Analysis Plan

Project Name: Counterfactual Equity—Evaluating the Fairness of Different Small Business Relief Allocation Methods
Project Code: 2105
Date Finalized: 02/23/2021

Contents

DRAFT - FOR INTERNAL USE

1 Project Description

In the wake of the COVID-19 crisis, local governments rapidly distributed emergency grants and loans to small businesses. The OES team recently released a report, "Increasing Access to Small Business Grant and Loan Programs for Historically Underserved Groups," that documents how local governments took a variety of approaches to making sure that business owners from historically-underserved groups were able to access funds. The report showed how local agencies used a mix of three primary methods to distribute funds when the demand for funding exceeded the amount of funding available:

1. **First-come, first-served**: the agency records timestamps associated with the application (date/time submitted; date/time all documents received), and gives funds in order of those timestamps
2. **Lottery**: the agency collects a pool of applications with a predetermined cutoff date. Then, after applications are in, agencies conduct a lottery to select businesses
3. **Points system**: similar to a lottery, the agency collects all applications. Then, after applications are in, the agency uses a scoring system that gives businesses more points for various "plus factors." Businesses were then ranked by order of points, with a threshold used to determine selection.

Agencies often tweaked these general methods with an eye towards promoting equity. For instance, an agency might use first-come first-served but then move businesses owned by members of underserved groups or that are located in economically-distressed areas up in the queue. An agency might give businesses from certain groups or areas higher odds of being selected in a lottery. As a result, examining the variety of ways that agencies can distribute a program's resources can inform discussions of equity in program access.

In turn, OES' equity report highlighted that each allocation method has benefits and drawbacks for at least four sets of stakeholders: (1) political leadership, (2) the agency implementing the disbursement method, (3) businesses interested in assistance, and (4) community members that depend on the business' survival for important needs/services. Since the report lent more insight into groups one and two, and since group four can be difficult to define due to the array of business types helped, here we focus primarily on equity from the standpoint of the applicant businesses (group three).

In this project, we look at the sample of businesses that apply for funding, and assess the impact that different allocation methods have on a business' likelihood of selection for funding.[1] We plan to use application microdata to investigate counterfactual equity. Using characteristics of the businesses that we observe in the application data (e.g., owner attributes; date established; revenue loss), we simulate how (1) the businesses would fare under different allocation methods and (2) differences between groups (e.g., women-owned businesses and not) in selection rates. For instance, businesses that apply early in a submission window and have prioritized attributes used in a points system might get selected using any method; businesses with prioritized attributes that apply late may only be selected if an agency uses a points system with a plus factor for that attribute.

1. As we formalize more in Figure 1, there are four distinct stages at which we can examine equity: (1) who applies? (2) among applicants, who is found eligible? (3) among eligible applicants, who is selected for funding and offered a chance at a grant/loan, (4) among those offered funding, who actually receives it.

1.1 Connection with federal priorities

Questions about the relative equity of different ways of allocating help are relevant not only for the local allocation of small business relief funds but also for (1) federal priorities for small business relief and (2) federal priorities for general equity in the distribution of cash and in-kind benefits. These questions are increasingly salient in light of Executive Order 13985, signed January 20, 2021, which prioritizes the advancement of equity, defined as the "systematic fair, just, and impartial treatment of all individuals, including individuals who belong to underserved communities that have been denied such treatment."

First, for federal small business relief, the new round of Paycheck Protection Program funding authorized in December of 2020 contained several measures to promote access for underserved businesses. These included opening up a separate queue for the first two days of the portal's opening (January 11th, 2021) where community financial institutions (CFIs), who specifically serve underserved businesses, could process applications.[2] This ensured rapid processing of applications from underserved businesses before funds were potentially exhausted.

Second, beyond small business relief, the findings are relevant for programs where federal entities give funds to local entities and then give the entities discretion over how to allocate those funds. These include (1) the Department of Housing and Urban Development (HUD), which gives Public Housing Authorities (PHAs) the discretion to use a variety of disbursement methods (first-come first-served; lotteries; points systems, called local preferences) to manage Section 8 Housing Choice Voucher (HCV) waiting lists and (2) COVID-19 vaccine distribution, where vaccines distributed to state and local public health departments were allocated using a variety of first-come first-served and points-based methods.

