What Happened to Shopping Center Foot Traffic in Pandemic World?

The Role of Socio-Demographics and Transport Modes

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ABSTRACT

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Apoorva Rajpurohit

In the wake of the COVID-19 pandemic, the retail sector, already dealt a severe blow by the boom of online retailers was brought to its knees as a result of social distancing regulations and consumer shifts. It can be considered one of the hardest-hit sectors. In this thesis, we performed a comparative study to analyze consumer foot traffic to over 1,000 shopping centers during the pre-pandemic (2018-2019) and the pandemic period (2020). Our study contributes to the research on the economic consequences of epidemics and pandemics. Specifically, we explore two central research questions: 1) how did trade area characteristics such as trade area size, socio-demographics, and transport modes affect consumer foot traffic before and during the COVID-19 pandemic? 2) What moderating effects did social distancing exert upon the consumer foot traffic through interaction with core trading area characteristics during the COVID-19 pandemic? Our observation demonstrates significant drops in foot traffic as social distancing intensifies, the varying effects of trade area attributes before and during the pandemic, and the moderating effect various levels of social distancing had on trade area characteristics. In summary, this work aims to create a foundation for further work to understand the impact of the pandemic on the retail sector. We propose that government officials and retail managers need to pay great attention to trade area characteristics such as socio-demographics and transport modes for better response to the outbreak of the COVID-19 pandemic and preparation for recovery from the COVID-19 pandemic.

***Key Words*:** pandemic response and recovery, shopping center, foot traffic, trade area, transport modes, socio-demographics

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1. Introduction

In December of 2019, the first case of COVID-19 was detected in Wuhan, China (Spiteri et al., 2020). What was initially thought to be instances of seasonal flu and pneumonia, raising little concern, soon demonstrated its potent effects by spreading rapidly first to multiple Chinese cities, then across the Eurasian continent and crossing oceans to the Americas and Australia causing untold amounts of suffering and leaving devastating economical damage in its wake. The situation continued to evolve and worsen, and by March 2020, a pandemic was declared by the WHO (Cucinotta & Vanelli, 2020). The virus transfixed many aspects of daily life and society. The hospitals, with short queues of patients and relaxed doctors and nurses become a fierce war waged between microscopic enemies and exhausted men and women in green scrubs with no shortage of casualties and rapidly dwindling supplies, the air is filled not with freshness but with a lingering smell of disinfectant and that of fear and uncertainty, finally stores usually buzzing with activity and radiance is now half-filled with somber lines of masked citizens, or sometimes none at all. Amidst the chaos, the retail industry, already dealt a severe blow by the boom of online retailers was brought to its' knees by the restrictions and customer shifts during the COVID pandemic and is perhaps one of the hardest hit sectors of all.

In 2020 alone, economic growth is estimated to have shrunk by 3.5% globally, and in the USA by 3.4% (IMF, 2021). Retail footfall decreased significantly as people chose or were restricted to remaining home and purchased daily necessities through digital means (Jones et al., 2021). At the beginning of the lockdowns, grocery stores and pharmacies saw a slight surge in retail footfall with concerned customers stockpiling supplies and medicine; however, sales eventually decline as well, joining the apparel, the luxury goods, the personal care sector, and the service industries (Bauer et al., 2020). With the pandemic continuing to worsen and no large-scale treatments or solutions in sight, retailers forced to adapt and adjust their business operations and structures to cater towards the growing preference for online shopping or the more recently popular delivery or curbside pickup techniques (EY, 2020).

To better understand the impact of the COVID-19 pandemic on the retail sector, we performed a comparative study to analyze consumer foot traffic to shopping centers during the pre-pandemic (2018-2019) and pandemic time periods (2020). Gupta et al (2020) outline six research directions for the study of pandemics and epidemics: a) disease prediction, b) mitigation and interventions, c) socio-political and economic consequences, d) national culture, e) resource planning, and f) analytical techniques. Our study contributes to research in the area of economical consequences of epidemics and pandemics. Specifically, we explore two central research questions: 1) how did trade area characteristics such as trade area size, socio-demographics, and transport modes affect consumer foot traffic before and during the COVID-19 pandemic? 2) What moderating effects did social distancing exert upon the consumer foot traffic through interaction with core trading area characteristics during the COVID-19 pandemic?

In this study, we focus on open-air shopping center chains with grocery stores as their anchor stores. Shopping center is defined as a group of retail and other commercial establishments at a single property, with parking and anchor stores (ICSC, 2017), which varies in size, anchor, acreage, anchor ratios (DeLisle, 2005). Shopping centers can be broadly categorised into open air-centers and hybrid centers (Pitt & Musa, 2009). In this study, we gathered consumer foot traffic data of over 1,000 properties from four major U.S. shopping mall chains, Brixmor Property Group, Kimco Realty, Phillips Edison Properties, and SITE Centers Corp on a daily level. We further collected annual-level trade area characteristics for each sample shopping center properties under the study, which includes trade area size, socio-demographic characteristics like age, ethnicity, gender, and income, and particular transport modes such as driving alone, carpooling, public transit, bicycling and walking. Finally, the daily social distancing policies were collected and factored into the research to further observe its impact upon the behavior of consumers.

Our major findings include:

- Trade area represents "*a geographical area containing the customers of a particular firm or group of firms for specific goods or services*" (Bennett, 1995). As expected, we find that trade area size is positively associated with consumer foot traffic during both the pre-pandemic and pandemic periods; however, these positive effects get weakened during times of strict social distancing measures. As a result, shopping centers with larger trade area might suffer more when social distancing measure was higher during the pandemic.
- Compared to driving alone, carpooling positively relates to foot traffic during the pandemic; however, the correlation becomes less established and visible as distancing measures grew tighter. Moreover, the usage of public transit has a notable negative impact on pandemic foot traffic, with little change throughout regardless of social distancing measures. Interestingly, the segment of working at home positively contributes to foot traffic pre-pandemic but is negatively associated with foot traffic in times of severe social distancing.
- Compared to the male population, female population significantly reduces foot traffic during the pandemic relative to the pre-pandemic norms, and the risk-averse behavior does not significantly change with the distancing measure. In comparison to minor population, the young adult, adult, and elder age group have a significant positive impact on foot traffic during the pandemic, decreasing in times of strict social distancing measures. With respect to Asian population, White, African American, and Hispanic population decrease foot traffic during the pandemic, but high social distancing index weakens the negative effects on foot traffic.

Our contributions are as follows. First, our work expands the domain of disaster management. We follow the needed directions for research on epidemic and pandemic emergencies (Gupta et al. 2020) by studying consumer foot traffic during the pre-pandemic and pandemic periods. Second, we apply big-data analytical techniques in this work. Our paper employs empirically grounded analysis to compare daily consumer foot traffic to over 1,000 open-air shopping centers over a three-year period from 2018 to 2020, providing managerial and policy implications for pandemic emergencies. Third, we show that consumer foot traffic during the pandemic was rather predictable, which decreased with social distancing measures; however, the effects differed significantly across trade areas. Last, the impact of trade area characteristics on consumer foot traffic, such as trade area size, transport modes, and socio-demographics, may differ before and during the pandemic. Moreover, we find that the effects also varied with social distancing measures during the pandemic. Overall, we propose that government officials and retail managers need to pay great attention to trade area characteristics such as socio-demographics and transport modes for better response to the outbreak of the COVID-19 pandemic and better preparation for the recovery from the COVID-19 pandemic.

