Executive Summary

During Harris County’s Say Yes to the Census Campaign, Houston in Action, Rice University, and various partners engaged in three interrelated programs to support the 2020 Census. First, a machine learning model based on satellite images of Harris County was developed to identify households that might not receive a Census questionnaire. While this program saw some initial success it was largely halted by the COVID-19 pandemic and cannot be fully evaluated at this time. The second program involved a field experiment exploring various Census-related messages and their efficacy for motivating Census response. While this program was also cut short by the pandemic, enough data was collected to perform an initial analysis. Unfortunately, the results of this analysis indicate that none of the messages performed any better than a simple message focusing on the basic factual information surrounding the 2020 Census. Finally, in-person and by-phone canvassing operations were conducted in an effort to inform residents about the 2020 Census and motivate them to respond. We evaluate these two canvassing campaigns separately and find that canvassing efforts are associated with higher observed response rates. In particular, despite low overall contact rates, areas that received substantial in-person canvassing coverage do exhibit higher response rates than similar areas with less canvassing coverage. We find a similar pattern when examining the phone canvassing efforts, but urge caution in the interpretation of this latter analysis since it is limited to a specific temporally and geographically bounded campaign initiative. Overall, we conclude that canvassing campaigns can be useful for raising response rates but recognize that more work must be done in order to guide these campaign and evaluate the cost effectiveness of the various forms of this outreach method.
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Outline and Motivation

This document evaluates efforts undertaken by Houston in Action and partners across Harris County, Texas during the 2020 “Say Yes to the Census” campaign. Our primary goal is to understand whether efforts to contact individuals in Harris County and inform them about the 2020 Census had an impact on the 2020 Census response rates. However, we also hope to evaluate whether certain canvassing tactics (e.g., canvassing specific populations, canvassing at specific times) led to higher contact success rates and to explore proposed methodologies for improving the targeting of outreach operations. We examine these topics in particular because we want to know both what activities to undertake in order to raise census response rates and how to most efficiently carry out those activities.

Background on the 2020 Census

Since 1790, the U.S. Census has conducted decennial counts of the nation’s population. Since 1790, the U.S. Census has conducted decennial counts of the nation’s population. This count determines congressional apportionment and the extent to which states and localities are represented. In addition, the census determines how federal funds (roughly $800 billion dollars) are spent each year (Reamer 2018). The census count is especially critical for cities and local communities since it guides infrastructure expenditures for highways and public transportation, the construction of new schools, hospitals, and fire departments, and direct funding to cities for resources like Community Development Block Grants (CDBG). In FY 2015, for example, Census Bureau data was used to allocate nearly $1.8 billion in CDBG grants across the country (U.S. Dept of Housing and Urban Development 2018). Closer to home, data from the 2010 census count was used to distribute more than $188 million in HUD funding to the city of Houston between 2011-2018 (Fischer & Fullenwider 2019: 8).

Given the programs at stake and the financial repercussions involved, getting an accurate and complete count of Houston’s population in Census 2020 is essential. According to a study cited by city and county officials, Houston stands to lose $1,500 in government funding for every Houstonian not counted in 2020 (Najarro 2019). However, beyond this economic imperative, an accurate and complete count of Houston’s (and the nation’s) population is important due to the innumerable ways in which census data are use in research, journalism, business, and infrastructure planning. Indeed, the census is “the people’s data, a shared public asset that is becoming increasingly important in a data-driven world It also forms the foundation upon which so much other data are based” (Fischer & Fullenwider 2019: 4).

Despite the tremendous consequences of a census complete count, in 2010, about 20 percent of U.S. households did not fill out their census questionnaires. Houston tends to have below-average response rates on the census form. Based on an analysis of social and demographic characteristics that were most predictive of response rates in Census 2010, the Census Bureau estimates that 1-in-4 households in Harris County - over 360,000 households - will need additional follow-up to complete their census questionnaire (McClendon 2018).

The Census Campaign In Houston, Texas

While a complete count is always challenging, Census 2020 is facing unprecedented challenges. For starters, since former Census Director John Thompson’s resignation in 2017, the Trump administration has failed to fill this position, leaving the Census Bureau without critical leadership leading up to the 2020 Census (Lessner 2019). Second, a Census Bureau program that previously provided millions of dollars of in-kind partner support for campaign materials and other resources to over 30,000 Community Based Organizations in some of the hardest to count regions across the country will not be funded in 2020 (Fischer & Fullenwider 2019). Third, unlike previous census counts, which were submitted through a paper form, Census 2020 will include an online census form for the first time in our nation’s history. This shift poses new technical vulnerabilities that the Census Bureau has never faced. And, while the Census Bureau is adding and integrating an internet-self-response option (ISR) aiming for approximately half of all respondents, many respondents, especially those considered hard to count, will prefer to use the paper form (Fischer & Fullenwider 2019). Fourth, the controversy (and continued uncertainty) surrounding the citizenship question, along with the rise in fake news and “disinformation” have deepened fear in immigrant populations, increased already high levels
of public distrust in government, and contributed to many communities’ and individuals’ reluctance to share personal information with the government.

The Response Rates

Households began responding to the 2020 Census in mid-March and the response window has remained open late into the year due to the COVID-19 pandemic. Figure 1 shows the daily response rates for all tracts in Harris County with the mean response rate for each day noted in red. As we can see, response rates began relatively high, experienced a few “jumps” and have since tapered off to much lower levels.

Figure 1: Daily Response Rates for Each Tract

![Graph showing daily response rates for each tract]

While the overall response rate is informative for the county as a whole, much of the census campaign has focused on improving response rates among populations within the county that are frequently undercounted. These populations can be identified at the tract level using the Low Response Score assigned by the Census Bureau (Erdman & Bates 2017). The Low Response Score is a model-based metric that the Census Bureau uses to estimate the non-response rate for a given tract - with higher numbers denoting fewer expected responses. Figure 2, modifies Figure 1 by grouping tracts according to whether they have a Low Response Score greater than the mean score for the entire county. It then recalculates the mean response rate for each of the two groups and, in the sub-plot, calculates the difference between these mean rates.

1 These undercounted groups are also often referred to as “hard to count” though we use the former terminology in this report.

2 A tract’s Low Response Score is created using a model informed by the demographic and structural characteristics of a tract as well as the tract’s response rate for the 2010 Census.
Figure 2 makes clear that tracts with above average Low Response Scores have, on average, lower daily response rates. This disparity is greatest early on in the response period and decreases to around zero in mid-May.\textsuperscript{3} This trend is in line with expectations and serves as further validation that attempts to reach historically undercounted communities and those considered unlikely to respond at high rates are greatly needed. With that in mind, we proceed to a discussion of the identification and outreach methods used during the 2020 campaign.