2 Research Design Overview

2.1 Analytic sample and conceptual overview of the process

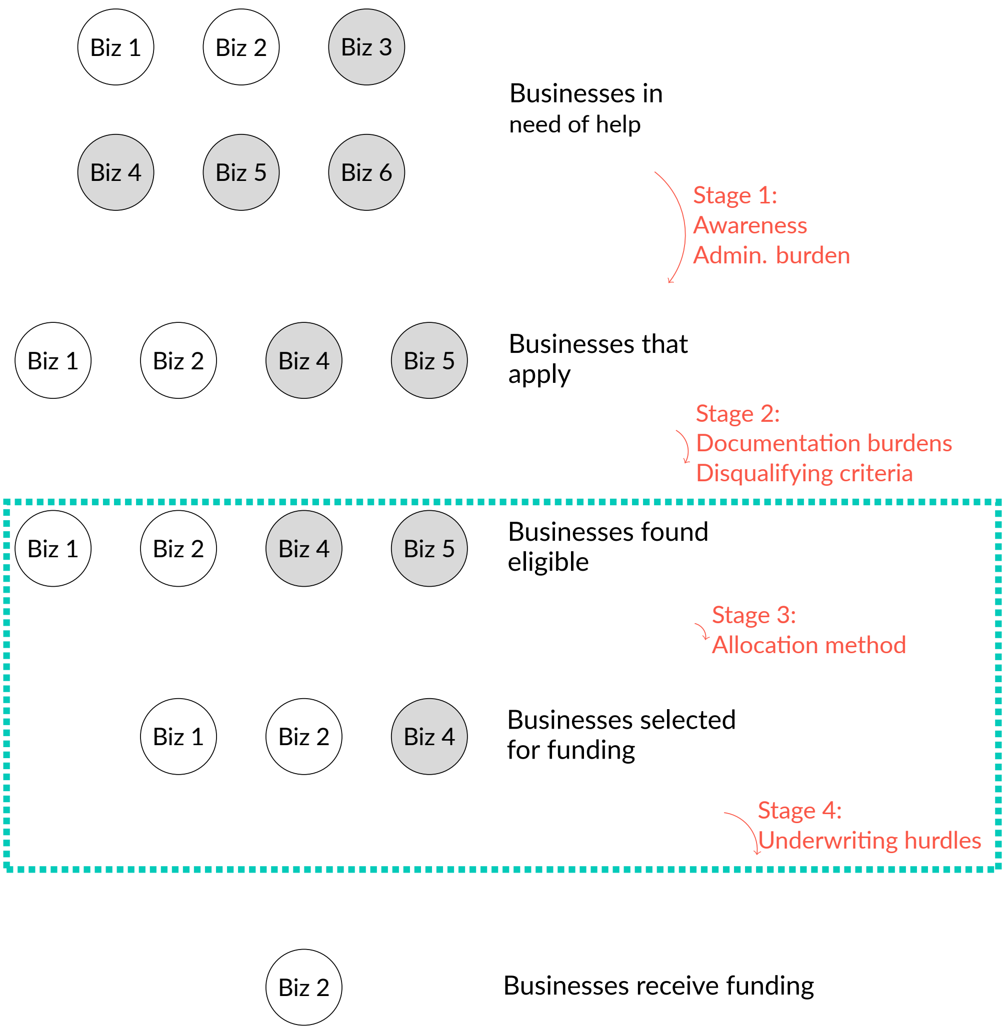
Disparities in outcomes between groups can stem from disparities at various stages of a multi-stage process. Figure 1 shows the four major stages where unequal outcomes can occur:

1. *Application stage:* which businesses apply for relief?
2. *Eligibility stage:* among the businesses that apply for help, which businesses are deemed eligible to progress to the selection process?
3. *Selection stage:* among the businesses that apply for help and are deemed eligible, which businesses are selected for help, or offered funding?
4. *Funding stage:* among the selected businesses, which businesses actually receive the funds?

Our analytic sample focuses on stages two and three. Among businesses that apply for funds, which businesses are selected for funding?

