ABSTRACT

Title of Dissertation:	**EXAMINING NEIGHBORHOOD SOCIOECONOMIC CHARACTERISTICS AND ACCESS TO THE NATIONAL DIABETES PREVENTION PROGRAM: A MARYLAND PERSPECTIVE**
	Portia Buchongo, Doctor of Philosophy, 2023
Dissertation directed by:	Dr. Luisa Franzini Professor and Chair, Health Policy and Management

Despite substantial federal and state investments made to promote the National Diabetes Prevention Program (NDPP) as a population health strategy for diabetes prevention it remains underutilized. Research has pointed to a variety of factors that have contributed to low uptake of this evidence-based lifestyle change program. However, the role neighborhood socioeconomic disadvantage plays in NDPP access and use has been underexplored. The state of Maryland is an ideal setting to investigate how neighborhood socioeconomic disadvantage impacts various dimensions of NDPP access due to the significant investments in primary care transformation and NDPP. This dissertation examines: (1) the relationship between neighborhood socioeconomic disadvantage and potential access to the NDPP using primary care providers geographic proximity to the NDPP sites in Maryland, (2) the relationship between neighborhood socioeconomic disadvantage and potential access

to the NDPP based on geographic proximity of individuals with prediabetes to the nearest NDPP site in Maryland, and (3) the relationship between neighborhood socioeconomic disadvantage and utilization of diabetes prevention intervention such as NDPP, metformin, or both among individuals with prediabetes in Maryland. Findings from this work underscore how targeted statewide public health and health care initiatives can enhance NDPP access and utilization in neighborhoods with higher levels of socioeconomic disadvantage.

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EXAMINING NEIGHBORHOOD SOCIOECONOMIC CHARACTERISTICS AND ACCESS TO THE NATIONAL DIABETES PREVENTION PROGRAM: A MARYLAND PERSPECTIVE

by

Portia Buchongo

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Advisory Committee:
Dr. Luisa Franzini, Chair
Dr. Jie Chen
Dr. Kellee White
Dr. Dushanka Kleinman
Dr. Quynh Nguyen, Dean's Representative

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List of Abbreviations

Centers for Disease Control and Prevention	CDC
Primary Care	PC
Primary Care Provider	PCP
National Diabetes Prevention Program	NDPP
Diabetes Prevention Recognition Program	DPRP
Social Deprivation Index	SDI
ZIP tabulation area	ZCTA
Maryland Primary Care Program	MPCP

Chapter 1: Introduction

The National Diabetes Prevention Program (NDPP), an evidence-based lifestyle change program, has been shown to be more effective in delaying the onset of diabetes compared to the medication metformin for individuals with prediabetes or at risk for developing diabetes.[1,2] Since the program's inception in 2010, substantial investments in training, program standardization, and coverage for NDPP have been made to increase the capacity to deliver NDPP across states,[3–7] yet program participation and retention remains low. Individuals with diabetes are at an increased risk of developing comorbidities such as hypertension and kidney failure, certain cancers and experience higher medical costs.[8] NDPP is a key population health strategy for diabetes prevention.

Most of the evidence on NDPP has focused on patient outcomes,[9–11] cost,[12–17] and organizational challenges[18–24] related to access such as training, recruitment, retention, and health care provider engagement and referrals. Effective engagement in NDPP requires a substantial time commitment and resources from participants to remain engaged. Transportation has been identified as a barrier to NDPP access,[25] but has not been well established in the literature. Long travel times have been linked to poor glycemic control[26] and reduced use of medication therapy[27] for individuals with diabetes. However, the association between travel time and access to NDPP has not been well studied.

Neighborhood socioeconomic disadvantage has been used to describe areas challenged by limited economic, human capital, or material resources,[28,29] and is associated with lacking a usual source of care, limited access to preventative health screenings,[28] higher rates of comorbidities,[30] and progression from prediabetes to diabetes.[31] Although limited, some research has shown that NDPPs are rarely located in areas that are socioeconomically disadvantaged.[32,33]

This creates disparities in access to a widely promoted diabetes prevention intervention, which likely to disproportionately impact minoritized racial and ethnic groups who often live in under resourced communities.[34] Therefore, it is critical to establish the extent to which neighborhood socioeconomic disadvantage contributes to access to the NDPP.

To my knowledge, this research will be the first to explore the relationship between neighborhood socioeconomic conditions and NDPP access and utilization. The objective of this research is to understand how neighborhood socioeconomic conditions affect access to NDPP by examining the geographic proximity of primary care practices and patients with prediabetes to the nearest NDPP and utilization of diabetes prevention interventions (i.e., NDPP and metformin). The State of Maryland has been chosen to explore these relationships due to its primary care transformation work[35] and extensive investments in diabetes prevention and NDPP which has spurred a myriad of cross-sector partnerships to support NDPP delivery.[36–38] Primary care providers play a critical role in making referrals to community-based NDPPs,[23,39] however their referral patterns may be influenced by factors such as geographic proximity to referral sites,[40–42] which could impact NDPP participation.[43]

To explore how neighborhood socioeconomic characteristics may contribute to inequitable access to NDPP the following aims will be pursued:

1. Examine the relationship between neighborhood socioeconomic disadvantage and potential access to the NDPP using primary care providers geographic proximity to the nearest NDPP site (in Maryland).

2. Examine the relationship between neighborhood socioeconomic disadvantage and potential access to the NDPP based on geographic proximity of individuals with prediabetes to the nearest NDPP site (in Maryland).

3. Examine the relationship between neighborhood socioeconomic disadvantage and utilization of diabetes prevention interventions such as NDPP, metformin, or both among individuals with prediabetes (in Maryland).

Chapter 2: Literature Synthesis

The National Diabetes Prevention Program (NDPP) has been widely promoted as an evidence-based intervention to prevent the onset of diabetes. After the landmark randomized clinical trials demonstrated a lifestyle modification intervention was more effective in delaying and preventing the onset of diabetes compared to traditional pharmacotherapies (i.e. metformin) for 10 or more years[1,2] federal and state initiatives focused on building the program infrastructure to implement lifestyle change programs. In 2010, the Prevention and Public Health Fund, financed by the Affordable Care and Patient Protections Act, established the NDPP within the Center for Disease Control and Prevention (CDC), which developed the curriculum and training for local NDPP sites. Two years later the CDC established the Diabetes Prevention Recognition Program (DPRP) to set and oversee national standards for the curriculum, delivery and program recognition of local NDPPs.[4] NDPP has been endorsed by the US Preventative Services Task Force, which gave a "B" recommendation for the use of lifestyle change programs such as NDPPs to prevent type 2 diabetes.[6] In addition CDC has collaborated with professional organizations such as the American Medical Association (AMA) to increase awareness of the benefits of NDPP, while public and private payers have helped promote the program as a first line evidence-based intervention to manage prediabetes and prevent the onset of diabetes.[4]

Diabetes Burden & Prediabetes

The diagnostic criteria for type 2 diabetes is defined as having a hemoglobin A1C equal to or greater than 6.5%, while an A1C of 5.7-6.4% is defined as prediabetes.[44] According to recent estimates 37.3 million adults in the U.S. have diabetes, while more than twice as a many adults are estimated to have prediabetes (96 million) have prediabetes.[8] Individuals with diabetes

area at an increased risk for developing co-morbidities such as renal failure and cardiovascular disease.[45] These comorbidities are associated with higher health care cost related to increased hospitalizations and disease management.[46]

The National Diabetes Prevention Program

NDPP is a lifestyle change program designed for non-pregnant adults with a body mass index $\geq 25 kg/m^2$, positive screening for prediabetes or clinical diagnostic markers for prediabetes (e.g., fasting glucose of 100 to 125 mg/dl or hemoglobin A1C of 5.7% to 6.4%), with the goal of losing 5-7% of baseline body weight and completing 150 minutes of physical activity per week.[47] This lifestyle change program was also designed to be delivered in a group setting to provide participants with social support. Prior to the NDPP being established a partnership between UnitedHealth Group and YMCA of USA (2010-2011), which spanned 46 communities and 23 states, helped develop what would come to be known as the NDPP. This partnership implemented as a group-based model of lifestyle change programming with 16 core sessions spanning 12-months, and was designed to be delivered in community settings in collaboration with health care organizations.[7] This early partnership between UnitedHealth Group and the YMCA of USA demonstrated program scalability and retained about 73% of the 2369 participants for nine or more core sessions, which helped to inform NDPP standards.[7] According to the CDC DPRP standards should be delivered over 12 months and includes weekly in-person meetings for the first 6-months (with a minimum of 16 sessions required) followed by monthly sessions during the last 6-months. NDPP sites that deliver the program as outlined by DPRP are eligible to reach one of three tiers, Preliminary, Pending, or Full recognition status.[47]

Meeting reporting requirements defined by the DPRP is an essential aspect of ensuring NDPP sites maintain standards for recognition. Reporting requirements generally include the

submission of weight and physical activity data for participants in each programs cohort every 6-months[48] Although individuals who do not have a diagnosis of prediabetes or positive screening for prediabetes may participate in the program, NDPP sites received the most benefits from reporting if their cohorts are predominately made up of individuals with a diagnosis of prediabetes or positive screening for prediabetes. The DPRP designations of preliminary or fully recognized position NDPP sites to benefit from being a preferred provider for the Medicare Diabetes Prevention Program, which was established in 2017 as a covered benefit for Medicare beneficiaries.[47] However, reaching preliminary or full recognition status can take programs a minimum of 18 to 36 months.[47]

Program Outcomes

Several large-scale demonstrations and translational studies also provided evidence to support the efficacy of NDPP, particularly in community-based settings. The YMCA-USA Medicare Demonstration (2013-2015) showed desirable patient outcomes, with NDPP participants having fewer inpatient and emergency department visits per 1,000 participants per quarter,[13] while the CMS Medicaid MCO Demonstration Project (2016-2019) showed on average DPP participant weight loss of 4.5% of their body weight.[49] In terms of costs, evidence has demonstrated both NDPP and metformin (a medication for diabetes prevention and management) have been found to be cost effective and cost saving over a 10-year period respectively.[15] Translational studies have shown that costs associated with NDPP start-up, delivery, and maintenance varies. For example, the CMS Medicaid Demonstration Project leveraged Managed Care Organizations (MCOs) and Coordinated Care Organizations to implement NDPP for their Medicaid beneficiaries in Maryland and Oregon and found that direct ($205,962) and indirect ($44,888) startup costs averaged $250,850.[49] This demonstration also

found that cost per enrolled patient varied based on whether the DPP site was new ($1,704), established ($1,529), or delivered online ($556).[49] While some studies have shown that metformin use can be cost-saving, evidence-based lifestyle change programs are still more cost-effective long term.[50] However, the American Diabetes Association recommends the use of metformin for individuals with prediabetes who are high risk due to history of gestational diabetes, body mass index >35 or have not had desirable outcomes with lifestyle change interventions, it is not FDA approved to treat prediabetes.[51] These cost outcomes associated with large scale demonstrations have also driven states, payers, and health care systems to increase NDPP capacity and delivery with the goal of long-term cost savings from delayed diabetes onset.

Barriers to the National Diabetes Prevention Program

Despite the infrastructure in place to establish program sites, standardize programming, and increase the number of sites, challenges in recruitment and retention of eligible participants in NDPP remains some of the many barriers to implementation. Several state funded initiatives have reported challenges with recruiting eligible patients which has often resulted in low enrollment and retention, across multiple types of settings including community-based and employer-based NDPPs.[52] While DPP retention rates have varied nationally, they are relatively low. National estimates from the CDCs DPRP from 2012 through 2017 showed that of the 41,203 in-person participants during this period, about 63% were retained through week 18 when many transition to monthly sessions, and 32% were retained at week 44.[19] When considering the number of eligible participants across nationally, these participation and retention estimates are very low.

NDPP as a Population Health Strategy for Diabetes Prevention

NDPP is well designed to incorporate population health approaches to reduce the burden of diabetes and achieve the goals of the triple aim by improving health care quality, health outcomes and reducing costs.[19] Within the context of CDC's 3 buckets of prevention framework (see Figure 1), NDPP promotes innovative clinical prevention by facilitating collaboration between the health care and public health sectors to create clinical-community linkages that provide preventive services outside of traditional clinical settings.[53] NDPP providers are not required to be licensed clinicians, instead they are required to be trained Lifestyle Coaches to deliver the program and can be non-clinicians such as individuals from faith-based or community-based organizations.[47] Although NDPP has been delivered in a variety of settings such as health systems, clinics, and pharmacies, it has been widely promoted as an ideal program

Figure 2.1 Centers for Disease Control and Prevention Three Buckets of Prevention

for community-based organizations (CBOs) and settings to deliver. The relaxed criteria for NDPP provider eligibility helps to expand the NDPP capacity in terms of provider types. States that implement policies and guidance that prioritizes and promotes the use of NDPP can

integrate this program into their population health strategies to reduce the burden of diabetes. To date there are 35 states that have a Diabetes Action Plan,[54] and 22 cover NDPP through their state Medicaid agency to some degree.[55] Still, a concertize effort is needed to ensure NDPP is promoted by health care providers as a diabetes prevention intervention, and to ensure NDPP sites have adequate administrative support, resources, and infrastructure necessary to deliver the program and meet reporting requirements.

Prediabetes Screening & Referrals

A large part of the strategy to increase NDPP access and availability has focused on educating health care providers and developing resources to support referrals to the program. National partnerships between the CDC and AMA helped developed an online learning platform entitled, Prevent Diabetes STAT-Screen, Test, and Act Today™, which is intended to target health care professionals and provide resources on how to identify, refer, and enroll patients into NDPPs.[56] In 2019, only 19% of individuals with prediabetes were aware of their diagnosis.[57] This reinforces the need to engage health care providers in screening for prediabetes to ensure early interventions to prevent the development of diabetes among individuals who may be unaware of their prediabetes status. A national survey of primary care providers revealed that only 27% of them screened patients for prediabetes and were more likely to refer patients to NDPP if they were aware of NDPP and the AMA Prevent Diabetes STAT resource.[23] Public payers have also been invested in incentivizing health care providers to screen, diagnose, and refer patients. In addition, national demonstrations and policies, including the establishment of the Medicare Diabetes Prevention Program in 2018 and Medicaid NDPP Demonstrations projects in Oregon and Maryland from 2016 to 2019 helped to expand coverage for NDPP to incentivize the utilization of this evidence-based program and expand access to the program.[58]

Primary care providers (PCPs) are well positioned to increase referrals to NDPP sites in community-based settings since they still serve as gatekeepers for many patients, particularly for referrals to specialist. While evidence suggest that health care providers are better with screening or testing patients for prediabetes, rather than referring patients to NDPP [23] they have also been show to influence patient engagement. Early research on NDPP found program sites that received referrals from healthcare providers or health systems had higher attendance and retention long-term.[24] Integrated health systems that established partnerships with local YMCAs have found that using patient's provider information in patient recruitment letters and follow-up calls have been effective in improving program retention.[9] Although some strategies to recruit eligible participants used large advertising and awareness campaigns, these have not been as effective as referrals from health care providers.[24] National estimates have shown that health care provider referrals to NDPP are about 4%, which is extremely low considering the prevalence of prediabetes in the population.[18]

Community-Clinical Linkages

Health system and NDPP demonstration projects have emphasized the need for community-based program sites to establish partnerships with health care systems, practices, and providers, that can drive patient recruitment and referrals to local NDPP sites. However, heath care systems and practices may be hesitant to establish partnerships with community partners due to concerns regarding program quality, and capacity to deliver the program. Evidence from health system-community partnerships have shown that organizations delivering NDPP experienced delays in program start dates for patients which reduce the likelihood of patient enrolment and attendance.[59]

Some health systems also created preferred partnerships with community-based organizations and developed mechanisms to deliver the program within the health system. Evidence from an integrated health system that partnered with YMCA found they were better positioned to negotiate higher reimbursement for patients based on risk adjustment, improved tracking of DPP participation, and were able to use internal billing and electronic health record referrals from providers when they offered NDPP onsite.[59] However, for the health system this resulted in a limited return on investment and high upfront costs for a small number of eligible patients. This makes it difficult to justify delivering NDPP within a health care system rather than a community-based setting. Though there may be some challenges in cross-sector partnership development, delivering NDPP in community-based settings has been shown to be effective for program outcomes, specifically maintaining weight loss and routine physical activity.[7,24,60,61]

Maryland Innovation

The state of Maryland has been invested in using NDPP as a population health strategy for diabetes prevention since their participation in the 2016 Medicaid Demonstration,[49] where they created NDPP networks and multi-sector partnerships between MCOs and NDPPs.. In Maryland, it is estimated that 1.6 million adults (34%) have prediabetes.[36] Maryland was also able to leverage the findings from their Medicaid CMMI demonstration to secure NDPP coverage for one of the largest Medicaid managed care organizations in the state, Health Choice, by extend their efforts through a Medicaid 1115 waiver in 2019.[35] Maryland has also integrated diabetes prevention in broader statewide health care initiatives by investing in primary care, with the Maryland Primary Care Program, which is intended to reduce Medicare's total cost of care,

improve health care quality by reducing avoidable hospitalizations, and includes a focus on diabetes prevention strategies such as NDPP.[38]

Gaps in the Literature

Barriers to NDPP access and utilization have focused largely on programmatic barriers. However, less focus has been given to how neighborhood socioeconomic conditions and environmental context such as travel time may be associated with access to NDPP. Transportation has been frequently noted as a barrier to NDPP access and utilization but evidence is scarce, with some studies showing shorter driving time to NDPPs encourages program participation.[62] Geographic proximity to sites that receive referrals has been identified in the literature as a facilitator for health care provider referrals[41,63] and cross-sector partnerships.[40,42] There has also been evidence that shows neighborhood socioeconomic conditions can contribute to how accessible health care resources are to referring providers, specifically in areas with higher levels of uninsured patients.[64]

Neighborhood socioeconomic conditions have also been associated with limited availability of health care resources.[28] Several studies that used geographical information systems approaches nationally and within specific states found NDPP sites were often not located in counties with high rates of diabetes. In addition, counties higher proportions of low household income or unemployment have been found to be associated with less available NDPPs.[32,33,65] Social drivers of health care such as low educational attainment and income have also been associated with the development of diabetes.[31]

Conceptual Framework

Access is multidimensional and has been described by Penchansky and Thomas using five dimensions, which include: availability (e.g.,. number of physician supply), accessibility (e.g.,. relationship between location of supply and location of clients/patients-travel time, distance costs), adequacy, affordability, and acceptability (of care by patients).[66],[67] This research focuses primarily on the accessibility of NDPPs in relation to PC practice locations and patient residence by examining the proximity of nearest NPP as measured by travel time. Potential access is defined as the presence of enabling resources which increase the likelihood of health care use, while realized access described the utilization of health care services.[68,69]

