# No-Show Management in Primary Care: A Quality Improvement Project

Timothy Gebhart

OHSU School of Nursing

**Purpose:** To determine features of appointments and demographic details at OHSU Family Medicine at Richmond Clinic that have led to no-show appointments in the past in order to both characterize trends and to make evidence-based recommendations in reducing the number of no-show appointments.

**Background:** No-shows can be significantly disruptive to clinical practices, with wide variation according to population served and specialty. In one clinic studied they found that 25% of clinic time is wasted and 14% of clinic revenue is lost to no-shows (Daggy et al., 2010). An analysis from a large academic family medicine group found an overall 31% no-show rate, similarly leading to 14% loss of income (Moore, Wilson-Witherspoon, & Probst, 2001). Upon reviewing appointment details from the U.S. Department of Veterans Affairs (VA), researchers found an overall 19% rate of no-show appointments amongst outpatient clinics, with most occurring in primary care clinics, and each representing an average $196 loss in revenue for the clinic (Kheirkhah, Feng, Travis, Tavakoli-Tabasi, & Sharafkhaneh, 2015).

No-shows can be devastating to the patients that fail to arrive. Multiple studies have shown that patients that chronically no-show for appointments are less likely to be adequately screened for cancers, have worse control of chronic illness, and have increased rates of emergency department (ED) visits and hospitalizations (Hwang et al., 2015; Nguyen & DeJesus, 2010; Nuti et al., 2012). Schectman, Schloring & Voss (2008), conducted a study specific to diabetes and found that every 10% rate of missed appointments increased the chance of poor diabetes control by 24% and decreased the chance of good diabetes control by 12%.

**Methods:** A plan for data extraction and data analysis from the electronic medical record (EMR) system utilities at Richmond was developed. IRB approval was obtained. Characteristics of all appointments occurring during the years 2014-2016 along with demographics of patients seen were extracted from the EMR and manipulated using the R programming language. Data was then analyzed using descriptive statistics and a multivariate linear regression model used to determine which characteristics were of statistical significance.

**Results:** 244,097 total appointments with 18,203 individual patients were analyzed from the 3-year period. An overall no-show rate of 17.1% was found for Richmond over that time. Multiple characteristics were found to significant for increasing or decreasing no-show rates, including race (Black compared to White odds ratio [OR] 1.29), patient age (bimodal distribution with young children and young adults having increased no-show rates), previous missed appointments (OR 1.11), previous attended appointments (OR 0.97), time block scheduled (Monday morning OR 1.15, Saturday afternoon OR 0.41), and provider type scheduled with (resident physician OR 1.25, family nurse practitioner OR 1.31, physician assistant OR 1.32, counsellor OR 2.19), amongst other findings.

**Implications for future:** Data analysis performed with Richmond data forms a foundation for specific recommendations in interventions to decrease the no-show rate at Richmond as well as a starting point for further research to determine characteristics not captured in the medical record and other barriers to clinic attendance.

## Introduction

Although Galen was likely to have received patients in the market, the medical historian Johann Baas placed medical office visits at least as far back as the 17$^{th}$ century (1889). Since that time clinicians have struggled with no-show appointments, with recent estimates finding 14-50% of primary care appointments are no-shows (Daggy et al., 2010). In clinical practice, a no-show appointment is generally defined as an appointment where the patient fails to appear, arrives too late for the appointment, or cancels with too short a notice to schedule a different patient during their appointment time (Cameron, Sadler, & Lawson, 2010).

No-shows can be significantly disruptive to clinical practices, with wide variation according to population served and specialty. In one clinic studied it was found that 25% of clinic time is wasted and 14% of clinic revenue is lost to no-shows (Daggy et al., 2010). An analysis from a large academic family medicine group found an overall 31% no-show rate, similarly leading to 14% loss of income (Moore, Wilson-Witherspoon, & Probst, 2001). Upon reviewing appointment details from the U.S. Department of Veterans Affairs (VA), researchers found an overall 19% rate of no-show appointments amongst outpatient clinics, with most occurring in primary care clinics, and each representing an average $196 loss in revenue for the clinic for each missed visit (Kheirkhah, Feng, Travis, Tavakoli-Tabasi, & Sharafkhaneh, 2015).

No-shows can be devastating to the patients that fail to arrive. Multiple studies have shown that patients that chronically no-show for appointments are less likely to be adequately screened for cancers, have worse control of chronic illness, and have increased rates of emergency department (ED) visits and hospitalizations (Hwang et al., 2015; Nguyen & DeJesus, 2010; Nuti et al., 2012). Schectman, Schloring & Voss (2008), conducted a study specific to diabetes and found that every 10% rate of missed appointments increased the chance of poor diabetes control by 24% and decreased the chance of good diabetes control by 12%.

Although no-show appointments affect patients across the spectrum, some general characteristics have been seen to increase the risk for missing appointments. Age is a strong predictor of no-show, with younger adults much more likely to miss appointments (Bennett & Baxley, 2009; Daggy et al., 2010; Kaplan-Lewis & Percac-Lima, 2013; Miller, Chae, Peterson, & Ko, 2015; Moore et al., 2001; Sorita, Funakoshi, Kashan, Young, & Park, 2014). Ethnicity is also a strong predictor, with black patients (Bennett & Baxley, 2009; Kaplan-Lewis & Percac-Lima, 2013; Miller et al., 2015; Moore et al., 2001; Shimotsu et al., 2016), Latinos (Kaplan-Lewis & Percac-Lima, 2013; Shimotsu et al., 2016), and Native Americans (Shimotsu et al., 2016) having higher rates of no-show appointments. Living within a deprived area (based upon unemployment rate, lack of car or home ownership, and household overcrowding) was identified as a 3-fold risk for no-show appointments in one study (DuMontier, Rindfleisch, Pruszynski, & Frey, 2013) and personally experiencing poverty was found to additionally increase risk two-fold (Bowser, Utz, Glick, & Harmon, 2010; Miller et al., 2015). Finally, psychiatric co-morbidity, particularly depression, was seen widely across studies as increasing no-show risk (Bowser et al., 2010; Daggy et al., 2010; DuMontier et al., 2013; Moscrop, Siskind, & Stevens, 2012; Shimotsu et al., 2016).

**Purpose of the Project**

This project will study the characteristics of missed appointments at OHSU Family Medicine at Richmond Clinic in an attempt to improve their own no-show appointment rate using evidence-based recommendations. As they are currently re-evaluating no-show policies and interventions, this is an opportune moment. Missed appointments are a significant concern for this safety-net clinic, both due to the loss of clinic effectiveness and the health effects of missed appointments on their patient population.

## Literature Review

In order to better understand current work on no-show management, a Medline search was performed in April 2016 using the Boolean search (("no show" OR "no-show" OR "missed appointment") AND ("primary care" OR outpatient OR clinic)) OR (care, primary health[MeSH Terms] AND appointments and schedules[MeSH Terms] AND ("no-show" OR "missed appointment" OR "no show")) OR (appointments and schedules[MeSH Terms] AND (patient compliance[MeSH Terms] OR patient dropouts[MeSH Terms])) with filters placed for English language publications from the past 10 years. This yielded 555 articles. Restricting results to clinical trials and review articles reduced the count to 93, which was further manually filtered to 21 for relevance to assessing interventions for missed appointments.

The EBSCOhost database Business Source Elite was next searched using the abbreviated Boolean term (("no show" OR "no-show" OR "missed appointment") AND ("primary care" OR outpatient OR clinic)) and filtering in academic journal articles published within the past 10 years. This generated a second list of 30 articles, which were then reviewed for duplication and relevance, leaving 16 additional articles largely drawn from industrial engineering and operations management, themes lacking in the more clinically focused Medline database.

From these searches two major interconnected themes emerged: the characteristics of no-show appointments and interventions to either eliminate missed appointments or to reduce disruption from no-shows. Both themes are explored below, in addition to the important ethical considerations when working with patients who chronically no-show.

### Identification of Appointments Likely to No-Show

A robust line of research has investigated patient and appointment characteristics associated historically with no-shows. By understanding these characteristics, interventions to reduce or limit impact can be greatly improved. Many interventions are specifically targeted to these patients that are most likely to benefit, and many of the methods to reduce no-shows are built upon accurate modelling of those likely to no-show.

The literature search produced a total of 15 articles describing patient and appointment characteristics that produced a higher rate of no-shows within their population. They form a relatively heterogeneous sample drawn from 4 pediatric clinic populations, 13 from primary care settings, and 2 from outpatient specialty clinics, and are representative of diverse regions (US, United Kingdom, and Switzerland). From these study populations a number of themes for missed appointments emerge, which can be divided amongst patient characteristics, appointment characteristics, and patient reasons for missing appointments.

## Interventions for No-Shows

By understanding patient and appointment characteristics that may lead to no-shows, interventions to reduce no-shows can be targeted to those most likely to benefit. Directly addressing the reasons patients provide for missing appointments should also provide benefit in helping them to make their appointments. A number of methods that have been utilized with varying success are discussed below.

### Reminders

Identification of simple forgetfulness is a common reason for patients to miss their appointments, thus reminding patients of their upcoming appointments ought to reduce no-show rates (Kaplan-Lewis & Percac-Lima, 2013). A number of methods are both commonly used in primary care and have research studying their effectiveness in helping patients keep appointments including mailed reminders (Kheirkhah et al., 2015; Stubbs, Geraci, Stephenson, Jones, & Sanders, 2012), phone reminders (Agarin et al., 2015; Hasvold & Wootton, 2011; Stubbs et al., 2012), text-message reminders (Gurol-Urganci, de Jongh, Vodopivec-Jamsek, Atun, & Car, 2013; Stubbs et al., 2012), and emailed reminders (Atherton, Sawmynaden, Meyer, & Car, 2012; Horvath et al., 2011; Sharp, Singal, Pulia, Fowler, & Simmons, 2015).

**Scheduling Methods**

With much site variation, there are three basic scheduling methods: traditional, where clinician time is sequentially booked in advance, often by months; carve-out, where the traditional approach is modified by blocking out time for urgent or same-day appointments; and advanced access (sometimes labelled open access), where same-day appointments are given priority and there is a fixed window (days to weeks) after which appointments are not scheduled (Murray & Berwick, 2003). These advanced access systems have been shown to have varying impacts on reducing no-show appointments (Rose, Ross, & Horwitz, 2011; Stubbs et al., 2012).

Overbooking of appointments, generally in the traditional scheduling model outlined above, is a common intervention for reducing the impact of no-shows. Similar to the airline industry, multiple patients are booked into the same appointment slot with the expectation some will fail to show, and in this way clinics can protect against the loss of revenue and provider idleness no-shows would otherwise cause. Unlike the airline industry, where many flights are taking off concurrently, making poor predictions on no-show patterns means increasingly long delays for patients to be seen by the provider in question and increasing overall staff overtime (Huang & Hanauer, 2014). As a result, many models have been published that either use historical no-show rates for the clinic modelled or patient demographics to calculate the relative risk for no-shows and to overbook schedule the day accordingly (Cronin & Kimball, 2014;

Harris, May, & Vargas, 2016; LaGanga & Lawrence, 2012; Lotfi & Torres, 2014; Muthuraman & Lawley, 2008; Tsai & Teng, 2014; Zacharias & Pinedo, 2014).

An interesting intervention trialed at some centers is placing patients who chronically no-show on a probationary status. As described in a recent paper, patients who chronically no-showed at an academic family medicine clinic were placed in a special cohort that were essentially overbooked to the clinic rather than a particular provider until their clinic attendance improved, which had a modest improvement in their overall no-show rate (DuMontier et al., 2013).

**Patient Education**

Another reason that patients gave for missed appointments is a lack of understanding of how clinics are scheduled and the impacts of missed appointments on the clinic. As a result, direct education around this topic has been employed as a method for reducing no-shows (Cibulka, Fischer, & Fischer, 2012; DuMontier et al., 2013; Johnson, Mold, & Pontious, 2007). Specifically, many sites have found decreased and lasting no-show rate reduction when patients have clinic policies and the importance of making or cancelling appointments explained after their first appointment (Guse, Richardson, Carle, & Schmidt, 2003).

**Patient Incentives**

Patient incentives for attending their appointments (financial or otherwise) have been used in some outpatient settings, but have not been extensively studied for actual benefit and the studies that have been published show limited or no benefit for no-show rates (Mehrotra, An, Patel, & Sturm, 2014; Smith, Weinman, Johnson, & Wait, 1990; Stanley, Chu, Brown, Sawyer, & Joiner, 2016). Some providers will limit the number of refills given for prescriptions in order to give patients a motivator for returning to clinic thereby reducing no-shows, although tactic is rarely described in the literature, published results find no benefit to no-show rates (Sorita et al., 2014).

### No-show Fee

Another commonly used intervention to reduce no-shows is to implement a fee for missed appointments, the efficacy of which has not been extensively studied. Recalling the relative expense of a missed appointment, these modest fees ($35-50) are meant as a deterrent to no-shows rather than recouping financial losses (Keohane, 2007). The literature search located one study that examined the effect of a missed appointment fee in an adolescent clinic, and found that it had no effect on no-show rates (Chariatte, Michaud, Berchtold, Akre, & Suris, 2007). A focused search for historical studies of similar fee implementation found one additional study of a student clinic in which the intervention had no effect on no-show rates (Wesch, Lutzker, Frisch, & Dillon, 1987).

### Discharge from Clinic

Finally, the most drastic option in no-show reduction is to discharge from the clinic patients who chronically miss appointments. As previous missed appointments are a strong indicator of subsequent missed appointments, this is a harshly logical intervention to reduce no-shows. No studies were located to determine if discharge policies have an effect on no-show rates, although it is widely employed (Johnson et al., 2007).

## Gaps in the Literature

The ethical considerations around no-show policies and underlying causes have received relatively little exposure in the literature. Many interventions tend to target “younger, healthier, and wealthier persons” through their reliance on fixed addresses and technology (Horvath et al., 2011), but in general there is little exploration of this disconnect between those least likely to no-show receiving a disproportionate response. Root causes growing from socioeconomic status are also rarely addressed. Arriving on time at an appointment is tremendously easier if you are financially stable enough to take time from employment, have child care, and access to reliable transportation: “Perfunctory attendance is a goal more suitable to middle-class patients than a working-class immigrant patient base” (Horton, 2006).

Many policy considerations were also not addressed in the literature search. The need for strict protocols was only described in relation to discharging patients from clinic due to legal considerations (Kreimer, 2016). Not addressed were the effects of no-shows on provider compensation (which is frequently dependent upon number of patients seen) and equitable methods to absorb that loss across clinics and provider panels that have disproportionately higher no-show rates.

**Proposed Project**

Although there are many interventions to decrease no-show appointments, most have varying effectiveness according to the population that they are addressing. Understanding the population is an essential step in selecting effective interventions (Guse et al., 2003). Therefore this project studies the population of OHSU Family Medicine at Richmond Clinic in an effort to determine statistically relevant details on missed appointments and use that to drive recommendations of evidence-based interventions to reduce their no-show appointments and thus their wasted time, lost revenue, and the ill health effects on their already vulnerable population.

## Approach to the Project

### Setting

OHSU Family Medicine at Richmond Clinic provides a full range of primary care services along with specialty clinics including sports medicine, podiatry, and prenatal. As a Federally Qualified Health Center they frequently serve as a safety-net clinic whose patients are predominately below 200% of the Federal Poverty Level (Angier et al., 2015). Patients are largely insured through Medicaid and a large percentage have mental health co-morbidities. These characteristics are well-described in the literature as risk factors for no-show appointments.

