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# Improve primary care performance through operations management: an application to emergency care and preventive care

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# IMPROVE PRIMARY CARE PERFORMANCE THROUGH OPERATIONS MANAGEMENT: AN APPLICATION TO EMERGENCY CARE AND PREVENTIVE CARE

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TESIS DOCTORAL

# Mejora del rendimiento en atención primaria a través de la gestión de operaciones: aplicación a atención de urgencia y al cuidado preventivo

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# Resumen

El propósito principal de esta tesis es aplicar el método de gestión de operaciones para mejorar el rendimiento de los responsables de proporcionar atención sanitaria en relación con dos componentes principales de la atención primaria: atención de urgencia y atención primaria. Durante muchos años, en la atención sanitaria se han aplicado los sistemas de gestión de operaciones (OM) y de investigación de operaciones (OR) con la finalidad de mejorar la eficiencia en la prestación de los servicios sanitarios. El núcleo del sistema de atención médica es la atención sanitaria, cuyas funciones principales incluyen el suministro de un punto de entrada, la prestación de atención médica y preventiva fundamental y ayudar a los pacientes a coordinar y a integrar la atención, aspectos que son fundamentales de cara a mejorar no solo el resultado sanitario de los pacientes, sino también el rendimiento en términos de coste de todo el sistema sanitario (Starfield 1998). En un estudio sobre el rendimiento de la atención primaria y del sistema de salud (Schoen et al., 2004), en EE. UU. se registró un índice de utilización del departamento de urgencias (ED) muy superior al de otros tres países, el cual venía acompañado de un menor porcentaje de adultos que dispusieran de un doctor, un lugar o una clínica habitual donde acudir al caer enfermos. Por este motivo, el capítulo 2 de esta disertación aborda la mejora del departamento de salas de urgencia a través del rediseño del proceso. Otro hallazgo fundamental de la encuesta es que Canadá cuenta con el menor índice de chequeos en términos de prueba de Papanicolaou y mamografías. Debido a la importancia de la atención preventiva para salvar vidas y reducir costes, el capítulo 3 de esta disertación analiza cómo mejorar el programa de atención preventiva financiado por el gobierno a través del diseño de la red.

El capítulo 2 establece el contexto de un departamento de urgencias (ED) en un hospital terciario con un censo anual de 55 000 pacientes, y analiza la forma en la que el proceso de rediseño de una prueba sanguínea específica tiene un determinado impacto sobre la congestión del ED. De forma más específica, analizamos en cambio en tres magnitudes de rendimiento después de que el análisis de la muestra de sangre del paciente para determinar los niveles de troponina fuera trasladada del laboratorio central del laboratorio al interior del ED. Mediante la teoría de la asignación de colas de prioridad, generamos hipótesis sobre las siguientes medidas de rendimiento: tiempo de espera (definido como la diferencia de tiempo entre el registro de entrada del paciente y la asignación de cama), tiempo de servicio (definido como la diferencia de tiempo entre la asignación de cama y la distribución, el metabolismo y la eliminación de un fármaco) y calidad del servicio (definido como el índice de revisión de los pacientes tras 72 horas).

Mediante un modelo de diferencias en diferencias, determinamos que el rediseño del proceso está asociado con unas mejoras estadísticamente significativas en casi todas las mediciones de rendimiento operativo. Concretamente, encontramos que la adopción de POCT está asociada a una reducción del 21,6 % en el tiempo de servicio entre los pacientes objeto de la prueba durante las horas punta, y en una reducción de entre el 5,9 % y el 35,5 % en el tiempo de espera en función de la categoría de prioridad del paciente durante esas mismas horas punta. Además, encontramos que la adopción de un POCT estaba asociada con una mejora de la calidad del servicio, puesto que la probabilidad de recaída pronosticada se redujo en un 0,64 % durante su uso. También descubrimos importantes efectos

indirectos a través de todo el sistema en pacientes que no habían sido objeto de un POCT (pacientes que no son objeto de prueba). En otras palabras, la adopción de un POCT está asociada con una reducción del tiempo de espera entre estos pacientes que no son objeto de prueba de un 4,73 % y a una reducción del 11,6 % en el tiempo de espera en función de la categoría de prioridad de los pacientes durante las horas punta. Al examinar el impacto del POCT entre ambas poblaciones de pacientes, tanto los que fueron sometidos a la prueba como los que no, se pudo determinar que esta investigación es única a la hora de identificar los grandes beneficios en el sistema que pueden lograrse a través del rediseño del proceso asociado al ED.

El tercer capítulo de esta tesis emplea un modelo de elección de preferencias para analizar las prioridades del cliente en la atención preventiva desde la perspectiva de la configuración del servicio. Aplicamos el modelo en el contexto de un programa de chequeos asociados con el cáncer de mama financiado por el gobierno en Montreal (Canadá), con el fin de identificar las contrapartidas que reciben los participantes del programa a la hora de acceder a un conjunto de instalaciones con diferentes configuraciones de servicio basadas en sus auténticas preferencias. De forma más concreta, analizamos estas preferencias en relación con el tiempo de espera para obtener cita, el tiempo de desplazamiento a la clínica en la que se vaya a practicar el chequeo, la disponibilidad del aparcamiento de la clínica, el horario de apertura de la clínica, el tiempo de espera dentro de la clínica el día del chequeo, la preparación del personal de enfermería, el proceso de chequeo y el tiempo de espera para recibir el resultado.

Pudimos comprobar que la preparación del personal de enfermería (es decir, si son capaces de responder preguntas relacionadas con el chequeo o con el cáncer de mama) y el tiempo de espera para obtener una cita eran los factores más determinantes a la hora de elegir una clínica, seguidos de cerca por la disponibilidad de aparcamiento. Mediante el análisis de clases latentes también podemos confirmar que, al contrario de lo apuntado por otras investigaciones, no existe una heterogeneidad clara entre los participantes del programa. Nuestro modelo Arena de simulación muestra que tener en cuenta las preferencias del cliente en el diseño de las configuraciones del servicio mejorará notablemente tanto el nivel de congestión como el índice de participación en las nuevas pruebas.

Como conclusión de ambos capítulos, esta tesis trata de generar implicaciones en términos de gestión en lo que respecta a la configuración de la atención sanitaria que puedan ayudar a mejorar la calidad del servicio mediante el uso de un enfoque de metodología empírica. Vemos que pueden acometerse importantes mejoras en los servicios existentes a través del rediseño del proceso de servicio y de la comprensión de las preferencias del cliente, sin necesidad de revisar todo el sistema de atención sanitaria.

# Conclusión

En el capítulo 2 ofrecemos datos de que el rediseño del proceso de ED, y en concreto la adopción de POCT, tiene un impacto considerable y valioso en el impacto del funcionamiento del propio ED. La adopción del POCT reduce el tiempo de servicio no solo de los pacientes que son sometidos a la prueba de la troponina en el centro de atención, sino también de otros pacientes dentro del ED que no tienen que someterse a esta prueba. Por otra parte, el hecho de que observemos que el impacto del tiempo de servicio en lo que respecta a la adopción del POCT es mayor durante las horas punta que durante las horas valle entre los pacientes tanto objeto de la prueba como entre aquellos que no están sometidos a ella sugiere que el POCT puede tener un impacto cuantificable sobre el rendimiento del ED durante los períodos operativos fundamentales.

La adopción del POCT también está asociada con una mejora en la calidad del servicio. Todos los pacientes que se presentaron en el ED durante el período piloto del POCT experimentaron una tasa de recaída menor que el de los demás períodos de comparación. Algunas de estas mejoras en la calidad pueden derivarse de los pronósticos asociados al modelo de cola de prioridad, en los que los pacientes con prioridades altas y bajas experimentan impactos diferentes. En términos empíricos, los pacientes con menor prioridad tienen una mayor propensión de recaída. Establecemos la conjetura de que los pacientes menos graves, *a priori,* pueden recibir menos atención. A medida que se acumula el ahorro en tiempos de servicio, igual que sucede con las colas de prioridad, los pacientes pueden cosechar los beneficios derivados de cualquier atención médica adicional.

Finalmente, determinamos que la adopción del POCT tiene un efecto positivo en el tiempo de espera para pacientes tanto objeto de prueba como no sometidos a ella; del mismo modo, observamos que los pacientes con una menor prioridad experimentan el mayor descenso en tiempo de espera al adoptar el POCT, mientras que los pacientes con una mayor prioridad registran el menor descenso de dicho tiempo, lo cual sirve para fundamentar nuestro pronóstico del comportamiento del ED basado en la teoría de las colas. Además, los datos también sugieren que el POCT deriva en una mejora operativa no solo a través de un impacto directo sobre el tiempo de servicio de los pacientes sometidos a la prueba, sino también merced a un impacto indirecto sobre el tiempo de espera para todos aquellos que se presentan en el ED cuando el POCT está utilizándose.

Hay muchas ampliaciones posibles de esta investigación: en primer lugar, ¿qué modelo debería utilizarse para ayudar a un administrador a determinar la cifra óptima de pruebas que deben convertirse a POCT? Este estudio analiza una configuración en la que una prueba sencilla se convierte en POCT. El hecho de que las cargas de trabajo de los enfermeros se incrementen con cada prueba adicional convertida sugiere la reducción del rendimiento marginal. ¿Qué distribución de pruebas entre la propia cama del paciente y el laboratorio central minimiza los tiempos de servicio sin comprometer la calidad de servicio sujeta a limitaciones del personal? En segundo lugar, ¿qué modelo ayudaría a un administrador a seleccionar la(s) prueba(s) óptima(s) que deberían convertirse en POCT? Los estudios anteriores detallan que, hasta la fecha, los motivos para la selección son muy específicos. ¿Cuáles son los criterios de selección fundamentales y el potencial para las economías de escala, en términos tanto de costes como de calidad, a partir del análisis de pruebas? Finalmente, ¿cómo estructuran los

administradores el impacto financiero de la conversión POCT? En nuestra configuración y en la de muchos estudios anteriores, la conversión a POCT está justificada únicamente sobre la base del tiempo de servicio y de la calidad de éste. No obstante, en el contexto de incrementar los costes de atención sanitaria, la adopción del POCT incurre tanto en un gasto de bienes de equipo como en costes marginales superiores por prueba. El hecho de que el POCT pueda reducir la congestión del ED y del laboratorio central e incrementar el volumen de pacientes, suficiente para compensar estos costes, garantiza la viabilidad de estudios adicionales.

En el capítulo 3, el estudio en materia de cáncer de mama, determinamos que la preparación y los conocimientos del personal de enfermería en relación con los chequeos y con el cáncer de mama, así como el tiempo de espera para obtener una cita, son los factores más influyentes a la hora de decantarse por una clínica, seguidos de la disponibilidad de aparcamiento. Pudimos comprobar que el horario de apertura de las clínicas era el único atributo que carecía de importancia en la toma de decisiones. Mediante el análisis de categorías latentes, podemos identificar la homogeneidad entre los participantes actuales del PQDCS, es decir, no hay pruebas de que existan diferencias entre las preferencias de factores estudiados en los participantes. Mediante los datos recopilados en 12 zonas de población del área metropolitana de Montreal y en 15 clínicas de chequeos actualmente designadas, creamos un modelo Arena de simulación para analizar el cambio en todo el sistema si se tienen en cuenta las preferencias. Nuestros resultados muestran una mejora significativa en las tres magnitudes, que se miden por número de chequeos al año, índice de utilización de las máquinas de mamografía y número de mujeres esperando a recibir una cita.

La aportación fundamental de nuestro estudio es ofrecer una herramienta que pueda utilizarse para mejorar notablemente la calidad del servicio en el programa de atención preventiva sin incurrir en una gran inversión de capital. Todos los factores analizados pueden ajustarse en costes más reducidos, o incluso sin necesidad de que supongan coste alguno; asimismo, aunque no se presente aquí, el resultado de nuestra encuesta también puede utilizarse en un modelo probit para generar la función de participación al someterse a un nuevo chequeo. Las personas que han respondido a nuestra encuesta son una muestra adecuada de los participantes actuales del programa PQDCS. Las investigaciones futuras pueden adoptar el mismo enfoque, aunque podrían incluir también a las personas que no participaran en el estudio con el fin de generar una función de participación general para así adquirir mayor perspectiva en lo que a la gestión se refiere.

UNIVERSIDAD DE ZARAGOZA

TESIS DOCTORAL

# Improve primary care performance through operations management- an application to emergency care and preventive care

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**Abstract**

# Improve primary care performance through operations management- an application to emergency care and preventive care

The main purpose of this thesis is to apply operations management method to improve health care providers' performance in two major component of primary care: emergency care and primary care. Operations Management (OM) and Operations Research (OR) has been applied to health care for many years to improve health care delivery efficiency. The center of medical care system is primary care, whose key functions include providing an entry point, delivering core medical and preventive care, and helping patients coordinate and integrate care, all of which are critical in improving not only health outcome of patients, but also cost performance of the whole health care system. In a study on primary care and health system performance, US reported much higher Emergency Department (ED) use rates than the other three countries, accompanied by lowest percentage of adults that have regular doctor, places or clinics to go when they are sick. Chapter 2 of this dissertation therefore target improving emergency room department through process redesign. Another key finding of the survey is that Canada has the lowest rate of screening for Pap test and mammogram. Given the significance of preventive care in saving lives and reducing cost, chapter 3 of this dissertation explores how to improve government funded preventive care program through network design.

Chapter 2 set the context in a tertiary hospital emergency department (ED) that have an annual census of 55,000 patients, and look at how does redesigning process for a specific blood test impact the congestion of the ED. More specifically, we look at the change in three performance metrics after the analysis of patients blood sample for troponin level was moved from the hospital's central lab to inside the ED. Use priority queueing theory, we generate hypotheses on the following performance measures: waiting time (defined as the time difference between patient intake registration and bed assignment), service time (defined as the time difference between bed assignment and disposition), and service quality (defined as patients' 72-hour revisit rate).

Using difference-in-difference model, we find the process redesign to be associated with statistically significant improvements in nearly all measures of operational performance. Specifically, we find the adoption of POCT to be associated with a 21.6% reduction in service time among test patients during peak hours and a 5.9% to 35.5% reduction in waiting time depending on the patient's priority class during peak hours. Moreover, we find the adoption of POCT to be associated with improved service quality as patients' predicted probability of bounce back decreased by 0.64% during its usage. We also find system wide spillover effects for patients

who do not receive a POCT (no-test patients). In other words, the adoption of POCT is associated with a service time reduction among these no-test patients of 4.73% and an 11.6% reduction in waiting time depending on the patients priority class during peak hours. By examining the impact of POCT among both the population of patients receiving the test and the population that does not, this research is unique in identifying the system-wide benefits that can be attained through ED process redesign.

The third chapter of this thesis uses stated preference choice model to explore client preference on preventive care, from the perspective of service configuration. We apply the model in the context of government-funded breast cancer screening program in Montreal, Canada to identify trade-offs program participants make when facing a set of facilities with difference service configurations, based upon their true preference. More specifically, we look at their preferences regarding waiting time for appointment, travel time to the screening clinic, clinic parking availability, clinic opening hours, waiting time inside clinic on the day of screening, nursing staff's manner, screening process, and waiting time for result.

We found nursing staff's manner (i.e. whether they can answer screening and/or breast cancer related questions) and waiting time for an appointment to be the most influential factors for choice of clinics, followed closely by parking availability. Using latent class analysis, we also confirm that unlike suggested by some other research, there is no clear heterogeneity among program participants. Our Arena simulation model shows that taking into account of client preferences into the design of service configurations will improve both the congestion level and participation rate of re-screeners significantly.

As a conclusion of both chapters, this thesis attempts to generate managerial implications in health care settings that help to improve service quality using empirical methodology approach. We find that significant improvement to the existing services can be achieved through redesigning service process, and understanding of client preferences, without an overhaul of the entire health care system.

# 1. Summary

Operations Management (OM) and Operations Research (OR) has been applied to health care for many years to improve health care delivery efficiency. There're many fields in the health care domain where OM can be applied to make its contribution. At the macro level, OM has been used for planning and strategic purposes, such as allocation of health care resources at national or regional level (Stinnett and Paltiel 1996), and finding optimal locations for multiple health care facilities (Verter and Lapierre 2002). At operational level, OM has been used for solving scheduling problem for both patients and hospital staff (Cayirli and Veral 2003; Green 2008), and for reservation of operation rooms (Olivares et al. 2008). From the perspective of context of problems, OM has been applied not only in developed and developing country for improving their long-existing health care systems, but also for underdeveloped countries to design new health supply chain and to treat epidemic diseases. Recently, emergency and disaster response has also start to get its fair share of the pie from OM. Other areas that has benefit from application of OM includes medical decision-making such as live organ transplant (David and Yechiali 1985), hospital performance measurement (Bowers et al. 1994; Jun et al. 1998), the list goes on.

In United States, especially in recent years, due to price deregulation and pressure from both government and managed care organizations, accompanied by decreased level of compensation from Medicare and Medicaid (Green 2008), there are ongoing pressure for hospitals to increase their efficiency while maintain a low operation cost at the same time. Since mid-1990s, there has been many downsizing and closures of hospitals, with the purposes of meeting target occupancy levels that were actually outdated by current standard (Green 2008). As a result, hospitals are getting crowded than ever, patients are kept waiting longer, which results in not only patients' low satisfaction with the services, but more importantly, delays in care or even loss of lives.

At the very center of medical care system is primary care, whose key functions include providing an entry point, delivering core medical and preventive care, and helping patients coordinate and integrate care, all of which are critical in improving not only health outcome of patients, but also cost performance of the whole health care system (Starfield 1998). In a study on primary care and health system performance, Schoen et al. (2004) surveyed adults in five countries (Australia, Canada, New Zealand, the United Kingdom, and the United States), on their experiences with access to care, emergency care, coordination, continuity, and doctor-patient interactions. Their finding shows that US has the lowest percentage of adults that have regular doctor, places or clinics to go. Compared to the rest of the countries, US and Canada also reported much longer waits for an

appointment when sick, with at least 20-25% waiting more than 6 days. On the issue of emergency care, US and Canada reported much higher Emergency Department (ED) use rates than the other three countries. The less satisfying performance of the counties in both categories is not by accident. A 1999 survey of insured adults younger than 65 shows that 27% of people with health problems cannot get timely access to a clinician, at the same time, 40% of ED visits are not urgent (Cunningham et al. 1995). In another word, lack of access to primary care physician is causing people to flood into ED whenever there's a health problem, even when the situation is not urgent, as a result, ED is getting crowded than ever, hospital administrators are struggling to accommodate more patients within existing infrastructure.

Researchers identify three sets of drivers of ED crowding: factors affecting patient arrivals, factor affecting patient departures from the ED (discharge or admittance into the hospital), and factors affecting patient treatment (Hoot and Aronsky 2008). Interventions to patient arrival patterns are largely beyond the scope of any one hospital, and usually require policy changes at the community level and beyond. The main factor affecting patient departures from the ED is boarding (Falvo et al. 2007). Boarding occurs when patients occupy ED beds long after they have been admitted to the hospital due to lack of inpatient hospital beds. Although ED alone can't solve boarding problems, studies have shown that coordinated management of ED beds and inpatient beds can have a direct impact on boarding (Balaji and Brownlee 2009; Green and Nguyen 2001). Solutions to factors that affect patient treatment have been focused on two areas, resource allocation and process redesign. The former targets problems such as shortage of ED physicians, nursing staff, and treatment beds, all of which result in long waiting time and further exacerbate the impact of crowding (Green 2008; Allon et al. 2009). Green et al. (2006) apply queueing theory to optimize ED staff scheduling to best accommodate seasonality in patient arrivals over the course of a single day and over an entire week. Some hospitals address boarding directly by allocating a few beds within the ED that are staffed by physicians, but dedicated to short-stay patients who would otherwise have to wait for an inpatient bed (Bazarian et al. 1996).

There are also many studies aim at redesigning patient treatment process to reduce congestion inside ED. One way to address long waiting time for low-severity patients is the practice of fast-track. Some hospitals set aside a few beds within the ED (fast-track), staff them with lower-cost nurse practitioners, and dedicate to serving low-priority patients with minor, specific, ambulatory, or acute illness or injury. Fast-track reduces waiting time for non-urgent patients while maintaining service quality (Meislin et al. 1998; Yoon 2003). Anon (2000) and Gorelick et al. (2005) studied changes in patient registration, such as deferring parts of the registration until after a patient is assigned a room and after the physician's initial evaluation. Another common

bottleneck for the ED treatment process is the share of central lab with all inpatients for test result delivery (Kilgore et al. 1998). Chapter 2 of this dissertation joins the studies of others on treatment process redesign, explores the impact of using point-of-care testing on reducing ED overcrowding.