2. CFIs include Community Development Financial Institutions (CDFIs), Minority Depository Institutions (MDIs), Certified Development Companies (CDCs) and Microloan Intermediaries, all of which are more accessible to underserved businesses. The process also tiered the time of access based on whether an applicant was a "first draw" borrower for PPP or not.

Figure 1: Four stages that impact equality of outcomes The gray dots reflect businesses from underserved groups; the white dots reflect other businesses. The figure shows how different outcomes—0 out of 4 underserved businesses selected—can stem from differences at each of the stages. The green box shows the stages we focus on in the simulation.



Within this analytic sample, we define two sets of characteristics:

1. **Equity-relevant attributes**: these are measured at the business level, but can reflect either business-level characteristics or characteristics of the area in which the business is located. We focus primarily on four, but may expand depending on specific local priorities (e.g., for veterans, those with disabilities, LGBTQ business owners, specific geographic zones):
   (a) *Race/ethnicity of the business owner*: we define underserved as one or more non-White, non-Hispanic/Latino owners;
   (b) *Gender of the business owner*: we define underserved as one or more female owners;
   (c) *Location in a low and moderate income area (LMA)*: this corresponds with the U.S. Department of Housing and Urban Development (HUD)'s Community Development Block Grant (CDBG) program, which defines an area as LMA if 51+ percent of its residents are of low or moderate income. In practice, cities defined this by geocoding business locations and using either block or tract-level American Community Survey (ACS) rates;
   (d) *Owner is low or moderate income:* some applications asked owners whether they themselves were low or moderate income.[3]
2. **Selection-relevant attributes:** these are attributes used for the selection method in question, and generally include:
   (a) *Application-related timestamps:* these include submission timestamps used for first-come, first-served allocation methods. They also might include timestamps for when the business' application was considered "complete" with all the required documentation;
   (b) *COVID-damage related characteristics:* these include factors like documented revenue loss due to COVID, membership in certain sectors (defined by NAICS codes) most impacted by city-mandated closures, number of full-time equivalent (FTE) employees;
   (c) *Probability of survival-related characteristics:* cities balanced trying to help businesses most in need with trying to help businesses for whom the grant might reasonably help survival. These include the length of time the business has been in operation (tenure), the business' holistic likelihood of profitability after COVID-19, and other factors.[4]

2.2 Data and Data Structure

We will conduct the analysis by pooling business-level application data from cities. We define two analytic samples:

1. **Main sample:** all applicant businesses
2. **Secondary sample:** all eligible businesses

Cities either (1) directly measured equity-relevant characteristics, usually by asking the business to self report the majority owner's race/ethnicity or gender, or (2) did not directly measure these

3. Another low and moderate-income related attribute is the income composition of a business' employees. While this is an equity-relevant attribute, it's measured less consistently across datasets so we do not include it.

4. As we discuss later, due to the complexity of predicting business survival in the wake of COVID-19—e.g., longer-tenure businesses potentially having more capital reserves for survival; shorter-tenure businesses potentially being more resilient and able to pivot in the new COVID-19 context—many cities had reviewers assess this factor holistically based on a range of documentation.

characteristics, but have fields relevant for probabilistically imputing these characteristics.[5]

For cities that did not ask owners about whether the business was women-owned, we will use the primary owner's first name and the `gender` package in R (Mullen 2018), using the Social Security Administration (SSA) names database that corresponds to names from the birth year of the median-aged small business owner (50 years). Names are then coded based on cutoffs into: (1) likely female, (2) likely male, (3) indeterminate.[6]

For an exploratory analysis, we may impute majority owner race/ethnicity using the `wru` package in R that calculates race/ethnicity probabilities on the basis of two inputs: last names and census tract location (Imai and Khanna 2016). This method has been used in analyses like the investigation in Hepburn et al. (2020) of how eviction rates vary across race/ethnicity. However, this process likely has higher error rates than gender imputation and we will not use the process to make inferences.

2.3 Phase one: descriptive analysis of equity-relevant attributes and attrition through the funding process

Before examining counterfactual outcomes under different allocation methods, we will descriptively examine how equity-relevant attributes relate to three stages in the process that Figure 1 depicts: (1) among businesses that apply for relief, which businesses are found eligible?; (2) among businesses that are found eligible, which businesses are selected for funding?; (3) among businesses selected for funding, which are actually funded?

