Report

Project Name: Who Receives Access to Small Business Relief? A Simulation-based Approach
Project Code: 2105

Contents

1 Executive Summary

In the wake of the COVID-19 crisis, local governments rapidly distributed emergency grants and loans to small businesses. Many local agencies used a mix of three primary methods to distribute funds when the demand for funding exceeded the amount available: First-come, first-served, Lottery and Points systems. The choice of method was often based in part on the desire to equitably support the businesses that have historically been less able to access financing, including those with owners who are women, Black or Hispanic, or low-income.

OES analyzed application data from three cities to investigate two questions. First, did these local programs reach underserved businesses? The application data suggests the answer is yes, as businesses owned by those from historically underserved groups both applied and received funds at high rates (Section 5).

Second, how did the method for deciding which businesses got funding affect the equity of outcomes? We investigate how businesses from different groups and geographic areas would fare under different allocation methods. This approach takes real applications and asks "what if" funding had been allocated to those that applied earliest, or using a lottery, or by assigning points based on certain characteristics. We use simulations to compare the portion of funding that would be awarded to applicants from businesses owned by women, businesses with other underserved owners, and businesses located in low-to-moderate income areas, under 10 different allocation methods including approaches that do or do not explicitly prioritize businesses from historically underserved groups (Section 6).

There are several lessons from examining the city application data, including:

1. **Focusing on area-level characteristics misses many underserved individuals.** In the three cities, there were many applications for small business funding from businesses in underserved areas (census block groups where the majority of residents have low-to-moderate incomes). However, focusing on area-level disadvantage misses a large portion of underserved individuals: many business owners who themselves had low-to-moderate incomes or who are Black or Hispanic had businesses located outside of these areas.

2. **Many applicants had at least one underserved characteristic, and often multiple.** Of the businesses applying for small business funding during COVID-19 in these three cities, about 60-90% were women-owned, had Black or Hispanic owners, or were located in a low-to-moderate income area. Thus, prioritizing any business with at least one of these characteristics (such as by giving them extra weight in a lottery) advantages a large number of businesses. Giving extra priority to businesses that had multiple characteristics advantages a smaller number of businesses with multiple underserved characteristics.

3. **Businesses owned by those from historically underserved groups progressed through the review process at rates similar to other businesses.** After submitting an application for funding, businesses must still be found eligible, selected for funding, and receive funding. Each stage involves new burdens (e.g., providing documentation, communicating with administrators). If these burdens fall disproportionately on businesses with owners from historically underserved groups, then inequities could arise even in a diverse and representative applicant pool. However, in these three cities, this was largely not the case.

The points above pertain to the three cities whose application data was examined, and may not be true of all local small business relief funding programs. However, lessons learned from using this data to conduct the simulations are likely to generalize beyond these specific cities. Those lessons include:

1. **Points systems that do not explicitly prioritize businesses from historically underserved groups can inadvertently disadvantage those businesses.** When a diverse set of businesses applied for funding, those owned by women and minorities or located in low-to-moderate income areas had lower pre-COVID revenue and were disadvantaged by points systems that prioritized businesses with higher levels of pre-COVID revenue.[1] Businesses owned by members of historically underserved groups also generally had fewer full-time employees, and in one of two cities where industry codes were reported, they were less likely to be in hard-hit industries prioritized by the points system. Because of these differences, points systems that prioritize factors like revenue loss, number of employees, and specific industries without assigning points to underserved demographic groups can result in less funding going to those groups.

2. **Weighted lotteries and set asides within first-come, first-served methods are a more consistent way to increase the funding going to historically underserved groups.** Points systems often prioritize factors that disadvantage the smaller and lower-income businesses owned by members of these groups. Lotteries weighted to give a higher chance of winning to some businesses, or setting aside a portion of first-come, first-served funding for these businesses, can drive funding to historically underserved groups.

3. **Basic first-come, first-served methods can disadvantage applicants from historically underserved groups.** Businesses owned by members of historically underserved groups generally took longer to submit an application after the application windows opened, although the results were somewhat different across the three cities. Processing applications and allocating funding in the order they are submitted, without using a separate queue or set-asides for underserved applicants, can result in less funding to these applicants.

Examining these general types of allocation methods, and variation within, can inform discussions of the equity of the methods agencies use in practice. These lessons are relevant not only for small business funding. When limited resources need to be allocated among applicants, some of whom belong to groups that have historically faced barriers to access, then the choice of allocation method affects equity of distribution.

2 Project Description

In the wake of the COVID-19 crisis, local governments rapidly distributed emergency grants and loans to small businesses. In early 2021, OES 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

1. In real-world points systems, this occurred via either including higher pre-COVID revenue within the eligibility limits as a plus factor or revenue loss during COVID as a plus factor, which could be easier to demonstrate for businesses with higher pre-COVID profitability.

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 factors. Businesses are 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, some agencies used first-come first-served but then moved businesses owned by members of underserved groups or that are located in economically-distressed areas up in the queue. Other agencies used lotteries but weighted those lotteries to give higher odds of selection to businesses located in certain areas or to owners in underserved demographic categories. Examining the variety of ways that agencies can distribute a program's resources can inform discussions of equity in program access.

The earlier OES report highlighted that each allocation method has benefits and drawbacks. Given the pressure to get funds to businesses quickly, as well as limited employee time, the choice of allocation method could be difficult. In some instances, local administrators expressed a personal preference for points systems or other methods that would prioritize underserved groups, but were wary of the extra documentation and processing time those methods would require, compared to a simple first-come, first-served approach. No one knew exactly how much more time one method would take, or how much better one method would be at getting funding to underserved businesses, making these decisions particularly challenging.

There are benefits and drawbacks of each method for many stakeholders including local political leadership, the agency implementing the allocation method, businesses interested in assistance, and community members that depend on the business' survival for important needs/services. The current project focuses primarily on equity from the standpoint of the applicant businesses. However, it is worth acknowledging that there are limitations to fully understanding that perspective with the methodology used here. We analyze application data, but without talking to applicants (and eligible non-applicants), we can only speculate about how applicant businesses perceive the fairness of different methods. For instance, applicants who expended a great detail of effort to submit their application quickly might have viewed first-come first-served as most fair; others may have preferred a lottery. Our focus on outcomes-based fairness—the percentage of awards that go to businesses from specific historically-underserved groups—thus misses important aspects of procedural fairness, or whether members of those groups feel that they are treated fairly in the process.

Given those caveats, in this project we pool a rich set of application microdata from small business relief programs located in three cities. These microdata contains all businesses that apply for relief. We investigate two questions:

1. **Did these local programs reach underserved businesses?** (Descriptive equity)

   We examine whether and how the applicant pool reflects equity in program outreach. In general, the applicant pools for the three cities had a diversity of business locations and business owners that resembled the diversity of the cities as a whole.

   We also examine whether underserved businesses progress from the application stage to later stages at similar, higher, or lower rates compared to other groups.[2]

2. Figure A.1 shows four generic stages from application to funding. In practice, cities often used a larger set of

2. **How did the method for deciding which businesses got funding affect the equity of outcomes?** (Counterfactual equity)

   The descriptive outcomes are influenced by a variety of factors that are not available in the city application data, including the demographic composition of eligible, small business owners in the city.[3] We focus on one factor that may impact outcomes: the allocation method (lottery; first-come first-served; points system, and variants of each) a city uses.

   Each city only used one *actual* allocation method. The small number of cities, and the fact that an allocation method is not assigned at random to a city but is the deliberate choice of policymakers and program planners, means that we cannot credibly identify the causal effect of an allocation method on outcomes using *actual* application data. Instead, we use simulation to (1) construct a variety of *counterfactual*, or potential, allocation methods a city could use, and (2) compare outcomes for underserved groups under each of the methods. Each of the potential methods we compare is based on real-world methods but abstracts from program-specific details.

   The analysis has two key takeaways. First, and less surprisingly, methods that set aside a portion of awards for the underserved group are a potent tool for ensuring that their award rates match or exceed their representation in the applicant pool. Second, demographically-neutral points systems can sometimes not only fail to give an extra boost to underserved groups but also can harm their outcomes relative to their applicant pool composition.

The remainder of the report proceeds as follows. Section 3 gives an overview of city programs and data sources. Section 4 outlines the methods for examining descriptive and counterfactual equity. Section 5 describes the descriptive equity of the programs. Section 6 describes counterfactual equity under different allocation methods.

3 Data sources

3.1 Application data from cities

Table 1 describes the three cities and four programs, rounding numbers to preserve de-identification. For City C, we examine two programs separately: a citywide program and a program where a specific ward/district in the city used its own funds to target assistance solely to members of that ward/district, which was significantly more underserved than the city as a whole.

Across the three cities and four programs, we focus on two sets of attributes to examine descriptive and counterfactual equity:

1. **Equity-relevant attributes:** in addition to demographic characteristics of the majority owners summarized in Table 1, we examine demographics of the community surrounding where the business is located, described further in Section 3.2.

2. **Economic attributes:** since many points systems used measures of pre COVID-19 vitality—for instance, revenue before COVID—or measures of COVID's potential or realized economic harm, we also use fields in the application data that gave applicants a boost in certain points systems.

program-specific statuses that map imperfectly onto these categories. We note limitations in trying to standardize across cities.

3. This is potentially observable using IRS tax data, but in general, business tax certificate and other "census"-like universes of businesses and business owners do not contain demographic fields.

As we describe further in the limitations section, the table also highlights important scope conditions for our analysis in light of the Equity EO:

1. **No representation of programs targeting rural businesses:** rurality is an important dimension of equity. However, the programs we examine are all city-based programs, preventing us from examining this dimension of equity.

2. **No information about staff capacity:** we do not have data on the number of staff members and application reviewers each city allocated to processing requests for funds. City agencies with more capacity may be more inclined to adopt methods like points systems that involve more staff time to process applications, while those with less capacity may view methods outside of first-come, first-served as too difficult to implement. It is likely that larger programs have more staff capacity, but without this data, we are unable to examine this dimension of equity.

Table 1: Cities and data sources

	City A	City B	City C	
			Program A	Program B
Census region	South	West	West	West
Area population size	1-2 million	1-2 million	>2 million	300,000-500,000
General eligibility criteria (excludes widely-shared criteria like valid business tax certificate)	50 or fewer FTEs; revenue under $1.5 million	100 or fewer FTEs; economic hardship due to COVID-19	25 or fewer FTE; revenue under $1 million depending on NAICS code	25 or fewer FTE; revenue under $5 million; economic hardship due to COVID-19
General allocation method	Weighted lottery	Fast-tracking underserved businesses in queue for first-come first served	Fast-tracking underserved businesses in queue for first-come first served	Unknown
Owner attributes we use (refers to majority owner, either through the self-report question wording or through our coding of ownership percentages)	Woman; Black or Hispanic	Impute possible gender based on first name of majority owner (Section ??); low or moderate income	Woman; minority (not separated by race/not restricted to Black or Hispanic)	Woman; minority (not separated by race/not restricted to Black or Hispanic)
Economic attributes available to use	FTE at time of application; 2019 annual revenue; NAICS code	FTE at time of application; 2019 annual revenue; NAICS code	FTE at time of application	FTE at time of application; 2019 annual revenue
Applicants	$\sim$ 1450	$\sim$ 9820	$\sim$ 4300	$\sim$ 800
Proportion applicants offered and accepted funding (approximate)	0.30	0.19	Unknown	0.21
Equity-relevant attributes in applicant pool (opt in)	38% women-owned businesses; 49% Black or Hispanic owned; 55% LMI area	29% women-owned businesses (imputed so possible underestimate); 44% low or moderate income owner; 40% LMI area	18% women-owned businesses; 19% minority-owned; 57% LMI area	39% women-owned; 41% minority-owned; 82% LMI area

3.2 Auxiliary data

We also use data from the American Community Survey (ACS) to measure characteristics of the neighborhoods where the businesses are located. We first use each business' address to geocode the business to a specific latitude and longitude.[4] We then find that location's intersection with Census blocks. Finally, we merge with block group level data (one higher level of geography due to

4. For home-based or non brick and mortar businesses, these addresses may also reflect the address of the business owner

data availability) on three characteristics of the surrounding neighborhood:[5]

1. **The block group's proportion of low-to-moderate income (LMI) residents:** we examine this characteristic because of priorities related to 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-to-moderate income. Some cities used this as an explicit targeting criteria either for outreach to businesses or for the allocation of funds.