Point-of-care testing, also called bedside testing, refers to the practice of analyzing patient specimens at or near the location of patient care rather than in a centralized laboratory (Jahn and Aken 2003). While waiting time for test result to become available from central lab can take anywhere from less than 30 minutes to hours, POCT equipment usually display test results in less than 10 minutes. Many research have been conducted to test whether using POCT can reduce the total time that a patient spends in the ED (length of stay, LOS), but results have been inconclusive (Fermann and Suyama 2002). Murray et al (1999) find a reduction of almost an hour in median LOS for discharged patients who received a specific POCT, but no decrease for similarly treated patients who were admitted. By contrast, Kendall et al. (1998) and Renaud et al. (2008) find no reduction in median LOS after installation of POCT. Lee-Lewandrowski et al. (2003) find that statistically significant reductions in median LOS require shifting multiple tests to the bedside. Shifting any single test produced no similar results. A common feature of the aforementioned studies is their use of prospective, randomized control trial to measure the differential impact of POCT versus central lab on patients who receive the test. While median LOS is a common measure in medical studies, it might dampen the effect of statistical outliers, and fail to eliminate resource constraints as alternative explanation. Green et al. (2006) argue that when staffing and congestion are misaligned during selected shifts, median results aggregated across shifts may appear similar, even when performance within a single shift may actually experience relative improvement. In addition, most existing studies on POCT do not analyze the impact of process change on patients that didn't receive the candidate test, raise the possibility that these inconsistent results might be driven by misallocation of resources between the two patient groups.

In view of lack of consistency conclusion from current research on bedside testing, we perform a retrospective analysis on the impact of POCT on the overall congestion of studied ED from an urban tertiary teaching hospital with an annual census of 55,000 , using data from a 16-month window with 8 months before and 8 months after the introduction of POCT. This is to the best of our knowledge, the first study on POCT that examine waiting time and service time separately, and apply priority queueing theory to generate separate hypotheses on the expected impact of POCT adoption, to gain insights in the improvement from a system point of view. We are also the first to apply propensity score matching to match test and no-test patients (patients who don't conduct candidate test, either at central lab, or by POCT), and study the impact of POCT on the overall

patient population. The purpose of our study is to answer a series of questions regarding the impact of POCT on ED overcrowding: (1) Will adoption of POCT lead to decreased service time and waiting time for test patients? (2) Will this improvement be universal across all patients, or will it have differential impact on different patient groups, depends on level of sickness, and arrival time during the day. (3) Will quality of care, measured by 72-hour revisit rate, be compromised as a result of the process change? (4) Is there spill-over effect on no-test patients, measured by service time and waiting time reduction?

Our results show that when converting a single test from central lab to POCT, a significant 21.6% decrease in service time is observed for test patients, with no-test patients also experience 4.7% decrease that's statistically significant. Such a result, however, doesn't come at the expense of service quality. Instead, we find the predicted probability of bounceback decreased by 0.6% after POCT is adopted. We further find the POCT impact waiting to similarly across test and no test patients during the peak hour, but lower priority patients enjoy much greater improvement in waiting time than patients in other priority classes.

Another key aspect of Schoen et al. (2004) survey on primary care is preventive care and health promotion. In all countries, they found that sizable shares of women are not being screened for Pap test (cervical cancer screen) and mammograms (breast cancer screening). Within the age rate of 25-64 (Pap test) and 50-64 (mammogram), UK and Canada have the lowest rate of screening rate, with US has the highest rate. Emphasis on preventive care is a hallmark of high-quality primary care (Schoen et al. 2004). In US, preventable causes of death such as smoking, poor diet have been estimated to be responsible for 900,000 deaths annually, almost 40% of total yearly mortality (Cohen et al. 2008). Successful implemented preventive care program not only save lives, but incur significant savings to the health care system. Using data from population-based epidemiological studies and multicenter 9clinic trials, Javitt et al. (1994) show that preventive eye care in type II diabetes patients can lead to a predicted net saving of more than $472.1 million US dollars and 94,304 person-year of sight, assume all patients receive recommended care.

Due to its significant potential life saving and cost saving, many countries have government funded programs for certain type of preventive care, especially diseases where evidences show that early diagnosis and treatment can increase changes of successful treating and managing of the diseases (2012). The above-mentioned Pap test and mammogram are two of the most popular programs implemented by many countries. Unlike acute health problems, preventive care clients have a choice of whether to participate in the programs or not, and which facility to patronize if they decide to participate (Zhang et al. 2011). Therefore, optimal configuration of preventive care facility networks with easy accessibilities plays critical role in the success of

such programs (Verter and Lapierre 2002). In chapter 3 of this dissertation, we turn our focus from one aspect of primary care at unit level, improving emergency care performance, to another important piece of primary care under a broader context, improving preventive care performance at regional level. We chose breast cancer screening (mammogram) program in Canada as our studied care program due to the importance of early detection in reducing mortality of breast cancer, and the lower screening rate in the chosen country.

Breast cancer is one of the most commom cancers in the world, accounts for 18% of women's cancers worldwide (Hamilton and Barlow 2003). In US alone in 2004, breast cancer is responsible for the death of 40954 women, among 186,772 diagnosed. It is also the second leading cancer cause of death among women in Canada (2011). Despite the fact that early detection of breast cancer through high quality mammographic screening has been proved to be able to reduce breast cancer mortality significantly (Aro et al. 1999), uptakes of government funded breast cancer screening are not meeting targets in many countries, especially for rate of rescreening participation (Lechner et al. 1997). Studies suggest that factors such as social demographic characteristics and health behaviors of participants play an important role in the decision to participate in preventive care programs, other factors, such as type of facilities, accessibility by public transport may also choices of facilities to visit (Gerard et al. 2003; Hamilton and Barlow 2003; Maheswaran et al. 2006). Efficiency of cancer screening depends heavily on the frequency of screening (Cohen et al. 2008), therefore improving rescreening participate rate of these programs can have great impact on the health outcome of target population.

There is very few studies aim at improving rescreening rate specifically for breast cancer screening. Existing research on improving breast cancer screening participation usually focus on three types of factors: (1) social-demographic factors, (2) psychological factors, (3) interventions (Aro et al. 1999; Kee et al. 1992; Munn 1993; Rimer et al. 1998; Sutton et al. 1994). Social-demographic factors are personal characteristics of population, such as their education level, income level, race group, age, living condition, etc. These studies use such information to predict the probability of participation for a known population. Psychological factors include self-perceived level of risk of cancer and concern about pain. Aro et al. (1999) conducted interview on women who were invited to a first round mammography in Finland, and found that high risk group may be related to more frequent earlier mammogram and weekly breast self examination, although their conclusion is contrary to that of Sutton et al. (1994), in which the authors found that women with self perceived high and low risk of breast cancer have lower attendance rate than women with moderate amount of perceived risk.

Kee et al. (1992) found that attitudes rather than access play the most important role in influencing uptake. In their interview with women invited for mammography and declined attendance, the most cited

reasons are feelings of indifference or ignorance of screening issues and fear of pain or embarrassment, only less than 4% interviewed women expressed preference for more accessible screening unit. Munn (1993) and Rimer et al. (1989) found similar results in their interviews of women who declined participation of mammography invitations. However, these results cannot be applied to women that have participated in the first round screening, but decided not to attend rescreening, where non-attitude related factors are more likely to be the main barrier.

In our study, using stated preference discrete choice modeling (SPDCM), we identify factors that affect current women's screening decision, and their choice of facilities when choosing among a set of screening clinics for their regular biannual breast cancer screening. We conducted survey on the current participants of the Québec Breast Cancer Screening Program (PQDCS) in Montreal, Canada, a population based breast cancer screening. This is, to the best of our knowledge, the first paper that combines focus group meeting and SPDCM on population based cancer screening program to generate managerial implications for configuration of preventive care facilities, from the perspective of service and accessibility of facilities. We also combine survey result with aggregated data at population level in a simulation model to predict change in certain performance metrics for the overall system based on different configuration of service attributes. Our result shows that nursing staff's manner and knowledge regarding breast cancer and screening, as well as waiting time for appointment are the most influential factors in choice of clinics. Using latent class analysis, we are also able to identify the homogeneity of program participants, judging by their preference over studied attributes. Our simulation models shows that when taking into account of clients preferences, great improvement to appointment time, utilization rate, and screening volume can be achieved in the current system. Such change can lead to significant increase in rescreening rate at very little cost, without an overhaul of the current facility network.

# 2. Point-of-Care Testing: Improving Emergency Department Performance through Process Redesign

## 2.1. Introduction

For more than a decade, U.S. hospital emergency departments (EDs) have been concerned about the adverse health consequences of overcrowding (Melissa et al. 2009), which has been linked to an increase in patient mortality (Bernstein et al. 2009, Richardson 2006), longer patient wait times (Melissa et al. 2009), lower patient satisfaction (Booth et al. 1992), higher ambulance diversion rates (Allon et al. 2009), and a growing proportion of patients leaving without being seen (Bernstein et al. 2009, Weiss et al. 2005). Among the most frequently cited reasons for overcrowding are closure of existing hospitals (Institute of Medicine 2006), use of EDs for routine medical care (Murray and Berwick 2003), and lack of ED physician and nursing staff (Green 2008).

Given the complexity of the overcrowding problem, hospital administrators looking to accommodate more patients within existing infrastructure have debated, among other process changes, point-of-care testing (POCT). POCT refers to the testing of specimens at or near the location of patient care (Jahn and Aken 2003) instead of transporting specimens drawn at bedside to a central lab for testing. Potential benefits of POCT include reductions in time to medical decision-making, length of patient stay, and ED overcrowding, and a concomitant improvement in patient satisfaction (Murray et al. 1999).

Previous studies of POCT adoption and benefits are inconclusive. Our study differs from these in that we control for such alternative explanations for observed reductions in length of stay as patient severity, ED congestion, and seasonality. Nor does our study, as do studies that employ randomized trials, depend on the compliance of hospital staff during the intervention period. Lack of compliance is often advanced as a reason for the lack of significance in POCT studies (Rust et al. 2008). Moreover, whereas previous studies have tended to focus exclusively on patients who receive POCT, we examine what happens to all patients, test patients and otherwise, who arrive at the ED at the same time upon adoption of POCT.

Our study, conducted in a large, urban, tertiary, academic hospital ED with an annual census of 55,000 patients, involves evaluating key ED metrics like service time, waiting time, and service quality pre and post POCT adoption. We use queuing theory to generate, and the data we collect to test, a number of hypotheses regarding ED performance. We examine not only how POCT adoption affects patients whose samples are analyzed at bedside, but also spillover effects on other patients in the ED at the same time. We further examine whether POCT adoption has a uniform impact across all patients or a differential impact based on patient severity, and whether the benefits of adoption vary across different periods throughout the day (i.e., peak vs. nonpeak). A summary of key findings follows.

We find converting a single test from central lab processing to POCT to be associated, among test patients who arrive during peak hours, with a statistically significant decrease in service time of, on average, 21.6% for test patients and 4.7% for patients who do not receive the test (hereafter referred to as no-test patients).[1] For test patients, we attribute the service time reduction largely to the difference in the time it takes to execute the test in the central lab compared to at bedside, for no-test patients, to the reduced demand for central lab resources, which may improve the lab's ability to process other tests required for existing patients.

We further show that the observed decrease in service time does not come at the expense of service quality. Using the 72-hour re-admission rate, a common measure of ED service quality (Mayer et al. 1998, Guttmann et al. 2006), we find that service quality improves upon adoption of POCT, the predicted probability of bounceback decreasing, in absolute terms, by 0.6% for a typical patient.

We find the impact of POCT adoption on waiting time to be similar across test and no-test patients during peak hours, and the magnitude of the effect to differ depending on patient severity. Patients who have the lowest priority, identified as those who are the least sick, experience the greatest improvement in waiting time, 35.5% during peak hours compared to patients in higher priority classes. This is because lower priority patients benefit from service time reductions in higher priority patients, whereas high priority patients are typically unaffected by the service times of lower priority patients.

The rest of the paper is organized as follows. We review in Section 2 the relevant literature on ED operational performance and POCT. In Section 3, we present our analytical queuing model and formulate our hypotheses. Our research setting and the data we collected are described in Section 4, the empirical methods

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[1] Although we analyze these data for both peak and non-peak periods, for brevity we describe only the peak hour results. In an overview of this analysis in Section 6, we reveal the impact of POCT adoption to be greater during high congestion, peak hour periods compared to other periods (non-peak hours).

used to test our hypotheses delineated, and our results summarized, in Section 5. Implication of our results and limitations of our research are discussed in Section 6.

# 2.2. Related Literature

We draw from and contribute to both the operations management and emergency care management research streams. The operations management literature includes numerous studies that address issues pertaining to the management of EDs, and calls for operations researchers to aid hospital administrators in developing a more efficient service delivery system are increasing (see, for example, Guarisco and Samuelson 2011 and Green 2008). Such studies in the medical literature as pertain to understanding and improving ED operations tend to focus on therapeutic rather than operational matters. Relevant to our work are the medical studies that examine specifically POCT, the findings of which we detail below.

Operations researchers have sought to improve ED performance by optimizing ED staff scheduling for observed seasonality in patient arrivals over the course of the day and throughout the week (Green et al. 2006, Vassilocopoulous 1985a), proposing novel triage systems (Saghafian et al. 2011), identifying drivers of ambulance diversions (Allon et al. 2009), and improving inpatient bed allocation (Vassilocopoulous 1985b, Green and Nguyen 2001, Balaji and Brownlee 2009). Wiler et al. (2011) review the operational literature pertaining to emergency department patient flow.

Hospital administrators have also explored process redesign as a way to improve the efficiency of EDs (Meislin et al. 1988, Considine et al. 2008). Cooke et al. (2004) and Gorelick et al. (2005) propose deferring part of the registration process until a patient is assigned a room and a physician has completed an initial evaluation. A "fast-track" system, by employing nurse practitioners to serve low priority patients (i.e., patients with minor, specific ambulatory or acute illness or injury), prevents long wait times and overcrowding among non-emergency care patients (Meislin et al. 1988, Yoon 2003). Kilgore et al. (1998) and Jahn and Aken (2003) posit POCT as one way to alleviate the bottleneck that results when a centralized laboratory serves the ED, inpatient units, and outpatient clinics. Converting a test ordinarily processed in the central lab to POCT, because the patient specimen no longer has to travel to, or await processing by, the central laboratory, may reduce the time required for diagnosis and treatment (i.e., service time). Deo and Sohoni (2011), approaching POCT adoption from a public policy perspective, examine, in a context in which resources are limited, which facilities in a network ought to adopt.

Our work is closest to studies in emergency medicine that evaluate POCT as an alternative to the traditional diagnostic process that relies on a central laboratory. Fermann and Suyama (2002), reviewing the emergency medicine literature on POCT, find results on the impact of adoption on the reduction of patient length of stay (LOS), being the total time a patient spends in the ED, to be inconclusive. Whereas Murray et al. (1999) find, among discharged patients who received POCT, a reduction in LOS of nearly an hour, but no decrease for similarly treated patients who were admitted, Kendall et al. (1998) and Renaud et al. (2008) find no reduction in LOS associated with the adoption of POCT. Lee-Lewandrowski et al. (2003), having observed no change in LOS from shifting any single test, argue that any meaningful reduction in LOS resulting from POCT adoption relies on shifting multiple tests to bedside.

Our study differs from this previous work in the following ways. One, we do not conduct a prospective, randomized control trial to measure the differential impact of POCT versus central lab testing on patients who experience the former. Such studies rely on the notion of appropriate sampling to control for plausible alternative explanations like ED congestion and patient complexity. We instead perform a retrospective analysis of the impact of POCT among patients who are tested, observing as well patients who are not tested and explicitly control for other factors through the use of propensity score analysis (as detailed in Section 5.1). Moreover, whereas previous studies examine primarily changes in patient length of stay, we divide LOS into two parts, waiting time and service time, and use queuing theory to generate separate hypotheses on the expected impact of POCT adoption on each of these elements.

In the emergency medicine literature, our study most closely resembles that of Parvin et al. (1996), who evaluate the adoption of POCT for a specific test and compare a period of adoption to a control period during which patient samples are processed by a central lab. They describe the impact of POCT on different patient populations (e.g., high complexity versus low complexity) by dividing the observed sample into subgroups according to such factors as presenting condition or disposition. We control for factors like patient complexity through regression and propensity score analysis. Although Parvin et al. (1996) evaluate both test and no-test patients, they document for neither patient population during their short, five-week window of observation any substantial difference in LOS resulting from POCT. We compare ED performance metrics during a four-month window post-introduction of POCT to three time periods during which only central lab processing was used, (1) the four-month window immediately preceding adoption of POCT, (2) the four months of the previous year that correspond to the POCT post-introduction period, and (3) the prior year fourth-month window that corresponds to the POCT pre-adoption period. We observe, after controlling for factors like ED congestion and patient

complexity, differences in patient service time, waiting time, and service quality, and find that POCT adoption not only benefits the patients who are tested, but also has important spillover effects for other patients concurrently in the ED.

In sum, our research makes unique contributions at the intersection of the ED and OM literatures. Being the first study of POCT rooted in a formal model that explains the source of potential gains or penalties in operational performance, ours is among the few papers in emergency medicine that employs the structure of a queuing model to make predictions within the ED, and among the few papers within OM to empirically test such predictions. Methodologically, ours is, to the best of our knowledge, the first study in the emergency medicine literature to apply propensity score analysis and use difference-in-differences to proxy for a randomized control trial. This methodological approach enables us to empirically test system-level impacts on the entire patient population (i.e., patients that receive POCT as well as those that do not), and thereby measure as well as the main effect of POCT adoption on test patients any spillover effects of adoption on other patients.

# 2.3. Hypothesis Formulation

In this section, we formalize our research questions by analyzing POCT from the perspective of a stylized, but data-independent, queuing model of the ED patient flow process (see Figure 1). Arriving patients receive a bed assignment *Priority* based on an initial assessment of severity, then *Wait* a randomly distributed amount of time until space becomes available and they receive a *Bed Assignment*. Patients assigned a bed spend a randomly distributed amount of time in *Service*, which time includes all activities related to diagnosis, treatment, and, if required, boarding. The *Disposition* of treated patients is either discharge from the ED or admission to the hospital. We incorporate POCT by assuming a single diagnostic test to be a candidate for conversion from central lab to bedside processing. This gives two types of patients: *Test* patients, whose candidate tests are processed by the central lab (control period) or at the point of care (study period); *No Test* patients given any number of non-candidate tests that are processed by the central lab. Note that, independent of POCT, *Test* patients may also have non-candidate tests ordered and thus experience central lab delays that will form part of their service times.
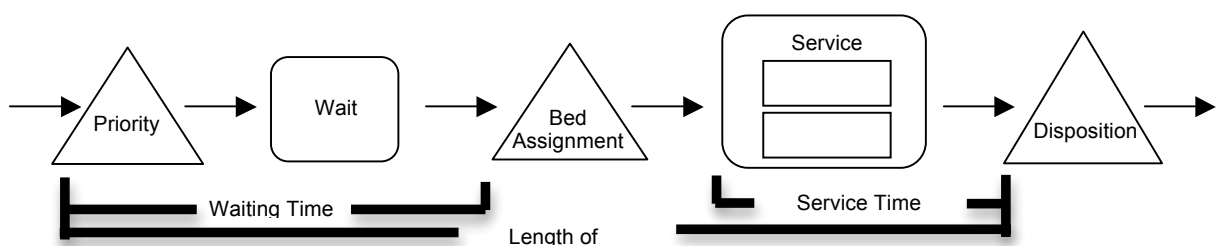
Formally, for a fixed number of beds ($n$) we can model patient flow by a G/G/n:NPP (Non-Preemptive Priority) queuing system. Patient type $t$, $t$=1, 2 denotes *Test* and *No Test*, respectively. Priority class $i$, $i$=1, 2, … $K$ denotes a patient's priority, where $i = 1$ is the highest, and $K$ the lowest, priority, $l_{it}$ is the arrival rate for patients of type $t$ in priority class $i$, and the mean and second moment of service time for patient type $t$ in priority class $i$ are denoted by $m_{it}$ and $m_{it}^{(2)}$, respectively. Utilization for patients of type $t$ in priority class $i$ is thus defined by $r_{it} = l_{it}m_{it}/n$. Note that, because such a model assumes a stationary system, we study subperiods of the data in which stationarity may be reasonably assumed. We use this model to generate hypotheses about the impact of POCT testing on service time, service quality, and waiting time for both test and no-test patients.