**A Machine Learning Models to Identify Undercounted Populations**

Currently, the distribution of Census questionnaires is largely guided by the Census Bureau’s Master Address File and the associated LUCA updating process. While this method is perfectly viable for traditional housing units, it has the potential to omit “irregular units” such as those that are actively concealed (i.e., the addition of a small “guest house” or shack that is rented out) or those that are sub-divided to house multiple families. To assist Houston in Action in identifying and serving the residents of these types of irregular housing units, we began the development of a machine learning model using satellite imagery to identify houses of concern.

In particular, we propose an interactive way of identifying these households via iterative machine teaching (IMT), a paradigm where a “teacher” (model) feeds examples iteratively and intelligently based on the current status of the “learner” (canvassers). In each iteration, the model detects irregular households from satellite imagery and marks them for investigation. Using this information, Houston in Action and its partners can assess the household, determine whether it is included on official lists, determine whether it has received a Census questionnaire, and ensure that the household is counted in the 2020 Census.

The crux of this model - and the only way that it can be effectively developed and deployed - is the iterative interaction between the model and in-person canvassers. By tentatively identifying households for the

\textsuperscript{3}Interestingly, on the first few day for which response rates were recorded, tracts with above average Low Response Scores exhibited \textit{higher} response rates. However, this pattern did not hold for long and should be viewed as a random deviation from the norm.
canvassers to investigate, the model serves as a teacher or guide to the canvassers who, by manually validating the model’s predictions, in turn serve to facilitate the development of the model. In essence, since neither the model nor the canvasser know how to perfectly identify these housing units, the two “team up” to collaboratively and iteratively learn exactly what features each of them should look for in doing so. Of course, this discussion of the proposed method also highlights the method’s greatest weakness and the reason why it has yet to be fully realized in the midst of the COVID-19 pandemic: the reliance on in-person canvassers. Unfortunately, since in-person canvassing was cut short just as the model entered its first validation stage, we are unable to present a fully developed model and will be unable to do so until similarly trained canvassers can take to the field again. That said, we can still outline the structure of the model and approach and discuss its future potential.

Preliminary Methods and Findings

Our proposed model uses three main data sources. First we use the Aerial Imagery 2018 dataset from the Kinder Institute, which contains 700 image tiles with map scale of 1’=100’ with a 6-inch ground sample distance (GSD) for Harris County.\(^4\) We also use the Harris County Appraisal District (HCAD) Advanced Records, which provided advanced property search metrics to identify multi-family addresses within a specified zip-code, and BI State Category (residential, multi-family)\(^5\). Finally, we use the HCAD Parcels and Address Points data to generate our single-family addresses.

To begin developing the model, we calculated - for each tract in Harris County - an estimate of the likelihood of a tract containing an irregular housing unit. This scoring method was based on previous research aimed at identifying irregular housing units in California communities. Since we were unsure whether this method would accurately identify these households in a context outside of California, we relied on canvasser input to validate specific tracts. In particular, from the list of all tracts, we designated around 200 for canvassing according to this score as well as the Low Response Score provided by the Census Bureau. After receiving initial feedback from canvassers, we used the modified list as a guide for selecting areas for further investigation using the satellite imagery model.

Since irregular housing is an umbrella term for a variety of potential housing arrangements, we initially limited our analysis to a particular type of housing arrangement - multi-family households. A multi-family household is a single traditional housing structure that has been sub-divided to accommodate multiple-families. These structures are different from apartment complexes or townhouses which feature a unique housing structure featuring originally planned and repeated divisions. Multi-family homes, on the other hand, often feature unplanned and ad hoc divisions such as the addition of an interior wall, an appended structure, or a fence designed to separate the multiple households that live in what is technically the same building.

In order for the model to properly identify multi-family housing units on its own, we must first train the model to identify such housing units from a base list of known multi- and single-family units. To do this, we relied on the data resources listed above as well as the Google Maps API to retrieve latitude/longitude coordinates for each single and multi-family address we observe in the address records data. We were able to finalize a satellite imagery dataset of ~300 multi-family, and ~10,000 single-family households. In our initial assessment this dataset only covered the zip code 77004 and contained corresponding image tiles per category (multi-family vs. single-family). The bounding boxes for each satellite image are 50 by 50 meters around each house, with each center location derived from the HGAC address points data. We began the training process by splitting the dataset into training, validation, and test sets, for which we used three different model types - ResNet-101 with ImageNet pretrained weights, VGG-16, and DenseNet-121 to train our model.\(^6\)

From our initial investigation, we were able to extract a number of satellite images that give us a sense of how the model is delineating multi-family from single-family households. For example, Figure 3 displays two satellite images of households labelled as single-family by the model. As noted before, these single-family

\(^4\)Available at: https://www.kinderudp.org/#/datasetCatalog/rlwyzyjx7z61

\(^5\)Available at: https://hcad.org/property-search/real-property-advanced-records/

\(^6\)Though the details of these models are too complex to cover in this report, it is sufficient to say that these models are all well-validated machine learning models relying on a particular learning strategy (neural networks) and differing in technical details relating to the number of layers used and the definition of the model weights.
units encompass both traditional single-family houses as well as townhouses and apartment complexes - something clearly reflecting in the images and the model predictions more broadly.

Figure 3: Imagery of Predicted Single-Family Homes

On the other hand, Figure 4 displays houses labelled as multi-family. These structures have unique characteristics visible from the satellite imagery that, while not definitive, do suggest that they are not typical single-family households. For instance, the large driveways, multiple cars, and multiple attached (or closely connected) structures all point to the presence of more than one family living at the location - despite the fact that it is, ostensibly, one address or parcel of land.

Figure 4: Imagery of Predicted Multi-Family Homes

After running the initial training model, we moved to the validation stage and compared our predictions to the true values contained in the address records data. For each model, we evaluate the success of the model by comparing these predicted and true values and noting how many misclassifications the model produces. Performance in this classification task can be assessed using the confusion matrices shown in Figures 5, 6 and
Figure 5: ResNet Confusion Matrix

Figure 6: DenseNet Confusion Matrix
From these matrices, we see that our initial algorithm does a relatively good job properly classifying housing units using the satellite images. This determination is made by observing the small number of misclassifications in the bottom left and top right quadrants of each figure. Further, close examination of these matrices along with other model checking methods suggests that the DenseNet algorithm produced the most accurate results when comparing our predictions to those in the associated housing records. That said, the ultimate test of the accuracy of the predictions, and the next step in the modeling process is the deployment of canvassers to validate the model predictions. Since this is not currently possible, the modeling process is currently stalled.