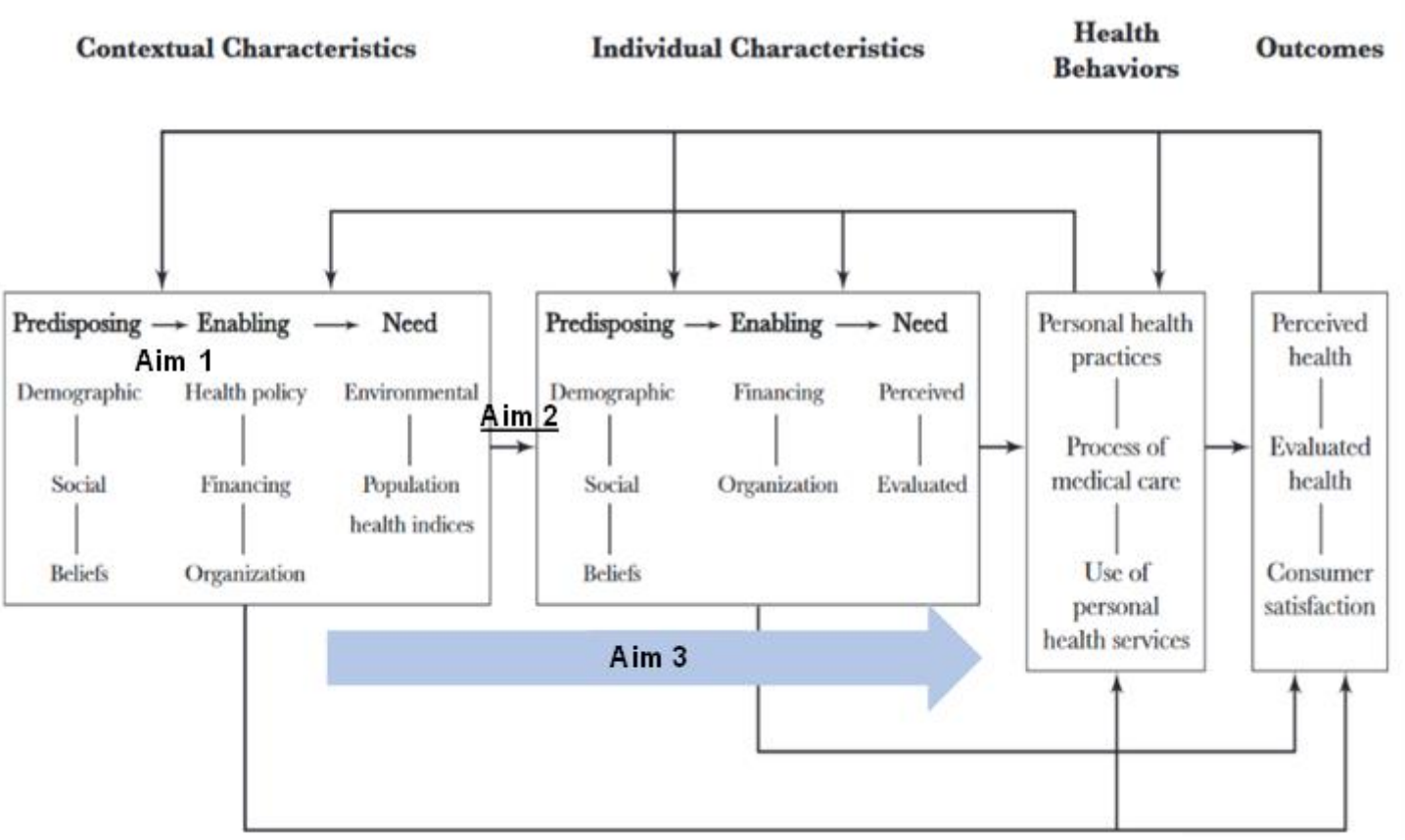

Figure 2.2 Andersen's Behavioral Model of Health Services Use and Research Aims

This research is informed by the 6th iteration of the Andersen's Behavioral Model of Health Services Use which recognizes the role of contextual characteristics that describe the communities or neighborhoods where health services are used, and include demographics (i.e., age, gender), social characteristics (i.e., education level racial and ethnic composition) and beliefs (i.e., political perspectives regarding how health services should be organized).[68] *Aim 1* will examine contextual characteristics, specifically the relationship between predisposing social characteristics (i.e., neighborhood socioeconomic disadvantage) and potential access as measured by enabling variables (i.e., organization-travel time to the nearest NDPP). *Aim 2*

examines predisposing contextual factors (social characteristics-neighborhood socioeconomic disadvantage) and individual enabling characteristics (i.e., organization-travel time to the nearest NDPP). Finally, *Aim 3* investigates the relationship between predisposing contextual characteristics (i.e., social characteristics- neighborhood socioeconomic disadvantage) and health behaviors (i.e., use of NDPP).

Chapter 3: Neighborhood Socioeconomic Characteristics of Provider Practices and Potential Access to the National Diabetes Prevention Program: A Maryland Perspective

Abstract

Background: Establishing clinical-community linkages between primary care providers (PCPs) and the National Diabetes Prevention Program (NDPP) sites is a population health strategy being used across various states to reduce the incidence of diabetes. PCPs are an essential referral source for NDPPs, which targets adults with prediabetes or at risk for developing type 2 diabetes. While geographic proximity to referral recipients has been shown to facilitate provider referrals, an adequate supply of referral recipients is also needed to support provider referrals. However, neighborhoods with higher levels of socioeconomic disadvantage have a limited supply of NDPPs.

Purpose: The purpose of this study is to examine the relationship between neighborhood socioeconomic disadvantage of primary care practice locations and geographic proximity to NDPP sites and using travel time to the nearest NDPP from primary care practices.

Methods: Data from the 2019 Maryland Medical Care Data Base Active Providers Directory were used to identify primary care practice locations and was linked to social deprivation index (SDI) 2015 data and population level characteristics. Google Maps Platform and Google Distance Matrix Application Programming Interface were used to calculate travel time estimates from primary care practices to the nearest NDPP site. Adjusted log-linear regression models were fitted to predict the log transformation of travel time using SDI quintiles (from least to most disadvantaged). The log transformation of travel time in minutes for driving and public transportation modes were estimated and population estimates for race and ethnicity, obesity and rurality were controlled for. We also performed stratified analyses that compared PC practices in

areas with the percentage of Non-Hispanic Black populations greater than 45% to those with Non-Hispanic Black populations less than 45%, and counties with higher concentrations of PC practices to those with a lower concentration of PC practices.

Results: Primary care practices located in areas with SDI scores in the 5th quintile (most disadvantaged) had significantly shorter drive times (by 51%) to the nearest NDPP compared to PC practices located in areas with SDI scores in the 1st quintile (least disadvantaged). For primary care practices in areas with SDI scores in the 5th quintile, public transportation travel times were significantly shorter (by 65%) compared to practices in areas with SDI scores in the 1st quintile. For PC practices located in areas with the percentage of Non-Hispanic Black populations greater than 45% SDI scores in higher quintiles (2nd, 3rd, 4th, and the quintiles) were significantly associated with longer drive times to the nearest NDPP compared practices in areas with SDI scores in the 1st quintile (least disadvantaged).

Conclusion: PC practices located in areas with higher levels of socioeconomic disadvantage were associated with significantly shorter drive times to the nearest NDPP site. These findings were consistent for both modes of transportation (driving and public transit). This study is limited to the state of Maryland but reveals the benefits of long-term statewide innovation efforts in primary care transformation and diabetes prevention, including the 2016 Medicaid Demonstration project.

Introduction

It is estimated that 96 million (38.0%) adults in the U.S. have prediabetes, which increases their risk for developing type 2 diabetes.[8] The Centers for Disease Control (CDC) National Diabetes Prevention Program (NDPP) has been offered for over two decades and is well established as an intensive evidence-based lifestyle change program that can delay the onset of type 2 diabetes.[1,2,49] Despite substantial federal and state investments to increase capacity to deliver NDPP, program recruitment and retention remains challenging.[9,19] A unique feature of NDPP is that non-clinical persons can be trained as lifestyle coaches to deliver this program. This has positioned NDPP to thrive in community-based settings and leverage population health strategies that encourage establishing clinical-community linkages between health systems, health care providers and community-based NDPP suppliers.[53] Evidence from translational studies have demonstrated that participants using NDPP in community-based settings have maintaining weight loss and routine physical activity.[7,24,60,61]

Primary care providers (PCPs) are essential in providing access to preventative care and can improve population health by connecting patients to community-based interventions. While referrals to NDPPs from health care providers have been associated with higher rates of program attendance and retention, on average health care providers refer about 5% of patients diagnosed with prediabetes to NDPP.[18,24] Geographic proximity has been shown to facilitate provider referrals and cross-sector collaboration.[40,63,70] Health care providers in closer proximity to referring sites are often more likely to make referrals to those specialist, including mental health services.[41,63] Given these dynamics, it is likely that other contextual factors may contribute to provider referral patterns.

Neighborhood socioeconomic disadvantage has been shown to influence the availability of community-based organizational resources.[71] Though there has been a national effort to increase the availability of NDPPs, evidence suggest that NDPPs are rarely located in areas that are socioeconomically disadvantaged.[32,33] Neighborhood socioeconomic disadvantage has been used to describe areas challenged by limited economic, human capital, or material resources[28] and is associated with not having a usual source of care, limited access to preventative health screenings,[29] higher rates of comorbidities,[30] and progression from prediabetes to diabetes.[31]

Evidence exploring neighborhood socioeconomic disadvantage and the availability and accessibility of health care referral resources for providers is scarce. However, the number of NDPPs available for PCPs to refer patients to is important for ensuring patients gain access to this program. Primary care practices located in neighborhoods with higher levels of socioeconomic disadvantage may have more challenges with the supply of NDPPs to support referrals. Geographic proximity may support the development of clinical-community linkages and referral networks between PCPs and NDPP sites, which can improve potential access to NDPP.

Potential access has been defined as the presence of enabling resources, which increase the likelihood of health care use[69,72] and being in the space and time with a healthcare system that is willing and available to provide health care to those in need.[73] The later encapsulates two dimensions of access to health care, specifically the availability (i.e., supply of health resources) and accessibility (i.e., travel time or distance) of health care services.[66] Prior research has measured potential access using travel time estimates to the nearest heath care facility or resource.[74]

Study Aims and Hypotheses

This study examines the association between neighborhood socioeconomic characteristics of PC practice locations and travel time to the nearest NDPP from PC practice locations. Using travel time rather than distance will account for variations in traffic patterns which can produce inconsistent travel times to destinations that have the same distance. We were specifically concerned with whether travel time to the nearest NDPP would be longer for PC practices located in areas with higher levels of socioeconomic disadvantage. Understanding factors that influence travel time between PC practices and NDPPs is important due to the significant role PCPs play as gatekeepers in facilitating patient access to healthcare resources, and their role as an essential referral source for NDPP providers. We hypothesize that travel time between PC practices and NDPPs is longer for PC practices located in areas with higher levels of socioeconomic disadvantage.

The state of Maryland (MD) is an ideal setting to explore this relationship due to its extensive work in primary care transformation[38] and statewide investments in NDPP which have helped to support educating health care providers on diabetes prevention and promoting referrals to NDPPs.[75] In prior research examining neighborhood socioeconomic disadvantage has not established a universal definition for conceptualizing neighborhood.[76–78] A variety of geographic units have been used to quantify a neighborhood and includes smaller geographic units such as census-block group, census tract, and ZIP tabulation areas (ZCTAs).[79] Our study explores the intersection of health care (i.e., PC practices) and public health (i.e., NDPPs) resources which are often organized by state and local public health departments. In MD county health departments are self-governed and direct diabetes prevention efforts such as the availability of community based NDPPs. Therefore, we examine PC practice locations at the ZCTA level since these are

typically well defined within county-level geographic borders. This approach will help make our findings more meaningful for translation across health care and public health sectors.

Study Data and Methods

Our sample included PC practice locations in MD, which were specified by unique addresses using the 2019 Maryland Medical Care Data Base (MCDB) Active Providers Directory file. The MD 2019 MCDB Active Provider Directory file provides administrative data for licensed health care providers (including primary care physicians, nurse practitioners and physician assistants) who had claims in the MD MCDB, which includes commercial, Medicaid, and Medicare claims, and information on provider NPI number, practice address, and taxonomy codes. The file was restricted to unique PCP addresses by identifying primary taxonomy codes for primary care. Primary care was defined based on the definition used by the Maryland Primary Care Program (MDPCP). The MDPCP is intended to improve the quality of care delivery and spur innovation in primary care across the state, and defines PCPs using primary taxonomy codes for the following areas of practice: *General Practice, Family Medicine, Internal Medicine, Obstetrics and Gynecology, Geriatric Medicine, Nurse Practitioner, Physician Assistant, and Preventive Medicine.* [80] Specialty related internal medicine practices (e.g., cardiology) and nurse practitioners and physician assistants that were specialist (e.g., critical care) were excluded. The PC practice location data included full unique addresses (i.e., street, city/town, state, zip code) which were used to link with population survey data to describe PC practice location area-level characteristics using ZCTAs.

Travel time

Potential access to NDPP was measured using travel time (in minutes) from PC practice locations to the nearest NDPP site and was the primary outcome of interest. To understand the

variability in travel time estimates by mode of transportation, we used two outcome variables: a) drive time (primary outcome) and b) public transportation time (secondary outcome). Travel time estimates for both travel modes were calculated using the Google Distance Matrix Application Programming Interface (API) key with the Google Maps Platform, which allows users with a unique API key to request distance and travel time data for various travel modes (i.e., driving, transit, walking, and biking) while accounting for road congestion, peak and off-peak hours in traffic patterns in their estimates.[81] Travel times were not specified with the Google Distance Matrix API key but were pulled during typically business hours (Monday through Friday 9am to 5pm EST). For unspecified departure times the Google Maps Platform default route and duration are based on road network and average time-independent traffic conditions, which may vary between nearly-equivalent routes at any time.[82] Users can input origin and destination information that converts to latitude/longitude coordinates and communicates with Google Maps Platform using the Google Distance Matrix API key to generate travel time in minutes. This process was done to calculate travel time to the nearest NDPP for all PC practice locations in our sample. NDPPs that were within the county of the PC practice location or adjacent counties were compiled, then the shortest drive times and public transit travel times were identified and linked to the corresponding PC practice location. To obtain addresses for the nearest NDPP, the CDC NDPP registry, which compiles site name, address and contact information for all NDPP sites and the Diabetes Prevention Recognition Program (DPRP) status (i.e., preliminary, pending, or full) was used. DPRP sets the program standards for delivering NDPP and is the reporting body for NDPP sites to gain and maintain recognition status, which positions programs to become preferred providers. Destinations for

travel time calculations included 51distinct NDPP sites that had CDC recognition (pending, preliminary, or full) in 2019.

Neighborhood Socioeconomic Characteristics

The social deprivation index (SDI) was used to measure neighborhood socioeconomic disadvantage. SDI is a geographic composite measure of area-level deprivation that was developed by Butler and colleagues at the Robert Graham Center and was originally used to measure the association between health care access and outcomes for primary care service areas.[83–85] using the SDI is a continuous variable ranked from 1 (least disadvantaged) to 100 (most disadvantaged) and is calculated using factor analysis directly at the ZCTA level, as well as other geographic units (e.g., census tract) using the following variables from the American Community Survey (ACS) 5- year estimates: *percent living in poverty, percent with less than 12 years of education, percent single parent household, percent living in rented housing unit, percent living in overcrowded housing unit, percent of households without a car, and percent non-employed adults under 65 years of age.* The ACS collects data on population level demographics, socioeconomic, and housing characteristics for the U.S.[86] The most recent publicly available SDI data uses ACS (2011-2015) 5-year estimates and were linked to PC practice locations using ZCTAs. There were three ZCTA that did not have SDI scores and 226 that did not have a PC practice located in the area. These ZCTAs were excluded from our analyses.

Area-Level Demographics

Population level characteristics were used to describe PC practice locations and control for ZCTA characteristics. To predict travel time to the nearest NDPP from PC practice locations using of the level of neighborhood socioeconomic disadvantage in PC practice locations we controlled for population level estimates of race and ethnicity, obesity, and rurality. Obesity is a strong risk factor for prediabetes and diabetes,[87] which may impact local public health diabetes prevention strategies, including NDPP placement. County level obesity prevalence estimates were obtained from the MD Behavioral Risk Factor Surveillance System (BRFSS) 2015-2019 5-year estimates, which collects data on health-related behaviors and conditions that place adults at risk for chronic diseases, injuries, and preventable infectious diseases.[88]

ACS (2015-2019) 5-year estimates files were used to include demographics, such as the percentage of the population that were Non-Hispanic Black, Hispanic, and age 65 years and older. These variables were linked to PC practice locations using ZCTA. The Medicare Diabetes Prevention Program is designed for participants aged 65 years and older, therefore it was important to control for any public health initiatives that may have placed NDPPs in areas with a larger proportion of older adults. Population level race and ethnicity data were used as a proxy measure for residential racial segregation, which has been associated with reduced access and utilization of health care services.[89,90] To account for urban rural variation, the 2010 Rural Urban Commuting Area (RUCA) codes were used to define level of rurality. RUCA codes use a census tract-based classification for commuting flow information to characterize all U.S. census tracts as metropolitan core to rural areas based on population density, urbanization and daily commuter flow.[91] RUCA code available at the ZCTA level were used to create a three-level categorical variable that was linked to PC practice locations and defined as: 0) metropolitan, 1) micropolitan, or 2) rural..

Statistical Analyses

Descriptive analyses of SDI scores for PC practice locations were performed and included population level demographics, obesity prevalence, rurality and number of NDPPs in PC practice locations. Travel time for driving and public transit we both skewed to the right, so the log transformation for these outcome variables were used. A multivariate log-linear regression model was used to examine the relationship between SDI scores of PC practice locations and travel time (i.e., driving and public transit) to the nearest NDPP site from PC practice locations. SDI scores were categorized into quintiles for ease of interpretation and used to predict travel time in our log-linear regression models. The first quintile (least disadvantaged) was designated as the referent group and our models controlled for population-level variables (i.e., percentage Non-Hispanic Black, percentage Hispanic, percentage age 65 years and older, and rurality). We also used robust clustered standard errors at the ZCTA level to adjust for heteroskedasticity (i.e., the variance of unobserved factors not being constant) and autocorrelation which may be a concern for PC practice locations in the same ZCTAs. Additional analyses were performed to compare differences in travel time between counties with the most PC practice locations and all other counties in MD. Finally, to explore the impact that racial residential segregation might have on our findings additional models were run to examine differences in travel time between based on the proportion of minoritized racial and ethnic groups within PC practice locations. Racial and ethnic composition of zip codes has been found to be associated with the use of health care provider services.[90] Statistical significance was evaluated at $p<0.05$. Data analyses and mapping were performed using Stata MP17 (STATACorp LP, College Station, TX). This study was approved by the University of Maryland Institutional Review Board.