## 2.3.1. Service Time

Two countervailing forces are at play with respect to the impact of adoption of POCT on service time. Shifting a single test from central lab processing to POCT can decrease service time by eliminating transport time and central lab congestion effects. But POCT could also increase service time by increasing the point of care workload. Assuming, as is standard for most queuing models, independence of service times, the average impact on *Test* patients of a shift from central lab to point-of-care processing is primarily captured by the change in $m_{i1}$ for any class $i$, and suggests the following hypothesis.

**H1a.** In a stationary system, patients who receive a candidate test that is processed at the point of care experience shorter expected service times than those who receive the same test processed by a central lab.

Under the G/G/n:NPP approximation, we assume stationarity, and that staffing is sufficient such that the number of beds ($n$) constitutes the primary bottleneck.[2] We thus would not expect conversion of one test from central lab processing to POCT to affect the service time of *No Test* patients ($t = 2$) for patients of any priority class. Hence, we hypothesize as follows.

**H1b.** In a stationary system, patients who do not receive a candidate test experience the same service times before and after the introduction of POCT.

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[2] If staffing is a binding constraint, the added burden of bedside test processing may result in shifting resources away from *No Test* patients.

## 2.3.2. Service Quality

With POCT, as with any process redesign, hospital administrators expect the quality of care to be at least maintained, if not improved. In fact, improving service quality is often a key motivation for adopting POCT, as patients are expected to receive lab results more quickly and providers begin their therapeutic courses sooner, with a concomitant improvement in patient outcomes (Jahn and Aken 2003). Kc and Terwiesch (2009), however, empirically demonstrate that in some hospital settings service time reduction may be negatively associated with service quality. Specifically, they show, in a study of cardiothoracic surgery patients, that the decreased service time associated with early discharge results in higher rates of mortality. In a different context, Oliva and Sterman (2001) demonstrate a negative relationship between speed and quality. For operational improvements that accrue to the introduction of POCT to satisfy the paramount health objective, we frame our null hypothesis as follows.

**H2.** Converting a candidate test from central lab processing to POCT does not reduce the quality of care delivered by the ED.

## 2.3.3. Waiting Time

Intuitively, service time reduction to a patient in priority class *i* should at least affect the waiting time of all patients in the same class, regardless of type, because a server (bed) becomes available more quickly. Formally, we assume that within a priority class *i* all patients are treated on a first-come, first-served (FCFS) basis independent of type (test or no-test). We define the nominal utilization for priority class *i* as $\rho_i = \sum_{\forall t} \rho_{it}$. Let $r^{(i)} = r_1 + r_2 + \ldots + r_i$ be the utilization for priority class *i* across all types of the same and higher priority, and $W^{(i)}$ be the waiting time (delay) for a patient with priority *i*. We use the approximation for waits in such systems given on page 88 of Buzacott and Shanthikumar (1993), as follows:

$$\mathrm{E}\big[W^{(i)}\big]_{G/G/n:NPP} \approx \frac{\mathrm{E}[W^{(i)}]_{M/G/1:NPP}}{\mathrm{E}[W^{(i)}]_{M/G/1:FCFS}} \mathrm{E}\big[W^{(i)}\big]_{G/G/n:FCFS} \approx \mathrm{E}\big[W^{(i)}\big]_{M/G/1:NPP} \frac{(c_a^2 + c_s^2)}{(1 + c_s^2)n} \tag{1}$$

where the second inequality follows by using the simple heavy-traffic approximation for delays in $G/G/n:FCFS$ queues (e.g., Whitt 1993, eqn (2.13)), $c_a$ is the coefficient of variation for the arrival distribution across all types and classes, and $c_s$ is the coefficient of variation for the service distribution across all types and classes. Our assumption that the overall variability ratio $(c_a^2 + c_s^2)/(1 + c_s^2)$ in (1) is not significantly affected by the

implementation of POCT will be the case if arrivals are approximately Poisson, which would imply that $c_a$ is approximately equal to 1 and the ratio is therefore also approximately equal to 1. Now

$$E\left[W^{(i)}\right]_{M/G/1:NPP} = \frac{\sum_{j=1}^{K} \lambda_{j1} m_{j1}^{(2)} + \lambda_{j2} m_{j2}^{(2)}}{2\left(1-\rho^{(i)}\right)\left(1-\rho^{(i-1)}\right)} \tag{2}$$

(e.g., Kleinrock 1976, eqn (3.31)). Note that under this equation, delays in queue for some priority class $i$ are proportional to $1/((1-r_1-r_2-...-r_i)(1-r_1-r_2-...-r_{i-1}))$. The direct effect of introducing a POCT test being a change in mean service time for test patients, for any class $i$ where *Test* patients are present, the resulting change in $r_i$ and expected waiting time $E[W^{(i)}]$ is the same for both *Test* and *No Test* patients. This suggests the following hypothesis.

**H3a.**    Within the same patient priority class, *Test* and *No Test* patients experience the same decrease in waiting time following the introduction of POCT for *Test* patients.

More significant, note that a change in waiting time is also experienced by patients of any priority class $j >= i$. Intuitively, waiting time changes from *Test* patients in priority class $i$ trickle down to all lower priority patients because the higher priority queues clear faster. Where test patients appear in multiple classes, we would expect waiting time impact to accumulate across classes. The greatest change should thus accrue to patients in the lowest priority class. This suggests the following hypothesis.

**H3b.**    Assuming that test patients appear in multiple classes, we expect a greater reduction in waiting time to be experienced by lower priority (*class j >= i*) than by higher priority (*class i*) patients.

# 2.4. Research Context

## 2.4.1. Research Setting

Our research site is an academic, urban, tertiary US hospital ED with an annual census of 55,000 patients and capacity of 47 beds. In 2008, the hospital ED decided to convert all cardiac troponin test processing from the central lab to point-of-care (i.e., bedside). Cardiac troponins in a patient's blood reliably indicate heart muscle damage and the need for critical cardiac care within the ED. The standard of care in our research setting stipulates that the troponin test be ordered for every patient who presents to the ED with chest pain. According to the 2007 National Health Statistics Report (Niska et al. 2010), chest pain is the second most frequent complaint among patients between the ages of 15 and 64 who present to the ED. Among the ED patients observed, 16.3% required a troponin test.

Our context includes two groups of patients: those who receive the cardiac troponin test (*Test*), and those who do not (*No-Test*). Prior to 9 July 2008, test patients' blood samples were drawn in the ED and analyzed in the hospital's central lab. Test results were automatically uploaded to the hospital's laboratory information system and electronically accessible in the ED. Beginning 9 July 2008, all cardiac troponin tests began to be processed on test-specific equipment located within the ED (see Figure 2), with results available to the nurse conducting the test within five minutes (although additional time may pass before the physician is informed of the result). Note that patients who do not receive the cardiac troponin test are labeled "no-test" patients even if they have had other tests processed by the central lab.
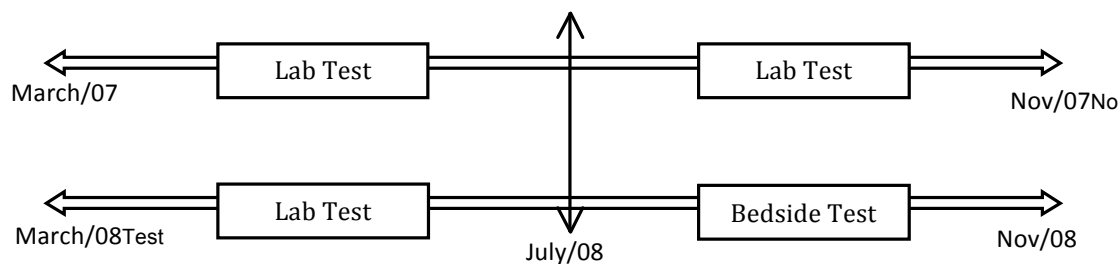


**Figure 2-2: Illustration of Test Status**

## 2.4.2. Data Collection and Measures

We observe all patient visits to the ED from 9 March through 8 November 2007 and 2008. Although the POCT pilot occurred in the 9 July through 8 November 2008 period, we collected data for the same period in the year prior to the adoption of POCT as well as from the previous year to account for seasonality in patient arrivals, an empirically documented phenomenon (Cooke et al. 2004). As is common practice (see, for example, Kendall et al. 1998 and Considine et al. 2008), we omit data that lack both waiting time and service time (1,362 observations, 2.1% of total observations) as well as visits in which the patient left without completing treatment or being seen (LWBS, approximately 0.22% of total observations). We also omit any patient visits associated with dispositions other than discharge or hospital admission. These include dead-on-arrival, death, or transfer to another hospital (less than 4.3% of the overall dataset). We also omitted, because we were unable to appropriately classify them, 585 patients (0.9% of total observations) whose troponin test was processed by the lab during the POCT pilot or who received both bedside and laboratory processed troponin tests. Table 2-1 reports the total number of patient visits in our final dataset as well as the number of patients who received the cardiac troponin test during their stay in the ED. Consistent with national trends, we observe an increase in the

total number of ED visits between 2007 and 2008, even as the metropolitan area served by our study hospital declined in population (Ginsberg 2009).

**Table 2-1: Summary of Observed Patient Visits**

|  | March 9$^{th}$ – July 8$^{th}$ | | July 9$^{th}$ – November 8$^{th}$ | |
|  | Total visits | Test patients | Total visits | Test patients |
|---|---|---|---|---|
| 2007 | 14,744 | 2,594 (17.6%) | 14,522 | 2,378 (16.4%) |
| 2008 | 15,107 | 2,696 (17.8%) | 15,044 | 2,012 (13.4%) |

For each patient visit in our final dataset, we observe up to four time stamps, (1) intake time, when the patient registers at the intake desk, (2) triage time, when the patient receives a priority class, (3) bed assignment time, when the patient is assigned an ED bed and leaves the waiting room, and (4) disposition time, when the patient physically leaves the ED, either through discharge or transfer to an inpatient bed (e.g., hospital admission). We use these time stamps to define for each patient two of our key outcome variables: waiting time (WAITING), and service time (SERVICE).

We define WAITING as the time between intake and bed assignment, and SERVICE as the time between bed assignment and disposition. Total length of stay, a commonly used measure in the emergency medicine literature, is the sum of WAITING and SERVICE. Should an observation lack patient intake time or a patient be triaged before intake (e.g., trauma patients), WAITING is calculated as the difference between triage and bed assignment.

To define service quality (BOUNCEBACK), we create a binary variable that indicates whether a patient returned to the ED within 72 hours of a previous visit. A unique identifier associated with each patient enabled us to observe whether a specific individual returned to the ED. Although BOUNCEBACK is a commonly used metric of service quality in both the operations management and emergency medicine literatures (Bernstein et al. 2009), previous studies of POCT have not explored this outcome metric. Kendall et al. (1998) demonstrated POCT to be associated with a shorter time to decision, an alternative measure of quality unobservable in our data.

The objective of our study being to evaluate the impact of POCT, we need to identify whether a patient receives a troponin test and whether the test is processed by the laboratory or at bedside. We do this by creating three dummy variables, namely: test, T, to represent whether a patient receives a troponin test; period, P, to represent whether a patient arrives in the July-November calendar months, regardless of year; and Y to represent whether patient arrival is in year 2008. These time specific variables are described in our discussion of control variables (see Section 4.3.1).

Depending on the specific hypothesis tested, we used a subset of the data with test patients only, a subset of the data with no-test patients only, or our dataset with both test and no-test patients (details of the data and samples used for each hypothesis test are reported in Section 5). We define POCT as an indicator of the group of patients of interest for each hypothesis by calculating it as the interaction among some or all of the three variables, T, Y, and P, and a priority class indicator (PRIORITY1 to PRIORITY4, as explained in following section). In the regression with test (no-test) patients only for testing hypothesis H1a (H1b), POCT is calculated as P*Y, POCT=1 representing that a POCT patient (no-test patient) arrives at the hospital during July-November 2008. In the full sample (test and no-test) used to test hypothesis H2, POCT=P*Y, POCT=1 representing any patient, regardless of test status, who arrives at the hospital during July-November 2008. POCT=P*Y*T is used to test hypothesis H3a, POCT=1 representing a test patient who arrives at the hospital during Jul-November 2008. To test H3b, POCT=P*Y (a patient who, regardless of test status, presents to the ED during July-November 2009), and is interacted with PRIORITY1-PRIORITY4. We therefore define POCT2 as POCT*PRIORITYY2, POCT3 as POCT*PRIORITY3, and POCT4 as POCT*PRIORITY4. This enables us to evaluate whether the impact of POCT on waiting time differs with patient priority class.

## 2.4.3. Control Variables

To isolate the effect of POCT on SERVICE, WAITING, and BOUNCEBACK, we need to control for other plausible correlates of these factors. We classify the control variables identified by previous researchers into two groups—those that characterize the patient and those that characterize the hospital context (i.e., system characteristics) at the time of patient arrival—and discuss each in turn.

*Patient characteristics*

Patient complexity is an important measure in the hospital context. Emergency departments employ triage systems for purposes of assessing patient complexity in order to ensure efficient allocation of ED resources as well as delivery of the level of care appropriate to the clinical need (Fitzgerald et al. 2010). Saghafian et al. (2011), Saghafian et al. (2010), and Vance and Spirvulis (2005) are among a number of researchers in operations management and emergency medicine who have sought to improve the triage process. Because patient complexity often determines priority in the ED queue, such that more severe patients are seen before patients needing only routine care (Fernandes et al. 2005), one might expect waiting time to differ with patient severity. Service time may also depend on patient severity in that, whereas routine medical care may be provided relatively quickly, a patient who presents to the ED with major complications may need additional

service time. That more complex and difficult cases require more time to process was among the findings of Schull et al. (2007). The likelihood of bounceback may also vary with patient severity, empirical evidence suggesting that lower acuity patients are more likely to bounce back (Pham et al. 2011, White et al. 2011). This may be because higher acuity patients are more likely to be admitted, but it could also be the case that, as with waiting time, because sicker patients receive the greatest attention, less severe patients are more likely to be overlooked and consequently experience a higher rate of return.

Researchers have measured patient complexity in a number of ways. Murray et al. (1999) control for patient complexity through the use of an indicator variable that discriminates between admitted and discharged patients, Vance and Sprivulis (2005) define complex patients as those who require at least two procedures, and still others (e.g., Welch et al. 2007) capture patient acuity through the Emergency Severity Index score assigned upon triage.

Our dataset supports the utilization of two of these three patient complexity metrics, namely, final disposition (admitted vs. discharged) and number of procedures. We are able to observe both whether a patient is admitted to the hospital or discharged and the number of procedures a patient undergoes during an ED visit. Partovi et al. (2001) find patient disposition to affect overall length of stay, patients admitted to hospital from the ED typically being more severe and thus having experienced a shorter waiting time but perhaps required additional service time. We create a binary variable DISCHARGE that takes the value of 1 for patients who are discharged from the ED and the value of 0 for admitted patients. Patients who present to the ED with high levels of complexity are expected to undergo more tests and procedures as physicians assess the nature of the trauma or illness and establish a course of action. We expect service time to grow with the tests and procedures ordered. We define NUM_ORDERS as the total number of billable services ordered by the medical team during a patient visit. Including both DISCHARGE and NUM_ORDERS in our analysis enables us to control for the impact of patient complexity on our outcome measures of interest, and to attribute any observed changes in these measures to the adoption of POCT.

The testing of hypothesis 3b requires that we control for a patient's priority level. Although we do not directly observe triage levels for patients throughout our entire data collection period, we do know that the focal hospital utilizes a four-level prioritization scale, with high priority patients (e.g., trauma patients, head injuries, etc.) assigned to level one and routine patients to level four. Vance and Sprivulis (2005) having found patient complexity, measured by number of procedures, to be highly correlated with assigned triage level, we create four distinct patient classes as follows. PRIORITY1 represents the highest priority patients, being those with the

largest number of orders (i.e., those belonging to the fourth quartile of NUM_ORDER). At the other end of the classification, PRIORITY4 represents the lowest priority patients (i.e., those belonging to the first quartile of NUM_ORDER). For those few patients whose triage level and NUM_ORDER we were able to observe, we find our measure and hospital assigned triage to be highly correlated (r=0.56, t=66.40, n=9,490).

We also include such controls commonly found in the medical literature as AGE (age of a patient upon arrival) and GENDER (an indicator variable that takes the value of 1 for female, and 0 for male, patients). Such patient demographics are often correlated with specific disease types and, by extension, with service and waiting times (Bertakis et al. 2000, Pitts et al. 2008).

### System characteristics

SERVICE, WAIT, and BOUNCEBACK are also influenced by ED census, a common proxy for ED workload found by previous research to affect patient length of stay (Gorelick et al. 2005, Chan et al. 1997). To isolate the effect of POCT on service time from that of other drivers of service time like workload, we introduce a variable that represents the total number of patients in the system at the time of patient arrival (TOTAL).

We also correct for the effect on LOS of temporal factors documented in the previous literature including time of day (PEAK), day of the week (SUN, MON, TUE, WED, THR, FRI, SAT) (Green et al. 2006), and month of the year (MONTH) (Gorelick et al. 2005). PEAK is a dichotomous variable that takes the value of 1 for patients who arrive between the hours of 15 and 23 (i.e., 3 p.m. and 10:59 p.m.) and the value of 0 otherwise (e.g., 11:00 p.m. and 2:59 p.m.). Cut-off times for this variable were established by aligning our choice with the planned ED staffing schedule. Although we do not directly observe daily staffing levels in our data, we do know the physician staffing schedule and that it was unchanged throughout the study period, staff levels being lowest in the early morning, with three residents and two attending physicians (attendings), and at the maximum of seven residents and three attendings during PEAK periods, seven days per week. The only scheduled deviation in staffing levels occurs on Wednesdays during the midday hours during which residents are in conference and the ED is staffed by attending physicians. Such deviations from the planned schedule as could occur, according to our interviews with ED staff, were unlikely and thus not expected to affect our analysis. Repeating our analysis with smaller increments of the day did not substantively affect our results. Our MONTH variable represents each month of a given calendar year; year is represented by Y. The variables are summarized and defined in Table 2-2, correlations among them reported in Table 2-3, and descriptive statistics of SERVICE (in seconds), WAITING (in second), and BOUNCEBACK for the full sample presented in Table 2-4.

**Table 2-2:  List of Variables**

| Variable name | Description |
|---|---|
| Service | Service time, measured in seconds, defined as the time between bed assignment time and disposition |
| Waiting | Waiting time, measured in seconds, defined as the time between intake and bed assignment |
| Bounceback | =1 for patients whose second visit is within 72 hour of their first visit |
| Peak | =1 if a patient registers at intake between 3 p.m. and 10:59 p.m., 0 otherwise (i.e., between 11 p.m. and 2:59 p.m.) |
| Sun, mon, tue, wed, thr, fri, sat | SUN=1 if the patient's intake day was recorded as a Sunday, 0 otherwise |
| | MON=1 if the patient's intake day was recorded as a Monday, 0 otherwise, and so on |
| Month1 to month8 | MONTH1 to MONTH4 represents each of the months between March $9^{th}$ and July $8^{th}$, MONTH5 to MONTH8 each of the months between July $9^{th}$ and November $8^{th}$ |
| Total | Number of patients in the ED at the time of patient intake |
| Age | Patient's age, measured in years |
| Gender | =1 if a patient is female, 0 otherwise |
| Num_orders | Total number of orders for a patient |
| Priority1 to priority4 | Priority class 1 represents the highest priority (sickest) patients, defined by the first through fourth quartile of NUM_ORDERS |
| Discharge | =1 if a patient is discharged, 0 if admitted |
| Y | =0 for 2007, 1 for 2008 |
| P | =1 for MONTH5 through MONTH8, 0 for MONTH1 through MONTH4, for both 2007 and 2008 |
| T | =1 for patients who receive either a lab or POCT troponin test, 0 for *No-Test* patients or patients that do not receive a troponin test |
| Poct | =P*Y  for H1a, H1b, H2 |
| | =P*Y*T for H3a |
| | =P*Y*Priority# for H3b |

**Table 2-3:  Correlation Table**

| | Service | Waiting | Total | Num_orders | Discharge |
|---|---|---|---|---|---|
| Service | 1.00 | | | | |
| Waiting | -0.02*** | 1.00 | | | |
| Total | 0.03*** | 0.43*** | 1.00 | | |
| Num_orders | 0.53*** | -0.11*** | 0.05*** | 1.00 | |
| Discharge | -0.18*** | 0.015*** | -0.06*** | -0.56*** | 1.00 |

**Table 2-4: Descriptive Statistics for Complete Data and by Test Status (2007 and 2008)**

| | Complete data (59,417 obs) | | | Test patients (9,680 obs) | | | No-test patients (49,737 obs) | | |
|---|---|---|---|---|---|---|---|---|---|
| | Wait | Service | Bounceback | Wait | Service | Bounceback | Wait | Service | Bounceback |
| Mean | 4,779 | 18,409 | 2.3% | 3,349 | 26,289 | 1.2% | 5,057 | 16,875 | 2.5% |
| σ | 5,432 | 18,735 | 1.5% | 4,546 | 23,141 | 1.1% | 5,546 | 17,340 | 1.6% |
| Min | 0 | 8 | 0 | 0 | 198 | 0 | 0 | 8 | 0 |

| Max | 47,286 | 365,704 | 1 | | 39,417 | 321,125 | 1 | | 47,286 | 365,704 | 1 |
|-----|--------|---------|---|--|--------|---------|---|--|--------|---------|---|

Tables 2-5 and 2-6, in presenting our descriptive statistics for test and no-test patients, respectively, across the four time periods of interest to us most closely resemble the empirical strategy employed in Section 5.0. We divide the data into four groups: Month1 to Month4 2007, Month1 to Month4 2008, Month5 to Month8 2007, and Month5 to Month8 2008 (the period during which POCT was adopted). We observe that, among test patients, average waiting time is nearly 9.7% lower during the period of bedside testing compared to the average of all other periods. Similarly, among test patients, service time is nearly 22.3% lower during the period of bedside testing compared to the average of all other periods. We observe the bounceback rate to be fairly stable among test patients across all periods.

