 | 1 |

Panel C: High Undercount Scenario

| State | Congressional Seats Using Estimated Total Population | Congressional Seats Removing Undocumented Immigrants | Seats Gained or Lost | Bootstrap Mean Change in Seats | Bootstrap 5th Percentile | Bootstrap Median Change in Seats | Bootstrap 95th Percentile |
|---|---|---|---|---|---|---|---|
| | [1] | [2] | [3] | [4] | [5] | [6] | [7] |
| Texas | 38 | 37 | -1 | -1.00 | -1 | -1 | -1 |
| California | 52 | 51 | -1 | -0.99 | -2 | -1 | 0 |
| New Jersey | 12 | 11 | -1 | -0.81 | -1 | -1 | 0 |
| Rhode Island | 1 | 1 | 0 | -0.04 | -1 | 0 | 1 |
| Pennsylvania | 17 | 17 | 0 | 0.01 | 0 | 0 | 0 |
| Florida | 28 | 28 | 0 | 0.03 | 0 | 0 | 0 |
| Idaho | 2 | 2 | 0 | 0.75 | 0 | 1 | 1 |
| New York | 25 | 26 | 1 | 0.04 | 0 | 0 | 0 |
| Michigan | 13 | 14 | 1 | 1.00 | 1 | 1 | 1 |
| West Virginia | 2 | 3 | 1 | 1.00 | 1 | 1 | 1 |

Each panel of this model is a variation on my analysis in Panel A of Table 6 . That is, each panel of this table uses my preferred quadratic trend model for estimation state population, and I estimate counts of overseas military population using Military Allocation Method 1, as in Table 6.

For each panel, I apply state-specific estimates of likely Census undercount rates as reported by the Urban Institute in "Assessing Miscounts in the 2020 Census." This report provides undercount estimates for three scenarios, designated "low risk" and "medium risk" and "high risk", with undercounting becoming more severe in the higher risk scenarios. Each panel in this table relies on one of those scenarios.

Military Allocation Method 1 assumes that the total estimated 2020 military population abroad is allocated to the States according to the relative population of the various states in the domestic duty-state portion of the DMDC data.

Column [1] adjusts my projections of state populations using the relevant undercount rates, then uses those undercount-adjusted estimates and my estimates of the relevant overseas military populations (using Allocation Method 1) to estimate congressional apportionment. This column ignores uncertainty in the population projections and the overseas military estimates; that is, it performs the apportionment calculation on these estimates as if they were known with certainty.

Column [2] calculates what congressional apportionment would be if undocumented immigrants were removed from the undercount-adjusted state population projections. That is, I subtract my estimates of undocumented immigrant populations from my estimates of state total populations (including overseas military) and then perform the apportionment calculation on the resulting adjusted population. As in Column [1], the point estimates (for undercount-adjusted total population, undocumented immigrant population, and overseas military population) are treated as if they are known with certainty.

Column [3] is equal to the difference Colum [1] – Column[2]. A negative number indicates that a state loses a seat when undocumented immigrants are removed from population totals, while a positive number indicates that a state gains a seat.

Columns [4]–[7] are based on my bootstrapped analysis. That analysis accounts for the uncertainty of my population projections by defining, for each state and for each population projection (state total, undocumented immigrant, and overseas military), a normal distribution that is centered on the corresponding estimate and whose standard deviation is equal to the standard error of that estimates. I then repeat my analysis 1000 times, in each case making random draws from those normal distributions and using those figures in the apportionment calculation.

Column [4] is the mean value of "seats gained or lost" across all the bootstrap iterations. Column [5] is the is fifth percentile of "seats gained or lost" across all the bootstrap iterations. Likewise, Column [6] is the median (or 50th percentile) of "seats gained or lost" and Column [7] is the 95th percentile. Taken together, columns [5] and [7] can be thought of us a 90% confidence interval for seats gained or lost due to removing undocumented immigrants for purposes of congressional apportionment.

