Abstract

Customers with more education may get better service after complaining, because they are better placed to advocate for themselves. It is unclear how digitization of the consumer complaint process will change this situation. To investigate this, we analyze 364,189 customer complaints to the city of Boston. Empirically, complaints that originate from areas with high levels of education are more likely to be solved quickly. However, dedicated mobile app technologies that automate the complaint process can help mitigate the advantage conferred by education. Since the adoption of digital devices is endogenous to wealth and education, we instrument their usage using granular geographic data on a proxy for cellular signal strength. This analysis again suggests that mobile applications can partially eliminate the disparity between educated and uneducated people. We present suggestive evidence that this is because mobile devices and the standardization of communication they require, eliminate potential differences in treatment of cases that arise due to differences in communication skills. This result suggests that using newer forms of automated digital communication tools enhances equality in customer service.

Keywords: Information Technology; Customer Service; Complaint Handling; Social Inequality

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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 without 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.

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 worsen 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.

We investigate this question using service performance data from customer complaint resolution in the public sector. We combine 364,189 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 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 instrument we use captures the app
use of city employees and 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). How-
ever, 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 Werner-
felt, 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 be-
tween 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 tool that substitutes the communication skills required 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 also important for managers who are interested in the emerging field of omni-channel marketing (Verhoef et al., 2015). Much of the managerial excitement about omni-channel marketing has focused on how best to connect the customer experience of a firm’s promotional marketing communications across mobile, other digital and offline channels. However, our paper also highlights the importance of an omni-channel approach for service resolution. In particular, it suggests that firms should consider directing portions of their customer-base towards channels which have the capacity to automate complaint submission in order to ensure effective resolution of service-issues. This supports recent movements by firms to expand their omni-channel messaging efforts towards apps for the purposes of
improving consumer support. As a recent article about customer support platform Zendesk stated “[This] underscores the big impact that messaging apps are making in customer service. While phone and internet are massive points of contact, messaging apps is one of the most-requested features Zendesk’s customers are requesting, ‘because they want to be where their customers are.’” See Zendesk Acquires Smooch, Doubles down on Support via Messaging Apps like WhatsApp: https://techcrunch.com/2019/05/22/zendesk-smooch/ Other firms such as Hilton and Uber are also emphasizing increasing customer support services via their apps.\(^1\) Our paper to our knowledge provides some of the first evidence on the efficacy of omni-channel approaches to providing customer support resolution.

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

\(^1\)See Hilton’s HHonors App Redesign Unlocks Mobile Chat, Digital Key Expansion (https://www.mobilemarketer.com/ex/mobilemarketer/cms/news/strategy/23419.html) and Are You Providing A Frictionless Customer Experience? (https://www.forbes.com/sites/shephyken/2019/06/09/are-you-providing-a-frictionless-customer-experience/#1f8594fd4b8c)

\(^2\)See QuickFacts: https://www.census.gov/quickfacts/table/PST045215/2507000.

\(^3\)The data is made publicly available online on the city government’s open data site as part of a commitment to increase transparency in government. However, sensitive personal information of request senders has been removed to protect individual privacy.
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 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 (http://www.cityofboston.gov/311) allows people to report non-emergency issues without help from a representative 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, and now people can download

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4 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.
it for free on iOS or Android as the BOS:311 App. Figure 1 shows a screenshot of the app. 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 a 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.

[Figure 1 about here.]

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, 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. Most of those open cases are general complaints or complaints that can’t be fixed with simple actions. We exclude those open cases because the overdue status here doesn’t indicate that no proper attempt has been made punctually. 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, while city workers can report the internal case through the traditional system (employee generated) or City Worker App.\textsuperscript{5} We don’t study complaints submitted on Twitter because there are only 7 cases in our data.

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 and the median of the target completion time. Cases generated internally were solved faster with an even longer target completion time. Though this of course does not condition for differences in case type, it still suggests that the internal cases and the external cases can be inherently different. Due to this reason we exclude all employee-generated cases in our initial analysis

\textsuperscript{5} 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. The lack of human intervention required means that we do not study complaints for this system.
and 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 return to employee-generated cases when we turn to identification.

Panel C of Figure 2 shows the histogram of actual completion times for different sources. 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. On the other hand, the distribution of target times is concentrated (Panel D), which 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 choose to focus on the actual completion time and use the “on-time” status calculated from target times as a robustness check when analyzing complaint resolution performance.

We summarize the type of cases in Table A1. More than 80% of the cases belong to the top seven categories (reasons) - 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 greatly among different types in Figure 3: an issue about trees takes on average about 3,000 hours for city employees to resolve it while this number is only 100 hours for an average sanitation issue. To address this we use category (reason) stratification to shed light on the baseline efficiency of customer complaint resolution in our survival model.

3.2 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\(^6\) – the peak of efficiency usually comes in January or February – while the average completion time is decreasing year by year. 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, sanitation issues dominate the system in the summer, and the peak of tree-related cases always arrives in New England during the foliage season. These findings are in line with the previous argument that the baseline efficiency should be stratified by reason in our model.

[Figure 4 about here.]

We also plot the total number of cases and the average completion time by weekday in Figure 4. Panels E and F of Figure 4 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 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.

\(^6\)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).
We control for these shifts over time by adding year, season and weekday fixed effects in our main model.

3.3 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 W1 shows those block groups on the map. 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 by citizens. 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 1. Each census block has 1,160 individuals and 460 households on average.

[Table 1 about here.]

Panel A and B of Figure 5 shows an example of how the number of requests varies with those social-demographic characteristics. Both the total number of external requests sent by citizens and the number of external requests per capita increase with the average years of education, while the number of internal requests sent by employees keeps almost constant across levels of education. Panel C of Figure 5 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 in Panel D. In both panels, the efficiency increases with the education level for external requests while the employee-generated cases show an opposite trend. Moreover,
we see that the external cases are more standardized in terms of efficiency but have a large variation in the frequency.

[Figure 5 about here.]