**Table 2-5: Descriptive Statistics for Unmatched Data (TEST Patients)**

| | Month1-4, 07 (lab processed) 2,594 obs. | | Month1-4, 08 (lab processed) 2,696 obs. | | Month5-8, 07 (lab processed) 2,378 obs. | | Month5-8, 08 (bedside) 2,012 obs. | |
|---|---|---|---|---|---|---|---|---|
| Variable | Mean | σ | Mean | σ | Mean | σ | Mean | σ |
| Waiting (Sec) | 3,367.7 | 4,630.3 | 3,600.1 | 5,138.9 | 3,264.6 | 4,064.0 | 3,088.0 | 4,094.4 |
| Service (Sec) | 26,848.9 | 24,528.8 | 29,187.1 | 26,294.8 | 26,511.6 | 23,421.8 | 21,418.2 | 13,828.1 |
| Bounceback | 1.2% | 1.1% | 1.3% | 1.1% | 1.2% | 1.1% | 1.3% | 1.1% |

For no-test patients, average waiting time after conversion to POCT is 8.6% lower than the average of the other three periods. Average service time among no-test patients, however, is 2% higher after conversion to POCT, without controlling for differences in patient population or system characteristics. The proportion of patients who bounce back during the period following adoption of POCT is 0.16% lower than during the other periods combined.

**Table 2-6: Descriptive Statistics for Unmatched Data for (NO-TEST Patients)**

| | Month1-4, 07 12,150 obs. | | Month1-4, 08 12,411 obs. | | Month5-8, 07 12,144 obs. | | Month5-8, 08 13,032 obs. | |
|---|---|---|---|---|---|---|---|---|
| Variable | Mean | σ | Mean | σ | Mean | σ | Mean | σ |
| Waiting (Sec) | 4,846.1 | 5,266.5 | 5,425.9 | 6,164. | 5,243.285 | 5,308.6 | 4,729.0 | 5,362.6 |
| Service (Sec) | 15,888.8 | 16,188.1 | 17,332.2 | 18,300.6 | 17,132.4 | 17,804.6 | 17,120.9 | 16,961.6 |
| Bounceback | 2.3% | 1.5% | 2.4% | 1.5% | 2.9% | 1.7% | 2.4% | 1.5% |

Patient gender, age, and disposition and number of orders are, as noted above, among the control variables included in our analysis. Our patients are mostly female (59%), average age, 42 years, most often discharged (73%), and associated with 7.85 tests during their stay. We interpret our results for a discharged female in Section 5.0. On average, the system is hosting 47 patients (waiting or in service) when a patient presents to the ED.

# 2.5. Estimation and Results

We test our hypotheses using an application of the difference-in-differences approach to compare SERVICE, WAITING, and BOUNCEBACK among different patient populations (test and no-test) before and after adoption of POCT. We employ propensity score analysis, a widely used technique, to construct a control group of test and no-test patients similar on key dimensions (i.e., patient and system characteristics) to the group of test and no-test patients who arrive during the POCT period. There are for both patient populations essentially four clusters of data: pre period 2007, post period 2007, pre period 2008, and post period 2008. The ED adopted POCT only in the post period 2008 quarter. To establish whether POCT had an impact on SERVICE, WAITING, or BOUNCEBACK, we could simply compare the months before and after adoption, but given the well-documented trend in ED usage and overcrowding, we used data from the same months in the prior year as a reference. This enables us to compare SERVICE, WAITING, and BOUNCEBACK pre- and post-POCT adoption, while controlling for any observed year-over-year changes. Our expectation, given that we have controlled for observed hospital-specific effects common to test and no-test patients, is that any incremental differences in SERVICE, WAITING, and BOUNCEBACK beyond those found when comparing pre-period 2007 to pre-period 2008 can be attributed to the adoption of POCT.

## 2.5.1. Propensity Score Analysis and Generation of Quasi-control Group

We identify quasi-control groups of test patients and no-test patients by matching test patients arriving in a given month in 2007 to test patients arriving in the same month in 2008, and no-test patients arriving in a given month in 2007 to no-test patients arriving in the same month in 2008. We match based on propensity score, which is the probability of ED arrival conditional on covariates (i.e., patient and system characteristics) for each patient population (test and no-test), and generate the probabilities for each patient within the population of test (no-test) patients using a logit model that predicts the probability of ED arrival controlling for patient AGE, GENDER, NUM_ORDERS, and DISCHARGE and such system characteristics as PEAK, MON-SUN, WAITING, SERVICE, and TOTAL (Becker and Ichino 2002). WAITING was not included as a covariate to generate our matched paired samples for the testing of any hypotheses in which WAITING was the outcome

variable, nor SERVICE included as a covariate to generate our matched paired samples for the testing of any hypotheses in which SERVICE was the outcome variable.

After estimating from our logit models a propensity score for each patient, we apply one-to-one nearest-neighbor matching (i.e., identify two patients with the closest propensity score) without replacement in order to pair each 2008 Test (No Test) patient with a 2007 Test (No Test) patient whose ED visit occurs in the same month (Leuven and Sianesi 2003). One-to-one nearest neighbor matching is preferred here because it matches each treated unit with only one unique control unit. Becker and Ichino (2002) observe that no one matching method is necessarily better than any other. Figure 3 depicts our matching process.

| Month/ Year | Mar | | Apr | | May | | Jun | | Jul | | Aug | | Sept | | Oct | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2007 | T | N | T | N | T | N | T | N | T | N | T | N | T | N | T | N |
| 2008 | T | N | T | N | T | N | T | N | POCT | N | POCT | N | POCT | N | POCT | N |

**Figure 2-3: Matching Process**

Note that descriptive statistics for our matched samples and unmatched data are similar, only a small proportion of data (3.3%) having been dropped during the matching process.

We use our selected matched pair samples to test our hypotheses on service time, waiting time, and service quality. We estimate our regression model on our matched pair sample with the inclusion of controls, and present our results. For robustness, we implemented the alternative approach of estimating our model using the full sample of observations (results are available upon request). Our results differ slightly with the approach employed, but our overall conclusion regarding the impact of POCT on SERVICE, WAITING, and BOUNCEBACK remains unchanged. Table 2-7 describes the quasi-control groups generated for each hypothesis tested.

**Table 2-7: Datasets Used for Hypothesis Testing**

| Hypothesis | H1a | H1b | H2 | H3a, H3b |
|---|---|---|---|---|
| Patient included in the sample | Dataset with just matched test patients | Dataset with just the matched no-test patients | Union of the matched test patient dataset with the matched no-test patient dataset | Union of the matched test patient dataset with the matched no-test patient dataset |

## 2.5.2. Service Time

We hypothesize service time to differ among test patients upon adoption of the test (H1a) and to remain the same among no-test patients (H1b). To test this hypothesis, we estimate on our matched pair sample of test patients for H1a and no-test patients for H1b the following model:

$$SERVICE = \beta_0 + \beta_1 Y + \beta_2 P + \beta_3 POCT + \boldsymbol{\beta_4 X_i} + \boldsymbol{\beta_5 Z_i} \qquad (3)$$

where $X_i$ is the set of system level control variables that includes MON-SUN, MONTH1-8, TOTAL, and WAITING and $Z_i$ is the set of patient characteristics that includes AGE, GENDER, NUM_ORDERS, and DISCHARGE. The coefficient of interest is $\beta_3$.

Because the queuing model assumes stationarity, we estimate the model twice for H1a and twice for H1b. Specifically, we estimate it for test patients (H1a) and no-test patients (H1b) who arrive during peak (i.e., PEAK=1) and nonpeak hours. This enables us to assess whether the impact of POCT adoption differs during different periods of ED staffing and crowding.[3] Our estimation results are reported in Table 2-8, columns 1-4 (we omit in all tables coefficients of control variables Month1-Month8, Mon-Sun, Age, and Gender).

In support of H1a, we find the POCT to be negative and significant in both peak ($\beta_3$= -5,251.94, t= -3.97) and off-peak periods ($\beta_3$= -4,204.75, t= -3.92). POCT adoption is associated with a statistically significant reduction in service time during peak hours of, on average, approximately 87 minutes (=5251.94/60) or 1.45 hours. Peak hour service time for a typical test patient[4] in 2007 March-July is 6.65 hours and in July-Nov 7.19 hours. Service time for a typical patient in 2008 March-July is 6.82 hours and in July-Nov 5.90 hours. This equates to a 21.6% drop in service time during the peak period.[5] The percentage change during off-peak periods is, by a similar calculation, 16.5%, using predicted service time for off-peak periods (not presented here).

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[3] We purposefully created subsamples consisting of peak and non-peak periods in order to run our models. Although we could have presented a single model that included a dichotomous variable defining peak and non-peak that we interacted with POCT, we found interpreting this interaction to be more complicated than analyzing each period separately. The two approaches nevertheless yield equivalent results.

[4] We define a typical patient as female, discharged, of average age (42.56), and associated with the average number of orders (7.41) who arrives at the ED on an average day of the week in an average month during which there are, on average, 44.80 other patients in the system. We do not use the overall means in the sample presented in Section 4, but rather the mean prior to the adoption of POCT (i.e., the variable means from the March-July 2007 period).

[5] (5.9-6.82)/6.82-(7.19-6.65)/6.65= -21.6%.

Our results fail to support H1b for peak or off-peak periods. Among no-test patients, we observe a statistically significant decline in service time ($\beta_3$= -877.32, t= -2.05, peak; $\beta_3$= -630.62, t= -1.91, off-peak). On average, POCT adoption is associated with a 10-15 minute decrease in service time among no-test patients (15 minutes for peak, 10 minutes for off-peak). This suggests unexpected spillover effects into other patient populations. Such spillover effects from the adoption of POCT have heretofore not been discussed in the literature. We observe for a typical no-test patient a reduction in service time during peak hours of 4.7% and during off-peak hours of 3.1%. We discuss this unexpected result in Section 6.

**Table 2-8: Regression Results for H1a, H1b, and H2**

| Variables | H1a-peak Service Test patients only | H1a-off-peak Service | H1b-peak Service No-test patients only | H1b-off-peak Service | H2 Bounceback All patients |
|---|---|---|---|---|---|
| Y | 606.09 | -706.80 | -122.62 | -805.06*** | 0.17** |
| | (953.54) | (834.27) | (313.66) | (229.94) | (0.08) |
| P | 2,192.35* | 888.72 | 1,025.81** | 102.02 | 0.24* |
| | (1,295.31) | (1,189.64) | (467.16) | (363.91) | (0.13) |
| POCT(Y*P) | -5,251.94*** | -4,204.75*** | -877.32** | -630.62* | -0.32*** |
| | (1,324.01) | (1,072.77) | (428.06) | (330.67) | (0.11) |
| Waiting | 0.30*** | 0.36*** | 0.07*** | -0.01 | 0.04 |
| | (0.08) | (0.08) | (0.02) | (0.02) | (0.00) |
| Service | | | | | 0.13*** |
| | | | | | (0.00) |
| Total | 50.83 | -40.00 | 50.41*** | 7.66 | -0.01*** |
| | (44.42) | (25.06) | (13.25) | (7.78) | (0.00) |
| Num_orders | 1,361.51*** | 1,642.55*** | 1,732.78*** | 1,804.74*** | -0.04*** |
| | (78.97) | (73.89) | (49.17) | (39.44) | (0.01) |
| Peak | | | | | 0.11* |
| | | | | | (0.07) |
| Discharge | 12,554.48*** | 13,693.82*** | 4,537.38*** | 5,565.01*** | -0.19** |
| | (1,049.85) | (818.45) | (522.60) | (420.62) | (0.09) |
| Constant | -6,587.40** | -2,289.05 | -3,063.48*** | -2,311.78*** | -2.93*** |
| | (2,951.94) | (2,019.15) | (1,022.97) | (700.43) | (0.20) |
| Obs | 3,465 | 5,661 | 18,160 | 30,168 | 57,428 |
| R-squared | 0.22 | 0.25 | 0.30 | 0.31 | |
| -2ll | | | | | -6137.758*** |

Robust standard errors in parentheses (*** p<0.01, ** p<0.05, * p<0.1)

## 2.5.3. Service Quality

We hypothesize that service quality does not decline upon adoption of POCT (H2). Being concerned with service quality for all patients, test and no-test, we estimate on the combined matched pair samples (both test and no-test patients) the following logistic model:

$$Logit(BOUNCEBACK) = \beta_0 + \beta_1 Y + \beta_2 P + \beta_3 POCT + \boldsymbol{\beta_4 X_i} + \boldsymbol{\beta_5 Z_i} \ (4)$$

where $X_i$ and $Z_i$ include all control variables in equation (3) as well as SERVICE. Again, $\beta_3$ is the coefficient of interest.

We find support for our hypothesis (Table 2-8, column 5, $\beta_3$= -0.32, z= -2.80, dividing both waiting and service time by 10,000) in that we observe a statistically significant decline in bounceback rate post POCT adoption. It thus appears that the decrease in service time does not come at the expense of quality, and that the decline in service time among all patients results in higher quality care overall.

The predicted probability for ED 72-hour revisit for a typical patient in 2007 March-July is 1.83%, in July-Nov 2.32%, in 2008 March-July 2.17%, and in July-Nov 2.01%. This equates to a 0.6%[6] drop that can be associated with the adoption of POCT.

# 2.5.4. Waiting Time

We hypothesize that test and no-test patients experience the same decrease in waiting time upon adoption of POCT, controlling for patient severity (H3a). We regress waiting time POCT for each priority class separately, controlling for patient and system characteristics. Utilizing our combined sampled of matched test and no-test patients, we estimate

$$WAITING = \beta_0 + \beta_1 Y + \beta_2 P + \beta_3 T + \beta_4 Y \cdot P + \beta_5 P \cdot T + \beta_6 Y \cdot T + \beta_7 POCT + \boldsymbol{\beta_8 X_i} + \boldsymbol{\beta_9 Z_i} \quad (5)$$

where $X_i$ is the set of system level control variables that includes MON-SUN, MONTH1-8, and TOTAL and $Z_i$ the set of patient characteristic control variables that includes AGE, GENDER, NUM_ORDERS, and DISCHARGE. Our coefficient of interest is $\beta_7$.

Tables 2-9 and 2-10 present the results of our test of hypothesis H3a for peak and off-peak hours, respectively. Supporting H3a, we find that the impact of POCT adoption on waiting time does not differ with test status (the coefficient of POCT is insignificant) during peak or off-peak hours. This is true across each of the four priority classes. We further observe that the main effect of POCT (Y*P) is insignificant in all but one of the priority classes, PRIORITY4, during peak hours. In other words, during peak hours POCT has a statistically significant impact on waiting time only among low priority patients.

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[6] Essentially, our approach compares the mean of each outcome variable between pre- and post-treatment for patient visits during 2008 and subtracts the difference between pre- and post-mean outcome variables for patient visits during 2007 (Card and Krueger 1994). We derive the percentage difference by calculating the difference in the predicted probability of a typical patient from July-Nov 2007 and March-July 2007 (=0.48%) and subtracting this value from the difference in the predicted probability of a typical patient from July-Nov 2008 and March-July 2008 (=-.16%). We find the percentage change associated with the adoption of POCT to be 0.48%-(-0.16%)=0.64%.

**Table 2-9: Regression Results for H3a at Peak Hours**

| Variables | Priority1 Waiting | Priority2 Waiting | Priority3 Waiting | Priority4 Waiting |
|---|---|---|---|---|
| Y | -804.15*** | -227.59 | -921.49*** | -71.11 |
| | (269.66) | (231.68) | (246.72) | (234.64) |
| P | 471.48 | 508.88* | 979.14*** | 1,003.67*** |
| | (351.26) | (308.01) | (333.07) | (327.17) |
| T | -1,395.83*** | -227.86 | -1,560.44* | 2,343.86* |
| | (279.83) | (297.33) | (827.68) | (1,282.17) |
| Y*P | -149.83 | -335.92 | -295.53 | -1,738.75*** |
| | (369.75) | (319.31) | (338.24) | (323.95) |
| P*T | -312.09 | -441.95 | 2,716.27* | -1,817.51 |
| | (381.04) | (415.32) | (1,589.19) | (1,326.20) |
| Y*T | 52.63 | -575.00 | 661.73 | -282.77 |
| | (382.78) | (472.33) | (1,816.51) | (2,899.21) |
| POCT (Y*P*T) | 425.96 | 17.46 | -613.05 | 781.76 |
| | (538.15) | (647.12) | (2,621.41) | (3,394.67) |
| Total | 173.20*** | 218.75*** | 222.42*** | 191.48*** |
| | (8.84) | (8.52) | (10.14) | (9.60) |
| Num_orders | -55.50*** | 1.67 | 78.18 | 373.04** |
| | (11.86) | (43.80) | (104.63) | (158.61) |
| Discharge | 1,677.94*** | 1,603.33*** | 1,768.75*** | 3,115.69*** |
| | (176.58) | (169.01) | (363.09) | (436.07) |
| Constant | -3,330.54*** | -6,792.15*** | -6,784.73*** | -7,678.29*** |
| | (537.56) | (633.30) | (819.69) | (729.91) |
| Obs | 5,388 | 6,201 | 5,196 | 4,923 |
| R-squared | 0.20 | 0.21 | 0.16 | 0.13 |

Robust standard errors in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$)

**Table 2-10: Regression Results for H3a during Off-peak Hours**

| Variables | Priority1 Waiting | Priority2 Waiting | Priority3 Waiting | Priority4 Waiting |
|---|---|---|---|---|
| Y | -818.96*** | -219.99 | -341.19** | -3.62 |
| | (180.54) | (160.79) | (143.20) | (126.53) |
| P | 116.91 | 924.14*** | 533.81** | 995.16*** |
| | (225.29) | (200.33) | (209.06) | (179.94) |
| T | -878.66*** | -317.93 | -375.09 | -323.47 |
| | (179.12) | (217.27) | (634.03) | (1,426.96) |
| Y*P | -152.79 | -777.26*** | -382.58** | -903.38*** |
| | (238.37) | (207.95) | (194.46) | (171.82) |
| P*T | 61.56 | -169.33 | -1,041.10 | 386.34 |
| | (245.80) | (279.80) | (743.76) | (2,175.94) |
| Y*T | 354.71 | -165.18 | -424.39 | -233.80 |
| | (248.91) | (319.79) | (1,033.47) | (2,110.99) |
| POCT (Y*P*T) | 249.26 | 516.29 | 1,742.73 | 922.89 |
| | (338.40) | (416.86) | (1,240.41) | (3,332.05) |
| Total | 128.17*** | 170.88*** | 190.28*** | 168.44*** |
| | (4.26) | (4.57) | (4.77) | (4.21) |
| Num_orders | -23.62*** | -43.73 | 97.63 | 165.96* |
| | (7.90) | (28.93) | (60.87) | (85.66) |
| Discharge | 982.62*** | 968.00*** | 1,732.80*** | 2,057.80*** |
| | (105.86) | (107.52) | (211.36) | (274.02) |
| Constant | -1,982.90*** | -4,549.81*** | -6,550.27*** | -5,887.82*** |
| | (297.04) | (387.37) | (448.11) | (408.31) |

| | | | | |
|---|---|---|---|---|
| Obs | 8,632 | 9,853 | 8,503 | 8,738 |
| R-squared | 0.17 | 0.22 | 0.23 | 0.22 |

These results differ slightly for off-peak hours, during which POCT adoption is associated with a statistically significant reduction in waiting time across all priority classes, excepting the most severe patients. The impact of POCT on waiting time seeming to differ depending on priority class, we formally test in H3b an interaction between POCT adoption and patient severity.