Study Results

Our analytic sample included 1,680 unique PC practice locations in MD for 2019, which represented 242 of the 468 ZCTAs included in the 2010 census. PC practice locations were represented across all 24 counties and jurisdictions in MD.. For travel time by public transit (secondary outcome) our sample size was reduced to 1,530 PC practice locations since the Google Cloud Platform was unable to generate public transit estimates for some areas of the state.. PC practice locations were predominately in metropolitan areas (95%) (see Table 1.). This is to be expected since there tends to be a shortage of primary care providers in rural areas compared to metropolitan areas. Overall, the average driving time from PC practice locations to the nearest NDPP was 15 minutes (driving) and 58 minutes (public transit).

Figure 3.1 Social Deprivation Index Score of Primary Care Practice Location ZCTAs in Maryland by SDI Quintiles (Q5=most disadvantaged).

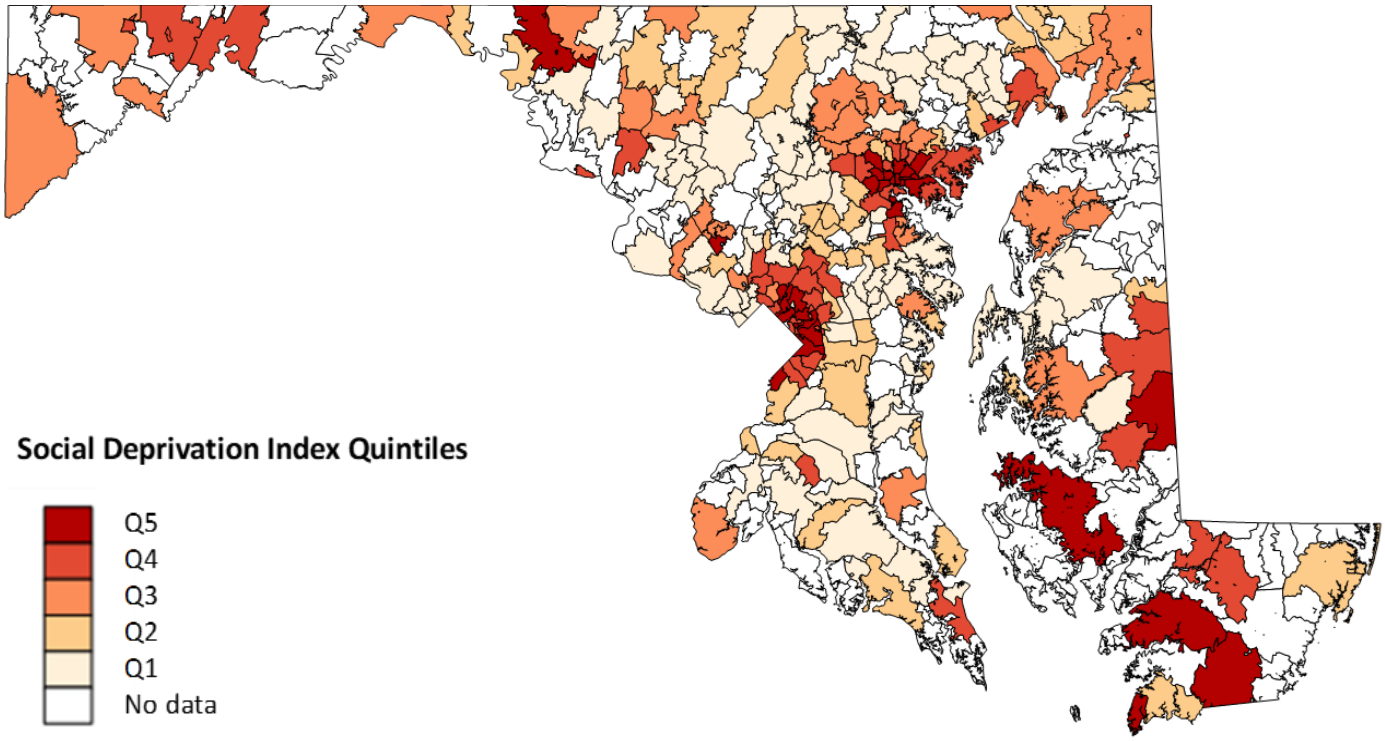

Table 3.1 Neighborhood (ZCTA-Level) Characteristics of Primary Care Practice Locations by Social Deprivation Index Quintile

Neighborhood Characteristics	Q1 (1 to 17) N=366	Q2 (18 to 34) N=307	Q3 (35 to 50) N=359	Q4 (51 to 72) N=385	Q5 (75 to 100) N=263	Overall N=1680
	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
Driving (mins)	18.70 (12.79)	14.18 (16.52)	15.10 (16.00)	15.54 (21.39)	11.79 (14.25)	15.30 (16.76)
LogDriving (mins)	2.72 (0.68)	2.31 (0.80)	2.31 (0.95)	2.31 (0.88)	2.10 (0.82)	2.37 (0.86)
Public Transit (mins)±	67.42 (69.53)	53.74 (74.89)	67.07 (170.89)	61.40 (114.82)	37.61 (67.75)	58.40 (111.40)
LogPublic Transit (mins)±	3.90 (0.83)	3.60 (0.89)	3.55 (1.04)	3.55 (0.94)	3.09 (0.98)	3.55 (0.97)
Non-Hispanic Black (%)	0.13 (0.19)	0.23 (0.22)	0.19 (0.15)	0.34 (0.19)	0.45 (0.25)	0.26 (0.23)
Hispanic (%)	0.06 (0.04)	0.06 (0.05)	0.10 (0.08)	0.11 (0.10)	0.14 (0.08)	0.09 (0.09)
Age 65 years or older (%)	0.16 (0.04)	0.17 (0.07)	0.18 (0.05)	0.14 (0.03)	0.13 (0.04)	0.16 (0.05)
Obesity Prevalence (%)	0.29 (0.05)	0.30 (0.06)	0.30 (0.04)	0.32 (0.05)	0.35 (0.04)	0.31 (0.05)
	n (%)	n (%)	n (%)	n (%)	n (%)	n (%)
Rurality						
Metropolitan	364 (99.45)	285 (92.83)	321 (89.42)	383 (99.48)	240 (91.25)	1,593 (94.82)
Micropolitan	2 (0.55)	20 (6.51)	20 (5.57)	2 (0.52)	11 (4.18)	55 (3.27)
Rural	0 (0)	2 (0.65)	18 (5.01)	0 (0)	12 (4.56)	32 (1.90)
NDPP sites						
0	316 (86.34)	216 (70.36)	116 (32.31)	230 (59.74)	173 (66.78)	1,051 (62.56)
1	50 (13.66)	73 (23.78)	168 (46.80)	126 (32.73)	90 (34.22)	507 (30.18)
2	0 (0)	10 (3.26)	48 (13.37)	29 (7.53)	0 (0)	87 (5.18)
3	0 (0)	8 (2.61)	27 (7.52)	0 (0)	0 (0)	35 (2.08)

Note: Higher quintiles indicate higher socioeconomic disadvantage. Driving time sample size: N=1,680. ±Public transportation time sample size: N=1,530.

Travel time averages prior to and post log transformation are reported to provide additional insight on the range of estimates by SDI quintile. PC practices located in neighborhoods with SDI score in the 1st SDI quintile (least disadvantage) had the highest average drive time (19 minutes). PC practices in neighborhoods with SDI scores in the 5th SDI quintile (most disadvantage) had the highest average proportion of Non-Hispanic Black (45%) and Hispanic (14%) populations. PC practices in neighborhoods with SDI scores in the 3rd SDI quintile had the highest percentage of PC practice locations with at least one NDPP site within its neighborhood boundary (47%).

In our adjusted log-linear regression model showed the PC practices in neighborhoods with SDI scores in the 2nd, 3rd, 4th and 5th SDI quintiles were statistically significantly associated

with shorter drive times to the nearest NDPP site compared to PC practices in neighborhoods with SDI scores in the 1st quintile (least disadvantaged) (see Table 2.). The magnitude of this relationship appears to increase across SDI quintiles, with PC practices in neighborhoods with SDI scores in the 5th SDI quintile (most disadvantaged) having the shortest drive times to the nearest NDPP. PC practices in neighborhoods with SDI scores in the 5th quintile (most disadvantaged) has significantly shorter drive times to the nearest NDPP (by 51%: exp(-0.71)-1)*100= 50.83) compared to PC practices in neighborhoods with SDI scores in the 1st quintile (least disadvantaged). When we consider the average drive time (15 minutes), this percentage decrease in drive time translates to a reduction in drive time by about 8 minutes. This relationship was similar for public transit trave time estimates. PC practices in neighborhoods with SDI scores in the 5th quintile had significantly shorter public transit travel time to the nearest NDPP (by -63% : exp(-0.98)-1) *100= 62.50) compared to PC practices in neighborhoods with SDI scores in the 1st quintile. When we consider the average public transit time (58 minutes), this percentage decrease in public transit time translates to a reduction in public transit time by about 38 minutes.

Each increase in the percentage of Non-Hispanic Black populations in PC practice neighborhoods were associated with a decrease in the percentage of drive time and an increase in the percentage of public transit travel time to the nearest NDPP. However, each increase in the percentage of Hispanic populations in PC practice neighborhoods had a significant increase in both driving and public transit travel times to the nearest NDPPs. Geographic differences were also found, and PC practices located in micropolitan areas were associated with statistically significantly shorter drive times (by -37%; exp(-0.46)-1)*100= 36.87) to the nearest NDPP site compared to PC practices located in metropolitan areas.

Table 3.2 Associations Between Neighborhood Socioeconomic Disadvantage of Primary Care Practice Locations and (Log)Travel Time to the Nearest National Diabetes Prevention Program

Neighborhood Characteristics (Higher quintiles indicate higher socioeconomic disadvantage)	**Driving Time** **Coefficient (95% CI)**	**Public Transportation Time** **Coefficient (95% CI)**
SDI Quintile Category		
1st Quintile (1 to 17)	Reference	Reference
2nd Quintile (18 to 34)	-0.38 (-0.64, -0.13)**	-0.31 (-0.642, -0.00)*
3rd Quintile (35 to 50)	-0.44 (-0.83, -0.05)*	-0.42 (-0.85, -0.00)*
4th Quintile (51 to 72)	-0.47 (-0.79, -0.16)**	-0.45 (-0.83, -0.07)**
5th Quintile (75 to 100)	-0.71 (-1.06, -0.36)**	-0.98 (-1.37, -0.60)**
Non-Hispanic Black (%)	-0.11 (-0.63, 0.42)	0.05 (-0.47, 0.57)
Hispanic (%)	1.32 (0.14, 2.50)*	1.57 (0.01, 3.14)**
65 years or Older (%)	-0.06 (-2.63, 2.51)	-0.39(-3.38, 2.59)
Obesity Prevalence (%)	0.38 (-1.38, 2.13)	-0.13 (-2.53, 2.28)
Rurality		
Metropolitan	Reference	Reference
Micropolitan	-0.45 (-0.91, -0.01)*	0.01 (-0.43, 0.46)
Rural	0.08 (-0.82, 0.97)	0.40(-0.45, 1.45)

Adjusted log-linear regression specifying clustering at the zip code-level and controlling for the following covariates: percentage of Non-Hispanic Black population, percentage of Hispanic population, percentage of population 65 years of age and older, prediabetes prevalence, and rurality. Driving time sample size: N=1,680. Public transportation time sample size: N=1,530. The 1st (lowest) quintile for social deprivation index quintiles is the referent.
Statistical significance: * $p < 0.05$ **$p<0.01$

Additional descriptive analysis revealed that five counties/jurisdictions (i.e., Anne Arundel, Baltimore, Montgomery, Prince Georges counties and Baltimore city) had a substantially higher number of PC practices located in their area (see Appendix Table A.). To understand how this might affect travel time estimates to the nearest NDPP, stratified analyses were performed to compare travel time estimates for PC practices located in the five counties/jurisdictions with the highest number of practices to all other counties within the state of MD. Travel estimates (driving and public transit) to the nearest NDPP for the subset analysis of PC practices located in counties with a higher concentration of PC practices and in neighborhoods with SDI scores in the 5th quintile were consistent with our primary model. (see Table 3). However, public transit times for the subset analysis of PC practices located in counties

with lower concentrations of PC practices showed that with each percentage increase of Non-Hispanic Black populations was associated with decreased public transit times to the nearest NDPP, but this was not statistically significant.

Table 3.3 Associations between Neighborhood Socioeconomic Disadvantage of Primary Care Practice Locations and (Log)Travel Time to the Nearest National Diabetes Prevention Program Site by Counties with the Highest vs. Lowest Concentration of Primary Care Practice Locations

Neighborhood Characteristics (Higher quintiles indicate higher socioeconomic disadvantage)	**High**		**Low**	
	Driving Coefficient (95% CI)	**Public Transportation Coefficient (95% CI)**	**Driving Coefficient (95% CI)**	**Public Transportation Coefficient (95% CI)**
SDI Quintile Category				
1st Quintile (1 to 17)	Reference	Reference	Reference	Reference
2nd Quintile (18 to 34)	-0.24 (-0.57, 0.09)	-0.25 (-0.61, 0.12)	-0.56 (-0.95, -0.17)**	-0.61 (-1.08, -0.13)*
3rd Quintile (35 to 50)	-0.07 (-0.60, 0.47)	-0.12 (-0.68, 0.44)	-1.12 (-1.60, -0.65)**	-1.29 (-1.78, -0.80)**
4th Quintile (51 to 72)	-0.32 (-0.76, 0.11)	-0.51 (-1.02, 0.00)	-0.64 (-1.01, -0.27)**	-0.38 (-0.85, 0.08)
5th Quintile (75 to 100)	-0.60 (-1.03, -0.17)**	-1.04 (-1.52, -0.55)**	-0.97 (-1.65, -0.30)**	-0.99 (-1.65, -0.33)**
Non-Hispanic Black (%)	-0.08 (-0.78, 0.61)	0.27 (-0.46, 0.99)	-1.43 (-2.77, -0.09)*	-0.86 (-2.40, 0.67)
Hispanic (%)	1.07(-0.27, 2.41)	1.65 (-0.09 3.40)	4.78 (1.08, 8.48)*	9.27 (5.45, 13.09)**
Age 65 years or Older (%)	-0.47 (-3.82, 2.89)	-0.93 (-4.65, 2.79)	-0.53 (-3.85, 2.80)	0.80 (-3.09, 4.67)
Obesity (%)	0.36 (-2.07, 2.79)	-0.34 (-3.49, 2.81)	2.18 (-0.63, 4.99)	0.29 (-4.04, 4.61)
Rurality	Omitted	Omitted		
Metropolitan			Reference	Reference
Micropolitan			-0.29 (-0.83, 0.25)	-0.03 (-0.47, 0.42)
Rural			0.44 (-0.44, 1.31)	0.77 (-0.07, 1.61)

Adjusted log-linear regression specifying clustering at the zip code-level and controlling for the following covariates: percentage of Non-Hispanic Black population, percentage of Hispanic population, percentage of population 65 years of age and older, prediabetes prevalence, and rurality. Counites with the highest concentration of primary care practice locations included the five following counties and jurisdiction: Anne Arundel, Baltimore City, Baltimore County, Montgomery County, and Prince George's County. Sample sizes varied for all estimates and are as follows from columns left to right: N=1,043, N=1,006, N=637, and N=524. The 1st (lowest) quintile for social deprivation index quintiles is the referent. Statistical significance: * $p < 0.05$ **$p<0.01$.

Table 3.4 Associations between Social Deprivation Index Quintiles of Primary Care Practice Locations and (Log)Travel Times to the Nearest National Diabetes Prevention Program Site by the Percentage of Non-Hispanic Black Populations in Primary Care Practice Locations

Neighborhood Characteristics	Non-Hispanic Black Population More than 45%		Non-Hispanic Black Population Less than 45%	
	Driving Coefficient (95% CI)	Public Transportation Coefficient (95% CI)	Driving Coefficient (95% CI)	Public Transportation Coefficient (95% CI)
SDI Quintile Category				
1st Quintile (1 to 17)	Reference	Reference	Reference	Reference
2nd Quintile (18 to 34)	0.33 (-0.48, 1.14)	0.18 (-0.78, 1.19)	-0.44 (-0.71, -0.18)**	-0.33 (-0.67, -0.01)*
3rd Quintile (35 to 50)	0.96 (0.44, 1.47)**	0.61 (0.15, 1.76)*	-0.60 (-1.01, -0.20)**	-0.50 (-0.96, -0.04)
4th Quintile (51 to 72)	0.54 (0.04, 1.12)*	0.33 (-0.11, 1.31)	-0.70 (-1.03, -0.36)**	-0.61 (-1.03, -0.19)**
5th Quintile (75 to 100)	0.16 (-0.41, 0.72)	-0.43 (-0.97, 0.68)	-1.00 (-1.37, -0.63)**	-0.98 (-1.41, -0.56)**
Hispanic (%)	1.77 (-0.94, 4.48)	2.71 (-1.00, 6.42)	1.83 (0.41, 3.25)*	1.42 (-0.36, 3.19)
Age 65 years or Older (%)	2.81 (-4.25, 9.86)	3.40 (-4.93, 11.72)	-0.18 (-3.01, 2.65)	-0.80 (-4.21, 2.61)
Obesity (%)	0.35 (-4.37, 3.68)	-0.71 (-5.81, 4.40)	-1.35 (-0.53, 3.22)	0.35 (-2.27, 2.98)
Rurality	Omitted	Omitted		
Metropolitan			Reference	Reference
Micropolitan			-0.43 (-0.92, 0.05)	-0.01 (-0.47, 0.48)
Rural			0.15 (-0.77, 1.08)	0.48 (-0.49, 1.46)

Adjusted log-linear regression specifying clustering at the zip code-level and controlling for the following covariates: percentage of Non-Hispanic Black population, percentage of Hispanic population, percentage of population 65 years of age and older, prediabetes prevalence, and rurality. Rurality was omitted in models due to collinearity. Sample sizes varied for all estimates and are as follows from columns left to right: N=351, N=345, N=1,329, and N=1,185. The 1st (lowest) quintile for social deprivation index quintiles is the referent.
Statistical significance: * $p < 0.05$ **$p<0.01$.