**Future Considerations and Broader Impact**

Overall, our machine learning model shows promise as a viable method to support Census operations, but is still limited in its applicability and efficiency due to the challenges posed by the pandemic. Aside from our inability to send canvassers to directly investigate tracts and households of interest, another major limitation our approach has faced is the lack of access to the Census Bureau’s Master Address File (or a similar document). While the HCAD data and other sources are helpful, they do not represent the “final word” on whether an address will receive a Census form nor do they necessarily indicated that a particular household is fully known to the Bureau. To move forward with this method, a more complete address list would be critical to reducing misclassification and maximizing resource allocation.

These challenges aside, this methodology has potential application to a broad array of challenges beyond counting in the decennial Census. For instance, a similar methodology could be developed in order to track the development of new housing units across a geographic area and note population trends across time. Similarly, efforts to identify multi-family housing could be especially useful during during times of displacement due to nature disasters like hurricanes. Finally, efforts to identify concealed housing in particular could also be used by community organization to locate potentially unregistered or inactive voters or simply to better understand community needs and identify especially at risk individuals. All of these applications are possible using the current or a similar model conditional on resources being devoted to the validation of the model predictions and the iterative development of model accuracy and highlights the great promise of using satellite imagery and machine learning to support activities around the Houston area.
Evaluation of Door to Door Canvassing Tactics

A major component of the 2020 Census Campaign as initially imagined was an in-person canvassing operation designed to send canvassers to communities likely to be undercounted. These canvassers were fully equipped with branded attire, badges, door hangers and other branded materials, and used a tablet to record responses to a series of questions. These interactions were recorded and provide a record useful for establishing the effectiveness of the operation.

Descriptive Assessment of Canvassing Efforts

Canvassers worked in 53 unique block groups across 36 days. Block groups were each canvassed an average of 2.75 days and canvassers went to an average of 4.06 block groups each day. These interactions produced data on approximately 14,638 canvass attempts. However, only 11,412 of those recorded attempts can be tied to a specific geographic unit within Harris County that was officially part of the canvass campaign. Additionally, of the recorded attempts, we note that only 2,252 resulted in successful contacts with respondents.

Figure 8 displays the location of each successful canvassing attempt across the U.S. Census Bureau block groups that make up Harris County. As the figure makes clear, canvassing efforts were largely concentrated in specific areas chosen by the canvassing team in accordance with the Campaign guidelines. More specifically, canvassing efforts were focused on block groups with demographic profiles deemed to be the most “at risk” for undercounting in the 2020 Census (i.e., these block groups were expected to have a low response rate to the 2020 Census).

7 While the canvassing operation ran for a total of 48 days, canvassers did not work every day during that period.
8 These other, unused data points are mostly the result of the address field simply being missing. Generally, we suspect that the missing data points are not missing in a systematic way and that their omission from the analysis will not impact our conclusions.
9 We define a successful contact as a recorded contact attempt that results in a respondent answering the question asking about their likelihood of responding to the 2020 Census. In most cases, if a respondent answered this question, they also answered most other questions. However, in some cases this question in unanswered while others are recorded. Thus, the contact rate could be said to be different - depending on how one defines a successful contact. Overall, respondents answered an average of 7.17 questions. Of the 2,498 individuals who answered any questions, 246 did not answer the question about their likelihood of response. These individuals responded to an average of 2.88 questions, an indication that their responses should not be considered complete in any meaningful way.
We consider the data displayed in Figure 8 the most reliable in-person canvassing data available. As such, we proceed with our evaluation of the campaign focusing on the number of contacts made overall and as a proportion of the number of occupied housing units in the geographic area canvassed.\textsuperscript{10}

That said, we must be clear about how well this method will work as an approximation for the true contact success rate i.e., the number of successful contacts out of the number of attempted contacts. In all the contact rate calculations we make, the contact rates we provide will almost certainly be a underestimate of the true contact success rate. This is because it is almost certainly the case that canvassers did not attempt contact at every household in a block group - despite our use of the number of households as the denominator in the contact success rate calculation. Indeed, we can think of a variety of reasons why canvassers might not attempt contact at every house. These reasons range from the presence of a fence and closed gate or a loose animal on the property to canvassers simply overlooking a household. However, the available data do not properly differentiate failed attempts at contact from non-attempts - leaving us with the number of households as the only approximation available for calculating the success rate.

With the limitations of our methods in mind, we obtain overall contact rates of 3.67\% when applied to block groups with at least one respondent and 4.41\% when only applied to block groups where more than five individuals were successfully canvassed.\textsuperscript{11} We believe the latter number is more reliable as it further omits cases where an individual was canvassed separately from the coordinated canvassing efforts or when an individual was canvassed because the canvasser unknowingly crossed into a block group not on the canvass list.\textsuperscript{12}

\textsuperscript{10}We employ the number of occupied housing units (drawn from the ACS) as the denominator in this calculation since canvassers were sent to houses and instructed to interact with one individual per house. Thus, the ideal result would be coverage of all households not all individuals.

\textsuperscript{11}We also note average contact rates of 3.77\% and 4.64\% for the 1 and 5 successes cases respectively

\textsuperscript{12}While our focus on data associated specifically with a block group officially targeted by the campaign eliminates most of these cases, some could still remain and are easily removed through the use of this threshold.
Determinants of Successful Contact

Figure 9: Canvass Contact Rates by Day of the Week

![Graph showing contact rates by day of the week. The x-axis represents the days of the week (Mon to Sat), and the y-axis represents the contact rate as a percentage. The data points are marked with their respective contact rates and confidence intervals.]

Investigating the contact rates further, we can also examine whether community-specific factors are associated with higher canvassing contact rates. The simplest way to make such a comparison uses each block’s Low Response Score as provided by the Census Bureau. Figure 10 compares the overall contact rates for those block groups with a Low Response Score greater than the average for Harris County to those with a Low Response Score less than or equal to the county average. Perhaps unsurprisingly, this comparison indicates that contact rates were lower in block groups with an above average Low Response Score. This finding is consistent with other work on historically undercounted populations and suggests a general difficulty in reaching these populations - both for counting by the Census and in general.

Figure 10: Contact Rates by Low Response Score

![Graph showing contact rates by Low Response Score. The x-axis represents whether the Low Response Score is above or below the average, and the y-axis represents the contact rate as a percentage. The data points are marked with their respective contact rates and confidence intervals.]