Our second waiting time hypothesis (H3b) expects a greater reduction in waiting time to be experienced by lower than by higher priority patients, independent of test status.[7] To test this hypothesis, we estimate, using our combined sample of test and no-test patients, the following regression model:

$WAITING = \beta_0 + \beta_1 Y + \beta_2 P + \beta_4 YP + \boldsymbol{\beta_3 PRIORITY_i} + \boldsymbol{\beta_5 PRIORITY_i \cdot P} + \boldsymbol{\beta_6 PRIORITY_i \cdot Y} +$

$\boldsymbol{\beta_7 POCT} + \boldsymbol{\beta_8 X_i} + \boldsymbol{\beta_9 Z_i}$ (6)

where $X_i$ is same as in equation (4) and $Z_i$ includes AGE, GENDER, and DISCHARGE. A significant coefficient on $\beta_7$ indicates that POCT adoption has a differential impact on waiting time that depends on patient priority. We use PROIRITY1 patients, the most severe, as our base case for comparison.

Table 2-11 presents our results from the regression. We find support for H3b, as, collectively, the interaction terms between the time period (P), year (Y), and PRIORITY (2-4) variables are statistically significant during both peak and off-peak hours (joint F-test p-value of 0.0001 during peak hours and 0.0027 during off-peak hours). This means that the impact of POCT on waiting time varies with patient priority class. During peak hours, we find the impact of POCT on waiting times to not be statistically different from one another among priority classes 1-3 (Table 2-12), but to differ substantially for the least severe patients (PRIORITY4). As highlighted in Table 2-13, POCT is associated, for the typical patient, with a nearly 35% reduction in waiting time (~30 minutes) for the least severe patients. Post POCT adoption, we observe an approximate 6% reduction in waiting time among PRIORITY3, and approximate 7% reduction in waiting time among PRIORITY2, patients, both of which equate, in absolute terms, to approximately six minutes. The typical PRIORITY1 patient, however, experiences a slight, and in absolute terms relatively small in magnitude, increase in waiting time of 2% (~ 2 minutes). We do not have a strong explanation for this increase, but, given its small magnitude, question its importance.

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[7] This hypothesis assumes that we have test patients in multiple priority classes. As part of our initial analysis, we verified that we do, indeed, have test patients across all four priority classes.

**Table 2-11: Regression Results for H3b**

| Variables | H3b-peak Waiting | H3b-off-peak Waiting |
|---|---|---|
| Y | -977.35*** | -842.65*** |
| | (195.58) | (126.51) |
| P | 141.04 | 453.48*** |
| | (233.32) | (147.27) |
| Priority2 | 117.04 | 197.84 |
| | (192.44) | (127.69) |
| Priority3 | 423.06* | 106.84 |
| | (215.88) | (131.82) |
| Priority4 | -312.22 | -74.56 |
| | (212.88) | (124.45) |
| Y*P | 140.29 | -6.59 |
| | (276.05) | (173.66) |
| Priority2*P | 290.66 | 89.33 |
| | (269.18) | (173.38) |
| Priority3*P | 767.84*** | 252.39 |
| | (291.19) | (175.47) |
| Priority4*P | 1,361.31*** | 570.17*** |
| | (285.37) | (164.86) |
| Priority2*Y | 737.87*** | 623.82*** |
| | (279.25) | (188.58) |
| Priority3*Y | 210.30 | 670.50*** |
| | (306.92) | (190.82) |
| Priority4*Y | 892.70*** | 850.58*** |
| | (300.62) | (180.21) |
| POCT2 (priority2*P*Y) | -491.33 | -688.45*** |
| | (392.57) | (251.31) |
| POCT3 (priority3*P*Y) | -516.52 | -427.14* |
| | (433.69) | (259.62) |
| POCT4(priority4*P*Y) | -1,949.94*** | -875.23*** |
| | (424.45) | (245.35) |
| Total | 201.35*** | 163.85*** |
| | (4.63) | (2.24) |
| Discharge | 1,944.94*** | 1,258.89*** |
| | (108.19) | (66.20) |
| Constant | -6,009.26*** | -4,583.96*** |
| | (292.47) | (160.74) |
| | | |
| Obs | 21,708 | 35,726 |
| R-squared | 0.18 | 0.21 |

Robust standard errors in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$)

**Table 2-12: P-value for F-test between POCT2, POCT3 and POCT4**

| | POCT2= POCT3 | POCT 3= POCT4 | POCT 2= POCT4 |
|---|---|---|---|
| Peak | 0.9538 | 0.0020 | 0.0006 |
| Off-Peak | 0.3236 | 0.0836 | 0.4564 |

**Table 2-13: Predicted percentage change in waiting time for patients in each priority class**

| | Peak (%) | Off-peak (%) | Peak (sec) | Off-peak (sec) |
|---|---|---|---|---|
| Priority Class 1 | 2.42% | -0.56% | 140.29 | -6.59 |
| Priority Class 2 | -6.52% | -14.11% | -351.04 | -695.04 |
| Priority Class 3 | -5.88% | -8.77% | -376.24 | -433.73 |

| Priority Class 4 | -35.54% | -18.07% | -1809.66 | -881.82 |
| --- | --- | --- | --- | --- |

# 2.6. Discussion and Future Research

We provide evidence that ED process redesign, specifically the adoption of POCT, has a substantial and valuable impact on ED operations. POCT adoption reduces the service time not only of patients who receive the troponin test at the point of care, but also of other patients within the ED who do not require a troponin test. That we further observe the service time impacts of POCT adoption to be greater during peak than during off-peak hours among both test and no-test patients suggests that POCT can have a measurable impact on ED performance during crucial operating periods.

POCT adoption is also associated with improved service quality. All patients who presented to the ED during the POCT pilot period experienced a lower bounceback rate than in the comparison periods. Some of this quality improvement may follow from the priority queue model predictions, whereby high and low priority patients experience differential impacts. Empirically, lower priority patients have a greater propensity for bounceback (Pham et al. 2011, White et al. 2011). We speculate that less severe patients may, *a priori*, receive less attention. As service time savings accrue, as with priority queuing, less severe patients stand to reap the greatest benefit from any surplus physician attention.

Finally, we find adoption of POCT to have a positive effect on waiting time for both test and no-test patients. We observe the lowest priority patients to experience the greatest, and highest priority patients the smallest, decrease in waiting time upon adoption of POCT, supporting our prediction of ED behavior based on queuing theory. It further suggests that POCT leads to operational improvement not only through a direct impact on the service time of test patients, but also through an indirect impact on waiting time for all who present to the ED when POCT is in use.

Our study admits several limitations. First, as our data are drawn from a single, urban, level 1 trauma center, generalizing our results to different institutions with different patient populations is not possible, even when converting the same test. Second, as with all research that combines analytical modeling with empirical testing, one can identify settings in which the modeling assumptions may not hold. For example, we follow the priority queue model and assume that beds are the primary bottleneck in this ED. If the nursing staff performing POCT is a bottleneck, then adopting POCT will exceed the bedside staffs' workload capacity, compromising

overall ED performance. If, however, physicians (who do not run the POCT) are also a key bottleneck, this would not affect our hypotheses.

The queuing model also assumes the service time impact of POCT to be equal to the test time, but our data contradicts this assumption. The average time to order and receive a troponin test result from the central laboratory is 40 minutes, the time to conduct and process the bedside equivalent approximately five minutes. The observed service time savings of 87 minutes far exceeds the test time savings. Reviewing this discrepancy with ED personnel revealed insights into the ED treatment and decision process.

Treatment and disposition decisions require approval of an attending physician, and attendings typically move from room to room when rounding on patients. The computer terminals at which physicians enter orders and review lab results are clustered in two stations within the ED. In the pre-POCT process, because physicians do not return to the computer clusters between every patient, there are often delays between when lab results are recorded in the electronic medical record and when they are reviewed. In the post-POCT process, the nurse who draws the blood and runs the test receives the results immediately, and often actively seeks out the attending physician. This enables physicians to establish a course of action sooner that they might otherwise.

We believe this finding to provide evidence that not all interruptions are bad. The literature in emergency medicine and operations management has traditionally viewed all interruptions or disruptions as detrimental to operational performance or patient outcomes. This need not be the case. Dobson et al. (2011) identify ways to mitigate the negative impact of interruptions by altering the way in which patients are prioritized, and Rivera and Karsh (2010) call for researchers to study interruptions from the perspective of the interrupter as well as of the one being interrupted. Interruptions, particularly if needed to accomplish a particular goal, may actually be beneficial (Harvey et al. 1994, Brixey et al. 2006. According to Rivera and Karsh (2010), few studies associate interruptions with specific outcomes. Our study suggests that interruptions may, indeed, result in better operational performance within a healthcare context.

There are several possible extensions of this research. First, what model should be used to help an administrator determine the optimal number of tests to be converted to POCT? This study analyzes a setting in which a single test is converted to POCT. That nursing workloads increase with each additional test converted suggests diminishing marginal returns. What distribution of tests between bedside and central lab minimizes service times without compromising service quality subject to staffing constraints? Second, what model would help an administrator select the optimal test(s) to be converted to POCT? Prior studies reveal the rationale for test selection to date to be largely ad hoc. What are the critical selection criteria and potential for scale

economies, in both cost and quality, from test analysis? Finally, how do administrators model the financial impact of POCT conversion? In our setting and that of many prior studies, the conversion to POCT is justified solely on the basis of service time and service quality. In the context of rising healthcare costs, however, POCT adoption incurs both a capital equipment expense and higher marginal per-test costs. Whether POCT can decrease ED and central lab congestion, and increase patient volume, sufficiently to offset these costs warrants further study.

In this paper, we use the introduction of POCT to show that an ED process change can reduce service and waiting time and improve service quality for patients. Ours is, to our knowledge, the first paper to empirically validate the priority queuing model result that predicts waiting time as a function of priority class. Methodologically, it is, to our knowledge, the first paper to use propensity score analysis in the ED operations context. Our approach complements the traditional gold standard in healthcare research, the randomized control trial (RCT), in two ways. First, we demonstrate that, under some conditions, a retrospective analysis can proxy for an RCT in clinical settings without the same protocol compliance and internal review board issues that face traditional clinical trials. Second, this methodology supports the measurement of system-related impacts. The equivalent RCT would compare service times of bedside test patients and central lab test patients. Owing to possible interaction effects between test and non-test patients, only by using a difference-in-differences approach can we measure spillovers that affect non-test patients, and, indeed, we show that POCT does not steal bedside staff resources from non-test patients, as evidenced by both service time and service quality. Moreover, we show that, as predicted, waiting time benefits accrue to all patients. For ED administrators, we use queuing theory to explain why converting different tests in the same setting and converting the same test in different settings do not always provide the same impact. We show queuing theory to provide at least a partial decision framework for exploring the conversion of a particular test to POCT.

# 3. Understand Client Preferences for Preventive Care

## 3.1. Introduction

Preventive care is the part of healthcare practice that aims at reducing the likelihood and development of a disease and early diagnosis of serious medical conditions (Verter and Lapierre 2002). Screening for cancers, immunization, measurement of weight, cholesterol levels and blood pressures, are a few examples of preventive care (Zhang et al. 2011). In US, preventable causes of death such as smoking, poor diet have been estimated to be responsible for 900,000 deaths annually, that is almost 40% of total yearly mortality (Cohen et al. 2008). Preventive care not only save lives, but also lead to significant cost saving for the healthcare system. Using data from population-based epidemiological studies and multicenter clinical trials, Javitt el al. (1994) show that preventive eye care in type II diabetes patients can lead to a predicted net saving of more than $472.1 million US dollars and 94,304 person-years of sight, assume all patients receive recommended care.

While some types of preventive care, such as daily exercise or healthy diet, only require participation of patients, others, such as immunization, need involvement of healthcare facilities. Due to its significant potential life saving and cost saving, many countries have government funded programs for certain type of preventive care, especially diseases where evidences show that early diagnosis and treatment can increase chances of successful treating and managing of the diseases (2012), such as screening for various types of cancers. For example, the Department of Health and Aging in Australia offers population based screening programs for breast cancer, cervical cancer, and bowel cancer to eligible sub-populations (2012).

A major difference between preventive care such as the above-mentioned immunization and cancer screening and acute health problems is that the clientele of preventive healthcare have a choice of whether to participate in the programs or not, and which facility to patronize if he decides to participate (Zhang et al. 2011). Optimal configuration of preventive care facility networks with easy accessibilities therefore plays an important role in the success of such programs (Verter and Lapierre 2002). In this study, using stated preference discrete choice modeling (SPDCM), we identify factors that affect participants' choice of preventive care facilities and trade-offs they make when choosing among a set of facilities, in the context of The Québec Breast Cancer Screening Program (PQDCS) in Montreal, Canada, a population based breast cancer screening. This is, to the

best of our knowledge, the first paper that combines focus group meeting and SPDCM on population based cancer screening program to generate managerial implications for configuration of preventive care facilities, from the perspective of service and accessibility of facilities. We also combine survey result with aggregated data at population level in a simulation model to predict change in certain performance metrics for the overall system based on different configuration of service attributes. Our result shows that nursing staff's manner and knowledge regarding breast cancer and screening, as well as waiting time for appointment are the most influential factors in choice of clinics. Using latent class analysis, we are also able to identify the homogeneity of program participants, judging by their preference over studied attributes. Our simulation models shows that when taking into account of clients preferences, significant improvement to appointment time, utilization rate, and screening volume can be achieved in the current system.

Breast cancer is one of the most common cancers in the world and accounts for 18% of women's cancers worldwide (Hamilton and Barlow 2003). It is the second leading cancer cause of death among women in Canada (2011). In US alone in 2004, breast cancer is responsible for the death of 40,954 women, among 186,772 diagnosed. Breast cancer screening is one of the earliest and most common population based public health programs. In Finland, breast screening for women aged between 50 to 59 every two years was carried out as a public health policy in as early as 1987 (Aro et al. 1999). UK is also one of the first European countries to implement free national breast screening program for women aged 50 to 64 in 1988. As of 2007, 22 out of 27 European Union member states have implemented or in the process of establishing population based breast cancer screening programs (2012). Many other western countries such as US, Canada, Australia have been offering free mammography for women of high risk age group, usually from 50 to 70, on a biannual or annual basis (Lechner et al. 1997; Aro et al. 1999; Hamilton and Barlow 2003; Linsell 2010).

Despite the fact that early detection of breast cancer through high quality mammographic screening has been proved to be able to reduce breast cancer mortality significantly (Aro et al. 1999), uptakes of government funded breast cancer screening are not meeting targets in many countries, especially for rate of rescreening participation (Lechner et al. 1997). Most studies aim to maximize population coverage of chosen facilities as a way to improve accessibility and participation, usually by optimally locating preventive care facilities, assuming travel distance or travel time to be the main determinant of participation (Weiss et al. 1971; Verter and Lapierre 2002). While such assumption is not unreasonable, empirical research has shown this is not always the case. Past studies suggest that factors such as social demographic characteristics and health behaviors of participants play an important role in the decision to participate in preventive care programs, other factors, such as type of

facilities, accessibility by public transport may also affect choices of facilities to visit (Gerard et al. 2003; Hamilton and Barlow 2003; Maheswaran et al. 2006).

Although service and facility attributes have been studied in primary care area, very few such studies can be found in population based preventive care setting. Using empirical data from a rank order survey, Parker and Srinivasan (1976) apply a composite criterion model to estimate weight for each attribute of facility such as accessibility or convenience, personal manner of physicians, etc, in their study of allocating rural primary care facilities under a budget constraint. Cunningham et al. (2008) use conjoint analysis to model patients' preference for 14 attributes of hospital services, mainly from the perspective of care process. In breast screening, many existing studies focus on factors such as socioeconomic deprivation (Haiart et al. 1990; Vernon et al. 1990; Sutton et al. 1994), and use variables such as race group, education level as predictors to predict expected participation rate of certain group. Some research found that psychological factors such as fear of positive results and fear of pain or embarrassment play an important role in influencing uptake. As insightful as these studies are, they focus more on identifying the problems rather than solving them.

In this study, by combining SPDCM and simulation, we are able to first identify trade-offs patients make when facing a set of facilities with difference attribute levels, based upon their true preference, then predict improvement in participation rate had these revealed preference been taken into account when change facility service configuration. Since many of the attributes we are looking at are "soft" attributes, such as opening hour and staff manner, we are able to recommend actions that can be taken to improve participation at low cost or no cost at all. Our patient-centered approach not only can be used when build new facilities, but also on existing facilities, either to choose a subset of facilities from existing ones for a certain program, such as in the case of PQDCS program, or change configuration of any facilities to improve accessibility. The remaining of the paper is organized as follow: Section 2 review current literature on the problem. Section 3 and 4 describe our model and survey background. We present our main result from the survey in section 5 and section 6, followed by latent class analysis in section 7, and Arena simulation modeling in section 8. We conclude the paper with discussion of our findings and limitations, as well as propose future research.

# 3.2. Literature review

Our work can be linked to literatures in several areas in operations management and marketing research. We first draw on literature in marketing domain, specifically on service quality in healthcare settings. Although traditionally the primary focus of healthcare, at least from the perspective of service providers, is on the

outcome, e.g. to cure, given the state of knowledge and technology, past studies have shown that patients are more concerned with the (perceived) quality of "care" (Parker and Srinivasan 1976; Donabedian 1988). Newcomer (1997) suggests this is partially due to the fact that most patients lack the knowledge and skill to evaluate the performance of medical service delivery. Therefore, health care consumers tend to judge service quality using nontechnical process-related dimensions such as patient-physician relationship or the surroundings of service encounter, and administrators should focus on the human components of delivery (Bowers et al. 1994; Choi et al. 2004). In a study of focused group interview, Jun et al. (1998) found that even when patients, physicians and administrators agree on the quality dimensions of healthcare to be considered important, there are gaps in their idea of what dimensions are critical. In particular, patients and administrators focus on functional quality while physicians are more concerned with the technical quality. Choi et al. (2004) found positive support that perceived healthcare service quality impact the perception of service value, where value is consumers' evaluation of utility of perceived benefits and sacrifices (Zeithaml 1988). We extend their work by modeling explicitly the kind of trade-off between benefits and sacrifices that are made by patients when choose among a set of healthcare service settings. Perceived service quality influences patient satisfaction, which is significant in healthcare setting as there're evidence that patients satisfaction influence the rate of patient compliance with physician advice and request, and thus affect the outcome of medical practices (Pascoe 1983; Choi et al. 2004). In the case of preventive care, where patient's health behavior or life style plays an important role in the expected health outcome, such compliance is even more desired.

Understandably, researches in participation of other preventive care are also closely related to our study. For example, Lurie et al. (1993) found that the sex of physicians has an significant impact on the participation rate of certain type of preventive care, in the case of Pap smear, the odds ratio for participation is 1.99 for the patients of female physicians as compared with those of male physicians. A large body of literature in this area is on the prediction of participation, using factors such as age, education level, health behavior and ethnicity, etc (Haiart et al. 1990; Vernon et al. 1990). Ioannou et al. (2003) found in their study of cervical cancer screening that the most modifiable predictors for participation are health care coverage and a routine doctor's visit in the previous year, and suggest that interventions should be developed to improve screening for the subgroups who reported the lowest screening rates. Stockbridge et al. (1989) studied motivation for cholesterol screening participation, and found the most commonly cited reason for cholesterol screening to be a desire to "watch" health, convenience, and low cost. These studies reveal the importance of "care" delivery in the participation of preventive care programs.