Not surprisingly, the providers and schedulers at Richmond Clinic struggle with apportioning time to patients when they have difficulty in identifying which patients are unlikely to show for which appointments. Current policies include automated reminders, a lengthy discharge process, and intensive follow-up for the most vulnerable, but the clinic recognizes the need to re-evaluate their current policies to attempt to improve their ability to do the most for their patients within financial constraints.

To support Richmond Clinic's re-evaluation of their no-show policies, this project has been driven by a statistical analysis of characteristics of patients (age, gender, etc.) that have had no-show appointments in the past as well as characteristics of missed appointments (day of week, time of day, etc.) to provide a baseline understanding of local conditions which will then be compared with findings from the literature to provide tailored suggestions for no-show policy changes that are evidence-based and support clinic aims.

### Participants

All patients scheduled within the past three years have been included in the data analysis. Three years is the time limitation for queries within the reporting interface, and with some 18,000 patients captured in the EMR, this was expected to produce a robust data set for analysis.

### Anticipated Challenges and Facilitators

The data set for study needed to be extracted from a complex EHR, and it was anticipated that the process of creating meaningful reports and programmatically connecting disparate data sets (e.g., patient demographics and scheduling details) would be technically challenging as well as time-consuming. Managing the size of the anticipated data set was also a secondary related challenge. Clinic staff expressed a desire in exploring the reporting capabilities highlighted by this project and were willing to support project efforts through consultation with clinic EHR experts.

## Proposed Implementation

### Data Collection and Analysis

As described above, the OCHIN implementation of the EpicCare EHR that Richmond uses for patient records and scheduling was planned to be queried through reporting interfaces, either from on-site or through an encrypted connection remotely. Reporting interfaces were also planned to be queried to determine patient demographics and appointment characteristics which was to then be inserted into a database on encrypted media for further analysis. The database was then to be used in a multivariate analysis to determine which factors are statistically significant for predicting no-show appointments. All data transmission was to be encrypted, all patient data de-identified, and resulting data sets stored on encrypted media to protect participants.

### Findings Dissemination

To support clinic re-evaluation of no-show policies, pertinent findings from the data analysis were to be presented to clinic leadership. These findings were to be placed in relation to similar studies in the literature providing a comparison to primary care sites in other geographic regions. Interventions from the literature were to be examined in the context of Richmond's patients in order to provide evidence-based recommendations in eliminating missed appointments and reducing disruption from no-shows.

## Actual Implementation

### Evolution over Time

After IRB approval and initial visits with the information technology team at Richmond, querying for appointment and patient data began. Limitations to what data was exposed via the Reporting Workbench became obvious at that point, which placed limitations on what characteristics were able to be analyzed. It was also discovered that only a month's worth of appointments could be run at a time, necessitating 36 separate queries for the full three years of data. Details exposed by the Reporting Workbench were also discovered, limiting the variety of demographic features that could be analyzed from EpicCare. Table 1 details hoped for characteristics with those that were actually available.

An unexpected resource for increased data depth was the Acuere website, which is a reporting tool used by OCHIN that has a secondary database of patient characteristics based on custom reporting from the EpicCare database. This was especially interesting as it included diagnosis coding and calculation of Charleson Comorbidity Indexes for all patients, details that were not available through Reporting Workbench.

For manipulating and analyzing the data resulting from these queries, the R programming language was chosen for its robustness and free-to-use licensing. With no prior exposure to this language, two months of directed study provided background skills for its use in the project. Appointment reports were concatenated and then transformed into a readily usable format, which resulted in a robust data set of 244,097 appointments. This set was then used to cross-reference to data from the patient report, excluding any that did not appear in appointments during the three year period of study. This was similarly transformed into more usable formats and then merged with data reported from the Acuere website to add in diagnosis codes. This resulted in an additional and similarly robust data set of 18,302 patients.

The R programming language was then used with these sets to generate a number of descriptive statistics (Appendix C), with potential trends being used in a multivariate linear regression to determine statistical significance (using Wald test) along with odds ratios with 95% confidence intervals (Appendix D). Finally, data were plotted in Microsoft Excel with descriptive statistics in mixed column/line formats (Appendix A) and results of regression model plotted as forest plots (Appendix B).

**Discovered Limitations**

Not surprisingly, the generated data sets (and thus findings from same) were not perfect. As seen in Table 1, marital status was a hoped-for variable to consider, but it was found that this was inconsistently coded within EpicCare (less than 5% of patient records had a value), so this was dropped from consideration. Some disconnect was found when merging Acuere data into the Reporting Workbench data, notably that a sizable proportion (about 10%) of patients within the Acuere data had either no medical record number (MRN), or had one that did not match the live data in EpicCare. This necessitated manually finding patients within EpicCare and correcting these MRNs, which increases chance of error. Finally, the accuracy of other details, particularly diagnosis codes, is strongly operator dependent and reliant upon both correctly coding these entities as well as correct interpretation with Acuere in collating all appropriate codes into individual diagnoses.

## Outcomes

### Key Findings

Multiple appointment and demographic features were found to be significant in predicting no-show appointments when modelled with the linear regression. These included the demographic features of race, age, previously completed or no-show appointments, and a number of health conditions including atrial fibrillation, chronic pain, drug or alcohol addiction, liver disease, previous myocardial infarction (MI), and schizophrenia. Similarly, multiple appointment characteristics were also found to be significant, including type of visit, type of provider seen, payor (e.g. insurance coverage), time block scheduled during the week, and lead time to appointment.

### Comparison to Literature

Analysis of data at Richmond shows a number of similarities to other sites detailed in the literature. Richmond's overall no-show rate was 17% which compares favorably to the 14-50% no-show rates seen across primary care sites (Daggy et al., 2010). Many other sites have found a higher rate of no-show appointments amongst African Americans (Bennett & Baxley, 2009; Kaplan-Lewis & Percac-Lima, 2013; Miller et al., 2015; Moore et al., 2001), and this was found at Richmond as well (odds ratio [OR] 1.29). Other researchers have suggested this increase may actually be confounded by socioeconomic factors that do not fall within model parameters (Moore et al., 2001).

Studies viewing age as a factor in no-show appointments have generally been confined to pediatric or adult populations, but Richmond's data across the spectrum broadly agrees with common findings in both with younger children less likely to make it to clinic (Arai, Stapley, & Roberts, 2014) and older adults overall more likely to keep appointments (Bennett & Baxley, 2009; Daggy et al., 2010; Kaplan-Lewis & Percac-Lima, 2013; Miller et al., 2015; Moore et al., 2001; Sorita et al., 2014). Patient gender has been shown to be inconsequential for prediction of no-shows in the literature (Bennett & Baxley, 2009; Kheirkhah et al., 2015; Lehmann, Aebi, Lehmann, Balandraux Olivet, & Stalder, 2007), and this is true at Richmond as well.

Previously missed appointments have been found to be a strong predictor for future no-show appointments in multiple studies (Bennett & Baxley, 2009; Daggy et al., 2010; DuMontier et al., 2013), and the model bears this out at Richmond as well (OR 1.11). Interestingly, the converse was also found to be true, with previous made appointments predictive for lower rates of no-show appointments (OR 0.97).

Payor was found to have strong significance in predicting no-show appointments, with the ranking of rates of missed appointments generally progressing from the highest from the uninsured, through Medicaid, Medicare, and to privately insured with the lowest rates of missed appointments. This ranking has been seen in the majority of the studies exploring this aspect (DuMontier et al., 2013; Kaplan-Lewis & Percac-Lima, 2013; Miller et al., 2015; Samuels et al., 2015; Sorita et al., 2014).

The only time block during the week that had a significant increase in no-show appointments was Monday morning, and although many sites have found day and time to be largely inconsequential (Lehmann et al., 2007), two previous studies did also find Mondays problematic for kept appointments (Bennett & Baxley, 2009; Kheirkhah et al., 2015). Interestingly, although there was no real variance through weekday slots other than Monday mornings, Saturday afternoon appointments were significantly better attended (OR 0.41).

The type of provider being seen for appointments was also found to be significant at Richmond. Overall, faculty physicians had the lowest rates of no-show appointments, with others by comparison having worse: resident physicians (OR 1.25), family nurse practitioners (OR 1.31), physician assistants (OR 1.32), and counsellors (OR 2.19) all saw much higher no-show rates. A study from another family medicine residency setting found a similar pattern between provider types (Moore et al., 2001).

**Unexpected Findings**

Remarkably, lead time to appointment at Richmond was found to be significant, but of very small effect (OR 1.01) for appointments made over 14 days in the future. Other sites have found this to be of much greater importance, with a widely-referenced study of Veteran's Administration data showing an OR 2.68 (Daggy et al., 2010). However, a study of an academic family medicine clinic in South Carolina found results similar to those at Richmond with an OR 1.02 (Bennett & Baxley, 2009), which further questions the importance of this 2-week window.

Although severe mental illness (i.e., schizophrenia) was found to be a significant factor in missed appointments (OR 1.26), depression was not found to be significant. Many other studies have shown that mental illness across the spectrum of severity to be significant in predicting no-show appointments (Bowser et al., 2010; Daggy et al., 2010; DuMontier et al., 2013; Moscrop et al., 2012; Shimotsu et al., 2016).

Also surprisingly, appointments to establish care were found to be significant and attended much better than other office visits (OR 0.58). This is not seen in the literature. More likely seen are the results of another academic site that found a 20% increase in chance of no-show for an initial appointment (Bennett & Baxley, 2009), and a 5% increase in a third academic family medicine clinic (Moore et al., 2001).

## Recommendations

After data analysis, key findings along with specific policy recommendations were provided to Richmond staff in April 2017. These were further developed through meeting with providers and other clinic staff in May 2017. Through comparison with sites with similar populations and no-show rates in the literature, two primary recommendations were developed.

Other interventions seen in the literature are unlikely to benefit Richmond based on the findings of the data analysis. Advanced access scheduling has been presented as an effective method to both reduce no-show rates as well as increase patient satisfaction, and studies have shown benefit for clinics with a baseline no-show rate of over 15% (Rose et al., 2011). The majority of benefit from this method is to remove appointments outside the 2-week lead time window (Murray & Berwick, 2003), which was not shown to be of strong benefit at Richmond, and in any case 70% of appointments are already within that window.

Similarly, implementing an appointment overbooking system would be problematic at Richmond. Apart from decreasing provider satisfaction, overbooking schemes can degrade overall clinic performance by lengthening patient wait times and staff increasing overtime (Huang & Hanauer, 2014). Interestingly, a simulation of a busy academic practice predicted that an overall 50% reduction in no-shows led to a 14% increase in patient length of stay, and that reducing the no-show rate to 0% would lead to “overcrowding that would require several hours to clear out” (Bard et al., 2014).

**Reminders**

Currently patients are given an automated reminder voice phone call before the day of their appointment. This has good evidence in the literature with an overall 9.4% reduced no-show rate when used (Hasvold & Wootton, 2011; Stubbs et al., 2012), and should be continued. Additional to this, it would be beneficial to add a second reminder method as this has been shown to be multiplicative rather than additive in reducing no-show rates – up to a 70% increase in effectiveness (Stubbs et al., 2012).

Mailed reminders would be the most attractive second method. These have a reasonable effectiveness even when used by themselves with a 7.6% reduction in no-show rates, and also have the benefit of being quite cost-effective, with a return on investment (ROI) of around $10 for every $1 invested (Stubbs et al., 2012). Another attractive second method would be text message; these have seen an 8.6% reduction in no-show rates and are also cost effective with a 10 to 30-fold ROI when implemented (Gurol-Urganci et al., 2013; Guy et al., 2012; Stubbs et al., 2012). Email cannot be recommended as a secondary method as there is no strong evidence that yet supports its use for reminders (Atherton et al., 2012).

**Probationary Cohort**

Analysis of Richmond data included the intriguing finding that 5% of patients accounted for 39% of the total no-show appointments for the entire practice. This compares favorably with the situation at a similar academic family medicine clinic that found that 2% of patients accounted for 17% of the total clinic no-shows, and then developed a probationary scheme to both reduce this cohort’s no-show appointments as well as reduce their disruption to the clinic

(DuMontier et al., 2013). Using this intervention, they reduced overall no-show rates in this cohort from a 33.3% baseline to 17.7%. Because of the outsized influence for this group, this significantly reduced the overall clinic no-show rate from 10% to 7%.

To implement at Richmond, current patients with the highest no-show rates would be assigned into a probationary cohort. These patients would no longer be scheduled with individual providers, but would instead be assigned to a “virtual provider” instead. When and if they present to clinic for appointments, they will be seen by the next available provider at the clinic – in effect they are overbooked to the clinic itself rather than to any particular provider. If patients in the cohort significantly improve attendance over the next 6 months-1 year, they can be moved back to scheduling normally. Patients within the cohort could be further targeted for outreach groups within the clinic to discover and reduce barriers to their attendance at clinic.

## Summary and Next Steps

No-shows are a significant issue in primary care, both for clinicians and their patients. Those that are socioeconomically disadvantaged are particularly susceptible to missing appointments. OHSU Family Medicine at Richmond Clinic primarily sees these patients and struggles with high no-show rates to provide excellent care while supporting the smooth functioning of the clinic. Through examination of the past three years of appointments and patients, trends in no-shows were discovered and used to generate recommendations for revision of clinic no-show policy.

Ideally the next steps in attempting to improve no-show rates at Richmond would be to take the characteristics found through this analysis and use that to drive focused research into variables not captured within the medical chart. This would likely take the form of interviews with patients to determine their own reasons for missing appointments in order to discover what barriers exist in them receiving care at Richmond. With knowledge of these barriers, even more effective interventions could be crafted for addressing no-show appointments.

**References**

Agarin, T., Okorafor, E., Kailasam, V., Agarin, A., Philias, W., Garcia, D., … Sharif, Z. (2015). Comparing kept appointment rates when calls are made by physicians versus behavior health technicians in inner city hospital: literature review and cost considerations. *Community Mental Health Journal*, *51*(3), 300–304. http://doi.org/10.1007/s10597-014-9812-x

Angier, H., Hoopes, M., Gold, R., Bailey, S. R., Cottrell, E. K., Heintzman, J., … DeVoe, J. E. (2015). An Early Look at Rates of Uninsured Safety Net Clinic Visits After the Affordable Care Act. *The Annals of Family Medicine*, *13*(1), 10–16. http://doi.org/10.1370/afm.1741

Arai, L., Stapley, S., & Roberts, H. (2014). "Did not attends" in children 0-10: a scoping review. *Child: Care, Health and D Evelopment*, *40*(6), 797–805. http://doi.org/10.1111/cch.12111

Atherton, H., Sawmynaden, P., Meyer, B., & Car, J. (2012). Email for the coordination of healthcare appointments and attendance reminders. *The Cochrane Database of Systematic Reviews*, *8*, CD007981. http://doi.org/10.1002/14651858.CD007981.pub2

Baas, J. H. (1889). *Outlines of the History of Medicine and the Medical Profession*. New York.

Bard, J. F., Shu, Z., Morrice, D. J., Wang, D., Poursani, R., & Leykum, L. (2014). Improving patient flow at a family health clinic. *Health Care Management Science*. http://doi.org/10.1007/s10729-014-9294-y

Bennett, K. J., & Baxley, E. G. (2009). The effect of a carve-out advanced access scheduling system on no-show rates. *Family Medicine*, *41*(1), 51–56.

Bowser, D. M., Utz, S., Glick, D., & Harmon, R. (2010). A systematic review of the relationship of diabetes mellitus, depression, and missed appointments in a low-income uninsured population. *Archives of Psychiatric Nursing*, *24*(5), 317–329.

http://doi.org/10.1016/j.apnu.2009.12.004

Cameron, S., Sadler, L., & Lawson, B. (2010). Adoption of open-access scheduling in an academic family practice. *Canadian Family Physician*, *56*(9), 906–911.