4 Main Effect

4.1 Model

To identify the effect of the use of mobile app usage on the complaint resolution performance with controlling for all the factors mentioned in the previous section, 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

\[ \lambda_i(t) = \lambda(t|CitizenConnectApp_i, WebSubmission_i, \omega, X_j, Y_k) \]

denote the hazard function\(^7\) for a case \(i\) belongs to category \(\omega(\omega \in \Omega)\) opened on day \(j\) and in census block group \(k\) at 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. \(X_j\) is a vector of time-specific covariates, including year, season, and weekday indicators. And \(Y_k\) a vector of block-group-specific covariates, including gender, age, race, language, income, housing status, and education controls. Leaving the reason-specific baseline hazard function \(\lambda_\omega(t) =

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\(^7\)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).
\( \lambda(t|0, 0, \omega, 0, 0) \) unspecific,\(^8\) we model the log hazard ratio, which is the relative “risk” of the case closing at time \( t \), as

\[
\log\left( \frac{\lambda_i(t)}{\lambda_0(t)} \right) = \beta_0 + \beta_1 \text{CitizenConnectApp}_i + \beta_2 \text{WebSubmission}_i + X'_j \lambda + Y'_k \mu. \tag{1}
\]

The parameters of interest are \( \beta_1 \) and \( \mu \), 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

\[
\log\left( \frac{\lambda_i(t)}{\lambda_0(t)} \right) = \beta_1 \text{CitizenConnectApp}_i + \beta_2 \text{WebSubmission}_i + X'_j \lambda + Y'_k \mu
+ \text{CitizenConnectApp}_i \tilde{Y}'_k \tau_1 + \text{WebSubmission}_i \tilde{Y}'_k \tau_2, \tag{2}
\]

where \( \tilde{Y}_k \) is a subset of \( Y_k \), incorporates the demographic characteristics of which the interactions with the channel used are studied.

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 \( (Y_k) \) so that the baseline hazard function is \( \lambda_0(t) = \lambda(t|0, 0, \omega, 0, \bar{Y}) \). \( \beta_1 \) captures the effect of using mobile information technologies for people in an average neighborhood, and \( \tau_1 \) 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., \( \tau_1 \) and \( \mu \) have different signs), this suggests that app usage alleviates social inequality.

\(^8\)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).
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 $Y_k$ 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.

Table 2 reports the estimation results of the Cox hazard model. Column (1) in the table presents the result of a regression that includes only $AverageYearsOfEducation_k$ as the independent variable. The reason stratification, the time fixed effects $X_j$ and other socio-demographic controls $Y_k$ are added into the model incrementally in Columns (2)-(4). Column (5) 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 (6). Column (7) replicates the results in Column (6) but excludes cases in 36 smaller categories where there was no case has been submitted via the App. Categories included in Column (7) are starred in Table A1.

The coefficient of $AverageYearsOfEducation_k$ is always significant and positive in Table 2. 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 (6), cases submitted via phone calls were $e^{0.028} - 1 = 2.8\%$ more likely to be completed at any time if the average level of education in the neighborhood increases by one.
year. The coefficient of CitizenConnectApp, is negative in the table, and WebSubmission, also always has a negative effect on the service performance. These results suggest that the mobile app, on average, worsens the complaint resolution performance compared to channels where customers have real-time interaction with representatives such as phones (by $1 - e^{-0.039} = 3.8\%$ for an average neighborhood) but outperforms traditional technologies such as desktop computers (by $e^{0.039 + 0.130} - 1 = 9.5\%$ for an average neighborhood). 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 and CitizenConnectApp, in Column (6) – the gap in the likelihood of case completion brought by a one-year increase in the average years of education in the neighborhood decreased by $1 - e^{-0.015} = 1.5\%$ if the app is used to submit the case, while it does not hold for the self-service website. Those numbers also imply that, the app expedited the complaint resolution compared to phones for all the citizens who live in a neighborhood where the average years of education are more than $-0.039 / -0.015 = 2.6$ years below the city-wide average level. All of those results hold for the robustness checks where the minor categories are removed (in Column (7)), which implies that the inclusion or exclusion of these smaller categories where the app is not used does not change our results.

A natural concern when interpreting these results is multicollinearity, given the fact that socio-demographic variables are usually correlated with each other. In Table A2, we show 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 AverageYearOfEducation, and other socio-demographic controls $Y_k$ has

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9This number is $e^{0.028 - 0.015} - 1 = 1.3\%$ for cases submitted via the app and $e^{0.025 - 0.001} - 1 = 2.4\%$ for cases submitted via the website.

10In other words, it helps the neighborhoods where the average years of education are lower than 11.2 years.
an absolute value higher than 0.7. Also, the variance inflation factor (VIF) of AverageYears Of Education_k 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).

[Table 2 about here.]

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 examine 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. The results in Table A3 are consistent with the main results, which implies that our results will not be changed by taking the extra information in target completion times into account.

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 A4 replicates the results in Column (6) of Table 2 for a series of alternative independent variables that measure the education level in different ways. We use the original independent variable “average years of education” 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).\(^\text{11}\) Those

\(^{11}\) 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
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.

4.3 Block-by-block Analysis

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. The black line in Figure 6 shows that a higher proportion of cases are sent via the app in neighborhoods with higher education levels, even though the correlation between $AverageYearsOfEducation_k$ and $CitizenConnectApp_i$, is only 0.13. To deal with the potential issues arising from this dependency we use a potential outcomes approach to appropriately adjust our measured treatment effects.

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, as: (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 between block groups but only slightly within block groups; (3) socio-demographic characteristics that vary within block groups, like age and gender, matter less for advanced technologies’

is significant at the $\alpha = 0.1$ level from Column (5) to Column (6).
adoption than for the adoption of traditional technology (Chinn and Fairlie, 2007). We will use instrumental variables to address the endogeneity if this assumption does not hold.

Therefore, we calculate the conditional treatment effect for each census block using a Cox proportional hazards model with only the case stratification and the date controls $X_j$. The effect of the Citizen Connect App use conditional on average years of education is represented by the grey line in Figure 6. The results are consistent with our main results: use of the app doesn’t improve the complaint resolution performance for everyone, and use of the app helps less educated people (people submitting complaints in neighborhoods with lower education levels). Surprisingly, we notice that the mitigating effect of the app is not monotonic in Figure 6 and the app amplifies the disadvantages of people with fewer than about 13 years of education. One interpretation is that using the app competently does require a baseline level of skills.

[Figure 6 about here.]

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.

5.1 Standardization of Case Locating

One potential way the app may be able to mitigate the influence of education on complaint resolution time, is simply by making it easier for the city worker to find the issue geographically. Unlike the cellphone and website channels, the app has the feature that it makes it easier to pinpoint where precisely the issue is and thus substitutes for the required communication skills.