The main contribution of our work is our extension to existing studies of preventive cancer screening in two areas, methodology and research focus. In the area of breast cancer screening, extensive review suggests that past studies mainly focus on the relationship between participation and three types of factors: 1) social-demographic factors, 2) psychological factors, and 3) interventions. The first stream of study focuses on the personal characteristics of population, such as their education level, income level, race group, age, living condition, and use these information to predict the probability of participation. Psychological factors that have been studied include self-perceived level of risk of cancer and concern about pain. For example, Sutton et al. (1994) found that main difference between attenders and non-attenders in their prospective design survey are health related behavior and attitude, belief and intention. Aro et al. (1999) conducted interview on women who were invited to a first round mammography in Finland, and found that high risk group may be related to more frequent earlier mammogram and weekly breast self examination, although their conclusion is contrary to that of Sutton et al. (1994), in which the authors found that women with self perceived high and low risk of breast cancer have lower attendance rate than women with moderate amount of perceived risk. Contrary to normal belief that accessibility is the biggest barrier to breast screening participation, Kee et al. (1992) found that attitudes rather than access play the most important role in influencing uptake. In their interview with women invited for mammography and declined attendance, the most cited reasons are feelings of indifference or ignorance of screening issues and fear of pain or embarrassment, only less than 4% interviewed women expressed preference for more accessible screening unit. Munn (1993) and Rimer et al. (1989) found similar results in their interviews of women who declined participation of mammography invitations. However, these results can not be applied to women that have participated in the first round screening, but decided not to attend rescreening, where non-attitude related factors are more likely to be the main barrier.

Research on breast screening interventions mainly uses random control trials to explore the impact on participation rate of certain type of interventions, such as physician recommendation, mobile mammography, media campaign, etc. This stream of literatures usually focuses on interventions directed at participants, few studies can be found that focus on intervention conducted at facility level. Our research method enables us to present a close-to-reality choice setting for current participants of breast cancer screening and force them to make trade-offs based on the priority they assign to each studied attribute of facility service. This is an area that has been largely overlooked in the past, but can have significant impact on the rescreening decision of existing patients. Efficiency of cancer screening depends heavily on the frequency of screening (Cohen et al. 2008),

therefore improving rescreening participate rate of these programs can have great impact on the health outcome of target population.

# 3.3. Methodology

We use Stated Preference Discrete Choice Modeling (SPDCM) as the basic framework of our survey design. Preference data come in different forms (Louviere et al. 2000). Market data, or Revealed Preference (RP) data, are data obtained through market observations (Samuelson 1947). Stated Preference (SP) data, on the other hand, are choice responses from the same economic agents (eg. choosers), but draw in hypothetical markets. While RP data contain information about behavior of interest of current market, SP data are rich in attribute tradeoff information and therefore more useful for forecasting changes in behavior (Louviere et al. 2000). Discrete Choice Modeling (DCM) is the generation and analysis of choice data, using hypothetical markets that are constructed to suit relevant research question. In DCM survey, respondents are given a set (or several sets) of *alternatives*, each alternative is described by a set of *attributes*, and each attribute can take on one of several *levels*. Levels are ranges over which attributes vary across alternatives. Respondents make a discrete choice of yes or no for each alternative, e.g. whether to visit a hypothetical store or not, based on their evaluation of overall utility of each alternative. The resulting choice can then be used to estimate the contribution of each attribute/level to the overall utility (Lancsar and Louviere 2008).

The SPDCM method is derived from McFadden's (1974) random utility theory (RUT) and Lancaster's economic theory of value (Lancaster 1966). Let $U_{ij}$ be the utility of *j*th alternative to *i*th individual, RUT posits that this utility can be decomposed into two parts, an systematics component $V_{ij}$ that is explainable, and $\varepsilon_{ij}$, a random part component:

$$U_{ij}=V_{ij}+ \varepsilon_{ij} \qquad (1)$$

Consumer will choose alternative j if the utility gained from j is greater than utility gained from other alternatives. Let $Y_{ij}=1$ if alternative j is chosen by respondent i, then:

$$\Pr(Y_{ij}=1)=\Pr(U_{ij}>U_{ik})=\Pr(V_{ij}+ \varepsilon_{ij} > V_{ik}+ \varepsilon_{ik} )=\Pr(V_{ij} - V_{ik} > \varepsilon_{ik} - \varepsilon_{ij}), \text{ for all } k\neq j \qquad (2)$$

Lancaster's economic theory of value suggests that a commodity can be decomposed into separable attributes, therefore allow for examination of preference of different choices by their attribute level, including those that are achievable yet not available (Gerard et al. 2003). Let $X_{ij}$ denote a vector of attribute of alternative j presented to respondent i, we have:

$$V_{ij}=\beta X_{ij} \quad (3)$$

When β are the utility parameters, and $\varepsilon_{ij}$ can be assumed to be identically distributed (iid) with the Weibull distribution, the probability of choosing alternative i can be calculated as (McFadden 1974):

$$\Pr(Y_{ij} = 1 | \{1, 2, ... J\}) = \frac{\exp(\beta X_{ij})}{\sum_{k=1}^{J} \exp(\beta X_{ik})} \qquad (4)$$

where J is the total number of alternatives presented to respondent i. This is conditional logit model that are used in our data analysis.

# 3.4. Methods

## 3.4.1. Focus group meeting current facilities

To ensure we can better understand the decision process of choosing screening unit, we conducted a focus group meeting that consists of five women. Among them four have breast screening experiences, either from government program or on their own, the other one shared experience from primary care facility selection. The meeting was voice-recorded and transcribed later. Two of the co-authors acted as moderators to facilitate the flow of discussion. We first gave an introduction about the research background, such as motivation and research setting, specifically, we stressed that this is for government-funded free screening. We then gave them few examples of type of factor that we are interested, such as traveling time, clinic opening hour, etc. The one-hour meeting was very helpful in shaping out the scope of attributes to be considered in the selection process, and revealed some interesting aspects that fail to be captured during literature review. Topics covered including accessibility such as traveling time, mode and parking availability, staffs' communication skill, and clinic's physical surroundings and so on. Besides providing information about facility attributes, focus group members were also asked about what type of personal factors will affect their choice process, such as income, education level. Overall, focus group provided an interactive dynamic for developing, challenging, and refining ideas (Hamilton and Barlow 2003).

One of the potential problems with SP data is it can be affected by the degree of `contextual realism' established for respondents (Louviere et al. 2000). When hypothetical settings of the alternatives are not achievable or realistic enough, respondents might not take the choice task seriously and therefore compromise the validity of the survey, as well as managerial implication generated from survey result. We therefore conducted phone survey with all current government designated screening centers in the studied area, and used

the data to finalize the attribute levels used in the survey. Data collected from current facilities include invitation process, accessibility by public transport, parking availability/price, opening hour, waiting time for appointment, waiting time inside clinic, and waiting time for screening result. Table 3-1 below lists our final attributes and attribute levels shaped by focus groups and clinic survey, name of the corresponding variables are in parentheses. Table 3-2 lists personal characteristics to be collected about survey respondents. Household income used 2009 government-reported median family income of the studied area as the dividing point.

**Table 3-1: Final attributes and levels**

| Attributes | Level |
| --- | --- |
| **Waiting time for appointment (WAITAPP)** | Less than 2 weeks [1]<br><br>Between 2-6 weeks [2]<br>Longer than 6 weeks [3] |
| **Travel time (TRAVEL)** | Less than 20 minutes [1]<br>21-40 minutes [2]<br>Longer than 40 minutes [3] |
| **Parking availability (PARKING)** | Free parking on-street or clinic parking [1]<br>On-street parking at $1.5 per hour [2]<br>Off-street parking at $4.5 per hour [3] |
| **Clinic opening hours (HOUR)** | 8am-4pm weekday only [1]<br>8am-8pm weekday only [2]<br>9am-5pm weekday and 9am-1pm weekend [3] |
| **Waiting time inside clinic (WAITCLINIC)** | Less than 15 minutes [1]<br><br>16 – 30 minutes [2]<br>31-60 minutes [3] |
| **Nursing stuff (NURSE)** | Knowledgeable, capable of answering breast cancer/screening related questions [1]<br>Provide information sheet, but does not answer questions [2]<br>Provide no information sheet, does not answer questions [3] |
| **Screening process (SCREENING)** | Technician explain the process while doing the screening [1]<br>Minimal amount of communication during the screening [2] |
| **Waiting time for result (WAITRESULT)** | Less than 4 days [1]<br><br>4-15 days [2]<br>16-30 days [3] |

**Table 3-2: Respondents' characteristics to be collected**

| Respondent Characteristics | Level |
| --- | --- |
| **Age** | 50-55 [1]<br>56-60 [2]<br>60-69 [3] |
| **Education Level** | High school diploma or lower [1]<br>Undergraduate degree [2]<br>Graduate degree or higher [3] |
| **Household annual income** | Below $66,000 [1] |

| | Above \$66,000 [0] |
|---|---|
| **Past screening experiences** | First time screener [1] <br> Regular screener [2] <br> Irregular screener, please specify the time since your last screening [3] |
| **First language** | English [1] <br> French [2] <br> Others [3] |
| **Do you have a referral from a family physician for current visit** | Yes [1] <br> No [0] |
| **Are you aware of the recommended rescreening frequency of once every two years for women after age 50** | Yes [1] <br> No [0] |
| **Are you knowledgeable of the risks of breast cancer for women of age 50 and above?** | Yes [1] <br> No [0] |
| **Do you have family members, friends, or acquaintances diagnosed with breast cancer?** | Yes [1] <br> No [0] |

# 3.4.2.  Survey design

### 3.4.2.1 Questionnaire- Orthogonal main effect

Let J denote number of alternatives in a choice set, and Lj be the number of levels of attribute J, then the total number of alternatives (combination of alternative/level) is the full factorial:

$$\prod_{j=1}^{J} L_j \qquad (5)$$

Although a full factorial design allow the estimation of both main effects of each attribute and interaction effects between two or more attributes, it's hard to implement in reality due to the fact that the resulting number grows exponentially as the number of attributes or attribute levels grows (Lancsar and Louviere 2008). Therefore when only main effects are of interest, many design use what's called fractional factorial, where only a subset of the alternatives are used in the choice set. This subset, however, usually are not selected randomly, instead there exist a large range of sampling methods that lead to practical designs with the purpose of estimating the effects of interest as efficiently as possible (Louviere et al. 2000). We used orthogonal main effect design for designing our choice set to ensure zero correlation among attributes/levels, so that main effects of each attribute/level can be estimated independently and unbiased (Louviere et al. 2000), we are not interested in any interaction between our chosen attributes. We obtained our orthogonal array from an online orthogonal library where number of attributes and levels suits our data (2011).

## 3.4.2.2 Size of choice set

Most empirical work in discrete choice model have used 1-16 choice tasks per person, although there're reports of 32 and 64 choice (Louviere et al. 2000). The number is usually context specific and depends on many factors, such as minimal number of choice set needed to test orthogonal main effect design. There are evidence that as the number of attributes and levels increase, task complexity increase, and might lead to increased unobserved variability and reduce choice consistency (Lancsar and Louviere 2008; Louviere et al. 2008).

Our initial choice set consists of 18 alternatives. Respondents are asked to make a yes or no decision for each alternative. Feedback from a pilot study of 5 women revealed that the number of alternative was too big. When this happens, after a few initial choice tasks, respondent will tend to start targeting on only one attribute that she considers the most important, and making Yes/No decisions solely on this one criteria. We subsequently divided the alternative into two groups of nine alternatives, questionnaire version one (V1) and two (V2). We randomly chose half of our respondents to answer version one, the other half version two to ensure balanced number of all 18 alternatives.

Although larger number of choice tasks per respondent can help to "blow up" the total number of choice tasks, it has the risk of violating the IID assumption for conditional logit model we prefer, where choice decision is assumed to be independent of each choice. In reality, very often a respondent's decision of one choice task might be affect by a previous choice task. In this view, the fewer choice tasks per respondent, the more confident we can be of our estimation of model parameters (Louviere et al. 2000). Therefore splitting alternatives into two groups is actually preferred from model estimation point of view. Table 3-3 below is an example of choice task. Respondents are free to choose any number of clinics to patronize from the nine alternatives.

**Table 3-3: Example of choice task**

| Attributes | Clinic 1 |
|---|---|
| Waiting time for appointment | Less than 2 weeks |
| Travel time | Less than 20 minutes |
| Parking availability | Free on-street parking or clinic parking |
| Opening hours | 8am - 4pm weekdays only |
| Waiting time inside clinic | Less than 15 minutes |
| Nursing staff | Knowledgeable, capable of answering breast cancer/screening related questions |
| Screening process | Technician explains the process while doing the screening |
| Waiting time for result | Less than 4 days |
| Please indicate whether you will choose the clinic | Yes ☐          No ☐ |

## 3.4.3. Sample size

The purpose of the DCM survey is to measure choice probability (or proportion) with a desired level of accuracy (Louviere et al. 2000). Let *n* is our target sample size, *p* be the actual (current) participate rate (choice probability) of studied program. If we want the estimated probability to be within *a* percent of the current value *p* with probability $\gamma$ or greater, we can calculate minimal sample size as (Louviere et al. 2000):

$$n \geq \frac{q}{p(\frac{a}{100})^2}\left[\Phi^{-1}(\frac{1+\gamma}{2})\right]^2 \qquad (6)$$

where q equals to 1-p, and $\Phi^{-1}(\cdot)$ is the inverse cumulative standard normal distribution function (CDF). In our design, we set to achieve within 10% of the true participation rate of studied area with probability of 95% or greater, this gave us a minimal sample size of 460. This sample size, however, is the number of choice task. The real sample size in terms of number of returned questionnaires needed, give that each respondents will be performing 9 choice tasks, is 52.

# 3.5. Data

## 3.5.1. Background

We conducted our survey in Montreal, Canada. The breast screening program in Montreal is part of The Québec Breast Cancer Screening Program (PQDCS). PQDCS was launched in 1998 to offer free breast cancer screening for women between 50 to 69 years old on a biannual basis. Every two year, an eligible woman receives an invitation letter sent by PQDCS. The letter also acts as prescription, hence referral from a personal physician is not necessary to participate in the program. There are a total of 15 designated screening center (CDD) in Montreal that are chosen by the program based on certain quality criteria, as well as to meet the requirement of geographical coverage. Participants are free to choose any of the 15 CDDs. Reported participate rate of Montreal has been very low at 45.5 as of 2010, below the province's overall participation rate of 57.6% (2011), and even far below the targeted screening rate of 70% set by the Quebec government (Zhang et al. 2011).

Our target population are all women in Montreal that are participating in PQDCS program. Given the fact that differences in average income, education and other demographic characteristics exist among residents of different regions, we try to cover as broadly geographically as possible. In an effort to do so, we approached all 15 CDDs and had 4 clinics agree to participate in the survey. By a pleasant coincidence, the final 4 clinics

happen to locate evenly across the city Montreal. Although we didn't compare our final sample to the target population, this still gave us reasonable confidence that final sample can be moderately representative of the true demographics characteristics of target population.

Our survey was conducted in all four clinics simultaneously for around two months. At each clinic, all current participants of PQDCS program that visit the clinic for breast screening were approached. Questionnaire V1 and V2 were given out interchangeably. Participants complete the survey at the clinics and return them before leaving. The complete questionnaire usually takes no more than 10 minutes. This includes reading the instruction, complete the choice task, and fill in demographic information.

# 3.5.2. Descriptive statistics

Our final number of returned survey is 287. Among them, eight are unusable due to all Yes or all No answers to all 9 alternatives. This gave us a total of 278 usable questionnaires and 2502 choice responses, greatly exceeding our target sample size. Estimated overall response rate is …. There are 140 V1 and 138 V2 questionnaires. Median of total number of chosen clinics is 3. A summary of demographic characteristics of respondents is shown in table 3-4.

**Table 3-4: Summary of respondents' characteristics**

| Respondent Characteristics | Level | Frequency (278 respondents) |
|---|---|---|
| **Age (AGE)** | 50-55 [1] | 100 |
| | 56-60 [2] | 76 |
| | 60-69 [3] | 79 |
| **Education Level (EDU)** | High school diploma or lower [1] | 107 |
| | Undergraduate degree [2] | 74 |
| | Graduate degree or higher [3] | 48 |
| **Household annual income (INC)** | Below $66,000 [0] | 139 |
| | Above $66,000 [1] | 105 |
| **Past screening experiences (EXP)** | First time screener [1] | 20 |
| | Regular screener [2] | 200 |
| | Irregular screener, please specify the time since your last screening [3] | 31 |
| **First language (LAN)** | English [1] | 44 |
| | French [2] | 194 |
| | Others [3] | 17 |
| **Do you have a referral from a family physician for current visit (REF)** | Yes [1] | 148 |
| | No [2] | 106 |
| **Are you aware of the recommended rescreening frequency of once every two years for women after age 50 (FRE)** | Yes [1] | 245 |
| | No [2] | 6 |

| | | | |
|---|---|---|---|
| **Are you knowledgeable of the risks of breast cancer for women of age 50 and above? (RISK)** | Yes [1] | | 245 |
| | No [2] | | 12 |
| | | | |
| **Do you have family members, friends, or acquaintances diagnosed with breast cancer? (FAM)** | Yes [1] | | 156 |
| | No [2] | | 94 |

Table 3-5 summarizes the level of attributes of chosen clinics. A clear and intuitive preference can be seen in all attributes except opening hour. Two sample binary t-test indicate differences in chosen levels are significant for all attributes at 95% confidence level, except for between TRAVEL1 and TRAVEL2, HOUR1 and HOUR3.

**Table 3-5: Summary of attribute level for chosen clinics**

| Attributes | Level | Frequency |
|---|---|---|
| WAITAPP | Less than 2 weeks [1] | 375 |
| | Between 2-6 weeks [2] | 295 |
| | Longer than 6 weeks [3] | 134 |
| | | |
| TRAVEL | Less than 20 minutes [1] | 324 |
| | 21-40 minutes [2] | 299 |
| | Longer than 40 minutes [3] | 181 |
| | | |
| PARKING | Free parking on-street or clinic parking [1] | 326 |
| | On-street parking at $1.5 per hour [2] | 293 |
| | Off-street parking at $4.5 per hour [3] | 185 |
| | | |
| HOUR | 8am-4pm weekday only [1] | 250 |
| | 8am-8pm weekday only [2] | 302 |
| | 9am-5pm weekday and 9am-1pm weekend [3] | 252 |
| | | |
| WAITCLINIC | Less than 15 minutes [1] | 286 |
| | 16 – 30 minutes [2] | 332 |
| | 31-60 minutes [3] | 186 |
| | | |
| NURSE | Knowledgeable, capable of answering breast cancer/screening related questions [1] | 389 |
| | Provide information sheet, but does not answer questions [2] | 248 |
| | Provide no information sheet, does not answer questions [3] | 167 |
| | | |
| SCREENING | Technician explain the process while doing the screening [1] | 534 |
| | Minimal amount of communication during the screening [2] | 270 |
| | | |
| WAITRESULT | Less than 4 days [1] | 327 |
| | 4-15 days [2] | 266 |
| | 16-30 days [3] | 211 |

# 3.6. Results

## 3.6.1. Numerical Result

One requirement for using the conditional logit model, which is based on McFadden's random utility theory, is the iid restriction on error term. The requirement of iid is to guarantee the independence of irrelevant alternatives (IIA) property on respondent's choice. The IIA property states that the odds ratio of selecting one

alternative over another is independent of the number or presence of other alternatives. This is a very strict requirement which leads to the very few application of conditional logit in DCM surveys . We test this assumption on our data using the popular Hausman Specification Test (Louviere et al. 2000) and the STATA command "suest" . We first run a conditional logit model on the complete data set, call it the full model, then a partial model that excluded one of the alternatives. If the IIA property holds, the coefficients on attribute should not differ significantly. We randomly selected alternative 5 from V2 to be excluded in the partial model, test result suggests IIA property indeed holds (chi2=-1.32 for Hausman and p=0.1383 for suest).

We divided our attributes into four groups and used hierarchical regression . The four groups are:

Group 1: WAITAPP

Group 2: TRAVEL, PARKING, HOUR

Group 3: WAITCLINIC, NURSE, SCREENING

Group 4: WAITRESULT

WAITAPP indicates the level of crowding of the clinic. TRAVEL, PARKING, and HOUR are all related to the ease of accessibility on the day of screening. Group 3 variables are concerned with service quality. While some might expect waiting time for result depends on the congestion level like WAITAPP, our survey of CDDs implies no relationship between WAITAPP and WAITREULT. We therefore put WAITRESULT in a separate group. Table 3-6 summarizes the regression result for hierarchical regression. Both coefficient and odds ratio are shown in the table.