2. Theoretical foundation

We investigate consumer foot traffic to shopping malls during the pre-pandemic and pandemic periods. Figure 1 illustrates our theoretical model with the dependent variable being consumer store visits. The explanatory variables include trade area size, socio-demographics (income, gender, age, and ethnicity), transport modes (drove alone, carpooled, public transit, bicycled, walked, and work at home). In this section, we survey relevant literature in the following areas: 1) *social distancing*, 2) *trade area*, 3) *socio-demographics*, and 4) *transport modes*.

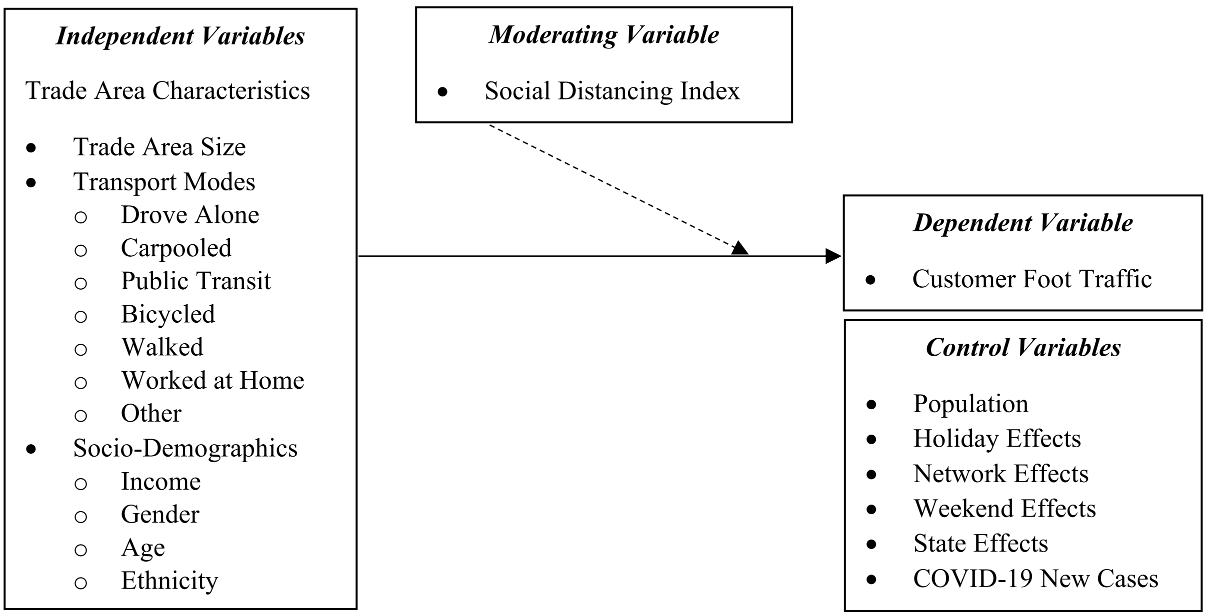


Figure 1: Theoretical Model

2.1 Social Distancing

Social distancing, also known as physical distancing, is the distancing of individuals and shifting of habits or behaviors in daily life, which reduces direct and indirect contact between individuals (CDC, 2020). Social distancing prevents and reduces the rate of disease transmission, thereby reducing the potential maximum of patients at a given time and thus reducing the strain on the healthcare infrastructure, i.e. flattening the curve (Chu et al., 2017; Fong et al., 2020). During the 1918 Spanish flu pandemic, Asia flu of 1957-58, and the 2009 swine flu pandemic, such restrictions played a significant role in mitigating the pandemic (Caley et al., 2008; Glass et al., 2006; Markel et al., 2007; Sebastian et al., 2009). Social distancing is motivated by two primary factors, government regulations and personal diligence. First, restrictive and punitive measures taken by the state or local administration such as school closure, mask mandates, stay-home orders and the associated fines establish a hard minimum of actions that people must undertake to effectively perform social distancing (Anderson et al., 2020). Secondly, individual concerns and behavior affect social distancing as well, from the usage of medical grade masks and avoiding certain times of the day when going out, to personal wellness checks and self-imposed quarantine, people develop avoidant behavior in the pandemics and proactively take measures to ensure their own well-being and that of others. (Houston & Bull, 1994; Li et al., 2020; Luttrell & Petty, 2020; Schaller et al., 2015).

Although social distancing and the associated restrictions and habit changes are undoubtedly effective in reducing transmission, they also have significant impacts on the economy, especially the retail and commercial sectors. The traditional physical ‘brick and mortar’ stores, already hard hit by customer flow to online platforms, was dealt a serious blow by the COVID-19 pandemic (Isidore, 2020). Due to the social distancing restrictions, half of the department stores in the USA are expected to close by the end of 2021 (Wetherell, 2020). Other non-essential businesses belonging to the dining, entertainment and personal care sectors were also heavily impacted by the pandemic with a multitude of closures (Barro, 2020). In general, at the beginning of the pandemic, retailers saw a surge in business with the commencement of stockpiling behavior, followed by a consistent decline in business as regulations were imposed and raised (Baker et al., 2020). The retail sector often relies heavily on significant physical interactions with customers and is particularly vulnerable to social distancing restrictions (Koren & Pető, 2020). Though in some areas, the social distancing restrictions were loosened, and shops were re-opened, they are still be impacted as only a fraction of the potential customers can be in the space and tailored to at a certain time, which will bring in lower profits or even push shops into financial deficit. Moreover, risk-averse consumers may be reluctant to return to physical stores even in the post pandemic world because of the developed avoidant behavior (Darnell et al., 2020). *In this study, we explore how social distancing index interacts with trade area characteristics such as transport modes and socio-demographics in affecting consumer foot traffic to shopping centers during the pandemic.*

2.2 Trade Area

It is imperative that, before establishing a shopping center that the developed facility meets the demands of the potential customers in the area and is able to be reached effectively by the designated audience. Bennett (1995) defined a trade area or a market area as “*a geographical area containing the customers of a particular firm or group of firms for specific goods or services”.* One of the early works by Reilly (1931) in determining the trade area is called *“The Law of Retail Gravitation*”. The work developed a heuristic to determine the size of the trading area. According to the law, large cities have a larger share of influence and thus people are willing to travel longer distances to reach a larger city. Reilly’s law can be used to determine the trade area, potential customers within that trade area, and possible competitors (Bozdo et al., 2013). However, the calculation by Reilly (1931) is under the assumption of a complete lack of any geographical features or obstacles that can affect customer demands. Converse (1949) revised Reilly’s Law (1931) which came to be known as the breaking point model. He extended the law by defining the breaking point of the trade area between two cities. According to Converse (1949), a customer at breaking point has equal probability of shopping at these two locations.