There are two types of locations in the record – the cases can be either submitted with a street address, such as “100 Second St.” or filled as an intersection, such as “the intersection
of Second St and Park St.” The number of cases where the location was reported as a street address and the number of cases at an intersection are plotted by source in Panel A of Figure 7. The mobile app automatically fills the location with either a street address or an intersection depends on the real-time geo-information captured by smartphones. This input can be overwritten only by dragging a marker to the desired place on an interactive map. Since the location can never be filled manually in the app, the app has the largest proportion (35%) of cases reported with an intersection. Complaints submitted by the website by contrast tend to have street addresses, because its autocomplete function is based on Google maps which does not use intersections – only 13% of the cases submitted via the website was reported at an intersection. Complaints that are submitted by phone are more likely to be reported with an intersection, perhaps reflecting the reporting preferences of service providers themselves. Indeed our interviews suggested that intersections are considered more useful, as they to not rely on having to identify a street number in a town where street numbers are often not visible and may refer to buildings that span city blocks and corners making locations imprecise. It seems possible that complaints that involve these street addresses generated by the app may need less context and explanation to pinpoint the location of the complaint than other channels. Therefore 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.

We investigate these hypotheses by interacting the main effects with an indicator which equals one if the case was submitted with a street address. First, based on the results reported in Column (2) of Table 3, we find that street addresses do slow down the complaint resolution process: cases submitted with street addresses were $1 - e^{-0.198} = 18.0\%$ less likely to be completed at any time compared to the cases submitted at intersections after reason

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12The results about the effects of website submission have been cut from Table 3 due to limited space. They are reported in a full version of this table in the appendix (Table A5).
stratification. Second, supported by the positive coefficient of the interaction term between $AverageYearOfEducation_k$ and the street address indicator, the advantage of educated people is significantly amplified by the street address use. It supports the hypothesis that the skills of communicating a complex location play a more crucial role in reporting these cases. Meanwhile, as expected the app provides better customer service performance when the location is complex: the mobile app, on average, expedited the complaint resolution of a case reported with a street address in an average neighborhood by $e^{0.185-0.025} - 1 = 17.4\%$ compared to a similar case submitted via a phone call. More importantly, the effect of app use on the gap between educated and less educated consumers is more significant when the communication about the location is complicated. This moderating effect is even larger than the amplification effect of the street address use on the advantage of educated people.

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. One hypothesis is that case complexity may be related to how much information it conveys. It may also be that, as case complexity increases, the case becomes more difficult to describe and needs more communication. Due to the limitations of the available data, we create proxies for case complexity from case titles. Following the standard process of neuro-linguistic programming (NLP) here, we first count the total number of words in each title and then filter out the insignificant words (like stop words) to count the number of meaningful words (Jurafsky and Martin, 2009).

The distribution of the total number of words in a case title is plotted in Panel B of Figure 7 and that of the number of filtered words is plotted in Panel C of the same figure. On average there are 3.6 words and 3.1 filtered words in a title. Titles are slightly more informative in the website channel while the representatives tended to write down a title
with fewer words during the phone call, but the correlation coefficient between the total number of words and the app use is only about -0.08. The gap becomes even smaller and the distributions look more similar when the case complexity is measured by the number of filtered words, which have a narrower definition.

In Column (3) and (4) of Table 3, we interact the main effects with the total number of words and the number of filtered words, respectively. Consistent with our hypotheses, we find that cases where the title contains more information were resolved less efficiently: cases were $1 - e^{-0.147} = 13.7\%$ less likely to be completed at any time if there was one more word in the title and this number was $1 - e^{-0.034} = 3.3\%$ for one more “meaningful” word in the title. And the lack of communication skills tends to widen this gap. Although the significantly positive coefficient of the interaction term between $AverageYearOfEducation_k$ and the title informativeness implies that educated people enjoyed more advantages and privileges coming from better communication skills when the title conveyed more information, this effect is mitigated by the app use: the mitigating effect of app use on the advantage of educated people was intensified by more than 50\% if there was one more word in the case title for an average case. This analysis provides supportive evidence for the hypothesis that the app substitutes for communication skills needed for describing complex cases.

Another hypothesis is that the ability of the app to convey visual information in the form of photos also substitutes for the need for communication skills. To investigate this we examine the effect of submitting cases included photos (photos are only conveyable through the app). 35.4\% cases submitted with the app included photos. Therefore, we replace the app-use indicator $CitizenConnectApp_i$ with $Photo_i$, a binary variable indicating whether the case submission included photos.\(^{13}\) As we can see from Column (5) - (7) of Table 3, all

\(^{13}\) A photo can be attached only when the case is submitted via the app, i.e., $CitizenConnectApp_i \leq Photo_i$ always holds.
the results mentioned before remain the same after changing the independent variable, which implies 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.

[Table 3 about here.]

To summarize, 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 found after replacing the average level of education by the percentage of Spanish speakers in the census block (see Table A6), which reinforces our conclusion about the diminished role of communication skills when mobile information technologies are used during request submission.

6 Endogeneity of App Adoption: Instrumental Variable Approach

We have addressed the issues arising from the uneven adoption of information technology across census blocks using the potential outcome approach in Section 4.3. 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 do not. To address this, we turn to instrumental variables.

Given uneven app adoption within census block groups, there may be concerns over endogeneity of adoption within a census block. First, the adoption decision and the complaint resolution efficiency can be affected by individuals’ wealth and education level, which is unobservable to researchers. Second, people who adopt an app are more likely to be the ones who had a better experience with the app (Buell et al., 2017). Third, selection issues may also arise from the possibility that people who adopt the app might be the ones that really care about public service and are aware of the app launch. Those people are more likely to report non-emergencies which won’t be resolved immediately.
6.1 Geographic Variation in Cell Tower Proximity

To address these potential endogeneity issues, we instrument the use of mobile devices with a proxy 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. The instrument we use is 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 84 registered cell towers located in the city of Boston and its surroundings. The average distance to the closest cell tower is 1.14 kilometers. Even though channel choices were affected by other factors such as the availability of in-home WiFi networks and case-by-case considerations, this instrument did significantly shift citizens’ app uses and provides a valid estimate of a local average treatment effect (LATE) of the app use. 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 – as shown in Appendix Table A7, the probability of submitting a case via the mobile app increases more than 1.2% when the case is located one kilometer closer to a cell tower.

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 decades prior to the present. The 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 to individual characteristics, especially when considering only the relative wealth or education level within census blocks. It is not even strongly related to neighborhood wealth. The difference between the distribution of the education level (Panel A of Figure W2) and that of distance to the closest tower (Panel B of Figure W2) provides supportive evidence for this.

