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Does IT Lead to More Equal Treatment? An Empirical Study of the Effect of Smartphone Use on Customer Complaint Resolution

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Report Summary

All firms have to deal with angry customers. Anecdotal evidence suggests that vociferous customers attract more attention from firms and get their problems solved sooner, while customers who have equally serious complaints but are not good at advocating for themselves are usually ignored and may eventually just stop saying anything. A particular concern for organizations may be that customers' ability to advocate for themselves in a consumer complaint situation may also be related to underlying demographic factors such as education.

Here, Catherine Tucker and Shuyi Yu ask whether new communication technology mitigates unequal attention in resolution of customer complaints relative to the traditional phone call or letter. It is not clear whether new communication technologies should improve or make worse the lot of customers who are potentially less able to advocate for themselves. On the one hand, rich and educated customers are believed to be better at using technology, which would give them further advantages in complaint resolution. On the other hand, technologies may resolve the disadvantages facing less-educated communities and lead to fairer customer service by systematizing the communication and reducing in-person interactions.

The authors investigate this question using service performance data from Boston's 311 system. They find that complaints that originate in more highly educated census blocks are more likely to be resolved quicker. However, they also find that the use of mobile information technologies improves the performance of customer service in the public sector and at least partially eliminates more educated customers' advantage in complaint resolution relative to people who submit complaints in neighborhoods with lower education levels, by providing a standardized communication tool. To address the endogeneity of mobile device use, they turn to an instrumental variables approach, where they use plausibly exogenous instruments which capture the strength of the local cellphone signal and shift the ability of customers to submit complaints using mobile apps. Also, they present suggestive evidence that it is on occasions when these advanced digital tools are used to automate data and for more complex requests that apps are most effective at closing the gap between educated and less-educated customers.

Their results are important for managers who want to improve their customer service by facilitating and automating communications. They show that providing digital tools might increase customer retention by encouraging them to advocate for themselves. The results are important for policy, too. In January 2016, the FTC published a report entitled "Big Data: A Tool for Inclusion or Exclusion?" It expressed concern that the advent of digital data and associated technologies may lead to disadvantaged groups being excluded by firms. This work is somewhat optimistic on this front, suggesting that, in their setting, mobile communication technologies (and the associated data they can generate) actually help reduce inequality in outcomes. The main policy implication of the work, therefore, is the need for digital inclusion.

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1 Introduction

All firms have to deal with angry customers. Anecdotal evidence suggests that vociferous customers attract more attention from firms and get their problems solved sooner, while customers who have equally serious complaints but are not good at advocating for themselves are usually ignored and may eventually just leave saying anything.[1] A particular concern for organizations may be that customers' ability to advocate for themselves in a consumer complaint situation may also be related to underlying demographic factors such as education.

In this study, we ask whether new communication technology mitigates unequal attention in resolution of customer complaints relative to the traditional phone call or letter. It is not clear *ex ante* whether new communication technologies should improve or make worse the lot of customers who are potentially less able to advocate for themselves. On the one hand, rich and educated customers are believed to be better at using technology, which would give them further advantages in complaint resolution. On the other hand, technologies may resolve the disadvantages facing less-educated communities and lead to fairer customer service by systematizing the communication and reducing in-person interactions.
We investigate this question using service performance data from customer complaint resolution in the public sector. We combine 464,683 Boston non-emergency public service operation records with demographic and socioeconomic census data. We find that complaints that originate in more highly educated census blocks, are more likely to be resolved quicker. However, we also find that the use of mobile information technologies improves the performance of customer service in the public sector and at least partially eliminates more educated customers' advantage in complaint resolution relative to people

[1] See *A Squeaky Wheel Gets The Grease, And Why It Pays To Be An Angry Customer*: `https://www.forbes.com/sites/blakemorgan/2016/12/05/a-squeaky-wheel-gets-the-grease-and-why-it-pays-to-be-an-angry-customer-2/`.

who submit complaints in neighborhoods with lower education levels, by providing a standardized communication tool. We present suggestive evidence that it is on occasions when these advanced digital tools are used to automate data and for more complex requests that apps are most effective at closing the gap between educated and less-educated customers.

An obvious concern about these findings is the endogeneity of mobile device use and how it might itself be related to education. To address this, we turn to an instrumental variables approach, where we use plausibly exogenous instruments which shift the ability of customers to submit complaints using mobile apps. The instruments we use capture the strength of the local cellphone signal. We present evidence that not only does this affect the ability to use the mobile application, but that also, due to the unusual topography and history of Boston, strength of local cellphone signal is not strongly correlated with the demographics of the local neighborhood. These instrumental variable results confirm our earlier findings.

We contribute to three distinct literatures. The first is the literature which explores the effects of complaint resolution. There is some evidence that customer complaint resolution is important for firm profitability. Satisfaction with how a complaint is resolved can have a positive effect on customer loyalty (Fornell and Wernerfelt, 1987; Andreassen, 1999; Tax et al., 1998) and may evoke positive word-of-mouth behavior (Blodgett et al., 1995). However, there is far less empirical evidence regarding the process by which a firm can best resolve customer complaints. In general, research is either theoretical (Fornell and Wernerfelt, 1988), or based around qualitative frameworks – for example Davidow (2003) describes six dimensions of defensive marketing and summarizes studies about how each of them affects post-complaint responses. One exception is Homburg and Fürst (2005), which suggests that both having guidelines and a positive culture can help with consumer complaint resolution. We contribute to this literature by providing empirical evidence about the roles of technology in fighting potential inequality in the complaint resolution process.

Second, our study also contributes to a more general debate about the relationship between technology and inequality. The current literature focuses on labor supply, and mostly shows that using information technology in the workplace has been contributing to growing inequality because it complements the skills of the educated labor force (Acemoglu, 1998, 2002; Bresnahan et al., 2002; Bartel et al., 2007). This implies that more educated workers are likely to earn more due to the higher productivity (Black and Lynch, 2001; Bartel et al., 2007; Bloom et al., 2012) and the changed structure of firms (Bloom et al., 2014) and industries (Tafti et al., 2013), while many unskilled positions are replaced by new technologies. Our work differs from those papers by approaching the problem from the demand side and investigating the effect of IT for consumers. We show that, in contrast to the supply-side, information technology reduces inequality by providing a more standardized communication tool for the resolution of complaints. This result builds on Morton et al. (2003), who find that the Internet has proved particularly beneficial to customers experiencing disadvantages in negotiating.

The final literature we contribute to is a literature studying how self-service technology affects the service performance and competitiveness of a business (Meuter et al., 2000; Ray et al., 2005; Jayachandran et al., 2005; Dotzel et al., 2013; Rust and Huang, 2014). Our work extends the literature by studying the use of those technologies in complaint handling and assessing the effect of self-service technologies on equality of treatment.

Our results are important for policy, too. In January 2016, the FTC published a report entitled *Big Data: A Tool for Inclusion or Exclusion?*. It expressed concern that the advent of digital data and associated technologies may lead to disadvantaged groups being excluded by firms. Our paper is somewhat optimistic on this front, suggesting that in our setting mobile communication technologies (and the associated data they can generate) actually help reduce inequality in outcomes. The main policy implication of our paper, therefore, is the need for digital inclusion. Our evidence supports policies that ensure that all consumers have access to these kind of mobile technologies which can help facilitate and automate communications.

2 Boston 311 Service

As the largest city in New England and the 23rd largest city in the United States, Boston has an estimated population of 667,137 distributed over an area of 89.6 square miles.[2] To provide better and more convenient public service, the city of Boston operates a multichannel system for non-emergency public service (311 constituent service) requests. All 311 service records since Jul 01, 2011 are available to the public on the website of the Boston city council.[3] The dataset has been studied in other disciplines such as sociology and communications (Clark et al., 2013; Buell et al., 2017). However, the focus of this prior research has been on who adopts the 311 mobile application, rather than considering how the use of different technologies affects actual complaint resolution time.

A typical complaint is street cleaning, an abandoned shopping cart that needs to be removed, or snow clearing that has not been done thoroughly. Though we recognize that these are data from a governmental organization, we believe that the nature of the complaints, which are mainly focused on services that were inadequately provided (and the channels used to resolve them) are similar to a traditional commercial service-based

[2] See QuickFacts: Boston on the Census Bureau's website: `https://www.census.gov/quickfacts/table/PST045215/2507000`.

[3] The data is made publicly available online on the city government's open data site (`https://data.cityofboston.gov`) as part of a commitment to increase transparency in government. However, sensitive personal information of request senders has been removed to protect individual privacy.

organization.

This complaint resolution service can be accessed in four ways:

- Phone Call
- Online Self-Service Website
- Mobile Application
- Social Media

Customers using a phone call access a 24-hour hotline (3-1-1 and previously 617-635-4500), where city workers take the call and log the service request into the computer system that routes requests and keeps records. This is the traditional means of submitting complaints. However, a unique feature of using the phone channel is that the interactive communication between representatives and reporters might make the accuracy of description depend on the oral communication skills of the person submitting the complaint and the extent to which the person taking down the complaint makes efforts to record the complaint completely.

The self-service website[4] allows people to report non-emergency issues by filling in contact information, the location of the issue and a brief description of the request. After a successful form submission, requesters receive a tracking ID, with which they can check the status of their cases on the same website. A desktop computer is necessary for sending the form out.

In contrast, the mobile application is not tied to a location. It was referred to as the 'Citizens Connect App' when it was first launched in 2009,[5] and now people can download it for free on iOS or Android as the BOS:311 App. Figure 1 shows a screenshot of the app.

[4] http://www.cityofboston.gov/311

[5] We talked to a city employee and confirmed that the aim of this launch was to better serve citizens, and that the introduction was not to their knowledge influenced by any technological constraints.

Three salient features make the app more technology (and data) - intensive than the other channels for submitting complaints. First of all, high-quality photos can be taken and uploaded together with the description, which helps city employees obtain a better and quicker understanding of the complaint, especially where the description is not very clear. Second, the app can use GPS in mobile devices to locate the case and fill out the address automatically. This provides more accurate address and avoids spelling mistakes in the address input. Third, people are able to track the status of their cases anytime and anywhere with their mobile devices, easing re-communication regarding the same case.

3 Data Description

We have two sources of data in this study: Public service operation records from the city of Boston and demographic and socioeconomic census data from the U.S. Census Bureau. Both of these are public datasets which are downloadable online.

3.1 311 Data

The public dataset on the website of Boston city council includes detailed information on each case opened after Jul 01, 2011: The open date/time, whether the case is still open or closed and the close date, reason, and result if it is closed, the completion time and the on-time status (the cut-off time for an "on-time" completion has been reported as target completion time for some but not all cases), the source of the case, the case type, the party responsible for the case, whether a photo is attached, the address, the latitude and the longitude of the case location, and the various districts or neighborhoods the case is within.

Since there was a major transition in the system – including changes in the website design, the name of the mobile application and the phone number, as well as some technological upgrades in the internal computer system – made on Aug 11, 2015,[6] we use only records that were opened from Jul 01, 2011 to Aug 10, 2015. There are 603,694 cases during this period. 408,503 of them were generated by citizens, and the other 27.2% by city employees. To study the efficiency of complaint resolutions, we calculate the completion time for each record and discard 41,951 open cases,[7] We also exclude 35,082 internal cases logged by employees after the complaint was resolved, 15,346 duplicate cases, 15,022 invalid cases generated by errors, 14,654 cases for general comments with which no case location is associated, 9,405 cases closed administratively, and 558 cases with incomplete completion time.

3.1.1 Source and Type of Cases

For the remaining 464,683 cases in our dataset, the use of information technology is indicated by the source of case — citizens can submit the external request via the constituent call, the self-service website or Citizens Connect App[8], while city workers can report the internal case through the traditional system (employee generated) or City Worker App.[9]

Panel A of Figure 2 reports the distribution of cases over those sources. It shows that city employees were generally more likely to use mobile devices to report a case than citizens. Panel B of the same figure shows the median of the actual completion time, the median of

[6]See *Mayor Walsh Launches Boston 311*: `http://www.cityofboston.gov/news/default.aspx?id=20283`.

[7]Most of those open cases are general complaints that can't be fixed with simple actions, like 8,974 general comments for a program, a policy or an employee, 8,177 general complaints about unsatisfactory living conditions or unsanitary conditions, and 4,672 animal generic requests or lost-and-founds. We exclude those open cases because the overdue status here doesn't indicate that no proper attempt has been made punctually.

[8]We don't study complaints submitted on Twitter because there are only 7 cases in our data.

[9]There is also a Maximo Integration system, which serves as a central repository for all reports of issues concerning street lights, control boxes, fire houses that are automated. See *EMA Success Stories City of Boston- IBM Maximo Implementation*: `http://www.ema-inc.com/success-stories/asset-management/city-of-boston-ibm-maximo-implementation`. The lack of human intervention required means that we do not study complaints for this system.

the target completion time,[10] and the on-time ratio for each source. Cases generated internally were solved faster and the on-time ratios for them are higher with an even longer target completion time, but this of course does not condition for differences in case type. It suggests that the internal cases and the external cases can be inherently different, and this is something we evaluate when we compare later on in the paper dispute resolution times for employee-generated complaints vs consumer-generated complaints. The highly skewed distribution and the long tail on the right suggest that a survival model may be an appropriate way to capture the distribution of complaint time resolution.