Leon (1954) modified Reilly’s model to estimate the trade area of shopping centers. Huff (1964) improved Leon’s (1954) method to delineate the trade area of shopping centers focusing on consumers rather than retailers. The new method focuses on merchandise offering and travel time. Huff (1964) defined the trade area for a shopping center as: “*A geographical delineated region, containing potential customers for whom there exists a probability greater than zero of their purchasing a given class of products or services offered for sale by a particular firm or by a particular agglomeration of firms*.” Huff & Batsel (1977) created a procedure to determine a trade area in terms of areal extent which is perfectly replicable. It helps to visualize the directional orientation and dispersion of customers. This process of delineating the trade area boundary was further refined by Huff & Rust (1984). They provide four descriptive measures for the comparison of market area boundaries (size of market area, shape of market area, irregularity of market area, and U coefficient), along with a statistical method for decomposing market boundary differences. *In this work, we contribute to previous work by studying how trade area characteristics such as trade area size, transport modes, and socio-demographics, affect consumer foot traffic to shopping centers before and during the pandemic.*

2.3 Transport Modes

In most of the urban scenarios, shopping trips constitute the second most frequent trips after work trips (Meena et al., 2019). Shopping malls are naturally large centers of attraction due to the wide range of services and commodities offered. In order to widen the appeal, shopping centers often are accessible through a large range of public and private means of transport. Generally, many factors may influence the transport mode choice such as time, cost, punctuality, accessibility, connectivity, and urban design (Boulange et al., 2017; Hergesell & Dickinger, 2013; Madhuwanthi et al., 2016; Schafer & Victor, 2000). For example, Meena et al. (2019) developed a choice model to demonstrate factors that affect transport mode decisions for shopping mall trips in Mumbai. They found that travel time significantly affect the mode choice. Specifically, walking time and access time affect the utility of public transport mode, while number of passengers and driving license possession influence private transport modes. In addition, socio-demographic factors like age, gender, and occupation also affects mode choice behavior of shopping mall trips. Michel & Scheiner (2016) analysed association between the location and accessibility of shopping center and customers travel modes using secondary data in 17 German shopping centers. Results show that shopping center location, urban environment at site and customer's residence location influence the choice of transport modes. Moreover, socio-demographics such as gender, household size, income also affects choice of transport mode to shopping centers.

Due to the pandemic, travelling patterns are bound to change. Government policies on social distancing affect the choices made by people. Despite cost and travel time, safety is bound to be an important factor during the pandemic. Studies conducted in different countries have shown the pattern of transport modes choice has changed since the COVID-19 pandemic (Abdullah et al., 2020; Eisenmann et al., 2021; Junior Dzisi et al., 2021; Pawar et al., 2020; Scorrano & Danielis, 2021). For example, Scorrano & Danielis (2021) analyzed mode choice to access the city center of Trieste before and during the COVID-19 emergency. They show that the COVID-19 pandemic has significantly altered the transport mode choice, a shift of choice of transport modes from bus to other private, motorised and non-motorised modes. Pawar et al. (2020) studied the impact of social distancing on decision of transport modes during the transition to lockdown in India. They found that safety perception of commuters did not significantly affect transport mode choices during the transition phase, although they perceived public transport mode is unsafe compared to personal vehicle. A possible reason is that availability of alternate modes of transport has limited commuters' capability to switch to other transport modes. *In this work, we study how various types of transport modes (drove alone, carpooled, public transit, bicycled, walked, and worked at home) affect consumer foot traffic, and we expect that the effects may differ before and during the pandemic and may shift with social distancing measure in the pandemic period.*

2.4 Socio-Demographics

Socio-demographic characteristics such as income, ethnicity, and gender determine consumers' involvement with the purchasing activities (Slama & Tashchian, 1985). However, the effects have been found to vary by individual characteristics and evolve with time. For example, early work by Ferber (1958) seeked to determine the factors influencing city variations in retail sales in Illinois. Contrary to the previous study by Russell (1957), Ferber (1958) showed that income is a major variable in variations in per capita retail sales between cities for most categories of sales. Ingene & Yu (1981) supported this argument that total, and per capita sales are influenced by the income. Slama & Tashchian (1985) showed that income has a curvilinear relationship with purchase involvement and thus people with moderate income have the highest purchasing involvement. Traditionally, women are expected to be the main customer for retail establishments in comparison to men (Davis, 1971; Hernandez, 1990). Slama & Tashchian (1985) showed that females are more involved in shopping in comparison to males. However, given changing times and social norms, men are now more involved than before as more women are employed outside the home (Gershuny & Robinson, 1988).

Moreover, the effects of socio-demographics on consumer foot traffic vary with retail formats (Carpenter & Moore, 2006). Many works have explored the relationship between mall patronage and consumer socio-demographics (Bearden et al., 1978; Korgaonkar et al., 1985; Mohan & Tandon, 2015; Roy, 1994). For example, Roy (1994) studied the role played by demographics and shopping motivation in mall shopping frequency. The results show that the frequent mall shopper are those recreational shoppers; that is, individuals who are around 40-60 years old with relatively high income, household size greater than three, and insensitive to deals. While the infrequent visitors are occasional shoppers, classified and was found to be generally individuals who are 18-39 years old, with relatively low income, small family size, and sensitive to deals. Kuruvilla & Joshi (2010) profiled the characteristics of different types of mall shoppers in India. The results indicate that the socio-demographics and behavioral factors of high-level spenders are significant different from that of low-level spenders. Shim & Eastlick (1998) examined whether one's ethnic identification serves as important factors that influence patronage behavior in the context of regional shopping malls. The results show that independent of ethic group membership, both self-actualizing and social affiliation values can be used effectively to position regional malls.

During the COVID-19 pandemic, some demographic groups were shown to be more impacted than others. The death rate in the U.S. shows that the people of color are often affected by circumstances which put them in a higher risk category (CDC, 2020). In comparison to the white population, African American and Hispanic people have death rate 1.9 times and 2.3 times higher, respectively, coincidentally being more economically vulnerable. The 2018 Census data states that median income of household is the lowest amongst African American ($41,361) and Hispanics ($51,450). African American have only 47% of Asian ($87,194) and 62% of White ($66,943) household income (Buckley & Barua, 2020). Further, African American, and Hispanic communities are mostly employed in low-wage occupations (Buckley & Barua, 2020). Moreover, biologically, women are more resistant to infections than men due to factors like sex hormones, high expression of coronavirus receptors, etc. (Bwire, 2020). However, economically women are more susceptible to economic effects of pandemic with women's jobs are 1.8 times more vulnerable than men's and globally women account for 54% of job losses despite them being only 39% of employment holders (Madgavkar et al., 2020). Another group effected is elder people. Trends suggest that hospitalisation and death rate is positively correlated with age with 8 of 10 reported deaths in US among over 65 years old (CDC, 2021). Another study shows that women, elderly, and racial/ethnic minorities are more likely to follow regulations like practicing better hygiene quarantining and social distancing (Kim and Crimmins, 2020). *In this work, we investigate* *how various types of socio-economic population groups (income, gender, age, and ethnicity) relate to foot traffic before and during the pandemic and how social distancing further affect their foot traffic during the pandemic.*

3. Research Methodology

We conduct empirical estimations to assess consumer foot traffic to shopping centers during the pre-pandemic and the pandemic periods. We first describe the data sources and proceed with the variable definitions and estimation models.