Table 9

Apportionment Analysis for Undercount Scenarios, Using Military Allocation Method 2

Panel A: Low Undercount Scenario

| State | Congressional Seats Using Estimated Total Population [1] | Congressional Seats Removing Undocumented Immigrants [2] | Seats Gained or Lost [3] | Bootstrap Mean Change in Seats [4] | Bootstrap 5th Percentile [5] | Bootstrap Median Change in Seats [6] | Bootstrap 95th Percentile [7] |
|---|---|---|---|---|---|---|---|
| New Jersey | 12 | 11 | -1 | -0.84 | -1 | -1 | 0 |
| California | 52 | 51 | -1 | -0.68 | -2 | -1 | 0 |
| Texas | 38 | 38 | 0 | -0.96 | -1 | -1 | -1 |
| Florida | 28 | 28 | 0 | -0.53 | -1 | -1 | 0 |
| New York | 25 | 25 | 0 | 0.01 | 0 | 0 | 0 |
| Rhode Island | 1 | 1 | 0 | 0.14 | 0 | 0 | 1 |
| Idaho | 2 | 2 | 0 | 0.86 | 0 | 1 | 1 |
| Michigan | 13 | 14 | 1 | 1.00 | 1 | 1 | 1 |
| West Virginia | 2 | 3 | 1 | 1.00 | 1 | 1 | 1 |

Panel B: Medium Undercount Scenario

| State | Congressional Seats Using Estimated Total Population [1] | Congressional Seats Removing Undocumented Immigrants [2] | Seats Gained or Lost [3] | Bootstrap Mean Change in Seats [4] | Bootstrap 5th Percentile [5] | Bootstrap Median Change in Seats [6] | Bootstrap 95th Percentile [7] |
|---|---|---|---|---|---|---|---|
| California | 52 | 51 | -1 | -1.22 | -2 | -1 | 0 |
| Texas | 38 | 37 | -1 | -1.00 | -1 | -1 | -1 |
| New Jersey | 12 | 11 | -1 | -0.88 | -1 | -1 | 0 |
| Florida | 28 | 28 | 0 | 0.01 | -1 | 0 | 1 |
| Rhode Island | 1 | 1 | 0 | 0.15 | -1 | 0 | 1 |
| Idaho | 2 | 2 | 0 | 0.88 | 0 | 1 | 1 |
| New York | 25 | 26 | 1 | 0.06 | 0 | 0 | 1 |
| Michigan | 13 | 14 | 1 | 1.00 | 1 | 1 | 1 |
| West Virginia | 2 | 3 | 1 | 1.00 | 1 | 1 | 1 |

Panel C: High Undercount Scenario

| State | Congressional Seats Using Estimated Total Population [1] | Congressional Seats Removing Undocumented Immigrants [2] | Seats Gained or Lost [3] | Bootstrap Mean Change in Seats [4] | Bootstrap 5th Percentile [5] | Bootstrap Median Change in Seats [6] | Bootstrap 95th Percentile [7] |
|---|---|---|---|---|---|---|---|
| Texas | 38 | 37 | -1 | -1.00 | -1 | -1 | -1 |
| California | 52 | 51 | -1 | -0.84 | -2 | -1 | 0 |
| New Jersey | 12 | 11 | -1 | -0.78 | -1 | -1 | 0 |
| Florida | 28 | 28 | 0 | -0.37 | -1 | 0 | 0 |
| Pennsylvania | 17 | 17 | 0 | 0.03 | 0 | 0 | 0 |
| Rhode Island | 1 | 1 | 0 | 0.08 | -1 | 0 | 1 |
| Idaho | 2 | 2 | 0 | 0.82 | 0 | 1 | 1 |
| New York | 25 | 26 | 1 | 0.08 | 0 | 0 | 1 |
| Michigan | 13 | 14 | 1 | 1.00 | 1 | 1 | 1 |
| West Virginia | 2 | 3 | 1 | 1.00 | 1 | 1 | 1 |

Each panel of this model is a variation on my analysis in Panel A of Table 7. That is, each panel of this table uses my preferred quadratic trend model for estimation state population, and I estimate counts of overseas military population using Military Allocation Method 2, as in Table 7.