- Points are proportions with 95% confidence intervals
- Annotation is total number of households in canvassed block groups in each category
Reported Likelihood of Census Response

In order to further understand the demographic profiles and attitudes of the individuals canvassed, we can also examine how specific groups reported their likelihood of responding to the 2020 Census.\(^\text{13}\)

Figure 11: Average Reported Likelihood of Census Response by Membership in a Sexual Minority Group

For example, Figure 11 separates respondents into two groups - individuals that do and do not belong to a sexual minority group - and displays the percentage of individuals in that group that reported a specific likelihood of response. While prior research would suggest that members of a sexual minority group will be less likely - on average - to respond to a census, our analysis does not show such a difference. Specifically, while the average likelihood of responding is lower among sexual minorities, it is not sufficiently distinct from the average likelihood among non-sexual minority respondents.\(^\text{14}\) However, this could be due to a true lack of underlying difference in response likelihood or simply to the small number of sexual minority respondents in the sample. Evidence for the latter possibility is found in the fact that there are only 76 individuals who report belonging to a sexual minority.

In general, we can examine differences such as those in Figure 11 for all of the questions asked to respondents. Figure 12 provides a similar representation as in Figure 11 where each sub-plot separates respondents according to their membership in a particular group.

Once again, while we might expect differences in reported likelihood of response for all of these groups, we only note statistically significant differences for two of the comparisons made in Figure 12. Specifically the data suggest that individuals with limited internet access and those belonging to a racial minority both report being less likely to respond to the 2020 Census.

\(^{13}\) The groups we examine in this section are members of the at-risk groups identified by Houston in Action.

\(^{14}\) Technically speaking, the difference is not statistically significant as a t-test to differentiate the two means yields a p-value of 0.19 where values above 0.05 are considered not statistically significant. This threshold of 0.05 is the traditional threshold used in analyses such as this and is the one we apply across this report.
Figure 12: Average Reported Likelihood of Census Response by Level of Internet Access

Limited Internet Access?
- Yes = 207
- No = 952
- p-value of difference in means = 0.01

Racial Minority?
- Yes = 854
- No = 139
- p-value of difference in means < .001

Born Outside of US?
- Yes = 421
- No = 700
- p-value of difference in means = 0.21

Renter?
- Yes = 295
- No = 905
- p-value of difference in means = 0.29
Finally, it is also possible that the reported likelihood of Census response is influenced by the canvassers themselves. For instance, some research has shown that respondents will respond more favorably to canvassers with specific demographic backgrounds or who interact with them in a specific way. Figure 13 displays the average recorded likelihood of Census response for each canvasser who recorded more than 20 responses. From this figure, it is clear that most canvassers consistently recorded relatively high likelihoods of response - indeed, the mean value recorded is never below 6.

![Figure 13: Average Recorded Likelihood of Response by Canvasser](image)

The Impact of Canvassing on Response Rates

To determine whether in-person canvassing had an effect on the 2020 Census response rates, we aggregate the in-person canvassing data to the tract level and use the reported cumulative response rate as of April 1, 2020. We use April 1st as the cutoff date because canvassing efforts largely concluded on March 23rd and April 1st was “Census Day” - the reference date individuals were told to use when responding to the 2020 Census.

To model response rates as a function of canvassing efforts, we begin by calculating, for each tract, the percent of households in the tract that were successfully canvassed. Figure 14 plots tract level response rates along with the associated contact success rate for all tracts in the county. From this basic graph, it seems unlikely that there exists a positive relationship between response rates and canvassing contact success rates. However, a revised version of this graph can be seen in Figure 15 and shows the same relationship but now colors each point according to the tract-level Low Response Score provided by the Census Bureau.

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15 Note that while the preceding descriptive analyses used data on block groups, we must use tract data in our assessment of the effects of canvassing since response rate data is only available at the tract level.

16 For the denominator in this calculation, we use the number of occupied households in the tract as estimated by the 2013-2017 5-year American Community Survey.
Since the Low Response Score is essentially a model-based prediction for a tract’s final non-response rate, it is natural to expect that it will exhibit a strong negative correlation with the cumulative response rate on April 1st. Indeed, this relationship is suggested in Figure 15, since the lighter (darker) data points - those with higher (lower) Low Response Scores - are associated with low (high) cumulative response rate values. This relationship is important for our analysis of the effect of canvassing on response rates since canvassing efforts were specifically targeted in areas with high Low Response Scores. Thus, any attempt to model the effects of canvassing must properly account for Low Response Scores.
Modeling Response Rates

For our primary model investigating the impact of canvassing effort, we use a quasi-binomial regression model that expresses the 2020 Census response rates for each tract as a function of the tract-level contact rate, Low Response Score, and a metric of other Census Campaign activity.\(^{17}\) We estimate this model specification on two different samples of the data: one using all tracts in the county and another using only the tracts that were actually canvassed along with a set of other comparable tracts.\(^{18}\) The regression coefficients and p-values of these models are displayed in Table 1. To understand the basic relationships the model identifies, one can simply observe whether the coefficients are positive or negative and whether the effect identified by the coefficient is statistically significant (i.e., has a p-value less than .05). Taken together, the coefficient and p-value for the contact rate variable indicate a positive and statistically significant effect of canvassing contact rates on response rates. More plainly, the model estimates that, when compared to other tract, tracts where canvassers succeed in making contact with a larger proportion of households are expected to have a higher response rate on Census Day.

\(^{17}\)The quasi-binomial model is a particular instance of the broader class of models known as Generalized Linear Models. This model is useful when the outcome of interest is a proportion with a known denominator.

\(^{18}\)In this case, "comparable tracts" are tracts in which all of the block groups contained within were listed as potential target block groups during the initial organization of the canvassing operation. This adds 33 "control" cases for comparison. Most of these block groups (and therefore the associated tracts) were ultimately not canvassed because the in-person canvassing effort was terminated due to the COVID-19 pandemic.
Table 1: Results of Quasi-Binomial Model

<table>
<thead>
<tr>
<th>Variable</th>
<th>All Tracts (N = 783)</th>
<th>Comparable Tracts Only (N = 67)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient  p-value</td>
<td>Coefficient  p-value</td>
</tr>
<tr>
<td>Percent of Houses Contacted</td>
<td>2.285   0.042</td>
<td>3.432    0.033</td>
</tr>
<tr>
<td>Low Response Score</td>
<td>-0.043   &lt; .001</td>
<td>-0.034   &lt; .001</td>
</tr>
<tr>
<td>Other Activity</td>
<td>0        0.646</td>
<td>0.001    0.194</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.331    &lt; .001</td>
<td>0.055    0.773</td>
</tr>
</tbody>
</table>

Of course, we want to know more than simply that the effect of canvassing contact is estimated to be positive; we would like to understand the substantive implications of this finding and, more specifically, how much of an increase we can expect after, for example, reaching 1% more of the households in a tract. To investigate this question, we can simulate predicted response rates across various possible values of the tract-level contact rate and evaluate how the response rate changes. Figure 16 displays these calculations and plots (with 95% confidence intervals) the predicted cumulative response rate on Census Day as a function of tract-level contact rates. Consistent with the model summary in Table 1, the figure suggests that contacting a larger proportion of residents in a tract will be associated with a higher response rate as of Census Day. More specifically, the figure highlights how a 1 percentage point increase in contact rates is expected to coincide with .5 percentage point higher response rates on Census Day.19

![Figure 16: Model Predicted Response Rate Across Contact Rates](image)

While an increase of .5 percentage points may not seem large, the financial impact of obtaining a response

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19In this case, these effects are also clearly relatively linear in the domain we examine as a 1 percentage point change in the contact rate has approximately 1/10 of the effect as a 10 percentage point change. However, note that this linear relationship need not be the case and is a direct result of the specific data at hand.
rate that is half a percentage point greater is substantial. For example, if the response rate in the canvassed tracts all rose by .5 percentage points, we would see approximately 1611 more individuals responding to the 2020 Census. Using the $1,578 per person amount provided by the City of Houston, we estimate that the additional responses would lead to an additional $2,541,401 in funding across the county.