3.1 Sample Description

Our first data source is the Placer for foot traffic and trade area data (Placer.ai, 2020). Placer.ai is a company which uses mobile data to analyze foot traffic and create consumer profiles which can be used by retailers to get insights and make decisions. We obtained daily mobile data to four major open air-center retailers from January 2018 to November 2020 from Placer. The retail chains included are Brixmor Property Group, Kimco Realty, Phillips Edison Properties, and SITE Centers Corp. In total, the four chains are in possession of 1,286 properties across 38 states. We obtained 1,169 properties in our analysis, accounting for 91% of the total 1,286 properties of the four sample chains. We also gathered trade area characteristics for each shopping mall under the study from Placer, including trade area size, socio-demographics (income, gender, ethnicity, and age), and transport modes (drove alone, public transit, carpooled, bicycled, walked, and work-at-home). Table 21 in the Appendix illustrates the property distribution of the four sample chains across the U.S. market.

Our second data source is the University of Maryland COVID-19 Impact Analysis Platform, which provide data and insight on COVID-19's impact on mobility, health, economy, and society for all states with daily data updates. The platform was developed by Dr. Lei Zhang's group at the Maryland Transportation Institute (MTI) in partnership with the Center for Advanced Transportation Technology Laboratory (CATT Lab) (Maryland Transportation Institute, 2020; Zhang et al., 2020). In particular, we collected daily state-level social distancing index as well as COVID-19 diffusion data from the platform.

3.2 Variable Definition

The purpose of our models is to determine how the interaction of trade area characteristics and social distancing measures affect consumer foot traffic to shopping centers during the pre-pandemic and pandemic periods. The dependent variable is the daily foot traffic (FOOT_TRAFFIC) to each shopping mall property.

Our moderating variable, social distancing index, represents the degree/strictness of social distancing measures imposed. SOCIAL_DISTANCE, ranging from 0 to 1, with "0" indicating no social distancing measures, while "1" indicates a complete lockdown (all residents at home). Both linear and quadratic terms for social distancing index are included in the model as previous research indicates presence of non-linear relationship between consumer behavior and intensity of the event (Pan et al., 2020).

Our independent variables include trade area characteristics for each property under the study, such as trade area size, transport modes, and socio-demographics. For transport modes, we use transportation to work as an approximation for the transport structure in that trade area, such as driving alone, carpooling, public transit, biking, walking, and remote workers. For socio-demographics, we consider income, gender, ethnicity, and age characteristics of the trade area. Ethnicity divided into African American, Asian, Hispanic, White, and Other (Olmsted-Hawala & Nichols, 2020). The age distribution of the population in the trade area is categorized into four groups: < 18 (young), 18-35 (young adult), 36-55(adult) and >55 (elderly) (Petry, 2002).

We also control for pandemic diffusion effect, trade area population, retail chain network, state-level effects, retail chain effects, weekend effects, holiday effects, and weekly effects in all the estimation models. Variable definitions are provided in Table 1. Table 2 and Table 3 represent the summary statistics of pre-pandemic and pandemic periods, respectively. In the Appendix, we present the correlation tables for pre-pandemic and pandemic period, respectively.

Table 1: Variable Definition

Variable	Definitions
FOOT_TRAFFIC	Consumer daily visits to a shopping center.
SOCIAL_DISTANCE	Index representing level of social distancing observed in the community.
TRADE_AREA_SIZE	Size of the trade area of a shopping center.
TRANS_DROVE_ALONE	Percent of population driving to work in the trade area of a shopping center.
TRANS_CARPOOLED	Percent of population using carpool to work in the trade area of a shopping center.
TRANS_PUBLIC	Percent of population using public transit to work in the trade area of a shopping center.
TRANS_BICYCLE	Percent of population using bicycle to work in the trade area of a shopping center.
TRANS_WALK	Percent of population walking to work in the trade area of a shopping center.
TRANS_OTHER	Percent of population using other modes in the trade area of a shopping center.
TRANS_HOME	Percent of population working at home in the trade area of a shopping center.
INCOME_MEDIAN	Median income of population in the trade area of a shopping center.
FEMALE	Percent of female population in the trade area of a shopping center.
MALE	Percent of male population in the trade area of the shopping center
AGE_YOUNG	Percent of young population (<18) in the trade area of a shopping center.
AGE_YOUNG_ADULT	Percent of young adult population (18-35) in the trade area of a shopping center.
AGE_ADULT	Percent of adult population (35-55) in the trade area of a shopping center.
AGE_ELDER	Percent of elder population (>55) in the trade area of a shopping center.
ETHNICITY_WHITE	Percent of White population in the trade area of a shopping center.
ETHNICITY_AF_AMER	Percent of African American population in the trade area of a shopping center.
ETHNICITY_HISPANIC	Percent of Hispanic population using in the trade area of a shopping center.
ETHNICITY_ASIAN	Percent of Asian population in the trade area of a shopping center.
ETHNICITY_OTHER	Percent of other ethnicity groups in the trade area of a shopping center.
POPULATION	Total population in the trade area of a shopping center.
NETWORK_REGIONAL	Number of shopping malls of a chain in a state market.
NETWORK_NATIONAL	Number of shopping malls of a chain in the U.S.
NEW_COVID 19_CASES	Number of new COVID-19 cases in a state.
WEEKEND_EFFECT	Dummy variables indicate weekend effects.
WEEKLY_EFFECT	Dummy variables indicate weekly effects.
MONTHLY_EFFECT	Dummy variables indicate monthly effects.
HOLIDAY_EFFECT	Dummy variables indicate holiday effects.
STATE_EFFECT	Dummy variables indicate state effects.