Additional stratified analyses were done to estimate the potential impact racial residential segregation might have on the association between SDI and travel time to the nearest NDPP. Prior research has used population-level proportions of minoritized racial and ethnic groups that were greater than 50% within a primary care service areas and ZCTA as a proxy measure for racial residential segregation.[89,90] Due to limited sample size of Hispanic populations in some of the areas where PC practices were located, we examined PC practice neighborhoods with where the percentage of Non-Hispanic Black populations were greater than 45% and less than 45% to gain insight on any potential impact racial residential segregation may have on our estimates. We found that for PC practices in neighborhoods with SDI scores in the 2nd, 3rd, 4th, and 5th SDI quintiles where the percentage of Non-Hispanic Black populations were less than 45%, drive

times to the nearest NDPP were significantly shorter compared to PC practices in neighborhoods with SDI scores in the 1st quintiles. This is consistent with findings in our main model for drive time. (see Table 4). However, for PC practices in neighborhoods with SDI scores in the 3rd and 4th SDI quintile where the percentage of Non-Hispanic Black populations were greater than 45%, drive times to the nearest NDPP were significantly longer compared to PC practices in neighborhoods with SDI scores in the 1st quintile. The direction of this relationship was similar for public transit travel estimates. PC practices in neighborhoods with SDI scores in the 3rd SDI quintile where the percentage of Non-Hispanic Black populations were greater than 45%, had significantly longer public transit travel times to the nearest NDPP compares to practices in neighborhoods with SDI scores in the 1st quintile. However, public transit travel time to the nearest NDPP was shorter for PC practices in neighborhoods with SDI scores in the 5th quintile where the percentage of Non-Hispanic Black populations were greater than 45%, but this was not statistically significant.

Discussion

Our study found that PC practices in neighborhoods with higher SDI scores were associated with significantly shorter driving and public transit travel times to the nearest NDPP site. This relationship was most prominent for PC practices in neighborhoods with the highest SDI scores. Although we expected that PC practices in neighborhoods with higher SDI scores would be associated with longer travel times to the nearest NDPP, these findings suggest that neighborhood socioeconomic disadvantage may not impact the availability of NDPP sites and potential access to this important diabetes prevention resource in the state of MD. Furthermore, geographic proximity between PC practices and NDPP sites may not be a barrier to potential clinical-community linkages and there appears to be potential for creating referral networks. Our

findings are promising in that they point to strategies unique to MD that could contribute to increasing potential access to NDPP, particularly in areas with highest levels of socioeconomic disadvantage.

Although patient addresses were not employed in this study, health care resources in close proximity to PC practices can benefit patients through referrals to community-based health resources like NDPPs. This is particularly true for PCPs who often have the most continuity of care with patients and represent a large portion of safety-net providers, which presents an opportunity to expand NDPP access and use among underserved populations. Some evidence has shown that the proximity of the referral entities to the primary care providers can inform patient referral patterns.[40,42] Although, there is no consensus on what constitutes reasonable travel time to NDPPs or other preventative services, the average driving times to medical or dental care in urban and rural areas have been estimated to be 21 and 27 minutes respectively.[92] In our study the average drive times to the nearest NDPP from PC practice locations was 15 minutes, which may indicate that the geographic placement of NDPPs is adequate. However, the average public transit travel time in our study was 58 minutes, which has implications for access and use NDPPs among patients who rely on public transit and live in an area where travel time to their PCP is 15 minutes or less.

Our findings suggest that the availability of PC practices and NDPPs can be used to create referral networks that address inequities in NDPP availability for individuals with prediabetes, particularly those living in neighborhoods with higher levels of socioeconomic disadvantage where PC practices are also located . Neighborhood socioeconomic characteristics and health outcomes have been found to be associated with reduced access to health care services and related resources and adverse health outcomes. For example, areas that are more

socioeconomically disadvantaged have been associated with poorly controlled diabetes,[93–95] higher incidence of diabetes and reduced colorectal cancer screening.[96] Subsequent stratified analyses reveal that residential segregation among Non-Hispanic Black populations may constrain the geographic proximity of PC practices to NDPPs sites. Our study revealed driving and public transit travel times to the nearest NDPP were actually longer for PC practices in neighborhoods with higher levels of socioeconomic disadvantage where the percentage of Non-Hispanic Black populations were greater than 45% compared to PC practices in neighborhoods with the least socioeconomic disadvantage. This can contribute to reduced provider referrals for prediabetes patients in these neighborhoods and lead to disparities in access to NDPP. Prior research has found that communities with predominately minoritized racial and ethnic groups often have less access to certain health care resources (e.g., psychiatrist).[90,97] Therefore, it is important that future studies continue to explore the role racial residential segregation plays in access and use of NDPPs.

Our findings are promising because they are likely a result of years of building the capacity to deliver NDPP by a strong public health planning and infrastructure in MD. In our study we found PC practices were primarily concentrated in five counties and jurisdictions (i.e., Anne Arundel, Baltimore, Montgomery, Prince Georges, and Baltimore city) which also had the highest population estimates within the state.[98] This is probably explained by primary care shortages more likely in rural areas compared to metropolitan areas.. Our findings also suggest that there were more available NDPPs within or in close proximity to PC practices with higher socioeconomic disadvantage. This is my be driven by the infrastructure, systems, and investments into NDPP that were initiated by the Medicaid Demonstration implemented in MD from 2016 to 2019, which laid the groundwork for integrating NDPP networks, multi-sector

partnerships, and innovative primary care delivery models to align with statewide diabetes prevention goals.[49] This demonstration included four managed care organizations (MCOs) that contracted directly with CDC-recognized NDPPs. The first year of the demonstration targeted Medicaid beneficiaries at risk for developing type 2 diabetes who primarily lived in Baltimore City, Baltimore County, Montgomery County, and Prince George's County. In 2019, through an 1115 HealthChoice Demonstration waiver for Medicaid, MD continued to offer NDPP across the state which spurred a myriad of cross-sector partnerships to support referrals and NDPP delivery. In addition to the health system and public health sector efforts, MDs statewide Diabetes Action Plan also promoted NDPP as a primary strategy to address prediabetes and populations at risk for developing type 2 diabetes.[36] These statewide interventions not only helped to address inequities in access to NDPP by targeting low-income populations at risk for diabetes, but also expanded the availability of NDPP sites and promoted community-clinical linkages between health care and public health sectors statewide.

Our study had several limitations. First, we examined associations between SDI and travel time estimates to the nearest NDPP from PC practices, so no causal inferences can be made. Future studies should measure PCP referrals to NDPPs to better understand referral networks between PCPs and community based NDPP sites. Second, NDPP site location relied solely on address information from the CDC NDPP registry. Due to flexibility in NDPP organizational structures, a site may include multiple locations that report up to the primary NDPP for CDC reporting purposes. This likely resulted in an undercount of NDPPs across MD. Our sample is not representative of every ZCTA within the state of MD due to the lack of PC practices located within these areas. Therefore, our findings should be interpreted within the context of ZCTA that have PC practices available. Although primary care shortage areas are a

challenge in many states the lack of primary care presence in these areas not only reduces access to primary care services but may also reduce access to additional preventative health care resources such as NDPPs. Additional research is needed to understand the relationship between primary care shortage areas and access to NDPP. This study does not consider the role of virtual NDPP offerings, which were widely promoted during COVID-19 to expand access, particularly in rural communities. Therefore, we are not able to account for any potential partnership development between PC practices and virtual NDPPs. However recent findings from a longitudinal study found that although adults referred to virtual NDPPs were more likely to enroll, participants that attended in-person NDPP met program goals of more than 5% weight loss more often than virtual participants.[99]

This study focused on potential access to NDPP, therefore we did not specifically explore any partnerships or referrals between PC practices and NDPP sites. However, future studies should examine how neighborhood socioeconomic disadvantage impacts partnership formation among these entities. In 2021 MD established the Regional Partnership Catalyst Program, which focuses on increasing collaboration between hospitals and community partners to support the state's population health goals, including the use of NDPP as a diabetes prevention. Leveraging data from this intervention could help examine partnership formation and referrals.

This study provides a foundational understanding of how neighborhood socioeconomics characteristics influence the organization of critical entities needed for NDPP (i.e., PC practice and NDPP sites) and has highlighted the need to characterize organizational structures, local referral networks, and partnerships that facilitate NDPP access and use. Future studies must also consider the impact COVID-19 pandemic had on the availability and accessibility of NDPPs, particularly in-person offerings. In addition to geographic proximity, there are other factors that

contribute to cross-sector partnerships that were not able to be capture in this study. As previously mentioned, MD has established coverage of NDPP by payers and MCO contracts created preferred NDPP suppliers. These activities also support the creation and sustainability of cross-sector partnerships. Although our findings are not generalizable, they can inform population health strategies that other states can adopt to ensure there is infrastructure and availability of NDPP sites in areas of high need.

Conclusion

PC practices located in neighborhoods with higher levels of socioeconomic disadvantage were significantly associated with shorter driving and public transit travel times to the nearest NDPP site. This study is focused on the state of MD, therefore findings may not be applicable to other states. However, this study appears to reinforce the benefits of strong public health and health system infrastructure. Other states can learn from and adopt many of the strategies employed in MD such as developing health care provider referral networks and MCO contracts with NDPP sites which can help facilitate cross-sector partnerships to increase program referrals and uptake, particularly in areas that are socioeconomically disadvantaged.

Chapter 4: Understanding Neighborhood Socioeconomic Disadvantage and Travel Time to National Diabetes Prevention Program: A Maryland Perspective

Abstract

Background: The relationship between neighborhood socioeconomic characteristics and health outcomes has been well studied. However, very few studies have explored how neighborhood socioeconomic characteristics may impact patient travel time to preventive health care resources.

Purpose: The purpose of this study is to assess whether neighborhood socioeconomic disadvantage prolongs travel time to the National Diabetes Prevention Program (NDPP), an evidence-based lifestyle change program for individuals with prediabetes or at risk for developing type 2 diabetes.

Data Methods: The Maryland Medical Care Data Base, which includes privately insured claims data and Medicaid claims data were used to identify patients diagnosed with prediabetes in 2019. To describe neighborhood socioeconomic disadvantage, claims data were linked to social deprivation index 2015 by zip code tabulation area (ZCTA). Google Maps Platform and Google Distance Matrix Application Programming Interface were used to calculate travel time estimates from patient ZCTA centroid to the nearest NDPP site. Generalized linear models were used to estimate driving and public transit travel times to the nearest NDPP using SDI quintiles controlling for sex, age, race and ethnicity, insurance type, rurality, chronic condition, and the interaction of SDI quintile and race and ethnicity.

Results: Beneficiaries living in neighborhoods with SDI scores in the 5th quintile (most disadvantaged) had on average significantly shorter drive times (average marginal effect (AME): -9.07; 95% CI:-11.60, -6.54) to the nearest NDPP compared to beneficiaries living in neighborhoods with SDI scores in the 1st quintile (least disadvantaged). We find a similar

relationship for public transit travel time estimates. The largest reduction in drive time to the nearest NDPP were among Non-Hispanic White beneficiaries living in neighborhoods with SDI scores in the 5th quintile who had on average significantly shorter drive times (AME: -12.03; 95 % CI:-14.79, -9.27) compared to Non-Hispanic Black beneficiaries (AME:-5.15; 95% CI:-8.97, -1.34) and other racial and ethnic groups (AME:-7.75 95% CI:-10.22, -5.29) living in similar neighborhoods compared to their counterparts living in neighborhoods with SDI scores in the 1st quintile.

Conclusion: We find that on average travel time to the nearest NDPP was shorter for beneficiaries living in neighborhoods with higher levels of socioeconomic disadvantage, particularly in neighborhood with the highest level of socioeconomic disadvantage. Our findings indicate the availability and placement of NDPPs in Maryland are in areas of high need. Though this study is restricted to Maryland, other states looking to invest in NDPP could learn from some of the diabetes prevention initiatives implemented by Maryland.

Introduction

The National Diabetes Prevention Program (NDPP) has been widely promoted as an evidence-based intervention to prevent diabetes after randomized clinical trials showed lifestyle change programs were more effective in delaying the onset of type 2 diabetes for 10 years or more compared to the mediation metformin.[1,2] Since the establishment of NDPP over a decade ago, coverage for NDPP has expanded to about 4 million public employees in 20 states, over 100 private payers, 22 state Medicaid agencies and Medicare beneficiaries through the Medicare Diabetes Prevention Program (MDPP).[55] It is estimated that 38% of adults in the U.S. have prediabetes,[8] still NDPP participation and retention remains low. There has been a concerted effort over the past decade to increase the capacity to deliver NDPP at the federal level and across states,[3–7] particularly in community-based settings. Still, the most recent estimates show that on average only 5% of patients with prediabetes are referred to NDPP or similar program, and of those referred about 40% participate.[18]

Patient recruitment and retention, staff training, health care provider engagement and referrals are often noted as challenges[19,20,22,24] to increasing NDPP access and utilization. The design of the NDPP has also created barriers to enrollment and retention among eligible individuals.[100] The NDPP is a 12-month lifestyle change program that requires participants attend 8 out of 16 weekly sessions offered in the first 6-months and monthly sessions for the last 6-months of the program, consume a nutrient dense diet and engage in weekly physical activity (150 minutes/week).[48] Although virtual NDPP offerings have been widely promoted to provide participants with a convenient alternative and mitigate barriers to engagement such as transportation, this mode of delivery can create barriers for communities that are under

resourced. Virtual offerings bring unique challenges related to technology literacy and access to broadband internet, particularly for underserved populations, including older adults, rural communities, or individuals with low income.[101–103] Evidence has also shown that in-person participants are more likely to achieve program goals compared to virtual participants.[99] This may be due to the social connections in-person engagement is able to cultivate in comparison to virtual alternatives. Still, the level of engagement required by in-person NDPP likely presents barriers for prospective participants who face challenges related to transportation or limited social supports to participate in a program that requires such frequent engagement.

Transportation barriers such as travel time has been identified as a barrier to NDPP access but has not been well explored in the literature. particularly with respect to how one's neighborhood socioeconomic characteristics might contribute to this relationship. Understanding the role social drivers of health plays in exacerbating barriers to NDPP access such as transportation can support developing targeted strategies that mitigate these factors for populations that may benefit the most from this preventative health care resource. The association between neighborhood environment and access to health care resources and outcomes has been well established in the literature.[28,77,104–107] Neighborhood socioeconomic disadvantage has been used to refer to areas that have been challenged by limited economic, human capital, or material resources[28,29] often due to inequitable long-term investments and resource allocation. Neighborhood socioeconomic disadvantage has also been shown to be associated with poorly controlled diabetes,[93] progression from prediabetes to diabetes,[31] and a lower availability of community-based organizations,[71] including NDPPs.[32,33] NDPP participants living in neighborhoods with higher levels of socioeconomic disadvantage may face challenges in accessing this program due to longer travel times.[25] Individuals who earn lower-income often

rely on public transportation, which has been associated with missed medical appointments and delayed care.[108,109]

Study Aims and Hypotheses

This study fills a major gap in the literature by examining the relationship between neighborhood socioeconomic disadvantage and travel time to nearest NDPP among individuals with prediabetes. This has important implications for potential access to NDPP. Potential access has been defined as the presence of enabling resources which increase the likelihood of health care use, and also includes enabling conditions such as one's neighborhood or.[68,69] We hypothesize that travel time to the nearest NDPP will be longer for individuals in neighborhoods with higher levels of socioeconomic disadvantage.

Maryland is an ideal setting to examine this relationship due to its extensive statewide investments in NDPP through its participation the Medicaid NDPP Demonstration in 2016, statewide Diabetes Action Plan and promotion of NDPP among health care providers in its Maryland Primary Care Program.[36,38,49,110] Neighborhood socioeconomic disadvantage will be measured using the social deprivation index, a validated small areal-level deprivation composite measure that includes seven population-level demographics related to socioeconomic conditions, including the percent households with no vehicle.[83,85] The concept of a neighborhood has not been explicitly defined[76–78] and has been measured using various geographic units such as census-block group, census tract, and ZIP Code Tabulated Areas (ZCTAs)[79] in research that examines neighborhood socioeconomic disadvantage. Our study is restricted to data prior to the COVID-19 pandemic that began in 2020 due to the drastic impact this event had on reducing access and use of preventative health care resources.[111,112] This study will provide insights on

how neighborhood socioeconomic disadvantage should be considered in improving access to NDPP.

Study Data and Methods

Data Source

The Maryland Medical Care Database (MCDB), which includes private insurance claims data for all care settings, and MD Medicaid Managed Care data were used to identify adults 18 years or older with a diagnosis of prediabetes enrolled for the entire year in 2019. Adults with prediabetes were identified in the MCDB commercial claims and Medicaid Managed Care claims for 2019 using the International Classification of Diseases (ICD)-10 codes used to diagnose patients with prediabetes (i.e., R7301-Impaired fasting glucose, R7302-Impaired glucose tolerance – Oral, and R7303-Prediabetes). MCDB and Medicaid Managed Care data were also used to characterize beneficiaries by sex, age, race and ethnicity, insurance type (commercial vs. Medicaid) and whether they had co-occurring chronic condition associated with increased risk for diabetes. Cardiometabolic conditions such as hypertension and hyperlipidemia have been found to be a risk factor for the development of diabetes among individuals with prediabetes or at risk for diabetes[8] and were used to defined chronic conditions in our sample. ICD-10 codes were used to identify diagnoses of hypertension or hyperlipidemia (i.e., E785) in our sample and were used to define chronic condition. MCDB and MD Medicaid Managed Care data are restricted use data that are made available to researchers by applying to the MD Health Care Commission (MHCC). MCDB and MD Medicaid Managed Care claims data were authorized for use by the Maryland Health Care Commission under a Data Use Agreement with the University of Maryland College Park School of Public Health.

Measures

Travel time

Beneficiaries potential access to NDPP was measured using travel time (in minutes) from beneficiary ZCTA to the nearest NDPP site and was the primary outcome of interest. The MCDB and MD Medicaid Managed Care data limited patient identifiable data, therefore ZCTAs were used to identify beneficiary neighborhood and estimate travel time by driving and public transit to the nearest NDPP site. It was important to estimate both drive time and public transit times to understand how variations in travel mode impacts the relationship between neighborhood socioeconomic disadvantage and travel time to the nearest NDPP.

The Google Distance Matrix Application Programming Interface (API) key for the Google Maps Platform was used to generate travel time estimates. The Google Maps Platform allows users with a unique Distance Matrix API key to request distance and travel time data for various travel modes (i.e., driving, transit, walking, and biking) and accounts for typical road congestion, as well as peak and off-peak hours in traffic patterns in their estimates.[81] Users can input origin and destination information using the Google Distance Matrix API key which communicates to the Google Maps Platform which then converted this information to geographic coordinates (latitude and longitude) and estimates travel time in minutes. For origins that are limited to ZCTAs, travel time estimates are calculated using the centroid of the ZCTA.