Equity-relevant attributes might be correlated with outcomes at each stage. For instance, for attrition between application and eligibility, research shows that women are more likely than men to operate home-based businesses as one solution to gender divisions in caregiving (Loscocco and Bird 2012). Therefore, there may be gender differences in eligibility depending on criteria related to home-based businesses and employee minimums/maximums. For attrition between selection for funding and actual funding, Internet or language barriers may play a role in responsiveness to requests for final paperwork.

2.4 Phase two: comparing possible allocation methods

Phase one helps us document descriptive differences in applicant businesses reaching the eligibility, selection, and funding stages. Phase two homes in on the selection stage and investigates how different *possible allocation methods*—or methods that a city could use when the demand for funds exceeds supply—impact the likelihood that different businesses are funded. Notably, the analysis abstracts away from the actual allocation method each city uses to investigate possible or counterfactual methods any city could use.

We compare the following allocation methods. For the lottery and first-come first-served simulations, we are specifying the exact methods. For the points system, we provide broad examples, but the final methods we compare will depend on what we can standardize across cities—e.g., standard measures of revenue loss during the early months of COVID-19 or date established fields.

To make the methods comparable, we will define N businesses selected by the method. For each of the analyses (the main analysis with the full applicant pool; the secondary analysis restricted to eligible businesses), the N selected will be 30% of the applicant pool (rounded).[7]

5. A middle case is where cities ask owners to self report but give owners the option of leaving the field blank. In that case, a combination of observed values and imputed ones can be used, or treating "nonreport" as a distinct category.

6. We may supplement with manual review to make sure, for instance, that we are able to impute for non-US born applicants whose names may be less likely to show up in SSA databases reflecting births.

7. While this decreases the realism, since the proportion selected is much higher among applicants deemed eligible

2.4.1 Lotteries

For the lottery methods, we compare three methods, with ties broken randomly.

1. **Unweighted lottery:** this gives all businesses (all applicants for applicant analytic sample; all eligible applicants for eligible sample) an equal odds of selection.

2. **Weighted lottery using business-level underserved status**: this lottery gives higher odds based on business-level equity-relevant attributes.

3. **Weighted lottery using area-level underserved status**: more commonly, cities, instead of creating separate pools based on *business-level*, equity-relevant attributes, created separate pools based on *area-level* attributes, or a business' location in a low-or-moderate income census tract (LMA). The third lottery will be one in which businesses located in these areas are given higher odds.[8]

2.4.2 First-come, first-served

For first-come first-served (FCFS), we compare three general types of methods, with businesses (1) ranked based on exact time since the first business submitted an application, and (2) a threshold drawn.

1. **One queue:** all businesses are placed in a single queue based on their date/time of submission.

2. **Two queues, with a separate queue for underserved businesses:** businesses are sorted into two queues—one for those that possess the attribute; another for others—with half of the awards given to each queue. Because underserved businesses represent less than half of the applicant pool, and if these businesses have a longer time to submit, this is equivalent to allowing later-submitting underserved businesses to still have a chance at funding.

3. **Two queues with area-level, equity-relevant attribute:** similar to above but with a LMA indicator.

2.4.3 Points systems

We compare six general types of points systems. Table 1 summarizes the systems in greater detail.

The six varieties result from the interaction of two factors: two (uses equity-relevant attribute directly or not) $\times$ three (does not include holistic judgment, includes holistic judgment and reviewer assessments are uncorrelated with the equity-relevant attribute, and includes holistic judgment and reviewers score underserved businesses lower). We include holistic judgments because some city systems include factors like the "probability that a business will survive if given funding" that, rather than measured directly in the data, were assessed holistically by reviewers. We simulate one version of the holistic judgment where the judgment is independent from underserved status; that is, two businesses—one underserved; one not—have the same probability of a reviewer rating that "yes" they are likely to survive (the code in Appendix Section A has details). We simulate another version where underserved businesses score lower.[9]

than the general applicant pool, this will allow us to disentangle differences in outcomes that stem from: (1) selection into the eligibility pool (which may be correlated with equity-relevant attributes) versus (2) the proportion of businesses selected.