Table 2: Summary Statistics (Pre-Pandemic 2018-2019)

Variable	Unit	Mean	SD	Min	Max
FOOT_TRAFFIC	Visits	5,476.83	4,889.87	0.00	102,131.00
TRADE_AREA_SIZE	100 Sq Miles	0.56	0.42	0.04	3.72
TRANS_DROVE_ALONE	Percent	0.77	0.09	0.14	0.90
TRANS_CARPOOLED	Percent	0.09	0.02	0.03	0.23
TRANS_PUBLIC	Percent	0.05	0.07	0.00	0.68
TRANS_BICYCLE	Percent	0.01	0.01	0.00	0.12
TRANS_WALK	Percent	0.02	0.02	0.00	0.22
TRANS_OTHER	Percent	0.01	0.01	0.00	0.23
TRANS_HOME	Percent	0.05	0.02	0.01	0.14
INCOME_MEDIAN	10k Dollars	8.26	2.30	3.88	19.94
FEMALE	Percent	0.51	0.01	0.42	0.56
MALE	Percent	0.49	0.01	0.44	0.58
AGE_YOUNG	Percent	0.23	0.03	0.07	0.35
AGE_YOUNG_ADULT	Percent	0.25	0.05	0.09	0.52
AGE_ADULT	Percent	0.27	0.03	0.09	0.36
AGE_ELDER	Percent	0.26	0.06	0.13	0.75
ETHNICITY_WHITE	Percent	0.55	0.21	0.01	0.97
ETHNICITY_AF_AMER	Percent	0.15	0.15	0.00	0.94
ETHNICITY_HISPANIC	Percent	0.20	0.17	0.01	0.96
ETHNICITY_ASIAN	Percent	0.06	0.06	0.00	0.53
ETHNICITY_OTHER	Percent	0.03	0.01	0.00	0.24
POPULATION	100K	2.02	2.05	0.01	30.86
NETWORK_REGIONAL	Tens	2.60	1.92	0.10	7.20
NETWORK_NATIONAL	Hundreds	3.49	0.79	1.71	4.04

Table 3: Summary Statistics (Pandemic 2020)

Variable	Unit	Mean	SD	Min	Max
FOOT_TRAFFIC	Visits	4,385.05	3,950.85	0.00	70,791.00
SOCIAL_DISTANCE	Index	0.34	0.13	0.10	0.83
TRADE_AREA_SIZE	100 Sq Mile	0.52	0.41	0.04	3.62
TRANS_DROVE_ALONE	Percent	0.76	0.09	0.13	0.90
TRANS_CARPOOLED	Percent	0.09	0.02	0.03	0.24
TRANS_PUBLIC	Percent	0.05	0.08	0.00	0.69
TRANS_BICYCLE	Percent	0.01	0.01	0.00	0.16
TRANS_WALK	Percent	0.02	0.02	0.00	0.20
TRANS_OTHER	Percent	0.01	0.01	0.00	0.19
TRANS_HOME	Percent	0.05	0.02	0.01	0.13
INCOME_MEDIAN	10k Dollars	8.23	2.37	3.82	18.83
FEMALE	Percent	0.51	0.01	0.46	0.56
MALE	Percent	0.49	0.01	0.44	0.54
AGE_YOUNG	Percent	0.23	0.04	0.06	0.35
AGE_YOUNG_ADULT	Percent	0.24	0.05	0.10	0.52
AGE_ADULT	Percent	0.27	0.03	0.12	0.37
AGE_ELDER	Percent	0.26	0.06	0.13	0.64
ETHNICITY_WHITE	Percent	0.55	0.21	0.01	0.98
ETHNICITY_AF_AMER	Percent	0.16	0.15	0.00	0.93
ETHNICITY_HISPANIC	Percent	0.20	0.17	0.01	0.95
ETHNICITY_ASIAN	Percent	0.06	0.06	0	0.53
ETHNICITY_OTHER	Percent	0.03	0.02	0.00	0.26
POPULATION	100K	1.88	1.96	0.01	29.36
NETWORK_REGIONAL	Tens	2.60	1.92	0.10	7.20
NETWORK_NATIONAL	Hundreds	3.49	0.79	1.71	4.04
NEW_COVID19_CASES	Cases	1,831.81	2,737.33	0.00	21,776.00

3.3 Estimation Models

Our goal is to investigate how trade area characteristics such as trade area size, socio-demographics, and transport modes affect foot traffic to shopping malls during the pre-pandemic (2018-2019) and pandemic (2020) periods. $\mathrm{FOOT\_TRAFFIC}_{ijsdwmy}$ represents foot traffic to property i of chain j in state s on day d of week w and month m in year y. We used a random effect model for our analysis as our main variable of interests (socio-demographics and transport modes) are relatively time-invariant which can not be analyzed using fixed effects model (Bell & Jones, 2015; Firebaugh et al., 2013).

We present three estimation models in Equations (1), (2), and (3). Equation (1) estimates the direct effects of trade area characteristics on foot traffic during the pre-pandemic period (2018-2019), where η_{ij} represents the unobserved property-chain random effects and $\varepsilon_{ijsdwmy}$ represents the error term. Equation (2) estimates the direct effect of the social distancing index and trade area characteristics on foot traffic during the pandemic period (2020), $\emptyset_{ij}$ represent the unobserved property-chain random effects and $\zeta_{ijsdwmy}$ represent the error term. Finally, Equation (3) estimates the moderating effect of social distancing index during the pandemic period (2020), where Ψ_{ij} and $\xi_{ijsdwmy}$represent the property-chain random effects and the error term.

$$
\begin{aligned}
&\mathrm{FOOT\_TRAFFIC}_{ijsdwmy} = \alpha_0 \\
&+ \alpha_1 \cdot \mathrm{TRADE\_AREA\_SIZE}_{ijsy} \\
&+ \alpha_2 \cdot \mathrm{TRANS\_CARPOOLED}_{ijsy} \\
&+ \alpha_3 \cdot \mathrm{TRANS\_PUBLIC}_{ijsy} \\
&+ \alpha_4 \cdot \mathrm{TRANS\_BICYCLE}_{ijsy} \\
&+ \alpha_5 \cdot \mathrm{TRANS\_WALK}_{ijsy} \\
&+ \alpha_6 \cdot \mathrm{TRANS\_OTHER}_{ijsy} \\
&+ \alpha_7 \cdot \mathrm{TRANS\_HOME}_{ijsy} \\
&+ \alpha_8 \cdot \mathrm{INCOME\_MEDIAN}_{ijsy} \\
&+ \alpha_9 \cdot \mathrm{FEMALE}_{ijsy} \\
&+ \alpha_{10} \cdot \mathrm{AGE\_YOUNG\_ADULT}_{ijsy} \\
&+ \alpha_{11} \cdot \mathrm{AGE\_ADULT}_{ijsy} \\
&+ \alpha_{12} \cdot \mathrm{AGE\_ELDER}_{ijsy} \\
&+ \alpha_{13} \cdot \mathrm{ETHNICITY\_WHITE}_{ijsy} \\
&+ \alpha_{14} \cdot \mathrm{ETHNICITY\_AF\_AMER}_{ijsy} \\
&+ \alpha_{15} \cdot \mathrm{ETHNICITY\_HISPANIC}_{ijsy} \\
&+ \alpha_{16} \cdot \mathrm{ETHNICITY\_OTHER}_{ijsy} \\
&+ \alpha_{17} \cdot \mathrm{POPULATION}_{ijsy} \\
&+ \alpha_{18} \cdot \mathrm{NETWORK\_REGIONAL}_{ijsy} \\
&+ \alpha_{19} \cdot \mathrm{NETWORK\_NATIONAL}_{ijy} \\
&+ \alpha_{20} \cdot \mathrm{NEW\_COVID19\_CASES}_{sdmy} \\
&+ \alpha_{21} \cdot \overline{\mathrm{HOLIDAY\_EFFECT}}_{dmy} \\
&+ \alpha_{22} \cdot \overline{\mathrm{WEEKEND\_EFFECT}}_{dmy} \\
&+ \alpha_{23} \cdot \overline{\mathrm{STATE\_EFFECT}}_{s} \\
&+ \alpha_{24} \cdot \overline{\mathrm{WEEKLY\_EFFECT}}_{w} \\
&+ \alpha_{25} \cdot \overline{\mathrm{MONTHLY\_EFFECT}}_{m} \\
&+ \eta_{ij} + \varepsilon_{ijsdwmy} \\
&\eta_{ij} \sim N(\mu_{\eta} + \sigma_{\eta}) \\
&\varepsilon_{ijsdwmy} \sim N(\mu_{\varepsilon} + \sigma_{\varepsilon})
\end{aligned}
$$