Drive time to the nearest NDPP was calculated for all beneficiaries in our sample. However, public transit travel time estimates were not available for all beneficiary ZCTAs, due to limited availability of public transportation in some areas of MD. Travel time estimates for NDPPs that were within the county of the beneficiary ZCTA or adjacent counties were compiled, then the shortest driving and public transit travel times were identified and linked to the corresponding beneficiary claims information by ZCTA. Travel time date and times were not

specified in our inputs with the Google Distance Matrix API key, instead travel time estimates were pulled during typically business hours (Monday through Friday 9am to 5pm EST). When departure times are not specified in the Google Maps Platform route and duration are based on road network and average and average time-independent traffic conditions, which may vary between nearly-equivalent routes at any time.[82] Destination data for travel time calculations were identified using the CDC NDPP registry and included 51distinct NDPP sites with CDC Diabetes Prevention Recognition Program (DPRP) recognition (i.e., pending, preliminary, or full). DPRP is the reporting body for NDPP sites to gain and maintain recognition status, which positions programs to become preferred providers.

Neighborhood Socioeconomic Disadvantage

The social deprivation index (SDI) was used to measure neighborhood level socioeconomic disadvantage. SDI is geographic composite measure of area-level deprivation developed by Butler and colleagues at the Robert Graham Center [85] using data from the American Community Survey (ACS) 5- year estimates which collects data on demographic, social, economic, and housing characteristics of the U.S. population.[86] SDI was originally used to measure the association between health care access and outcomes for primary care service areas,[83,84] and is a continuous variable ranked from 1 (least disadvantaged) to 100 (most disadvantaged). Factor analysis is used to calculate SDI scores directly at the ZCTA level using the following ACS variables: percent living in poverty, percent with less than 12 years of education, percent single parent household, percent living in rented housing unit, percent living in overcrowded housing unit, percent of households without a car, and percent non-employed adults under 65 years of age.[85] SDI scores are also available in other geographic units (e.g., census tract), but ZCTAs could easily be linked to beneficiary 5-digit zip codes which overlap

with most ZCTAs[113] The most recent publicly available SDI data using ACS (2011-2015) 5-year estimates were used.

Covariates of Interest

The selection of covariates were informed by Andersen's Behavior Health Use model.[68] Predisposing variables included sex which was categorized as male or female, and age which was categorized as defined as follow: 0) 18 to 34 years, 1) 35 to 44 years, and 2) 45 to 64 years. Although our entire sample was insured, insurance type, and enabling resource was also controlled and dichotomized as commercial or Medicaid plan. To account for urban rural variation, the 2010 Rural Urban Commuting Area (RUCA) codes were used to define level of rurality. RUCA codes use a census tract-based classification for commuting flow information to characterize all U.S. census tracts as metropolitan core to rural areas based on population density, urbanization and daily commuter flow.[91] RUCA code files available for ZCTA were used to create a three-level categorical rurality variable which was defined as: 0) metropolitan, 1) micropolitan, or 2) rural, and were linked to beneficiaries by ZCTA. Race and ethnicity were used in the analysis as: non-Hispanic White, non-Hispanic Black, and other racial and ethnic groups. These included Asian, Hispanic, multiracial, and racial and ethnic groups that could not be identified due to small sample sizes.

Statistical Analyses

Descriptive and bivariate analyses of beneficiary characteristics and SDI quintiles were performed, including chi-square tests. SDI scores for beneficiary neighborhoods were categorized into quintiles for ease of interpretation, where the 5th SDI quintile represented neighborhoods with the highest levels of socioeconomic disadvantage and the 1st SDI quintile

represented neighborhoods with the lowest levels of socioeconomic disadvantage. Due to the right skewness of our travel time variables (drive time and public transit time) we used the log transformation of these outcome variables in a log-linear regression model to examine the relationship between neighborhood socioeconomic disadvantage and travel time to the nearest NDPP site among beneficiaries with prediabetes. Then SDI quintiles were used as the primary predictors in an adjusted log-linear regression model that used the 1st SDI quintile as the reference group. To understand the interaction race and ethnicity and SDI scores may have on travel time, interaction terms for SDI quintiles and racial and ethnicity were included in our models. In addition, stratified models by race and ethnicity were also performed to further understand how beneficiary characteristics impact travel time to the nearest NDPP site.

Sensitivity analyses were conducted using a generalized Linear Model (GLM) with gamma distribution with log link . All models controlled for sex, age, race and ethnicity, insurance type, rurality and chronic condition and used robust clustered standard errors at the beneficiary zip code level to adjust for heteroskedasticity (i.e., the variance of unobserved factors not being constant) and autocorrelation which may be a concern for beneficiaries within the same zip code. Adjusted log-linear regression and GLM with gamma distribution and log link estimates were consistent, therefore average marginal effects for GLM estimates were reported for ease of interpretation in understanding how neighborhood socioeconomic disadvantage may contribute to travel time to the nearest NDPP. Statistical significance was evaluated at $p<0.05$. Data analyses were performed using Stata MP16 (STATACorp LP, College Station, TX). This study was approved by the University of Maryland Institutional Review Board.

Study Results

The final analytic sample included a total of 15,525 beneficiaries, of these 11,047

beneficiaries were in neighborhoods where public transit travel time estimates could be generated. Our sample represented 406 out of the 468 ZCTAs in MD and all 24 counties and jurisdictions within the state. Beneficiaries were predominately 45 to 64 years of age (80%), female (57%), commercially insured (78%), and lived primarily in metropolitan areas (96%) (See Table 1).

Table 4.1 Beneficiary Characteristics by Neighborhood Social Deprivation Index Quintile.

Beneficiary Characteristics	**Overall**	**Q1** *Low SDI* **(1 to 10)**	**Q2** **(11 to 26)**	**Q3** **(27 to 47)**	**Q4** **(48 to 71)**	**Q5** *High SDI* **(72 to 100)**	***P***
	N=15,527 Mean (SD)	**N=3,054** Mean (SD)	**N=3,092** Mean (SD)	**N=2,902** Mean (SD)	**N=3,190** Mean (SD)	**N=3,289** Mean (SD)	
Travel Time							
Drive Time	14.4 (7.1)	19.6 (7.7)	15.2 (6.0)	16.0 (6.8)	12.6 (5.9)	9.0 (3.6)	
Public Transit	47.9 (31.9)	74.0 (40.9)	51.9 (26.4)	57.2 (42.4)	47.4 (23.4)	28.6 (14.5)	
	n(%)	**n(%)**	**n(%)**	**n(%)**	**n(%)**	**n(%)**	
Age							
18 to 34 years	1,064 (7%)	141 (5%)	191 (6%)	180 (6%)	267 (8%)	285 (9%)	<.01
35 to 44 years	1,970 (13%)	329 (11%)	385 (13%)	363 (13%)	454 (14%)	439 (13%)	
45 to 64 years	12,493 (80%)	2,584 (84%	2,516 (81%)	2,359 (81%)	2,469 (78%	2,565 (78%)	
Sex							
Male	6,700 (43%)	1,466 (48%)	1,409 (46%)	1,247 (43%)	1,306 (41%)	1,272 (39%)	<.01
Female	8,827 (57%)	1,588 (52%)	1,683 (54%)	1,655 (57%)	1,884 (59%)	2,017 (61%)	
Race and ethnicity							
Black	5,698 (37%)	385 (12%)	795 (26%)	792 (27%)	1603 (50%)	2,123 (65%)	<.01
White	8,271 (53%)	2,217 (73%	1,908 (62%	1,808 (62%)	1,310 (41%)	1,028 (31%)	
Other Racial Groups	1,558 (10%)	452 (15%)	389 (12%)	302 (11%)	277 (9%)	138 (4%)	
Insurance type							
Medicaid	3,379 (22%)	245 (8%)	408 (13%)	477 (16%)	845 (27%)	1,404 (43%)	<.01
Commercial	12,148 (78%)	2,809 (92%)	2,684 (87%)	2,425 (84%)	2,345 (73%)	1,885 (57%)	
Chronic Condition							
No	6,671 (43%)	1,420 (46%)	1,297 (42%)	1,269 (44%)	1,346 (42%)	1,339 (41%)	<.01
Yes	8,856 (57%)	1,634 (54%)	1,795 (58%)	1,633 (56%)	1,844 (58%)	1,950 (59%)	
Rurality							
Metropolitan	14,856 (96%)	3,046(99.7%)	2,908 (94%)	2,796 (96%)	2,984 (94%)	3,122 (95%)	<.01
Micropolitan	443 (3%)	**	166 (5%)	60 (2%)	146 (4%)	71 (2%)	
Rural	228 (1%)	**	18 (1%)	46 (2%)	60 (2%)	96 (3%	

Note: **Cell count less than 10. Higher quintiles indicate higher levels of socioeconomic disadvantage. Chi-square statistical test performed. Statistical significance: $p < 0.05$ and $p<0.01$

The proportion of racial and ethnic groups in our sample varied by SDI quintile, with higher percentages of Non-Hispanic White beneficiaries in neighborhoods with SDI scores in the

3rd SDI quintile or mid-range levels of socioeconomic disadvantage and higher percentages of Non-Hispanic Black beneficiaries in neighborhoods with SDI scores in the 4th SDI quintiles or higher levels of socioeconomic disadvantage. The average drive time for beneficiaries was 14.4 minutes and public transit time averaged 48.0 minutes. As beneficiary neighborhood SDI quintiles increased so did the average driving and public transit times.

Average marginal effects from our GLM model showed that compared to beneficiaries located in neighborhoods with SDI scores in the 1st quintile, beneficiaries in neighborhoods with SDI scores in higher quintiles were significantly associated with shorter drive times to the nearest NDPP (See Table 2). In comparison to beneficiaries living in neighborhoods with SDI scores in the 1st quintile (least disadvantaged), beneficiaries living in neighborhoods with SDI scores in the 5th quintiles (most disadvantaged) had on average a 9.07 minute shorter drive time (average marginal effect (AME):-9.07 mins; 95% CI:11.60 to -6.54) to the nearest NDPP. In addition, beneficiaries that lived in micropolitan areas, compared to metropolitan areas also has statistically significantly shorter drive times (AME:-5.71 mins; 95% CI:-9.23, -2.20) to the nearest NDPP.

Table 4.2 Associations Between Social Deprivation Index Quintile and Drive Time to the Nearest National Diabetes Prevention Program for Beneficiaries with Prediabetes by Race and Ethnicity -Average Marginal Effects

Beneficiary Characteristics	**Driving Time**			
	All Beneficiaries	**Non-Hispanic Black**	**Non-Hispanic White**	**Other Race and Ethnicity**
	AME (95% CI)	AME (95% CI)	AME (95% CI)	AME (95% CI)
SDI Quintile Category				
Q1 (1 to 10)	Reference	Reference	Reference	Reference
Q2(11 to 26)	-2.86 (-5.53, -0.19)*	-0.73 (-5.25, 3.78)	-4.37 (-7.09, -1.66)**	-3.16 (-6.02, -0.30)*
Q3 (27 to 47)	-1.91 (-4.80, 0.97)	2.32 (-1.67, 6.30)	-5.00 (-8.17, -1.84)**	-1.60 (-4.90, 1.70)
Q4 (48 to 71)	-5.20 (-7.98, -2.41)**	-1.60 (-5.78, 2.59)	-8.11 (-11.05, -5.17)**	-3.73 (-6.26, -1.20)**
Q5 (72 to 100)	-9.07 (-11.60, -6.54)**	-5.03 (-8.83,-1.22)*	-12.17 (-14.93, -9.40)**	-7.85 (-10.30, -5.40)**
SDI Quintile*Race and ethnicity				
Q1 (1 to 10)*Race and ethnicity	Reference			
Q2*Non-Hispanic White	-4.25 (-6.96, -1.54)**			
Q2 *Non-Hispanic Black	-0.77 (-5.29, 3.74)			
Q2* Other Race and Ethnicity	-3.15 (-5.98, -0.33)*			
Q3*Race and ethnicity				
Q3*Non-Hispanic White	-4.89 (-8.05, -1.73)**			
Q3 *Non-Hispanic Black	2.30 (-1.68, 6.29)			
Q3* Other Race and Ethnicity	-1.56 (-4.83, 1.71)			
Q4*Race and ethnicity				
Q4*Non-Hispanic White	-7.91 (-10.85, -4.97)**			
Q4 *Non-Hispanic Black	-1.69 (-5.88, 2.49)			
Q4* Other Race and Ethnicity	-3.65 (-6.19, -1.12)**			
Q5*Race and ethnicity				
Q5*Non-Hispanic White	-12.03 (-14.79, -9.27)**			
Q5 *Non-Hispanic Black	-5.15 (-8.97, -1.34)**			
Q5*Other Race and Ethnicity	-7.75 (-10.22, -5.29)**			
Race and ethnicity				
Non-Hispanic White	Reference			
Non-Hispanic Black	-2.09 (-3.19, -1.00)**			
Other Race and Ethnicity	-1.34 (-2.07, -0.60)**			
Sex				
Male	Reference	Reference	Reference	Reference
Female	-0.06 (-0.25, 0.13)	0.01 (-0.23, 0.26)	-0.12 (-0.41, 0.17)	-0.14 (-0.64, 0.36)
Age				
18 to 34 years	Reference	Reference	Reference	Reference
35 to 44 years	-0.05 (-0.44, 0.34)	-0.17 (-0.65, 0.30)	0.13 (-0.55, 0.82)	-0.14 (-1.30, 1.01)
45 to 64 years	-0.04 (-0.40, 0.31)	-0.10 (-0.57, 0.38)	0.21 (-0.41, 0.83)	-0.52 (-1.61, 0.56)
Insurance type				
Medicaid	Reference	Reference	Reference	Reference
Commercial	0.11 (-0.36, 0.58)	0.55 (-0.03, 1.13)	-0.71 (-1.43, 0.01)	-0.26 (-1.26, 0.74)
Chronic Condition				
No	Reference	Reference	Reference	Reference
Yes	0.16 (-0.09, 0.41)	-0.04 (-0.34, 0.26)	0.28 (-0.09, 0.65)	0.40 (-0.15, 0.95)
Rurality				
Metropolitan	Reference	Reference	Reference	Reference
Micropolitan	-5.71 (-9.23, -2.20)**	-5.98 (-8.80, -3.16)**	-5.78 (-10.06, -1.49)**	-6.49 (-11.08, -1.89)**
Rural	5.32 (-0.43, 11.07)	4.84 (-2.21, 11.90)	5.64 (-0.54, 11.81)	7.57 (3.49, 11.65)**
Average Travel Time	14.40**	11.90**	16.80**	14.60**
N	15, 527	5,698	8,271	1,558

Note: Higher quintiles indicate higher socioeconomic disadvantage. AME=Average marginal effect. Adjusted generalized linear log-link model with gamma distribution specifying clustering at the zip code-level and controlling for the following covariates: sex, age, insurance type, chronic condition, and rurality. The 1st (lowest) quintile for social deprivation index quintiles is the reference group. Statistical significance: * p < 0.05 **p<0.01

The interaction between SDI quintile and race and ethnicity revealed that drive times were progressively shorter as the SDI scores increased. Beneficiaries living in neighborhoods with SDI scores in the 5th quintile (most disadvantaged) had the shortest drive times overall compared to the 1st quintile (least disadvantaged) across all racial and ethnic groups. The largest reduction in drive time to the nearest NDPP were among Non-Hispanic White beneficiaries (AME:-12.03 mis; 95% CI:-14.79 to -9.27) compared to Non-Hispanic Black (AME: -5.15 mins; 95% CI:-8.97 to -1.34) and other racial and ethnic groups (AME:-7.75 mins; 95% CI:-10.22 to -5.29) living in areas with SDI scores in the 5th quintile, which were statistically significant. In our race and ethnicity stratified analyses, among Non-Hispanic Black beneficiaries, those living in micropolitan areas had significantly shorter drive times (AME: -5.98 mins; 95% CI: -8.80, -3.16) compared to those living in metropolitan areas which is consistent with findings from our main model. This relationship was similar among Non-Hispanic White beneficiaries and those from other racial and ethnic groups that lived in a micropolitan areas compared to metropolitan areas (See Table 2).

In our public transit travel time estimates findings were similar to drive time estimates. Compared to beneficiaries located in neighborhoods with SDI scores in the 1st quintile (least disadvantaged), beneficiaries in areas with SDI scores in 2nd, 4th and 5th quintile (most disadvantaged) had on average significantly shorter public transit travel times to the nearest NDPP (See Table 3). Beneficiaries living in neighborhoods with SDI scores in the 5th quintile (most disadvantaged) had significantly shorter public transit travel times (AME:-38.04 mins;

95% CI: -55.16 to -20.92) to the nearest NDPP compared to those living in neighborhoods with SDI scores in the 1st quintile. Compared to beneficiaries with Medicaid insurance, beneficiaries with commercial insurance had significantly longer public transit travel times (AME:2.55 mins; 95% CI: 0.39 to 4.71) to the nearest NDPP. Beneficiaries living in rural areas had significantly longer public transit travel times (AME:19.01 mins; 95% CI: 0.41 to 37.76) to the nearest NDPP compared to beneficiaries living in metropolitan areas. We also find differences in public transit travel time by race and ethnicity, with significantly shorter travel times (AME:-6.80 mins; 95% CI:-11.50, -2.10) for Non-Hispanic Black beneficiaries compared to Non-Hispanic White beneficiaries.

The interaction between SDI quintile and race and ethnicity showed that public transit travel times were also progressively shorter for beneficiaries in neighborhoods with higher SDI scores. This is consistent with our drive time estimates. Similarly, the largest reduction in public transit travel time to the nearest NDPP were among Non-Hispanic White beneficiaries (AME:-39.16 mins; 95% CI: -55.27 to -23.05) compared to Non-Hispanic Black (AME:-37.32 mins; 95% CI:-62.11 to -12.52) and other racial and ethnic groups (AME:-36.13 mins; 95% CI:-49.00 to -23.25) and living in neighborhoods with SDI scores in the 5th quintile compares to neighborhoods with SDI scores in the 1st quintile (least disadvantaged), which were statistically significant. However, differences in the magnitude of public transit travel times estimates for the interaction between SDI scores and race and ethnicity were not as large between Non-Hispanic White and Non-Hispanic Black beneficiaries compared to drive times estimates (1.84 mins vs. 6.88 mins respectively). In our stratified analyses we find some variations in public transit travel time for some beneficiary characteristics among racial and ethnic groups.