Panel D of Figure 2 shows the histogram of target completion times for those sources. The concentrated distribution of target times suggests that this cut-off time for an "on-time" completion might be a preset number and case-by-case adjustments are rare. Therefore, we take both the completion time and the reported "on-time" status into account when analyzing complaint resolution performance.

We focus on identifying the effect of using the Citizens Connect App and the associated mobile information technologies and distinguish the app from the self-service website or phone service. We exclude all employee-generated cases in our initial analysis, but return to these cases when we turn to identification.

We summarize the type of cases in Table 1. More than 80% of the cases belong to the top seven categories - which have more than 20,000 cases: Sanitation, street cleaning, highway (and road) maintenance, street lights, recycling, signs & signals, and trees. We see that the average completion time varies among different types in Figure 3. To address this we use category fixed effects to shed light on the baseline efficiency of customer complaint resolution and the difference between the self-service website and the constituent call

[10]The target completion time is missing for 199 cases generated via Citizens Connect App, 20,210 cases generated via the self-service website, 59,153 cases generated via traditional phone calls, 1,468 cases generated via City Worker App, and 11,418 cases generated via the traditional internal system. The disproportionate reduction in missing records shows the advantage of advanced technology in automatic recording.

service.

3.1.2 Increasing Efficiency, Seasonality and Weekly Variations

Using a local polynomial regression, we display a smoothed trend over time of the number of cases opened in Panel A of Figure 4 and a trend over time of the average actual completion time in Panel B of the same figure. They suggest a strong seasonality in efficiency but not in frequency[11] – the peak of efficiency usually comes in January or February – while the average completion time is decreasing over time. A further investigation in Panel D of Figure 4 shows this seasonality varies among different types of cases: Some types, like recycling and highway maintenance work, have obvious delays in extreme weather, while service performance for other types, such as sanitation and signs & signals, is quite stable. Even though the composition of cases shown in Panel C of the same figure is more stable than the performance for all types except street cleaning work, the number of cases for most types still exhibits a seasonal pattern. For example, the number of street cleaning cases increases dramatically in winter, and highway maintenance problems are also amplified during that tough time. Sanitation issues dominate the system in the summer, and the peak of tree-related cases always arrives in New England during the foliage season.

We also plot the total number of cases and the average completion time by weekday in Figure 5. Figure 5 implies variation across the day of the week the case was submitted in the waiting time for citizens, while this pattern is more subtle for the cases generated by employees. This is even though the number of cases submitted during the weekend is significantly lower than that on weekdays for both citizens and employees. For the requests sent by citizens, the weekly variation might be explained by a "stock effect," which is the

[11] There is a decrease on the right of Panel A because we have removed those incomplete cases which were opened late and had not been finished until our data collection date (Feb 09, 2016).

difference in case completion time resulting from a varying number of open cases in the system when it was opened, and a "peer effect," which is the difference in case completion time resulting from a varying number of cases opened at the same time.

We control for these shifts over time by adding year, season and weekday fixed effects in our main model.

3.2 Census Data

We use 2010 census data for each block group, which is the smallest geographic unit used by the United States Census Bureau. There are 646 census block groups in the city of Boston and each of them has been labeled with a unique 12-digit ID number. Figure 6 shows those block groups on the map.[12] 10 out of those 646 census block groups are fully covered by lakes or parks and are reported to have no population living inside. The public service data also confirms that no requests have been sent from those block groups. We match each public service case with census block groups using the exact latitude and longitude of the case and approximate the reporter's characteristics using group-level socio-demographic variables about gender, age, race, language spoken, income and housing status. There are 545 census block groups from which requests were sent, and a summary of those socio-demographic variables in these 545 census block groups is provided in Table 2. Each census block has 1,160 individuals and 460 households on average. Panel A and B of Figure 7 shows how the number of requests varies with the average level of education in the neighborhood. Both the total number of external requests sent by citizens and the number of external requests per capita increase sharply with the average years of education initially and they decline gradually. The number of internal requests sent by employees doesn't increase as dramatically with level of education, though it does decline more

[12] From Boston Redevelopment Authority: http://www.bostonredevelopmentauthority.org/research-maps/maps-and-gis/census-and-demographic-maps.

sharply at the highest levels of education. Panel C of Figure 7 shows how complaint resolution performance varies with the average level of education. To take the difference in case type across internally vs externally generated complaints, we plot the on-time rate rather than completion time on the y-axis.

Figure 8 depicts the average completion time by both neighborhood and source of the complaint. We see different patterns in Panel A of Figure 8, where the average completion time for cases submitted through the App is plotted for each census block, than in Panel B of the Figure 8, which plots the average completion time for cases submitted through the other channels.

4 Main Effect

4.1 Model

To identify the effect of the use of mobile app usage on the complaint resolution performance, we use a Cox proportional hazards model to analyze how long it takes for a complaint to be resolved. We focus on the distribution of completion times and model the time it takes for completion to occur. The validity of this survival analysis approach is supported by the model-free evidence regarding the distribution of completion time provided in the histogram depicted in Panel C of Figure 2.

Let

$$\lambda(t) = \lambda(t|CitizenConnectApp_i, WebSubmission_i, \mathbf{X}_i, \mathbf{Y}_j, \mathbf{Z}_k)$$

denote the hazard function[13] for case i opened on day j and in census block group k at

[13] Hazard function assesses the instantaneous risk of demise at time t, conditional on survival to that time: $lim_{\Delta t \to 0} \frac{Pr[(t \leq T < t+\Delta t)|T \geq t]}{\Delta t}$ (Fox and Weisberg, 2010).

time t, where $CitizenConnectApp_i$ is an indicator which equals one if the case was submitted via the mobile app, and $WebSubmission_i$ is an indicator which equals one if the case was submitted on the self-service website. $\mathbf{X}_i$, $\mathbf{Y}_j$ and $\mathbf{Z}_k$ are vectors of case-, time- or block-group-specific covariates listed in Table 3. Leaving the baseline hazard function $\lambda_0(t) = \lambda(t|0, 0, \mathbf{0}, \mathbf{0}, \mathbf{0})$ unspecific,[14] we models the log hazard ratio, which is the relative "risk" of the case closing at time t, as

$$\log(\frac{\lambda(t)}{\lambda_0(t)}) = \beta_0 + \beta_1 CitizenConnectApp_i + \beta_2 WebSubmission_i + \mathbf{X}_i'\gamma + \mathbf{Y}_j'\mu + \mathbf{Z}_k'\eta. \quad (1)$$

The parameters of interest are β_1 and μ, which capture the effect of using mobile information technologies and that of complainer's socio-demographic characteristics on the case completion time.

Furthermore, an extension of this model

$$\begin{aligned}\log(\frac{\lambda(t)}{\lambda_0(t)}) = {} & \beta_1 CitizenConnectApp_i + \beta_2 WebSubmission_i + \mathbf{X}_i'\gamma + \mathbf{Y}_j'\mu + \mathbf{Z}_k'\eta \\ & + CitizenConnectApp_i \tilde{\mathbf{Z}}_k'\tau_1 + WebSubmission_i \tilde{\mathbf{Z}}_k'\tau_2, \end{aligned} \quad (2)$$

where $\tilde{\mathbf{Z}}_k$ is a subset of $\mathbf{Z}_k$, incorporates the interactions between the channel used and some demographic characteristics.

To enhance interpretability of coefficients and reduce numerical instability caused by the multicollinearity in interaction models (Afshartous and Preston, 2011), we use mean-centered transformations for all socio-demographic variables ($\mathbf{Z}_k$). β_1 captures the effect of using mobile information technologies for people in an average neighborhood, and

[14] Even though the Cox model is semi-parametric with unspecific baseline hazard and linear covariate terms, it can still be estimated by the method of partial likelihood (Cox, 1972).

τ_1 implies how smartphone app use changes the relative public service performance for different subpopulations. If the use of advanced technologies enhances complaint resolution for less educated people (i.e., τ_1 and μ have different signs), this suggests that app usage alleviates social inequality.

4.2 Initial Analysis

We initially focus on the 364,189 requests sent by citizens via phone calls, the self-service website or the Citizen Connect App. We pick "average years of education" as the variable of interest out of those socio-demographic variables $\mathbf{Z}_k$ since level of education is widely believed to affect a person's skills and inherent ability to advocate for themselves (Bresnahan et al., 2002). This has also been widely documented in healthcare. Both Zimmerman et al. (2015) and Berkman et al. (2011) suggest that more educated people received better healthcare service because education enhances their communication skills and ability to advocate for themselves. Willems et al. (2005) point out that higher patient educational levels are associated with better doctor-patient communication, which has a strong and positive influence on patients' satisfaction and compliance.

Panel A of Table 5 reports the estimation results of the Cox hazard model. Panel B of Table 5 reports an alternative specification which uses logistic regression where the dependent variable equals one if the case was recorded as being solved "on time" on the same set of regressors to investigate robustness to functional form. Column (1) in both panels presents the result of a regression that includes only $AverageYearsOfEducation_k$ as the independent variable. The case type controls X_i, the date controls Y_j and other socio-demographic controls Z_k are added into the model incrementally in Columns (2)-(3). Column (4) adds the variables $CitizenConnectApp_i, WebSubmission_i$ to the model to take the effect of submission channels into account. Interactions between the channel and the level of education are added to the model in Column (5).

The coefficient of $AverageYearsOfEducation_k$ is always significant and positive in Panel A of Table 5, and this is also true for the full logistic regression. It implies that people who submit complaints in neighborhoods with lower education levels experience longer waiting times for their complaints to be resolved – particularly, based on Column (5) of Panel A, cases submitted were $e^{0.022} - 1 = 2.2\%$ more likely to be completed at any time if the average level of education in the neighborhood increases by one year.[15] The coefficient of $CitizenConnectApp_i$ is significant and positive in Column (5) of Panel A but an insignificantly negative coefficient has been found in the same column of Panel B, while $WebSubmission_i$ always has a negative effect on the service performance. These results suggest that the mobile app improves the complaint resolution performance compared to traditional technologies such as phones (by $e^{0.033} - 1 = 3.4\%$ for an average neighborhood) and desktop computers (by $e^{0.033+0.119} - 1 = 16.4\%$ for an average neighborhood). Also, based on the results of the full logistic regression (Column (5) of Panel B), the app increases the probability that the complaint is resolved on time for all of the citizens who live in a neighborhood where the average years of education are more than $-0.023/-0.042 = 0.55$ years below the city-wide average level. Meanwhile, app use leads to relatively better service for people who submit complaints in neighborhoods with lower average education levels. This mitigating effect is supported by the significantly negative coefficient of the interaction term between $AverageYearOfEducation_i$ and $CitizenConnectApp_i$ in Column (5) of both panels – the effect of app use on the likelihood of case completion will decrease by $1 - e^{-0.011} = 1.1\%$ if there is a one-year increase in the average years of education in the neighborhood, while it does not hold for the self-service website.[16]

A natural concern when interpreting these results is multicollinearity, given the fact that socio-demographic variables are usually correlated with each other. In Table 4, we show

[15] This number is $e^{0.022-0.011} - 1 = 1.1\%$ for cases submitted via the app and $e^{0.022-0.003} - 1 = 1.9\%$ for cases submitted via the website.

[16] This decrease is $1 - e^{-0.042} = 4.1\%$ for the probability that the complaint is resolved on time.

the correlation matrix of all those socio-demographic variables at both group level (N=545, Panel A) and individual case level (N=364,189, Panel B). None of those correlation coefficients between $AverageYearsOfEducation_k$ and other socio-demographic controls Z_k has an absolute value higher than 0.7. Also, the variance inflation factor (VIF) of $AverageYearsOfEducation$ in Column (3) is 4.1, below the threshold of 10, indicating that multicollinearity is not a likely threat to the parameter estimation (Cohen et al., 2003).

We also examine the effect of the app use using the percentage of black people in the neighborhood, rather than the level of education, as the variable of interest. The results in Column (6) and (7) show that people who submit complaints in neighborhoods with larger black populations are disadvantaged in terms of public service and the use of the Citizen Connect App mitigates this inequality. The results may be stronger for improving equality in treatment across races[17] because the additional prejudice that black people may suffer during the complaint resolution process would be changed by the standardized communication provided by the app - since it won't reveal the skin of the person complaining.

Since this is both new, and somewhat complex, data which required us to make some judgment calls about how to structure it, we ran a battery of robustness checks to ensure that none of our judgment calls affected our results. First, we ran the same set of regressions but excluded cases in 46 smaller categories where there was no case has been submitted via the App.[18] The results in Table 6 are consistent with the main results, which

[17]With each increase of one standard deviation in average years of education, the effect of app use on the likelihood of case completion decreases by $1 - e^{-0.011} = 1.1\%$. While with each increase of one standard deviation in proportion of black people living in the neighborhood, this effect decreases by $1-e^{-0.128} = 12.0\%$.