2. **The block group's proportion of Black residents:** this is consistent with the Equity EO's focus on underserved communities in addition to underserved individuals.

3. **The block group's percentage of Hispanic residents:** similarly, this is consistent with the Equity EO's focus on underserved communities and, depending on the language status of residents, may also reflect outreach barriers discussed in the OES Equity Report based on language status.

Approximately 1.4 percent of businesses were either missing an address in the underlying application, had an address that could not be geocoded, or had a geocoded address that did not overlap with a valid block. Due to the low prevalence of missingness, we do not believe it impacts our conclusions.

4 Methods

All analyses were pre-registered in a plan posted on February 24th, 2020 at the following link: https://oes.gsa.gov/assets/analysis/2105_SBequity_analysisplan.pdf

4.1 Preprocessing of data: imputation of owner sex/gender in City B

Two of the three cities directly asked the majority owner about their gender. For the third city that did not ask owners about whether the business was women-owned, we used 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 were then coded based on cutoffs into: (1) likely female (29% of the owners), (2) likely male (50% of the owners), (3) indeterminate (20% of the owners; coded as "not female" for the purposes of the equity analysis). Appendix Figures A.2 and A.3 show, for the male and female categories, the proportions of infants with that birth certificate sex with that name.

4.2 Simulation to compare counterfactual equity

To make the distribution comparable, we defined the proportion of applicant businesses selected by the method as 15%. The actual rates in the four programs were in the 20-30% range (Table 1).[6] However, the results of the counterfactual equity simulations would be similar if we chose a different arbitrary proportion.

4.2.1 Lotteries

For the lottery methods, we compared two methods, with ties broken randomly.

5. The race/ethnicity attributes are from the 2019 ACS; the LMI measure is from the 2015 ACS due to the availability of block group level, rather than tract level, data.

6. These rates in the table reflect award rates for all applicants, rather than award rates among applicants deemed eligible, which were substantially higher.

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.[7]

4.2.2 First-come, first-served

For first-come first-served (FCFS), we compared two general types of methods. In each of these, businesses were ranked based on how much time had elapsed since the first business submitted an application[8] and a threshold is drawn based on N awards. There are no ties in this system since time is always at least slightly different.

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.

4.2.3 Points systems

We compared six general types of points systems. Table 2 summarizes the systems in greater detail.

Some cities assigned points for membership in one or more historically underserved groups (for example, they gave extra points to women-owned or Black-owned businesses). Thus, we simulated some points systems that included these equity-relevant attributes.

A second frequent element of a points system is a holistic judgment such as "the probability that a business will survive if given funding." Rather than being measured directly in the data, these sorts of factors were assessed holistically by reviewers and given a score which attracted a pre-determined amount of points.

We simulated 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.3 has details). We simulated another version where underserved businesses score lower.[9]

Altogether these variations produce six varieties of points system: 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).

7. 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.

8. City C Program 2 had two application windows so, in that city, we first code each applicant business to one of the windows based on its submission timestamp and then examine the relative time within the window.

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 process 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).

Table 2: 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 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 parametrized the weights given to the factors. Appendix Section A.3 shows the weights for the results in this report.

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 randomly broke ties to keep the number of businesses selected fixed.

4.2.4 Simulation steps and inference about subgroup differences

The analysis was at the business level. It used three fields:

1. **Woman-owned:** this was either observed (three of four programs) or imputed (one of four programs).
2. **Underserved majority owner:** this varies across the cities due to the availability of different fields:
    - City A: Black or Hispanic owned

- City B: owner is low or moderate income
- City C: minority owned

3. **Located in a low-and-moderate income area:** across the three cities, this was based on block group-level data and defined as the area having 51% or more LMI residents.

Appendix Section A.4 has details of the procedure. For the main results, we present a descriptive proportion: what proportion of awards go to members of the underserved group? At baseline, or in a regular lottery with equal odds, the group will receive awards that parallel their proportions in the applicant pool. For instance, if woman-owned businesses are 20% of applicants, in a regular lottery, they will receive 20% of awards. Methods that lead those businesses to receive fewer than 20% of awards disadvantage them relative to their applicant pool proportions; methods that lead those businesses to receive more than 20% of awards give them an extra boost.

We complement the descriptive proportions with more inferential examinations of whether the differences in receipt between disbursement methods are statistically significant.

4.3 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 explored these correlations descriptively.

5 Results: descriptive equity

When examining descriptive equity, we define equity in terms of proportionality: are there a similar proportion of underserved owners and areas in the applicant pool as in the broader target population from which those applications are drawn?

This is a difficult question to answer because there is limited data about the target population. For example, if a city publicizes a small business relief program for businesses located inside city limits, with fewer than 10 full-time employees, and with COVID-related revenue loss of at least 20% compared to the year before. While cities release public data on registered businesses (e.g., business tax certificate data), there is no dataset to say how many businesses are likely applicants for this program, let alone how many of the likely applicant businesses have women owners, Black or Hispanic owners, and so on.

With these limitations in mind, we take two approaches to examining descriptive equity:

1. **At the area level, compare the diversity of the block groups where applicant businesses are located to the diversity of the block groups in the area as a whole:** this comparison gives us a general sense of whether applicant businesses are concentrated in (1) block groups that experience similar levels of poverty and that have similar racial/ethnic diversity to the city as a whole, (2) block groups that are less underserved, or (3) block groups that are more underserved (as described in Section 3.2). The limitation is that the distribution of *business locations* in a city may differ from the distribution of residents. Therefore, this comparison is more valid for cities with interpersed businesses and neighborhoods and less valid for cities with a metropolitan business core and residential outer ring.

2. **For owners, report applicant diversity without target population comparisons:** since our data on demographic characteristics of small business owners is significantly more limited than our data on demographic characteristics of city locations, we do not conduct a comparison. However, our presentation of the raw proportions of each group allows readers to compare with their target rates (e.g., if the goal is that 40% of applicant businesses are woman-owned, comparing to that target).

5.1 Which businesses apply?

5.1.1 Are the businesses located in underserved areas?

Here, we descriptively explore:

- The distribution of characteristics in the block groups where businesses are located
- **The median block group of an applicant business (solid red line)**: the red vertical line on each plot shows the median block group—for instance, one with 40% LMI residents versus one with 62% LMI residents—across all applicant businesses
- **The median block group in the surrounding area (dashed red line)**: for City A, City B, and City C, Program 1, we use the surrounding Census county for simplicity, since although programs sometimes restricted eligibility to those located inside the city limits, (1) these limits lack a clear census geography and (2) the cities received many applications from businesses in the county. For the geographically-targeted program in City C (Program 2), we use the precise boundaries of the ward/district to define the "area" demographics.

Figure 1 shows the results for the poverty in the areas where the businesses were located. We see that notably, Program 2 in City C, which restricted outreach to residents in that ward/district, had a distribution that skews towards significantly higher poverty levels than the citywide programs. Across all cities, applications came from businesses located in areas broadly reflective of the area's general poverty levels.

Figure 2 shows the results for the proportion of residents who are Black in the areas where the businesses were located, showing similar patterns as the previous Figure. The alignment of the solid and dotted lines in Figures 1 and 2 suggests that on the whole, these local programs attracted an applicant pool that reflected the regional levels of poverty and Black residents.

Figure 3 shows the results for the proportion of residents who are Hispanic in the areas where the businesses were located. Unlike the previous, in this Figure the solid lines—the business locations of actual applicants—are below the dotted lines—the median block group in the area.

The pattern of Figure 3 could reflect either (1) different distributions of businesses across areas (e.g., if those areas have fewer businesses located there, we would expect fewer applications) or (2) lower application rates from businesses located in Hispanic communities. If option (1) is the underlying reason, then we might also observe a difference in the proportion of White applicants versus residents. Appendix Figure A.4 shows these distributions for the proportion of White residents in a block group. Those results do not show consistent patterns across the four cities. The lack of a systematic divergence for White applicants does not rule out option (1) - there may be fewer businesses in the heavily Hispanic parts of these cities. It remains possible that option (2), lower application rates from businesses in Hispanic communities, is the reason for the pattern seen in Figure 3. If so, then these local programs did **not**, on the whole attract an applicant pool that reflected regional levels of Hispanic residents.

Figure 1: Where are applicant businesses located? Proportion LMI by block group The figure shows either nearly equal representation (solid red line for median applicant block group overlaps with dashed red line for median area tract) or slightly higher representation.

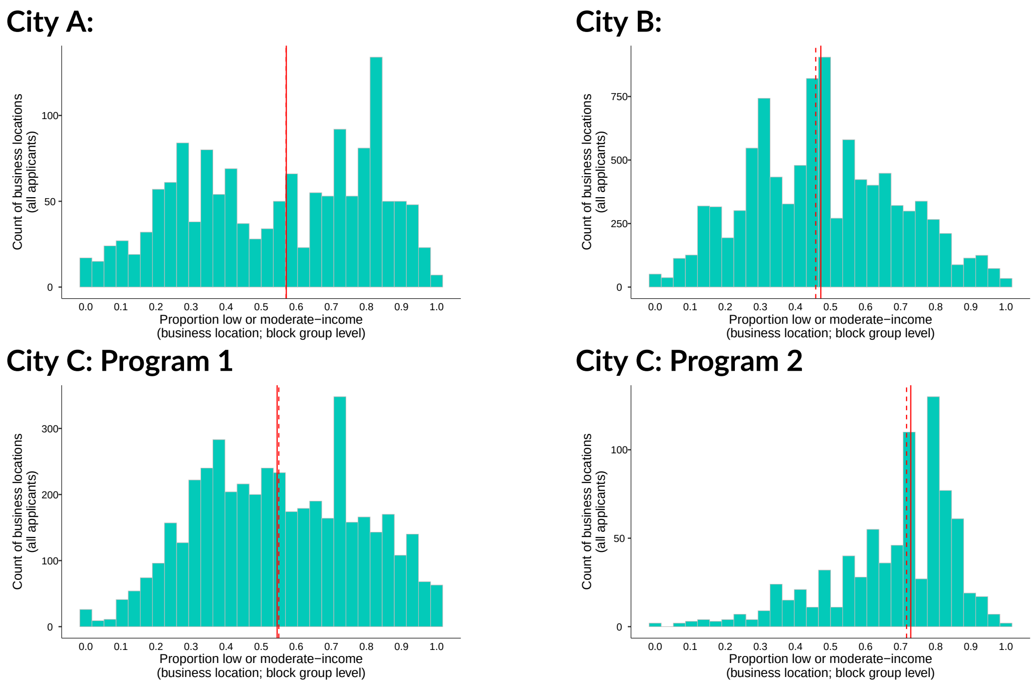


Figure 2: Where are applicant businesses located? Proportion Black by block group The figure shows higher representation in City A, with the median applicant block group having about 15% of residents who are Black compared to the median area block group having about 10% of residents who are Black.