For each panel, I apply state-specific estimates of likely Census undercount rates as reported by the Urban Institute in "Assessing Miscounts in the 2020 Census." This report provides undercount estimates for three scenarios, designated "low risk" and "medium risk" and "high risk", with undercounting becoming more severe in the higher risk scenarios. Each panel in this table relies on one of those scenarios.

Military Allocation Method 2 assumes that the total estimated 2020 military population abroad is allocated to the States in the same proportion that they were allocated during the 2010 census.

Column [1] adjusts my projections of state populations using the relevant undercount rates, then uses those undercount-adjusted estimates and my estimates of the relevant overseas military populations (using Allocation Method 2) to estimate congressional apportionment. This column ignores uncertainty in the population projections and the overseas military estimates; that is, it performs the apportionment calculation on these estimates as if they were known with certainty.

Column [2] calculates what congressional apportionment would be if undocumented immigrants were removed from the undercount-adjusted state population projections. That is, I subtract my estimates of undocumented immigrant populations from my estimates of state total populations (including overseas military) and then perform the apportionment calculation on the resulting adjusted population. As in Column [1], the point estimates (for undercount-adjusted total population, undocumented immigrant population, and overseas military population) are treated as if they are known with certainty.

Column [3] is equal to the difference Colum [1] – Column[2]. A negative number indicates that a state loses a seat when undocumented immigrants are removed from population totals, while a positive number indicates that a state gains a seat.

Columns [4]–[7] are based on my bootstrapped analysis. That analysis accounts for the uncertainty of my population projections by defining, for each state and for each population projection (state total, undocumented immigrant, and overseas military), a normal distribution that is centered on the corresponding estimate and whose standard deviation is equal to the standard error of that estimates. I then repeat my analysis 1000 times, in each case making random draws from those normal distributions and using those figures in the apportionment calculation.

Column [4] is the mean value of "seats gained or lost" across all the bootstrap iterations. Column [5] is the is fifth percentile of "seats gained or lost" across all the bootstrap iterations. Likewise, Column [6] is the median (or 50th percentile) of "seats gained or lost" and Column [7] is the 95th percentile. Taken together, columns [5] and [7] can be thought of us a 90% confidence interval for seats gained or lost due to removing undocumented immigrants for purposes of congressional apportionment.

Table 10

Panel A: Percent Hispanic

| Plaintiff | Location | PUMA | In State MSA | State | Nation |
|---|---|---|---|---|---|
| Dodani | West Hills, California | 34.38% | 45.21% | 39.60% | 18.70% |
| Lira | Fontana, California | 84.62% | 52.63% | 39.60% | 18.70% |
| Brown | Greenacres, Florida | 57.20% | 46.89% | 27.16% | 18.70% |
| Useche | Miami, Florida | 50.24% | 46.89% | 27.16% | 18.70% |
| Hernandez | Las Vegas, Nevada | 46.78% | 31.92% | 29.53% | 18.70% |
| Kagan | Las Vegas, Nevada | 53.99% | 31.92% | 29.53% | 18.70% |
| Cohen | Jersey City, New Jersey | 21.34% | 23.39% | 21.28% | 18.70% |
| Park | Jackson Heights, New York | 66.85% | 26.27% | 19.41% | 18.70% |
| Kang | Austin, Texas | 19.83% | 32.86% | 40.07% | 18.70% |
| Ulloa | El Paso, Texas | 75.23% | 80.73% | 40.07% | 18.70% |
| White | Houston, Texas | 65.21% | 38.30% | 40.07% | 18.70% |