[18]Those 46 reasons are: Administration, Administrative, Administrative & General Requests, Air Pollution Control, Alert Boston, Animal Issues, Billing, Boston Bikes, Bridge Maintenance, Building, Call Center Intake, Call Inquiry, Catchbasin, Cemetery, Check Investigation, Consumer Affairs Issues, Current Events, Disability, Employee & General Comments, Fire Department, Fire Hydrant, Generic Noise Disturbance, Health, Hero Square Sign, Investigations and Enforcement, MBTA, Massport, Metrolist, Neighborhood Services Issues, Noise Disturbance, Notification, Office of The Parking Clerk, Operations, Parking Complaints, Participatory Budgeting Idea Collection, Pothole, Programs, Recycling, Sidewalk Cover Manhole, Survey,

implies that the inclusion or exclusion of these smaller categories where the app is not used does not change our results.

We also wanted to check that the way we specified our key explanatory variable for average education level in that census block did not affect our results. Table 7 replicates the results in Column (5) in Panel A of Table 5 for a series of alternative independent variables that measure the education level in different ways. We use the original independent variable $AverageYearsOfEducation_k$ in Column (1), the log of average years of education in Column (2), the percentage of people in neighborhoods with high school diploma and above in Column (3), the percentage of people with some college education (stay at least 2 years in college) and above in Column (4), the percentage of people with a bachelor's degrees and above in Column (5), and the percentage of people who attended graduate school in Column (6). The results in this table reinforce the previous conclusion – we see the same signs in all columns. The coefficient of the education level decreases from Column (3) to Column (5) while the absolute value of the interaction term increases from Column (4) to Column (6).[19] Those trends suggest that the higher the degree is, the less important the skills gained during it are to the complaint resolution and the easier its effect is to be mitigated by digital technologies. A similar replication of the results in Column (5) in Panel B of Table 5 is shown in Table 8.

5 Mechanism: Standardized Communication

We then turn to investigate the mechanism behind our key result which is that the use of the app appears to mitigate the influence of education on complaint resolution time.

Test Cases, Traffic Management & Engineering, Valet, Volunteer & Corporate Groups, Water Issues, Weights and Measures.

[19] A series of Z-tests shows that the decrease in the coefficient of the education level is significant at the $\alpha = 0.1$ level from Column (4) to Column (5) and the increase in the absolute value of the interaction term is significant at the $\alpha = 0.1$ level from Column (5) to Column (6).

5.1 Standardization of Case Locating

One potential way the app may be able to mitigate the influence of communication skills and education on complaint resolution time, is simply by making it easier for the city worker to find the issue geographically. Unlike the phone and cellphone channels, the app has the feature that it makes it easier to pinpoint where precisely the issue is. Ordinarily, for the phone and cellphone channels this may not be an issue simply because a street address or intersection will suffice to geographically place the problem. However, with highways it is not so easy to geographically pinpoint a location simply because there are generally no street addresses and infrequent intersections to help highlight an issue. Therefore to successfully pinpoint an issue with a highway may take quite a complex description. Such cases are where the ability of the app to use GPS to pinpoint a precise location may be very helpful for people who are less able to communicate a complex location.

Consistent with this, we find that the app improves complaint resolution time especially for less educated people in particular for highways: Column (2) of Table 9 shows that the mobile app improves the likelihood of case completion for a highway maintenance case by $e^{0.200} - 1 = 22.1\%$ times to phones for an average neighborhood, and this effect of app use on the likelihood of case completion will decrease by $1 - e^{-0.025} = 2.5\%$ times if there is a one-year increase in the average years of education in the neighborhood. Those effects are larger than the average effects showed in Column (1) with the full dataset, which confirms that the app contributes to a more efficient complaint resolution by standardizing those complicated communication. It is notable that in general the app does not work that effectively for submitting highway complaints as they have on average a slower resolution time than non-highway complaint resolution times when submitted by the app - perhaps, speculatively, because users find it hard to use the app in busy traffic in a highway context successfully. In contrast, the results in Column (3) of Table 9 for non-highway related cases, the app does not reduce the gap between educated-and less educated people's complaint time resolution as successfully.

5.2 Standardization of Case Description

As a corollary to this evidence that the automation of data input is most beneficial when it is difficult to describe location, it is possible too that the app may substitute for communication for complex cases more generally. We investigate this in Figure Table 9. One hypothesis is that case complexity may be related to its title length. And that as case complexity increases then the case is more difficult to describe and needs more communication. Figure 9 plots the distribution of title lengths. There are 213,438 cases with short titles (if the title contains 25 characters or less) and 150,751 cases with long titles (if the title contains more than 25 characters). Title length is more evenly distributed in the written channel while the representatives tend to write down a very short or a very long title during the phone call, however, the proportion of the cases where the title lengths are below (or above) the bar remain stable across those channels. Column (4) of Table 9 presents the estimates for the cases submitted with long titles, while Column (5) of the same table presents the estimates for the cases submitted with short titles. The results in Column (4) are consistent with our main results with the full dataset (in Column (1)). The mobile app improves on the likelihood of case completion with a long title by $e^{0.178} - 1 = 19.5\%$ times to phones for an average neighborhood, and this effect of app use on the likelihood of case completion will decrease by $1 - e^{-0.041} = 4.0\%$ times if there is a one-year increase in the average years of education in the neighborhood. However, neither the app nor the website is effective in reducing complaint resolution time for cases with short titles and the app does not help less educated census blocks in this case. The comparison between Column (4) and (5) suggests that the app eases complex case description for those who live in less educated areas.

Another hypothesis is that the ability of the app to convey visual information in the form of photos also substituted for the need for communication skills. To investigate this we examine the cases submitted by the app which included photos (photos are only conveyable through the app) and compare them to cases that did not include a photo. 35.4% cases submitted with the app included photos. Therefore, we substituted the indicator $CitizenConnectApp_i$ with an indicator for $Photo_i$, a binary variable indicating whether the case submission includes a photo in the model.[20]

Column (6) of Table 9 presents estimates for the subset of cases submitted with long titles, and Column (7) of Table 9 presents the estimates for the subset of cases submitted with short titles. The pattern observed in the above subgroup analysis is similar in the new model – the attached photos mitigate the social inequality by decreasing the likelihood of long-title case completion by $1 - e^{-0.047} = 4.6\%$ times for a one-year increase in the neighborhood-wide average level of education while there is an insignificant increase in the hazard rate for cases with short titles. Even this mitigating effect is not significant with the full dataset, we can still claim that the app improves the efficiency of complaint resolution by allowing those who live in less educated areas to upload the photos that can substitute accurate case descriptions.

In conclusion, we find that the use of mobile information technology appears to reduce inequality by providing a standardized communication tool that substitutes for the need to communicate and have this communication appropriately recorded in complicated cases. Similar results are reported for the percentage of black people in the census block in Table 10.

[20] A photo can be attached only when the case is submitted via the app, i.e., $CitizenConnectApp_i \leq Photo_i$ always holds.

6 Endogeneity of App Adoption: The Digital Divide

Adoption of information technology is not equally distributed across the population. This "digital divide" has been discussed for a long time. Evidence shows that more educated and high-income people are more likely to adopt Internet technologies (Chinn and Fairlie, 2007; Goldfarb and Prince, 2008).

One concern this raises is that there is likely to be uneven adoption of the app across census blocks which may affect the measurement of the treatment effect. To deal with this concern we use a potential outcomes approach to appropriately adjust our measured treatment effects. These results are discussed in detail in the appendix.

However, an even more serious concern is that even within a census block there may be differences in the people who use the app and the people who don't. To address this, we turn to instrumental variables.

6.1 Using Instrumental Variables To Address Endogeneity

Given uneven app adoption within census block groups, there may be concerns over endogeneity of adoption within a census block. First, people who adopt the app might be the ones that really care about public service and are aware of the app launch. Those people may get better service because they are more likely to track the case and complain again and again until the problem is solved. Second, according to Buell et al. (2017), people who adopt an app are more likely to be the ones who had a better experience with the app. Finally, since all of our controls and measures of education are at census block level, there is the possibility that the app may be used by the more educated people within that census block and that this selection is the effect we are measuring.

To address these potential endogeneity issues, we instrument the use of mobile devices with different proxies of cellular signal strength. There is reason to think that the quality of cellular signal will affect usage of the mobile app – people will not be able to use the app when the signal is very weak, even if they wished to do so.

For our first instrument we use the geographic distance to the closest cell tower of the complaint. The idea is that if cell phone towers are reasonably randomly distributed across Boston, then this will affect mobile app usage but will not directly affect complaint resolution time.

Based on the records found on antennasearch.com, we identify 599 cell towers located in the city of Boston and its surroundings. Even though only 84 out of them are registered officially, we take all of these 599 towers into account given the fact that many non-registered ones are owned by wireless carriers like Sprint and Verizon Wireless.

A natural question is whether the closest cell tower of the complaint is a good proxy of cellular signal strength. To address this, we collected data at 19 randomly chosen places and found that there is a statistically significant negative relationship between the distance to the closest cell tower and the upload speed (r=-0.524).[21] The correlation check results shown in Table 11 suggest that the upload speed increases 0.03 Mbps when it is 1 meter closer to the closest cell tower even with taking the census group fixed effects into account.

Another key question is whether this instrument meets the exclusion restriction which requires that the location of the cell phone tower be unrelated to any underlying geographic features which might also explain complaint resolution time. In an old city such as Boston, cell towers are attached to existing tall buildings like church towers. The number of tall buildings is further restricted by building codes, which mean that the presence (or absence) of tall buildings is related to the social geography of Boston many

[21] The t-statistics, which is calculated to test the alternative hypothesis that the correlation coefficient is significantly different from zero, is -2.540, with a p-value of 0.021.

decades prior to the present. In Boston the historical pattern of settlement by different socio-economic groups in Boston has changed over time, meaning that the presence of historic "tall" buildings is not related strongly to neighborhood wealth. The difference between the distribution of the education level (Panel A of Figure 10) and that of distance to the closest tower (Panel B of Figure 10) provides supportive evidence for this.

For every request in our dataset, we calculated the geographic distance to all cell towers according to the coordinate of a case. The average minimum distance is 563 meters with a standard deviation of 398 meters. The case closest to a cell tower is 3 meters away, while the distance between the farthest case from a tower and its closest tower is about 2,219 meters. Column (3) and (4) of Table 12 show 2SLS estimates where mobile app use is instrumented with the distance to the closest cell tower and its square, which estimate cellular signal strength according to the geographic location. The dependent variable in this model is the same "on time" indicator as the one used in Panel B of Table 5. Comparing to the marginal effects at means from the original logit estimates reported in Column (1) and (2) of Table 12, the LATEs are similar in sign but are larger in magnitude – now the effect of app use will increase by 4.4% if there is a one-year decrease in the education level of the neighborhood. One possible explanation for this is that we are looking at the narrow effect of app-use in cases where the ability to have signal strength is a factor in the use of the mobile app, so we are overconfident in the effect of the app use itself and the mitigating effect of it has been underestimated in the model with endogenous app adoption. It is also possible that people whose app-use behavior can be switched by the mobile signal constraint are those people who don't have other access to digital technologies, like WIFI at home or workspace. With little exposure to digital technologies, they are more likely to experience difficulties in using the app while the app can still substitute the important communication skills correlated with education. The first stage for Column (3) is reported in Column (1) of Table 13 and the first stages for Column (4) are shown in Column (2) and (3) of the same table. All test statistics suggest that indeed the first stage results for the instrument are strong: the probability of submitting a case via the mobile app increases more than 5% when the case is located one kilometer closer to a cell tower. It is reasonable that the signal becomes stronger and more stable when it is closer to a cell tower and the loss in signal quality diminishes with the distance.

As an alternative but complementary instrument we also use whether a city worker used a mobile to submit a complaint in the same location. The idea here is that if signal strength is an issue, the worker would not have been able to use the mobile app easily at that location either. As we have seen in Figure 7, employees' interests do not align with citizens' actions, and display a different relationship between more and less educated neighborhoods than do citizens' complaint patterns. So these decisions should not be correlated with the efficiency of complaint handling except via the same constraint on digital usage, which is mobile signal availability. To find the most similar employee-generated case, we calculate the Mahalanobis distance between every citizen-generated case and employee-generated case in the same census tract based on the location. We report these 2SLS estimates, where mobile app usage for a similarly located employee-generated case is used as the instrument in Column (5) and (6) of Table 12. The LATEs keep the same sign and are closer to the marginal effects at means shown in Column (1) and (2) of the same table in terms of magnitude. We report the first stage for Column (5) in Column (4) of Table 13 and the first stages for Column (6) in Column (5) and (6) of the same table. As the previous case, the test statistics suggest that the first stage of the instrument is strong and that the employee submission channel is a good predictor of citizens' behavior – the probability of submitting a case via the app increases about 2% when the closest case reported by an employee is submitted via the mobile channel. Based on the plots in Panel A and C of Figure 10, we can also infer that the app use of employees doesn't depend on the education level in the neighborhood.

7 Conclusion

In this study, we investigate the extent to which technology can help reduce inequality in the resolution of customer complaints. Using extensive data from non-emergency complaints issued about public services, we show that for older technologies such as phone calls, complaint resolution tends to be slower for people living in neighborhoods with less educated people. We show that this inequality is mitigated by the use of newer technologies such as mobile apps which help consumers more accurately describe and locate their complaint. Since there are endogeneity concerns surrounding the adoption of new mobile technologies, we confirm this finding using instrumental variables and exogenous variation in mobile app adoption which can be explained by differences in cell phone signal.