Conclusion

Our analysis of the in-person canvassing efforts undertaken by Houston in Action and its partners suggests that in-person canvassing had a positive and statistically significant influence on the cumulative Census response rates for tracts within Harris County as of April 1, 2020. While this estimated effect is small, it does indicate that canvassing efforts were successful in motivating communities to respond to the 2020 Census. Since these efforts were largely concentrated in areas where especially low response rates were expected - something we control for in our statistical analysis - we find this effect especially encouraging. However, in-person canvassing constituted only a small portion of the overall canvassing effort. To further understand how canvassing has influenced response rates, we must also examine the by-phone canvassing effort. Before we undertake such an analysis however, we will briefly turn to another component of the in-person canvassing effort - a field experiment examining canvass messaging.

A Field Experiment to Increase Intention to Respond

As part of the initial, in-person canvassing effort, Houston in Action and partners coordinated with the Rice University research team to design a small field experiment to evaluate whether different canvassing messages caused respondents to report a higher or lower likelihood of census response. Unfortunately, the COVID-19 pandemic lead to the field experiment’s premature closure and only a relatively small number of households were included in the experimental canvassing groups. That said, we can still briefly examine the data that was collected and see whether any obvious relationships can be identified.

Theoretical Background

Previous research on canvassing in general and Census participation in particular has hypothesized that certain canvassing messages may be more effective at promoting participation when compared to other messages. This hypothesis is grounded in the finding that certain issues matter more to certain individuals or to certain demographic and socio-economic groups. Thus, by focusing on specific issues as they relate to the Census, canvassing messages can be designed to pique the interest of a target audience and motivate participation in the Census in a more effective way when compared to traditional, generic messages.

While the basic finding that specific groups focus more on certain issues rather than others is well-validated in the context of Census participation, there is little research demonstrating that specially crafted canvassing messages are more effective than simple motivational messages conveying the history and overall importance of the Census. Thus in order to add to this research body and aid in the development of Houston in Action’s canvassing program, we designed and implemented a field experiment assessing the effectiveness of four canvassing messages and their impact on self-reported intent to participate in the 2020 Census.

Experimental Design and Partial Implementation

Our experiment required in-person canvassers to deliver one of four canvassing messages to participants before asking them a series of questions (including the respondent’s intent to respond to the Census on a 10-point scale). The four conditions include (1) a baseline “Census Background” message focusing solely on the factual background of the Census (its purpose, when it will happen, etc.), (2) a “Civic Duty” message additionally emphasizing completing the Census as an important part of living in the United States, (3) a “Community Benefit” message adding a focus on the financial benefits one’s community will receive by filling out the Census, and (4) a “Combined” message that incorporates elements from the Civic Duty and Community Benefits messages to present a complete picture of the background, importance, and benefits of the Census. Due to the complexity of the canvassing operation and the limitations of the canvassing software,
we implemented a door-by-door randomization procedure that placed each respondent into one of these four categories and recorded associated answers.

While the goal of the experiment was to have at least one canvassing team utilize the experimental protocol for the entire canvassing operation, two challenges arose that led to the premature termination of the experiment. First, after receiving feedback from partner organizations, Houston in Action was instructed by Harris County leadership to restructure parts of the canvassing operation and cease prioritizing the messaging experiment. The reasoning behind these instructions was clear: since another organization had already been contracted to do message testing for the Census Campaign, having Houston in Action do so would constitute a duplication of effort and a waste of resources. Though our intent was to dispute this reasoning on the grounds that, despite the perceived duplication, this message testing was nonetheless useful since it utilized different messages, messaging strategies, an experimental design, and a large sample, any such discussion was rendered moot by the second challenge: the COVID-19 pandemic and the end of all in-person canvassing activities. Thus, though the experiment was fully implemented before termination, it did not run long enough to collect a sample size conducive to definitive analysis and, while we present preliminary results below, we recommend caution in their interpretation.

**Preliminary Results**

As noted above, the number of observations for each experimental condition is relatively small given the total sample and overall population size. While this is not technically a major problem for a well-executed field experiment, our analysis is also hampered by the limited variation on the outcome variable of interest. As noted in our discussion of Figure 13, most responses to the question about the likelihood of responding to the 2020 Census are coded as a 10. This is further evidenced by the barplots in Figure 17 displaying the count of each recorded likelihood of response across the for experimental groups.

![Figure 17: Histograms of Reported Likelihood of Census Response (by Experimental Condition)](image)

Bearing in mind the small sample and limited variation, we can still calculate group means for each
Figure 18 displays these mean estimates along with 95% confidence intervals. The substantial overlap visible in these estimates and intervals makes clear that there are no statistically significant differences between the experimental conditions. In other words, we find no evidence that the specific message provided to respondents influenced their reported likelihood of response.

**Tentative Conclusions**

In some ways, we can consider the lack of differences in the field experiment to be a positive finding - since we find that all that matters for motivating response is that a message is provided. However, in other ways we could see this as a disappointing finding - since we have not discovered a specific message that is especially motivating. That said, as noted before, the data used to perform this analysis are not of sufficient quality to merit any strong conclusions. Not only is it possible that more, higher-quality data would exhibit important relationships, it is also possible that, with more data, we could reliably investigate how these specific messages influence reported response likelihood among specific sub-populations. Indeed, we consider this latter possibility likely, since much of the previous research on response motivation has focused on differentiating messages by demographic populations in order to maximize the overall impact of the messaging.

**Evaluation of Phone Canvassing Tactics**

As a result of the COVID-19 pandemic, the majority of canvassing undertaken during the campaign was done through phone canvassing. This canvassing effort includes both the use of text messages and phone

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20 A regression using the individual experimental conditions as a categorical predictor of the reported likelihood of Census response validates this finding and shows no significant relationships.