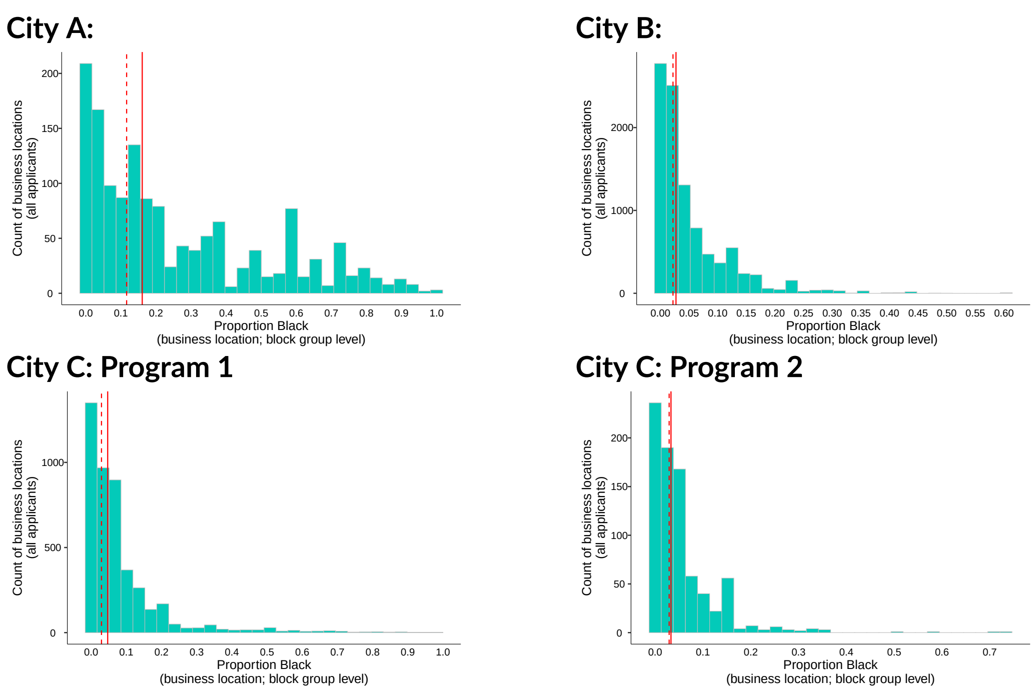
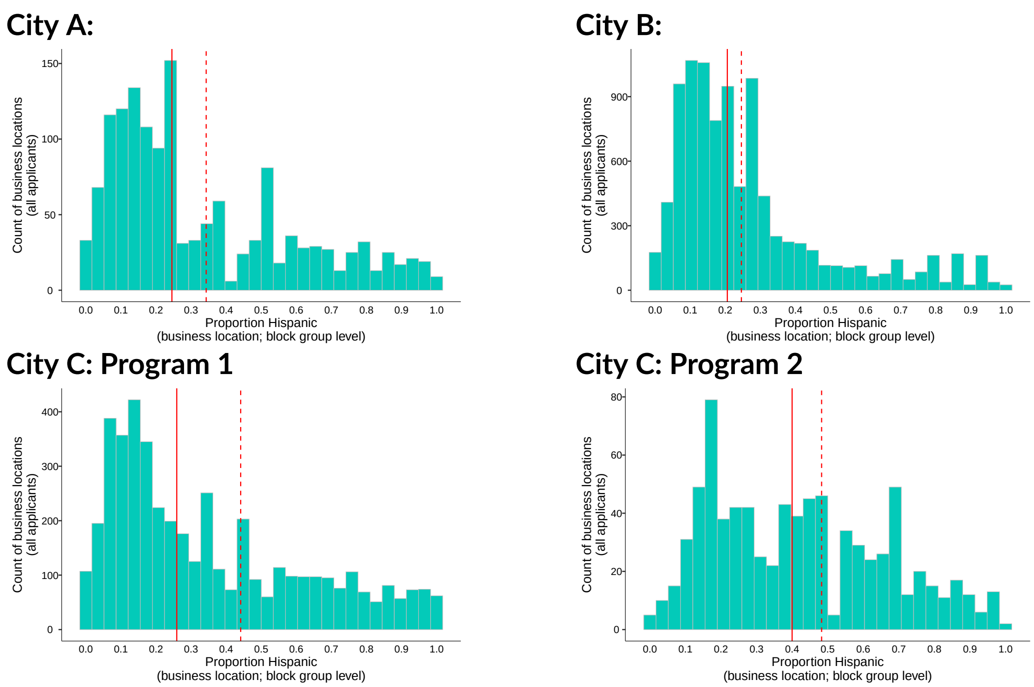


Figure 3: Where are applicant businesses located? Proportion Hispanic by block group The figure shows a lower median tract proportion for applicant businesses (solid line) than all block groups in the surrounding area (dashed line), which could either be due to the distribution of businesses across residential neighborhoods or lower applications.



5.1.2 Area versus owner demographics

The previous figures focus on whether the businesses applying are located in and potentially serve underserved communities. Here, we focus on how that form of disadvantage—characteristics of the areas where the businesses are located—overlaps with a second form of disadvantage: the majority owner is from an underserved group. While Table 1 shows the attribute-by-attribute breakdown of these characteristics, here, we focus on how they intersect.

Each city collected a different set of demographic fields, with Section 3 describing how we define underserved owner in each city and program. Figure 4 shows the intersection of underserved status at the owner level with the business being located in an underserved community.

This comparison shows two key takeaways:

1. **Using area-level disadvantage as the sole measure of underserved misses a significant proportion of underserved individuals:** even using block group, which provides a granular measure of area demographics, Figure 4 shows that there are many underserved owners whose businesses are located outside of LMI areas: for instance, in City A, over 30% of Black or Hispanic owners have businesses located outside these areas; in City B, over 60% of owners who themselves are low-to-moderate income have located their businesses outside of LMI areas.[10] This shows that while funding sources like CDBG funding emphasize area-level measures of disadvantage,[11] these measures may be insufficient proxies for assistance going to owners from

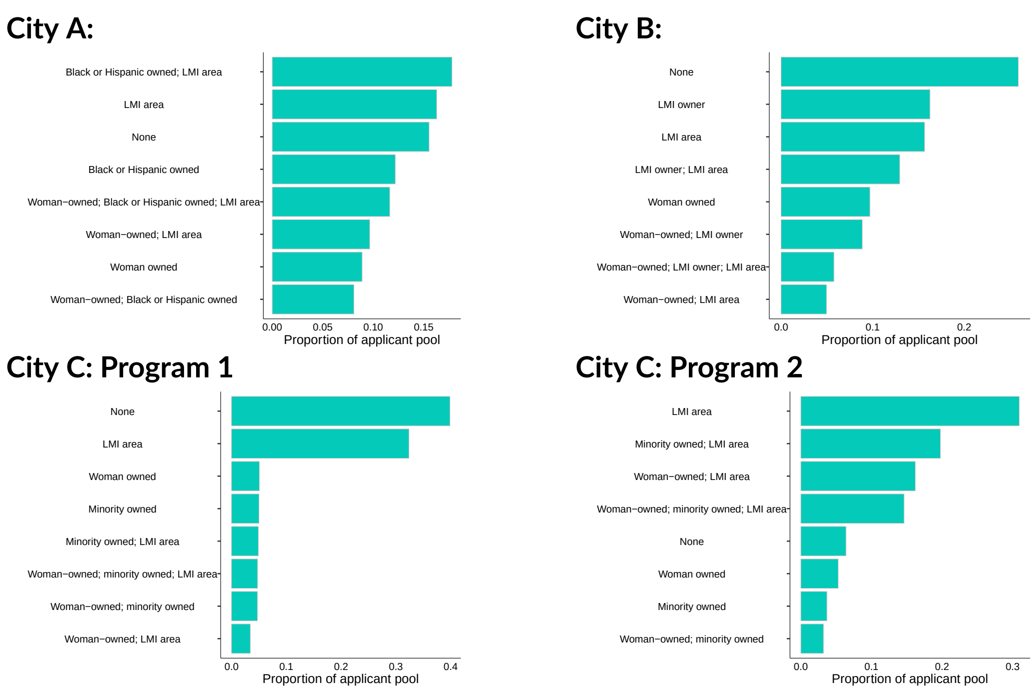
10. Only one city collected location information for where the owner lives, preventing a systematic cross-city examination of equity based on the owner's location rather than the business' location.

11. CDBG regulations allow grantees to presume a person is LMI when either the census tract where they live or the

underserved communities.

2. **Many of the applicants had at least one underserved characteristic, and often multiple:** allocation methods like weighted lotteries and points systems can use various approaches to upweighting underserved characteristics. One approach is an *or* approach—if the business has any underserved characteristic at the owner or area level, that business gets extra points. Figure 4 shows that this approach may effectively end up advantaging a large swath of the applicant pool, since very few businesses fell in the "None" category of no underserved characteristics (fewer than 20% in City A; fewer than 30% in City B; fewer than 40% in the citywide City C program; fewer than 10% in the geographically-targeted City C fund). The second approach is an *and* approach—give separate points for each underserved characteristic (for instance, Black or Hispanic-owned businesses located in LMI areas receiving higher priority than Black or Hispanic-owned businesses in other areas). While these choices are ultimately a matter of policy, the *or* approach would result in weaker priority for businesses with a high number of intersecting statuses; the *and* approach would lead to more differentiation.

Figure 4: Intersection of owner and area demographics



5.2 Progression through award pipeline

The previous section showed general characteristics of the applicant pool in each of the sites. It showed that cities' application pools were comprised of high concentrations of businesses located in underserved areas and owned by underserved individuals.

Yet as Appendix Figure A.1 highlights, applying is only the first hurdle for underserved businesses to pass. Here, using *applicant businesses* as the denominator, we look at the percentage of businesses that progress through later stages.[12] Each city defines stages that differ slightly from the general

census tract where the assisted business is located falls below a defined poverty threshold.

12. Since the previous section showed how underserved groups comprise different proportions of the applicant pool,

ones shown in Appendix Figure A.1, but we simplify them to eligibility, funding offer, and funding receipt for ease of comparison. An important caveat is that in some cases, the city was still processing applications when the application data was extracted, so the numbers for each might have changed in the final disbursement.

Figure 5 highlights the results for City A, which the previous section showed had high rates of underserved businesses in the applicant pool (38% of applicants were women-owned businesses; 49% were Black or Hispanic owned; 55% were located in an LMI area)(Table 1). We see that these underserved groups progress at similar rates through the eligibility, funding offer, and funding receipt stage, with a slightly higher percentage of Black or Hispanic owners clearing eligibility hurdles once they are in the applicant pool. Similarly, City B's diverse applicant pool (at least 29% women-owned; 44% of owners low-to-moderate income; 40% of businesses located in LMI areas) is accompanied by a good degree of progression of underserved businesses; for instance, though businesses located in LMI areas had slightly lower rates of passing eligibility screens,[13] once they passed screens, their prioritization in the review process led to higher rates of funding offers.