8. This can occur either through the creation of a separate pool with a lower number of businesses than the main pool, in which case the program administrators can pre-specify the number of businesses to be selected, higher odds in one pool, or two chances—one in the equity set-aside pool; another in the main lottery.

9. Rather than overt bias, this could arise from real differences between the groups in economic attributes like pre-COVID profitability. For instance, if women-owned businesses are less profitable pre-COVID, judgments about future profitability might assess women-owned businesses more negatively. However, one can also imagine a holistic review pro-

Table 1: Points systems we compare X refers to placeholders for specific thresholds used in the system.

Shorthand	**Non-holistic economic criteria (examples)**	**Does it include a plus factor for underserved status?**	**Does it include a holistic judgment? If so, do underserved businesses have similar scores or lower scores?**
Economic only, no holistic judgment	Lost more than X% of revenue during first month of COVID-19; business' NAICS code is in an economically hard-hit industry; business has been in operation for X+ years; business has retained X+ employees	No	No
Economic and uncorrelated holistic judgment	Same as above	No	Yes and reviewer assessments uncorrelated with equity-relevant attribute
Economic and negatively-correlated holistic judgment	Same as above	No	Yes and reviewer assessments rate underserved businesses lower
Economic, no holistic judgment, and plus factor for underserved status	Same as above	Yes	No
Economic, uncorrelated holistic judgment, and plus factor for underserved status	Same as above	Yes	Yes and reviewer assessments uncorrelated with equity-relevant attribute
Economic, negatively-correlated holistic judgment, and plus factor for underserved status	Same as above	Yes	Yes and reviewer assessments rate underserved businesses lower

For each of the systems, we parametrize the weights given to the factors. Appendix Section A shows the current weights—for instance, pre-COVID revenue thresholds and weights for each bucket. The final weights will be designed to balance parsimony—what might cities reasonably measure and use?—with promoting dispersion in the scores.

After scoring, businesses are ranked based on the number of points and a threshold is drawn based on N awards. If there are businesses near the threshold with identical points values (e.g., the threshold would fall among businesses that each receive 9 points), we will randomly break ties to keep the number of businesses selected fixed.[10]

cess that tries to make holistic judgments uncorrelated with equity-relevant attributes by using group-specific judgments—for instance, if women-owned businesses have an average of $\$100,000$ a year in revenue, and male-owned businesses $\$140,000$, a reviewer could give women-owned businesses points for the attribute if they are *profitable within their gender*. For a discussion of group-specific thresholds and the fairness of scoring systems, see Corbett-Davies and Goel (2018).

10. An additional analysis may explore using another attribute as a tie breaker.

3 Simulation procedure and inference about subgroup differences

The analysis will be at the business level and the main analysis will pool across cities.[11] It will use a mix of two types of fields:

1. **Directly-observed fields**: all equity-relevant and points system attributes besides the holistically-assessed likelihood of survival
2. **Simulated fields**: the holistically-assessed likelihood of survival. Appendix Section A provides the code.

The procedure proceeds in three steps:

1. **Apply each method once:** This results in a "wide" dataframe for each business in the data, with a binary flag for "yes selected by method" or "not selected by method."
   - **Details:** for the regular and weighted lottery, instead of actual simulating the lottery, the main descriptive comparison and the chi-squared test will use a business' empirical probability of selection for the relevant proportions and counts. The regression analysis will simulate the lottery $m = 1000$ times and take a business' majority outcome.
2. **Compare descriptive proportions of yes selected by equity-relevant attribute**: this descriptively tells us whether a method awards funding to a higher proportion of businesses than another method. We examine two descriptive differences:
   - **Proportion of each group given awards:** in a regular lottery, the proportion of each group given awards will be the overall selection probability (0.3 in our case). Methods can either increase this proportion for the underserved group or decrease this proportion.
   - **Proportion of total awards given to each group:** in a regular lottery, the proportion of total awards given to each group will equal that group's proportion of the applicant/lottery pool.[12] Methods can either increase the proportion of awards that go to the underserved group above that application proportion or decrease it.
3. **Inference:** we will use two methods for inference about whether the proposed method causes between-group differences in selection rates:
   (a) **Chi-squared test (separately for each method) of independence between equity-relevant outcome and selection status**: the null and alternative hypotheses are as follows, framed in terms of our case, with $p < 0.05$ used to assess significance:
   - H_0: the equity-relevant attribute (e.g., the business owner race/ethnicity) is independent of whether or not the business is selected for funding
   - H_1: the business' equity-relevant attribute helps us predict whether or not that business is funded