Chariatte, V., Michaud, P. A., Berchtold, A., Akre, C., & Suris, J. C. (2007). Missed appointments in an adolescent outpatient clinic: Descriptive analyses of consultations over eight years. *Swiss Medical Weekly*, *137*(47–48), 677–681. http://doi.org/2007/47/smw-12050

Cibulka, N. J., Fischer, H. W., & Fischer, A. J. (2012). Improving communication with low-income women using today's technology. *Online Journal of Issues in Nursing*, *17*(2), 9. http://doi.org/10.3912/OJIN.Vol17No01PPT01

Cronin, P. R., & Kimball, A. B. (2014). Success of automated algorithmic scheduling in an outpatient setting. *American Journal of Managed Care*, *20*(7), 570–576.

Daggy, J., Lawley, M., Willis, D., Thayer, D., Suelzer, C., DeLaurentis, P.-C., … Sands, L. (2010). Using no-show modeling to improve clinic performance. *Health Informatics Journal*, *16*(4), 246–259. http://doi.org/10.1177/1460458210380521

DuMontier, C., Rindfleisch, K., Pruszynski, J., & Frey, J. J. (2013). A multi-method intervention to reduce no-shows in an urban residency clinic. *Family Medicine*, *45*(9), 634–641.

Gurol-Urganci, I., de Jongh, T., Vodopivec-Jamsek, V., Atun, R., & Car, J. (2013). Mobile phone messaging reminders for attendance at healthcare appointments. *The Cochrane Database of Systematic Reviews*, *12*, CD007458. http://doi.org/10.1002/14651858.CD007458.pub3

Guse, C. E., Richardson, L., Carle, M., & Schmidt, K. (2003). The Effect of Exit-Interview Patient Education on No-Show Rates at a Family Practice Residency Clinic. *The Journal of* *the American Board of Family Medicine*, *16*(5), 399–404. http://doi.org/10.3122/jabfm.16.5.399

Guy, R., Hocking, J., Wand, H., Stott, S., Ali, H., & Kaldor, J. (2012). How effective are short message service reminders at increasing clinic attendance? A meta-analysis and systematic review. *Health Services Research*, *47*(2), 614–632. http://doi.org/10.1111/j.1475-6773.2011.01342.x

Harris, S. L., May, J. H., & Vargas, L. G. (2016). Predictive analytics model for healthcare planning and scheduling. *European Journal of Operational Research*, *253*(1), 121–131. Retrieved from http://10.0.3.248/j.ejor.2016.02.017

Hasvold, P. E., & Wootton, R. (2011). Use of telephone and SMS reminders to improve attendance at hospital appointments: a systematic review. *Journal of Telemedicine and Telecare*, *17*(7), 358–364. http://doi.org/10.1258/jtt.2011.110707

Horton, S. (2006). The double burden on safety net providers: Placing health disparities in the context of the privatization of health care in the US. *Social Science and Medicine*, *63*(10), 2702–2714. http://doi.org/10.1016/j.socscimed.2006.07.003

Horvath, M., Levy, J., Engle, P., Carlson, B., Ahmad, A., & Ferranti, J. (2011). Impact of health portal enrollment with Email reminders on adherence to clinic appointments: A pilot study. *Journal of Medical Internet Research*, *13*(2). http://doi.org/10.2196/jmir.1702

Huang, Y., & Hanauer, D. a. (2014). Patient no-show predictive model development using multiple data sources for an effective overbooking approach. *Applied Clinical Informatics*, *5*(3), 836–60. http://doi.org/10.4338/ACI-2014-04-RA-0026

Hwang, A. S., Atlas, S. J., Cronin, P., Ashburner, J. M., Shah, S. J., He, W., & Hong, C. S. (2015). Appointment “no-shows” are an independent predictor of subsequent quality of care and resource utilization outcomes. *Journal of General Internal Medicine*, *30*(10), 1426–1433. http://doi.org/10.1007/s11606-015-3252-3

Johnson, B. J., Mold, J. W., & Pontious, J. M. (2007). Reduction and Management of No-Shows by Family Medicine Residency Practice Exemplars. *The Annals of Family Medicine*, *5*(6), 534–539. http://doi.org/10.1370/afm.752

Kaplan-Lewis, E., & Percac-Lima, S. (2013). No-Show to Primary Care Appointments: Why Patients Do Not Come. *Journal of Primary Care & Community Health*, *4*(4), 251–255. http://doi.org/10.1177/2150131913498513

Keohane, P. (2007). How to Bill for Missed Appointments. Retrieved from https://www.aapc.com/blog/23888-how-to-bill-for-missed-appointments/

Kheirkhah, P., Feng, Q., Travis, L. M., Tavakoli-Tabasi, S., & Sharafkhaneh, A. (2015). Prevalence, predictors and economic consequences of no-shows. *BMC Health Services Research*, *16*(1), 13. http://doi.org/10.1186/s12913-015-1243-z

Kreimer, S. (2016). Dismissing patients: how to do it the right way. *Medical Economics*, *93*(1), 48.

LaGanga, L. R., & Lawrence, S. R. (2012). Appointment Overbooking in Health Care Clinics to Improve Patient Service and Clinic Performance. *Production & Operations Management*, *21*(5), 874–888. Retrieved from http://10.0.4.87/j.1937-5956.2011.01308.x

Lehmann, T. N. O., Aebi, A., Lehmann, D., Balandraux Olivet, M., & Stalder, H. (2007). Missed appointments at a Swiss university outpatient clinic. *Public Health*, *121*(10), 790–799. http://doi.org/10.1016/j.puhe.2007.01.007

Lotfi, V., & Torres, E. (2014). Improving an outpatient clinic utilization using decision analysis-based patient scheduling. *Socio-Economic Planning Sciences*, *48*(2), 115–126. Retrieved from http://10.0.3.248/j.seps.2014.01.002

Mehrotra, A., An, R., Patel, D. N., & Sturm, R. (2014). Impact of a patient incentive program on receipt of preventive care. *The American Journal of Managed Care*, *20*(6), 494–501. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/25180436

Miller, A. J., Chae, E., Peterson, E., & Ko, A. B. (2015). Predictors of repeated "no-showing" to clinic appointments. *American Journal of Otolaryngology - Head and Neck Medicine and Surgery*, *36*(3), 411–414. http://doi.org/10.1016/j.amjoto.2015.01.017

Moore, C. G., Wilson-Witherspoon, P., & Probst, J. C. (2001). Time and money: effects of no-shows at a family practice residency clinic. *Family Medicine*, *33*(7), 522–7. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/11456244

Moscrop, A., Siskind, D., & Stevens, R. (2012). Mental health of young adult patients who do not attend appointments in primary care: A retrospective cohort study. *Family Practice*, *29*(1), 24–29. http://doi.org/10.1093/fampra/cmr053

Murray, M., & Berwick, D. M. (2003). Advanced Access. *JAMA*, *289*(8), 1035. http://doi.org/10.1001/jama.289.8.1035

Muthuraman, K., & Lawley, M. (2008). A stochastic overbooking model for outpatient clinical scheduling with no-shows. *IIE Transactions*, *40*(9), 820–837. Retrieved from http://10.0.4.56/07408170802165823

Nguyen, D. L., & DeJesus, R. S. (2010). Increased Frequency of No-Shows in Residents' Primary Care Clinic Is Associated With More Visits to the Emergency Department. *Journal of Primary Care & Community Health*, *1*(1), 8–11. http://doi.org/10.1177/2150131909359930

Nuti, L. a, Lawley, M., Turkcan, A., Tian, Z., Zhang, L., Chang, K., … Sands, L. P. (2012). No-shows to primary care appointments: subsequent acute care utilization among diabetic patients. *BMC Health Services Research*, *12*(1), 304. http://doi.org/10.1186/1472-6963-12-304

Rose, K. D., Ross, J. S., & Horwitz, L. I. (2011). Advanced access scheduling outcomes: a systematic review. *Archives of Internal Medicine*, *171*(13), 1150–1159. http://doi.org/10.1001/archinternmed.2011.168

Samuels, R. C., Ward, V. L., Melvin, P., Macht-Greenberg, M., Wenren, L. M., Yi, J., … Cox, J. E. (2015). Missed Appointments: Factors Contributing to High No-Show Rates in an Urban Pediatrics Primary Care Clinic. *Clinical Pediatrics*, *54*(10), 976–82. http://doi.org/10.1177/0009922815570613

Schectman, J. M., Schorling, J. B., & Voss, J. D. (2008). Appointment adherence and disparities in outcomes among patients with diabetes. *Journal of General Internal Medicine*, *23*(10), 1685–1687. http://doi.org/10.1007/s11606-008-0747-1

Sharp, B., Singal, B., Pulia, M., Fowler, J., & Simmons, S. (2015). You've got mail ... and need follow-up: the effect and patient perception of e-mail follow-up reminders after emergency department discharge. *Academic Emergency Medicine*, *22*(1), 47–53. http://doi.org/10.1111/acem.12564

Shimotsu, S., Roehrl, A., McCarty, M., Vickery, K., Guzman-Corrales, L., Linzer, M., & Garrett, N. (2016). Increased Likelihood of Missed Appointments ("No Shows") for Racial/Ethnic Minorities in a Safety Net Health System. *Journal of Primary Care & Community Health*, *7*(1), 38–40. http://doi.org/10.1177/2150131915599980

Smith, P. B., Weinman, M. L., Johnson, T. C., & Wait, R. B. (1990). Incentives and their influence on appointment compliance in a teenage family-planning clinic. *Journal of*

*Adolescent Health Care*, *11*(5), 445–8. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/2211279

Sorita, A., Funakoshi, T., Kashan, G., Young, E. R., & Park, J. (2014). Impact of Prescription Patterns on Compliance With Follow-Up Visits at an Urban Teaching Primary Care Continuity Clinic. *Journal of Primary Care & Community Health*, *5*(3), 188–193. http://doi.org/10.1177/2150131914523294

Stanley, I. H., Chu, C., Brown, T. A., Sawyer, K. A., & Joiner, T. E. (2016). Improved Clinical Functioning for Patients Receiving Fee Discounts That Reward Treatment Engagement. *Journal of Clinical Psychology*, *72*(1), 15–21. http://doi.org/10.1002/jclp.22236

Stubbs, N. D., Geraci, S. A., Stephenson, P. L., Jones, D. B., & Sanders, S. (2012). Methods to reduce outpatient non-attendance. *The American Journal of the Medical Sciences*, *344*(3), 211–219. http://doi.org/10.1097/MAJ.0b013e31824997c6

Tsai, P.-F. J., & Teng, G.-Y. (2014). A stochastic appointment scheduling system on multiple resources with dynamic call-in sequence and patient no-shows for an outpatient clinic. *European Journal of Operational Research*, *239*(2), 427–436. Retrieved from http://10.0.3.248/j.ejor.2014.04.032

Wesch, D., Lutzker, J. R., Frisch, L., & Dillon, M. M. (1987). Evaluating the impact of a service fee on patient compliance. *Journal of Behavioral Medicine*, *10*(1), 91–101. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/3586004

Zacharias, C., & Pinedo, M. (2014). Appointment Scheduling with No-Shows and Overbooking. *Production & Operations Management*, *23*(5), 788–801. Retrieved from http://10.0.4.87/poms.12065

**Table 1**

**Appointment and Patient Characteristics in Reported Data**

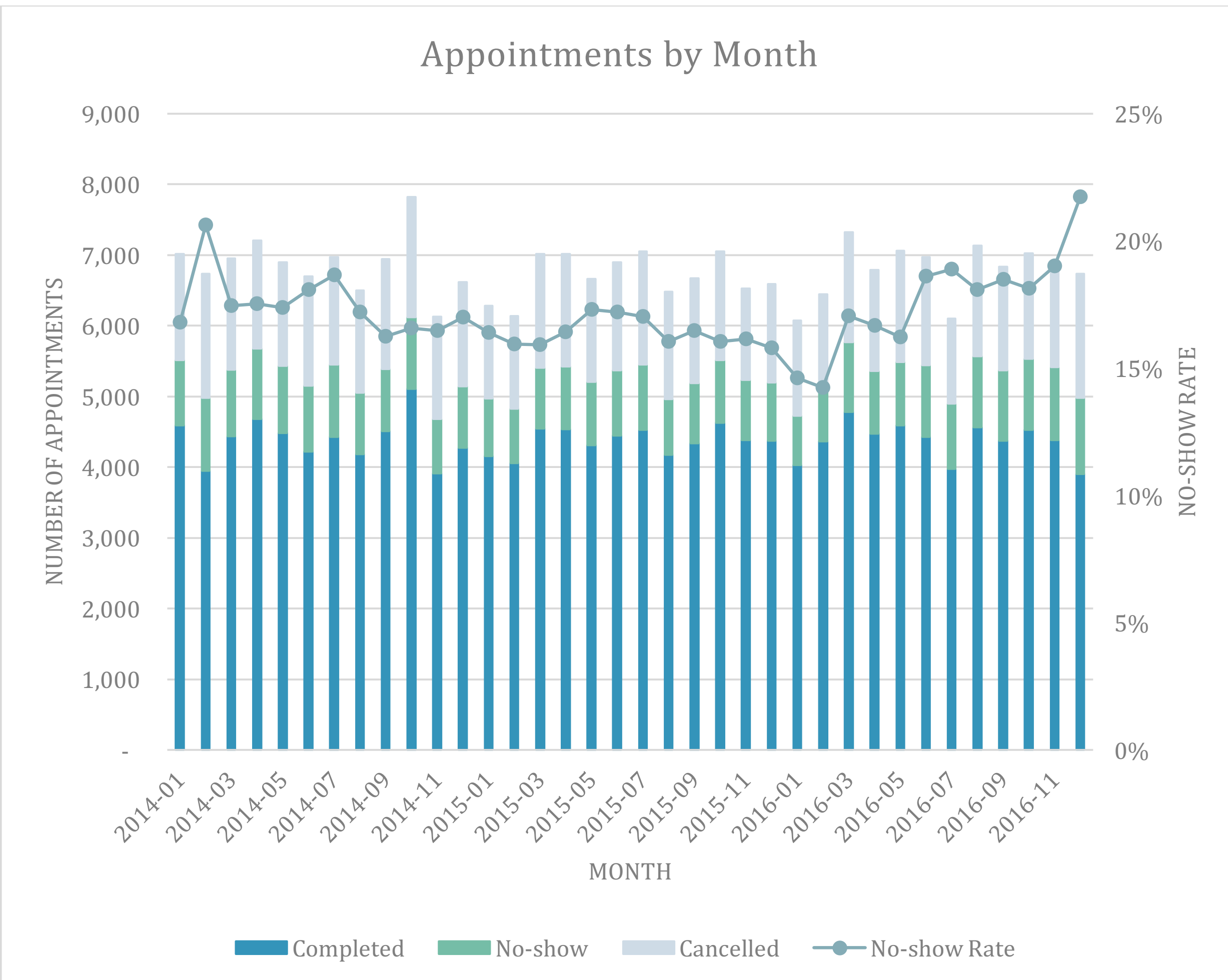
| | Hoped For | Able to Analyze |
|---|---|---|
| **Demographic Details** | ○ Age (within 5y range 0-5, 5-10, etc.)<br>○ Race/ethnicity<br>○ Gender<br>○ Marital status<br>○ Home address zip code<br>○ Total appointments<br>○ Total missed appointments<br>○ Insurance coverage (private, Medicaid, Medicare, self-pay, etc.)<br>○ Preferred language<br>○ Diabetic? (y/n, based on ICD10 from problem list)<br>○ Heart failure? (y/n, based on ICD10 from problem list)<br>○ Depression? (y/n, based on ICD10 from problem list)<br>○ Dementia? (y/n, based on ICD10 from problem list) | ○ Age (within 5y range 0-5, 5-10, etc.)<br>○ Race/ethnicity<br>○ Gender<br>○ Home address zip code<br>○ Total appointments<br>○ Total missed appointments<br>○ Preferred language<br>○ Total of 40 different medical diagnoses<br>○ BMI<br>○ Carlson Comorbidity Index |
| **Appointment Details** | ○ Made or missed<br>○ Type of appointment (establish care, well-child check, acute visit, etc.)<br>○ Month<br>○ Day<br>○ Day of week<br>○ Time (within 2h block 8-10, 11-12, etc.)<br>○ Type of provider (attending physician, resident physician, NP, PA, RN, MA, etc.)<br>○ Provider is primary provider? (y/n)<br>○ Lead time (days between appointment and when made) | ○ Made, missed, or cancelled<br>○ Type of appointment (establish care, well-child check, acute visit, etc.)<br>○ Month<br>○ Day<br>○ Day of week<br>○ Time (within 2h block 8-10, 11-12, etc.)<br>○ Type of provider (attending physician, resident physician, NP, PA, RN, MA, etc.)<br>○ Lead time (days between appointment and when made)<br>○ Insurance coverage (private, Medicaid, Medicare, self-pay, etc.) |