Panel B: Percent Immigrant

| Plaintiff | Location | PUMA | In State MSA | State | Nation |
|---|---|---|---|---|---|
| Dodani | West Hills, California | 36.05% | 32.29% | 26.44% | 13.83% |
| Lira | Fontana, California | 33.89% | 20.79% | 26.44% | 13.83% |
| Brown | Greenacres, Florida | 38.78% | 41.64% | 21.37% | 13.83% |
| Useche | Miami, Florida | 48.26% | 41.64% | 21.37% | 13.83% |
| Hernandez | Las Vegas, Nevada | 22.27% | 22.13% | 19.16% | 13.83% |
| Kagan | Las Vegas, Nevada | 28.30% | 22.13% | 19.16% | 13.83% |
| Cohen | Jersey City, New Jersey | 42.44% | 26.98% | 23.32% | 13.83% |
| Park | Jackson Heights, New York | 63.01% | 30.99% | 22.59% | 13.83% |
| Kang | Austin, Texas | 13.95% | 15.93% | 17.46% | 13.83% |
| Ulloa | El Paso, Texas | 25.14% | 23.58% | 17.46% | 13.83% |
| White | Houston, Texas | 26.34% | 23.61% | 17.46% | 13.83% |

Panel C: Percent Non-Citizen

| Plaintiff | Location | PUMA | In State MSA | State | Nation |
|---|---|---|---|---|---|
| Dodani | West Hills, California | 10.32% | 14.55% | 11.93% | 6.61% |
| Lira | Fontana, California | 19.71% | 8.78% | 11.93% | 6.61% |
| Brown | Greenacres, Florida | 22.91% | 17.04% | 8.92% | 6.61% |
| Useche | Miami, Florida | 23.43% | 17.04% | 8.92% | 6.61% |
| Hernandez | Las Vegas, Nevada | 11.90% | 10.32% | 8.96% | 6.61% |
| Kagan | Las Vegas, Nevada | 16.57% | 10.32% | 8.96% | 6.61% |
| Cohen | Jersey City, New Jersey | 26.67% | 10.41% | 9.02% | 6.61% |
| Park | Jackson Heights, New York | 40.31% | 12.04% | 8.84% | 6.61% |
| Kang | Austin, Texas | 9.27% | 10.02% | 10.71% | 6.61% |
| Ulloa | El Paso, Texas | 7.66% | 11.31% | 10.71% | 6.61% |
| White | Houston, Texas | 20.86% | 13.81% | 10.71% | 6.61% |

Notes:
For the PUMA and In State MSA estimates the PUMA populations are projected using a regression with PUMA-specific LINEAR time trends, with data restricted to the years 2016-2018. Missouri Census Data Center's database MABLE (Master Area Block Level Equivalency) provides a crosswalk that the connects PUMAs to Counties. I then connect counties to MSA's using a crosswalk provided by Census Bureau. The crosswalk from MABLE includes the proportion of the PUMA population that fits inside each county. I estimate the MSA population as the total of the PUMA population estimates multiplied by this proportion for each county inside the given MSA.

State and National population numbers the State populations are projected using a regression with State-specific LINEAR time trends, with data restricted to the years 2016-2018.

Table 11
Undocumented Immigrant Shares

| Plaintiff(s) | Metro Area | MSA 2020 Undocumented Immigrant Population Share | State 2020 Undocumented Immigrant Population Share | US 2020 Undocumented Immigrant Population Share |
|---|---|---|---|---|
| Kang | Austin-Round Rock-Georgetown, TX | 3.8% | 5.4% | 3.1% |
| Ulloa | El Paso, TX | 6.6% | 5.4% | 3.1% |
| White | Houston-The Woodlands-Sugar Land, TX | 6.7% | 5.4% | 3.1% |
| Hernandez, Kagan | Las Vegas-Henderson-Paradise, NV | 7.2% | 6.3% | 3.1% |
| Dodani | Los Angeles-Long Beach-Anaheim, CA | 5.7% | 4.9% | 3.1% |
| Brown, Useche | Miami-Fort Lauderdale-Pompano Beach, FL | 6.0% | 3.4% | 3.1% |
| Cohen, Park | New York-Newark-Jersey City, NY-NJ-PA | 4.3% | 3.1% | 3.1% |
| Lira | Riverside-San Bernardino-Ontario, CA | 4.2% | 4.9% | 3.1% |

The New York-Newark-Jersey City MSA spans multiple states. Accordingly, the State 2020 Undocumented Immigrant Population Share is calculated as a weighted average across the three component states. For the individual states, the relevant population shares are: 3.2% in NY, 5.2% in NJ, and 1.6% in PA.