These results matter because usually policy makers and firms might fear that promoting new technologies would lead them to be less inclusive. However, our results show that in our setting mobile communication technologies can actually mitigate potential inequality in the treatment of customers by standardizing communication. It can be generalized to other types of new technology which ease personal interactions by boosting standardized communication. A great example is the menu-based in-app customer complaint resolution system, which fully automates the communication in the app by analyzing keywords and doesn't require any human interaction.[22]

There are of course limitations to our study. First, we do not have individual customer data on levels of education and instead infer education from the surrounding census block. Second, since this is a public service setting, we are not able to relate our findings to individual customer profitability. Last, we do not know how the availability of a mobile app changed the likelihood of a complaint being reported. Notwithstanding these

[22]See *Uber's Customer Support is about to Get a Lot Better*: `http://www.businessinsider.com/uber-beefs-up-customer-support-in-app-2016-3`.

limitations, we feel our study is a useful first step in understanding how technology can alter inequality in the complaint resolution process.

A Appendix

A.1 Conditional Treatment Effects

One other concern about our estimates, is that app use is not consistently distributed across census blocks. In this section, we use a potential outcomes approach to address this measurement issue.

Panel A of Figure 11 shows that a higher proportion of cases are sent via the app in neighborhoods with higher education levels and the same pattern for the adoption of the self-service website, even the trends on education levels are not monotone. Similar but monotone patterns on race can be observed in Panel B of the same figure: A higher proportion of cases are sent via the app (or the website) where there are larger white populations.

Rubin (1977) suggests that if assignment to treatment group is made based only on the value of a covariate, then averaging conditional treatment effects over the distribution of those covariates will give a valid estimate of the treatment effect and any other sources of bias are ignorable. Therefore, if we believe that the treatment assignment (app adoption) is different among census block groups but uniform within each group, then the treatment effect calculated for each census block group should be valid and show the causality. This assumption might be realistic: (1) The census block group is small in size – on average there are only 1160 people in a block group; (2) socio-demographic characteristics that affect the app adoption most significantly, such as education and income, vary dramatically among block groups but slightly within block groups; (3) socio-demographic characteristics that vary within block groups, like age and gender, matter less for advanced technologies' adoption than for the adoption of traditional technology (Chinn and Fairlie, 2007).

Therefore, we calculate the conditional treatment effect for each census block using a Cox proportional hazard model with only the case type controls X_i and the date controls Y_j. The effect of the Citizen Connect App use and that of the self-service website use – conditional on average years of education and the percentage of black people – are shown in Figure 12. The results are consistent with our main results: Use of the app improves the complaint resolution performance to some extent while website use does not; Use of the app helps less educated or historically discriminated groups (people submitting complaints in neighborhoods with lower education levels and larger black populations). Surprisingly, we notice that the mitigating effect of the app is not monotonic in Figure 12 and the app amplifies the disadvantages of people with fewer than 13 years of education and that of people who live in a neighborhood where more than half of the population is black. One interpretation is that using the app competently does require a baseline level of skills.

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Table 1: Types of Cases

Case Type	Freq.	Percent	Cum. Percent
Sanitation	109,501	23.56	23.56
Street Cleaning	98,090	21.11	44.67
Highway Maintenance	65,052	14.00	58.67
Street Lights	26,898	5.79	64.46
Recycling	26,684	5.74	70.20
Signs & Signals	25,558	5.50	75.70
Trees	22,063	4.75	80.45
Housing	16,769	3.61	84.06
Graffiti	14,515	3.12	87.18
Building	13,814	2.97	90.16
Enforcement & Abandoned Vehicles	12,202	2.63	92.78
Environmental Services	10,285	2.21	95.00
Administrative & General Requests	5,944	1.28	96.28
Notification	3,655	0.79	97.06
Park Maintenance & Safety	2,464	0.53	97.59
Health	2,215	0.48	98.07
Catch Basin	1,450	0.31	98.38
Employee & General Comments	1,388	0.30	98.68
Traffic Management & Engineering	1,296	0.28	98.97
Operations	1,203	0.26	99.22
Sidewalk Cover Manhole	724	0.16	99.37
Abandoned Bicycle	664	0.14	99.52
Fire Hydrant	591	0.13	99.64
General Request	320	0.07	99.71
Code Enforcement	259	0.06	99.77
Weights and Measures	237	0.05	99.82
Water Issues	168	0.04	99.85
Needle Program	150	0.03	99.89
Programs	92	0.02	99.91
Animal Issues	91	0.02	99.93
Pothole	77	0.02	99.94
Bridge Maintenance	54	0.01	99.95
Billing	42	0.01	99.96
Boston Bikes	41	0.01	99.97
Parking Complaints	38	0.01	99.98
Fire Department	23	0.00	99.99
Valet	18	0.00	99.99
Office of The Parking Clerk	8	0.00	99.99
Air Pollution Control	7	0.00	99.99
Volunteer & Corporate Groups	7	0.00	99.99
Noise Disturbance	6	0.00	100.00
Administrative	5	0.00	100.00
Disability	4	0.00	100.00
Cemetery	3	0.00	100.00
Generic Noise Disturbance	3	0.00	100.00
Investigations and Enforcement	2	0.00	100.00
Call Center Intake	1	0.00	100.00
Consumer Affairs Issues	1	0.00	100.00
Metrolist	1	0.00	100.00
Total	464,683	100.00	100.00

Table 2: Summary of Demographic Variables

Variable	Mean	Std. Dev.	Min.	Max.
#Population	1160.191	526.878	13	3716
#Households	460.927	224.634	4	1424
Gender				
%Male	0.476	0.083	0.097	0.76
%Female	0.524	0.083	0.24	0.903
Age				
%< 18 years old	0.167	0.105	0	0.489
%18 - 29 years old	0.282	0.188	0	0.97
%30 - 44 years old	0.222	0.093	0	0.615
%45 - 59 years old	0.17	0.078	0	0.438
%≥ 60 years old	0.159	0.102	0	0.903
Race				
%White	0.537	0.317	0	1
%Black	0.257	0.297	0	1
%Asian	0.088	0.117	0	0.885
%Other Single Race	0.076	0.105	0	0.538
%Multiple Races	0.043	0.067	0	0.498
Education				
%Less than High school	0.146	0.13	0	0.583
%High School Diploma	0.225	0.137	0	0.844
%Some College	0.142	0.084	0	0.46
%Bachelor Degree	0.287	0.143	0	0.725
%Graduate School	0.199	0.166	0	0.781
Average Years of Education	13.763	1.857	8.505	17.781
Language				
%English Only	0.635	0.196	0	1
%Spanish	0.153	0.152	0	0.678
%Bilingual	0.248	0.13	0	0.697
%Limited English Speaking	0.117	0.132	0	1
Income				
Poverty Ratio for Households	0.217	0.168	0	1
Housing Status				
%Owner-occupied	0.358	0.24	0	1
%Renter-occupied	0.642	0.24	0	1
%Living in Same House 1 Year Ago	0.795	0.144	0.19	1
%Living in Greater Boston Area 1 Year Ago	0.142	0.098	0	0.788
%Living Abroad 1 Year Ago	0.017	0.031	0	0.188

Note: Observations = 545 and there is one observation for each block group.

Table 3: Summary of Covariates

	Category	Covariates
$\mathbf{X}_i$	case	case type (reason)
$\mathbf{Y}_j$	time	year, season, weekday
$\mathbf{Z}_k$	block group	gender, age, race, language, income, housing status, education*

* All of those demographic variables are measured at block group level.

Table 4: Correlation Matrix

Panel A: Census Block Level

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1 Average Years of Education	1.00																
2 %Male	-0.03	1.00															
3 %< 18 years old	-0.57	-0.17	1.00														
4 %18 - 29 years old	0.37	0.03	-0.63	1.00													
5 %30 - 44 years old	0.14	0.18	0.08	-0.39	1.00												
6 %45 - 59 years old	-0.24	0.07	0.25	-0.61	-0.03	1.00											
7 %White	0.68	0.07	-0.58	0.27	0.14	-0.20	1.00										
8 %Black	-0.52	-0.11	0.54	-0.32	-0.14	0.25	-0.87	1.00									
9 %Asian	0.07	0.01	-0.23	0.25	-0.11	-0.16	-0.00	-0.33	1.00								
10 %Other Single Race	-0.44	-0.03	0.40	-0.15	-0.03	0.03	-0.50	0.21	-0.12	1.00							
11 %English Only	0.61	-0.05	-0.28	-0.01	0.12	0.08	0.50	-0.17	-0.27	-0.50	1.00						
12 %Spanish	-0.60	0.05	0.43	-0.17	0.03	0.05	-0.41	0.22	-0.23	0.57	-0.68	1.00					
13 %Limited English Speaking	-0.57	0.02	0.15	-0.01	-0.11	-0.09	-0.32	0.03	0.31	0.30	-0.75	0.48	1.00				
14 Poverty Ratio for Households	-0.36	-0.15	0.17	0.30	-0.40	-0.26	-0.44	0.27	0.22	0.28	-0.48	0.32	0.45	1.00			
15 %Owner-occupied	0.28	0.06	0.04	-0.44	0.21	0.41	0.30	-0.12	-0.26	-0.23	0.47	-0.34	-0.44	-0.70	1.00		
16 %Living in Greater Boston Area 1 Year Ago	0.18	0.04	-0.36	0.49	-0.09	-0.37	0.15	-0.17	0.09	-0.07	-0.01	-0.07	0.04	0.14	-0.31	1.00	
17 %Living Abroad 1 Year Ago	0.17	-0.01	-0.27	0.44	-0.18	-0.29	0.08	-0.17	0.27	-0.04	-0.14	-0.06	0.11	0.18	-0.23	0.20	1.00

Panel B: Individual Case Level

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1 Average Years of Education	1.00																
2 %Male	-0.00	1.00															
3 %< 18 years old	-0.53	-0.27	1.00														
4 %18 - 29 years old	0.30	0.13	-0.61	1.00													
5 %30 - 44 years old	0.22	0.14	-0.01	-0.34	1.00												
6 %45 - 59 years old	-0.21	0.02	0.23	-0.59	-0.08	1.00											
7 %White	0.70	0.10	-0.56	0.23	0.23	-0.19	1.00										
8 %Black	-0.54	-0.12	0.53	-0.27	-0.23	0.23	-0.88	1.00									
9 %Asian	0.03	-0.02	-0.20	0.19	-0.09	-0.10	-0.03	-0.28	1.00								
10 %Other Single Race	-0.45	-0.02	0.36	-0.12	-0.07	0.04	-0.53	0.26	-0.12	1.00							
11 %English Only	0.66	-0.03	-0.29	0.02	0.15	0.04	0.55	-0.24	-0.27	-0.51	1.00						
12 %Spanish	-0.60	0.02	0.40	-0.15	-0.02	0.05	-0.44	0.25	-0.21	0.55	-0.69	1.00					
13 %Limited English Speaking -0.61	0.02	0.15	-0.02	-0.13	-0.06	-0.37	0.08	0.32	0.33	-0.77	0.50	1.00					
14 Poverty Ratio for Households -0.41	-0.12	0.16	0.29	-0.42	-0.22	-0.48	0.34	0.19	0.29	-0.49	0.33	0.47	1.00				
15 %Owner-occupied 0.30	-0.03	0.10	-0.47	0.18	0.40	0.30	-0.16	-0.21	-0.21	0.44	-0.32	-0.43	-0.66	1.00			
16 %Living in Greater Boston Area 1 Year Ago	0.14	0.22	-0.39	0.51	-0.00	-0.33	0.13	-0.13	0.03	-0.03	-0.02	-0.05	0.01	0.14	-0.35	1.00	
17 %Living Abroad 1 Year Ago	0.12	0.08	-0.21	0.38	-0.13	-0.25	0.08	-0.16	0.18	-0.00	-0.14	-0.01	0.10	0.15	-0.20	0.20	1.00

Notes: For Panel A, observations=545 and there is one observation for each block group. For Panel B, observations=364,189 and there is one observation for each case.