6.2 Instrumental Variables Estimation

In order to apply the instrument variables method here, we first obtain a discrete-time approximation for the proportional-hazards model by running a logistic regression on a set of pseudo-observations generated as follows. Let \( t = (t_1, t_2, \ldots) \) be a series of cut points which divide the timeline into small intervals: Each day in the first week, each week of the remaining weeks in the first month, and each month of the remaining months in the first year serves as a time interval, while the rest of time constitutes the remainder.\(^{14}\) Suppose case \( i \) is resolved at time \( t \) where \( t \in [t_{n-1}, t_n) \), we generate one resolution indicator \( d_{im} \) (\( m=i, \ldots, n \)) for each time interval from \([0, t_1) \) to \([t_{n-1}, t_n) \). This variable takes the value one for the interval \([t_{n-1}, t_n) \) and zero otherwise. To each of these indicators we associate a copy of the covariate vector \((CitizenConnectApp_i, WebSubmission_i, X_j, Y_k)\), a group of indicators that identify the time interval, and a group of reason indicators and their interactions with the time interval indicators (for reason stratification). Treating the \( d_{im} \) as independent Bernoulli observations with probability given by the individual hazard rate \( \lambda_{im} \) is equivalent to fitting the Cox proportional hazard model in equation (1) (Holford, 1980; Laird and Olivier, 1981). We fit the new model using a logit regression specification and replicate the results from Column (1)-(4) of Table 3 with this discrete-time approximation, while marginal effects at means, rather than the original coefficients, are reported in Panel A of Table 4. The results are very close to what we get from the Cox model in terms of

\(^{14}\) An approximation with fewer small intervals is used here to reduce the number of observations. We conducted various tests and proved that neither increasing the number of intervals nor changing the cut points significantly improves the precision of our results.
significance and relative magnitude.

We report the 2SLS estimates, where mobile app usage for a similarly located employee-generated case is used as the instrument in Panel B of Table 4. The first stages for Column (1) are reported in Appendix Table A7. The Wald statistic is 539.83, which suggests a strong first stage. Comparing the marginal effects at means from the original logit estimates reported in Panel A, the measured treatment effects are similar in sign but are larger in magnitude for most of the mitigating effects – now the mitigating effect of app use on case complexity will increase by 1.6% if there is a one-year decrease in the education level of the neighborhood. However, the coefficient of the interaction term between $AverageYearOfEducation_k$ and $CitizenConnectApp_i$ is not significant on average. One possible explanation for this is that the effect of signal strength on the use of the mobile app is heterogeneous among people. For example, people whose app-use behavior can be switched by the mobile signal constraint are less likely to 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 so that the app can not substitute the important communication skills correlated with education. So we might be 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. This issue is addressed in the next subsection by allowing the first stage coefficients to vary by neighborhood.

[Table 4 about here.]

6.3 First-Stage Heterogeneity

The instrumental variable estimation described above assumes that the effect of cell tower proximity on app adoption is the same across the population. However, it is possible that some people are more likely to overcome the mobile signal constraint by installing in-home WiFi or switching to a provider which has better network coverage.
As a robustness check, we allow the first stage coefficients to vary by neighborhood, which is equivalent to having a set of interacted instruments where $MinDistance_i$ is interacted with neighborhood dummies (Abadie et al., 2019). To tackle the over-identification caused by the large number of instruments (and controls), we use high-dimensional machine-learning methods to select which instruments and which controls to include (Chernozhukov et al., 2015). Lasso estimators are used twice here: first, to select the controls by estimating a Lasso regression of $d_{in}$ on all the controls; second, to select the instruments and controls by by estimating a Lasso regression of $CitizenConnectApp_i$ on all the instruments and controls. The final choice of control variable is the union of the controls selected in the two Lasso regressions.

The 2SLS estimates are reported in Panel C of Table 4. The first stages for Column (1) are reported in Appendix Table A7. Although the Wald statistic does not suggest a stronger first stage, multiple interacted instruments show significant effects on app use. The results shown in Column (1) are consistent with our hypothesis that the first-stage heterogeneity leads to the confusion between the effect of app use on the service performance and its mitigating effect which reduces inequality in the resolution of customer complaints. Now the coefficient of $CitizenConnectApp_i$ becomes positive – the mobile app, on average, improves the complaint resolution performance by 22.4% for those people whose app-use behavior would be shifted by the mobile signal strength. It is different from not only the instrumental variable estimate reported in Panel B but also the marginal effect from the logit estimation shown in Panel A. It suggests that the app might be selected to report some difficult non-emergency complaints. The coefficient of the interaction term between $AverageYearOfEducation_k$ and $CitizenConnectApp_i$ is -0.049, which indicates a strong mitigating effect of the use of mobile app on social inequality in the complaint resolution process. The results shown in Column (2)-(4) reinforce our conclusion about the underlying mechanism behind this mitigating effect.
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 tower proximity.

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 does not require any human interaction.\textsuperscript{15}

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 limitations, we feel our study is a useful first step in understanding how technology can alter inequality in

\textsuperscript{15}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.

Electronic copy available at: https://ssrn.com/abstract=3011633
the complaint resolution process.
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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 1 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 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. 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.
Notes: Figure 2 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 3 is based on both external cases and internal cases. The number of daily service requests 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. 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 E, so does the average actual completion time in Panel F. There are 364,189 external observations and 100,494 internal observations in both Panel E and F.
Notes: Figure 4 is based on both external cases and internal cases. The number of cases opened in a neighborhood is plotted over average years of education in the neighborhood in Panel A and the number of cases per capita is plotted over average years of education in Panel B. The average completion time in the neighborhood is plotted over average years of education in Panel C while the average on-time rate in the neighborhood is plotted in Panel D. All of them have been plotted separately for external (submitted by citizens) and internal (submitted by city employees) cases. There are 541 neighborhoods in those panels.
Notes: Figure 7 is based on external cases only. The percentage of cases reported via Citizens Connect App is plotted over the average years of education in the neighborhood in Panel A. The conditional treatment effect of the app use in each census block, calculated using a Cox proportional hazards model with only the case type stratification and the date controls $X_j$, are plotted separately over average years of education in Panel B. There are 541 observations in both panels. Local linear regressions with a 50% smoothing span are used here to smoothen the trends.
Figure 7: Length and Informativeness of Titles by Source