Table 4.3 Associations Between Neighborhood Socioeconomic Disadvantage and Public Transit Travel Time to the Nearest National Diabetes Prevention Program for Beneficiaries with Prediabetes with Sub-analysis by Race and Ethnicity – Average Marginal Effects

Beneficiary Characteristics	**Public Transportation Time**			
	Overall	**Non-Hispanic Black**	**Non-Hispanic White**	**Other Race and Ethnicity**
	AME (95% CI)	AME (95% CI)	AME (95% CI)	AME (95% CI)
SDI Quintile Category				
Q1 (1 to 10)	Reference	Reference	Reference	Reference
Q2(11 to 26)	-17.68 (-36.59, 1.23)	-15.26 (-43.57, 13.05)	-19.37 (-35.42, -3.32)*	-20.81 (-37.89, -3.73)*
Q3 (27 to 47)	-10.90 (-29.85, 8.048)	1.05 (-26.58, 28.69)	-21.68 (-38.14, -5.21)*	-12.90 (-31.19, 5.39)
Q4 (48 to 71)	-21.45 (-39.01, -3.89)*	-16.19 (-42.25, 9.88)	-26.38 (-41.40, -11.36)**	-22.34 (-35.17, -9.51)**
Q5 (72 to 100)	-38.04 (-55.16, -20.92)**	-37.08 (-61.67, -12.49)**	-39.12 (-55.24, -22.97)**	-35.96 (-48.73, -23.19)**
SDI Quintile*Race and ethnicity				
Q1 (1 to 10)	Reference			
Q2*Non-Hispanic White	-19.37 (-35.42, -3.33)*			
Q2 *Non-Hispanic Black	-15.10 (-43.59, 13.39)			
Q2* Other Race and Ethnicity	-20.94 (-38.32, -3.56)*			
Q3*Race and ethnicity				
Q3*Non-Hispanic White	-21.50 (-38.01, -4.98)*			
Q3 *Non-Hispanic Black	0.87 (-26.92, 28.67)			
Q3* Other Race and Ethnicity	-13.24 (-31.46, 4.99)			
Q4*Race and ethnicity				
Q4*Non-Hispanic White	-26.05 (-41.11, -11.00)**			
Q4 *Non-Hispanic Black	-16.29 (-42.50, 9.93)			
Q4* Other Race and Ethnicity	-22.71 (-35.66, -9.77)**			
Q5*Race and ethnicity				
Q5*Non-Hispanic White	-39.16 (-55.27, -23.05)**			
Q5 *Non-Hispanic Black	-37.32 (-62.11, -12.52)**			
Q5* Other Race and Ethnicity	-36.13 (-49.00, -23.25)**			
Race and Ethnicity				
Non-Hispanic White	Reference			
Non-Hispanic Black	-6.80 (-11.50, -2.10)**			
Other Race and Ethnicity	-2.77 (-6.15, 0.61)			
Sex				
Male	Reference	Reference	Reference	Reference
Female	-0.32 (-0.48, 1.11)	-0.70 (-1.88,0.49)	2.38 (0.84, 3.93)**	-3.61 (-7.12, -0.11)*
Age				
18 to 34 years	Reference	Reference	Reference	Reference
35 to 44 years	-2.01 (-4.15, 0.14)	-3.29 (-5.76, -0.82)**	-0.05 (-3.24, 3.15)	3.89 (-2.11, 9.89)
45 to 64 years	-2.31 (-4.29, -0.32)*	-3.21 (-6.03, -0.38)*	-0.79 (-3.48, 1.90)	3.27 (-2.54, 9.07)
Insurance type				
Medicaid	Reference	Reference	Reference	Reference
Commercial	2.55 (0.39, 4.71)*	3.64 (1.13, 6.14)**	0.43 (-2.75, 3.60)	0.16 (-4.77, 5.09)
Chronic Condition				
No	Reference	Reference	Reference	Reference

Yes	0.28 (-1.05, 1.62)	0.08 (-1.34, 1.49)	1.48 (-0.37, 3.33)	-3.33 (-6.50, -0.16)*
Rurality				
Metropolitan	Reference	Reference	Reference	Reference
Micropolitan	-20.54 (-30.78, -10.29)**	-14.91 (-23.41, -6.41)**	-24.03 (-36.31, -11.74)**	-29.18 (-44.44, -13.92)**
Rural	19.09 (0.41, 37.76)*	30.58 (7.33, 53.82)*	11.82 (-4.98, 28.62)	15.17 (-0.67, 31.00)
Average Travel Time	48.01**	39.64**	54.62**	53.78**
N	11, 047	4,812	5,089	1,146

Note: Higher quintiles indicate higher socioeconomic disadvantage. Adjusted generalized linear log-link model with gamma distribution specifying clustering at the zip code-level and controlling for the following covariates: sex, age, insurance type, chronic condition, and rurality. The 1st (lowest) quintile for social deprivation index quintiles is the reference group. Statistical significance: * $p < 0.05$ **$p<0.01$

For example, Non-Hispanic White female beneficiaries have significantly longer public transit travel time (AME: 2.38 mins; 95% CI: 0.84 to 3.93), while female beneficiaries from other racial and ethnic groups had significantly shorter public transit travel times (-3.61 mins; 95% CI:-7.12 to -0.11) compared to their male counterparts. Non-Hispanic Black beneficiaries ages 35 to 44 and 45 to 64 years of age had significantly shorter public transit travel time to the nearest NDPP compared to those who were ages 18 to 34 years. However, among beneficiaries form other racial and ethnic groups ages 35 to 44 and 45 to 64 years of age, public transit travel time was longer to the nearest NDPP, thought this relationship was not statistically significant.

Discussion

We found that on average travel time to the nearest NDPP was reduced for beneficiaries living in neighborhoods with higher levels of socioeconomic disadvantage, particularly in neighborhood with the highest levels of socioeconomic disadvantage. The shortest travel time estimates were among beneficiaries living in neighborhoods with SDI scores in the 5^{th} quintile (most disadvantaged), regardless of travel mode (driving vs. public transit), across all racial and ethnic groups. When we explored the interaction between beneficiary neighborhood SDI scores and race and ethnicity we found that drive times were generally shorter among all racial and ethnic groups. However, we found differences in the magnitude of drive time reductions, with

the shortest drive times for Non-Hispanic White beneficiaries living in neighborhoods with SDI scores in the 5th quintile (by 12 mins) compared to Non-Hispanic Black beneficiaries living in neighborhoods with SDI score in the 5th quintile (5 mins shorter). These findings indicate that the use of area-level deprivation indices such as SDI alone, is not sufficient, and that including individual and neighborhood level estimates of race and ethnicity can uncover underlying disparities which can impact access to NDPP. Prior research has also shown differences in travel time to health care resources among Non-Hispanic Black and Non-Hispanic White patients.[92,114]

Our results also highlight disparities in accessing health resources based on travel mode. We find the average travel time estimates for public transit travel times were longer compared to drive time. Although this is to be expected, our average public transit travel time to the nearest NDPP was 48 minutes, which is more than three times our average drive time estimates (14 mins). This is concerning for individuals who rely on public transportation to access health care resources. Evidence from a study using a nationally representative sample showed the average driving time to medical or dental care in urban and rural areas was roughly 21 and 27 minutes respectively.[92] Individuals that rely on public transportation to access health care resources have also been found to be more likely to miss appointments or experience delayed care.[108,109]

We hypothesized that beneficiaries in neighborhoods with higher levels of socioeconomic disadvantage would have longer travel times to the nearest NDPP, however this study showed that beneficiaries in neighborhoods with the highest levels of socioeconomic disadvantage had shorter travel times to the nearest NDPP, which indicate NDPPs were widely available throughout the state of MD. This is likely due to the statewide efforts to increase the capacity to deliver NDPP by ensuring sites are located in areas of high need. The Medicaid Demonstration implemented in Maryland from 2016 to 2019 laid the groundwork for integrating NDPP

networks, leveraging multi-sector partnerships across payers and NDPP suppliers and health care providers to facilitate NDPP access and drive utilization.[49] During the first year of the demonstration Medicaid beneficiaries at risk for developing type 2 diabetes were targeted which may help to explain our findings. In 2019 through an 1115 HealthChoice Demonstration waiver for Medicaid, Maryland continued to focus on increasing access to and use of NDPP among low-income populations.[49] It seems that targeting low-income populations at risk for type 2 diabetes helped to expand the availability of NDPP sites within high need areas. States looking to address inequities in access to NDPP should consider these strategies.

The reduction in travel time is also closely tied to the placement of NDPPs across MD. It should be noted that although community-based NDPPs have been widely promoted, organizations such as non-profits, employer-based, health systems or practices, and also faith-based organizations have offered this program. However, the NDPP organizational type may not necessarily impact program placement. In our study the 2019 NDPP sites in MD used as destinations for beneficiary travel time estimates included 51 sites that were predominately public health or community-based organizations and about one-third were affiliated with a health system or practice. NDPPs affiliated with both public health and health systems were located in both densely populated counties and rural counties across the state. In addition, although the 1115 HealthChoice Medicaid Demonstration waiver targeted Baltimore County, Baltimore City, Prince George's County, and Montgomery County, these represented less than half of the 2019 NDPPs included in our destination for travel time estimates. The availability of NDPPs is likely driven by a combination of local public health initiatives at the county level to increase the capacity to deliver NDPP and initiatives in the health care sector. For example, in 2019 the MD Total Cost of Care Model's Maryland Primary Care Program, which was designed to improve

the quality of care in primary care settings, prioritized diabetes prevention and promoted the use of NDPP.[38,49,110] In addition, in 2019 CDC recognized NDPPs became a Medicaid provider type in MD.[116] This positioned programs to bill and be reimbursed through Medicaid, instead of going through another party for reimbursement, and likely helped to incentivize the formation of NDPP sites across the state. Implementing both public health and health sector initiatives is an approach that can adopted by other states to ensure NDPP availability.

Our study had several limitations. First, no causal inferences can be made from our findings, however they can be used to further explore how travel times to NDPP may vary based in neighborhoods with higher levels of socioeconomic disadvantage. Our beneficiary location data relied solely on ZCTA data, which used centroid estimates to determine travel time to the nearest NDPP. Therefore, beneficiary travel time estimates may be underestimated or overestimated, still they provide meaningful information for public health and statewide planning initiatives to improve NDPP access. Due to limitations of the claims data, we were unable to control for beneficiary income levels, which may have modified the relationship between SDI quintile and travel time to the nearest NDPP. However, we do control for insurance type (Medicaid vs. private insurance), which has often been used as a proxy measure for income level.[117] It should also be noted that we did not have representation from every ZCTA within the state (406 out of 468), which excluded more rural areas of the state, therefore estimates comparing rural vs. metropolitan variations in travel time are limited. NDPP site location relied solely on address information from the CDC NDPP registry. Due to flexibility in NDPP organizational structures, some sites may represent multiple locations that report up to the backbone entity which provides its address to the CDC NDPP registry. This likely resulted in an undercount of NDPPs across Maryland. Lastly, our study was limited to the Maryland. However, states engaging in similar

work to increase NDPP availability, particularly in neighborhoods with higher levels of socioeconomic disadvantage, can gain insight from the strategies used by Maryland to target high need populations to ensure NDPP availability.

Conclusion

Beneficiaries living in neighborhoods with higher levels of socioeconomic disadvantage, especially neighborhoods with the highest levels of socioeconomic disadvantage, had significant reductions in drive time and public transit travel time to the nearest NDPP. However, we find this varied across racial and ethnic groups. Maryland's investments in diabetes prevention, specifically NDPP appears to have ensured this program is available in neighborhoods with higher levels of socioeconomic disadvantage. States looking to use NDPP as a diabetes prevention strategy should consider how to best target NDPPs in areas of high need, which can support access to this evidence-based program for a broader range of populations. States should also consider how racial residential segregation might contribute to disparities in access to NDPP. Future studies should examine how travel time to NDPP effect program utilization and retention for individuals in neighborhoods with higher levels of socioeconomic disadvantage, and how the neighborhood race and ethnicity composition might modify this relationship. present an opportunity to further explore how diabetes prevention strategies are being implemented in under resourced communities in Maryland.

Chapter 5: Neighborhood Socioeconomic Disadvantage and Use of Diabetes Prevention Interventions in Maryland

Abstract

Background: The National Diabetes Prevention Program (NDPP) has been established as an evidence-based intervention for diabetes prevention, yet utilization of the program remains low. There are a variety of factors that contribute to low program uptake. However, little is known about the role neighborhood socioeconomic characteristics may play in NDPP utilization or other diabetes prevention interventions such as metformin.

Purpose: This study explores the association between neighborhood socioeconomic disadvantage and the use of diabetes prevention interventions among individuals with prediabetes. The association between neighborhood socioeconomic disadvantage and the type of diabetes prevention intervention used, specifically NDPP, metformin, or both is also estimated.

Data Methods: The Maryland Medical Care Data Base, which includes privately insured claims data and Medicaid claims data from 2017 through 2019 were pooled and used to identify patients diagnosed with prediabetes. Maryland health claims data were then linked with social deprivation index 2015 data to measure beneficiary neighborhood socioeconomic disadvantage. Claims for lifestyle change interventions such as nutrition counseling were used as a proxy measure for NDPP. Three multivariate logistic regression models using SDI quintile were used to predict beneficiary use of NDPP, metformin and any type of diabetes prevention intervention. To compare the typed of diabetes prevention intervention used among beneficiaries a multinomial logistic regression model estimating relative risk ratios was used to compare the use of NDPP only and NDPP and metformin to beneficiaries that only used metformin(reference).

All models adjusted for beneficiary characteristics, including age, sex, race and ethnicity, insurance type and chronic condition.

Results: Beneficiaries were significantly more likely to use some type of diabetes prevention intervention (i.e., NDPP, metformin or both) if they lived in neighborhoods with SDI scores in the 3rd quintile (OR=1.15; 95% CI:1.02 to 1.29), 4th quintile (OR=1.14; 95% CI:1.00 to 1.29) or 5th quintile (most disadvantaged) (OR=1.21; 95% CI:1.04 to 1.41) compared to beneficiaries that lived in neighborhoods with SDI scores in the 1st quintile (least disadvantaged). This relationship was similar for NDPP utilization. In our multinomial logistic regression model, beneficiaries that lived in neighborhoods with SDI scores in the 5th quintile had a significantly higher relative risk (RRR=1.49; 95% CI: 1.12 to 1.99) of using NDPP only versus metformin only compared to beneficiaries living in neighborhoods with SDI scores in the 1st quintile.

Conclusion Our study found beneficiaries with prediabetes living in neighborhoods with the higher levels of socioeconomic disadvantage were more likely to use NDPP. This was also true among beneficiaries that used some type of diabetes prevention intervention, who had higher risk of using NDPP only compared to metformin only if they lived in neighborhoods with higher levels of socioeconomic disadvantage. Though these findings are specific to Maryland, states invested in using NDPP as a diabetes prevention strategy should consider the role neighborhood socioeconomic disadvantage may have on utilization of NDPP to ensure NDPPs are available in areas of high need.

Introduction

The establishment of the National Diabetes Prevention Program (NDPP) over a decade ago has spurred investments from both public health and health care sectors to ensure access, utilization and coverage for this evidence-based lifestyle change program[3–7] that has been shown to delay the onset of diabetes.[1,2] As of 2022, there are 18 states with statewide Medicaid coverage for NDPP, 29 states with public employee coverage and 55 commercial health plans that cover this diabetes prevention intervention.[55] Although it is estimated that 38% of adults in the U.S. have prediabetes,[8] recent estimates show that on average only 5% of patients with prediabetes are referred to NDPP or similar program and of those referred about 40% participate.[18]

Alternative interventions for diabetes prevention include the medication metformin, which has also had low utilization among patients with prediabetes.[118] Although not FDA approved for the treatment of prediabetes, health care providers rely on guidance from the American Diabetes Association which recommends the use of metformin for individuals with prediabetes who are high risk due to history of gestational diabetes, body mass index (BMI)>35 or have not has desirable outcomes with a lifestyle modification intervention.[51] Over the past fifteen years, evidence from studies using national estimates, large health systems have shown that metformin use among patients with prediabetes has varied, ranging from 1% to 8% based on patient characteristics.[119–121] Patients who are women, younger, have higher BMI, or had a comorbid condition have been found to be more likely to use metformin of be prescribed metformin by a health care provider. Given the high prevalence of prediabetes and low utilization of both NDPP and metformin, it is important to identify barriers that may contribute to the utilization of these diabetes prevention interventions.

Transportation has been identified as a barrier for NDPP utilization and can disproportionately impact those living in neighborhoods with higher levels of socioeconomic disadvantage which has been found to be associated with longer travel times.[25] Neighborhood socioeconomic disadvantage has also been shown to be associated with lower availability of community-based organizations,[71] including NDPPs.[32,33] Neighborhood socioeconomic disadvantage has been used to describe areas challenged by limited economic, human capital, or material resources,[28] and is associated with not having a usual source of care and limited access to preventative health screenings,[29] and progression from prediabetes to diabetes.[31]Neighborhood socioeconomic disadvantage may also create barriers to NDPP access and utilization, which may prompt health care providers to consider the use of metformin, particularly for individual with prediabetes who are high risk. Understanding this relationship is important for states that have invested in diabetes prevention, expanding NDPP coverage and looking to address barriers to NDPP access and increase uptake.

Study Aims and Hypothesis

This study will examine the relationship between neighborhood socioeconomic disadvantage and the utilization of diabetes prevention interventions (i.e., NDPP, metformin or both). We hypothesize that beneficiaries living in neighborhoods with higher levels of socioeconomic disadvantage will be more likely to have claims for metformin rather than NDPP.

Maryland has made extensive statewide investments in diabetes prevention and systems to engage with health care providers and NDPPs to increase program use and a good setting to explore this research. In addition to Maryland participating in the Medicaid NDPP Demonstration in 2016, diabetes prevention has been prioritized in the Maryland Primary Care

Program as part of the Total Cost of Care Model and the Diabetes Action Plan.[36,38,49,110] How to measure neighborhood has not been explicitly defined[76–78], but has been measured using various geographic units such as census-block group, census tract, and ZIP Code Tabulated Areas (ZCTAs) [79] in research that has examined neighborhood socioeconomic disadvantage. This study will use measure neighborhood socioeconomic disadvantage at the ZCTA level and use health care claims data prior to the COVID-19 pandemic, which reduced health care utilization and preventative screenings.[111,112]

Study Data and Methods

Data Source

The Maryland Medical Care Database (MCDB) which has private insurance claims for the state of MD across all care settings and MD Medicaid Managed Care data from 2017 through 2019 were pooled and used to identify adults 18 to 64 years of age with a diagnosis of prediabetes in a primary care setting. Eligibility, pharmacy and professional files were linked to identify our study sample. Adults with prediabetes were defined using the International Classification of Diseases (ICD)-10 codes that are used to diagnose prediabetes (i.e., R7301-impaired fasting glucose, R7302-impaired glucose tolerance – oral, and R7303-prediabetes). Although beneficiaries with a clinical diagnosis of gestational diabetes during a previous pregnancy (and not currently pregnant) are eligible to enroll in NDPP, administrative claims data presents challenges in identifying this population, therefore they were excluded from our sample. Beneficiaries that were not enrolled for each full calendar year were excluded. Claims data were also used to describe beneficiary characteristics including sex, age, race and ethnicity, insurance type (commercial vs. Medicaid) and co-occurring chronic conditions associated with increased

risk for diabetes. MCDB and MD Medicaid Managed Care claims data were authorized for use by the Maryland Health Care Commission under a Data Use Agreement with the University of Maryland College Park School of Public Health.