Table 5: Effects on the Completion Time of 311 Cases

Panel A: Cox Proportional Hazards Model

	(1) Hazards	(2) Hazards	(3) Hazards	(4) Hazards	(5) Hazards	(6) Hazards	(7) Hazards
Average Year of Education	0.008***	0.013***	0.019***	0.020***	0.022***		
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)		
Citizen Connect App				0.027***	0.033***	0.027***	0.039***
				(0.006)	(0.006)	(0.006)	(0.007)
Web Submission				-0.119***	-0.119***	-0.119***	-0.121***
				(0.005)	(0.005)	(0.005)	(0.005)
Average Years of Education					-0.011***		
× Citizen Connect App					(0.003)		
Average Years of Education					-0.003		
× Web Submission					(0.003)		
%Black						-0.053***	-0.054***
						(0.009)	(0.010)
%Black							0.128***
× Citizen Connect App							(0.025)
%Black							-0.027
× Web Submission							(0.017)
Year Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Season Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Weekday Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Reason Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Gender Fixed Effects	No	No	Yes	Yes	Yes	Yes	Yes
Age Fixed Effects	No	No	Yes	Yes	Yes	Yes	Yes
Race Fixed Effects	No	No	Yes	Yes	Yes	No	No
Language Fixed Effects	No	No	Yes	Yes	Yes	Yes	Yes
Income Fixed Effects	No	No	Yes	Yes	Yes	Yes	Yes
Housing Status Fixed Effects	No	No	Yes	Yes	Yes	Yes	Yes
Education Fixed Effects	No	No	No	No	No	Yes	Yes
Observations	364,189	364,189	364,189	364,189	364,189	364,189	364,189
AIC	8,598,758	8,523,767	8,523,578	8,522,798	8,522,787	8,522,815	8,522,789

Panel B: Logistic Regression

	(1) On-Time	(2) On-Time	(3) On-Time	(4) On-Time	(5) On-Time	(6) On-Time	(7) On-Time
Average Years of Education	0.002	0.006**	0.005	0.007	0.020***		
	(0.002)	(0.003)	(0.005)	(0.005)	(0.006)		
Citizen Connect App				-0.040***	-0.023	-0.036**	-0.009
				(0.014)	(0.015)	(0.014)	(0.015)
Web Submission				-0.405***	-0.400***	-0.404***	-0.406***
				(0.014)	(0.014)	(0.014)	(0.014)
Average Years of Education					-0.042***		
× Citizen Connect App					(0.007)		
Average Years of Education					-0.027***		
× Web Submission					(0.008)		
%Black						-0.160***	-0.186***
						(0.027)	(0.028)
%Black							0.344***
× Citizen Connect App							(0.061)
%Black							0.026
× Web Submission							(0.054)
Year Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Season Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Weekday Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Reason Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Gender Fixed Effects	No	No	Yes	Yes	Yes	Yes	Yes
Age Fixed Effects	No	No	Yes	Yes	Yes	Yes	Yes
Race Fixed Effects	No	No	Yes	Yes	Yes	No	No
Language Fixed Effects	No	No	Yes	Yes	Yes	Yes	Yes
Income Fixed Effects	No	No	Yes	Yes	Yes	Yes	Yes
Housing Status Fixed Effects	No	No	Yes	Yes	Yes	Yes	Yes
Education Fixed Effects	No	No	No	No	No	Yes	Yes
Observations	364,189	364,189	364,189	364,189	364,189	364,189	364,189
AIC	397,523	277,617	277,394	276,550	276,614	276,554	276,523

Notes: The population variable is cases. A hazard model for the completion time is used in Panel A and the dependent variable in Panel B is the "on-time" indicator. Standard errors are in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Effects on the Completion Time of 311 Cases (Selected Reasons)

Panel A: Cox Proportional Hazards Model

	(1) Hazards	(2) Hazards	(3) Hazards	(4) Hazards	(5) Hazards	(6) Hazards	(7) Hazards
Average Year of Education	0.005***	0.012***	0.026***	0.027***	0.032***		
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)		
Citizen Connect App				0.012**	0.019***	0.011*	0.024***
				(0.006)	(0.006)	(0.006)	(0.007)
Web Submission				-0.162***	-0.160***	-0.162***	-0.162***
				(0.005)	(0.005)	(0.005)	(0.005)
Average Years of Education					-0.015***		
× Citizen Connect App					(0.003)		
Average Years of Education					-0.011***		
× Web Submission					(0.003)		
%Black						-0.043***	-0.051***
						(0.010)	(0.010)
%Black							0.145***
× Citizen Connect App							(0.025)
%Black							0.016
× Web Submission							(0.018)
Year Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Season Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Weekday Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Reason Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Gender Fixed Effects	No	No	Yes	Yes	Yes	Yes	Yes
Age Fixed Effects	No	No	Yes	Yes	Yes	Yes	Yes
Race Fixed Effects	No	No	Yes	Yes	Yes	No	No
Language Fixed Effects	No	No	Yes	Yes	Yes	Yes	Yes
Income Fixed Effects	No	No	Yes	Yes	Yes	Yes	Yes
Housing Status Fixed Effects	No	No	Yes	Yes	Yes	Yes	Yes
Education Fixed Effects	No	No	No	No	No	Yes	Yes
Observations	310,736	310,736	310,736	310,736	310,736	310,736	310,736
AIC	7,238,089	7,173,426	7,173,141	7,171,958	7,171,928	7,172,004	7,171,976

Panel B: Logistic Regression

	(1) On-Time	(2) On-Time	(3) On-Time	(4) On-Time	(5) On-Time	(6) On-Time	(7) On-Time
Average Years of Education	-0.007***	-0.002	0.005	0.007	0.020***		
	(0.002)	(0.003)	(0.006)	(0.006)	(0.006)		
Citizen Connect App				-0.024	-0.010	-0.020	0.004
				(0.015)	(0.015)	(0.015)	(0.016)
Web Submission				-0.447***	-0.442***	-0.447***	-0.450***
				(0.015)	(0.015)	(0.015)	(0.015)
Average Years of Education					-0.037***		
× Citizen Connect App					(0.007)		
Average Years of Education					-0.029***		
× Web Submission					(0.009)		
%Black						-0.129***	-0.152***
						(0.029)	(0.030)
%Black							0.288***
× Citizen Connect App							(0.062)
%Black							0.011
× Web Submission							(0.058)
Year Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Season Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Weekday Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Reason Fixed Effects	No	Yes	Yes	Yes	Yes	Yes	Yes
Gender Fixed Effects	No	No	Yes	Yes	Yes	Yes	Yes
Age Fixed Effects	No	No	Yes	Yes	Yes	Yes	Yes
Race Fixed Effects	No	No	Yes	Yes	Yes	No	No
Language Fixed Effects	No	No	Yes	Yes	Yes	Yes	Yes
Income Fixed Effects	No	No	Yes	Yes	Yes	Yes	Yes
Housing Status Fixed Effects	No	No	Yes	Yes	Yes	Yes	Yes
Education Fixed Effects	No	No	No	No	No	Yes	Yes
Observations	310,736	310,736	310,736	310,736	310,736	310,736	310,736
AIC	337,633	241,265	241,024	240,107	240,081	240,111	240,093

Notes: The population variable is cases. A hazard model for the completion time is used in Panel A and the dependent variable in Panel B is the "on-time" indicator. Standard errors are in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Effect of Education: Alternative Independent Variables

	(1) Hazards	(2) Hazards	(3) Hazards	(4) Hazards	(5) Hazards	(6) Hazards
Citizen Connect App	0.033***	0.032***	0.031***	0.032***	0.038***	0.037***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Web Submission	-0.119***	-0.119***	-0.117***	-0.119***	-0.119***	-0.119***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Average Years of Education	0.022***					
	(0.002)					
Average Years of Education	-0.011***					
× Citizen Connect App	(0.003)					
Average Years of Education	-0.003					
× Web Submission	(0.003)					
In(Average Years of Education)		0.291***				
		(0.027)				
In(Average Years of Education)		-0.128***				
× Citizen Connect App		(0.038)				
In(Average Years of Education)		-0.039				
× Web Submission		(0.035)				
%High School and Above			0.206***			
			(0.025)			
%High School and Above			-0.089**			
× Citizen Connect App			(0.042)			
%High School and Above			-0.067*			
× Web Submission			(0.039)			
%Some College and Above				0.171***		
				(0.016)		
%Some College and Above				-0.080***		
× Citizen Connect App				(0.024)		
%Some College and Above				-0.025		
× Web Submission				(0.021)		
%Bachelor and Above					0.136***	
					(0.014)	
%Bachelor and Above					-0.112***	
× Citizen Connect App					(0.020)	
%Bachelor and Above					-0.011	
× Web Submission					(0.017)	
%Graduate School						0.154***
						(0.018)
%Graduate School						-0.181***
× Citizen Connect App						(0.032)
%Graduate School						-0.047*
× Web Submission						(0.028)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Season Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Weekday Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Reason Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Gender Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Age Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Race Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Language Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Income Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Housing Status Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	364,189	364,189	364,189	364,189	364,189	364,189
AIC	8,522,787	8,522,795	8,522,848	8,522,796	8,522,805	8,522,827

Notes: The population variable is cases and a hazard model for the completion time is used. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Effect of Education: Alternative Independent Variables (Logit Regressions)

	(1) On-Time	(2) On-Time	(3) On-Time	(4) On-Time	(5) On-Time	(6) On-Time
Citizen Connect App	-0.022	-0.024	-0.032**	-0.022	-0.010	-0.017
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Web Submission	-0.401***	-0.401***	-0.402***	-0.400***	-0.400***	-0.399***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Average Years of Education	0.020***					
	(0.006)					
Average Years of Education	-0.042***					
× Citizen Connect App	(0.007)					
Average Years of Education	-0.027***					
× Web Submission	(0.008)					
In(Average Years of Education)		0.292***				
		(0.078)				
In(Average Years of Education)		-0.541***				
× Citizen Connect App		(0.097)				
In(Average Years of Education)		-0.347***				
× Web Submission		(0.107)				
%High School and Above			0.306***			
			(0.073)			
%High School and Above			-0.440***			
× Citizen Connect App			(0.107)			
%High School and Above			-0.285**			
× Web Submission			(0.118)			
%Some College and Above				0.114**		
				(0.046)		
%Some College and Above				-0.320***		
× Citizen Connect App				(0.060)		
%Some College and Above				-0.217***		
× Web Submission				(0.065)		
%Bachelor and Above					0.016	
					(0.041)	
%Bachelor and Above					-0.344***	
× Citizen Connect App					(0.050)	
%Bachelor and Above					-0.176***	
× Web Submission					(0.053)	
%Graduate School						0.095*
						(0.051)
%Graduate School						-0.498***
× Citizen Connect App						(0.080)
%Graduate School						-0.361***
× Web Submission						(0.086)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Season Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Weekday Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Reason Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Gender Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Age Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Race Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Language Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Income Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Housing Status Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	364,189	364,189	364,189	364,189	364,189	364,189
AIC	276,514	276,516	276,528	276,522	276,499	276,506

Notes: The population variable is cases and the dependent variable is the "on-time" indicator. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Mechanism

	(1) Full	(2) Highway	(3) Non-Highway	(4) Long Title	(5) Short Title	(6) Long Title	(7) Short Title
Average Years of Education	0.022***	0.020***	0.020***	0.034***	0.003	0.034***	0.002
	(0.002)	(0.007)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Citizen Connect App	0.033***	0.200***	-0.106***	0.178***	-0.197***		
	(0.006)	(0.013)	(0.007)	(0.011)	(0.008)		
Average Years of Education	-0.011***	-0.025***	-0.009***	-0.041***	0.006*		
× Citizen Connect App	(0.003)	(0.007)	(0.003)	(0.005)	(0.004)		
Photo					-0.017	-0.171***	
					(0.015)	(0.012)	
Average Years of Education					-0.047***	0.008	
× Photo					(0.007)	(0.006)	
Web Submission	-0.119***	-0.020	-0.136***	0.185***	-0.388***	0.167***	-0.369***
	(0.005)	(0.019)	(0.005)	(0.008)	(0.007)	(0.008)	(0.007)
Average Years of Education	-0.003	-0.024**	-0.003	-0.009**	0.014***	-0.010**	0.016***
× Web Submission	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Season Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weekday Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Reason Fixed Effects	Yes	No	Yes	Yes	Yes	Yes	Yes
Gender Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Race Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Language Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Income Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Housing Status Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	364,189	33,751	330,438	150,751	213,438	150,751	213,438

Notes: The population variable is cases and a hazard model for the completion time is used. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$,*** $p < 0.01$.

Table 10: Mechanism: Race

	(1) Full	(2) Highway	(3) Non-Highway	(4) Long Title	(5) Short Title	(6) Long Title	(7) Short Title
%Black	-0.054***	-0.010	-0.077***	-0.059***	-0.020	-0.052***	-0.008
	(0.010)	(0.036)	(0.010)	(0.014)	(0.013)	(0.014)	(0.013)
Citizen Connect App	0.039***	0.212***	-0.103***	0.174***	-0.190***		
	(0.007)	(0.014)	(0.008)	(0.011)	(0.009)		
%Black	0.128***	0.248***	0.084***	0.242***	0.023		
× Citizen Connect App	(0.025)	(0.056)	(0.029)	(0.042)	(0.032)		
Photo						-0.037**	-0.162***
						(0.016)	(0.013)
%Black						0.164**	0.036
× Photo						(0.065)	(0.055)
Web Submission	-0.121***	-0.015	-0.138***	0.186***	-0.393***	0.168***	-0.373***
	(0.005)	(0.019)	(0.005)	(0.008)	(0.007)	(0.008)	(0.007)
%Black	-0.027	0.216***	-0.029*	0.043	-0.156***	0.057**	-0.178***
× Web Submission	(0.017)	(0.077)	(0.017)	(0.028)	(0.021)	(0.028)	(0.021)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Season Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weekday Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Reason Fixed Effects	Yes	No	Yes	Yes	Yes	Yes	Yes
Gender Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Education Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Language Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Income Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Housing Status Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	364,189	33,751	330,438	150,751	213,438	150,751	213,438

Notes: The population variable is cases and a hazard model for the completion time is used. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$,*** $p < 0.01$.