**APPENDIX A**

# Ruth Gilgenbach

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## Professional Experience

**Partner** — **January 2015- Present**
**Economist** — **September 2013-Present**
**Ashenfelter & Ashmore** — **Princeton, New Jersey**

Perform economic research and empirical analysis for litigation, arbitration, and mediation. Provide analysis and support for a wide variety of topics, including: age, race, and gender discrimination in hiring, promotions, terminations and compensation; price fixing; wage fixing; anticompetitive behavior; merger review; international trade (antidumping and safeguard) proceedings; auction theory; network neutrality regulation; international arbitration; proposed questions on the decennial US Census.

**Economist** — **May 2012-September 2013**
**Texas Attorney General, Antitrust Section** — **Austin, Texas**

Responsible for providing theoretical and empirical analysis in support of the Texas Attorney General. Provided analysis for a wide range of antitrust issues, including merger review, monopolization, anticompetitive conduct, and price-fixing cases. Additionally provided analysis of impact for consumer protection and environmental protection cases. Worked as part of large multi-state groups in drafting and responding to Daubert motions, case briefs, and other legal filings. Assisted in preparation for and attended multiple expert depositions. Participated in multiple mediation proceedings with a federal judge.

## Teaching Experience

**Lecturer,** Rutgers University, New Brunswick, Department of Economics
Law & Economics. Fall 2015- Present

**Lecturer**, Southern Methodist University, Department of Economics
Price Theory. Fall 2009, Fall 2010, Spring 2011, Fall 2011

## Education

**Southern Methodist University, Dallas Texas.** Ph.D. in Economics, 2012. M.A. in Economics, 2008.
Doctoral Dissertation: *Market Segmentation and Market Frictions*

**Agnes Scott College, Atlanta, Georgia.** B.A. in Economics and Political Science, 2006.
*Magna cum laude.*

## Fields of Interest

Industrial Organization, Microeconomic Theory, Applied Microeconomics, International Economics, Labor Economics

## Published Papers

Can a Decline in Search Cost Increase Prices? *Canadian Journal of Economics,* Volume 48, No. 4. November 2015.

Engaging an Economist in an Antitrust Matter. *Practical Law The Journal.* Volume 7, Issue 3. April 2015.

## Working Papers

On Price Competition with Captive Segments and Costly Search. Working paper.
A Note on Targeted Advertising, Consumer Search, and Overlapping Market Segments. Working paper.

## Presentations

Eastern Economic Association Conference, Boston, Massachusetts. 2012
Southern Economics Association Conference, Washington D.C. 2011
Southern Methodist University, Department of Economics. 2011
Southern Methodist University, Graduate Research Day. 2011
Southern Economics Association Conference, Atlanta, Georgia. 2010

## Honors, Awards, and Professional Associations

Dean's Graduate Dissertation Fellowship, Southern Methodist University, 2011-2012
Summerfield G. Roberts Research Fellowship, 2010
Dean's Award, Graduate Research Day, Southern Methodist University, 2010
Phi Beta Kappa, inducted 2006
*Wall Street Journal* Student Achievement Award, 2006
Omicron Delta Epsilon, inducted 2005
American Bar Association (Associate)

**APPENDIX B**

## Documents Relied Upon

**Legal Filings**
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Warren, Robert and John Robert Warren. 2013. “Unauthorized Immigration to the United States: Annual Estimates and Components of Change, by State, 1990 to 2010.” International Migration Review, February.