Measures

Neighborhood Socioeconomic Disadvantage

The social deprivation index (SDI) was our primary predictor variable and used to measure neighborhood socioeconomic disadvantage. SDI is geographic composite measure of area-level deprivation developed by Butler and colleagues at the Robert Graham Center using data from the American Community Survey (ACS) 5- year estimates which collects data on demographic, social, economic, and housing characteristics of the U.S. population.[86] SDI scores area a continuous variable ranked from 1 (least disadvantaged) to 100 (most disadvantaged), and are calculated directly at the ZCTA level using the following ACS variables: percent living in poverty, percent with less than 12 years of education, percent single parent household, percent living in rented housing unit, percent living in overcrowded housing unit, percent of households without a car, and percent non-employed adults under 65 years of age.[83,85] The most recent publicly available SDI data uses ACS (2011-2015) 5-year estimates were used. SDI scores for ZCTAs were linked to MD claims data using beneficiary 5-digit zip codes.

Diabetes Prevention Interventions

Diabetes prevention interventions included the use of NDPP, metformin or both, which were used as our outcomes of interest. NDPP utilization was defined based on claims identified using Current Procedural Terminology (CPT) codes and Healthcare Common Procedure Coding System (HCPCS) codes developed by the Center for Medicare and Medicaid Services for

medical coding and billing. In 2016 the CPT code 0403T was made available for use by CDC recognized NDPP providers for in-person NDPP, then in 2018 CPT 0488T was made available for online modes of NDPP.[122] To address any issues related to provider adoption and usage of NDPP CPT codes, in addition to using the recommended billing codes from the Maryland Medicaid HealthChoice Diabetes Prevention Program, CPT codes recommended by a large health plan for lifestyle change intervention such as nutrition counseling were also used as a proxy for NDPP. Details on billing codes used can be found in Appendix Table A.1. NDPP use was categorized as yes if beneficiaries had any NDPP claims for any of the designated billing codes and no if there were no NDPP claims. Metformin use was defined based on pharmacy claims using the National Drug Code for metformin hydrochloride only and no other combinations of this drug. Metformin use was defined and yes if beneficiaries who had at least one claim for metformin during a calendar year and no if there were no claims for metformin. The use of both NDPP and metformin was categorized as yes if beneficiaries had claims for both and no if there were no claims for both of these prediabetes prevention interventions.

Covariates of Interest

The selection of covariates was informed by Andersen's Behavior Health Use model (R. Andersen & Davidson, 2014). We controlled for predisposing variables such as sex and age which was categorized as: 0) 18 to 44 years, 1) 45 to 64 years. Although our entire sample was insured, insurance type, and enabling resource was also controlled and dichotomized as commercial or Medicaid plan. To control for geographic variations in rurality, the 2010 Rural Urban Commuting Area (RUCA) codes were used to define level of rurality. RUCA codes use a census tract-based classification for commuting flow information to characterize all U.S. census

tracts as metropolitan core to rural areas based on population density, urbanization and daily commuter flow.[91] RUCA code files available for ZCTA were used to create a three-level categorical rurality variable which was defined as: 0) metropolitan, 1) micropolitan, or 2) rural, and were linked to beneficiaries by ZCTA. Racial and ethnic groups were categorized as: non-Hispanic White, non-Hispanic Black, and other racial groups which included Asian, Hispanic, multiracial, and racial and ethnic groups that could not be measured or identified due to small sample size. Cardiometabolic conditions such as hypertension and hyperlipidemia have been found to be a risk factor for the development of diabetes among individuals with prediabetes or at risk for diabetes[8] and were used to defined chronic conditions in our sample. Chronic conditions were defined using ICD – 10 codes for beneficiaries with prediabetes who also had a diagnosis of hypertension or hyperlipidemia (i.e., E785), and was dichotomized as yes or no.

Statistical Analyses

Descriptive and bivariate analyses of beneficiary characteristics by SDI quintile and type of diabetes prevention intervention used were performed including chi-square tests. SDI scores of beneficiary neighborhoods were categorized into quintiles for ease of interpretation. The 5th quintile represented areas with the most socioeconomic disadvantage, and the 1st quintile represented areas with the least socioeconomic disadvantage and was designated as the reference group for all models.

Three adjusted logistic regression models were estimated using SDI quintiles to predict the use of NDPP (vs. no NDPP), metformin use (vs. no metformin), and the use of type of any diabetes prevention intervention (vs. no intervention). Then we restricted our sample to beneficiaries that used any type of diabetes prevention intervention (i.e., NDPP, metformin or

both) and used an adjusted multinomial logistic regression model using beneficiary neighborhood SDI quintiles to estimate the risk ratios for the type of using a particular diabetes prevention intervention. A three level variable for mutually exclusive diabetes prevention interventions was defined as: 0) metformin only, 1) metformin and NDPP, or 2) NDPP only, and the outcome of interest for the adjusted multinomial model. Metformin only was used as the reference group to calculate relative risk ratios (RRR) and simultaneously compare beneficiaries that used metformin only to those that used both NDPP and metformin, and those that used metformin only to NDPP only. Beneficiaries that did not use any diabetes prevention intervention were excluded from the multinomial regression analysis. All models controlled for sex, age, insurance type, race and ethnicity, chronic condition, claim year and used robust clustered standard errors at the beneficiary zip code level to adjust for autocorrelation which may be a concern for beneficiaries within the same zip code. Since over 95% of our sample were in metropolitan areas, rurality was not controlled for in our models. The highest proportion of NDPP use amongst insurance type and race and ethnicity groups were designated as the reference group in our models. Statistical significance was evaluated at $p<0.05$. Data analyses were performed using Stata MP16 (STATACorp LP, College Station, TX). This study was approved by the University of Maryland Institutional Review Board.

Study Results

There were 48,442 beneficiaries with prediabetes in our sample. Most beneficiaries with prediabetes used NDPP (61.7%), while 31.2% did not use any diabetes prevention intervention, 5.4% used both metformin and NDPP and 1.7% used metformin only (see Table 1). The percentage of metformin use only was highest amongst beneficiaries ages 45 to 64 years

(79.3%), female (57.5), Non-Hispanic White (55.2), with commercial insurance (85.2%), and no chronic condition (54.1%).

Table 5.1 Descriptive Characteristics of Beneficiaries with Prediabetes by Type of Diabetes Prevention Intervention (2017 to 2019)

	No. (%) of beneficiaries					
Beneficiary Characteristics	**Total** N=48,442 (100%)	**None** N=15,099 (31.2%)	**Metformin Only** N=835 (1.7%)	**Both** N=2,617 (5.4%)	**NDPP Only** N=29,891 (61.7%)	***P***
Age						
18 to 44 years	9,293 (19.2)	3,019 (20.0)	173 (20.7)	626 (23.9)	5,475 (18.3)	<.01
45 to 64 years	39,149 (80.8)	12,080 (80.0)	662 (79.3)	1,991 (76.1)	24,416 (81.7)	
Sex						
Male	20,651 (42.6)	6,580 (43.6)	355 (42.5)	940 (35.9)	12,776 (42.7)	<.01
Female	27,791 (57.4)	8,519 (56.4)	480 (57.5)	1,677 (64.1)	17,115 (57.3)	
Race and ethnicity						
Non-Hispanic Black	17,519 (36.2)	4,487 (29.7)	294 (35.2)	1,073 (41.0)	11,665 (39.0)	<.01
Non-Hispanic White	26,397 (54.5)	8,996 (59.6)	461 (55.2)	1,289 (49.3)	15,651 (52.4)	
Other Racial and ethnic groups	4,526 (9.3)	1,616 (10.7)	80 (9.6)	2,575 (9.7)	2,575 (8.6)	
Insurance type						
Commercial	38,832 (80.2)	13,601 (90.1)	711 (85.2)	1,805 (69.0)	22,715 (76.0)	<.01
Medicaid	9,610 (19.8)	1,498 (9.9)	124 (14.9)	12 (31.0)	7,176 (24.0)	
Chronic Condition						
No	21,614 (44.6)	8,496 (56.3)	452 (54.1)	1,003 (38.3)	11,663 (39.0)	<.01
Yes	26,828 (55.4)	6,603 (43.7)	383 (45.9)	1,614 (61.7)	18,228 (61.0)	

Note: NDPP= National Diabetes Prevention program. Both= utilization of metformin and NDPP. Chi-square statistical test performed. Statistical significance: $p < 0.05$ and $p<0.01$

Table 5.2 Characteristics of Beneficiaries with Prediabetes by Neighborhood Social Deprivation Index Quintile

Beneficiary Characteristics	**Overall**	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**	***P***
	N=48,442 %	(1 to 10) N=9,922 %	(11 to 26) N=10,055 %	(27 to 47) N= 9,139 %	(48 to 71) N=9,712 %	(72 to 100) N=9,614 %	
Any Prediabetes Intervention							
No	31.2	37.0	33.6	31.5	29.2	24.2	<.01
Yes	68.8	63.0	66.4	68.5	70.8	75.8	
NDPP Use							
No	32.9	39.0	35.4	33.4	30.9	25.6	<.01
Yes	67.1	61.0	64.6	66.6	69.1	74.4	
Metformin Use							
No	92.9	92.6	93.9	92.8	92.7	92.4	<.01
Yes	7.1	7.4	6.2	7.2	7.3	7.6	
NDPP and Metformin							
No	94.6	94.6	95.6	94.6	94.4	93.7	<.01
Yes	5.4	5.4	4.4	5.4	5.6	6.3	
Age							
18 to 44 years	19.2	14.7	18.1	18.8	21.7	22.8	<.01
45 to 64 years	80.8	85.3	81.9	81.2	78.3	77.3	
Sex							
Male	42.6	47.0	44.0	43.6	40.6	37.8	<.01
Female	57.4	53.0	56.0	56.4	59.4	62.2	
Race and ethnicity							
Non-Hispanic Black	36.2	13.0	26.3	27.5	49.7	65.0	<.01
Non-Hispanic White	54.5	74.0	62.5	62.6	42.1	30.8	
Other Racial Groups	9.3	13.1	11.3	9.9	8.2	4.2	
Insurance type							
Medicaid	19.8	6.7	11.1	15.5	24.3	42.2	<.01
Commercial	80.2	93.3	88.9	84.5	75.8	57.8	
Chronic Condition							
No	44.6	47.7	43.3	45.6	44.3	42.3	<.01
Yes	55.4	52.3	56.7	54.4	55.7	57.7	
Rurality							
Metropolitan	96.2	99.7	94.7	96.8	94.6	95.3	<.01
Micropolitan	2.5	**	4.7	1.9	3.9	1.8	
Rural	1.3	0.3	0.6	1.3	1.5	2.9	

Note: **Cell count less than 10. Higher quintiles indicate higher levels of socioeconomic disadvantage. Chi-square statistical test performed. Statistical significance: $p < 0.05$ and $p<0.01$

The pattern was similar for NDPP use only, except NDPP use only was higher among beneficiaries with a chronic condition (61%). In our chi-square analysis of beneficiary characteristics by SDI quintile, the highest percent of NDPP use (74.4%), metformin use (7.6%), NDPP and metformin use (6.3%) or the use of any prediabetes prevention intervention (75.8%) were among beneficiaries living in neighborhoods with SDI scores in the 5th quintile (most disadvantage) (See Table 2.).

In the logistic regression models, we found that beneficiaries living in neighborhoods with SDI scores in the 3rd quintile (OR=1.15; 95% CI:1.02 to 1.29) 4th quintile (OR=1.14; 95% CI:1.00 to 1.29) or 5th quintile (OR=1.21; 95% CI:1.04 to 1.41) were statistically significantly more likely to use some type of diabetes prevention intervention (NDPP, metformin or both) versus no intervention, compared to those living in neighborhoods with SDI scores in the 1st quintiles (least disadvantage) (See Table 3.) Beneficiaries were significantly more likely to use a diabetes prevention intervention if they were 45 to 64 years of age (OR=1.10; 95% CI:1.04 to 1.17), female (OR=1.10; 95% CI:1.05 to 1.15) or have a chronic condition (OR=2.02; 95% CI:1.91 to 2.13). Diabetes prevention interventions were significantly less likely to be used if beneficiaries had commercial insurance (OR=0.36; 95% CI:0.33 to 0.40), were Non-Hispanic White (OR=0.84; 95% CI:0.79 to 0.90), or from other racial and ethnic groups (OR=0.84; 95% CI:0.77to 0.92).

In our logistic regression model examining the relationship between SDI quintiles and NDPP use (vs. no NDPP use), findings were consistent with those from our model estimating the use of any type of diabetes prevention intervention. We also find that beneficiaries were less likely to use NDPP if they were Non-Hispanic White (OR=0.85; 95% CI:0.80, 0.91) or from

other racial and ethnic groups (OR=0.86; 95% CI:0.78, 0.94) compared to Non-Hispanic Black beneficiaries. In examining metformin use (vs. no metformin use) beneficiaries were statistically

Table 5.3 Associations between Social Deprivation Index Quintile and Type of Diabetes Prevention Interventions Among Beneficiaries with Prediabetes

Beneficiary Characteristics	**Diabetes Prevention Intervention Used**		
	Any vs. None	**NDPP vs. No NDPP**	**Metformin vs. No Metformin**
	Odds Ratio (95% CI)	Odds Ratio (95% CI)	Odds Ratio (95% CI)
SDI Quintile Category			
Q1 (1 to 10)	Reference	Reference	Reference
Q2 (11 to 26)	1.07 (0.96, 1.19)	1.08 (0.96, 1.20)	0.77 (0.66, 0.91)**
Q3 (27 to 47)	1.15 (1.02, 1.29)*	1.15 (1.02, 1.30)*	0.90 (0.77, 1.05)
Q4 (48 to 71)	1.14 (1.00, 1.29)*	1.15 (1.02, 1.30)*	0.84 (0.73, 0.97)*
Q5 (72 to 100)	1.21 (1.04, 1.41)*	1.24 (1.06, 1.43)**	0.81 (0.67, 0.98)*
Age			
18 to 44 years	Reference	Reference	Reference
45 to 64 years	1.10 (1.04, 1.17)**	1.10 (1.04, 1.17)**	0.79 (0.72, 0.87)**
Sex			
Male	Reference	Reference	Reference
Female	1.10 (1.05, 1.15)**	1.10 (1.05, 1.15)**	1.28 (1.18, 1.38)**
Race and ethnicity			
Non-Hispanic Black	Reference	Reference	Reference
Non-Hispanic White	0.84 (0.79, 0.90)**	0.85 (0.80, 0.91)**	0.94 (0.85, 1.04)
Other racial and ethnic groups	0.84 (0.77, 0.92)**	0.86 (0.78, 0.94)**	1.05 (0.89, 1.25)
Insurance type			
Medicaid	Reference	Reference	Reference
Commercial	0.36 (0.33, 0.40)**	0.37 (0.33, 0.40)**	0.65 (0.59, 0.72)**
Chronic Condition			
No	Reference	Reference	Reference
Yes	2.02 (1.91, 2.13)**	2.04 (1.94, 2.16)**	1.19 (1.10, 1.29)**
Year			
2017	Reference	Reference	Reference
2018	0.84 (0.80, 0.88)**	0.84 (0.80, 0.88)**	1.06 (0.98, 1.14)
2019	0.85 (0.81, 0.89)**	0.84 (0.80, 0.89)**	1.18 (1.08, 1.28)**

Note: Higher quintiles indicate higher socioeconomic disadvantage. [a]Any= NDPP, metformin or both. Adjusted logistic regression models specifying clustering at the zip code-level and controlling for the following covariates: sex, age, insurance type, race and ethnicity, chronic condition, and claims year. The 1st (lowest) quintile for social deprivation index quintiles is the reference group.
Statistical significance: * p < 0.05 **p<0.01

significantly less likely to use metformin if they lived in neighborhoods with SDI scores in the 2nd quintile (OR=0.77; 95% CI:0.66 to 0.91), 4th quintile (OR=0.84; 95% CI:0.73 to 0.97)

or 5th quintile (OR=0.81; 95% CI:0.67 to 0.98) compared to beneficiaries living in neighborhoods with SDI scores in the 1st quintiles (least disadvantage). Metformin use was also less likely among beneficiaries ages 45 to 64 years (OR=0.79; 95% CI: 0.72 to 0.87) or with commercial insurance (OR=0.65; 95% CI:0.59 to 0.72).

Table 5.4 Multinomial Logistic Regression Estimates of Diabetes Prevention Intervention Type Among Beneficiaries with Prediabetes who Used NDPP only, Metformin only or Both NDPP and Metformin

Beneficiary Characteristics	**NDPP and Metformin vs. Metformin only** Relative Risk Ratio (95% CI)	**NDPP only vs. Metformin only** Relative Risk Ratio (95% CI)
SDI Quintile Category		
Q1 (1 to 10)	Reference	Reference
Q2 (11 to 26)	0.84 (0.65, 1.09)	1.18 (0.92, 1.51)
Q3 (27 to 47)	0.97 (0.73, 1.29)	1.16 (0.88, 1.52)
Q4 (48 to 71)	1.02 (0.78, 1.34)	1.27 (0.99, 1.63)
Q5 (72 to 100)	1.16 (0.82, 1.64)	1.49 (1.12, 1.99)**
Age		
18 to 44 years	Reference	Reference
45 to 64 years	0.80 (0.66, 0.97)*	1.10 (0.93, 1.31)
Sex		
Male	Reference	Reference
Female	1.42 (1.21, 1.67)**	1.04 (0.91, 1.19)
Race and ethnicity		
Non-Hispanic Black	Reference	Reference
Non-Hispanic White	1.04 (0.85, 1.27)	1.04 (0.89, 1.23)
Other racial and ethnic groups	1.25 (0.96, 1.64)	1.06 (0.82, 1.39)
Insurance type		
Medicaid	Reference	Reference
Commercial	0.40 (0.31, 0.51)**	0.57 (0.46, 0.70)**
Chronic Condition		
No	Reference	Reference
Yes	2.13 (1.80, 2.52)**	1.86 (1.62, 2.12)**
Year		
2017	Reference	Reference
2018	1.03 (0.85, 1.25)	0.91 (0.78, 1.06)
2019	0.99 (0.82, 1.20)	0.79 (0.67, 0.94)**
N	33,343	

Note: Higher quintiles indicate higher socioeconomic disadvantage. Adjusted multinomial regression models specifying clustering at the zip code-level and controlling for the following covariates: sex, age, insurance type, race and ethnicity, chronic condition, and claims year. The 1st (lowest) quintile for social deprivation index quintiles is the reference group. Sample size=33,343. Statistical significance: * p < 0.05 **p<0.01

Estimates from our adjusted multinomial model showed that beneficiaries living in neighborhoods with SDI scores in the 4th and 5th quintiles had higher risk of using both NDPP and metformin compared to metformin only compared to beneficiaries living in neighborhoods with SDI scores in the 1st quintile (least disadvantaged). However, this was not statistically significant. Beneficiaries had significantly higher risk of using use both NDPP and metformin compared to metformin only if they were female (RRR=1.42; 95% CI:1.21 to 1.67) or had a chronic condition (RRR=2.13; 95% CI:1.80 to 2.52). Beneficiaries that lived in neighborhoods with SDI scores in the 5th quintile (most disadvantaged) compared to those living in neighborhoods with SDI scores in the 1st quintile (least disadvantaged) had a significantly higher risk of using NDPP only compared to metformin only among (RRR=1.49; 95% CI: 1.12 to 1.99).