Equation (1)

$$
\begin{aligned}
&\mathrm{FOOT\_TRAFFIC}_{ijsdwmy} = \beta_0 \\
&+ \beta_1 \cdot \mathrm{SOCIAL\_DISTANCE}_{sdmy} \\
&+ \beta_2 \cdot (\mathrm{SOCIAL\_DISTANCE})^2_{sdmy} \\
&+ \beta_3 \cdot \mathrm{TRADE\_AREA\_SIZE}_{ijsy} \\
&+ \beta_4 \cdot \mathrm{TRANS\_CARPOOLED}_{ijsy} \\
&+ \beta_5 \cdot \mathrm{TRANS\_PUBLIC}_{ijsy} \\
&+ \beta_6 \cdot \mathrm{TRANS\_BICYCLE}_{ijsy} \\
&+ \beta_7 \cdot \mathrm{TRANS\_WALK}_{ijsy} \\
&+ \beta_8 \cdot \mathrm{TRANS\_OTHER}_{ijsy} \\
&+ \beta_9 \cdot \mathrm{TRANS\_HOME}_{ijsy} \\
&+ \beta_{10} \cdot \mathrm{INCOME\_MEDIAN}_{ijsy} \\
&+ \beta_{11} \cdot \mathrm{FEMALE}_{ijsy} \\
&+ \beta_{12} \cdot \mathrm{AGE\_YOUNG\_ADULT}_{ijsy} \\
&+ \beta_{13} \cdot \mathrm{AGE\_ADULT}_{ijsy} \\
&+ \beta_{14} \cdot \mathrm{AGE\_ELDER}_{ijsy} \\
&+ \beta_{15} \cdot \mathrm{ETHNICITY\_WHITE}_{ijsy} \\
&+ \beta_{16} \cdot \mathrm{ETHNICITY\_AF\_AMER}_{ijsy} \\
&+ \beta_{17} \cdot \mathrm{ETHNICITY\_HISPANIC}_{ijsy} \\
&+ \beta_{18} \cdot \mathrm{ETHNICITY\_OTHER}_{ijsy} \\
&+ \beta_{19} \cdot \mathrm{POPULATION}_{ijsy} \\
&+ \beta_{20} \cdot \mathrm{NETWORK\_REGIONAL}_{ijsy} \\
&+ \beta_{21} \cdot \mathrm{NETWORK\_NATIONAL}_{ijy} \\
&+ \beta_{22} \cdot \mathrm{NEW\_COVID19\_CASES}_{sdmy} \\
&+ \beta_{23} \cdot \overline{\mathrm{HOLIDAY\_EFFECT}}_{dmy} \\
&+ \beta_{24} \cdot \overline{\mathrm{WEEKEND\_EFFECT}}_{dmy} \\
&+ \beta_{25} \cdot \overline{\mathrm{STATE\_EFFECT}}_{s} \\
&+ \beta_{26} \cdot \overline{\mathrm{WEEKLY\_EFFECT}}_{w} \\
&+ \beta_{27} \cdot \overline{\mathrm{MONTHLY\_EFFECT}}_{m} \\
&+ \varnothing_{ij} + \zeta_{ijsdwmy} \\
&\varnothing_{ij} \sim N(\mu_{\varnothing} + \sigma_{\varnothing}) \\
&\zeta_{ijsdwmy} \sim N(\mu_{\zeta} + \sigma_{\zeta})
\end{aligned}
$$

Equation (2)