This comparison can be summarized with the following takeaway:

> **Businesses owned by those from historically underserved groups progressed through the review process at rates similar to other businesses.** After submitting an application for funding, businesses must still be found eligible, selected for funding, and receive funding. Each stage involves new burdens (e.g., providing documentation, communicating with administrators). If these burdens fall disproportionately on businesses with owners from historically underserved groups, then inequities could arise even in a diverse and representative applicant pool. However, in these three cities, this was largely not the case.

here, we standardize representation at later phases with each group's count of applications.

13. These figures pool across application rounds; the City relaxed certain eligibility criteria, like restrictions on eligibility for sole proprietors. Therefore, the aggregated data may conceal increased rates of eligibility amidst changing restrictions.

Figure 5: How do underserved businesses progress through the application and award stage? City A and City B The *left panel* shows the progression breakdowns for City A; the *right panel* for City B.

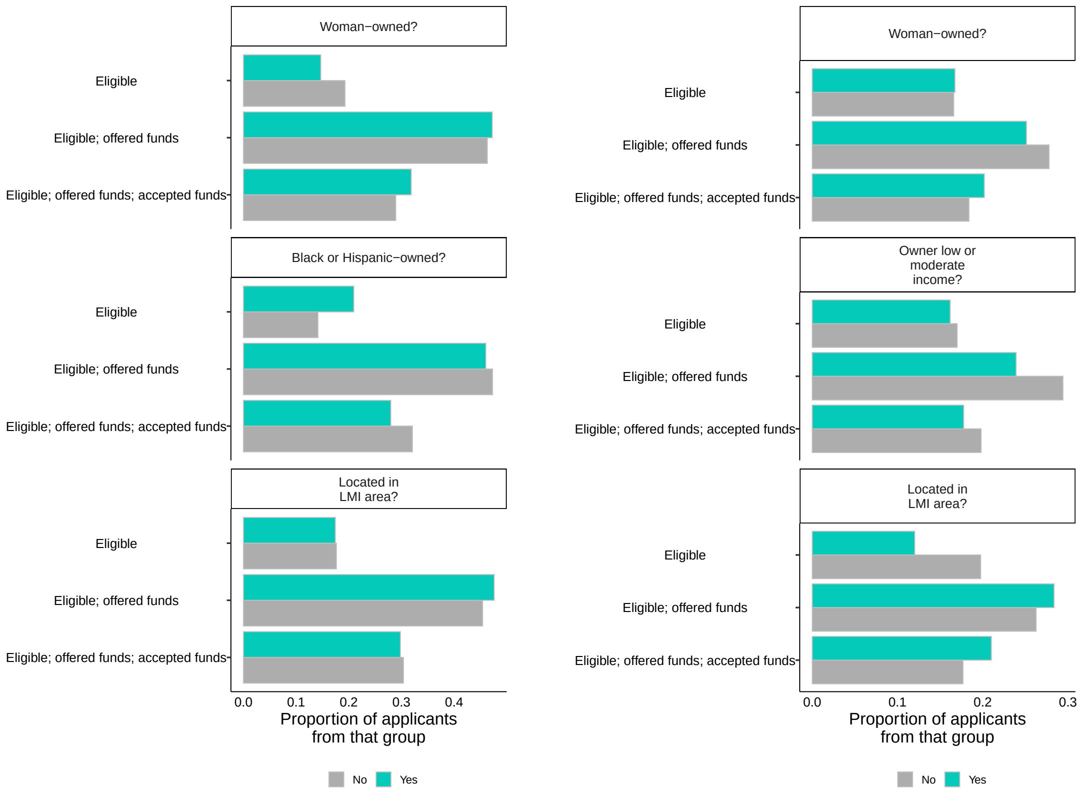
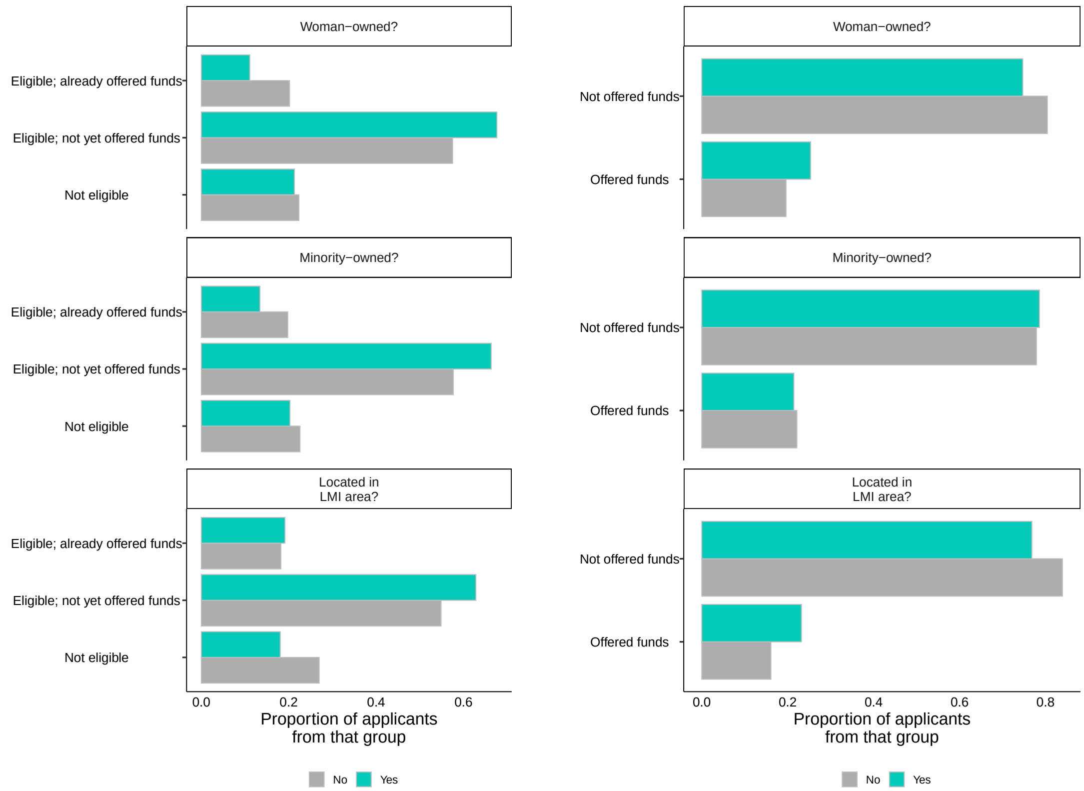


Figure 6 shows the same progression plots for the two programs in City C, for which the data extract (1) still reflects ongoing disbursement/status changes and (2) has coarser status categories. We see that the applicant pool diversity is accompanied by similar stages of passing eligibility screens.

Figure 6: How do underserved businesses progress through the application and award stage? City C The *left panel* shows the citywide program 1; the *right panel* the geographically-targeted program.



6 Results: Counterfactual equity

The previous analyses focus on *what actually happened* in the different relief programs.

Here, we focus on the impact of the ten different allocation methods outlined earlier on the proportion of awards given to applicants from each of the underserved categories: women-owned businesses, other underserved owner (defined differently in each city), and located in an LMI area.[14]

6.1 Overall results

We present results separately for each city.[15]

Figure 7 shows the results for women-owned businesses in each of the four cities/programs. Figure 8 shows the results for other underserved owners (Black or Hispanic owned; LMI owner; or minority

14. For City C Program 1, because the submission timestamp reflects a mix of actual submission times and timestamps of status updates, we omit $N \sim 350$ applicant businesses where the timestamp reflects anything but for the submission time, since otherwise, our results for first-come first-served would be skewed.

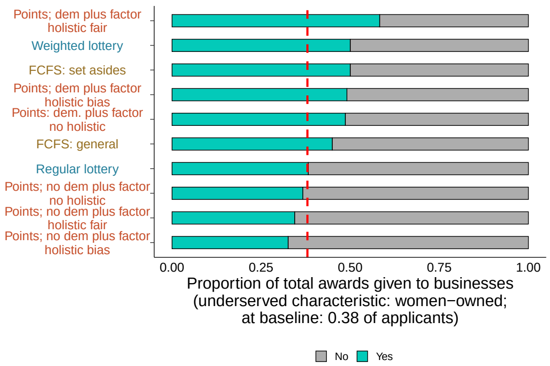
15. This deviates from the pre-analysis plan, which emphasized aggregate analyses as the main results and separate-by-city analyses as a robustness check. We make this change for three reasons. First, as the previous sections show, the cities had very different distributions of baseline characteristics of applicant businesses. Second, the cities have different numbers of businesses that remain in the analytic sample for the simulation, with City B comprising 71% of the remaining applications ($\sim$ 9820 out of $\sim$ 16,300 applications total). Finally, for the City C programs, the points systems are most comparable within the city/program, since, City C: Program 1 is missing both NAICS codes and pre-COVID revenue (therefore, the points system relies solely on FTE and a demographic or holistic attribute when relevant) and City C: Program 2 is missing NAICS codes.

owned). Figure 9 shows the results for businesses located in LMI areas. For three of the four programs, the percentage of businesses in LMI areas exceeded 50% of the applicant pool, so we omit their results, since a regular lottery already gives those businesses 50% of awards. Appendix Section A.6 presents the results of the chi-squared analyses for non-independence between the underserved characteristic and outcomes under a given allocation method.

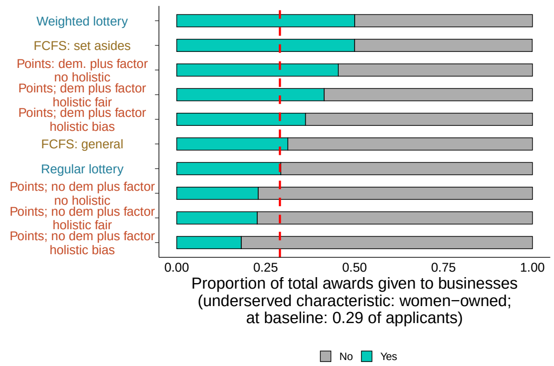
- **Points of commonality across programs:**
  - **In heterogeneous contexts, points systems without demographic plus factors can inadvertently disadvantage underserved businesses:** in the three cities/programs with heterogeneous contexts (City A, City B, and the citywide Program 1 in City C), points systems can lead to underserved businesses being given a lower share of awards than an unweighted regular lottery. This is consistent across all three definitions of underserved: being a woman-owned business; being a business owned by a minority or lower-SES individual; and being located in an LMI area. Section 6.4 discusses mechanisms in greater depth.
  - **Weighted lotteries and set asides within first-come first-serve provide more consistent tools for increasing the group's share of awards**: less surprisingly, when an underserved group comprises less than 50% of the applicant pool, setting aside 50% of awards for that group either through a weighted lottery or a separate FCFS queue increases their award rates. Since each involves the same process of setting aside a portion of awards for the underserved groups, cities could decide on one depending on other program goals and achieve similar outcomes. For instance, if a city hopes to disburse money in waves as applications come in, a FCFS with separate queue, with rolling applications and rolling disbursement, may make more sense than waiting for a large-enough pool of applicants to run a weighted lottery.
- **Points of divergence:**
  - **Extent to which first-come first served disadvantaged underserved applicants:** cities varied in the extent to which using a "pure" FCFS system disadvantages underserved applicants relative to the baseline of a regular lottery. This could be related to differences in the application window (e.g., longer versus more compressed windows) or other differences in program design that future research could examine more systematically.