**Table 3-6: Hierarchical regression result**

|  | Step 1 |  | Step 2 |  | Step 3 |  | Step 4 |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Attributes | Coef. | O.R. | Coef. | O.R. | Coef. | O.R. | Coef. | O.R. |
| waitapp1 | 1.54*** | 4.69*** | 1.57*** | 4.81*** | 1.97*** | 7.18*** | 1.8*** | 6.06*** |
| waitapp2 | 1.12*** | 3.07*** | 1.12*** | 3.06*** | 1.45*** | 4.25*** | 1.36*** | 3.91*** |
| travel1 |  |  | 0.86*** | 2.35*** | 1.30*** | 3.68*** | 1.24*** | 3.44*** |
| travel2 |  |  | 0.74*** | 2.10*** | 1.09*** | 2.98*** | 1.00*** | 2.73*** |
| parking1 |  |  | 1.54*** | 4.68*** | 1.30*** | 3.67*** | 1.61*** | 5.01*** |
| parking2 |  |  | 1.04*** | 2.82*** | 0.51** | 1.67** | 0.81*** | 2.26*** |
| hour1 |  |  | (0.4)*** | 0.67*** | (0.48)*** | 0.62*** | (0.29) | 0.75 |
| hour2 |  |  | (0.39)** | 0.68** | (0.09) | 0.92 | (0.14) | 0.87 |
| waitclinic1 |  |  |  |  | 0.62*** | 1.86*** | 0.65*** | 1.91*** |
| waitclinic2 |  |  |  |  | 0.40 | 1.48 | 0.42* | 1.53* |
| nurse1 |  |  |  |  | 1.95*** | 7.04*** | 1.92*** | 6.83*** |
| nurse2 |  |  |  |  | 0.94*** | 2.56*** | 0.76*** | 2.13*** |
| screening1 |  |  |  |  | 1.39*** | 4.03*** | 1.3*** | 3.67*** |
| waitresult1 |  |  |  |  |  |  | 0.86*** | 2.36*** |
| waitresult2 |  |  |  |  |  |  | 0.56*** | 1.75*** |

| | | | | |
|---|---|---|---|---|
| Pseudo-R2 | 0.0882 | 0.1744 | 0.3497 | 0.3638 |

(*** indicates a *p*-value of <1%, ** indicates a *p*-value of <5%, * indicates a *p*-value of <10%)

All coefficients and odds ratio are in comparison to the baseline levels that are not shown in the regression result. We see that Pseudo-R2 doubles from step 1 to 2 and from step 2 to 3, indicates strong predictive power of the variable groups. Final (full) model has a good fit and Pseudo-R2 of 36.38%. WAITAPP, TRAVEL, PARKING, NURSE, SCREENING and WAITRESULT are all significant and the sign of coefficient are as expected in all four regressions. NURSE1 has an odds ratio of almost 7, indicates that holding all other attribute levels constant, a change of nurse's service from the base level (Provide no information sheet, does not answer questions) to "Knowledgeable, capable of answering breast cancer/screening related questions" will increase the likelihood of that clinic being visited by 7 folds. And note one property of odds ratio for conditional logit model is that it is independent of value of other covariates. Therefore this 7-fold increase in probability is regardless of levels of other attributes.

HOUR2 turned out to be not significant in the third model, and both HOUR1 and HOUR2 are not significant in the final model. This is not completely counter-intuitive since unlike travel time or parking price, where peoples' preferences follow a common sense, preference for opening hour depends largely on respondents' personal schedule, therefore we may not observe an overall trend. WAITCLINIC2 (15-30 minutes) is not significant in third regression and has a p-value of 0.09 in the final model. Our base level is 31-60 minutes. We expected such a difference should lead to a preference to the former, and one possible explanation could be that the difference between two levels is not big enough to induce a clear trade-off.

## 3.6.2. Application example

To illustrate the relative preferences and trade-off among different attributes, below we show an example of choice making decision that as close to the reality of Montreal as possible. Assume a woman eligible for PQDCS program lives in Westmount, a suburb close to downtown Montreal, needs to choose a CDD for her next breast screening. Figure 1 below is the map of the city of Montreal (star indicates the woman's location). The red circle in the map covers exactly 9 CDDs in reality. Call them CDD1 through CDD9. Their attribute level is summarized in Table 3-7 below. Note none of these 9 configurations is included in the 18 alternatives used in the survey. WAITAPP, HOUR, PARKING, WAITCLINIC and WAITRESULT used the real data from the CDD survey of these 9 clinics, other attribute levels were assigned arbitrarily.
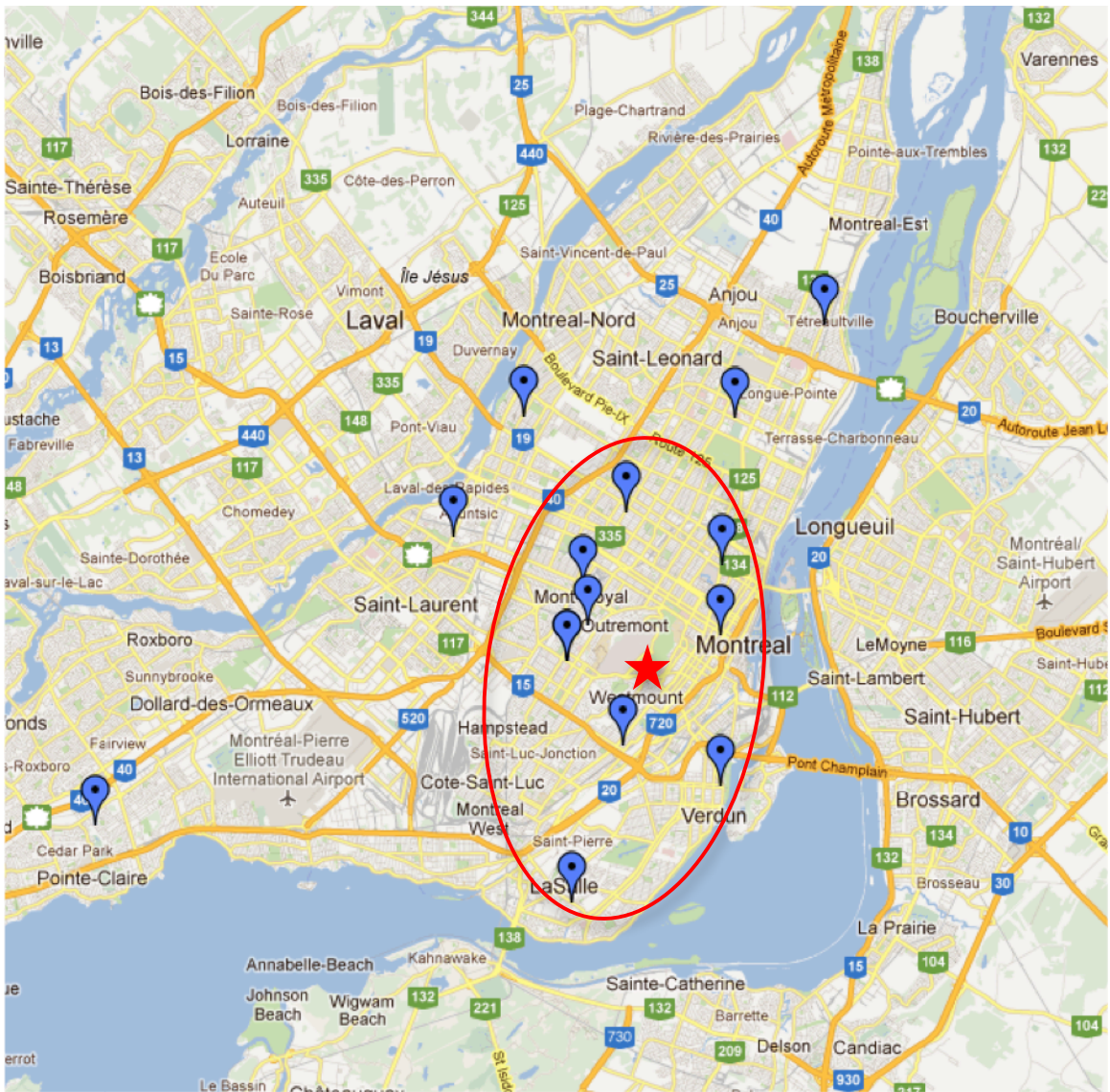
**Figure 3-1: Coverage of the 9 clinics**

Give the choice set, the conditional probability for visiting each of the clinics can be predicted using the full mode regression result in table 3-6 (step 4) and is presented in table 3-7.

**Table 3-7: A realistic choice set faced by a woman lives in Westmount**

| Attributes | CDD1 | CDD2 | CDD3 | CDD4 | CDD5 | CDD6 | CDD7 | CDD8 | CDD9 |
|---|---|---|---|---|---|---|---|---|---|
| WAITAPP | 3 | 3 | 1 | 1 | 1 | 1 | 2 | 1 | 2 |
| TRAVEL | 1 | 2 | 2 | 2 | 1 | 3 | 3 | 1 | 3 |
| PARKING | 2 | 1 | 3 | 1 | 3 | 2 | 1 | 2 | 1 |
| HOUR | 1 | 1 | 3 | 3 | 2 | 1 | 1 | 1 | 1 |
| WAITCLINIC | 2 | 3 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| NURSE | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 |
| SCREENING | 1 | 2 | 1 | 2 | 1 | 2 | 1 | 2 | 1 |
| WAITRESULT | 3 | 3 | 2 | 1 | 2 | 1 | 2 | 1 | 2 |

**Table 3-8: Predicted probability of choosing each clinic**

| Clinics | CDD1 | CDD2 | CDD3 | CDD4 | CDD5 | CDD6 | CDD7 | CDD8 | CDD9 |
|---|---|---|---|---|---|---|---|---|---|
| Prob. | 0.0424 | 0.0042 | 0.0386 | 0.4840 | 0.0897 | 0.0088 | 0.2339 | 0.0643 | 0.0343 |

To show the separate influence of each of the attributes on a clinic's screening rate (probability of being visited), we show the marginal change in the probability using CDD5 as the base case, which currently has a conditional probability of 8.9%. The level of impact of each attribute level can be evaluated by the improvement (or reduction) in probability (calculated using odds ratio) when change one attribute level at a time, holding all other attribute levels constant. Figure 2 shows the marginal change in the probability. The base case is indicated by zero changes. As an example, we see the biggest improvement will occur if CDD5 provides free parking (compared to current situation of 4.5 dollar per hour parking), which lead to a probability improvement of more than 35%. On the other hand, if waiting time for appointment is increase from current level of less than 2 weeks to longer than 6 weeks, probability will decrease by 7.5%.

**Figure 3-2: Marginal change of probability**
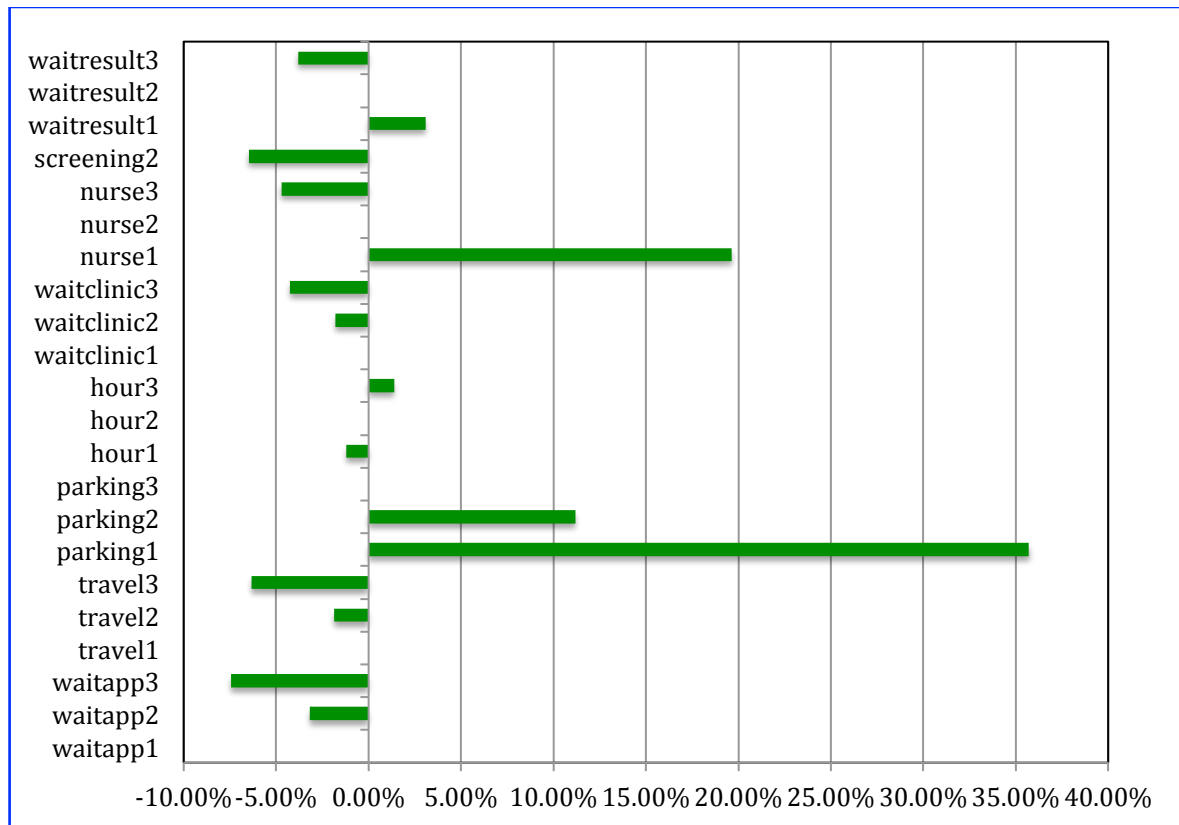


# 3.7. Latent Class Analysis

Past research has shown that health care clients might not be as homogeneous as we have assumed. In their survey on preferences for patient-centered care conducted in a Canadian teaching hospital, Cunningham et al. (2008) found their survey respondents can be divided into two groups with different choice preference and demographic characteristics, labeled informed care group and convenient care group. The former one was composed of younger, higher educated patients that are mostly born in Canada and use English as first language, when compared to the latter, and place the highest importance on health information transfer, as opposed to easy accessibility to the hospital by convenient care group. If differences in preference do exist among breast screening clients, the result from our conditional logit model will lead to unrealistic prediction. We therefore conduct latent class analysis using Sawtooth Software's Latent Class module to test the existence of heterogeneity among survey respondents (Sawtooth Software 2004).

We set the minimum and maximum number of groups to be 1 and 4, respectively, and computer the data from 10 different starting points to avoid local optimal. We set constraints for WAITAPP, TRAVEL,

PARKING, WAITICLINIC, and WAITRESULT to be monotonically and decreasingly preferred from level 1 to level 3, and replicate each run 5 times.

## 3.7.1. Number of possible latent groups

Latent Class solution provides two statistics for deciding the best number of latent groups. Consistent Akaike Information Criterion (CAIC) is the most widely accepted measure for deciding how many groups to accept, a smaller value is preferred. Relative Chi Squre is another indicator where a bigger value is usually preferred, although it's not as strong an indicator as CAIC. Table 3-9 below summarized CAIC and Relative Chi Square for 1 to 4 groups of our $10^{th}$ run, each based on the replication that produced biggest maximum likelihood. All our 10 runs produced similar result in terms of log-likelihood, part worth utilities, attribute importance, and group sizes, indicated that global optimum was reached (Sawtooth Software 2007).

**Table 3-9: Summary of CAIC and Relative Chi Square of best replications**

| 1 group | | 2 groups | | 3 groups | | 4 groups | |
|---|---|---|---|---|---|---|---|
| CAIC | Rel Chi Sq | CAIC | Rel Chi Sq | CAIC | Rel Chi Sq | CAIC | Rel Chi Sq |
| 2573.04 | 64.79 | 2590.72 | 35.42 | 2708.88 | 24.02 | 2801.02 | 18.79 |

Based on CAIC and Rel Chi Sq, 1 group produced the best result, i.e. there's no strong evidence of multiple latent groups. However, t while 3 and 4 groups solution have much bigger CAIC than 2 group analysis, the CAIC for 1 group and 2 groups are very close. We therefore can't completely rule out the possibility of two latent groups, and need to further explore the possibility of client heterogeneity. The following analysis uses result from 2-group latent class analysis from the $5^{th}$ replication of the $10^{th}$ run, starting seed was set manually to be 20. Convergence reached after 15 iterations.

## 3.7.2. Group Comparison of Attribute Preferences

The two-group latent class solution computes the probability that each respondent belongs to each group. We assigned each respondent to the group that he/she has the highest probability, and got 36.6% percent of respondents to group 1 and 63.4% of them in group 2. Table 3-10 below displays attribute importance for the two groups. Attribute importance can be obtained from rescaled part-worth utilities for comparison between the two groups. The sum of attribute importance for all 8 attributes adds up to 100, therefore each number represents the weight of a particular attribute as percentage of total importance. We list the attributes in the order of importance for Group 1.

**Table 3-10: Attribute importance of two latent groups**

| Attributes | Group 1 | Group 2 |
|---|---|---|
| WAITAPP | 22.32340 | 22.02385 |
| NURSE | 20.61555 | 14.96968 |
| TRAVEL | 16.55237 | 6.21378 |
| PARKING | 10.85653 | 12.58565 |
| WAITRESULT | 10.08153 | 6.27004 |
| WAITCLINIC | 8.01396 | 14.62550 |
| HOUR | 5.85365 | 3.07962 |
| SCREENING | 5.70301 | 20.23188 |

Waiting time for an appointment (WAITAPP) appears to be the most important attribute for both groups. This means differences in the level of this attribute will have the biggest effect on the screening rate of given clinics. This is consistent to the result from our conditional logit model, where the odds ratio of WAITAPP is second largest among all attributes, only slightly smaller than NURSE. Here nurse's knowledge (NURSE) ranked second highest for group 1 respondent and 3rd for group 2 respondent, also similar to the conditional logit result, indicating both groups value communication with nurses on general knowledge of breast cancer and mammography. Screening process (SCREENING), on the other hand appears to have a much greater influence on the choices of group 2 respondents than group 1. It's the second most important attribute for group 2, but the least one for group 1. Travel time (TRAVEL) has a biggest impact on the choices of group 1 respondents, while group 2 respondents attached similar importance to how long they have to wait inside clinic (WAITCLINIC). All other attributes such as parking availability (PARKING), waiting time for result (WAITRESULT), and clinic opening hours (HOUR) don't differ much between the two groups, and don't appear to be as important as other attributes.

## 3.7.3. Group Comparison of Demographic Characteristics

The comparison of attribute importance between the two groups revealed some differences in the order of respondents' preference, however it's not clear whether these differences are statistically significant, or whether respondents' preference differ according to this in a systematic way, for example, can be predicted using some observable variables. Existing research have shown that social-demographic characteristics usually plays a role in how people form their preference for certain products or services (Gerard and Lattimer 2005; Cunningham et al. 2008). To test whether this is the case with our sample, we next use the demographic information we collected to test whether respondents in two groups actually differ significantly in these social-demographic factors, and whether latent group membership can be predicted using these factors. Table 3-11 below shows the percentage of respondents that belong to each social-demographic class for each group, and statistics from one-

sample binary t-test. P-value is for alternative hypothesis that there's difference between the two groups in these social-demographic classes. We see that none of the p-values are small enough to reject the null hypothesis (same for p-values for other alternative hypothesis, e.g. group 1> group 2, and group 1< group 2), indicating there's no evidence of significant differences between the two groups. We also run a logit model using group 1 membership as dependent variable, and all listed social-demographic variables as predictor, again found no predictors to be significant. Table 3-12 summarizes the result from logit prediction model.