$$
\begin{aligned}
&\mathrm{FOOT\_TRAFFIC}_{ijsdwmy} = \gamma_0 \\
&+ \gamma_1 \cdot \mathrm{SOCIAL\_DISTANCE}_{sdmy} + \gamma_2 \cdot (\mathrm{SOCIAL\_DISTANCE}_{sdmy})^2 \\
&+ \gamma_3 \cdot \mathrm{TRADE\_AREA\_SIZE}_{ijsy} + \gamma_4 \cdot \mathrm{TRADE\_AREA\_SIZE}_{ijsy} \cdot \mathrm{SOCIAL\_DISTANCE}_{sdmy} + \gamma_5 \cdot \mathrm{TRADE\_AREA\_SIZE}_{ijsy} \cdot (\mathrm{SOCIAL\_DISTANCE}_{sdmy})^2 \\
&+ \gamma_6 \cdot \mathrm{TRANS\_CARPOOLED}_{ijsy} + \gamma_7 \cdot \mathrm{TRANS\_CARPOOLED}_{ijsy} \cdot \mathrm{SOCIAL\_DISTANCE}_{sdmy} + \gamma_8 \cdot \mathrm{TRANS\_CARPOOLED}_{ijsy} \cdot (\mathrm{SOCIAL\_DISTANCE}_{sdmy})^2 \\
&+ \gamma_9 \cdot \mathrm{TRANS\_PUBLIC}_{ijsy} + \gamma_{10} \cdot \mathrm{TRANS\_PUBLIC}_{ijsy} \cdot \mathrm{SOCIAL\_DISTANCE}_{sdmy} + \gamma_{11} \cdot \mathrm{TRANS\_PUBLIC}_{ijsy} \cdot (\mathrm{SOCIAL\_DISTANCE}_{sdmy})^2 \\
&+ \gamma_{12} \cdot \mathrm{TRANS\_BICYCLE}_{ijsy} + \gamma_{13} \cdot \mathrm{TRANS\_BICYCLE}_{ijsy} \cdot \mathrm{SOCIAL\_DISTANCE}_{sdmy} + \gamma_{14} \cdot \mathrm{TRANS\_BICYCLE}_{ijsy} \cdot (\mathrm{SOCIAL\_DISTANCE}_{sdmy})^2 \\
&+ \gamma_{15} \cdot \mathrm{TRANS\_WALK}_{ijsy} + \gamma_{16} \cdot \mathrm{TRANS\_WALK}_{ijsy} \cdot \mathrm{SOCIAL\_DISTANCE}_{sdmy} + \gamma_{17} \cdot \mathrm{TRANS\_WALK}_{ijsy} \cdot (\mathrm{SOCIAL\_DISTANCE}_{sdmy})^2 \\
&+ \gamma_{18} \cdot \mathrm{TRANS\_OTHER}_{ijsy} + \gamma_{19} \cdot \mathrm{TRANS\_OTHER}_{ijsy} \cdot \mathrm{SOCIAL\_DISTANCE}_{sdmy} + \gamma_{20} \cdot \mathrm{TRANS\_OTHER}_{ijsy} \cdot (\mathrm{SOCIAL\_DISTANCE}_{sdmy})^2 \\
&+ \gamma_{21} \cdot \mathrm{TRANS\_HOME}_{ijsy} + \gamma_{22} \cdot \mathrm{TRANS\_HOME}_{ijsy} \cdot \mathrm{SOCIAL\_DISTANCE}_{sdmy} + \gamma_{23} \cdot \mathrm{TRANS\_HOME}_{ijsy} \cdot (\mathrm{SOCIAL\_DISTANCE}_{sdmy})^2 \\
&+ \gamma_{24} \cdot \mathrm{INCOME\_MEDIAN}_{ijsy} + \gamma_{25} \cdot \mathrm{INCOME\_MEDIAN}_{ijsy} \cdot \mathrm{SOCIAL\_DISTANCE}_{sdmy} + \gamma_{26} \cdot \mathrm{INCOME\_MEDIAN}_{ijsy} \cdot (\mathrm{SOCIAL\_DISTANCE}_{sdmy})^2 \\
&+ \gamma_{27} \cdot \mathrm{FEMALE}_{ijsy} + \gamma_{28} \cdot \mathrm{FEMALE}_{ijsy} \cdot \mathrm{SOCIAL\_DISTANCE}_{sdmy} + \gamma_{29} \cdot \mathrm{FEMALE}_{ijsy} \cdot (\mathrm{SOCIAL\_DISTANCE}_{sdmy})^2 \\
&+ \gamma_{30} \cdot \mathrm{AGE\_YOUNG\_ADULT}_{ijsy} + \gamma_{31} \cdot \mathrm{AGE\_YOUNG\_ADULT}_{ijsy} \cdot \mathrm{SOCIAL\_DISTANCE}_{sdmy} + \gamma_{32} \cdot \mathrm{AGE\_YOUNG\_ADULT}_{ijsy} \cdot (\mathrm{SOCIAL\_DISTANCE}_{sdmy})^2 \\
&+ \gamma_{33} \cdot \mathrm{AGE\_ADULT}_{ijsy} + \gamma_{34} \cdot \mathrm{AGE\_ADULT}_{ijsy} \cdot \mathrm{SOCIAL\_DISTANCE}_{sdmy} + \gamma_{35} \cdot \mathrm{AGE\_ADULT}_{ijsy} \cdot (\mathrm{SOCIAL\_DISTANCE}_{sdmy})^2 \\
&+ \gamma_{36} \cdot \mathrm{AGE\_ELDER}_{ijsy} + \gamma_{37} \cdot \mathrm{AGE\_ELDER}_{ijsy} \cdot \mathrm{SOCIAL\_DISTANCE}_{sdmy} + \gamma_{38} \cdot \mathrm{AGE\_ELDER}_{ijsy} \cdot (\mathrm{SOCIAL\_DISTANCE}_{sdmy})^2 \\
&+ \gamma_{39} \cdot \mathrm{ETHNICITY\_WHITE}_{ijsy} + \gamma_{40} \cdot \mathrm{ETHNICITY\_WHITE}_{ijsy} \cdot \mathrm{SOCIAL\_DISTANCE}_{sdmy} + \gamma_{41} \cdot \mathrm{ETHNICITY\_WHITE}_{ijsy} \cdot (\mathrm{SOCIAL\_DISTANCE}_{sdmy})^2 \\
&+ \gamma_{42} \cdot \mathrm{ETHNICITY\_AF\_AMER}_{ijsy} + \gamma_{43} \cdot \mathrm{ETHNICITY\_AF\_AMER}_{ijsy} \cdot \mathrm{SOCIAL\_DISTANCE}_{sdmy} + \gamma_{44} \cdot \mathrm{ETHNICITY\_AF\_AMER}_{ijsy} \cdot (\mathrm{SOCIAL\_DISTANCE}_{sdmy})^2 \\
&+ \gamma_{45} \cdot \mathrm{ETHNICITY\_HISPANIC}_{ijsy} + \gamma_{46} \cdot \mathrm{ETHNICITY\_HISPANIC}_{ijsy} \cdot \mathrm{SOCIAL\_DISTANCE}_{sdmy} + \gamma_{47} \cdot \mathrm{ETHNICITY\_HISPANIC}_{ijsy} \cdot (\mathrm{SOCIAL\_DISTANCE}_{sdmy})^2 \\
&+ \gamma_{48} \cdot \mathrm{ETHNICITY\_OTHER}_{ijsy} + \gamma_{49} \cdot \mathrm{ETHNICITY\_OTHER}_{ijsy} \cdot \mathrm{SOCIAL\_DISTANCE}_{sdmy} + \gamma_{50} \cdot \mathrm{ETHNICITY\_OTHER}_{ijsy} \cdot (\mathrm{SOCIAL\_DISTANCE}_{sdmy})^2 \\
&+ \gamma_{51} \cdot \mathrm{POPULATION}_{ijsy} + \gamma_{52} \cdot \mathrm{NETWORK\_REGIONAL}_{ijsy} + \gamma_{53} \cdot \mathrm{NETWORK\_NATIONAL}_{ijy} + \gamma_{54} \cdot \mathrm{NEW\_COVID19\_CASES}_{sdmy} \\
&+ \gamma_{55} \cdot \overline{\mathrm{HOLIDAY\_EFFECT}}_{dmy} + \gamma_{56} \cdot \overline{\mathrm{WEEKEND\_EFFECT}}_{dmy} + \gamma_{57} \cdot \overline{\mathrm{STATE\_EFFECT}}_{s} + \gamma_{58} \cdot \overline{\mathrm{WEEKLY\_EFFECT}}_{w} + \gamma_{59} \cdot \overline{\mathrm{MONTHLY\_EFFECT}}_{m} \\
&+ \Psi_{ij} + \xi_{ijsdwmy} \\
&\Psi_{ij} \sim N(\mu_{\Psi} + \sigma_{\Psi}) \\
&\xi_{ijsdwmy} \sim N(\mu_{\xi} + \sigma_{\xi})
\end{aligned}
$$

Equation (3)

4. Results and Discussion: Social Distancing and Trading Area Size

In this section, we discuss how social distancing and trading area size affect consumer foot traffic during the pre-pandemic and pandemic periods. We first investigate the effects of social distancing during the pandemic period (§4.1), followed by a comparison of the impact of the trade-area size during the pre-pandemic and pandemic periods (§4.2). Table 6 illustrates the estimation results from pre-pandemic model (Model 1.1 based on Equation 1), pandemic model (Model 1.2 based on Equation 2 and Model 1.3 based on Model 1.3).