Figure 7: How does the allocation method impact outcomes? Women-owned businesses.

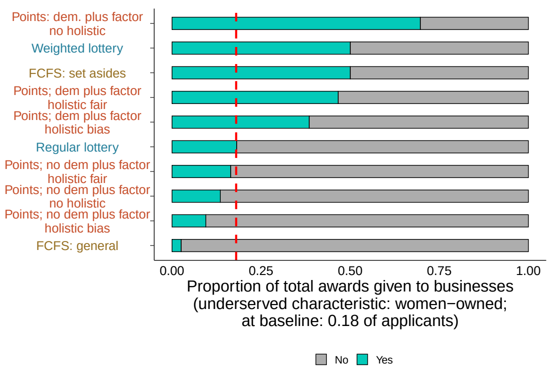
City A:



City B:



City C: Program 1



City C: Program 2

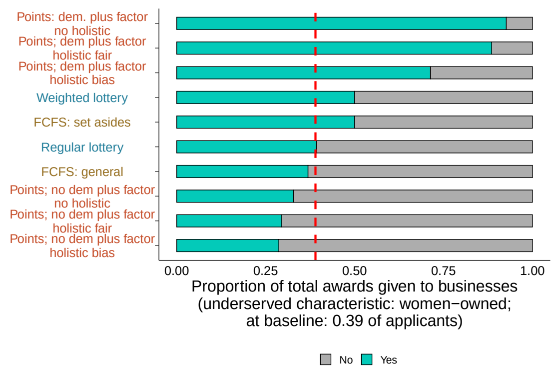
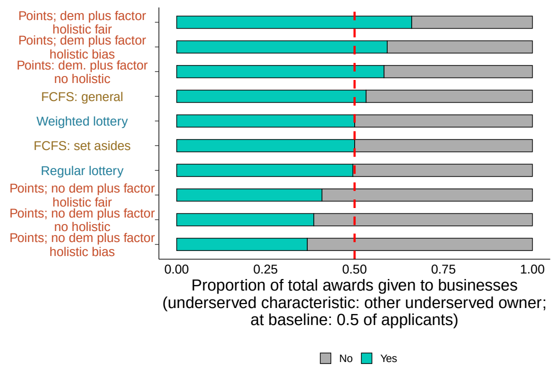
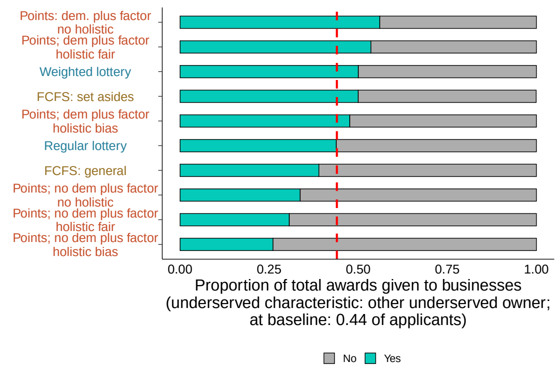


Figure 8: How does the allocation method impact outcomes? Businesses with other underserved owners.

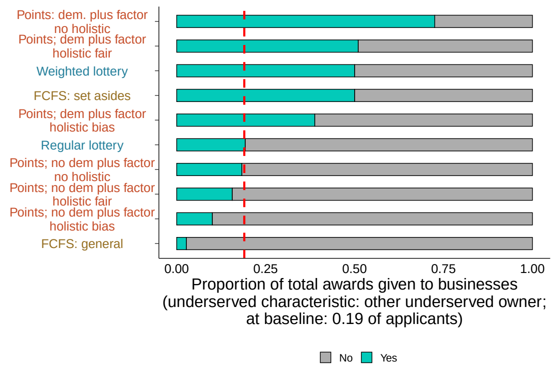
City A:



City B:



City C: Program 1



City C: Program 2

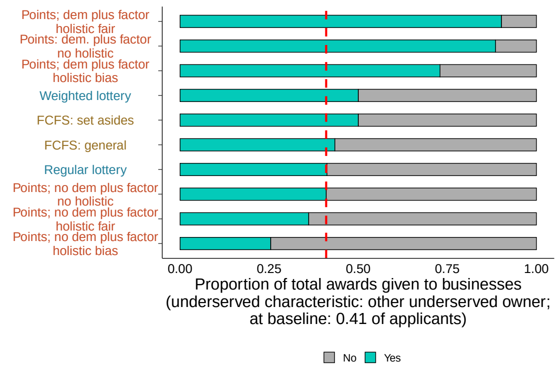
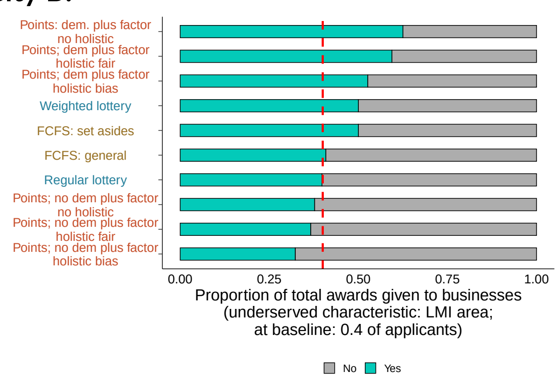


Figure 9: How does the allocation method impact outcomes? Businesses located in LMI areas.

City A: businesses exceed 50% of the applicant pool (55% of applicants), so we omit the results.

City B:



City C: Program 1 businesses exceed 50% of the applicant pool (60% of applicants), so we omit the results.

City C: Program 2: businesses exceed 50% of the applicant pool (82% of applicants), so we omit the results.

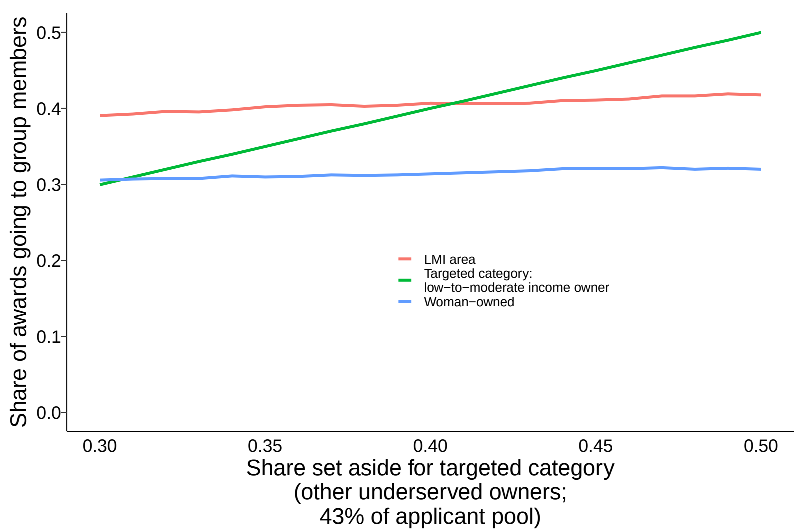
6.2 How do results vary when we change the proportion of awards set aside for the underserved group?

The previous results highlight what happens when an underserved group comprises less than 50% of the applicant pool but where a city sets aside 50% of awards for those businesses, either choosing the ones to receive awards through a lottery or a separate first-come first-served queue. Yet if the underserved group comprises a relatively low percentage of the applicant pool—for instance, in some cities, women-owned businesses were closer to 20-30% of applicants—the city may want to set aside a smaller proportion of awards than half.

Here, we focus on the largest city (City B) and underserved owners (owners who have low-to-moderate income, which comprise 44% of the applicant pool). Since, by construction, weighted lotteries and first-come first-served with a set aside give awards to a pre-determined proportion of applicants—e.g., a weighted lottery designed to give women-owned businesses 40% of awards will 40% of awards to those businesses; similar with a first-come first-served queue that sets aside 40% of awards—we investigate whether setting aside different proportions of awards for one targeted criteria (low-to-moderate income owners) improves outcomes for other targeted criteria (women-owned and LMI areas).

Figure 10 shows that bolstering award rates for one targeted category—in this case, low-to-moderate income owners—only weakly improves award rates for businesses with other underserved attributes. This highlights one drawback with set asides: while their effect on award rates for one categories are clear and easier for program planners to control than points systems, if underserved attributes are only loosely correlated, they do not meaningfully alter outcomes across categories.[16]

Figure 10: How do set asides for one targeted category impact award rates for another category?



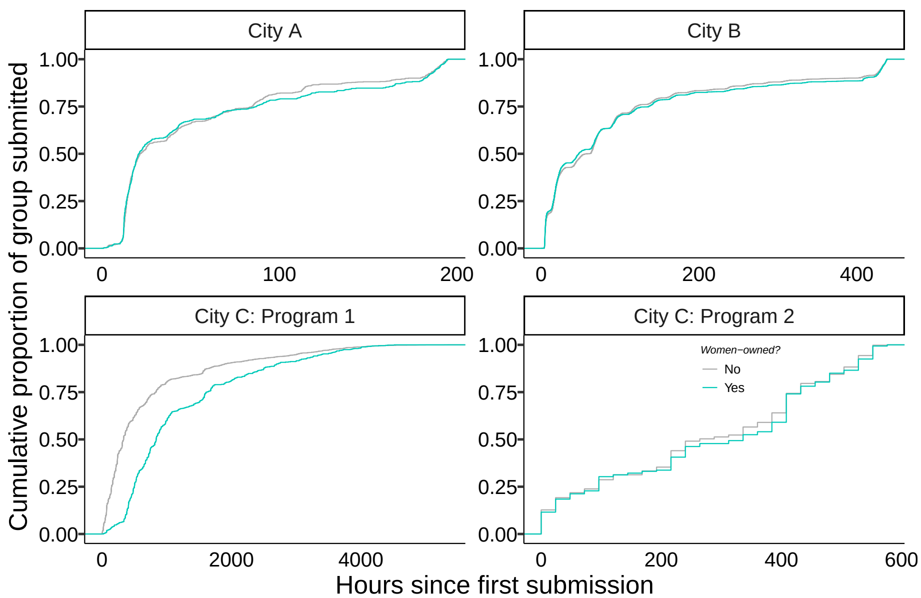
16. One scope condition is that these results are for a FCFS set aside with a particular design: a city sets aside a portion of awards for the underserved group and forms a separate waiting list for that group. However, cities could and did implement more complex approaches. For instance, cities could put underserved businesses in both the main award queue and a separate queue and offer them funds if they get selected on either waiting list as other businesses withdraw/drop out.

6.3 Exploring mechanisms behind inequality in first-come first-served

The previous results show that, depending on the city, first-come first-served without a separate queue can disadvantage underserved businesses, with the results most pronounced in City C. Here, we use the *relative submission time*—how long after the first submission did a focal business submit their application—to explore mechanisms.[17]

Appendix Section A.7 shows regression tables, while here in Figure 11 we highlight the cumulative density functions for women-owned businesses. For the CDF, steeper curves indicate a more rapid time to submit for the group relative to the first submission; flatter curves, a longer timeline. City C: Program 1 (the citywide program) shows gradients where the women-owned businesses have a longer time to submit, while the other programs show no gradients.

Figure 11: How quickly did businesses submit applications relative to the first application in the window?



6.4 Exploring mechanisms behind inequality in points systems

While inequality from first-come first-served is more well-recognized, a second takeaway was that demographically-neutral points systems, in some cases, not only failed to *help* businesses relative to their share in the application pool, but could reduce that share. The one exception is the points system implemented in a relatively demographically homogeneous context (City C: Program 2), where it serves as more of a tie breaker between the high share of businesses with underserved attributes.