Panel A: Location Type

Panel B: Total Number of Words

Panel C: Number of Filtered Words

Notes: Figure 8 is based on external cases only. The distribution of address types is plotted by source in Panel A. The histogram of total numbers of words in a title and that of numbers of filtered words in a title are plotted by source in Panel B and Panel C, respectively. There are 364,189 external observations.
Table 1: 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 2: Main Effects on the Completion Time of 311 Cases

|                    | (1) Hazards | (2) Hazards | (3) Hazards | (4) Hazards | (5) Hazards | (6) Hazards | (7) Hazards |
|--------------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|
| Average Year of Education | 0.008***     | 0.017***     | 0.017***     | 0.023***     | 0.025***     | 0.028***     | 0.036***     |
|                     | (0.001)      | (0.001)      | (0.001)      | (0.002)      | (0.002)      | (0.002)      | (0.002)      |
| Citizen Connect App | -0.048***    | -0.039***    | -0.042***    | (0.006)      | (0.006)      | (0.006)      |            |
| Web Submission     | -0.130***    | -0.130***    | -0.161***    | (0.005)      | (0.005)      | (0.005)      |            |
| Average Years of Education × Citizen Connect App | -0.015***    | -0.018***    |            | (0.003)      | (0.003)      |            |            |
| Average Years of Education × Web Submission | -0.001       | -0.007**     |            | (0.003)      | (0.003)      |            |            |
| Reason Stratification | No          | Yes         | Yes         | Yes         | Yes         | Yes         | Yes         |
| Year Fixed Effects  | No           | No          | Yes         | Yes         | Yes         | Yes         | Yes         |
| Season Fixed Effects | No           | No          | Yes         | Yes         | Yes         | Yes         | Yes         |
| Weekday Fixed Effects | No           | No          | No          | Yes         | Yes         | Yes         | Yes         |
| Gender Controls     | No           | No          | No          | Yes         | Yes         | Yes         | Yes         |
| Age Controls        | No           | No          | No          | Yes         | Yes         | Yes         | Yes         |
| Race Controls       | No           | No          | No          | Yes         | Yes         | Yes         | Yes         |
| Language Controls   | No           | No          | No          | Yes         | Yes         | Yes         | Yes         |
| Income Controls     | No           | No          | No          | Yes         | Yes         | Yes         | Yes         |
| Housing Status Controls | No          | No          | No          | Yes         | Yes         | Yes         | Yes         |
| Observations        | 364,189      | 364,189      | 364,189      | 364,189      | 364,189      | 364,189      | 310,736      |
| AIC                 | 8,598,758    | 6,842,089    | 6,835,968    | 6,835,666    | 6,834,835    | 6,834,811    | 5,968,633    |

Notes: The population variable is cases and a hazard model for the completion time is used. There are only 310,736 observations in Column (7) because some minor categories are removed. Standard errors are in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01
Table 3: Mechanism

| Main Effect                  | (1)        | (2)        | (3)        | (4)        | (5)        | (6)        | (7)        |
|-----------------------------|------------|------------|------------|------------|------------|------------|------------|
| Citizen Connect App         | None       | Address    | #Total     | #Filtered  | None       | #Total     | #Filtered  |
| Average Year of Education   | 0.028***   | 0.026***   | 0.028***   | 0.029***   | 0.025***   | 0.025***   | 0.026***   |
| Citizen Connect App         | -0.039***  | -0.025***  | -0.060***  | -0.063***  | -0.063***  | -0.063***  | -0.063***  |
| Average Years of Education  | -0.015***  | -0.014***  | -0.013***  | -0.015***  | -0.015***  | -0.015***  | -0.015***  |
| × Citizen Connect App       |            |            |            |            |            |            |            |
| Photo                       |            |            |            |            |            |            |            |
| Average Years of Education  |            |            |            |            |            |            |            |
| × Photo                     | -0.198***  | -0.147***  | -0.034***  | -0.143***  | -0.143***  | -0.143***  | -0.143***  |
| × Average Year of Education | 0.023***   | 0.012***   | 0.013***   | 0.011***   | 0.011***   | 0.011***   | 0.011***   |
| × Citizen Connect App       | 0.185***   | 0.038***   | -0.093***  | 0.009***   | 0.009***   | 0.009***   | 0.009***   |
| × Avg. Education × App      | -0.026***  | -0.011***  | -0.013***  |           |           |           |           |
| Interactions with Web Use   | Yes        | Yes        | Yes        | Yes        | Yes        | Yes        | Yes        |
| Reason Stratification       | Yes        | Yes        | Yes        | Yes        | Yes        | Yes        | Yes        |
| 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        |
| Gender Controls             | Yes        | Yes        | Yes        | Yes        | Yes        | Yes        | Yes        |
| Age Controls                | Yes        | Yes        | Yes        | Yes        | Yes        | Yes        | Yes        |
| Race Controls               | Yes        | Yes        | Yes        | Yes        | Yes        | Yes        | Yes        |
| Language Controls           | Yes        | Yes        | Yes        | Yes        | Yes        | Yes        | Yes        |
| Income Controls             | Yes        | Yes        | Yes        | Yes        | Yes        | Yes        | Yes        |
| Housing Status Controls     | Yes        | Yes        | Yes        | Yes        | Yes        | Yes        | Yes        |
| Observations                | 364,189    | 364,189    | 364,149    | 364,149    | 364,189    | 364,149    | 364,149    |

Notes: The population variable is cases and a hazard model for the completion time is used. The presence of missing values leads to a smaller sample size in Column (3), (4), (6), and (7). Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. 

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# Table 4: Instrumental Variables Estimation

## Panel A: Logit Approximation of Cox Model

|                | (1)     | (2)     | (3)     | (4)     |
|----------------|---------|---------|---------|---------|
| **Moderating Factor** | None    | Address | #Total  | #Filtered|
| Average Year of Education | 0.007*** | 0.006*** | 0.007*** | 0.007*** |
| Citizen Connect App       | -0.016*** | -0.011*** | -0.016*** | -0.019*** |
| Average Years of Education | -0.002*** | -0.002*** | -0.002*** | -0.002*** |
| × Citizen Connect App     | 0.000    | 0.001    | (0.001)  | (0.001)  |
| **Moderating Factor**     | -0.054*** | -0.035*** | -0.002*** | -0.002*** |
| × Average Year of Education | 0.000    | 0.001    | (0.001)  | (0.001)  |
| **Moderating Factor**     | 0.006*** | 0.023*** | -0.018*** | -0.018*** |
| × Citizen Connect App     | 0.000    | 0.001    | (0.001)  | (0.001)  |
| **Moderating Factor**     | 0.006*** | 0.003*** | -0.003*** | -0.003*** |
| × Avg. Education × App    | 0.002    | 0.001    | (0.001)  | (0.001)  |