   (b) **Linear regression modeling the outcome of change from "no to yes" selection**: while the chi-squared tests tell us, method by method, the dependency between equity-relevant attributes and selection, we are most interested in the *relative equity* of the methods

11. As we outline in Section 4, while pooling has the advantage of abstracting away from a given city's eligibility rules, applicant pool composition, and other factors, it could lead to potential aggregation biases. As a result, in a robustness check, we will conduct the simulation separately for each city.
12. Since we are using real application data, this proportion varies based on attribute and city.

according to some baseline. Therefore, we supplement the method-by-method tests with a single test at the business level that uses an unweighted lottery as the baseline. We use an unweighted lottery as the baseline since that is a method that (1) neither explicitly takes into account equity-relevant attributes (2) nor is based on things like submission time that might be correlated with those attributes.

More formally, we estimate the following model, where i indexes a business, a indexes a particular allocation method, and y_{ai} represents the business' outcome for that method, and each business is repeated a times for the number of methods, with standard errors clustered at the business level. The estimand of interest is the conditional average treatment effect (CATE), or how the main effect of the allocation method is moderated by the pre-treatment, business attribute (e.g., race/ethnicity):

$$\begin{aligned} y_{ai} = &\alpha + \beta_1 \text{Equity-relevant attribute}_i + \beta_2 \text{Method}_a + \\ &\beta_3 \text{Equity-relevant attribute}_i \text{Method}_a + \epsilon_{ai} \end{aligned}$$

We will interpret a positive coefficient on β_3 and $p < 0.05$ as rejecting the null that the method has no impact on increasing award rates for the underserved group.

3.1 Understanding mechanisms through which points systems increase or decrease equity

Points systems impact outcomes for groups like women-owned businesses not only through direct prioritization of that attribute, but also through the relationship between that attribute and economic measures like the revenue lost during COVID-19. For instance, if women-owned businesses are less profitable pre-COVID, they may have smaller proportional revenue losses than male-owned businesses. We will explore these correlations descriptively. While the empirical correlations will be fixed in the data, we can also examine counterfactual outcomes when the correlations are weakened or reversed.

4 Robustness checks/exploratory analyses

Here, we outline potential exploratory analyses depending on data availability and city priorities:

1. *Poststratification to adjust estimates for selection into applying:* returning to the process outlined in Figure 1, one drawback of the present method is that we are only examining outcomes among applicant businesses. We can think of applicant businesses as a non-representative sample of a broader target population composed of potential applicants.[13] In turn, the applicant businesses fall into cells defined by attributes like majority owner gender and location in an LMA area. We can use the differences between each group proportion in the sample (applicant businesses) and proportion in the population (city businesses) to reweight the sample descriptive statistics like the percent of minority-owned businesses chosen by method X.

2. *Analyses separated by city:* the main analysis plans to pool application data from multiple cities. However, three factors may vary substantially across cities: (1) the overall size of the applicant pool, (2) the proportion of that pool with an equity-relevant attribute, and (3) empirical correlations between economic indicators and those attributes. This could lead to results, for instance, driven by the correlations observed in the city with the largest applicant pool. We will analyze the robustness of the results to separate simulations by city.

13. Notably, and as the high degree of attrition between applicants and eligible businesses shows, the target population is closer to something like "possibly-eligible businesses" rather than "definitely-eligible businesses.

3. *Variation across points systems:* Table 1 describes points systems that vary along dimensions like whether they include a specific plus factor for underserved businesses or a holistic reviewer judgment. Yet points systems can vary not only in *which inputs* are included. They also vary in aspects like (1) the relative weight given to each input—e.g., a "flatter" points system might give 1 point for each attribute, a more hierarchical points system might give 1 point for FTEs above a threshold, 10 points for revenue loss, and so on; and (2) how many inputs the points system factors in. While the complexity of the points systems we compare is limited based on which fields we can standardize across application datasets, city-specific analyses may examine more varieties than those outlined in Table 1.