21 In our original plan, we did intend to perform this type of analysis. However, the limited sample size makes such an analysis impossible at this time.
calls, covers a large swath of the county, and includes over 1 million contact attempts. This operation was a coordinated effort lead by Houston in Action and supported by various partner organization. Calls were made by trained phone banking personnel who, in addition to recording the outcome of the contact attempt, also recorded various pieces of information from respondents including answers to survey questions. These data were collected by Houston in Action and geocoded in order to associate phone numbers and addresses with specific locations.

Descriptive Assessment of All Phone Canvassing

Our data on the phone canvassing effort includes 1,287,245 contact attempts. We have geographic data tying 1,227,575 (95%) of these attempts to a specific tract in Harris County. These geocoded attempts cover 702 of the 783 tracts in the county. Using the subset of attempts for which geographic data exists, Figure 19 displays each tract in Harris County colored according to how many attempts were made in each tract. The figure clearly shows that, while canvassing efforts covered the bulk of the county, a select set of tracts received substantially more attention than others. This is, once again, a direct result of Houston in Action and partners focusing on at-risk areas.

Figure 19: Phone Outreach Attempts by Tract

Out of all of the recorded contact attempts, 111,154 resulted in successful contact with the sought after individual - yielding an overall contact success rate of 9%.\textsuperscript{22}

\textsuperscript{22}In some cases, the individual who answered the phone was not the one listed with the phone number. These 44,688 cases where recorded as "wrong number" and are not included in the contact success rate calculation.
Determinants of Successful Contact

In addition to the overall contact success rate, we can - for the subset of attempted contacts which can be tied to a geographic unit - also examine variation in contact success rate across tract. Figure 20 displays each Harris County tract colored according to the contact success rate for all tracts where more than 100 attempts were made. The figure clearly emphasizes the variation in contact success rates across tracts - with some tracts seeing contact success rates near 0 while others have success rates approaching 31.9%.

Figure 20: Phone Contact Rate by Tract

<table>
<thead>
<tr>
<th>Contact Rate</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.00 to 0.05</td>
<td>0.05</td>
</tr>
<tr>
<td>0.05 to 0.10</td>
<td>0.10</td>
</tr>
<tr>
<td>0.10 to 0.15</td>
<td>0.15</td>
</tr>
<tr>
<td>0.15 to 0.20</td>
<td>0.20</td>
</tr>
<tr>
<td>0.20 to 0.25</td>
<td>0.25</td>
</tr>
<tr>
<td>Missing</td>
<td></td>
</tr>
</tbody>
</table>

Noting the considerable variation across tracts, we can also examine the contact success rates in tracts with above and below average Low Response Scores. Figure 21 separately plots the contact success rates for tracts with below and above average Low Response Scores along with the total number of calls made to said tracts. Once again, we see that tracts with above average Low Response Scores exhibit a lower contact success rate compared to other tracts. In particular, we note that the contact success rate is expected to differ by around 2.5 percentage points, with above average tracts exhibiting a contact success rate of around 7% while below average tracts are at 9.5%. This reinforces our findings concerning the in-person canvassing effort and suggests that it is especially difficult to canvass historically undercounted communities.

23 Once again, we restrict our attention to a subset of tracts where a larger number of attempts were made in order to avoid including tracts which were canvassed outside of the general canvassing initiative.
Finally, we can also examine more closely how the day the contact was attempted impacted the contact success rate. Figure 22 displays this variation and indicates that attempts on Saturdays resulted in the highest contact rates, followed by attempts on Tuesday. More specifically, we see that almost 20% of the contact attempts made on Saturday were successful and around 12% of the calls made on Tuesday were successful. Compared to the other days of the week - when contact rates were regularly less than 5% - these contact success rates are notable and should be taken into account as further canvassing is pursued. That said, note that the high contact success rate observed on Saturday is possibly an artifact of the smaller number of total contact attempts made on that day (only 12,542), and that increasing the volume of contact attempts to the levels observed on most other days (around 200,000) may result cause Saturday’s contact success rate to come more in line with that of other days.
The Effect of Phone Canvassing on Response Rates

Under ideal circumstances, we would like to examine the phone banking efforts - using a similar analysis as for the in-person canvassing efforts - in order to determine whether phone banking successfully raised response rates in targeted areas. Unfortunately, the COVID-19 pandemic created a situation in which such a simplistic analysis is no longer possible. Generally speaking, this is due to our limited ability to track all of the Census-related activities in all tracts across the county that received some form and intensity of phone outreach.\(^{24}\) As a result, instead of attempting to evaluate the effectiveness of the entire phone canvassing effort as a whole, we will examine the phone banking efforts undertaken during a specific campaign effort: the Communities Respond initiative.

Communities Respond

Communities Respond was envisioned as an initiative to raise response rates in 10 Houston-area communities that were considered especially at risk of being undercounted in the 2020 Census. Figure 23 displays the ten communities using a simplified name drawn from one of the constituent neighborhoods.\(^{25}\) These communities were selected not only because of their high Low Response Score, but also because they exhibited response

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\(^{24}\)The more specific reasons why such an analysis would be problematic are numerous and include, but are not limited to: variation in the reason for targeting a tract for phone canvassing efforts (i.e., variable causes of treatment assignment), increased uncertainty about the substantive content of phone banking messaging (i.e., varying treatments), and both increased variance and uncertainty about other, simultaneous forms of outreach (i.e., the presence of unobserved confounders). These issues make subsetting our analysis to a particular time and place crucial to our ability to discern any meaningful relationships involving phone canvassing.

\(^{25}\)Since the communities included in the initiative sometimes include more than one neighborhood as defined by the Kinder Institutes list of neighborhoods, we use these simplified names for brevity.
rates far below the expected levels and observed levels across the county. As such, Houston in Action implemented a coordination program to support targeted interventions in each of the communities on a week-by-week basis beginning in early May. Each of these weekly interventions saw Houston In Action facilitating the coordination and deployment of a variety of resources including phone canvassing, visits with community leaders, and assistance with and distribution of materials at community events (including food distribution events associated with the COVID-19 pandemic).

Figure 23: The Communities Respond Communities

Since the Communities Respond initiative involved targeting specific communities over time, it is important to consider the time trend in response rates within and across these neighborhoods. Figure 24 displays the weekly response rates for these communities beginning on Census Week with a red line indicating the week when the community was the subject of the initiative. As expected from Figure 1, response rates in these communities have generally experienced a steady drop over time after Census Day and exhibit response rates at or below 1% by the time the initiative began in mid-May. This observation clearly indicates that our models of the relationship between phone canvassing and Census response rates will need to carefully take time into consideration.