**Appendix A**

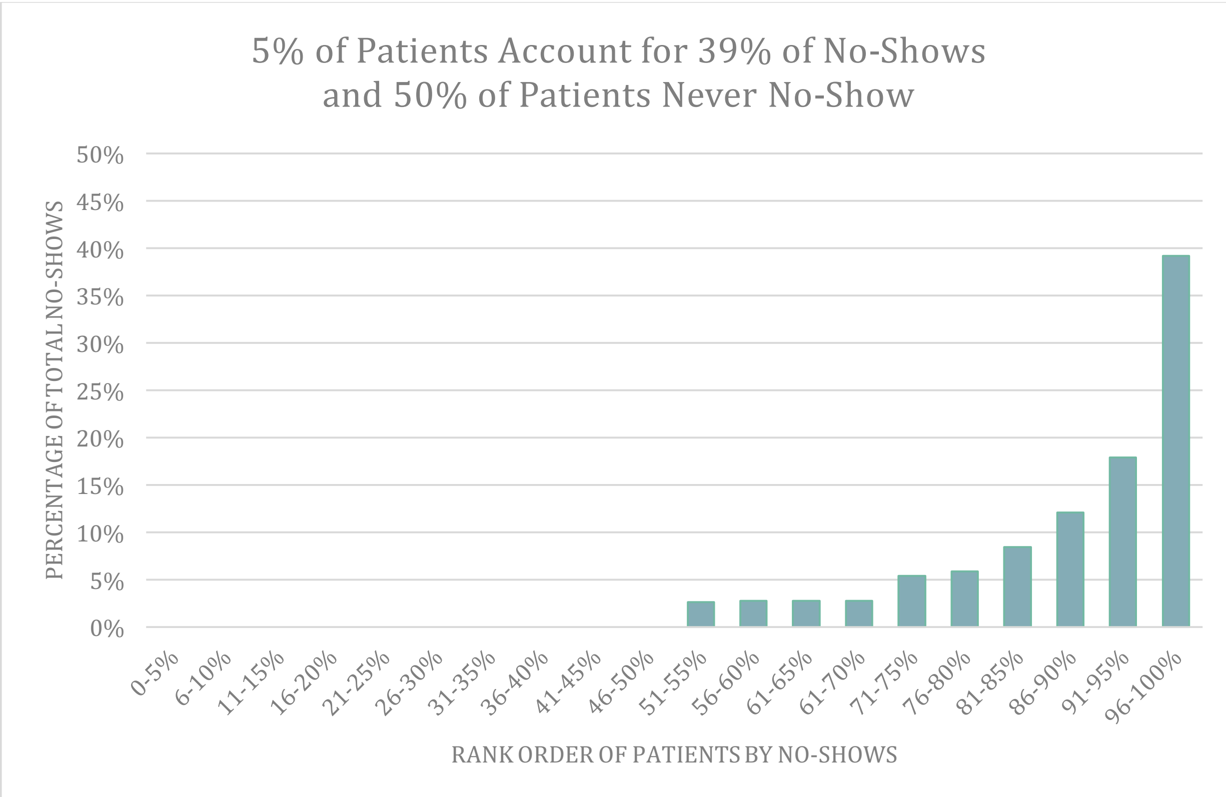
**Descriptive Statistics**

| Measurement | Value |
|---|---|
| **Patients** | 18,302 |
| **Total Appointments** | 244,097 |
| • **Cancelled** | 53,855 |
| • **Completed** | 157,563 |
| • **No-shows** | 32,679 |
| **No-show Rate** | 17.2% |