Table 11: Instrumental Variables: Correlation Check

	(1) Upload Speed	(2) Upload Speed
Min Distance (in km)	-28.682**	-25.506*
	(11.293)	(12.900)
Census Group Fixed Effects	No	Yes
Observations	19	19

Notes: A linear regression model where the dependent variable is the upload speed (in Mbps) is used here. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 12: Robustness Check: Instrumental Variables

	(1) Logit-MFX	(2) Logit-MFX	(3) Min Distance	(4) Min Distance	(5) Employee	(6) Employee
Average Years of Education	0.001	0.002***	0.006***	0.015***	-0.000	0.005
	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)	(0.003)
Citizen Connect App	-0.004***	-0.002	-0.334***	-0.268***	-0.049	-0.046
	(0.002)	(0.002)	(0.066)	(0.077)	(0.056)	(0.057)
Web Submission	-0.048***	-0.048***	-0.086***	-0.080***	-0.056***	-0.057***
	(0.002)	(0.002)	(0.008)	(0.008)	(0.007)	(0.006)
Average Years of Education		-0.005***		-0.044***		-0.026
× Citizen Connect App		(0.001)		(0.016)		(0.016)
Average Years of Education		-0.003***		-0.015***		-0.005*
× Web Submission		(0.001)		(0.002)		(0.003)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Season Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Weekday Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Reason Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Gender Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Age Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Race Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Language Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Income Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Housing Status Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	364,189	364,189	364,189	364,189	364,189	364,189

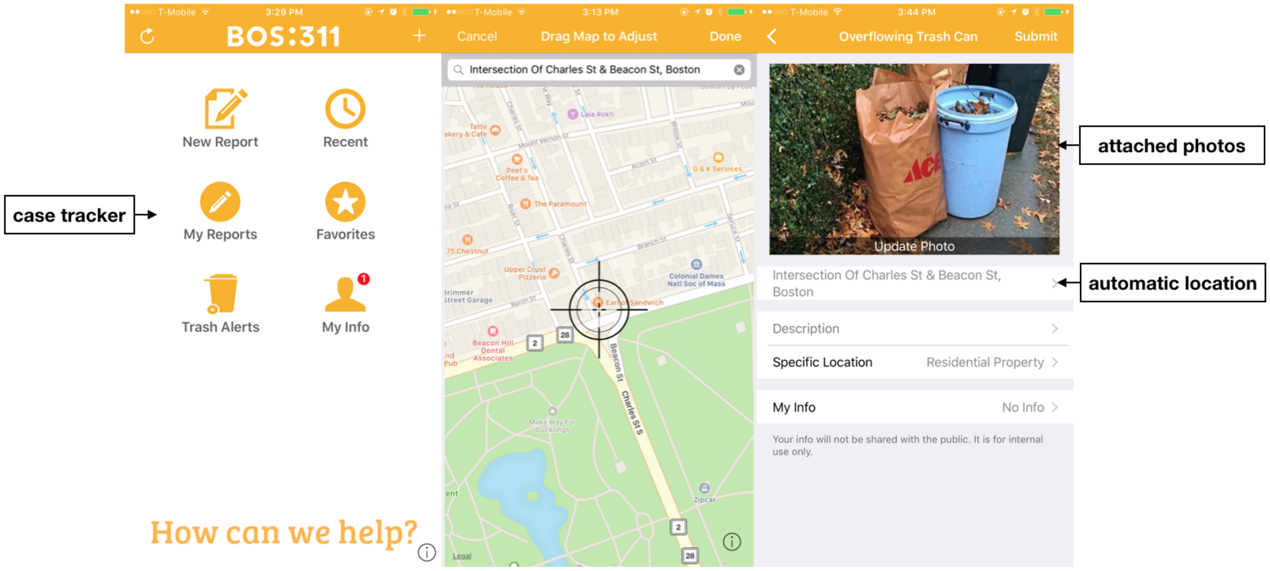
Notes: The population variable is cases and the dependent variable is the "on-time" indicator. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 13: Robustness Check: Instrumental Variables (First Stage)

	Min Distance			Employee		
	(1)	(2)	(3)	(4)	(5)	(6)
	App	App	Interaction	App	App	Interaction
Average Years of Education	0.013***	0.017***	0.236***	0.015***	0.018***	0.173***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Min Distance (in km)	-0.054***	-0.053***	-0.037***			
	(0.004)	(0.004)	(0.008)			
Min Distance^2 (in km^2)	0.019***	0.018***	-0.013***			
	(0.002)	(0.002)	(0.005)			
Average Years of Education		0.002	-0.137***			
× Min Distance		(0.002)	(0.005)			
Average Years of Education		-0.005***	0.043***			
× Min Distance^2		(0.002)	(0.003)			
Employee				0.022***	0.022***	0.002
				(0.001)	(0.001)	(0.002)
Average Years of Education					0.003***	0.043***
× Employee					(0.001)	(0.001)
Web Submission	-0.116***	-0.111***	-0.073***	-0.115***	-0.109***	-0.078***
	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)	(0.003)
Average Years of Education		-0.021***	-0.169***		-0.024***	-0.173***
× Web Submission		(0.001)	(0.002)		(0.001)	(0.002)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Season Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Weekday Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Reason Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Gender Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Age Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Race Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Language Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Income Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Housing Status Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	364,189	364,189	364,189	364,189	364,189	364,189
Under-identification Test:						
Anderson Under-identification LM statistic	432.1	327.7	327.7	556.1	568.3	568.3
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Weak Identification Test:						
Cragg-Donald Wald F statistic	216.3	81.98	81.98	556.9	284.6	284.6
(10% critical value)	(19.93)	(16.87)	(16.87)	(16.38)	(7.030)	(7.030)

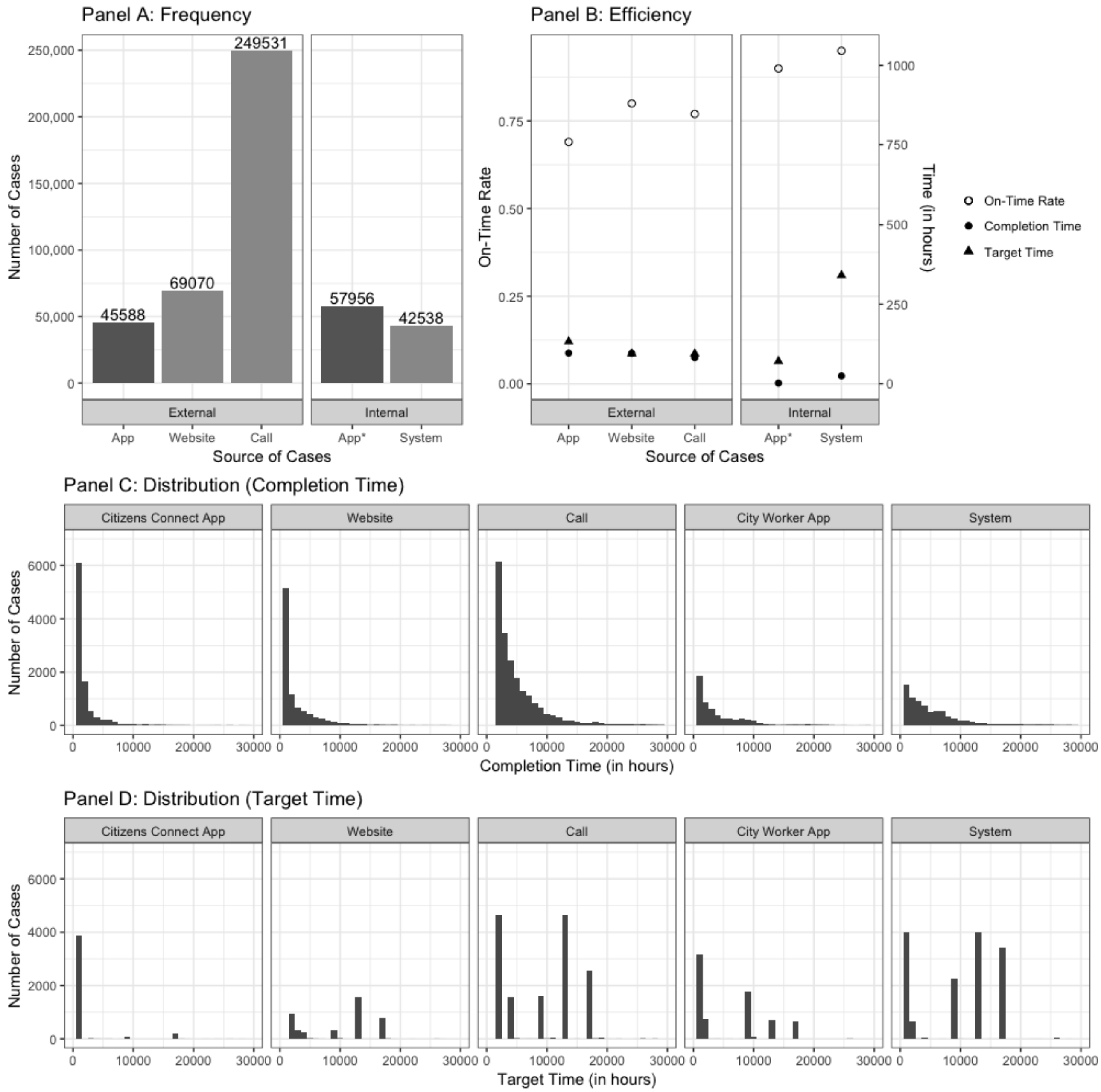
Notes: The population variable is cases and the dependent variable is the app use in Column (1), (2), (4), and (5) and the app use × the average years of education in Column (3) and (6). Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 1: BOS:311 App



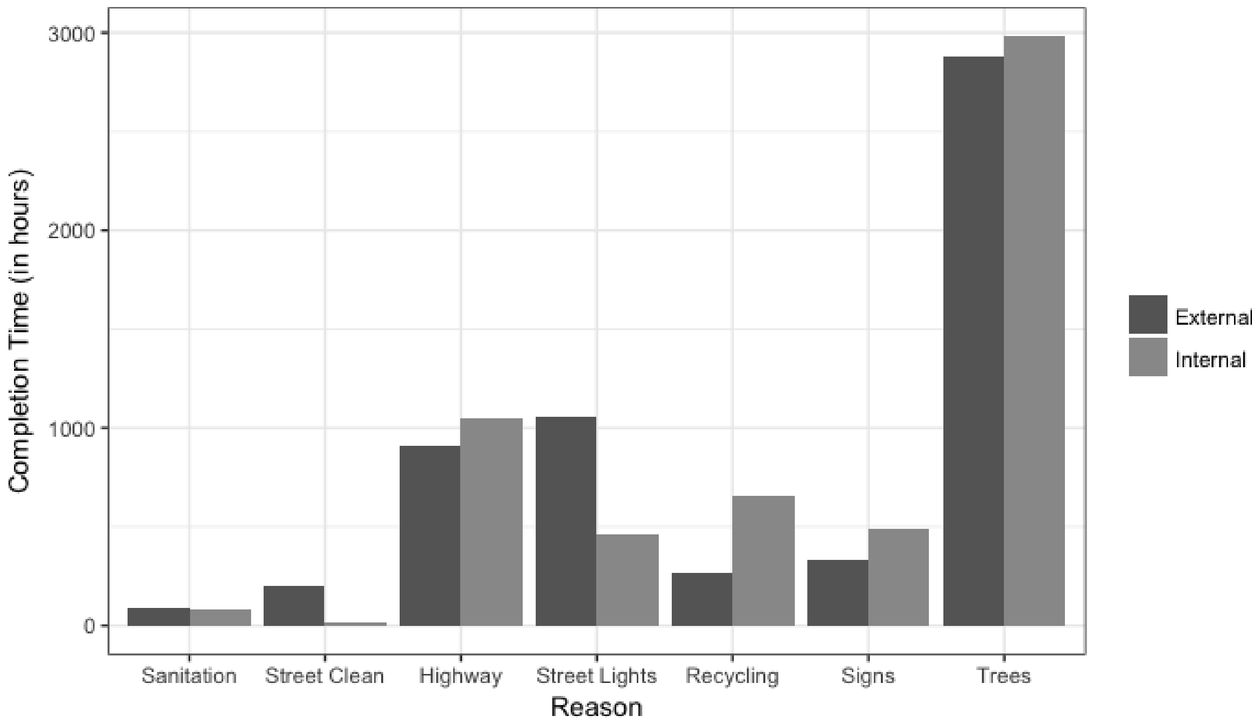
Notes: The homepage of BOS:311 app (with navigation menu) is shown on the left. The page of case submission is shown on the right. A screenshot of the interactive map where people overwrite the auto-filled location by dragging a marker to the desired place is shown in the middle.