Additional, while the Communities Respond initiative involved coordination around a variety of outreach activities, we focus our attention on the phone canvassing efforts undertaken by Houston in Action and partners during the initiative. As of June 22nd, this includes, 292,851 phone canvassing attempts across the targeted communities. These canvassing efforts, coupled with concurrent efforts and patterns of responses in other neighborhoods across the county, form the core of our analysis.

26 The current data does not cover the treatment period for all of these communities and, as such, some communities may not have an associated treatment line.
Figure 24: Weekly Response Rates for Communities Respond Communities (beginning on Census Day)

As with our examination of the in-person canvassing data, we use a quasi-binomial regression model to examine the relationship between the number of successful phone canvassing contacts and the observed weekly response rates in communities of interest. Specifically we estimate regression models at the community-level using the number of contacts and the average Low Response Score, along variables denoting the calendar week.\(^{27}\) Once again, we estimate these models using two samples: one using all of the communities and another using the 10 communities selected to be a part of the initiative along with a set of other comparable communities.\(^{28}\)

Table 2 displays the results of the phone canvassing models for the two samples. In line with our previous findings regarding in-person canvassing, we continue to see a positive and statistically significant relationship between the percent of a community canvassed and the Census response rate for that neighborhood. In particular, we note that, in any given week, communities where more phone contacts are successfully established report higher response rates to the 2020 Census. This relationship is visible when comparing the communities included in the initiative to all other neighborhoods and when comparing them to the subset of comparable neighborhoods - an indication of the robust nature of the relationship.

\(^{27}\)The use of week indicators amounts to what is called a “fixed-effect” specification and allows use to capture the (likely decreasing) time trend in response rates. Further this specification effectively allows us to examine the relationship between contact rates and response rates within each week but across each neighborhood.

\(^{28}\)In this case, comparable communities were identified as those that could have been selected to be part of the Communities Respond initiative. Since this selection process involved looking at communities that had average Low Response Scores below the county average and low cumulative response rates around Census Day, we restrict our analyses to communities with both an average Low Response Score greater than 25 and a cumulative response rates on Census Day of less than 50%.
Table 2: Results of Quasi-Binomial Models for Communities Respond Initiative

<table>
<thead>
<tr>
<th>Variable</th>
<th>All Communities (N = 1496)</th>
<th>p-value</th>
<th>Comparable Communities Only (N = 748)</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Contact Rate</td>
<td>0.067</td>
<td>&lt; .001</td>
<td>0.067</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>Low Response Score</td>
<td>0.01</td>
<td>&lt; .001</td>
<td>0.004</td>
<td>0.176</td>
</tr>
<tr>
<td>Week 1</td>
<td>-0.547</td>
<td>&lt; .001</td>
<td>-0.57</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>Week 2</td>
<td>-1.034</td>
<td>&lt; .001</td>
<td>-1.064</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>Week 3</td>
<td>-1.329</td>
<td>&lt; .001</td>
<td>-1.355</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>Week 4</td>
<td>-1.455</td>
<td>&lt; .001</td>
<td>-1.468</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>Week 5</td>
<td>-1.514</td>
<td>&lt; .001</td>
<td>-1.483</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>Intercept</td>
<td>-4.657</td>
<td>&lt; .001</td>
<td>-4.501</td>
<td>&lt; .001</td>
</tr>
</tbody>
</table>

Once again, we can use the predictions from the regression models to examine how we expect canvassing effort to translate into high response rates in practice. In this case, Figure 25 displays the predicted response rate (with 95% confidence bounds) in a hypothetical community across values of the contact rate. This figure further demonstrates the positive relationship between contacts and response rates but also stresses how small - at least in this stage of the campaign - this relationship is. In fact, our estimates suggest that by canvassing another 10% of a community’s population, we would only observe an increase in the weekly response rate of .01 percentage points. This means, for example, that by canvassing 10% more of the population of a community, one might observe a change in weekly response rates from 1.23% to 1.24%. While this number is indeed small, it nonetheless constitutes an increase and means that more residents are counted in the long term as weeks go by.
Tentative Conclusions

Our brief analysis of the phone canvassing efforts undertaken in support of the 2020 Census suggests a link between canvassing effort and community-level response rates such that successful phone canvassing is associated with higher weekly response rates. However, due to the complexity of the Census Campaign during the COVID-19 pandemic, this evaluation effort focused on a specific time period and only evaluates phone canvassing efforts within the context of the Communities Respond initiative. Further, due to the multifaceted nature of the Communities Respond initiative, we are unable to evaluate the phone banking data alongside a holistic evaluation of all related Census Campaign activities. With these concerns in mind, we do not recommend drawing strong conclusions from the limited analysis we have performed. Instead, we suggest waiting until more data are available and re-evaluating the efforts - using a more thorough set of controls and model specifications - at a later date.

Fortunately, this does not mean that we have learned nothing from the phone canvassing effort and cannot use our analytic tools to improve canvassing. For example, our analysis of the phone canvassing operation pointed to some noteworthy patterns when we examined variation in response rate across days of the week and by tract. These results can be used to better target canvassing efforts by, for example, identifying the best days to focus more calls on. While these strategies cannot, given our current results, be definitely said to raise Census response rates, they are suggestive of such a relationship and will help Houston in Action and partners reach more members of the community - something that almost certainly has benefits well beyond Census participation.
Conclusions and Recommendations

Our primary goal in this report has been to understand whether the canvassing operations associated with the 2020 Say Yes to the Census Campaign had a positive impact on Census response rates in Harris County. While our analysis is hindered by the difficulties faced by the campaign, our general finding is that canvassing activity did indeed improve response rates although our conclusions about the degree to which this relationship holds across time and methods of canvassing are preliminary and warrant further analysis. In addition, our analysis also shows that some steps could be taken to improve response rates during canvassing operations.

Aside from evaluating the canvassing campaigns, we also set out to develop identification and messaging strategies to assist in the Say Yes to the Census Campaign. Unfortunately, our analysis of the messaging experiment was unable to identify canvassing messages that provide an additional motivation for individuals to respond to the 2020 Census. In fact, our results suggest that offering a message about the general importance of the Census is just as effective as messages focusing on “civic duty” or the benefits the community will receive via Census-related funding. In a similar way, our efforts to use machine learning algorithms to identify historically undercounted populations were largely stymied by the COVID-19 pandemic. While initial model performance suggests that the method may be useful for identifying households that will not receive a Census questionnaire (due to their omission from the Master Address File), the lack of in-person canvassers meant that we were unable to verify the existence of these households.