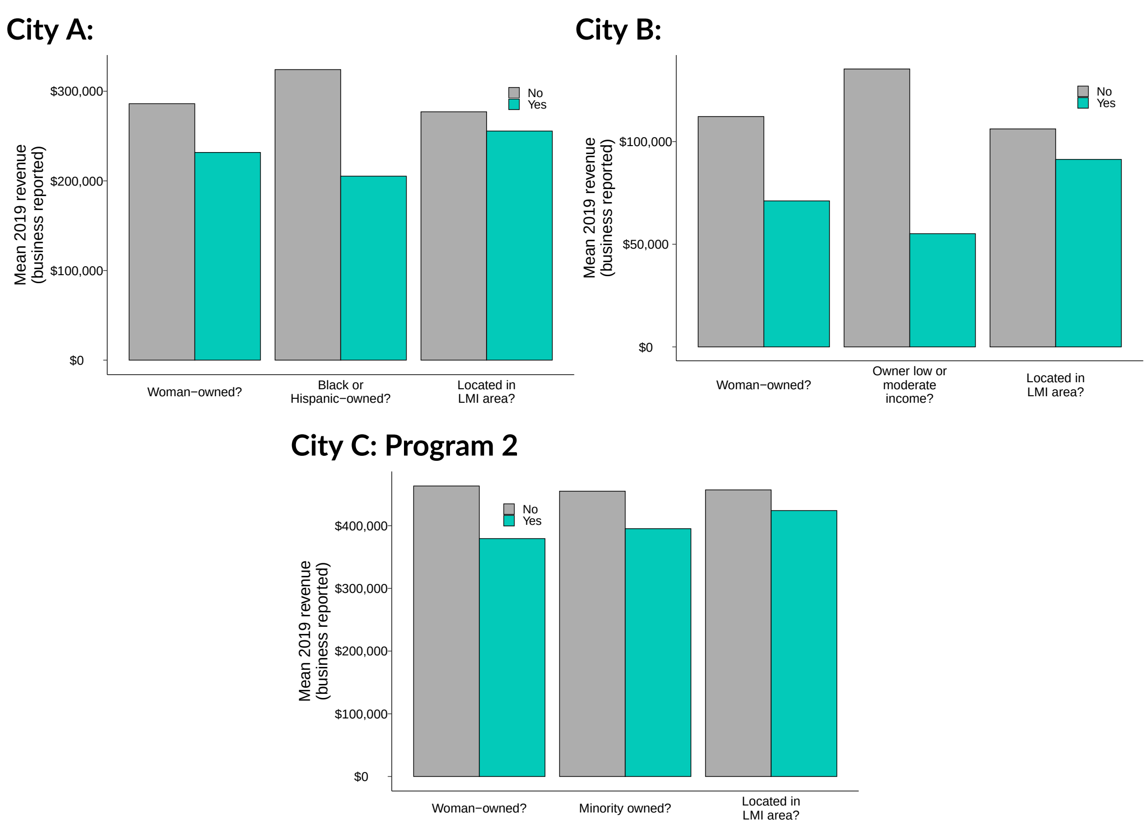
Here, we focus on mechanisms that stem from the three inputs to the points systems: pre-COVID revenue (with businesses with higher revenue below the eligibility cap getting extra points); FTE retained at the time of application (with a similar boost for higher FTE businesses); and a NAICS code in an economically hard-hit industry.[18]

17. Similar to the allocation methods analysis, for City C, Program 1, this subsets to businesses whose timestamp has not been updated post-submission. This may contribute to the patterns if the ones that remain at the "submitted stage" are a subset of very late submitters in general.

18. We define these using the following two and three-digit codes: 61, 71, 72, 213, 315, 448, 451, 481, 485, 487, 511, 512, 515, 532, 812.

Figure 12 shows the results for pre-COVID revenue, which show the most consistent disparities across underserved categories and cities. Appendix Figure A.5 shows the results for FTE; and Figure A.6 shows the results for hard-hit NAICS codes, with each restricted to the cities that collected these fields as part of the application. Strikingly, even though applicants in the three cities had very different *levels* of pre-COVID revenue—for instance, City A and C being closer to $300,000 in annual revenue; City V closer to the $100,000 range (perhaps due to a higher prevalence of sole proprietors)—the disparities where underserved businesses had lower pre-COVID profitability are consistent across cities. This suggests that points systems that either prioritize pre-COVID profitability or revenue loss may inadvertently disadvantage those businesses.

Figure 12: Exploring mechanisms behind inequality in points systems: pre-COVID revenue. The figure omits City C: Program 1, which did not contain pre-COVID revenue in the data extract.



7 Discussion

In the wake of the COVID-19 crisis, local governments rapidly distributed funding to small businesses, using a variety of different allocation methods. The choice of method was often based in part on the desire to equitably support the businesses that have historically been less able to access financing, including those with owners who are women, Black or Hispanic, or low-income.

This report described OES analysis of application data from three cities. We first used that data to investigate descriptive equity, asking whether these local programs reached underserved businesses, and whether those that applied progressed through the stages to receive funding. Descriptively, the application data suggests that businesses owned by those from historically underserved groups both applied and received funds at high rates. However, focusing on area-level disadvantage misses a large portion of underserved individuals: many business owners who themselves had low-to-moderate incomes or who are Black or Hispanic had businesses located outside of these areas.

We then went beyond describing the patterns in the application data, using the actual data in a series of simulations. The simulations allowed us to investigate counterfactual equity, asking "what if" different allocation methods had been used. This approach shows that the allocation method affects how much funding flows to businesses from different groups and geographic areas. Specifically, basic first-come, first-served methods can disadvantage applicants from historically underserved groups. However, weighted lotteries and set asides within first-come, first-served methods are a consistent way to increase the funding going to historically underserved groups. And in fact, these methods in some cases drove more funding to underserved applicants than points systems that assigned points to members of those groups.

And of particular note, points systems that do not explicitly prioritize businesses from historically underserved groups can inadvertently disadvantage those businesses. When a diverse set of businesses applied for funding, those owned by women and minorities or located in low-to-moderate income areas had lower pre-COVID revenue and were disadvantaged by points systems that prioritized losing a higher percent of revenue during COVID-19. Businesses owned by members of historically underserved groups also generally had fewer full-time employees, and in one of two cities where industry codes were reported, they were less likely to be in hard-hit industries prioritized by the points system. Because of these differences, points systems that prioritize factors like revenue loss, number of employees, and specific industries without assigning points to underserved demographic groups result in less funding going to those groups.

A better understanding of these effects of allocation methods on the amount of funding flowing to historically underserved businesses will allow government programs to make informed decisions about the criteria they use to determine eligibility and prioritization for relief funds. It is clear that cities that intend to use a points system should, at minimum, be aware of the correlation between points systems factors and underserved demographic and geographic attributes in the applicant pool. In some cases, legal or political considerations may preclude explicit prioritization for funding based on demographic attributes.[19] Cities may be able to achieve similar goals by prioritizing characteristics that are typical of, for instance, Black-owned or women-owned businesses such as having lower revenue levels. However, more research is needed to identify the way such methods would work in practice.

It may also be possible to reduce disadvantages of specific allocation methods by applying other interventions. For instance, SBA has explored the effectiveness of technical assistance for helping prepare funding applications as well as helping businesses make the best use of capital. There is a growing body of research on the types of technical assistance that are most effective, but there is still a pressing need for better **causal** evidence on the extent to which different advisors, durations, formats, etc. affect business outcomes.

Future research can complement the present findings by using alternative methods to understand the perspective of applicant businesses. Our simulations focused on the proportion of awards that went to members of specific historically underserved groups. However, the members of those groups themselves may not necessarily see this as the most important equity outcome. For instance,

19. See Eligon, John. (Jan. 3, 2021). A Covid-19 relief fund was only for Black residents. Then came the lawsuits. The New York Times. Retrieved from: https://www.nytimes.com/2021/01/03/us/oregon-cares-fund-lawsuit.html

potential applicants might be more interested in the time demands of an application process, or in the dignity of treatment from agency staff, or in any number of other outcomes. Conversations with these key stakeholders can help to develop future complementary outcomes to target and methodologies to investigate those outcomes.

7.1 Relevance for examining equity in other programs

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.[20] 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) the Treasury Department's Emergency Rental Assistance (ERA) program, where grantees, within the same broad eligibility criteria, have discretion to prioritize which renters they assist.

20. 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.

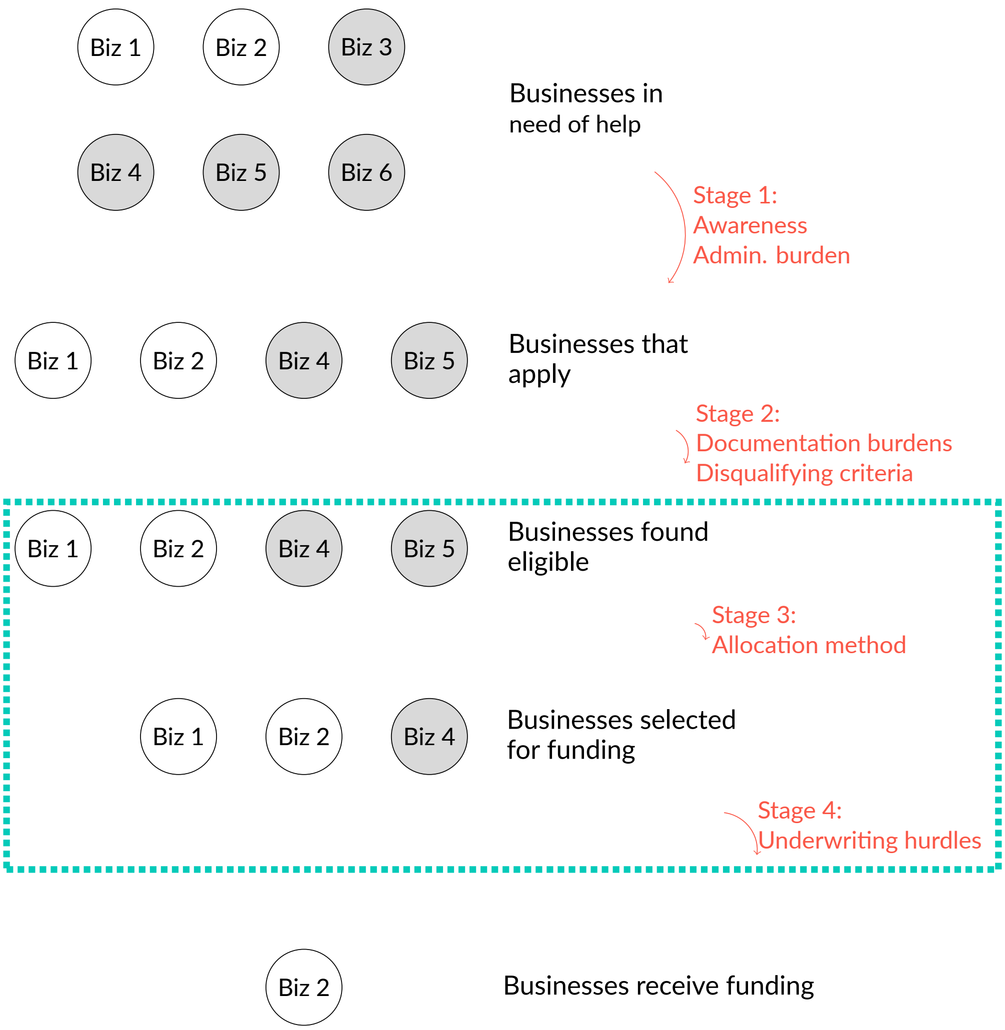
A Appendix

A.1 Stages of applications

Although the details differ across cities, businesses must pass through four stages before receiving funding. Burdens at each stage can fall disproportionately on businesses owned by those from historically underserved groups, creating inequity in the receipt of funding. The four stages are:

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?