Figure 2: Sources of Cases



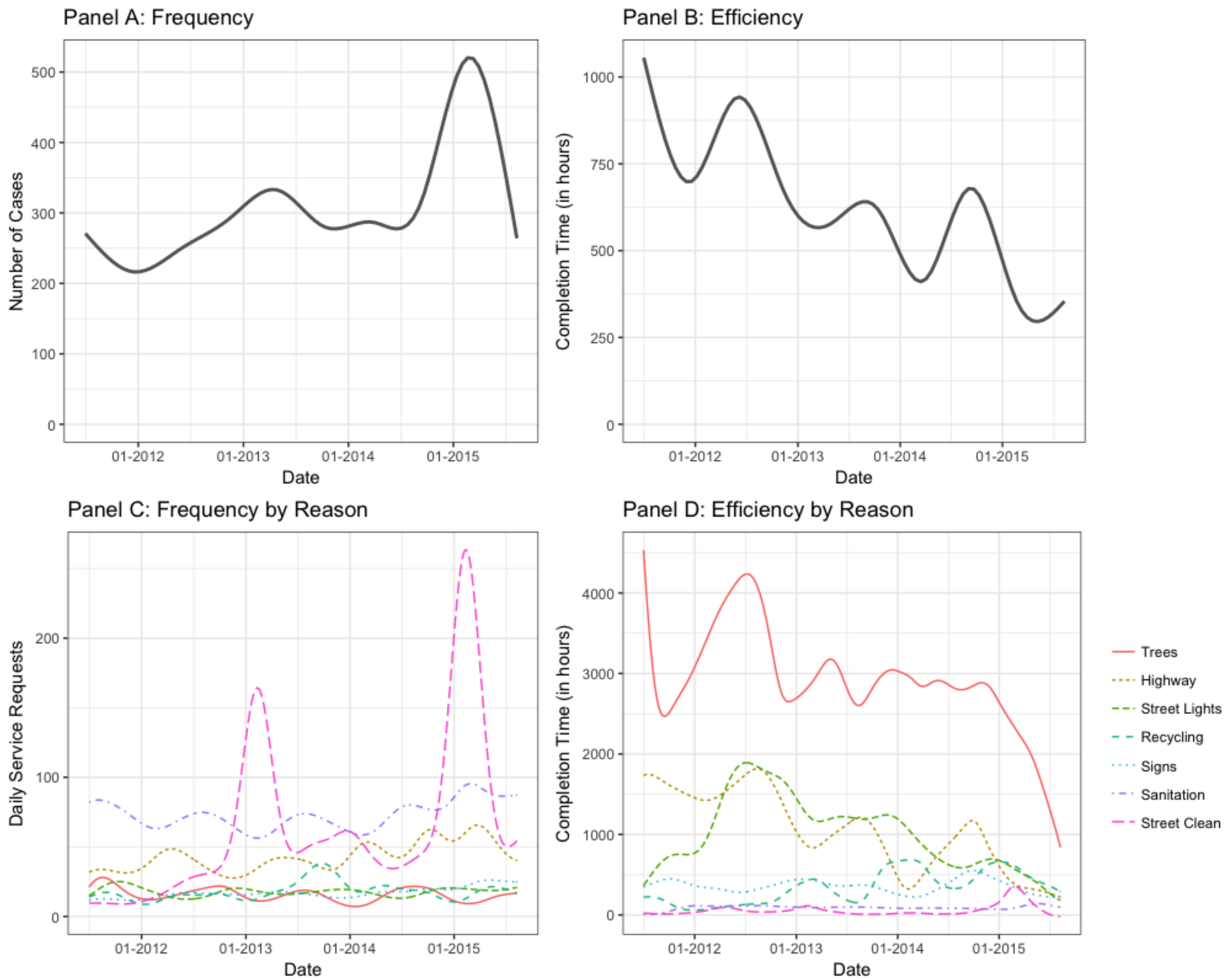
Notes: Figure 2 is based on both external cases and internal cases. External cases were submitted by citizens through Citizen Connect App, the self-service website, or traditional phone calls. Internal cases were submitted by city employees through the traditional system or City Worker App. The number of cases for each source is plotted in Panel A. The on-time rate, the average actual completion time, and the average target completion time for each source are plotted in Panel B. The distribution of actual completion times is plotted in Panel C by source, and the distribution of target completion times is plotted in Panel D by source. There are in total 464,683 external and internal observations in Panel A, B, and C. There are in total 372,235 external and internal observations in Panel D due to missing values in target completion time.

Figure 3: Completion Time by Type



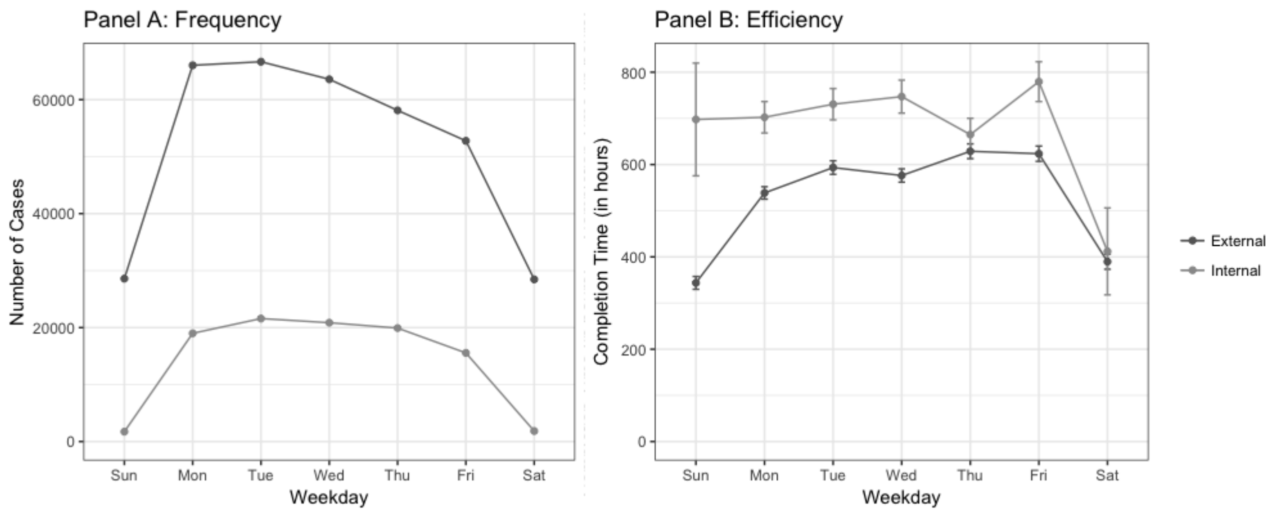
Notes: Figure 3 is based on both external cases and internal cases. The average completion time of cases is plotted separately for external and internal cases in seven major case types where there are more than 20,000 cases. There are 94,962 external and 14,539 internal observations for sanitation, 69,434 external and 28,656 internal observations for street cleaning, 33,751 external and 31,301 internal observations for highway (and road) maintenance, 23,423 external and 3,475 internal observations for street lights, 21,633 external and 5,051 internal observations for recycling, 21,824 external and 3,734 internal observations for signs & signals, and 12,498 external and 9,565 internal observations for trees.

Figure 4: Trends in Completion Time and Number of Cases



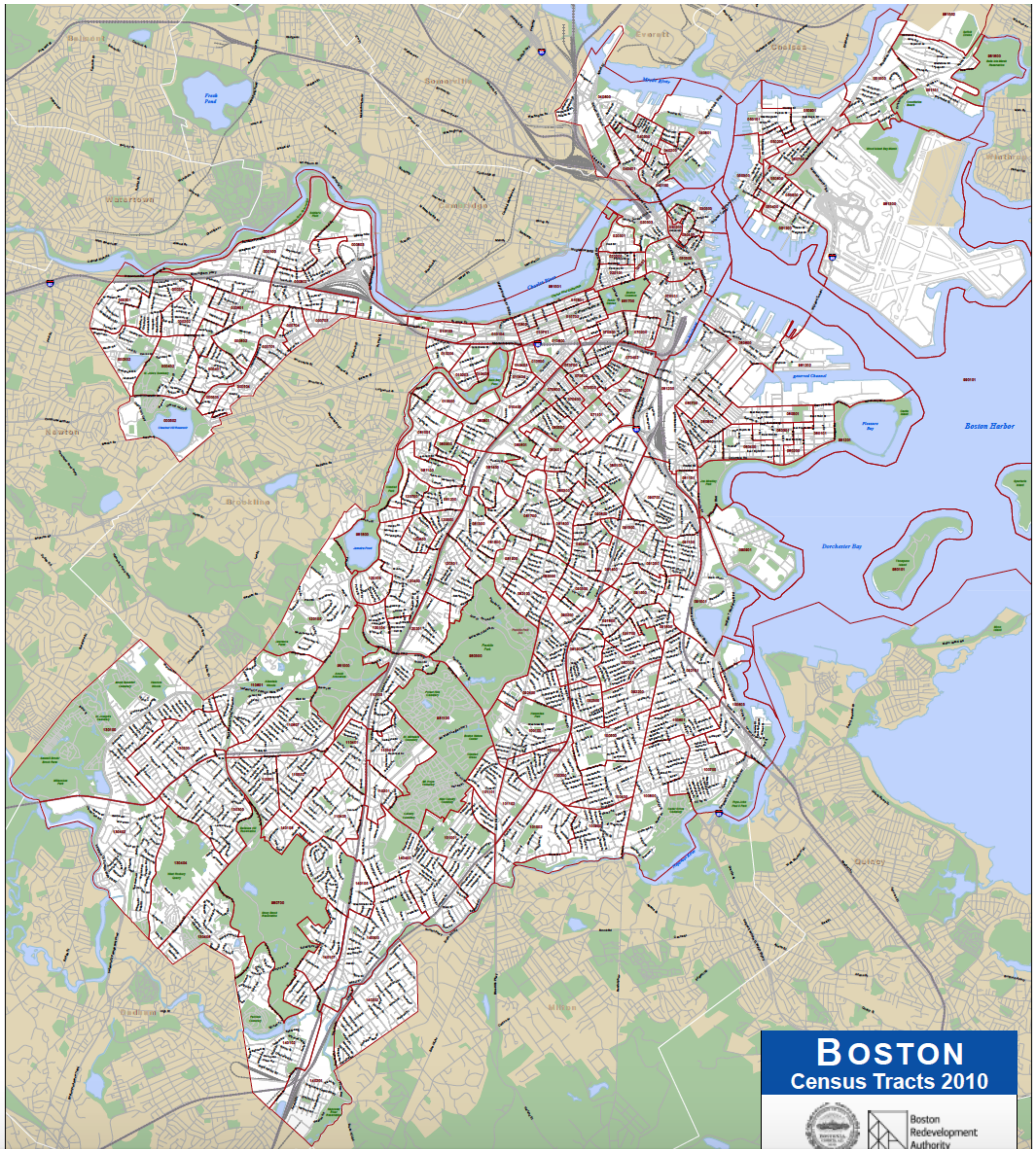
Notes: Figure 4 is based on both external cases and internal cases. The number of cases opened over time in Panel A has been smoothed using local polynomial regression, so does the average actual completion time in Panel B. Those smoothed trends are broken down by reason in Panel C and Panel D, respectively. There are in total 464,683 external and internal observations in Panel A and B. In Panel C and D, there are 109,501 observations for sanitation, 98,090 observations for street cleaning, 65,052 observations for highway (and road) maintenance, 26,898 observations for street lights, 26,684 observations for recycling, 25,558 observations for signs & signals, and 22,063 observations for trees.

Figure 5: Completion Time and Number of Cases by Weekday



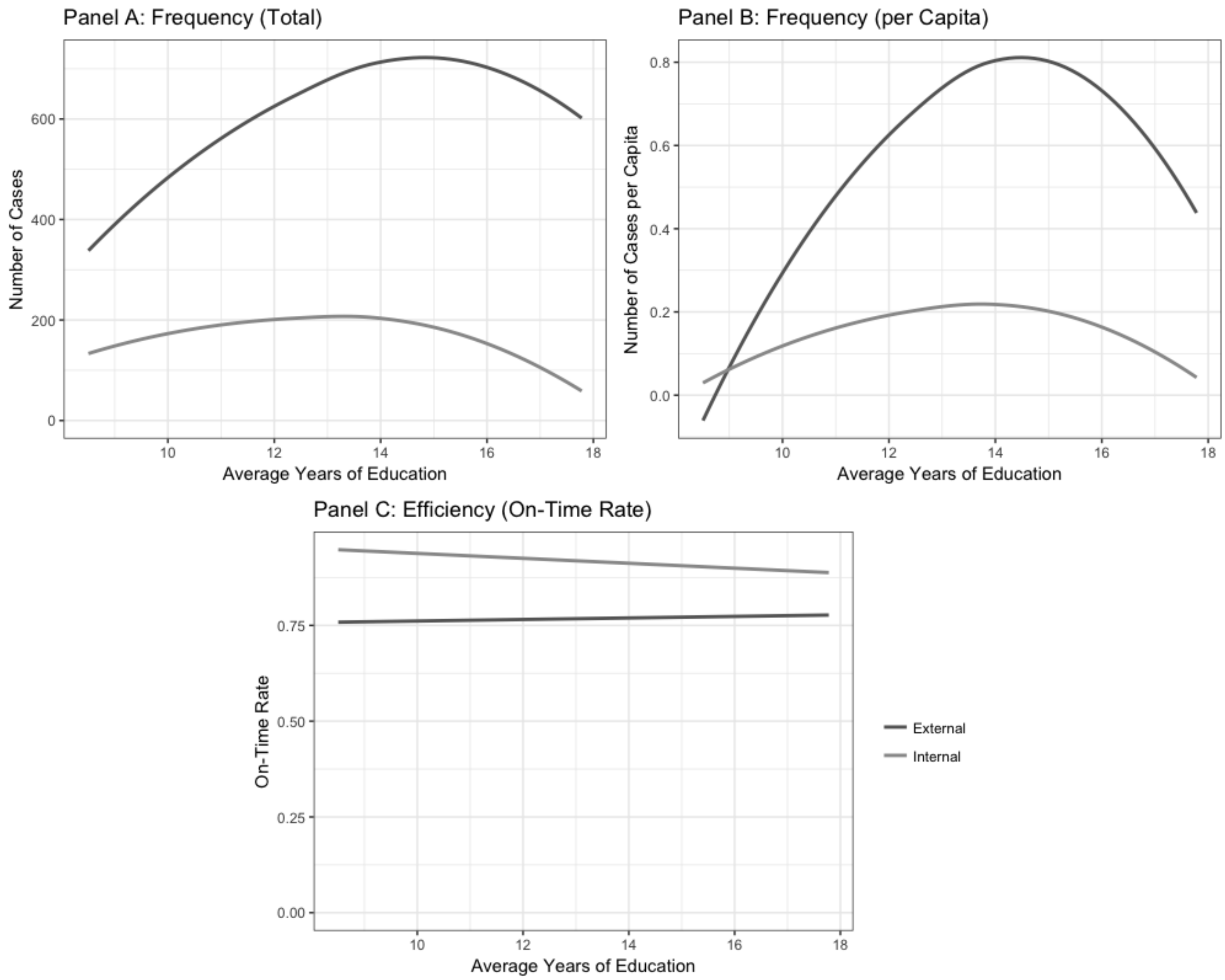
Notes: Figure 5 is based on both external cases and internal cases. The total number of cases opened on each weekday have been plotted separately for external (submitted by citizens) and internal (submitted by city employees) cases in Panel A, so does the average actual completion time in Panel B. There are 364,189 external observations and 100,494 internal observations in both Panel A and B.