**Table 3-11: Demographic characteristics' comparison between two groups**

|  | group 1 | group 2 | z-value | p-value |
|---|---|---|---|---|
| **AGE** |  |  |  |  |
| 50-55 | 38,6 | 39,5 | -0.1375 | 0.8906 |
| 56-60 | 29,5 | 29,9 | -0.0655 | 0.9478 |
| 61-70 | 31,8 | 30,5 | 0.2100 | 0.8337 |
| **EDU** |  |  |  |  |
| Highs school diploma or lower | 44,4 | 48,0 | -0.5117 | 0.6089 |
| Undergraduate degree | 33,3 | 31,8 | 0.2439 | 0.8073 |
| Graduate degree or higher | 22,2 | 20,3 | 0.3470 | 0.7286 |
| Below average income (**INC**) | 60,9 | 54,8 | -0.9282 | 0.3533 |
| **EXP** |  |  |  |  |
| First time screener | 7,0 | 8,5 | -0.4187 | 0.6754 |
| Regular screener | 82,6 | 78,2 | 0.8178 | 0.4135 |
| Irregular screener | 10,5 | 13,3 | -0.6555 | 0.5122 |
| **LAN** |  |  |  |  |
| English | 15,9 | 18,0 | -0.4129 | 0.6797 |
| French | 76,1 | 76,0 | 0.0157 | 0.9874 |
| Others | 8,0 | 6,0 | 0.5985 | 0.5495 |
| Has family doctor referral (**REF**) | 60,7 | 57,0 | 0.5712 | 0.5679 |
| Aware of recommended frequency of 2 years (**FRE**) | 97,7 | 97,6 | 0.0486 | 0.9613 |
| Aware of risk of breast cancer for women age 50 and above (**RISK**) | 94,4 | 100,0 | -0.4944 | 0.6210 |
| Has family or friends diagnosed with breast cancer (**FAM**) | 64,7 | 61,2 | 0.5402 | 0.5890 |

**Table 3-12: Logit prediction model result**

| Group 1 | Coef. | Std. Err. | z | P>z |
|---|---|---|---|---|
| **age1** | -.2216667 | .3781772 | -0.59 | 0.558 |
| **age2** | -.2289872 | .3906771 | -0.59 | 0.558 |
| **edu1** | -.4385267 | .4209581 | -1.04 | 0.298 |
| **edu2** | -.203273 | .4257177 | -0.48 | 0.633 |
| **inc** | -.2829239 | .3269181 | -0.87 | 0.387 |
| **exp1** | .1246325 | .7204419 | 0.17 | 0.863 |
| **exp2** | .6044719 | .4844607 | 1.25 | 0.212 |
| **lan1** | -.5103114 | .6820413 | -0.75 | 0.454 |
| **lan2** | -.1838424 | .5904224 | -0.31 | 0.756 |
| **ref** | .1294552 | .3171549 | 0.41 | 0.683 |
| **fre** | .0096676 | .9751531 | 0.01 | 0.992 |

| | | | | |
|---|---|---|---|---|
| **risk** | -.7372943 | .6704594 | -1.10 | 0.271 |
| **fam** | .0720999 | .3130271 | 0.23 | 0.818 |
| **_cons** | .236171 | 1341235,00 | 0.18 | 0.860 |

# 3.8. Simulation Analysis

Our final step is to show how our analysis can be used in the close-to -reality scenario of Montreal breast cancer screening at a macro level, we use Arena simulation that incorporates real population data and econometrics analysis to illustrate how changing of attribute levels will affect the screening rate of current clinics.

## 3.8.1. Basic model

Our basic model aims to simulate current screening situation in Montreal. To achieve that, we used data provided from PQDCS program office to separate Montreal into 12 population zones. Table 3-13 lists total eligible population (women 50-69 years old), current participation rate and number of participants for each population zone (as of December 2010).

**Table 3-13: Montreal population zone and corresponding participation rate**

| Population Zone | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Participation Rate** | 50% | 38,3% | 47,3% | 50% | 45,6% | 48,1% | 47,9% | 38% | 47,1% | 41,3% | 48,1% | 43,4% |
| **Eligible Populatoin** | 27117 | 14556 | 21072 | 19923 | 10441 | 12446 | 15265 | 23495 | 17287 | 14727 | 18055 | 28543 |
| **# of Participants** | 13559 | 5575 | 9967 | 9962 | 4761 | 5987 | 7312 | 8928 | 8142 | 6082 | 8684 | 12388 |

The process of the basic model is as follows:

**Step 1: Participants arrival**

There're a total of 12 entity modules, each correspondents to an arrival from a population zone. The total number of opening hour of current 15 CDDs is 2100 hours per year at the time of interview, not consider holidays. We therefore assume 250 working days per year and 8 working hours per day (2000 hours per year). Current participation rate is reported on a biannual basis, i.e. number of individual screening in the past 24 month. For each population zone, we assume possion arrival, and calculate the arrival interval as 4000 hours divided by eligible population.

**Step 2: Screening decision**

We have one decision module for each arrival, where a decision of whether to screen or not is made. This is a two-way by chance decision module, where participation rate for each zone is used as probability to screen.

**Step 3: Clinic choice**

A second decision module follows each screening decision, where participants need to decide which clinic to visit. This is a 15-way by chance module, where participants from each zone are assigned 15 probabilities, represents probability of visiting each of the clinics, calculated using results from conditional logit model (column of step 4, table 3-6). We believe this is more realistic than sending participants to the one clinic with the highest probability, as in reality, people don't always go to the choice with highest utility level due to different limitations.

We try to mimic the true clinic configurations as closely as possible. We used interview data on WAITAPP, PARKING, HOUR, WAITCLINIC, and WAITRESULT for most clinics where available, and randomly assigned value on NURSE and SCREENING. For attribute TRAVEL, we generate a 12 by 15 matrix, represents travel time from each of the 12 population zone to each of the 15 CDDs, roughly calculated based on geographic distance. This means for each clinic, while 7 of the attributes are invariant across all population zones, TRAVEL varies for each clinic-population zone pair.

**Step 4: Waiting for appointment**

We add a HOLD module before each SCREENING module to hold participants until the queue in its corresponding SCREENING module reaches zero. This is a close proxy for the waiting time for appointment, although by doing so, our HOLD module also captures some waiting time inside the clinic. Currently all 15 CDDs in Montreal accept participants by appointment only. Screening time for mammography is fairly constant at 20-30 minutes, waiting time inside clinics are usually not very long, hardly goes over one hour. Therefore incorporating it into waiting time for appointment wouldn't affect accuracy since the latter is usually measured by days, sometimes even months.

**Step 5: Screening**

We have 15 process module, each represent one screening clinic. We set service time for all clinics to be constant at 30 minutes. True number of mammography machines in each CDD is used in assigning resources. Clinic 5 has 3 machines, clinic 3, 8 and 12 each has 2 machines, the rest of clinics each has one machine only.

**Step 6: Disposition**

Participants leave clinic after screening.

Figure 3 below presents the basic process of the Arena model. There is another dispose module after each screening decision module, represent non-participants, that we didn't show here since it's not of our interest.

Note there are 12 modules for each of Arrival, Screening decision, and Clinic choice, represent 12 population zones. Waiting for appointment, Screening, and Disposition each has 15 modules, represents 15 current CDDs.
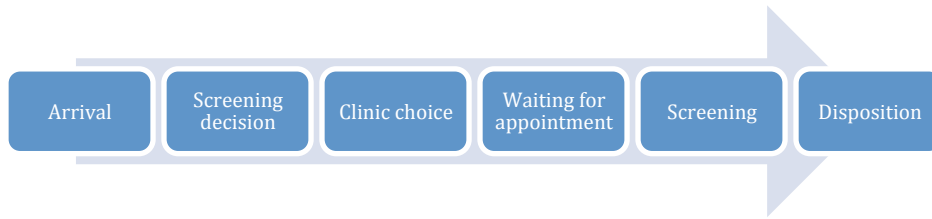


**Figure 3-3: Simplified Arena model**

We set up Arena to fun for 2000 hours (one year) at 8 hours a day for 10 replications, and report the average of the 10 replications for the rest of the section. Our key performance metrics are number of screenings, waiting time for appointment, utilization rate, and total number of participants waiting for screening (participants with an appointment). Columns labeled Basic in Table 3-14 below presents result from our basic model.

With current configuration, we see that participants are far from evenly distributed among 15 clinics. While 11 out of 15 clinics has zero days of waiting time of appointment, mostly with an utilization rate of below 25%, clinic 4 and 7 both have waiting time of almost 3 months, together holding almost 10000 people waiting in line for screening. Clinic 10 also has an average of 40 days waiting time for appointment. Clinic 3, 5, 8 and 12 all have multiple machines, therefore ideally their total number of screening should also be greater than the rest of the clinics, which is not the case in basic model. CDD2 and 12 have the lowest screening, with 115 screenings performed in CDD2 and as few as 22 in CDD12.

At the time of our interview, 6 of current CDDs have waiting time for appointment of less than 1 week, another one can make next day appointment. 3 CDDs have waiting time of 2 to 3 weeks. Two CDDs have waiting time of 1 to 2 month, and the other 3 CDDs all have waiting time longer than 3 months. Although the attribute level of current clinics that we used in calculating probability distributions are not 100% accurate, our simulation result is nonetheless reflective of reality of unbalanced screening load among current CDDs. Our first step then is to adjust current system by changing some of the attribute levels.

**Table 3-14: Arena result from Basic model and Adjust1 model**

| | Total number of screening | | Waiting time for appointment | | Utilization rate | | Number of participants waiting for screening | |
|---|---|---|---|---|---|---|---|---|
| Clinics | Basic | Adjust1 | Basic | Adjust1 | Basic | Adjust1 | Basic | Adjust1 |
| 1 | 995 | 1092 | 0 | 0 | 24.88% | 27.31% | 0 | 0 |
| 2 | 115 | 401 | 0 | 0 | 2.87% | 10.03% | 0 | 0 |
| 3 | 1137 | 6293 | 0 | 0 | 14.21% | 78.67% | 0 | 1 |
| 4 | 4000 | 2597 | 90 | 0 | 100.00% | 64.94% | 5214 | 0 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 5 | 1938 | 10538 | 0 | 0 | 16.15% | 87.83% | 0 | 2 |
| 6 | 743 | 817 | 0 | 0 | 18.56% | 20.44% | 0 | 0 |
| 7 | 4000 | 3740 | 85 | 0 | 100.00% | 93.51% | 4286 | 6 |
| 8 | 1397 | 4761 | 0 | 0 | 17.47% | 59.53% | 0 | 0 |
| 9 | 2655 | 2833 | 0 | 0 | 66.38% | 70.83% | 0 | 0 |
| 10 | 3999 | 3906 | 40 | 1 | 99.99% | 97.67% | 959 | 18 |
| 11 | 3986 | 3998 | 5 | 21 | 99.67% | 99.95% | 76 | 399 |
| 12 | 22 | 335 | 0 | 0 | 0.56% | 8.37% | 0 | 0 |
| 13 | 3197 | 3486 | 0 | 0 | 79.94% | 87.16% | 1 | 3 |
| 14 | 789 | 867 | 0 | 0 | 19.73% | 21.67% | 0 | 0 |
| 15 | 581 | 4161 | 0 | 0 | 7.27% | 52.02% | 0 | 0 |
| Total | 29554 | 49825 | | | | | 10537 | 429 |

# 3.8.2. Adjust1 model

Our adjustment mainly focuses on three attributes, waiting time for appointment (WAITAPP), parking availability (PARKING), and nurses' knowledge (NURSE). Table 3-15 below summarizes the change of attributes from Basic model to Adjust1 model. Note to make the screening load more balanced, on one hand we improved attributes level for some of the clinics, at the same time we try to make clinic 4, 7 less attractive by changing their waiting time for appointment longer than before. In reality, this can easily be accomplished by arbitrarily offering a much later appointment than necessary. Clinic 2, 12 and 15 all have a long waiting time for appointment. Although appointment time has a big impact on clinic screening rate, we avoid changing it to acknowledge the fact that this can't be done in a short time, unless extra resources (mammography machines) are available.

**Table 3-15: Arena result from Basic model and Adjust1 model**

| Attribute level | WAITAPP | | PARKING | | NURSE | |
|---|---|---|---|---|---|---|
| Clinics | Basic | Adjust1 | Basic | Adjust1 | Basic | Adjust1 |
| 2 | - | - | - | - | 1 | 2 |
| 3 | - | - | 3 | 1 | - | - |
| 4 | 1 | 3 | - | - | - | - |
| 5 | - | - | 3 | 1 | - | - |
| 7 | 2 | 3 | - | - | - | - |
| 8 | - | - | - | - | 1 | 2 |
| 12 | - | - | 2 | 1 | 1 | 3 |
| 15 | - | - | - | - | 1 | 3 |

Columns labeled Adjust1 in table 3-14 show the key performance metrics for our adjusted model. The most notable improvement to the system is total number of screening improved by almost 70% from 29554 to close to 50000. Note the total eligible population is 222927, at the current 45% biannual screening rate, we

expect the system to performance around 50000 screenings (222927*45%*0.5). Only one out of all 15 clinics now have a queue for appointment (clinic 11). Utilization rate of most clinics have improved significantly for most previously under-used clinics, and number of participants waiting for screening is now only a small fraction of the number from basic model. Although our basic model didn't reflect the current screening volume due to lack of information on true attribute level, our adjusted model demonstrates that current system is far from ideal, as the same screen rate can be achieved with much better performance, for example, measured by appointment time.

## 3.8.3. Adjust2 and Adjust3 model

The targeted screening rate set by the Quebec government is 70%. The current 15 CDDs together can handle a screening rate of 79%[8] at full capacity. In our Adjust2 model summarized in table 3-17, we keep all attributes level same as Adjust1 model, but increase screening rate of all population zones by 25% to reach 70% screening rate. We see from table 3-16 that more than half of the clinics now have a queue for appointment, most of them with waiting time between 3 weeks to 2 months. This, however, hasn't even taken into account that all these CDDs also perform non-PQDCS screening.

In our final model Adjust2, we add one extra clinic (clinic 16) in the same population zone where clinic 1 located, after considering the total screening load of the area. We then assigned TRAVEL level to be same as clinic 1, WAITAPP=2, PARKING=2, HOUR=2, WAITCLINIC=2, NURSE=1, SCREENING=1, and WAITRESULT=1 for clinic 16, and present the result for this scenario in table 3-16 labeled Adjust2.

Our result shows that clinic 16 is a bit overloaded. However performance of other previously congested clinics all improved dramatically in terms of waiting time for appointment and number of participants waiting for screening. Total number of screening increased by 3108, total number of waiting in queue reduced by more than 1500. Utilization rate of most clinics decreased a little due to added capacity from clinic 16. Overall the system is much less crowded as before, although there's still room for improvement by further adjusting the attribute levels of some clinics.

**Table 3-16: Arena result from Adjust2 model and Adjust3 model**

| | Total number of screening | | Waiting time for appointment | | Utilization rate | | Number of participants waiting for screening | |
|---|---|---|---|---|---|---|---|---|
| Clinics | Adjust2 | Adjust3 | Adjust2 | Adjust3 | Adjust2 | Adjust3 | Adjust2 | Adjust3 |
| 1 | 1710 | 1390 | 0 | 0 | 42.75% | 34.75% | 0 | 0 |

---

[8] This can easily be computed by dividing the total number of machine minutes of all 15 CDDs per 2 years by 30 minutes per screening.

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **2** | 625 | 506 | 0 | 0 | 15.63% | 12.65% | 0 | 0 |
| **3** | 7996 | 7903 | 23 | 1 | 99.97% | 98.79% | 891 | 32 |
| **4** | 3973 | 3276 | 3 | 0 | 99.33% | 81.91% | 46 | 1 |
| **5** | 11998 | 11997 | 33 | 12 | 100.00% | 99.99% | 2126 | 643 |
| **6** | 1255 | 1009 | 0 | 0 | 31.36% | 25.23% | 0 | 0 |
| **7** | 3999 | 3997 | 39 | 18 | 99.98% | 99.94% | 923 | 342 |
| **8** | 7366 | 5955 | 0 | 0 | 92.09% | 74.44% | 4 | 1 |
| **9** | 3997 | 3581 | 12 | 0 | 99.93% | 89.54% | 208 | 3 |
| **10** | 4000 | 3998 | 41 | 25 | 99.99% | 99.96% | 996 | 489 |
| **11** | 4000 | 3999 | 58 | 42 | 99.99% | 99.98% | 1725 | 1004 |
| **12** | 530 | 416 | 0 | 0 | 13.24% | 10.40% | 0 | 0 |
| **13** | 3998 | 3996 | 31 | 12 | 99.96% | 99.91% | 683 | 211 |
| **14** | 1321 | 1070 | 0 | 0 | 33.02% | 26.76% | 0 | 0 |
| **15** | 6521 | 5303 | 0 | 0 | 81.53% | 66.30% | 1 | 0 |
| **16** | | 7999 | | 57 | | 99.99% | | 3330 |
| **Total** | 63287 | 66395 | | | | | 7602 | 6057 |

# 3.9. Conclusion

Breast cancer is one of the most common cancers in the world, and the second leading cancer cause of death among women in Canada (Hamilton and Barlow 2003). Early detection of breast cancer through mammographic screening can lead to significant reduction of breast cancer mortality (Aro et al. 1999). Optimal design of government-funded breast cancer screening program therefore plays an important role in the prevention and early diagnosis of breast cancer. In this paper, use stated preference discrete choice modeling, we conduct a survey in Montreal, Canada, under the setting the Quebec breast cancer screening program- PQDCS program, to explore client preference regarding the service configuration of screening clinics.

Of the eight studied service attributes, we found nursing staff's manner and knowledge regarding screening and breast caner, as well as waiting time for appointment are the most influential factors in choice of clinics, followed by parking availability. We found clinics' opening hours to be the only attributes that are not significant in the decision-making. Use latent class analysis, we are able to identify the homogeneity among PQDCS current participants, i.e., there's no evidence of difference among participants' preference of studied attributes. Use the collected data on 12 population zones in metropolitan Montreal, and 15 current designated screening clinics, we build an Arena simulation model to explore the change in the overall system if preferences are taking into account. Our results show significant improvement in all three metrics, measured by number of screening per year, utilization rate of mammography machines, as well as number of women waiting for appointment.

The main contribution of our research is to provide a tool that can be used to improve service quality of preventive care program significantly, without incurring vast capital investment. All the studied attributes can be adjusted at low or even no cost. And although not presented here, our survey result can also be used in a probit model to generate re-screening participation function. Our survey respondents are a convenient sample of current participants of the PQDCS program. Future research can use the same approach, but include non-participant in the survey as well, to generate a general participant function to gain more managerial insights.

# 4. Conclusion

In chapter 2, we provide evidence that ED process redesign, specifically the adoption of POCT, has a substantial and valuable impact on ED operations. POCT adoption reduces the service time not only of patients who receive the troponin test at the point of care, but also of other patients within the ED who do not require a troponin test. That we further observe the service time impacts of POCT adoption to be greater during peak than during off-peak hours among both test and no-test patients suggests that POCT can have a measurable impact on ED performance during crucial operating periods.

POCT adoption is also associated with improved service quality. All patients who presented to the ED during the POCT pilot period experienced a lower bounceback rate than in the comparison periods. Some of this quality improvement may follow from the priority queue model predictions, whereby high and low priority patients experience differential impacts. Empirically, lower priority patients have a greater propensity for bounceback. We speculate that less severe patients may, *a priori,* receive less attention. As service time savings accrue, as with priority queuing, less severe patients stand to reap the greatest benefit from any surplus physician attention.

Finally, we find adoption of POCT to have a positive effect on waiting time for both test and no-test patients. We observe the lowest priority patients to experience the greatest, and highest priority patients the smallest, decrease in waiting time upon adoption of POCT, supporting our prediction of ED behavior based on queuing theory. It further suggests that POCT leads to operational improvement not only through a direct impact on the service time of test patients, but also through an indirect impact on waiting time for all who present to the ED when POCT is in use.

There are several possible extensions of this research. First, what model should be used to help an administrator determine the optimal number of tests to be converted to POCT? This study analyzes a setting in which a single test is converted to POCT. That nursing workloads increase with each additional test converted suggests diminishing marginal returns. What distribution of tests between bedside and central lab minimizes service times without compromising service quality subject to staffing constraints? Second, what model would help an administrator select the optimal test(s) to be converted to POCT? Prior studies reveal the rationale for test selection to date to be largely ad hoc. What are the critical selection criteria and potential for scale economies, in both cost and quality, from test analysis? Finally, how do administrators model the financial impact of POCT conversion? In our setting and that of many prior studies, the conversion to POCT is justified solely on the basis

of service time and service quality. In the context of rising healthcare costs, however, POCT adoption incurs both a capital equipment expense and higher marginal per-test costs. Whether POCT can decrease ED and central lab congestion, and increase patient volume, sufficiently to offset these costs warrants further study.

In chapter 3, study on breast cancer screening, we found nursing staff's manner and knowledge regarding screening and breast caner, as well as waiting time for appointment are the most influential factors in choice of clinics, followed by parking availability. We found clinics' opening hours to be the only attributes that are not significant in the decision-making. Use latent class analysis, we are able to identify the homogeneity among PQDCS current participants, i.e., there's no evidence of difference among participants' preference of studied attributes. Use the collected data on 12 population zones in metropolitan Montreal, and 15 current designated screening clinics, we build an Arena simulation model to explore the change in the overall system if preferences are taking into account. Our results show significant improvement in all three metrics, measured by number of screening per year, utilization rate of mammography machines, as well as number of women waiting for appointment.

The main contribution of our research is to provide a tool that can be used to improve service quality of preventive care program significantly, without incurring vast capital investment. All the studied attributes can be adjusted at low or even no cost. And although not presented here, our survey result can also be used in a probit model to generate re-screening participation function. Our survey respondents are a convenient sample of current participants of the PQDCS program. Future research can use the same approach, but include non-participant in the survey as well, to generate a general participant function to gain more managerial insights.

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