**Overall Trend**

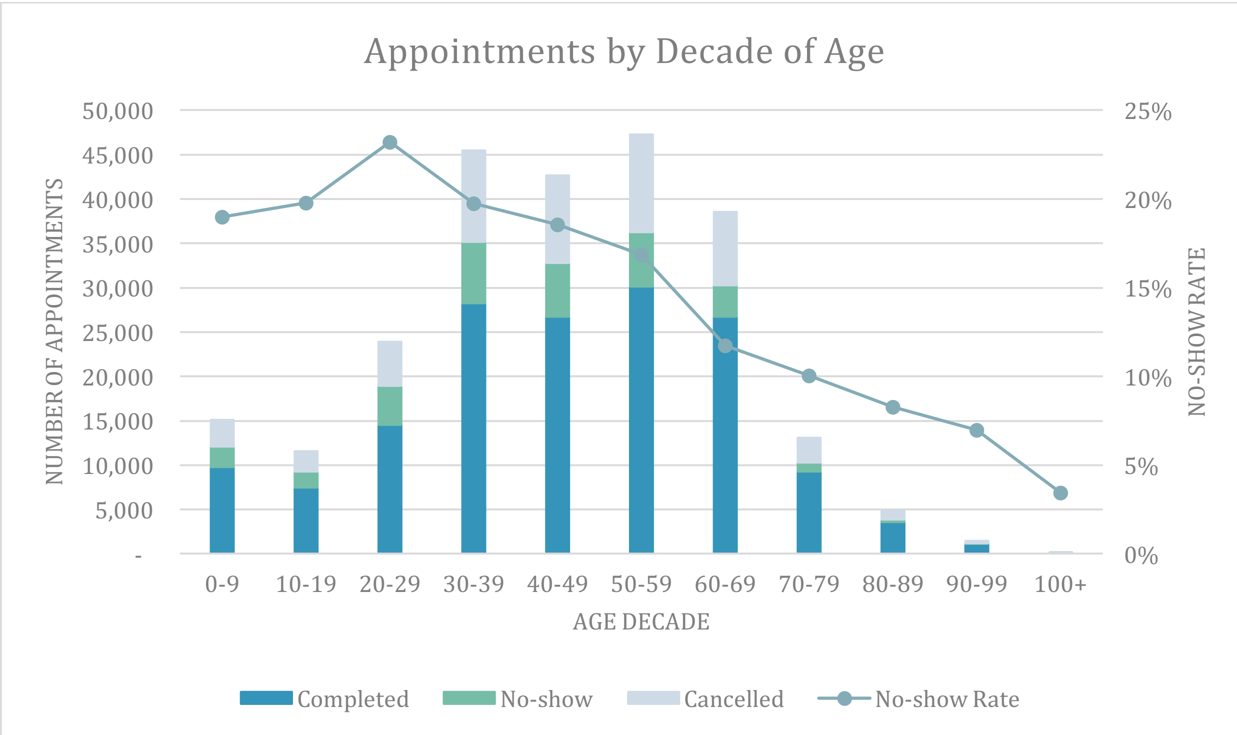


**Rank Order by No-Show**

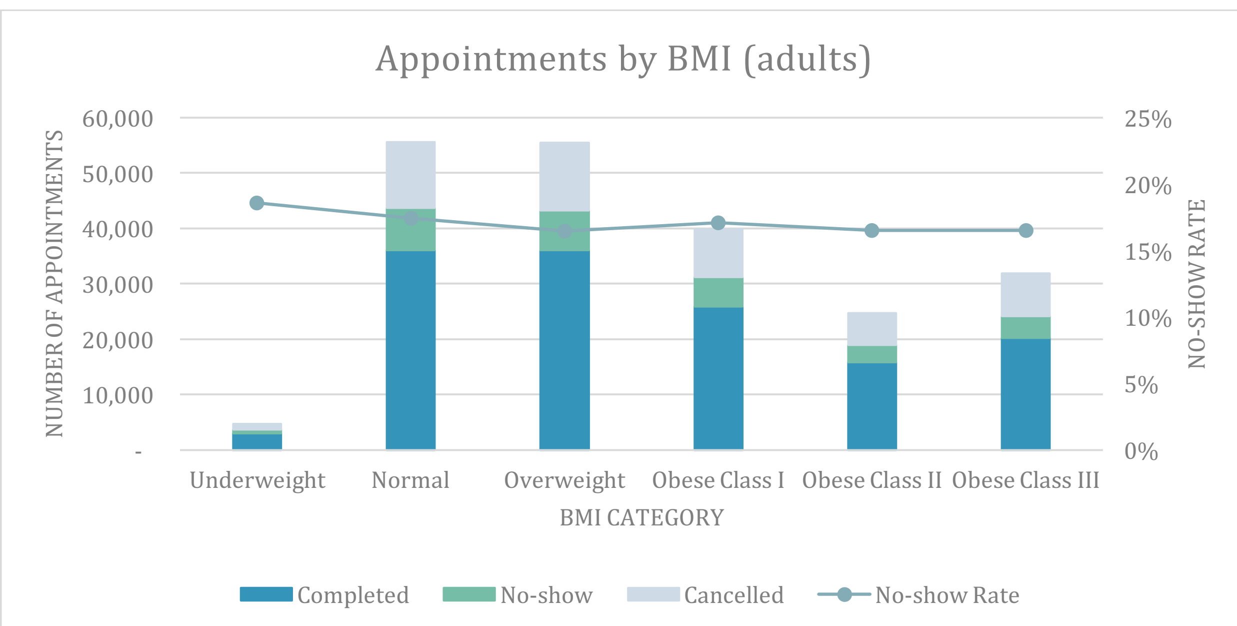


**Patient Characteristics**

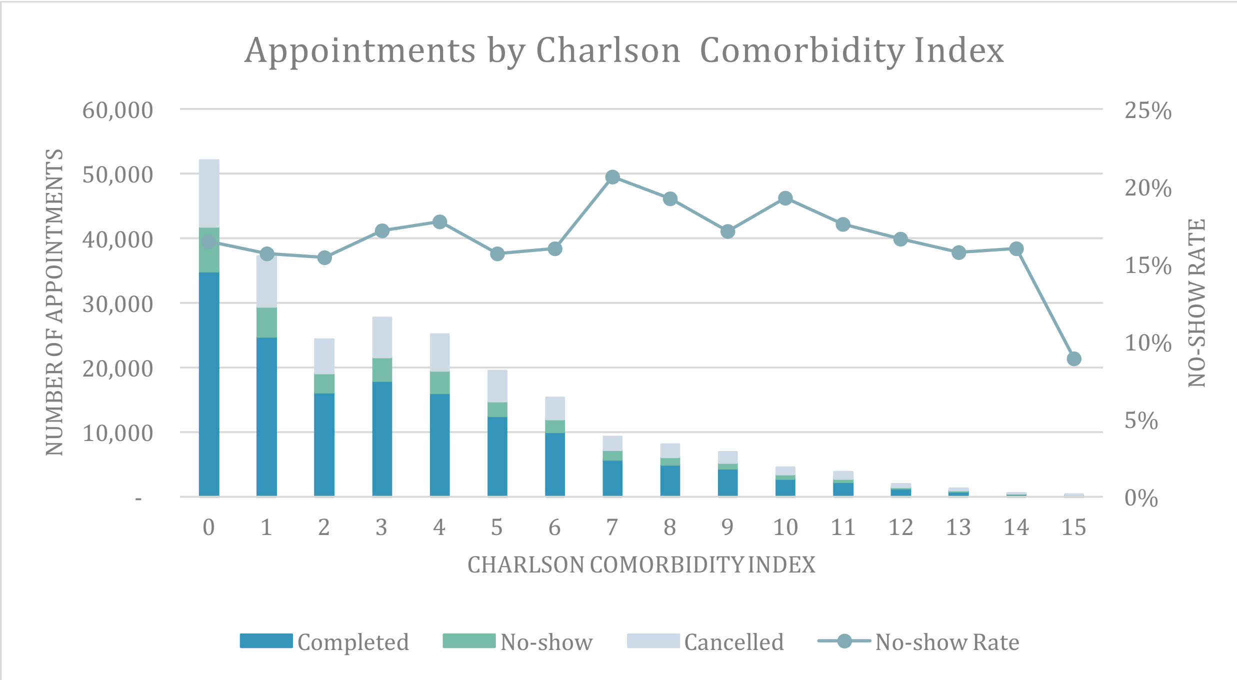
**Decade of Age**



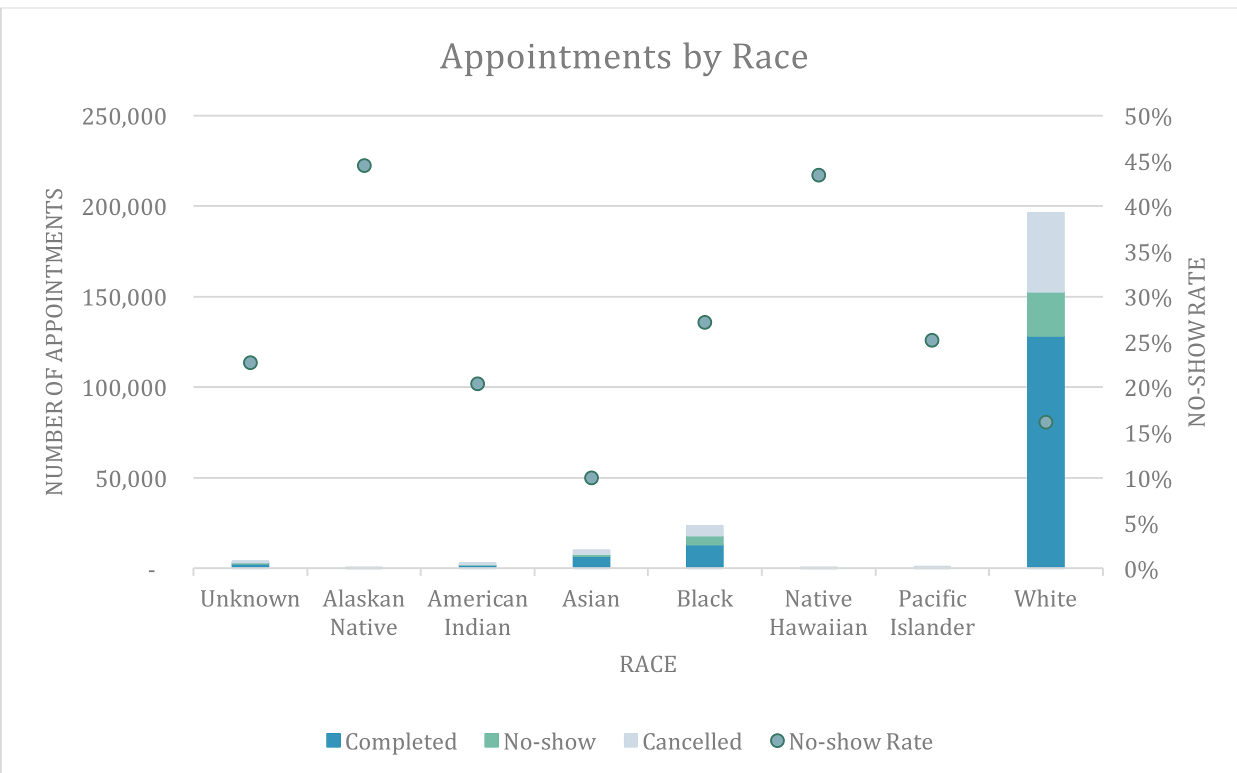

**BMI (Adults)**



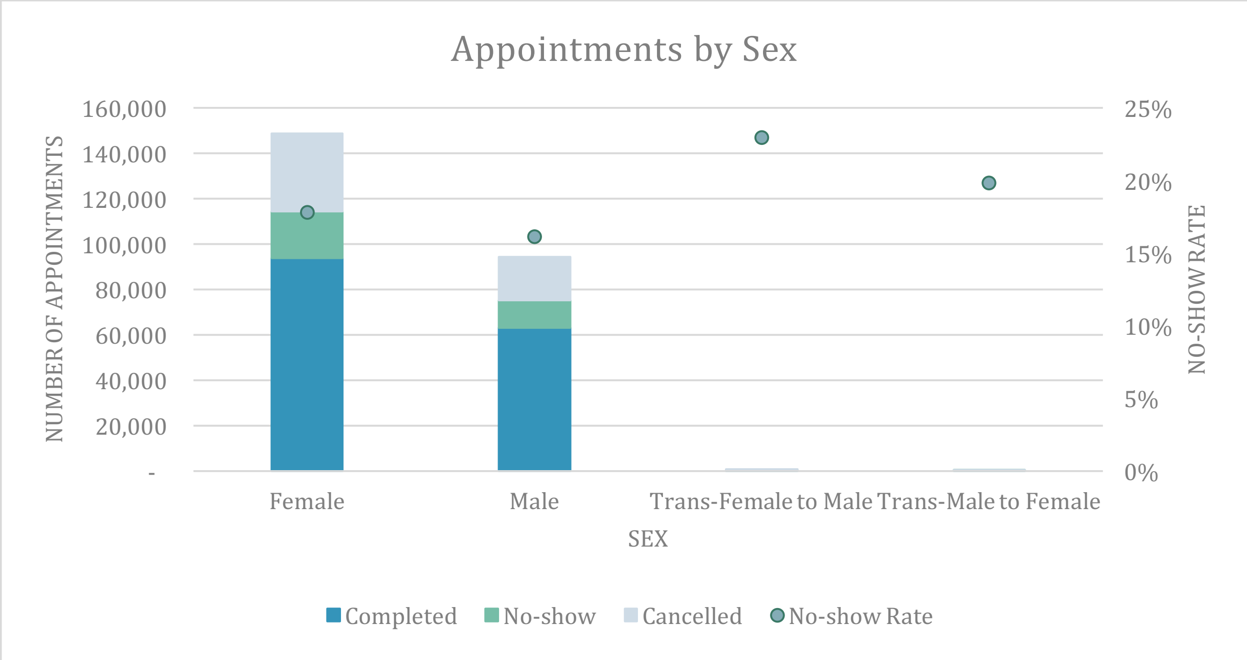
**Charlson Comorbidity Index**




**Race**

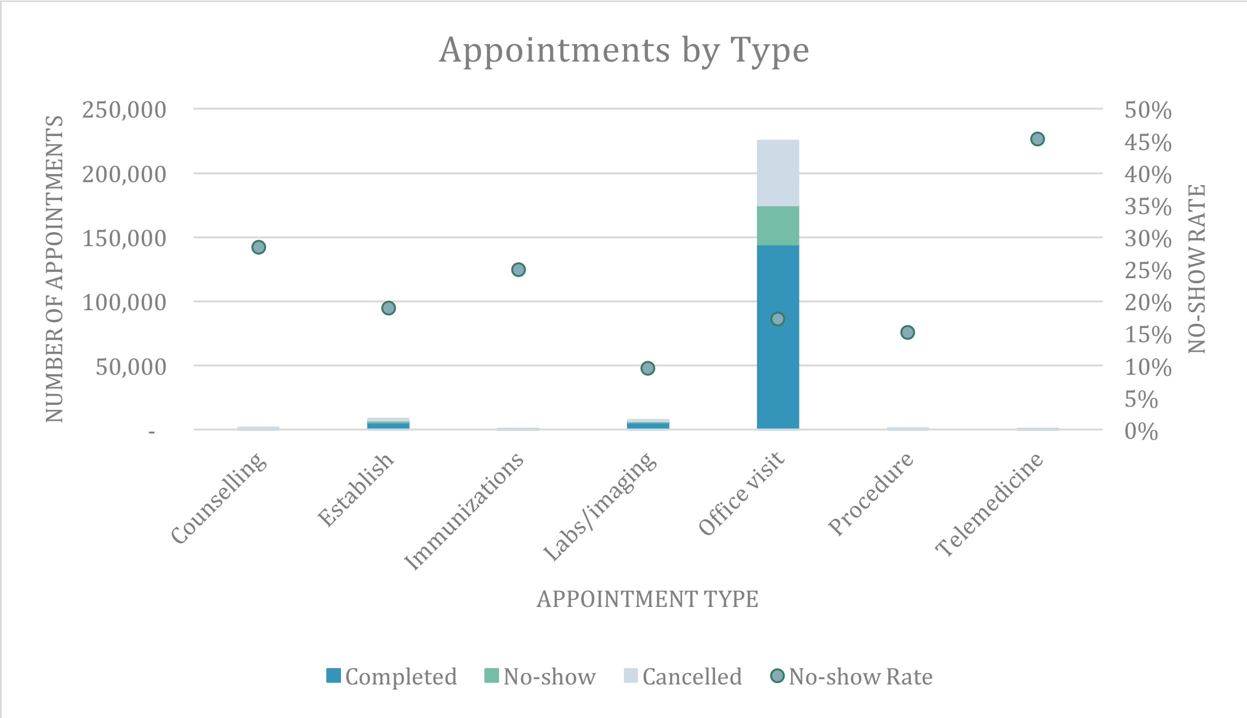


### Sex

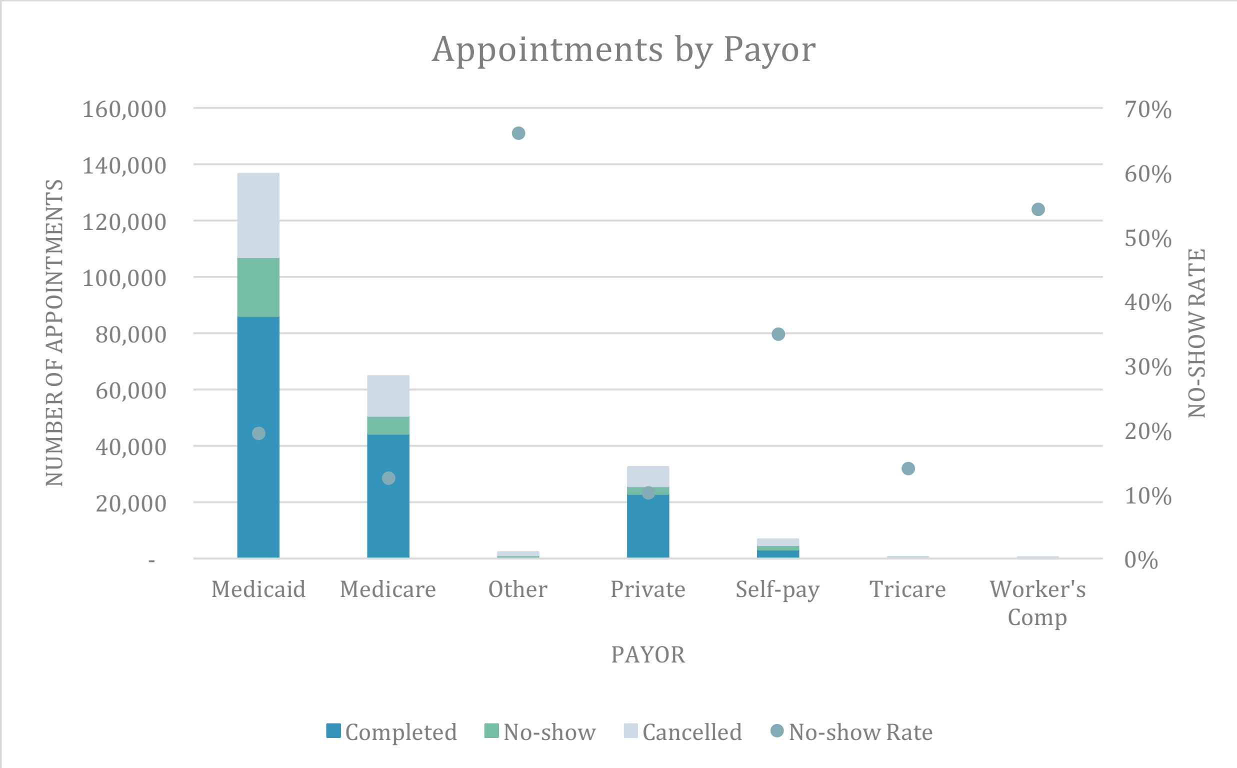



## Appointment Characteristics

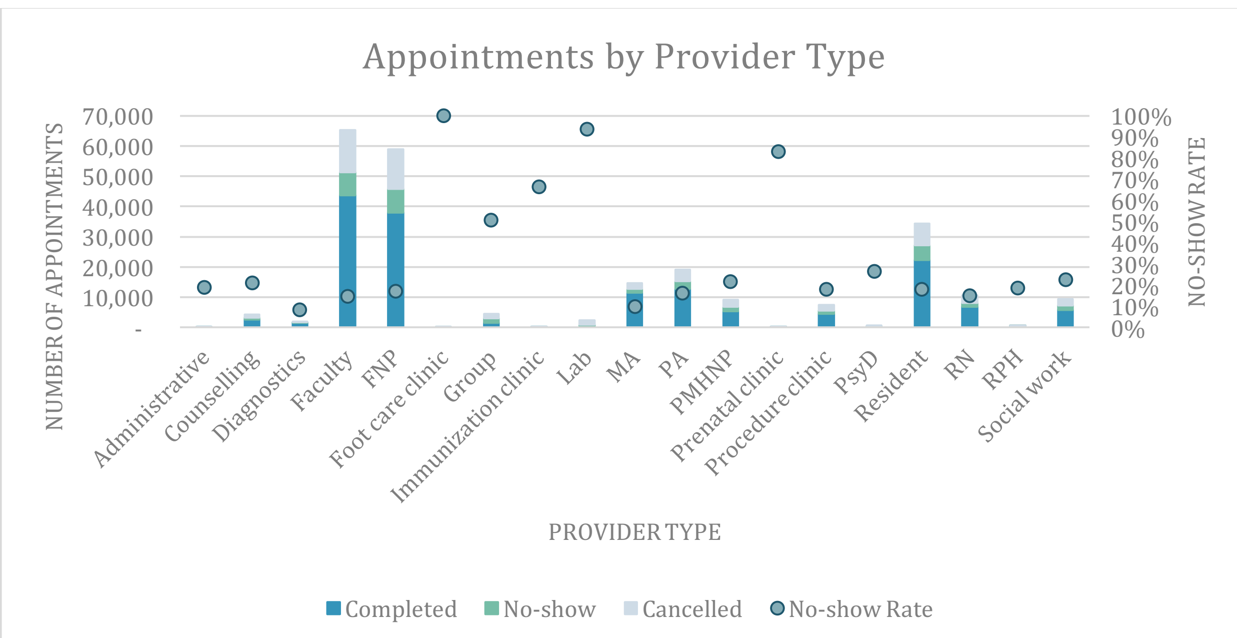
### Appointment Type



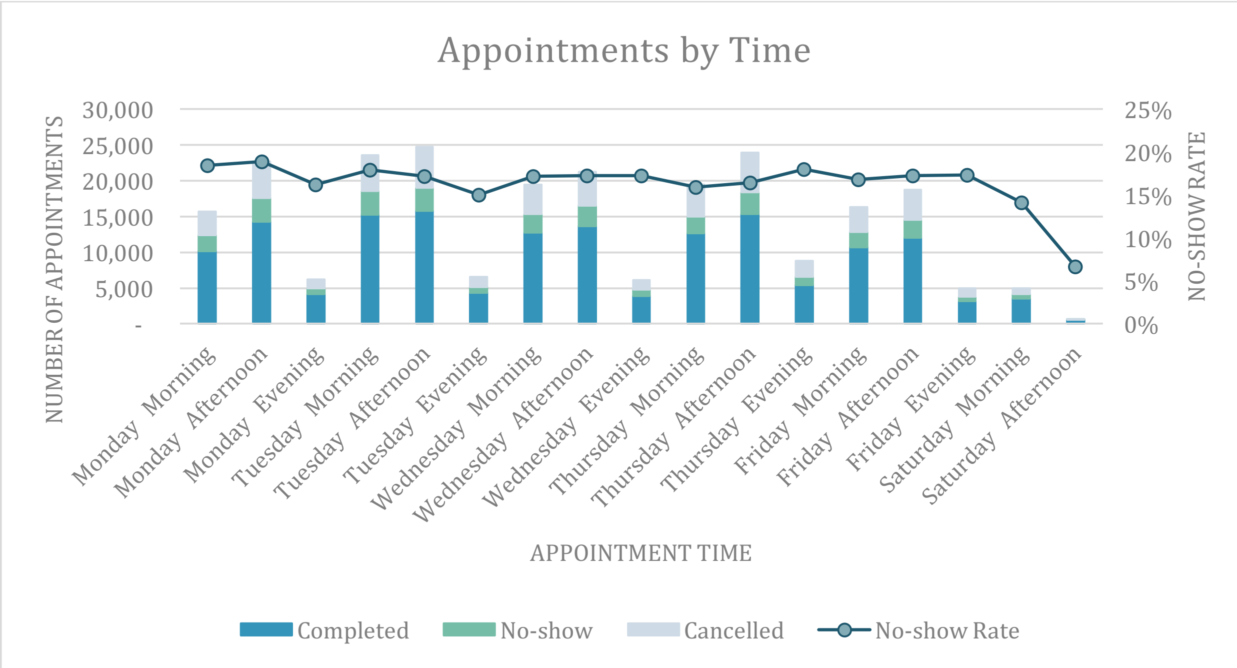
**Payor**



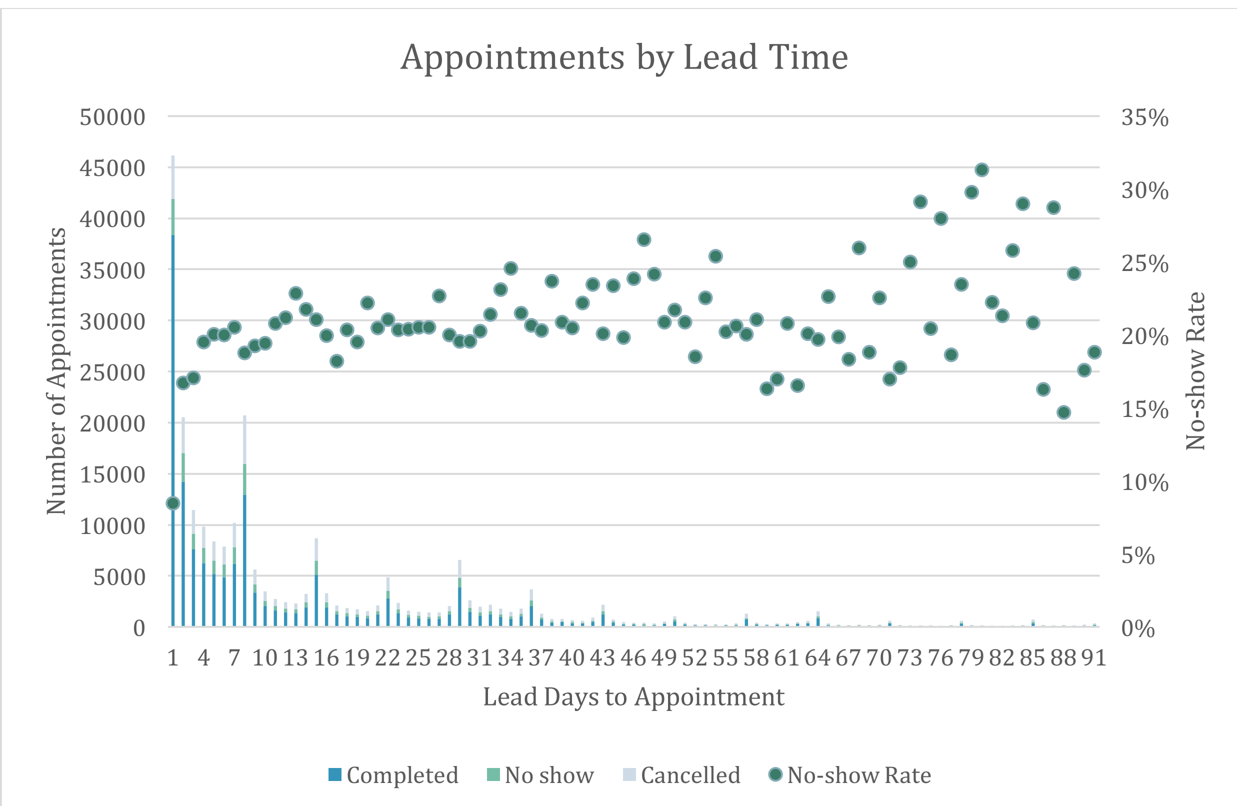

**Provider Type**



**Appointment Time**



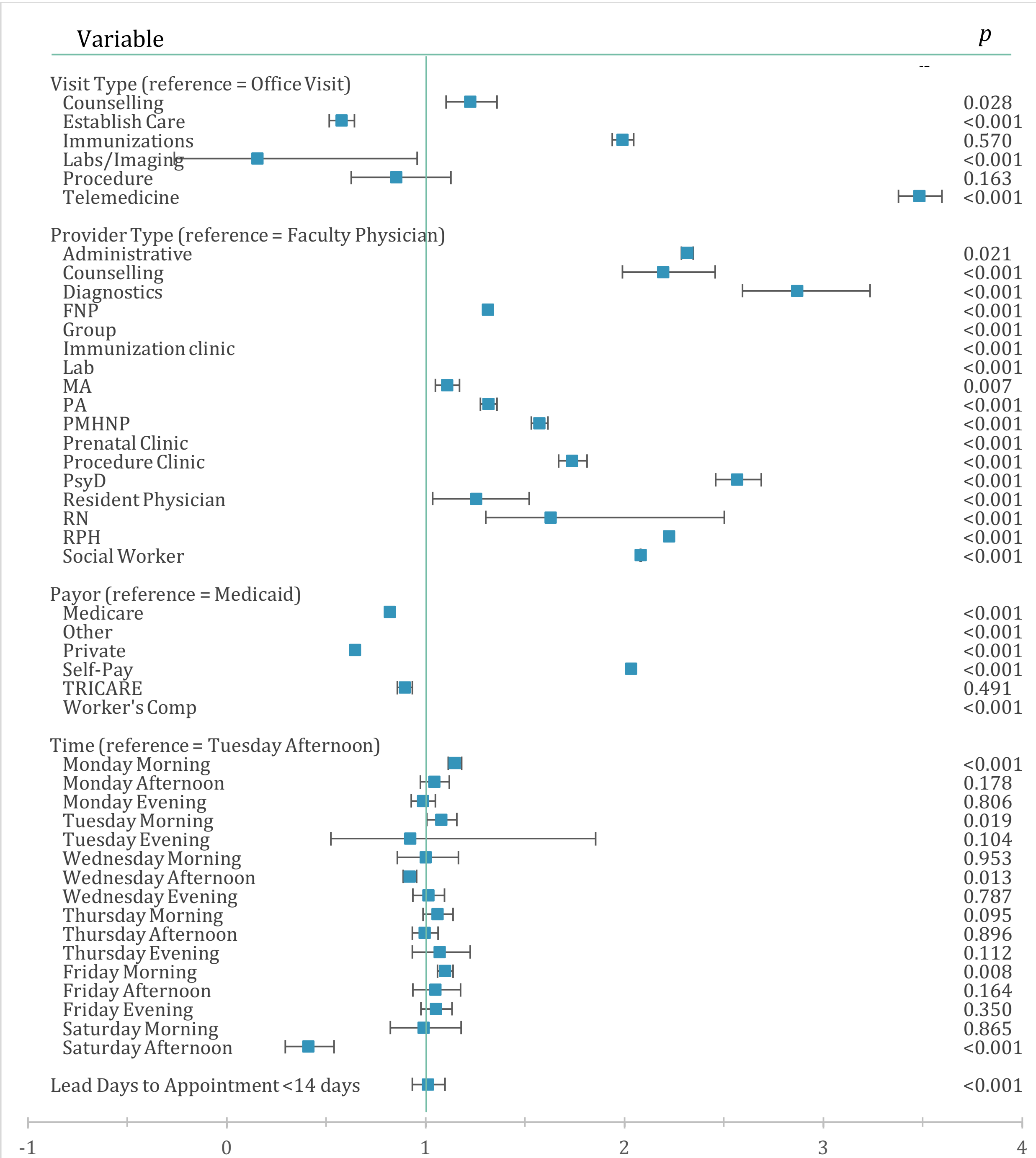

**By Lead Time**



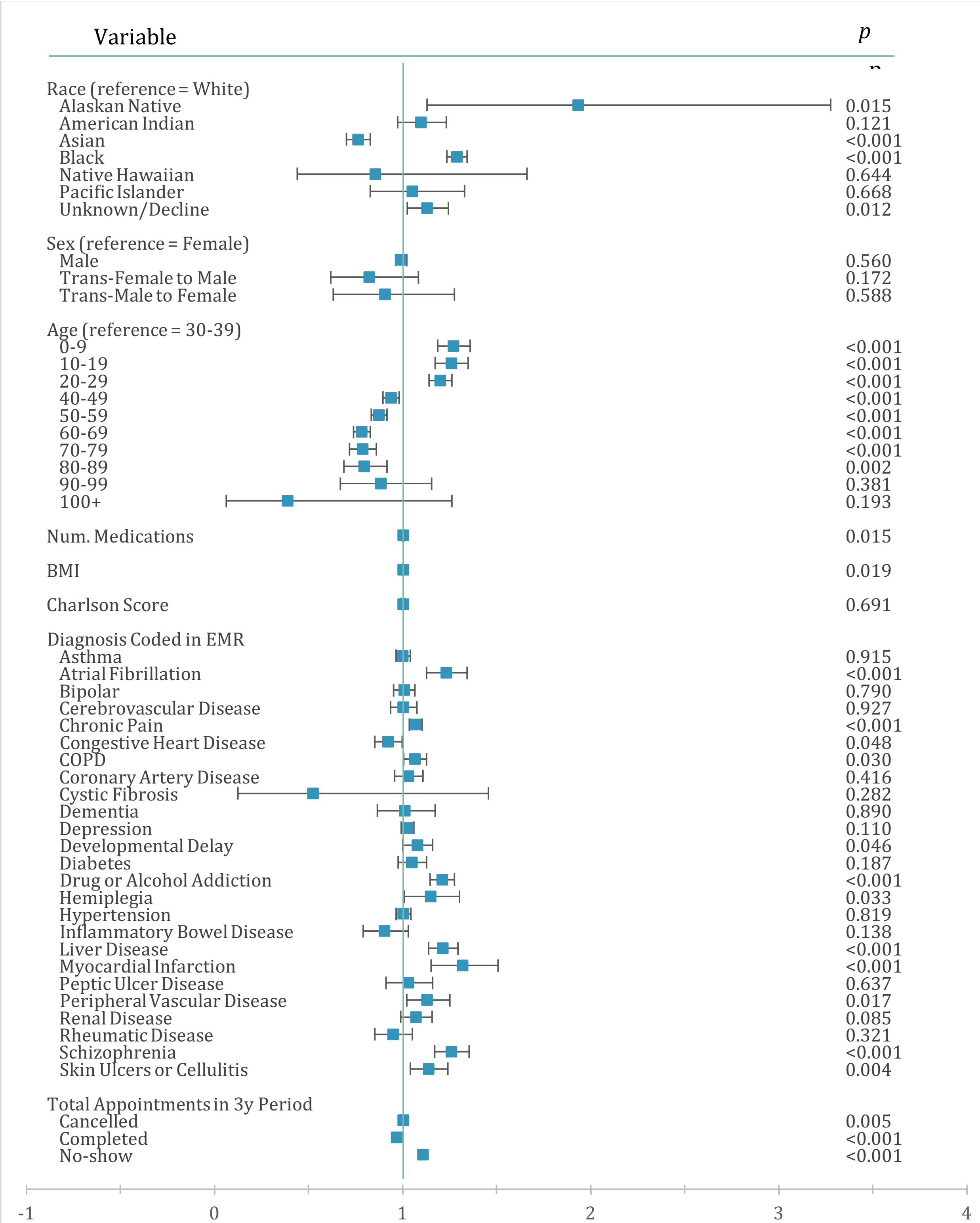
## Appendix B

## Multivariate Linear Regression

### Appointment Characteristics Odds Ratio



**Patient Characteristics Odds Ratio**



# Appendix C

## Data Tables for Descriptive Statistics

### Overall Trend

| Month | Cancelled | Completed | No-show | No-show Rate |
|---|---|---|---|---|
| 2014-01 | 1,501 | 4,586 | 926 | 17% |
| 2014-02 | 1,756 | 3,950 | 1,026 | 21% |
| 2014-03 | 1,582 | 4,436 | 937 | 17% |
| 2014-04 | 1,536 | 4,677 | 994 | 18% |
| 2014-05 | 1,468 | 4,483 | 943 | 17% |
| 2014-06 | 1,545 | 4,218 | 930 | 18% |
| 2014-07 | 1,524 | 4,429 | 1,015 | 19% |
| 2014-08 | 1,448 | 4,182 | 869 | 17% |
| 2014-09 | 1,561 | 4,508 | 874 | 16% |
| 2014-10 | 1,706 | 5,101 | 1,013 | 17% |
| 2014-11 | 1,442 | 3,912 | 771 | 16% |
| 2014-12 | 1,473 | 4,269 | 874 | 17% |
| 2015-01 | 1,319 | 4,152 | 814 | 16% |
| 2015-02 | 1,317 | 4,052 | 769 | 16% |
| 2015-03 | 1,608 | 4,546 | 860 | 16% |
| 2015-04 | 1,594 | 4,532 | 890 | 16% |
| 2015-05 | 1,454 | 4,304 | 900 | 17% |
| 2015-06 | 1,526 | 4,444 | 923 | 17% |
| 2015-07 | 1,602 | 4,523 | 928 | 17% |
| 2015-08 | 1,520 | 4,168 | 796 | 16% |
| 2015-09 | 1,480 | 4,334 | 854 | 16% |
| 2015-10 | 1,536 | 4,629 | 884 | 16% |
| 2015-11 | 1,295 | 4,383 | 844 | 16% |
| 2015-12 | 1,390 | 4,375 | 821 | 16% |
| 2016-01 | 1,349 | 4,030 | 690 | 15% |
| 2016-02 | 1,364 | 4,359 | 723 | 14% |