A Code to apply allocation methods

The code here is illustrative for the points system, which may change as we add more cities and standardize more fields. It also focuses on one equity-relevant characteristic, with the final simulation using other owner and area level ones.

```
########################################
# Parameters
########################################

# can sub out different equity chars
eq_char <- "derived_is_wob"
n_biz <- nrow(business_pop)
n_under <- sum(business_pop[[eq_char]])
n_notunder <- sum(!business_pop[[eq_char]])
gen_prob_holistic <- 0.4
gen_prob_holistic_favored <- 0.5
gen_prob_holistic_disfavored <- 0.25


########################################
# Simulate reviewer judgment
########################################

business_pop <- business_pop %>%
        mutate(holistic_surv_uncor = sample(c(TRUE, FALSE),
                                            prob = c(gen_prob_holistic,
                                                     1-gen_prob_holistic),
                                            replace = TRUE,
                                            size = n_biz),

               ## holistic correlated
               ## mob have higher likelihood of being rated
               ## holistically to be unlikely to survive post-covid
               holistic_surv_cor = ifelse(!!sym(eq_char),

                                   ## those with equity char less likely to get good rating
                                   sample(c(TRUE, FALSE),
                                          prob = c(gen_prob_holistic_disfavored,
                                                   1-gen_prob_holistic_disfavored),
                                          replace = TRUE,
                                          size = n_under),

                                   ## those without equity char more likely to get good rating
```

```
                                  sample(c(TRUE, FALSE),
                                         prob = c(gen_prob_holistic_favored,
                                              1-gen_prob_holistic_favored),
                                         replace = TRUE,
                                         size = n_notunder)))



########################################
# Get lottery probabilities
########################################

## n_choose
n_choose_overall <- round(nrow(business_pop) * 0.3)

prob_unweighted_lot <- n_choose_overall/nrow(business_pop)
prob_weighted_noter <- (n_choose_overall/2)/n_notunder
prob_weighted_er <- (n_choose_overall/2)/n_under


#######################################
# Run FCFS
########################################


## fcfs 1--- one queue
select_onequeue <- business_pop %>%
            arrange(derived_seconds_sincefirstsub) %>%
            slice(1:n_choose_overall) %>%
            pull(biz_id)

## fcfs 2-- two queue
select_twoqueue <- c(business_pop %>%
              filter(.data[[eq_char]]) %>%
              arrange(derived_seconds_sincefirstsub) %>%
              slice(1:(n_choose_overall/2)) %>% # could change prop allocated by queue
              pull(biz_id),
              business_pop %>%
                filter(!.data[[eq_char]]) %>%
                arrange(derived_seconds_sincefirstsub) %>%
                slice(1:(n_choose_overall/2)) %>% # could change prop allocated by queue
                pull(biz_id))

## create indicators
business_pop <- business_pop %>%
  mutate(is_chosen_onequeue = ifelse(biz_id %in% select_onequeue, TRUE, FALSE),
         is_chosen_twoqueue = ifelse(biz_id %in% select_twoqueue, TRUE, FALSE))

########################################
# Run simple points system
########################################

## fn define points system
## set default values for each att and can vary later
points_system <- function(df, include_er = TRUE, include_holistic = FALSE,
                        name_er_attribute,
                        name_holistic_attribute,
                        points_naics = 10,
```

```
                        points_med_rev = 5,
                        points_high_rev = 10,
                        points_low_fte = 5,
                        points_med_fte = 10,
                        points_high_fte = 15,
                        er_pointsval = 5,
                        holistic_pointsval = 5){

  ## points for naics
  naics_points <- case_when(df[["derived_naics_hardhit"]] ~ points_naics,
                            TRUE ~ 0)

  ## more points for more pre-covid revenue
  rev_points <- case_when(is.na(df[["derived_rev_2019"]]) | df[["derived_rev_2019"]] < 5000 ~ 0,
                  df[["derived_rev_2019"]] <= 50000 ~ points_med_rev,
                  df[["derived_rev_2019"]] <= 500000 ~ points_high_rev,
                  TRUE ~ 0) # code outlier to zero as well

  ## more points for retaining more fte
  fte_points <-  case_when(is.na(df[["derived_current_fte"]]) | df[["derived_current_fte"]] == 0 ~ 0,
                            df[["derived_current_fte"]] == 1 ~  points_low_fte,
                          df[["derived_current_fte"]] <= 20  ~ points_med_fte,
                          TRUE ~ points_high_fte)



  ## conditional points depending on condition
  er_points <-0
  hol_points <- 0
  if(include_er){
    er_points <- ifelse(df[[name_er_attribute]],
                       er_pointsval, 0)
  }
  if(include_holistic){
    hol_points <- ifelse(df[[name_holistic_attribute]],
                        holistic_pointsval, 0)
  }

  ## final step, for each person, return the sum
  total_points <- naics_points + rev_points + fte_points + er_points + hol_points
  return(total_points)

}

## fn to rank, break ties if needed,
## and create selection indicator
rank_discretize <- function(df, var_arrange,
                            n_select){

  ## rank and break ties randomly
  selected_biz <- df %>%
    ## create rank var with random tiebreak
    mutate(rank_var = rank(!!sym(var_arrange),
                           ties.method = "random")) %>%
    ## high points -> high rank so desc
    arrange(desc(rank_var)) %>%