Figure A.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 an outcome—in this case, 0 out of 4 underserved businesses selected—can stem from burdens at each of the stages. The green box shows the stages we focus on in the simulation.



A.2 Name-based imputation

Similar to other articles examining inequality using administrative records (Hepburn et al. 2020), lacking a direct measure of applicant sex or gender in City B, we use the first name of the majority business owner, along with the methods described in main text Section 4, to try to infer impute the sex or gender of the majority owner.[21]

Figure A.2 shows, within the categories, the distribution of female babies born in 1970 in the SSA data with each name. As expected, those coded as as a women-owned business for our attribute

21. We use the term sex or gender since it is based on names that are either assigned by the parents at birth or that the person freely chooses.

have names with high representation amongst female birth certificates in 1970. Figure A.3 shows the same breakdown by category but where the x axis is proportion male.

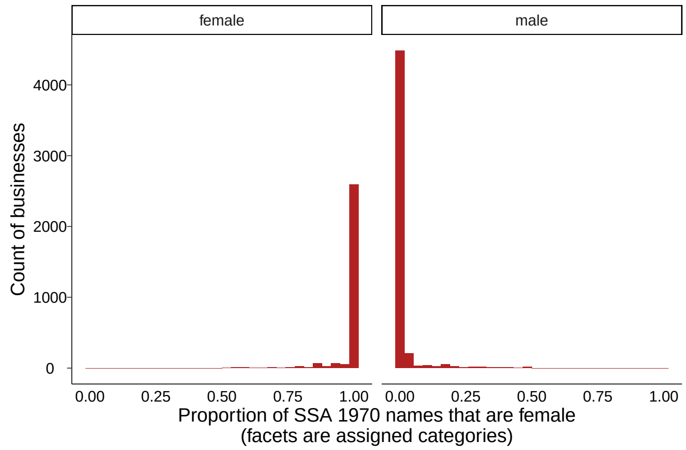


Figure A.2: Distribution of female name proportions in SSA data by assigned category

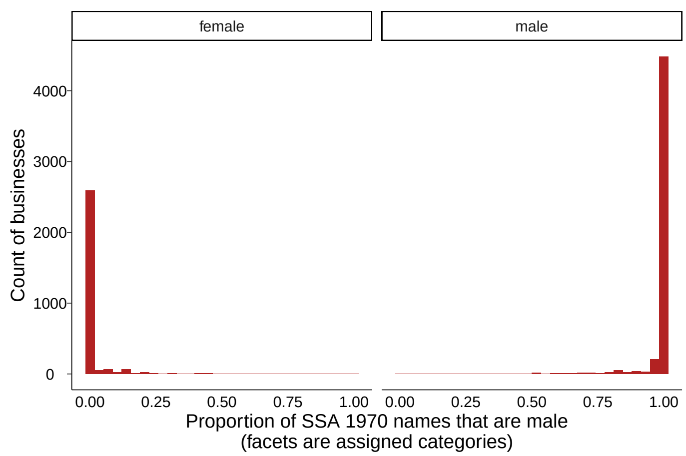


Figure A.3: Distribution of female name proportions in SSA data by assigned category

A.3 Code to apply allocation methods

Here is the code to apply the allocation methods, after subsetting to: (1) one equity-relevant characteristic (e.g., woman-owned) and (2) one program.

```
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
#######################################
```

```r

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) * 0.15)

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_hours_sincefirstsub) %>% # rj flag- standardized but could be weird with window
            slice(1:n_choose_overall) %>%
            pull(biz_id)

## fcfs 2-- two queue
select_twoqueue <- c(business_pop %>%
              filter(.data[[eq_char]]) %>%
```

```
                arrange(derived_hours_sincefirstsub) %>%
                slice(1:(n_choose_overall/2)) %>% # could change prop allocated by queue
                pull(biz_id),
                business_pop %>%
                  filter(!.data[[eq_char]]) %>%
                  arrange(derived_hours_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)) %>%

    ## 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)

}
```

A.4 Simulation method details

The procedure proceeded 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.
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 pre-specified the following two descriptive differences, focusing on the second for the graphs in the main text:
    - **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.[22] Methods can either increase the proportion of awards that go to the underserved group above that application proportion or decrease it.

3. **Inference:** we use the following method for inference about whether the proposed method causes between-group differences in selection rates:

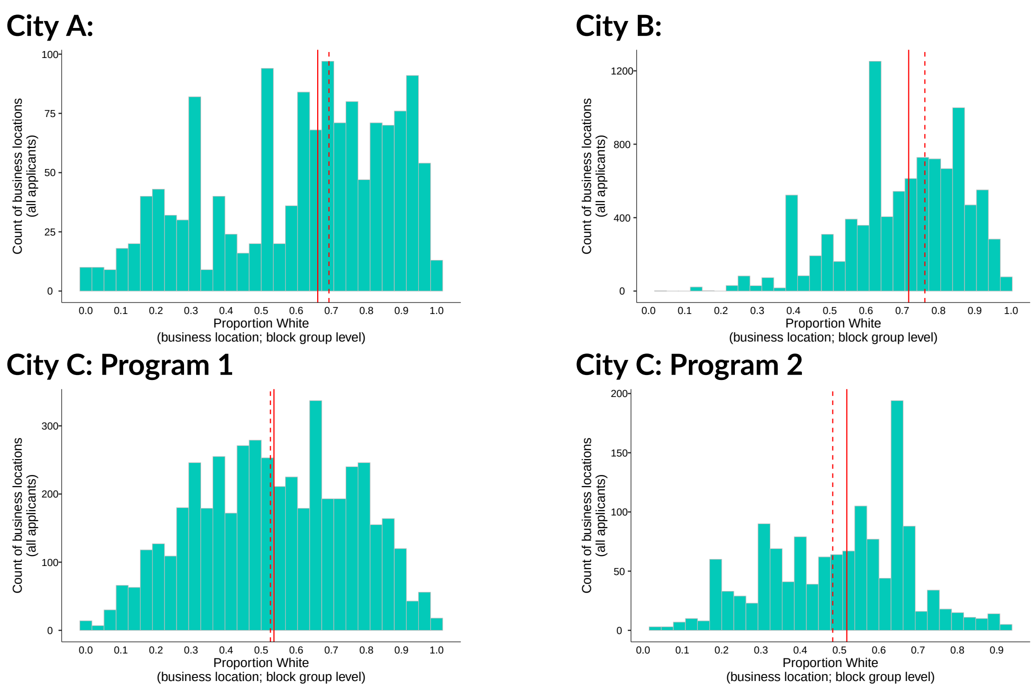
   (a) **Chi-squared test (separately for each method) of independence between equity-relevant outcome and selection status**: the null and alternative hypotheses are as follows, framed in terms of our case, with $p < 0.05$ used to assess significance:

      - 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

We 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.

A.5 Descriptive equity: additional figures

Figure A.4: Where are applicant businesses located? Proportion White by block group.



A.6 Inference about differences in allocation methods

Here, we present the results of the pre-registered chi-squared tests of independence between a business' underserved status and whether or not the business is funded by that allocation method. Of note, significant differences can come from either the allocation method leading to *significantly lower award rates* for the underserved businesses or *significantly higher award rates*, with the graphs in Section 6 showing the direction of differences.

22. Since we are using real application data, this proportion varies based on attribute and city.

First, Table 1 shows the tests of differences for women-owned businesses. We see differences for nearly all methods beyond a regular lottery, though differences are least pronounced for City C: Program 2, which restricted eligibility already to an underserved ward/district. Table 2 shows the differences for owners from other underserved backgrounds, which are similar to women-owned businesses. Finally, Table 3 shows the differences for businesses located in LMI areas for the one city where these were a numerical minority (City B), which show similar but slightly weaker patterns.

Table 1: Chi-squared test of differences in award rates for underserved businesses by distribution method: women-owned businesses

Method	P value ($p = 0.0000$ is $p < 0.001$)
City A	
Points; dem plus factor holistic fair	0.0000
Weighted lottery	0.0000
Points; dem plus factor holistic bias	0.0000
Points: dem. plus factor no holistic	0.0000
FCFS: set asides	0.0001
Points; no dem plus factor holistic bias	0.0250
FCFS: general	0.0321
Points; no dem plus factor no holistic	0.2367
Regular lottery	0.4448
Points; no dem plus factor holistic fair	0.6691
City B	
FCFS: set asides	0.0000
Weighted lottery	0.0000
Points: dem. plus factor no holistic	0.0000
Points; dem plus factor holistic fair	0.0000
Points; no dem plus factor holistic bias	0.0000
Points; dem plus factor holistic bias	0.0000
Points; no dem plus factor holistic fair	0.0000
Points; no dem plus factor no holistic	0.0000
FCFS: general	0.0763
Regular lottery	0.5546
City C: Program 1	
Points: dem. plus factor no holistic	0.0000
FCFS: set asides	0.0000
Weighted lottery	0.0000
Points; dem plus factor holistic fair	0.0000
Points; dem plus factor holistic bias	0.0000
FCFS: general	0.0000
Points; no dem plus factor holistic bias	0.0000
Points; no dem plus factor holistic fair	0.0010
Points; no dem plus factor no holistic	0.0568
Regular lottery	0.5736
City C: Program 2	
Points: dem. plus factor no holistic	0.0000
Points; dem plus factor holistic fair	0.0000
Points; dem plus factor holistic bias	0.0000
Weighted lottery	0.0024
FCFS: set asides	0.0113
Points; no dem plus factor holistic bias	0.0127
Points; no dem plus factor holistic fair	0.0219
Points; no dem plus factor no holistic	0.1367
FCFS: general	0.6292
Regular lottery	0.8627

Table 2: Chi-squared test of differences in award rates for underserved businesses by distribution method: other underserved owner

Method	P value ($p = 0.0000$ is $p < 0.001$)
City A	
Points; dem plus factor holistic fair	0.0000
Points; no dem plus factor holistic bias	0.0001
Points; no dem plus factor no holistic	0.0006
Points; dem plus factor holistic bias	0.0025
Points: dem. plus factor no holistic	0.0064
Points; no dem plus factor holistic fair	0.0067
Regular lottery	0.1357
FCFS: general	0.2672
FCFS: set asides	0.9355
Weighted lottery	0.9513
City B	
Points; no dem plus factor holistic bias	0.0000
Points; no dem plus factor holistic fair	0.0000
Points: dem. plus factor no holistic	0.0000
Points; no dem plus factor no holistic	0.0000
Points; dem plus factor holistic fair	0.0000
FCFS: set asides	0.0000
Weighted lottery	0.0000
FCFS: general	0.0001
Points; dem plus factor holistic bias	0.0017
Regular lottery	0.3954
City C: Program 1	
Points: dem. plus factor no holistic	0.0000
Weighted lottery	0.0000
Points; dem plus factor holistic fair	0.0000
FCFS: set asides	0.0000
Points; dem plus factor holistic bias	0.0000
FCFS: general	0.0000
Points; no dem plus factor holistic bias	0.0000
Points; no dem plus factor holistic fair	0.1729
Points; no dem plus factor no holistic	0.2559
Regular lottery	0.4072
City C: Program 2	
Points; dem plus factor holistic fair	0.0000
Points: dem. plus factor no holistic	0.0000
Points; dem plus factor holistic bias	0.0000
Points; no dem plus factor holistic bias	0.0002
FCFS: set asides	0.0418
Weighted lottery	0.2233
Points; no dem plus factor holistic fair	0.2476
Regular lottery	0.4968
FCFS: general	0.6604
Points; no dem plus factor no holistic	1.0000