## Panel B: Instrumental Variables Estimation (2SLS)

|                | (1)     | (2)     | (3)     | (4)     |
|----------------|---------|---------|---------|---------|
| **Moderating Factor** | None    | Address | #Total  | #Filtered|
| Average Year of Education | 0.008*** | 0.008*** | 0.008*** | 0.009*** |
| Citizen Connect App       | -0.142*** | -0.152*** | -0.164*** | -0.142*** |
| Average Years of Education | 0.002    | -0.000   | 0.003    | 0.002    |
| × Citizen Connect App     | 0.010    | 0.012    | (0.010)  | (0.010)  |
| **Moderating Factor**     | -0.108*** | -0.051*** | -0.011*** | -0.011*** |
| × Average Year of Education | 0.001    | 0.003*** | -0.001   | -0.001   |
| **Moderating Factor**     | 0.222*** | 0.108*** | 0.017    | 0.017    |
| × Citizen Connect App     | 0.031    | (0.011)  | (0.013)  | (0.013)  |
| **Moderating Factor**     | -0.008   | -0.019*** | 0.007    | 0.007    |
| × Avg. Education × App    | 0.016    | (0.005)  | (0.005)  | (0.005)  |

## Panel C: 2SLS where First Stage Coefficients Vary by Neighborhood

|                | (1)     | (2)     | (3)     | (4)     |
|----------------|---------|---------|---------|---------|
| **Moderating Factor** | None    | Address | #Total  | #Filtered|
| Average Year of Education | 0.012*** | 0.011*** | 0.011*** | 0.012*** |
| Citizen Connect App       | 0.224*** | 0.235*** | 0.202*** | 0.234*** |
| Average Years of Education | -0.049*** | -0.053*** | -0.046*** | -0.049*** |
| × Citizen Connect App     | 0.006    | (0.005)  | (0.005)  | (0.005)  |
| **Moderating Factor**     | -0.090*** | -0.047*** | -0.005*  | (0.007)  |
| × Average Year of Education | 0.009*** | 0.001    | -0.002*  | (0.002)  |
| **Moderating Factor**     | 0.244*** | 0.106*** | 0.029*** | 0.029*** |
| × Citizen Connect App     | 0.026    | (0.011)  | (0.012)  | (0.012)  |
| **Moderating Factor**     | -0.064*** | -0.012*** | 0.006    | 0.006    |
| × Avg. Education × App    | 0.012    | (0.005)  | (0.005)  | (0.005)  |

| Interactions with Web Use | Yes | Yes | Yes | Yes |
| Reason Stratification     | Yes | Yes | Yes | Yes |
| Year Fixed Effects        | Yes | Yes | Yes | Yes |
| Season Fixed Effects      | Yes | Yes | Yes | Yes |
| Weekday Fixed Effects     | Yes | Yes | Yes | Yes |
| Gender Controls           | Yes | Yes | Yes | Yes |
| Age Controls              | Yes | Yes | Yes | Yes |
| Race Controls             | Yes | Yes | Yes | Yes |
| Language Controls         | Yes | Yes | Yes | Yes |
| Income Controls           | Yes | Yes | Yes | Yes |
| Housing Status Controls   | Yes | Yes | Yes | Yes |

**Notes:** The population variable is time intervals and the dependent variable is whether the case was resolved during the time interval.

Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. 

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A Appendix

A.1 Figures

Figure W1: Boston Census Block Groups Boundary 2010

Note: The map shows the boundaries for 646 census block groups in the city of Boston. From Boston Redevelopment Authority: http://www.bostonredevelopmentauthority.org/research-maps/maps-and-gis/census-and-demographic-maps
Figure W2: Instrumental Variables: Exclusion Restriction

(a) Average Years of Education

(b) IV: Employee’s Choice

Notes: The average years of education are plotted for each census block in Panel A. 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 B.
### Table A1: 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        |
| Enroll & Enrollment*                   | 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 A2: 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   |
|-----------------------------------|-----|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|
| Average Years of Education       | 1.00|      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |
| % Male                           | -0.03|      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |      |
| % < 18 years old                 | -0.57| -0.17| 1.00 |      |      |      |      |      |      |      |      |      |      |      |      |      |      |
| % 18 - 29 years old              | 0.37 | 0.03 | -0.63| 1.00 |      |      |      |      |      |      |      |      |      |      |      |      |      |
| % 30 - 44 years old              | 0.14 | 0.18 | 0.08 | -0.39| 1.00 |      |      |      |      |      |      |      |      |      |      |      |      |
| % 45 - 59 years old              | -0.24| 0.07 | -0.25| -0.61| -0.03| 1.00 |      |      |      |      |      |      |      |      |      |      |      |
| % White                          | 0.68 | 0.07 | -0.58| 0.27 | 0.14 | -0.20| 1.00 |      |      |      |      |      |      |      |      |      |      |
| % Black                          | -0.52| -0.11| 0.54 | -0.32| -0.14| 0.25 | -0.87| 1.00 |      |      |      |      |      |      |      |      |      |
| % Asian                          | 0.07 | 0.01 | -0.23| 0.25 | -0.11| -0.16| -0.00| -0.33| 1.00 |      |      |      |      |      |      |      |      |
| % Other Single Race              | -0.44| -0.03| 0.40 | -0.15| -0.03| 0.03 | -0.50| 0.21 | -0.12| 1.00 |      |      |      |      |      |      |      |
| % English Only                   | 0.61 | -0.05| -0.28| -0.01| 0.12 | 0.08 | 0.50 | -0.17| -0.27| -0.50| 1.00 |      |      |      |      |      |      |
| % 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 |      |      |      |      |      |
| % 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 |      |      |      |      |
| 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 |      |      |      |
| % 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 |      |      |
| % 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 |      |
| % 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 |

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 A3: Main Effects (Alternative Model – Logit 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 | 0.005** | 0.006** | 0.005 | 0.007 | 0.020*** | 0.020*** |
|              | (0.002) | (0.003) | (0.003) | (0.005) | (0.005) | (0.006) | (0.006) |
| Citizen Connect App | -0.040*** | -0.022 | -0.009 | | | | |
|              | (0.014) | (0.015) | (0.015) | | | | |
| Web Submission | -0.405*** | -0.401*** | -0.442*** | | | | |
|              | (0.014) | (0.014) | (0.015) | | | | |
| Average Years of Education × Citizen Connect App | -0.042*** | -0.037*** | | | | | |
|              | (0.007) | (0.007) | | | | | |
| Average Years of Education × Web Submission | -0.027*** | -0.029*** | | | | | |
|              | (0.008) | (0.009) | | | | | |
| Reason Fixed Effects | No | Yes | Yes | Yes | Yes | Yes | Yes |
| Year Fixed Effects | No | No | Yes | Yes | Yes | Yes | Yes |
| Season Fixed Effects | No | No | Yes | Yes | Yes | Yes | Yes |
| Weekday Fixed Effects | No | No | Yes | Yes | Yes | Yes | Yes |
| Gender Controls | No | No | No | Yes | Yes | Yes | Yes |
| Age Controls | No | No | No | Yes | Yes | Yes | Yes |
| Race Controls | No | No | No | Yes | Yes | No | No |
| Language Controls | No | No | No | Yes | Yes | Yes | Yes |
| Income Controls | No | No | No | Yes | Yes | Yes | Yes |
| Housing Status Controls | No | No | No | Yes | Yes | Yes | Yes |
| Observations | 364,189 | 364,189 | 364,189 | 364,189 | 364,189 | 364,189 | 310,736 |
| AIC | 397,523 | 296,664 | 277,617 | 277,394 | 276,550 | 276,514 | 240,078 |