| 2016-03 | 1,564 | 4,780 | 982 | 17% |
| 2016-04 | 1,429 | 4,468 | 894 | 17% |
| 2016-05 | 1,580 | 4,593 | 889 | 16% |
| 2016-06 | 1,527 | 4,427 | 1,012 | 19% |
| 2016-07 | 1,204 | 3,969 | 924 | 19% |
| 2016-08 | 1,566 | 4,563 | 1,006 | 18% |
| 2016-09 | 1,464 | 4,374 | 992 | 18% |
| 2016-10 | 1,496 | 4,528 | 1,002 | 18% |
| 2016-11 | 1,376 | 4,383 | 1,029 | 19% |

| | | | | |
|---|---|---|---|---|
| **2016-12** | 1,756 | 3,897 | 1,082 | 22% |

## Rank Order by No-Show

| Patient Rank Order by No-Shows | Percentage of Total No-Shows |
|---|---|
| 0-5% | 0% |
| 6-10% | 0% |
| 11-15% | 0% |
| 16-20% | 0% |
| 21-25% | 0% |
| 26-30% | 0% |
| 31-35% | 0% |
| 36-40% | 0% |
| 41-45% | 0% |
| 46-50% | 0% |
| 51-55% | 3% |
| 56-60% | 3% |
| 61-65% | 3% |
| 61-70% | 3% |
| 71-75% | 5% |
| 76-80% | 6% |
| 81-85% | 8% |
| 86-90% | 12% |
| 91-95% | 18% |
| 96-100% | 39% |

## Patient Characteristics

### Decade of Age

| Age | Number of Patients | Appointments | | | |
|---|---|---|---|---|---|
| | | Cancelled | Completed | No-show | No-show Rate |
| **0-9** | 1,609 | 2,999 | 9,800 | 2,298 | 19% |
| **10-19** | 1,584 | 2,262 | 7,450 | 1,839 | 20% |
| **20-29** | 2,420 | 4,970 | 14,543 | 4,397 | 23% |
| **30-39** | 3,766 | 10,323 | 28,215 | 6,946 | 20% |
| **40-49** | 2,954 | 9,887 | 26,713 | 6,088 | 19% |
| **50-59** | 2,574 | 11,038 | 30,131 | 6,115 | 17% |
| **60-69** | 2,023 | 8,268 | 26,719 | 3,557 | 12% |

| | | | | | |
|---|---|---|---|---|---|
| 70-79 | 833 | 2,809 | 9,240 | 1,032 | 10% |
| 80-89 | 366 | 994 | 3,547 | 320 | 8% |
| 90-99 | 160 | 281 | 1,121 | 84 | 7% |
| 100+ | 13 | 24 | 84 | 3 | 3% |

**BMI (Adults)**

| BMI Category | Number of Patients | Appointments | | | |
|---|---|---|---|---|---|
| | | Cancelled | Completed | No-show | No-show Rate |
| Underweight | 289 | 1,045 | 2,957 | 675 | 19% |
| Normal | 4,566 | 11,929 | 36,045 | 7,612 | 17% |
| Overweight | 3,913 | 12,244 | 36,100 | 7,112 | 16% |
| Obese Class I | 2,299 | 8,756 | 25,839 | 5,322 | 17% |
| Obese Class II | 1,204 | 5,750 | 15,814 | 3,129 | 17% |
| Obese Class III | 1,210 | 7,706 | 20,162 | 3,993 | 17% |