Discussion

Our study found beneficiaries with prediabetes living in neighborhoods with higher levels of socioeconomic disadvantage were more likely to use some type of diabetes prevention intervention (i.e., NDPP, metformin or both). Beneficiaries living in neighborhoods with the higher levels of socioeconomic disadvantage were more likely to use NDPP and less likely to use metformin. When we compared the three types of diabetes prevention interventions we found that beneficiaries living in neighborhoods with the highest levels of socioeconomic disadvantage were more likely to use NDPP only compared to metformin only. We also found Non-Hispanic White beneficiaries were less likely to use NDPP compared to Non-Hispanic Black beneficiaries. Prior research has shown that Black patients were more likely to be referred to lifestyle modification interventions like medical nutrition therapy compared to White patients.[121] However, some evidence has shown that Black patients are more likely to use metformin for

diabetes prevention.[123] Our findings also showed that beneficiaries insured by Medicaid were also more likely to use NDPP only compared to metformin only. This finding is likely related to diabetes prevention and NDPP promotion efforts specific to Maryland.

Although we expected beneficiaries living in neighborhoods with higher levels of socioeconomic disadvantage to be more likely to use metformin compared to NDPP, these findings highlight benefits of continued statewide investments in NDPP. During the Maryland 2016 Medicaid Demonstration project nine managed care organizations participated in the state's Medicaid managed care program, HealthChoice, created partnerships with NDPPs and targeted areas of the with Medicaid beneficiaries with high rates of type 2 diabetes. These efforts continued through an 1115 Medicaid HealthChoice demonstration waiver in 2019 which was extended for five more years in 2022. NDPP has also been prioritized in Maryland's Diabetes Action Plan, and in the Maryland Primary Care Program, started in 2019 which includes a focus on diabetes prevention and supports primary care practice transformation to improve quality of care.[36] There have also been investments made to support NDPP use through Maryland's health information exchange, Maryland CRISP-Chesapeake Regional Information System for Our Patients, which uses provider alerts for patients with prediabetes to support bidirectional referrals to NDPP.[115] These investments and the targeted approach used by Maryland likely explains the use of NDPP among beneficiaries insured by Medicaid and those living in neighborhoods with higher levels of socioeconomic disadvantage.

Our study had several limitations. First, our sample included beneficiaries with billing codes primarily for lifestyle modification interventions such as nutritional counseling instead of NDPP specific codes for in-person or virtual offerings, which had very low usage in our sample. This may highlight a larger issue around adoption of the NDPP billing code. Therefore, our

findings may underestimate true NDPP use, however they proxy billing codes used provide insight on provider referrals or engagement in services to address diabetes prevention. Additional studies should examine the use and adoption of billing codes for in-person and virtual NDPP offerings. Second, because we used claims data it is possible that diagnoses and metformin use were misclassified. Third, we focused on claims for adults 18 to 64, which may not be generalizable to Medicare beneficiaries. However, since NDPP is a covered by Medicare through the Medicare Diabetes Prevention Program, future studies should explore the relationship between neighborhood socioeconomic disadvantage and NDPP use among this population. Lastly, these findings are specific to Maryland, and are likely not generalizable to other states. Still states invested in using NDPP as a diabetes prevention strategy should consider the role neighborhood socioeconomic disadvantage may have on utilization of NDPP.

Conclusion

Beneficiaries living in neighborhoods with higher levels of socioeconomic disadvantage were significantly more likely to use NDPP and less likely to use metformin. Those living in neighborhoods with higher levels of socioeconomic disadvantage were significantly more likely to use NDPP only compared to metformin only as a diabetes prevention intervention. Our findings indicate that neighborhood socioeconomic disadvantage may not create a barrier for beneficiaries with prediabetes to use NPP or metformin to prevent type 2 diabetes. However, this likely relies on states making long-term targeted investments that target low-income populations at risk for diabetes to expand access to NDPP. Future studies should examine this relationship across states that have had long-term investments in NDPP to better understand the impact of stateside diabetes prevention policies, particularly coverage expansion efforts.

Chapter 6: Conclusion

This study investigated the relationship between neighborhood socioeconomic disadvantage and travel time the nearest NDPP and utilization of diabetes prevention intervention (i.e., NDPP, metformin or both) among individuals with prediabetes. Neighborhood socioeconomic disadvantage was measured using social deprivation index (SDI), composite measure of area deprivation which captures seven population level variables related to socioeconomic deprivation such as poverty, low educational attainment, and overcrowded housing. We examined the association between area-level socioeconomic characteristics of PC practice location and travel time to the nearest NDPP using population survey data and travel time estimates generated using the Google Distance Matrix API with Google Maps Platform. Then, Maryland All-Payer claims data were examined to investigate the association between neighborhood socioeconomic disadvantage and travel time to the nearest NDPP among beneficiaries with prediabetes. Finally, Maryland All-Payer claims data was evaluated to determine the associations between neighborhood socioeconomic disadvantage and utilization of diabetes prevention intervention (i.e., NDPP, metformin or both) among those with prediabetes over a three year period.

Key Findings

Aim 1: Examine the relationship between neighborhood socioeconomic disadvantage and potential access to the NDPP using primary care providers geographic proximity to the nearest NDPP site in Maryland. Primary care practices located in areas with higher levels of socioeconomic disadvantage were significantly associated with shorter drive times to the nearest NDPP site. This was consistent in estimates for travel time by public transportation. PC practices located in areas with SDI scores in the 5th quintile (most disadvantaged) had

significantly shorter travel times (by 51%) and public transit (by 65%) compared to PC practices located in the areas with SDI scores in the 1st quintile (least disadvantaged). We also find that a large proportion of PC practices were located in five counties and jurisdictions (i.e., Anne Arundel, Baltimore, Montgomery, Prince Georges counties and Baltimore city), however, when comparing these counties to all other counties in Maryland, we still find that PC practices located in areas with SDI scores in the 5th quintile (most disadvantaged) had shorter travel times to the nearest NDPP compares to PC practices located in areas with SDI scores in the 1st quintile (least disadvantaged) for both modes of travel (driving and public transit). In terms of geographical differences, PC practices located in micropolitan areas were significantly associated with shorter drive times to the nearest NDPP (by 37%) compared to PC practices in metropolitan areas. When stratifying our analysis by PC practice locations by the percentage of Non-Hispanic Black populations in their area (greater than 45% vs. less than 45%) we found that compared to the lowest SDI quintile, PC practice locations in areas with SDI scores in the 3rd and 4th quintiles has significantly longer drive time to the nearest NDPP. While PC practice locations in areas with SDI scores in the 2nd through 5th quintiles had significantly shorter drive times to the nearest NDPP compared to areas with SDI scores in the 1st quintile (least disadvantaged).

Aim 2: Examine the relationship between neighborhood socioeconomic disadvantage and potential access to the NDPP based on geographic proximity of individuals with prediabetes to the nearest NDPP site in Maryland. We found that on average travel time to the nearest NDPP was shorter for beneficiaries living in neighborhoods with higher levels of socioeconomic disadvantage, particularly in neighborhood with the highest level of socioeconomic disadvantage. The shortest travel time estimates were among beneficiaries living in neighborhoods with SDI scores in the 5th quintile (most disadvantaged) regardless of travel

mode (driving vs. public transit) and across all racial and ethnic groups. In comparison to beneficiaries living in neighborhoods with SDI scores in the 1st quintile (least disadvantaged), beneficiaries living in neighborhoods with SDI scores in the 5th quintiles (most disadvantaged) had on average shorter drive times by 9 mins to the nearest NDPP. However, in examining the interaction between beneficiary race and ethnicity and their neighborhood SDI scores we found differences in the in the magnitude of reductions in drive time. On average the largest reduction in drive time to the nearest NDPP were among Non-Hispanic White beneficiaries (by 12 mins) compared to Non-Hispanic Black (by 5 mins) and other racial and ethnic groups (8 by mins) living in neighborhoods with SDI scores in the 5th quintile (most disadvantaged), which were statistically significant.

Travel time by public transit was significantly shorter among beneficiaries living in neighborhoods with SDI scores in the 5th quintile (most disadvantaged), compared to beneficiaries living in neighborhoods with SDI scores in the 1st quintile (least disadvantaged). We found that overall, the average public transit travel time was 38 minutes to the nearest NDPP. In exploring the interaction between beneficiary race and ethnicity and their neighborhood SDI scores we found significantly shorter public transit travel time to the nearest NDPP among all racial and ethnic groups that lived in neighborhoods with higher levels of socioeconomic disadvantage. However, on average the largest reduction in public transit travel time to the nearest NDPP were among Non-Hispanic White beneficiaries (by 39 mins) compared to Non-Hispanic Black (by 37 mins) and other racial and ethnic groups (by 36 mins) living in neighborhoods with SDI scores in the 5th quintile (most disadvantaged) compared to those in neighborhoods with SDI scores in the 1st quintile, which were statistically significant.

Aim 3: Examine the relationship between neighborhood socioeconomic disadvantage and utilization of diabetes prevention interventions such as NDPP, metformin, or both among individuals with prediabetes in Maryland. Our study found beneficiaries with prediabetes living in neighborhoods with the higher levels of socioeconomic disadvantage were more likely to use some type of diabetes intervention (i.e., NDPP, metformin or both), specifically NDPP. Beneficiaries were significantly more likely to use a diabetes prevention intervention (i.e., NDPP, metformin or both) if they lived in neighborhoods with SDI scores in the 3rd quintile (OR=1.15; 95% CI:1.02 to 1.29), 4th quintile (OR=1.14; 95% CI:1.00 to 1.29) or 5th quintile (OR=1.21; 95% CI:1.04 to 1.41) compared to beneficiaries that lived in neighborhoods with SDI scores in the 1st quintile (least disadvantaged). NDPP was significantly more likely to be used if beneficiaries lived in neighborhoods with SDI scores in the 3rd quintile (OR=1.15; 95% CI:1.02 to 1.30), 4th quintile (OR=1.15; 95% CI:1.02 to 1.30) or 5th quintile (OR=1.24; 95% CI:1.06 to 1.43) compared to beneficiaries that lived in neighborhoods with SDI scores in the 1st quintile (least disadvantaged). We then found beneficiaries were significantly less likely to use metformin if they lived in neighborhoods with SDI scores in the 2nd quintile (OR=0.77; 95% CI:0.66 to 0.91), 4th quintile (OR=0.84; 95% CI:0.73 to 0.97) and 5th quintile (OR=0.81; 95% CI:0.67 to 0.98) compared to beneficiaries that lived in neighborhoods with SDI scores in the 1st quintiles (least disadvantaged). Finally, in our multinomial analysis that compared the types of diabetes prevention interventions to using metformin only, beneficiaries that lived in neighborhoods with SDI scores in the 5th quintile (most disadvantaged) had a significantly higher risk of using NDPP use only versus metformin use only (RRR=1.49; 95% CI: 1.12 to 1.99) compared to those living in neighborhoods with SDI scores in the 1st quintile (least disadvantaged). Beneficiaries had a higher risk of using both NDPP and metformin compared to

metformin only if they lived in neighborhoods with SDI scores in the 4th and 5th quintile (most disadvantaged), however this was not statistically significant.

Policy Implications

Our findings are a departure from prior research which has typically shown that neighborhoods with higher levels of neighborhoods socioeconomic disadvantage have been associated with reduced access to health care resources or adverse health outcomes.[29,31,104,124] PC practice locations and beneficiaries with prediabetes living in neighborhoods with higher levels of socioeconomic disadvantage having shorter travel times to NDPP sites is likely the result of years of targeted diabetes prevention interventions in Maryland. Although our findings are not generalizable to other states, they can inform statewide diabetes prevention population health strategies that can be adopted by other states that develops the infrastructure to ensure NDPP availability in areas of high need. This research also highlights the need to make long-term investments in ensuring NDPP is covered. Currently, there are 22 out of 50 states that have some level of Medicaid coverage for NDPP.[55] To address disparities in access to this program for marginalized populations, it is important for states to leverage Medicaid to cover NDPP. In addition to covering Medicaid, states should also be strategic about how they use cross-sector collaboration to increase NDPP capacity and consider putting resources in place to support primary care providers, practices, and health systems to refer patients to NDPP. Establishing resources and infrastructure to support bidirectional referrals between NDPP and health care providers can help sustain NDPPs that generally rely on referrals. States that have established NDPP as a Medicaid benefit should consider where primary care providers are located with respect to where NDPPs are and how travel time estimates rather than distance to NDPPs may create barriers for populations that have limited transportation resources.

Areas for Future Research

Additional research should examine the relationship between neighborhood socioeconomic disadvantage across other states that have invested in NDPP, particularly those that have covered NDPP as a Medicaid benefit for as long or longer than Maryland (e.g., Oregon, California). A comparative analysis between states that cover NDPP through Medicaid and those that do not could help measure the effect of implementing diabetes prevention policies that target low-income populations with prediabetes. It is also imperative to understand how differences in state Medicaid billing and reimbursement structures contribute to the availability of NDPP providers. States like Maryland have established NDPP as a provider type in Medicaid and may be better positioned to increase the volume of NDPP providers to meet population demands to support utilization of this evidence-based diabetes prevention program compared to states restricting NDPP providers to existing Medicaid provider types (e.g., health system) which can limit program uptake.[125] Future studies must also consider the impact the COVID-19 pandemic had on the availability and accessibility of NDPPs, particularly in-person offerings. Although our research focused primarily on in-person NDPP, future research should be done to further characterize patients and neighborhood socioeconomic characteristics associated with in-person vs virtual NDPPs. This study reinforced that strong public health and health system infrastructure built by long-term investments in statewide NDPP coverage, cross-sector partnerships, and targeting high risk populations is a viable population health strategy for diabetes prevention.

Appendices

Appendix A.

Table A.1 Count and Percentage of Primary Care Practices within Maryland Counties and Jurisdictions by Social Deprivation Index Quintiles

	No. (%) of Primary care practices					
County	**Q1 (1 to 17) N=366 n (%)**	**Q2 (18 to 34) N=307 n (%)**	**Q3 (35 to 50) N=359 n (%)**	**Q4 (51 to 72) N=385 n (%)**	**Q5 (75 to 100) N=263 n (%)**	**Total N=1680 n (%)**
Allegany	0 (0)	0 (0)	2 (0.6)	34 (8.8)	0	36 (2.1)
Anne Arundel	60 (16.4)	13 (4.2)	50 (13.9)	34 (8.8)	7 (2.7)	164 (9.8)
Baltimore	39 (10.7)	51(16.6)	104 (29.0)	55 (14.3)	0	249 (14.8)
Baltimore City	0 (0)	2 (0.7)	0	26 (6.8)	139 (52.9)	167 (9.9)
Calvert	5 (1.47)	6 (2.0)	10 (2.8)	0	0	21 (1.3)
Caroline	2 (0.6)	1 (0.3)	0	9 (2.3)	4 (1.5)	16 (1.0)
Carroll	24 (6.6)	39 (12.7)	0	0	0	63 (3.8)
Cecil	0 (0)	4 (1.3)	19 (5.3)	1 (0.3)	0	24 (1.4)
Charles	20 (5.5)	11 (3.6)	1 (0.3)	15 (3.9)	0	47 (2.8)
Dorchester	0	0	0	2 (0.5)	11 (4.2)	13 (0.8)
Frederick	11 (3.0)	3 (1.0)	43 (12.0)	8 (2.1)	0	65 (3.9)
Garrett	0	0	9 (2.5)	0	0	9 (0.5)
Harford	37 (10.1)	6 (2.0)	17 (4.7)	7 (1.8)	0	67 (4.0)
Howard	30 (8.2)	56 (18.2)	0	0	0	86 (5.1)
Kent	0	0	7 (2.0)	0	0	7 (0.4)
Montgomery	84 (23.0)	43 (14.0)	60 (16.7)	69 (17.9)	22 (8.4)	278 (16.6)
Prince Georges	29 (7.9)	36 (11.7)	0	76 (19.7)	44 (16.7)	185 (11.0)
Queen Annes	12 (3.3)	0	0	0	0 (0)	12 (0.7)
Somerset	0	1 (0.3)	0	0	5 (1.9)	6 (0.4)
St. Mary's	10 (2.7)	10 (3.3)	0	2 (0.5)	0	22 (1.3)
Talbot	0	1 (0.3)	20 (5.6)	0	0	21 (1.3)
Washington	3 (0.8)	4 (1.3)	17 (4.7)	0	25 (9.5)	49 (2.9)
Wicomico	0	0	0	47 (12.2)	0	47 (2.8)
Worcester	0	20 (6.5)	0	0	6 (2.3)	26 (1.6)

Table A.2 Billing Codes Used to Define Lifestyle Change Programs and Diagnostic Codes for Prediabetes

Billing or Diagnosis Category	**CPT or ICD-10 Code**
Diabetes Prevention Program[126,127]	0403T; 99412; G98733; G9874; G9875; G9876; G9877
Diabetes Prevention Program (Online)[126,127]	0488T; 99421; 99422; 99423; 98970; 98971; 98972
Lifestyle Modification Codes[128,129]	99401; 99402; 99403; 99404; 99411; 99429; 97802; 97803; S9470; 97804; 99201; 99202; 99203; 99401-99404; 99201-99215
Impaired fasting glucose[130]	R7301
Impaired glucose tolerance - Oral[130]	R7302
Prediabetes[130]	R7303

Notes: CPT= Current Procedural Terminology; ICD= International Classification of Diseases

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