Notes: The population variable is cases and a logit model for the “on-time” indicator is used. There are only 310,736 observations in Column (7) because some minor categories are removed. Standard errors are in parentheses. sym* p < 0.10, ** p < 0.05, *** p < 0.01
|                           | (1)     | (2)     | (3)     | (4)     | (5)     | (6)     |
|---------------------------|---------|---------|---------|---------|---------|---------|
| **Citizen Connect App**   | -0.039*** | -0.040*** | -0.042*** | -0.039*** | -0.033*** | -0.036*** |
|                           | (0.006) | (0.006) | (0.006) | (0.006) | (0.007) | (0.006) |
| Web Submission            | -0.130*** | -0.130*** | -0.128*** | -0.130*** | -0.131*** | -0.130*** |
|                           | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) |
| Average Years of Education| 0.028*** |         |         |         |         |         |
|                           | (0.002) |         |         |         |         |         |
| **Average Years of Education** |         | -0.015*** |         |         |         |         |
| Citizen Connect App       |         | (0.003) |         |         |         |         |
| Web Submission            |         |         | (0.005) |         |         |         |
| In(Average Years of Education) |         | 0.356*** |         |         |         |         |
|                           | (0.027) |         |         |         |         |         |
| %High School and Above    | 0.226*** |         |         |         |         |         |
|                           | (0.025) |         |         |         |         |         |
| %High School and Above    |         | -0.129*** |         |         |         |         |
| Web Submission            |         | (0.043) |         |         |         |         |
| %High School and Above    |         | -0.035  |         |         |         |         |
| Web Submission            |         | (0.039) |         |         |         |         |
| %Bachelor and Above       |         |         |         | 0.189*** |         |         |
|                           |         |         |         | (0.014) |         |         |
| %Bachelor and Above       |         |         |         | -0.151*** |         |         |
| Web Submission            |         |         |         | (0.024) |         |         |
| %Bachelor and Above       |         |         |         | -0.008  |         |         |
| Web Submission            |         |         |         | (0.021) |         |         |
| %Graduate School          |         |         |         |         |         | 0.215*** |
|                           |         |         |         |         |         | (0.018) |
| %Graduate School          |         |         |         |         |         | -0.220*** |
| Web Submission            |         |         |         |         |         | (0.032) |
| Reason Stratification     | Yes     | Yes     | Yes     | Yes     | Yes     | Yes     |
| Season Fixed Effects      | Yes     | Yes     | Yes     | Yes     | Yes     | Yes     |
| Weekday Fixed Effects     | Yes     | Yes     | Yes     | Yes     | Yes     | Yes     |
| Gender Controls           | Yes     | Yes     | Yes     | Yes     | Yes     | Yes     |
| Age Controls              | Yes     | Yes     | Yes     | Yes     | Yes     | Yes     |
| Race Controls             | Yes     | Yes     | Yes     | Yes     | Yes     | Yes     |
| Language Controls         | Yes     | Yes     | Yes     | Yes     | Yes     | Yes     |
| Income Controls           | Yes     | Yes     | Yes     | Yes     | Yes     | Yes     |
| Housing Status Controls   | Yes     | Yes     | Yes     | Yes     | Yes     | Yes     |
| Observations              | 364,189 | 364,189 | 364,189 | 364,189 | 364,189 | 364,189 |
| AIC                       | 6,834,811 | 6,834,829 | 6,834,932 | 6,834,823 | 6,834,801 | 6,834,850 |

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 A5: Mechanism (Full Table)

| Main Effect                      | Citizen Connect App | Photo Attachment |
|----------------------------------|---------------------|------------------|
|                                  | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Average Year of Education        | 0.028*** | 0.026*** | 0.028*** | 0.029*** | 0.025*** | 0.025*** | 0.026*** |
|                                  | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| Web Submission                   | -0.142*** | -0.098*** | -0.148*** | -0.118*** | -0.126*** | -0.140*** | -0.114*** |
|                                  | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) |
| Citizen Connect App              | -0.039*** | -0.025*** | -0.060*** | -0.063*** | (0.006) | (0.007) | (0.006) |
|                                  | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| Average Years of Education       | -0.015*** | -0.014*** | -0.013*** | -0.015*** | (0.003) | (0.003) | (0.003) |
| × Citizen Connect App            | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| Average Years of Education       | -0.001 | -0.007*** | -0.002 | -0.006** | (0.003) | (0.003) | (0.003) |
| × Web Submission                 | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| Photo                            | -0.040*** | -0.061*** | -0.058*** | (0.009) | (0.009) | (0.010) |
|                                  | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) |
| Moderator Factor                 | -0.198*** | -0.147*** | -0.034*** | -0.143*** | -0.060*** | (0.006) | (0.003) |
|                                  | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| × Average Year of Education      | 0.023*** | 0.012*** | 0.013*** | 0.011*** | 0.009*** | (0.012) | (0.005) |
|                                  | (0.003) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Moderator Factor                 | 0.185*** | 0.038*** | -0.093*** | (0.014) | (0.005) | (0.005) |
| × Citizen Connect App            | (0.012) | (0.005) | (0.006) | (0.004) | (0.005) | (0.005) | (0.005) |
| Moderator Factor                 | 0.247*** | -0.022*** | -0.043*** | -0.025*** | -0.027*** | (0.008) | (0.003) |
| × Web Submission                 | (0.014) | (0.005) | (0.005) | (0.004) | (0.005) | (0.005) | (0.005) |
| Moderator Factor                 | -0.026*** | -0.011*** | -0.013*** | (0.006) | (0.002) | (0.003) |
| × Avg. Education × App           | (0.006) | (0.002) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| Moderator Factor                 | 0.006 | 0.000 | 0.003 | 0.001 | 0.007** | (0.008) | (0.003) |
| × Avg. Education × Web           | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) |
| Moderator Factor                 | 0.064*** | -0.030*** | (0.009) | (0.009) | (0.009) | (0.009) | (0.009) |
| × Photo                          | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) |
| Moderator Factor                 | -0.009** | -0.014** | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) |
| × Avg. Education × Photo         | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) |

| Reason Stratification | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| 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 |
| Gender Controls        | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Age Controls           | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Race Controls          | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Language Controls      | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Income Controls        | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Housing Status Controls| Yes | Yes | Yes | Yes | Yes | Yes | Yes |

| Observations | Observations | 364,189 | 364,189 | 364,149 | 364,149 | 364,189 | 364,149 | 364,149 |