**Charlson Comorbidity Index**

| Charlson | Number of Patients | Appointments | | | |
|---|---|---|---|---|---|
| | | Cancelled | Completed | No-show | No-show Rate |
| 0 | 7,101 | 10,371 | 34,908 | 6,878 | 16% |
| 1 | 2,807 | 7,903 | 24,776 | 4,615 | 16% |
| 2 | 1,596 | 5,249 | 16,144 | 2,945 | 15% |
| 3 | 1,515 | 6,093 | 17,905 | 3,712 | 17% |
| 4 | 1,113 | 5,675 | 16,054 | 3,468 | 18% |
| 5 | 683 | 4,716 | 12,470 | 2,321 | 16% |
| 6 | 575 | 3,420 | 10,042 | 1,916 | 16% |
| 7 | 349 | 2,053 | 5,756 | 1,496 | 21% |
| 8 | 250 | 2,017 | 4,945 | 1,178 | 19% |
| 9 | 207 | 1,736 | 4,317 | 892 | 17% |
| 10 | 106 | 1,112 | 2,787 | 665 | 19% |
| 11 | 75 | 1,058 | 2,318 | 495 | 18% |
| 12 | 50 | 433 | 1,262 | 252 | 17% |
| 13 | 27 | 291 | 812 | 152 | 16% |
| 14 | 16 | 140 | 377 | 72 | 16% |
| 15 | 11 | 53 | 235 | 23 | 9% |

## Race

| Race | Number of Patients | Appointments | | | |
|---|---|---|---|---|---|
| | | Cancelled | Completed | No-show | No-show Rate |
| Unknown | 298 | 895 | 2,451 | 719 | 23% |
| Alaskan Native | 7 | 13 | 35 | 28 | 44% |
| American Indian | 221 | 604 | 1,802 | 462 | 20% |
| Asian | 886 | 2,088 | 6,986 | 775 | 10% |
| Black | 1,422 | 5,397 | 13,219 | 4,938 | 27% |
| Native Hawaiian | 4 | 30 | 30 | 23 | 43% |
| Pacific Islander | 65 | 159 | 375 | 126 | 25% |
| White | 14,204 | 43,380 | 128,219 | 24,627 | 16% |

## Sex

| Sex | Number of Patients | Appointments | | | |
|---|---|---|---|---|---|
| | | Cancelled | Completed | No-show | No-show Rate |
| Female | 10,119 | 34,506 | 93,977 | 20,375 | 18% |
| Male | 8,118 | 19,159 | 63,075 | 12,162 | 16% |
| Trans-Female to Male | 29 | 123 | 308 | 92 | 23% |
| Trans-Male to Female | 35 | 65 | 202 | 50 | 20% |

## Disease Condition

| Condition | Number of Patients | Appointments | | | |
|---|---|---|---|---|---|
| | | Cancelled | Completed | No-show | No-show Rate |
| Afib | 378 | 2,332 | 7,481 | 958 | 11% |
| AIDS | 31 | 107 | 398 | 44 | 10% |
| Any malignancy | 935 | 4,432 | 13,733 | 2,011 | 13% |
| Any transplant | 46 | 242 | 741 | 128 | 15% |
| Asthma | 2,040 | 10,953 | 29,781 | 6,329 | 18% |
| Autism | 83 | 221 | 728 | 132 | 15% |
| Bipolar | 852 | 5,985 | 15,174 | 3,513 | 19% |
| CAD | 523 | 3,364 | 10,137 | 1,530 | 13% |
| Cerebral Palsy | 88 | 417 | 1,199 | 184 | 13% |
| Cerebralvascular | 560 | 3,303 | 9,452 | 1,491 | 14% |
| CHF | 429 | 3,167 | 8,841 | 1,509 | 15% |
| Chronic Pain | 3,840 | 22,874 | 62,444 | 12,824 | 17% |
| COPD | 670 | 4,665 | 13,346 | 2,507 | 16% |
| Cystic Fibrosis | 185 | 17 | 40 | 3 | 7% |
| Dementia | 185 | 608 | 2,074 | 243 | 10% |
| Depression | 4,370 | 23,659 | 65,109 | 13,753 | 17% |

| | | | | | |
|---|---|---|---|---|---|
| **Developmental Delay** | 509 | 3,313 | 8,530 | 1,473 | 15% |
| **Diabetes Chronic** | 1,617 | 10,836 | 29,427 | 5,090 | 15% |
| **Downs Syndrome** | 19 | 62 | 205 | 21 | 9% |
| **Drug or Alcohol Addiction** | 1,186 | 7,790 | 19,875 | 6,304 | 24% |
| **Hemiplegia** | 177 | 906 | 2,676 | 422 | 14% |
| **Hemophilia** | 11 | 27 | 110 | 16 | 13% |
| **HIV** | 32 | 119 | 416 | 52 | 11% |
| **HTN** | 3,672 | 19,630 | 56,337 | 9,943 | 15% |
| **IBD** | 124 | 632 | 1,667 | 388 | 19% |
| **IVD** | 720 | 4,285 | 12,799 | 1,972 | 13% |
| **Liver Disease** | 542 | 3,251 | 8,826 | 2,521 | 22% |
| **Mental Retardation** | 55 | 880 | 2,408 | 420 | 15% |
| **Metastatic Solid Tumor** | 55 | 278 | 767 | 126 | 14% |
| **MI** | 113 | 751 | 2,035 | 373 | 15% |
| **Mild Liver Disease** | 957 | 5,616 | 15,556 | 3,790 | 20% |
| **Muscular Dystrophy** | 25 | 104 | 307 | 57 | 16% |
| **Peripheral Vascular** | 218 | 1,323 | 4,048 | 610 | 13% |
| **PUD** | 130 | 955 | 2,563 | 461 | 15% |
| **Renal Disease** | 469 | 3,219 | 9,382 | 1,394 | 13% |
| **Rheumatic Disease** | 211 | 1,119 | 3,222 | 563 | 15% |
| **Schizophrenia** | 507 | 3,080 | 7,761 | 1,753 | 18% |
| **Sickle Cell Disease** | 25 | 84 | 262 | 96 | 27% |
| **Skin Ulcer or Cellulitis** | 301 | 1,695 | 4,938 | 925 | 16% |
| **Uncontrolled Seizures** | 6 | 24 | 80 | 25 | 24% |

### Primary Language

| Language | Number of Patients | Appointments | | | |
|---|---|---|---|---|---|
| | | Cancelled | Completed | No-show | No-show Rate |
| **Albanian** | 8 | 7 | 40 | 9 | 18% |
| **American Sign Language** | 27 | 134 | 338 | 38 | 10% |
| **Amharic** | 9 | 19 | 51 | 6 | 11% |
| **Arabic** | 29 | 71 | 217 | 21 | 9% |
| **Bengali** | 4 | 16 | 32 | - | 0% |
| **Bosnian** | 25 | 62 | 247 | 37 | 13% |
| **Burmese** | 26 | 22 | 151 | 11 | 7% |
| **Cambodian** | 41 | 106 | 479 | 61 | 11% |
| **Chinese** | 19 | 33 | 115 | 9 | 7% |
| **Chinese-Cantonese** | 125 | 348 | 1,227 | 97 | 7% |
| **Chinese-Mandarin** | 27 | 56 | 211 | 9 | 4% |
| **Creole French** | 3 | 3 | 12 | 1 | 8% |
| **Croatian** | 10 | 30 | 112 | 12 | 10% |

| | | | | | |
|---|---|---|---|---|---|
| **Czech** | 1 | - | 1 | 1 | 50% |
| **Dari** | 3 | 2 | 13 | 4 | 24% |
| **Dutch** | 1 | 8 | 7 | 1 | 13% |
| **English** | 16,513 | 50,467 | 146,052 | 31,118 | 18% |
| **Farsi** | 14 | 31 | 98 | 15 | 13% |
| **Finnish** | 1 | 3 | - | 1 | 100% |
| **French** | 6 | 6 | 32 | 1 | 3% |
| **German** | 1 | - | 3 | - | 0% |
| **Greek** | 1 | 8 | 53 | 1 | 2% |
| **Hindi** | 3 | 3 | 24 | 4 | 14% |
| **Hmong** | 3 | 5 | 36 | 5 | 12% |
| **Ilocano** | 1 | - | 4 | - | 0% |
| **Italian** | 2 | 7 | 18 | 1 | 5% |
| **Japanese** | 5 | 10 | 25 | 1 | 4% |
| **Kanjobal** | 2 | 1 | 3 | 1 | 25% |
| **Khmer** | 6 | 8 | 24 | 7 | 23% |
| **Korean** | 13 | 53 | 155 | 6 | 4% |
| **Kurdish** | 2 | - | 1 | 1 | 50% |
| **Laotian** | 10 | 11 | 50 | 9 | 15% |
| **Mai Mai** | 8 | 14 | 80 | 21 | 21% |
| **Mien** | 7 | 49 | 89 | 12 | 12% |
| **Nepali** | 1 | - | 3 | - | 0% |
| **Norwegian** | 1 | - | - | 1 | 100% |
| **Oromo** | 6 | 1 | 11 | 1 | 8% |
| **Orono** | 1 | - | 1 | - | 0% |
| **Oth African** | 2 | 5 | 6 | 1 | 14% |
| **Oth Pac Islands** | 2 | 3 | 3 | - | 0% |
| **Other** | 5 | 5 | 14 | 10 | 42% |
| **Persian** | 1 | 2 | 4 | - | 0% |
| **Punjabi** | 1 | 3 | 6 | - | 0% |
| **Pushtu** | 1 | - | 5 | - | 0% |
| **Rohingya** | 6 | 4 | 14 | 3 | 18% |
| **Romanian** | 20 | 47 | 167 | 28 | 14% |
| **Russian** | 148 | 233 | 969 | 109 | 10% |
| **Samoan** | 1 | - | 1 | - | 0% |
| **Sign Language** | 12 | 64 | 106 | 12 | 10% |
| **Somali** | 46 | 102 | 262 | 87 | 25% |
| **Spanish** | 468 | 829 | 2,706 | 454 | 14% |
| **Swahili** | 7 | - | 16 | 5 | 24% |
| **Tagalog** | 17 | 26 | 102 | 20 | 16% |
| **Taishan** | 4 | 19 | 60 | 11 | 15% |

| | | | | | |
|---|---|---|---|---|---|
| Thai | 6 | 13 | 39 | 9 | 19% |
| Tibetan | 4 | 3 | 11 | - | 0% |
| Tigrinya | 5 | 49 | 79 | 9 | 10% |
| Tongan | 2 | 10 | 31 | 13 | 30% |
| Trukese/Chuukese | 2 | 3 | 10 | - | 0% |
| Ukrainian | 7 | 30 | 83 | 8 | 9% |
| Unknown | 13 | 36 | 106 | 23 | 18% |
| Urdu | 1 | 5 | 7 | - | 0% |
| Vietnamese | 122 | 374 | 1,246 | 124 | 9% |
| Yoruba | 1 | 3 | 8 | - | 0% |
| omi | 8 | 24 | 81 | 17 | 17% |

## Appointment Characteristics

### Appointment Type

| Appointment Type | Appointments | | | |
|---|---|---|---|---|
| | Cancelled | Completed | No-show | No-show Rate |
| Counselling | 282 | 748 | 298 | 28% |
| Establish | 1,801 | 5,669 | 1,333 | 19% |
| Immunizations | 1 | 3 | 1 | 25% |
| Labs/imaging | 1,015 | 5,858 | 627 | 10% |
| Office visit | 50,434 | 144,436 | 30,155 | 17% |
| Procedure | 270 | 675 | 121 | 15% |
| Telemedicine | 55 | 175 | 145 | 45% |

### Payor

| Payor | Appointments | | | |
|---|---|---|---|---|
| | Cancelled | Completed | No-show | No-show Rate |
| Medicaid | 29,502 | 86,101 | 20,981 | 20% |
| Medicare | 14,079 | 44,408 | 6,409 | 13% |
| Other | 1,100 | 384 | 754 | 66% |
| Private | 6,946 | 23,049 | 2,657 | 10% |
| Self-pay | 1,894 | 3,193 | 1,718 | 35% |
| Tricare | 84 | 341 | 56 | 14% |
| Worker's Comp | 253 | 88 | 105 | 54% |

### Provider Type

| Provider Type | Appointments |
|---|---|

| | Cancelled | Completed | No-show | No-show Rate |
|---|---|---|---|---|
| Administrative | 39 | 47 | 11 | 19% |
| Counselling | 1,139 | 2,586 | 691 | 21% |
| Diagnostics | 181 | 1,628 | 150 | 8% |
| Faculty | 14,026 | 43,754 | 7,448 | 15% |
| FNP | 13,098 | 37,995 | 7,742 | 17% |
| Foot care clinic | 18 | - | 16 | 100% |
| Group | 1,507 | 1,499 | 1,532 | 51% |
| Immunization clinic | 164 | 37 | 73 | 66% |
| Lab | 1,345 | 63 | 916 | 94% |
| MA | 1,914 | 11,559 | 1,240 | 10% |
| PA | 3,807 | 12,820 | 2,448 | 16% |
| PMHNP | 2,439 | 5,323 | 1,456 | 21% |
| Prenatal clinic | 91 | 7 | 34 | 83% |
| Procedure clinic | 1,990 | 4,540 | 991 | 18% |
| PsyD | 171 | 378 | 135 | 26% |
| Resident | 7,177 | 22,254 | 4,837 | 18% |
| RN | 2,520 | 6,929 | 1,209 | 15% |
| RPH | 101 | 420 | 95 | 18% |
| Social work | 2,131 | 5,725 | 1,656 | 22% |