Figure 6: Boston Census Block Groups Boundary 2010



Note: The map shows the boundaries for 646 census block groups in the city of Boston.

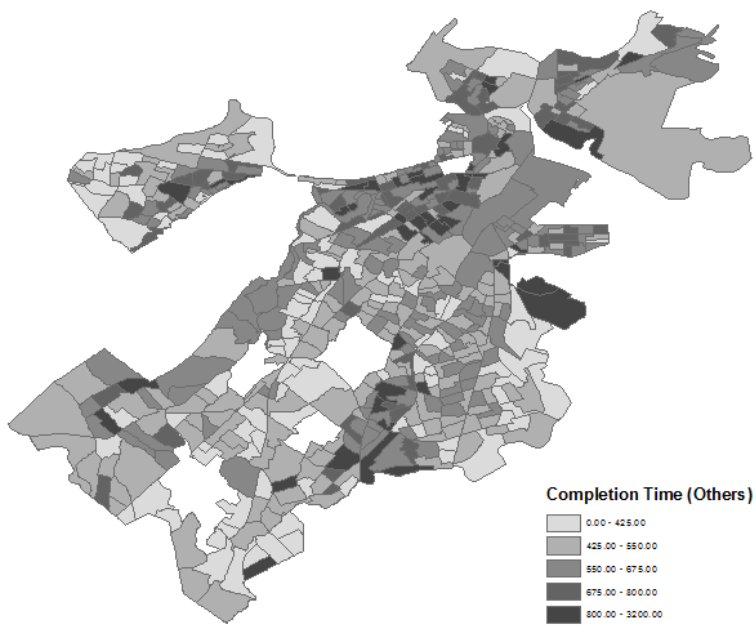
Figure 7: Completion Time and Number of Cases on Education



Notes: Figure 7 is based on both external cases and internal cases. The smoothed total number of cases is plotted over average years of education in Panel A using local polynomial regression, the smoothed number of cases per capita is plotted over average years of education in Panel B using local polynomial regression, and the smoothed on-time rate is plotted over average years of education in Panel C using linear regression. All of them have been plotted separately for external (submitted by citizens) and internal (submitted by city employees) cases. There are 364,189 observation for external cases and 100,494 observations for internal cases in those panels.

Figure 8: Completion Time by Neighborhood and Source

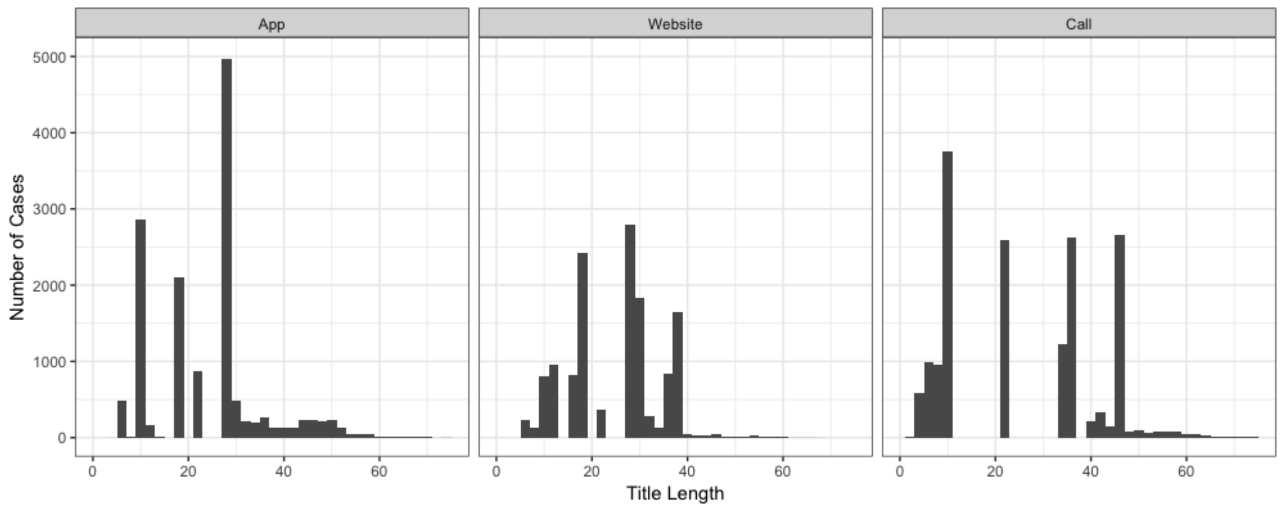
(a) External Cases Submitted through App



(b) Other External Cases

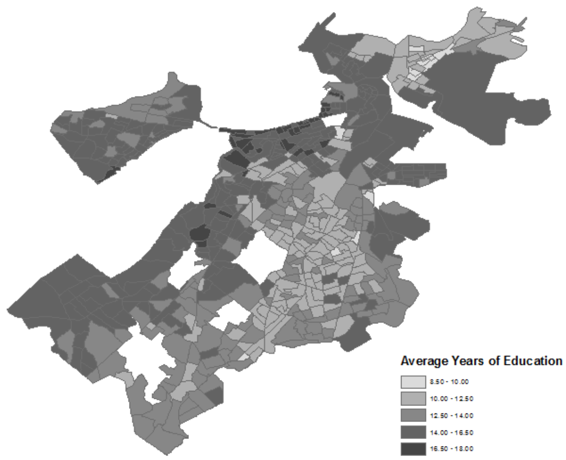
Notes: Figure 8 is based on external cases only. The average completion time (in hours) for a case submitted through the App is plotted for each census block in Panel A. The average completion time (in hours) for a case submitted through the other channels is plotted for each census block in Panel B.

Figure 9: Title Length by Source

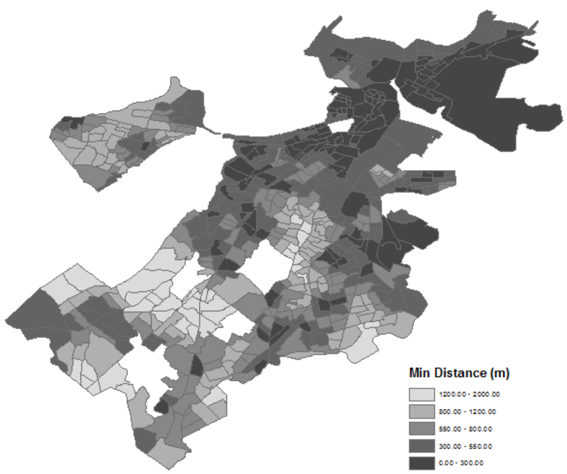


Notes: Figure 9 is based on external cases only. The distribution of title lengths is plotted by source. There are 364,189 external observations.

Figure 10: Instrumental Variables: Exclusion Restriction



(a) Average Years of Education

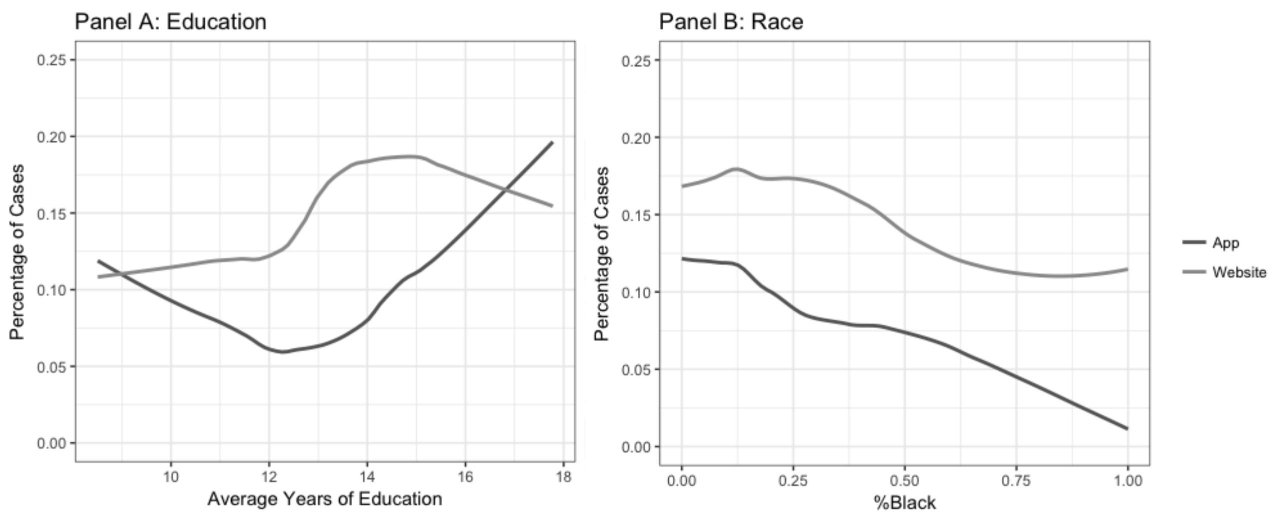


(b) IV1: Distance to the Closest Tower

(c) IV2: Employee's Choice

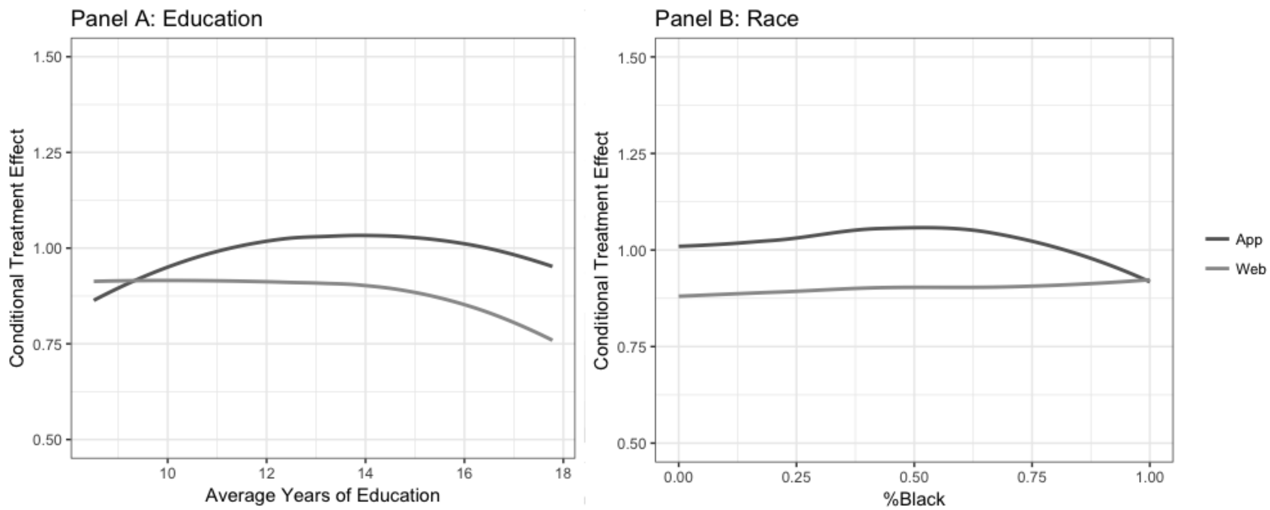
Notes: Figure 12 is based on external cases only. The average years of education are plotted for each census block in Panel A. The average distance to the closest tower for an external case is plotted for each census block in Panel B. The average value of the indicator whether a city worker used a mobile to submit a complaint in the same location for an external case is plotted for each census block in Panel C.

Figure 11: Treatment Assignment Conditional on Demographic Variables



Notes: Figure 10 is based on external cases only. The percentage of cases reported via Citizens Connect App and the percentage of cases reported via the self-service website are plotted over the average years of education in the neighborhood in Panel A and over the proportion of black population in the neighborhood in Panel B. There are 545 observations in both panels.

Figure 12: Conditional Treatment Effects



Notes: Figure 11 is based on external cases only. The conditional treatment effect of the app use and that of the website use in each census block, calculated using a Cox proportional hazard model with only the case type controls X_i and the date controls Y_j, are plotted separately over average years of education in Panel A and over proportion of black population in the neighborhood in Panel B. There are 545 observations in both panels.