Notes: The population variable is cases and a hazard model for the completion time is used. The presence of missing values leads to a smaller sample size in Column (3), (4), (6), and (7). Standard errors are in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.
| Main Effect | Citizen Connect App | Photo Attachment |
|-------------|---------------------|------------------|
| % Spanish   | -0.044*** -0.030*** -0.063*** -0.068*** | 0.045** 0.043** 0.043*** |
|            | (0.006) (0.007) (0.006) (0.006) | (0.021) (0.021) (0.021) |
| Citizen Connect App | -0.130*** -0.141*** -0.147*** -0.119*** | -0.125*** -0.138*** -0.115*** |
|            | (0.005) (0.005) (0.005) (0.005) | (0.005) (0.005) (0.005) |
| % Spanish   | 0.185*** 0.189*** 0.163*** 0.188*** | -0.036 -0.031 -0.036 |
|            | (0.038) (0.040) (0.038) (0.038) | (0.033) (0.033) (0.034) |
| % Spanish   | -0.012 -0.016 -0.010 -0.013 | -0.042*** -0.060*** -0.059*** |
|            | (0.033) (0.034) (0.033) (0.034) | (0.009) (0.009) (0.009) |
| % Spanish   | 0.111* 0.104* 0.131** | 0.111* 0.104* 0.131** |
| Photo       | -0.197*** -0.148*** -0.034*** | -0.134*** -0.059*** |
|            | (0.006) (0.003) (0.003) | (0.002) (0.003) |
| % Spanish   | -0.187*** -0.025** -0.040** | -0.024** -0.027* |
|            | (0.037) (0.011) (0.016) | (0.011) (0.014) |
| % Spanish   | 0.184*** 0.040*** -0.033*** | 0.066*** -0.033*** |
|            | (0.012) (0.005) (0.006) | (0.009) (0.010) |
| % Spanish   | 0.253*** -0.017*** -0.036*** | 0.064 0.102 |
|            | (0.014) (0.004) (0.005) | (0.009) (0.010) |
| % Spanish   | 0.267*** 0.038 0.053 | 0.064 0.102 |
|            | (0.081) (0.031) (0.036) | (0.009) (0.010) |
| % Spanish   | -0.006 -0.011 0.046 | 0.066*** -0.033*** |
|            | (0.101) (0.033) (0.040) | (0.010) (0.010) |
| % Spanish   | 0.064 0.102 | 0.066*** -0.033*** |
|            | (0.061) (0.071) | (0.010) (0.010) |
| Reason Stratification | Yes Yes Yes Yes Yes Yes Yes Yes | Yes Yes Yes Yes Yes Yes Yes Yes |
| Year Fixed Effects | Yes Yes Yes Yes Yes Yes Yes Yes | Yes Yes Yes Yes Yes Yes Yes Yes |
| Season Fixed Effects | Yes Yes Yes Yes Yes Yes Yes Yes | Yes Yes Yes Yes Yes Yes Yes Yes |
| Weekday Fixed Effects | Yes Yes Yes Yes Yes Yes Yes Yes | Yes Yes Yes Yes Yes Yes Yes Yes |
| Gender Controls | Yes Yes Yes Yes Yes Yes Yes Yes | Yes Yes Yes Yes Yes Yes Yes Yes |
| Age Controls | Yes Yes Yes Yes Yes Yes Yes Yes | Yes Yes Yes Yes Yes Yes Yes Yes |
| Race Controls | Yes Yes Yes Yes Yes Yes Yes Yes | Yes Yes Yes Yes Yes Yes Yes Yes |
| Language Controls | Yes Yes Yes Yes Yes Yes Yes Yes | Yes Yes Yes Yes Yes Yes Yes Yes |
| Income Controls | Yes Yes Yes Yes Yes Yes Yes Yes | Yes Yes Yes Yes Yes Yes Yes Yes |
| Housing Status Controls | Yes Yes Yes Yes Yes Yes Yes Yes | Yes Yes Yes Yes Yes Yes Yes Yes |
| Observations | 364,189 364,189 364,149 364,149 | 364,189 364,149 364,149 |

Notes: The population variable is cases and a hazard model for the completion time is used. The presence of missing values leads to a smaller sample size in Column (3), (4), (6), and (7). Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. 

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Table A7: Instrumental Variables Estimation (First Stages)

|                          | (1)          | (2)          | (3)          | (4)          |
|--------------------------|--------------|--------------|--------------|--------------|
|                          | App Interaction | App Interaction | App Interaction | App Interaction |
| Min Distance (in km)     | -0.012***    | -0.022***    | -0.004***    | -0.010***    |
|                          | (0.000)      | (0.001)      | (0.000)      | (0.001)      |
| Average Year of Education| -0.005***    | -0.046***    | -0.003***    | -0.042***    |
| × Min Distance (in km)   | (0.000)      | (0.000)      | (0.000)      | (0.000)      |
| Interactions with Web Use| Yes          | Yes          | Yes          | Yes          |
| Reason Stratification    | Yes          | Yes          | Yes          | Yes          |
| Year Fixed Effects       | Yes          | Yes          | Yes          | Yes          |
| Season Fixed Effects     | Yes          | Yes          | Yes          | Yes          |
| Weekday Fixed Effects    | Yes          | Yes          | Yes          | Yes          |
| Gender Fixed Effects     | Yes          | Yes          | Yes          | Yes          |
| Age Fixed Effects        | Yes          | Yes          | Yes          | Yes          |
| Race Fixed Effects       | Yes          | Yes          | Yes          | Yes          |
| Language Fixed Effects   | Yes          | Yes          | Yes          | Yes          |
| Income Fixed Effects     | Yes          | Yes          | Yes          | Yes          |
| Housing Status Fixed Effects | Yes        | Yes          | Yes          | Yes          |
| Observations             | 1,941,987    | 1,941,987    | 1,941,987    | 1,941,987    |
| Wald Statistic           | 539.83       | 444.58       |              |              |

Notes: The population variable is time intervals and the dependent variable is whether the case was resolved during the time interval. Standard errors are in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.