The 2020 Say Yes to the Census Campaign was fraught with challenges as the country and the campaign team grappled with the numerous changes brought about by the COVID-19 pandemic. While the initial campaign plan emphasized in-person canvassing, the development of data-driven strategies for identifying and motivating communities, and a thorough evaluation of campaign programs, none of these plans reached their full potential and each was severely limited by the pandemic. That said, the campaign has pushed forward as a result of the efforts of Houston in Action, its partner organizations, and local government officials. Their dedication to making each person count and to giving a voice to residents across the county have been instrumental in overcoming the many challenges that have beset the campaign. Indeed, nothing in this report should be construed as indicating a failure on the part of Houston in Action, their partners, or the array of individuals who participated in the campaign and did their best in what is likely to be one of the most difficult Census operations the country has ever undertaken. While the current situation limits what can be done to support the Census, our hope is that our analysis provides some guidance for both understanding the current campaign efforts as well as planning future efforts.
References


Appendix

I: Alternative Regression Model Specifications

In our primary evaluation the relationship between in-person canvassing and response rates, we examined every tract in the county and used the tract-level contact rate as our metric of canvassing effort/success. However, we could use a number of different versions of effort and success, including the number of individuals successfully canvassed, the proportion of the block groups in a tract that were canvassed, and a simple indicator of whether canvassing occurred at all in a tract. Table 3 displays the results of these revised regression models.

Table 3: Results of Alternative Quasi-Binomial Models

<table>
<thead>
<tr>
<th>Variable</th>
<th>All Tracts (N = 783)</th>
<th></th>
<th>Comparable Tracts Only (N = 67)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Houses Contacted</td>
<td>0.001</td>
<td>0.022</td>
<td>0.001</td>
<td>0.015</td>
</tr>
<tr>
<td>Low Response Score</td>
<td>-0.043</td>
<td>&lt; .001</td>
<td>-0.034</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>Other Activity</td>
<td>0</td>
<td>0.637</td>
<td>0.001</td>
<td>0.191</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.331</td>
<td>&lt; .001</td>
<td>0.037</td>
<td>0.845</td>
</tr>
<tr>
<td>Percent of Block Groups Canvassed</td>
<td>0.032</td>
<td>0.581</td>
<td>0.011</td>
<td>0.907</td>
</tr>
<tr>
<td>Low Response Score</td>
<td>-0.043</td>
<td>&lt; .001</td>
<td>-0.037</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>Other Activity</td>
<td>0</td>
<td>0.658</td>
<td>0.001</td>
<td>0.283</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.331</td>
<td>&lt; .001</td>
<td>0.184</td>
<td>0.372</td>
</tr>
<tr>
<td>Any Canvassing in Tract</td>
<td>0.042</td>
<td>0.217</td>
<td>0.077</td>
<td>0.241</td>
</tr>
<tr>
<td>Low Response Score</td>
<td>-0.043</td>
<td>&lt; .001</td>
<td>-0.034</td>
<td>&lt; .001</td>
</tr>
<tr>
<td>Other Activity</td>
<td>0</td>
<td>0.599</td>
<td>0.001</td>
<td>0.359</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.331</td>
<td>&lt; .001</td>
<td>0.047</td>
<td>0.834</td>
</tr>
</tbody>
</table>

From Table 3 we see that, among the alternative metrics of canvassing effort, only the first - using the number of households in a tract that were canvassed - is statistically associated with increased response rates. This finding is somewhat expected in light of the results presented in Table 1 and holds true regardless of whether we examine all tracts in the county or only comparable tracts. That said, the estimated relationship between the raw number of canvassing contacts and response rates - while still positive - is drastically smaller when compared to the relationship between the percent of households reached and the response rate. Theoretically, this is likely unsurprising since the outcome of interest is also calculated as a percentage of the number of households in a tract. Theory aside, in practice, this results provides yet another motivation to focus on contacting a larger percentage of the households in a tract and not simply reaching larger absolute numbers of contacts.
II: Text of Messages in Experimental Conditions

Our field experiment on Census messaging used four messages with partially overlapping content aimed at motivating participation in the 2020 Census using specific messaging appeals. The text of these messages are reproduced below.

**Condition 1: Census Background Motivation**

Hello, my name is __________ and I’m with the Harris County Say Yes to the Census campaign. Would you mind taking a few minutes to answer a few questions about the 2020 Census?

The US Census is a count of all of the people who resides in the United States on April 1st. It happens every 10 years and asks questions about how many people live in your household, their age, and ethnicity. This information is used for a variety of purposes and helps us understand population change in the US.

This year, the census will take place around April 1st. Your household will receive either a form to fill out and return or an invitation to participate electronically on the web. On or around March 13th.

**Condition 2: Civic Duty Motivation**

Hello, my name is __________ and I’m with the Harris County Say Yes to the Census campaign. Would you mind taking a few minutes to answer a few questions about the 2020 Census?

The US Census is a count of all of the people who resides in the United States on April 1st. It happens every 10 years and asks questions about how many people live in your household, their age, and ethnicity. This information is used for a variety of purposes and helps us understand population change in the US.

This year, the census will take place around April 1st. Your household will receive either a form to fill out and return or an invitation to participate electronically on the web. On or around March 13th.

Completing the Census is a way that everyday people can participate in our democracy. The Constitution provides every person residing in the country the opportunity to participate in the census.

**Condition 3: Community Benefit Motivation**

Hello, my name is __________ and I’m with the Harris County Say Yes to the Census campaign. Would you mind taking a few minutes to answer a few questions about the 2020 Census?

The US Census is a count of all of the people who resides in the United States on April 1st. It happens every 10 years and asks questions about how many people live in your household, their age, and ethnicity. This information is used for a variety of purposes and helps us understand population change in the US.

This year, the census will take place around April 1st. Your household will receive either a form to fill out and return or an invitation to participate electronically on the web. On or around March 13th.

Completing the Census contributes to a better future for our community by determining funding for public services like schools, streets, parks, emergency services, and disaster recovery. The more people in this community who participate, the more funds this community will get to improve the overall quality of life.

**Condition 4: Combined Motivation**
Hello, my name is _____________ and I’m with the Harris County Say Yes to the Census campaign. Would you mind taking a few minutes to answer a few questions about the 2020 Census?

The US Census is a count of all of the people who resides in the United States on April 1st. It happens every 10 years and asks questions about how many people live in your household, their age, and ethnicity. This information is used for a variety of purposes and helps us understand population change in the US.

This year, the census will take place around April 1st. Your household will receive either a form to fill out and return or an invitation to participate electronically on the web. On or around March 13th.

Completing the Census is a way that everyday people can participate in our democracy. The Constitution provides every person residing in the country the opportunity to participate in the census.

In addition, completing the Census contributes to a better future for our community by determining funding for public services like schools, streets, parks, emergency services, and disaster recovery. The more people in this community who participate, the more funds this community will get to improve the overall quality of life.