Table 3: Chi-squared test of differences in award rates for underserved businesses by distribution method: located in LMI area

Method	P value ($p = 0.0000$ is $p < 0.001$)
City B	
Points: dem. plus factor no holistic	0.0000
Points; dem plus factor holistic fair	0.0000
Points; dem plus factor holistic bias	0.0000
Weighted lottery	0.0000
FCFS: set asides	0.0000
Points; no dem plus factor holistic bias	0.0000
Points; no dem plus factor holistic fair	0.0078
Regular lottery	0.0081
Points; no dem plus factor no holistic	0.0834
FCFS: general	0.3776

A.7 Time to submit regressions

The dependent variable is the focal business' relative number of hours since the earliest submission for that city. Positive coefficients indicate that the characteristic is associated with a longer time to submit. For City C: Program 1 (citywide program), we conduct two analyses. First is an analysis using the main analytic sample of $N \sim 3900$ businesses with a valid submission timestamp. Second is a robustness check that includes $N \sim 350$ additional businesses that had a timestamp that could reflect an application status update rather than a submission, with the results similar across the two samples.

Table 4: City A: time to submit

	Dependent variable:		
	sprintf("derived_hours_sincefirstsub ~%s", one_attribute)		
	(1)	(2)	(3)
Women-owned	2.490 (3.199) p = 0.437		
Other underserved owner		−1.561 (3.109) p = 0.616	
LMI area			−1.243 (3.126) p = 0.692
Constant	54.253 (1.977) p = 0.000	55.978 (2.191) p = 0.000	55.915 (2.318) p = 0.000
Observations	1,438	1,438	1,437
R^2	0.0004	0.0002	0.0001
Adjusted R^2	−0.0003	−0.001	−0.001
Residual Std. Error	58.938 (df = 1436)	58.945 (df = 1436)	58.957 (df = 1435)
F Statistic	0.606 (df = 1; 1436)	0.252 (df = 1; 1436)	0.158 (df = 1; 1435)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 5: City B: time to submit

	Dependent variable:		
	sprintf("derived_hours_sincefirstsub ~%s", one_attribute)		
	(1)	(2)	(3)
Women-owned	3.227 (2.916) p = 0.269		
Underserved owner		18.599 (2.667) p = 0.000	
LMI area			5.660 (2.724) p = 0.038
Constant	103.704 (1.577) p = 0.000	96.501 (1.765) p = 0.000	102.396 (1.718) p = 0.000
Observations	9,823	9,823	9,704
R^2	0.0001	0.005	0.0004
Adjusted R^2	0.00002	0.005	0.0003
Residual Std. Error	131.466 (df = 9821)	131.150 (df = 9821)	131.342 (df = 9702)
F Statistic	1.225 (df = 1; 9821)	48.628*** (df = 1; 9821)	4.318** (df = 1; 9702)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 6: City C: Program 1 time to submit

	Dependent variable:		
	sprintf("derived_hours_sincefirstsub ~%s", one_attribute)		
	(1)	(2)	(3)
Women-owned	502.301 (38.288) p = 0.000		
Other underserved owner		704.347 (36.537) p = 0.000	
LMI area			96.741 (33.455) p = 0.004
Constant	702.337 (16.300) p = 0.000	657.840 (16.027) p = 0.000	722.336 (25.276) p = 0.000
Observations	3,934	3,934	3,157
R^2	0.042	0.086	0.003
Adjusted R^2	0.042	0.086	0.002
Residual Std. Error	925.083 (df = 3932)	903.385 (df = 3932)	930.416 (df = 3155)
F Statistic	172.112*** (df = 1; 3932)	371.626*** (df = 1; 3932)	8.362*** (df = 1; 3155)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 7: City C: Program 1 time to submit (robustness check including possible status update timestamps)

	Dependent variable:		
	sprintf("derived_hours_sincefirstsub ~%s", one_attribute)		
	(1)	(2)	(3)
Women-owned	475.131 (37.875) p = 0.000		
Other underserved owner		688.074 (35.955) p = 0.000	
LMI area			105.189 (32.885) p = 0.002
Constant	744.257 (16.063) p = 0.000	696.289 (15.833) p = 0.000	752.315 (24.822) p = 0.000
Observations	4,270	4,270	3,412
R^2	0.036	0.079	0.003
Adjusted R^2	0.035	0.079	0.003
Residual Std. Error	950.562 (df = 4268)	928.895 (df = 4268)	951.045 (df = 3410)
F Statistic	157.368*** (df = 1; 4268)	366.227*** (df = 1; 4268)	10.232*** (df = 1; 3410)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 8: City C: Program 2 time to submit

	Dependent variable:		
	sprintf("derived_hours_sincefirstsub ~%s", one_attribute)		
	(1)	(2)	(3)
Women-owned	9.008 (13.521) p = 0.506		
Other underserved owner		16.418 (13.405) p = 0.222	
LMI area			27.223 (17.411) p = 0.119
Constant	272.242 (8.472) p = 0.000	269.010 (8.607) p = 0.000	253.259 (15.793) p = 0.000
Observations	815	815	807
R^2	0.001	0.002	0.003
Adjusted R^2	−0.001	0.001	0.002
Residual Std. Error	188.496 (df = 813)	188.374 (df = 813)	188.859 (df = 805)
F Statistic	0.444 (df = 1; 813)	1.500 (df = 1; 813)	2.445 (df = 1; 805)
Note:			*p<0.1; **p<0.05; ***p<0.01

A.8 Additional comparisons of point system inputs

Figure A.5: FTE comparison.

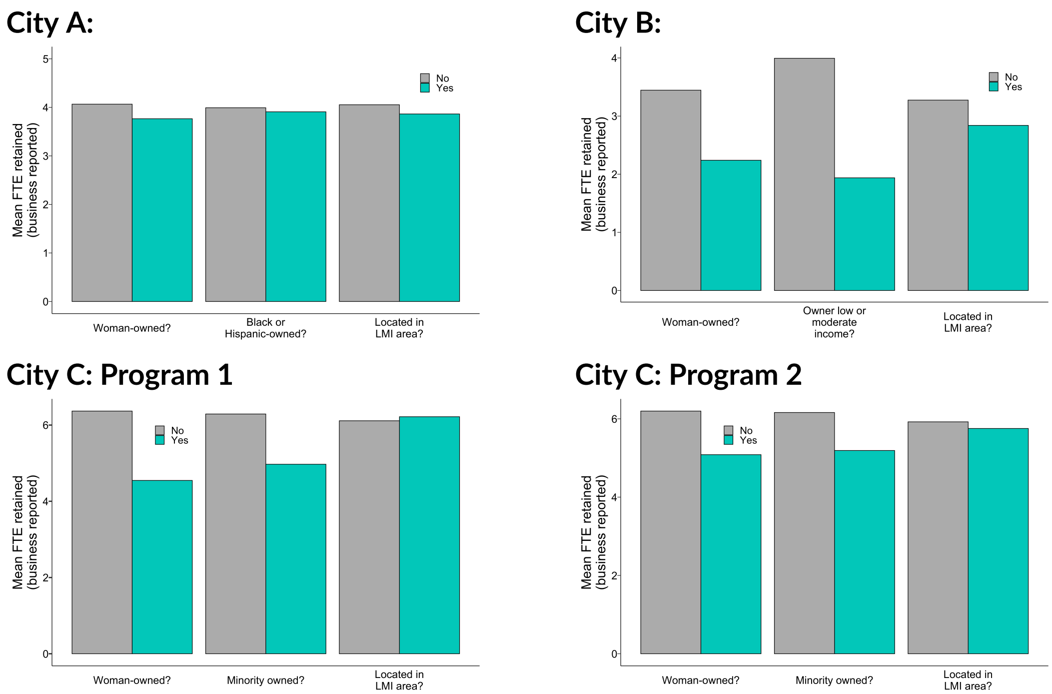
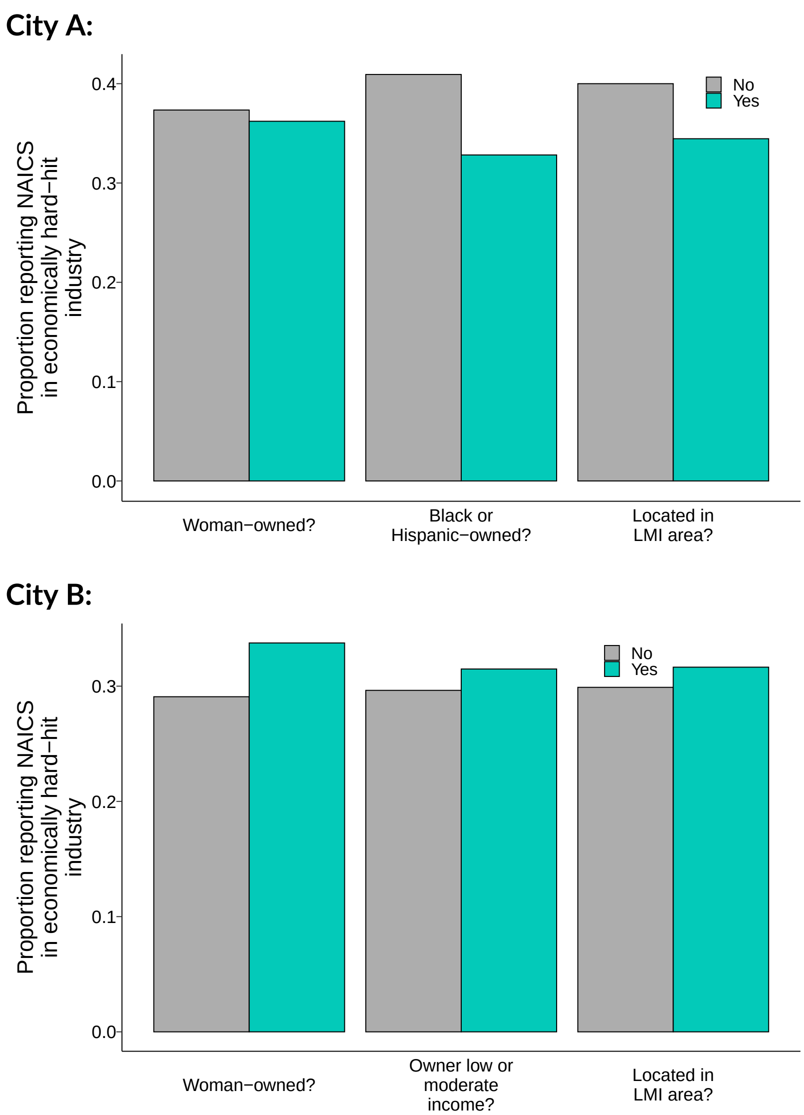


Figure A.6: Economically hard-hit NAICS code comparison.



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.

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