## Appointment Time

| | Appointments | | | |
|---|---|---|---|---|
| Appointment Time | Cancelled | Completed | No-show | No-show Rate |
| Monday Morning | 3,264 | 10,127 | 2,296 | 18% |
| Monday Afternoon | 5,031 | 14,288 | 3,329 | 19% |
| Monday Evening | 1,269 | 4,148 | 805 | 16% |
| Tuesday Morning | 4,968 | 15,250 | 3,336 | 18% |
| Tuesday Afternoon | 5,682 | 15,765 | 3,274 | 17% |
| Tuesday Evening | 1,439 | 4,346 | 770 | 15% |
| Wednesday Morning | 4,140 | 12,730 | 2,637 | 17% |
| Wednesday Afternoon | 4,702 | 13,682 | 2,859 | 17% |
| Wednesday Evening | 1,344 | 3,926 | 821 | 17% |
| Thursday Morning | 4,466 | 12,637 | 2,392 | 16% |
| Thursday Afternoon | 5,586 | 15,338 | 3,023 | 16% |
| Thursday Evening | 2,226 | 5,369 | 1,177 | 18% |
| Friday Morning | 3,541 | 10,650 | 2,157 | 17% |
| Friday Afternoon | 4,186 | 12,023 | 2,514 | 17% |
| Friday Evening | 1,131 | 3,177 | 665 | 17% |
| Saturday Morning | 829 | 3,562 | 586 | 14% |

| | | | | |
|---|---|---|---|---|
| Saturday Afternoon | 54 | 545 | 39 | 7% |

### By Lead Time

| Lead Days | Appointments | | | |
|---|---|---|---|---|
| | Completed | No show | Cancelled | No-show Rate |
| 0 | 38347 | 3555 | 4229 | 8% |
| 1 | 14184 | 2845 | 3469 | 17% |
| 2 | 7596 | 1561 | 2316 | 17% |
| 3 | 6255 | 1517 | 2068 | 20% |
| 4 | 5173 | 1298 | 1885 | 20% |
| 5 | 4894 | 1222 | 1765 | 20% |
| 6 | 6215 | 1606 | 2395 | 21% |
| 7 | 12934 | 2991 | 4774 | 19% |
| 8 | 3380 | 805 | 1454 | 19% |
| 9 | 2065 | 498 | 907 | 19% |
| 10 | 1610 | 423 | 725 | 21% |
| 11 | 1428 | 384 | 626 | 21% |
| 12 | 1351 | 400 | 582 | 23% |
| 13 | 1914 | 532 | 809 | 22% |
| 14 | 5140 | 1369 | 2165 | 21% |
| 15 | 1925 | 480 | 923 | 20% |
| 16 | 1267 | 282 | 578 | 18% |
| 17 | 1061 | 271 | 526 | 20% |
| 18 | 1001 | 243 | 479 | 20% |
| 19 | 855 | 244 | 430 | 22% |
| 20 | 1215 | 313 | 579 | 20% |
| 21 | 2792 | 745 | 1346 | 21% |
| 22 | 1361 | 348 | 659 | 20% |
| 23 | 916 | 235 | 440 | 20% |
| 24 | 870 | 225 | 398 | 21% |
| 25 | 806 | 208 | 395 | 21% |
| 26 | 825 | 242 | 351 | 23% |
| 27 | 1216 | 304 | 555 | 20% |
| 28 | 3870 | 941 | 1739 | 20% |
| 29 | 1493 | 363 | 743 | 20% |
| 30 | 1140 | 290 | 546 | 20% |
| 31 | 1233 | 336 | 594 | 21% |
| 32 | 975 | 293 | 521 | 23% |
| 33 | 807 | 263 | 434 | 25% |
| 34 | 1020 | 279 | 509 | 21% |
| 35 | 2082 | 542 | 1053 | 21% |

| | | | | |
|---|---|---|---|---|
| **36** | 718 | 183 | 385 | 20% |
| **37** | 435 | 135 | 250 | 24% |
| **38** | 455 | 120 | 254 | 21% |
| **39** | 373 | 96 | 190 | 20% |
| **40** | 340 | 97 | 187 | 22% |
| **41** | 489 | 150 | 293 | 23% |
| **42** | 1236 | 311 | 630 | 20% |
| **43** | 397 | 121 | 212 | 23% |
| **44** | 255 | 63 | 176 | 20% |
| **45** | 220 | 69 | 129 | 24% |
| **46** | 202 | 73 | 130 | 27% |
| **47** | 160 | 51 | 125 | 24% |
| **48** | 307 | 81 | 188 | 21% |
| **49** | 574 | 159 | 307 | 22% |
| **50** | 212 | 56 | 132 | 21% |
| **51** | 163 | 37 | 86 | 19% |
| **52** | 158 | 46 | 99 | 23% |
| **53** | 141 | 48 | 79 | 25% |
| **54** | 142 | 36 | 83 | 20% |
| **55** | 177 | 46 | 125 | 21% |
| **56** | 706 | 177 | 396 | 20% |
| **57** | 225 | 60 | 142 | 21% |
| **58** | 169 | 33 | 108 | 16% |
| **59** | 210 | 43 | 123 | 17% |
| **60** | 206 | 54 | 111 | 21% |
| **61** | 283 | 56 | 175 | 17% |
| **62** | 334 | 84 | 206 | 20% |
| **63** | 852 | 209 | 483 | 20% |
| **64** | 195 | 57 | 133 | 23% |
| **65** | 125 | 31 | 95 | 20% |
| **66** | 107 | 24 | 68 | 18% |
| **67** | 114 | 40 | 69 | 26% |
| **68** | 82 | 19 | 63 | 19% |
| **69** | 110 | 32 | 86 | 23% |
| **70** | 342 | 70 | 221 | 17% |
| **71** | 111 | 24 | 53 | 18% |
| **72** | 66 | 22 | 60 | 25% |
| **73** | 56 | 23 | 37 | 29% |
| **74** | 74 | 19 | 46 | 20% |
| **75** | 54 | 21 | 41 | 28% |
| **76** | 83 | 19 | 75 | 19% |

| | | | | |
|---|---|---|---|---|
| **77** | 310 | 95 | 213 | 23% |
| **78** | 92 | 39 | 58 | 30% |
| **79** | 57 | 26 | 49 | 31% |
| **80** | 56 | 16 | 57 | 22% |
| **81** | 59 | 16 | 45 | 21% |
| **82** | 69 | 24 | 51 | 26% |
| **83** | 93 | 38 | 65 | 29% |
| **84** | 376 | 99 | 256 | 21% |
| **85** | 108 | 21 | 68 | 16% |
| **86** | 77 | 31 | 59 | 29% |
| **87** | 87 | 15 | 77 | 15% |
| **88** | 72 | 23 | 67 | 24% |
| **89** | 103 | 22 | 82 | 18% |
| **90** | 190 | 44 | 109 | 19% |

## Appendix D

### Multivariate Analysis Model Data

| Variable | Estimate | SE | p Value | OR (95% CI) |
|---|---|---|---|---|
| **Race (reference = White)** | | | | |
| **Alaskan Native** | 0.66 | 0.27 | 0.015 | 1.93 (1.13-3.28) |
| **American Indian** | 0.09 | 0.06 | 0.121 | 1.10 (0.97-1.23) |
| **Asian** | -0.27 | 0.04 | <0.001 | 0.76 (0.70-0.83) |
| **Black** | 0.25 | 0.02 | <0.001 | 1.29 (1.24-1.34) |
| **Native Hawaiian** | -0.16 | 0.34 | 0.644 | 0.86 (0.44-1.66) |
| **Pacific Islander** | 0.05 | 0.12 | 0.668 | 1.05 (0.83-1.33) |
| **Unknown/Decline** | 0.12 | 0.05 | 0.012 | 1.13 (1.03-1.24) |
| | | | | |
| **Sex (reference = Female)** | | | | |
| **Male** | -0.01 | 0.02 | 0.560 | 0.99 (0.96-1.02) |
| **Trans-Female to Male** | -0.20 | 0.14 | 0.172 | 0.82 (0.62-1.08) |
| **Trans-Male to Female** | -0.10 | 0.18 | 0.588 | 0.91 (0.63-1.28) |
| | | | | |
| **Age (reference = 30-39)** | | | | |
| **0-9** | 0.24 | 0.03 | <0.001 | 1.27 (1.19-1.36) |
| **10-19** | 0.23 | 0.04 | <0.001 | 1.26 (1.17-1.35) |
| **20-29** | 0.18 | 0.03 | <0.001 | 1.20 (1.14-1.26) |
| **40-49** | -0.06 | 0.02 | <0.001 | 0.94 (0.90-0.98) |
| **50-59** | -0.13 | 0.02 | <0.001 | 0.87 (0.83-0.92) |
| **60-69** | -0.24 | 0.03 | <0.001 | 0.78 (0.74-0.83) |
| **70-79** | -0.24 | 0.05 | <0.001 | 0.79 (0.72-0.86) |
| **80-89** | -0.23 | 0.07 | 0.002 | 0.80 (0.69-0.92) |
| **90-99** | -0.12 | 0.14 | 0.381 | 0.89 (0.67-1.15) |
| **100+** | -0.94 | 0.72 | 0.193 | 0.39 (0.06-1.26) |
| | | | | |
| **Num. Medications** | 0.00 | 0.00 | 0.015 | 1.00 (1.00-1.01) |
| | | | | |
| **BMI** | 0.00 | 0.00 | 0.019 | 1.00 (1.00-1.00) |
| | | | | |
| **Charlson Score** | 0.00 | 0.01 | 0.691 | 1.00 (0.99-1.01) |
| | | | | |
| **Diagnosis Coded in EMR** | | | | |
| **Asthma** | 0.00 | 0.02 | 0.915 | 1.00 (0.96-1.04) |
| **Atrial Fibrillation** | 0.21 | 0.04 | <0.001 | 1.23 (1.13-1.34) |
| **Bipolar** | 0.01 | 0.03 | 0.790 | 1.01 (0.95-1.07) |
| **Cerebrovascular Disease** | 0.00 | 0.04 | 0.927 | 1.00 (0.94-1.08) |

| | | | | |
|---|---|---|---|---|
| **Chronic Pain** | 0.07 | 0.02 | <0.001 | 1.07 (1.04-1.10) |
| **Congestive Heart Disease** | -0.08 | 0.04 | 0.048 | 0.92 (0.85-1.00) |
| **COPD** | 0.06 | 0.03 | 0.030 | 1.06 (1.01-1.13) |
| **Coronary Artery Disease** | 0.03 | 0.04 | 0.416 | 1.03 (0.96-1.11) |
| **Cystic Fibrosis** | -0.65 | 0.60 | 0.282 | 0.52 (0.13-1.46) |
| **Dementia** | 0.01 | 0.08 | 0.890 | 1.01 (0.87-1.17) |
| **Depression** | 0.03 | 0.02 | 0.110 | 1.03 (0.99-1.06) |
| **Developmental Delay** | 0.08 | 0.04 | 0.046 | 1.08 (1.00-1.16) |
| **Diabetes** | 0.05 | 0.04 | 0.187 | 1.05 (0.98-1.13) |
| **Drug or Alcohol Addiction** | 0.19 | 0.03 | <0.001 | 1.21 (1.15-1.28) |
| **Hemiplegia** | 0.14 | 0.06 | 0.033 | 1.15 (1.01-1.30) |
| **Hypertension** | 0.00 | 0.02 | 0.819 | 1.00 (0.97-1.04) |
| **Inflammatory Bowel Disease** | -0.10 | 0.07 | 0.138 | 0.90 (0.79-1.03) |
| **Liver Disease** | 0.19 | 0.03 | <0.001 | 1.21 (1.14-1.30) |
| **Myocardial Infarction** | 0.28 | 0.07 | <0.001 | 1.32 (1.15-1.51) |
| **Peptic Ulcer Disease** | 0.03 | 0.06 | 0.637 | 1.03 (0.91-1.16) |
| **Peripheral Vascular Disease** | 0.12 | 0.05 | 0.017 | 1.13 (1.02-1.25) |
| **Renal Disease** | 0.07 | 0.04 | 0.085 | 1.07 (0.99-1.16) |
| **Rheumatic Disease** | -0.05 | 0.05 | 0.321 | 0.95 (0.85-1.05) |
| **Schizophrenia** | 0.23 | 0.04 | <0.001 | 1.26 (1.17-1.35) |
| **Skin Ulcers or Cellulitis** | 0.13 | 0.04 | 0.004 | 1.14 (1.04-1.24) |
| | | | | |
| **Total Appointments in 3y Period** | | | | |
| **Cancelled** | 0.00 | 0.00 | 0.005 | 1.00 (1.00-1.00) |
| **Completed** | -0.03 | 0.00 | <0.001 | 0.97 (0.97-0.97) |
| **No-show** | 0.10 | 0.00 | <0.001 | 1.11 (1.11-1.11) |
| | | | | |
| **Visit Type (reference = Office Visit)** | | | | |
| **Counselling** | 0.20 | 0.09 | 0.028 | 1.23 (1.02-1.47) |
| **Establish Care** | -0.55 | 0.04 | <0.001 | 0.58 (0.53-0.63) |
| **Immunizations** | 0.69 | 1.21 | 0.570 | 1.99 (0.09-17.26) |
| **Labs/Imaging** | -1.88 | 0.10 | <0.001 | 0.15 (0.13-0.19) |
| **Procedure** | -0.16 | 0.12 | 0.163 | 0.85 (0.68-1.06) |
| **Telemedicine** | 1.25 | 0.13 | <0.001 | 3.48 (2.68-4.51) |
| | | | | |
| **Provider Type (reference = Faculty Physician)** | | | | |
| **Administrative** | 0.84 | 0.36 | 0.021 | 2.32 (1.09-4.56) |
| **Counselling** | 0.79 | 0.05 | <0.001 | 2.19 (1.98-2.43) |
| **Diagnostics** | 1.05 | 0.12 | <0.001 | 2.87 (2.27-3.61) |
| **FNP** | 0.27 | 0.02 | <0.001 | 1.31 (1.26-1.37) |
| **Group** | 2.33 | 0.05 | <0.001 | 10.25 (9.26-11.36) |

| | | | | |
|---|---|---|---|---|
| Immunization clinic | 3.15 | 0.23 | <0.001 | 23.45 (15.20-36.92) |
| Lab | 6.07 | 0.17 | <0.001 | 433.09 (312.83-610.37) |
| MA | 0.10 | 0.04 | 0.007 | 1.11 (1.03-1.19) |
| PA | 0.28 | 0.03 | <0.001 | 1.32 (1.24-1.39) |
| PMHNP | 0.45 | 0.04 | <0.001 | 1.57 (1.46-1.69) |
| Prenatal Clinic | 2.67 | 0.50 | <0.001 | 14.39 (5.70-41.20) |
| Procedure Clinic | 0.55 | 0.05 | <0.001 | 1.74 (1.57-1.92) |
| PsyD | 0.94 | 0.11 | <0.001 | 2.57 (2.06-3.18) |
| Resident Physician | 0.23 | 0.02 | <0.001 | 1.25 (1.20-1.31) |
| RN | 0.49 | 0.04 | <0.001 | 1.63 (1.50-1.76) |
| RPH | 0.80 | 0.13 | <0.001 | 2.22 (1.73-2.83) |
| Social Worker | 0.73 | 0.04 | <0.001 | 2.08 (1.94-2.24) |
| | | | | |
| Payor (reference = Medicaid) | | | | |
| Medicare | -0.20 | 0.02 | <0.001 | 0.82 (0.79-0.85) |
| Other | 2.22 | 0.07 | <0.001 | 9.24 (8.03-10.66) |
| Private | -0.44 | 0.03 | <0.001 | 0.64 (0.61-0.68) |
| Self-Pay | 0.71 | 0.04 | <0.001 | 2.03 (1.89-2.19) |
| TRICARE | -0.11 | 0.16 | 0.491 | 0.90 (0.65-1.21) |
| Worker's Comp | 1.91 | 0.16 | <0.001 | 6.73 (4.92-9.24) |
| | | | | |
| Time (reference = Tuesday Afternoon) | | | | |
| Monday Morning | 0.14 | 0.04 | <0.001 | 1.15 (1.07-1.23) |
| Monday Afternoon | 0.04 | 0.03 | 0.178 | 1.04 (0.98-1.11) |
| Monday Evening | -0.01 | 0.05 | 0.806 | 0.99 (0.90-1.09) |
| Tuesday Morning | 0.08 | 0.03 | 0.019 | 1.08 (1.01-1.15) |
| Tuesday Evening | -0.08 | 0.05 | 0.104 | 0.92 (0.83-1.02) |
| Wednesday Morning | 0.00 | 0.03 | 0.953 | 1.00 (0.94-1.07) |
| Wednesday Afternoon | -0.08 | 0.03 | 0.013 | 0.92 (0.86-0.98) |
| Wednesday Evening | 0.01 | 0.05 | 0.787 | 1.01 (0.92-1.12) |
| Thursday Morning | 0.06 | 0.03 | 0.095 | 1.06 (0.99-1.13) |
| Thursday Afternoon | 0.00 | 0.03 | 0.896 | 1.00 (0.93-1.06) |
| Thursday Evening | 0.07 | 0.04 | 0.112 | 1.07 (0.98-1.17) |
| Friday Morning | 0.09 | 0.04 | 0.008 | 1.10 (1.02-1.18) |
| Friday Afternoon | 0.05 | 0.03 | 0.164 | 1.05 (0.98-1.12) |
| Friday Evening | 0.05 | 0.05 | 0.350 | 1.05 (0.95-1.17) |
| Saturday Morning | -0.01 | 0.06 | 0.865 | 0.99 (0.89-1.10) |
| Saturday Afternoon | -0.89 | 0.19 | <0.001 | 0.41 (0.28-0.58) |
| | | | | |
| Lead Days to Appointment <14 days | 0.01 | 0.00 | <0.001 | 1.01 (1.01-1.01) |