```

```r
    ## n selected
    slice(1:n_choose_overall) %>%
    pull(biz_id)

  ## create binary indicator
  df[[sprintf("is_chosen_%s",
              var_arrange)]]  <- ifelse(df[["biz_id"]] %in%
                                          selected_biz,
                                        TRUE,
                                        FALSE)
  ## return
  return(df)
}

# init new df to help with naming stuff
add_p <- business_pop
## system 1: no direct er, no holistic
add_p$noer_nohol <- points_system(business_pop, include_er = FALSE,
                           include_holistic = FALSE)

## system 2: yes direct er, no holistic
add_p$yeser_nohol <- points_system(business_pop, include_er = TRUE,
                          include_holistic = FALSE,
                          name_er_attribute = eq_char)


## system 3: no direct er, yes holistic uncor
add_p$noer_yeshol_uncor <- points_system(business_pop, include_er = FALSE,
                                include_holistic = TRUE,
                                name_holistic_attribute = "holistic_surv_uncor")

## system 4: yes direct er, yes holistic uncor
add_p$yeser_yeshol_uncor <- points_system(business_pop,
                                include_holistic = TRUE,
                                name_holistic_attribute = "holistic_surv_uncor",
                                include_er = TRUE,
                                name_er_attribute = eq_char)

## system 5: no direct er, yes holistic cor
add_p$noer_yeshol_cor <- points_system(business_pop, include_er = FALSE,
                                include_holistic = TRUE,
                                name_holistic_attribute = "holistic_surv_cor")

## system 6: yes direct er, yes holistic cor
add_p$yeser_yeshol_cor <- points_system(business_pop,
                                              include_holistic = TRUE,
                                              name_holistic_attribute = "holistic_surv_cor",
                                              include_er = TRUE,
                                              name_er_attribute = eq_char)


## create binary indicator for all
points_cols <- c("noer_nohol", "yeser_nohol",
                 "noer_yeshol_uncor",
                 "yeser_yeshol_uncor",
                 "noer_yeshol_cor",
                 "yeser_yeshol_cor")

```

```
for(var in points_cols){

  add_p <- rank_discretize(add_p,
                                      var,
                                      n_select)

}
```

References

Corbett-Davies, Sam, and Sharad Goel. 2018. "The measure and mismeasure of fairness: A critical review of fair machine learning." *arXiv preprint arXiv:1808.00023.*

Hepburn, Peter, Renee Louis, and Matthew Desmond. 2020. "Racial and Gender Disparities among Evicted Americans." *Sociological Science* 7:649–662.

Imai, Kosuke, and Kabir Khanna. 2016. "Improving ecological inference by predicting individual ethnicity from voter registration records." *Political Analysis,* 263–272.

Loscocco, Karyn, and Sharon R Bird. 2012. "Gendered paths: Why women lag behind men in small business success." *Work and occupations* 39 (2): 183–219.

Mullen, Lincoln. 2018. *gender: Predict Gender from Names Using Historical Data.* R package version 0.5.2. https://github.com/ropensci/gender.