4.1 Social Distancing

We expect that social distancing may significantly affect consumer foot traffic to shopping malls. In Model 1.2 and Model 1.3, we include social distancing index to observe its effects. In Model 1.2, the coefficient for SOCIAL_DISTANCE is positive but insignificant (432.58, p>0.10) and the coefficient for $(\text{SOCIAL\_DISTANCE})^2$ is significant and negative (-6,661.10, p<0.001). In Model 1.3, the coefficient for SOCIAL_DISTANCE is significant and negative (-56,310.86, p<0.01) and $(\text{SOCIAL\_DISTANCE})^2$ is positive and significant (55,169.13, p<0.01). Figure 2 illustrate the marginal effects of social distancing on consumer foot traffic using the estimation results of Model 1.2. As shown in Figure 2, the increase in social distancing results with a curvilinear drop in foot traffic. For example, as social distancing index increased from 0.1 to 0.7, on average foot traffic dropped by 2,937 visits.

Table 4: Margins for Social Distancing

At	Social Dis.	Margin	Std. Error	Z	P>|z|	95% confidence interval	
1	0.10	5083.43	414.41	12.27	0.00	4271.21	5895.65
2	0.30	4637.05	295.88	15.67	0.00	4057.13	5216.97
3	0.50	3657.79	200.20	18.27	0.00	3265.41	4050.17
4	0.70	2145.65	237.66	9.03	0.00	1679.84	2611.45

Pandemic 2020

Direct Effect based on Model 1.2
(Significant)

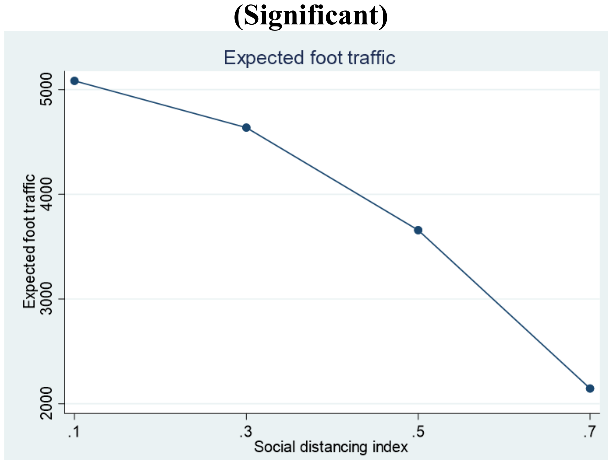


Figure 2: Foot Traffic vs Social Distancing

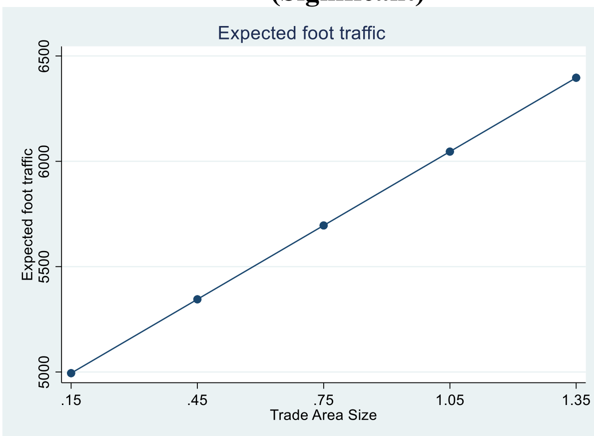
4.2 Trade Area Size

Trade area size may significantly affect foot traffic to shopping centers. We first observe the direct effect of trade area size on foot traffic before and during the pandemic. In Model 1.1, during the pre-pandemic period, the coefficient of $\mathrm{TRADE\_AREA\_SIZE}$ is significantly positive, (1,168.40, $p<0.01$). In Model 1.2, during pandemic period, the coefficient of $\mathrm{TRADE\_AREA\_SIZE}$ is significantly positive (2,475.36, $p<0.001$). Figure 3(a) and 3(b) present the marginal effects of trade area size on foot traffic during the pre-pandemic and pandemic periods. *The results suggest that trade area size is positively associated with consumer foot traffic during both the pre-pandemic and pandemic periods.*

Next, we demonstrate the moderating effect of social distancing during the pandemic. In Model 1.3, the coefficient of $\mathrm{TRADE\_AREA\_SIZE} \cdot \mathrm{SOCIAL\_DISTANCE}$ is significantly positive (8,394.05, $p<0.001$), and the coefficient of $\mathrm{TRADE\_AREA\_SIZE} \cdot (\mathrm{SOCIAL\_DISTANCE})^2$ is significantly negative (-19,638.99, $p<0.001$). Figure 3(c) and Table 5 present the combined marginal effects of trade area size and social distancing index on foot traffic during the pandemic period. The figure shows that the positive impact of trade area size on foot traffic decreases with social distancing index during the pandemic. For example, when social distancing increased from 0.1 to 0.7, at $\mathrm{TRADE\_AREA\_SIZE}$=15 square miles, $\mathrm{FOOT\_TRAFFIC}$ decreased from 4,036 to 2,552 by 1,484; while at $\mathrm{TRADE\_AREA\_SIZE}$=135 square miles, $\mathrm{FOOT\_TRAFFIC}$ decreased from 7,274 to 522 by 6,752. *Overall, shopping malls with larger trade area suffers more when social distancing index is higher during the pandemic.*

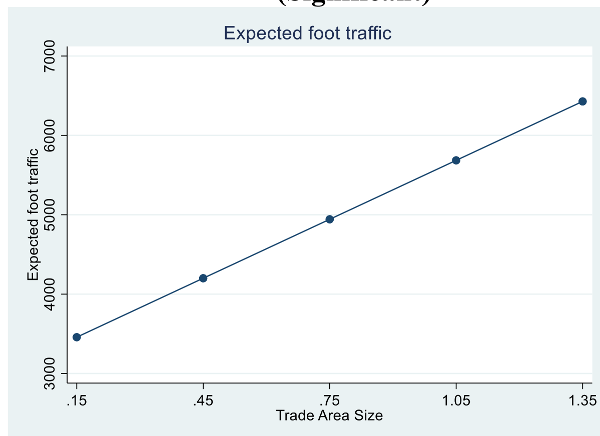
Pre-pandemic 2018-2019

(a) Direct Effects Based on Model 1.1 **(Significant)**



Pandemic 2020

(b) Direct Effects Based on Model 1.2 **(Significant)**



(c) Moderating Effects Based on Model 1.3 **(Significant)**

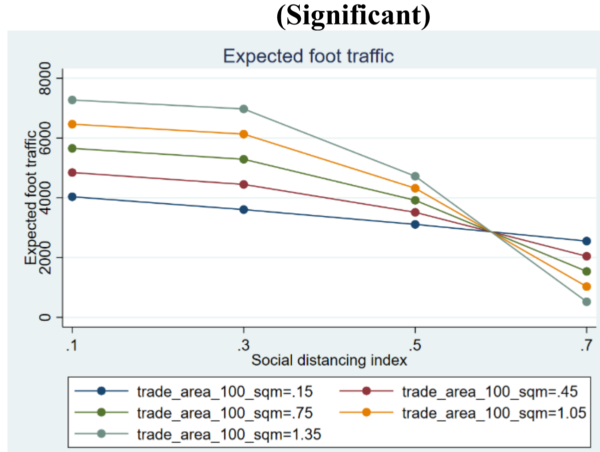


Figure 3: Foot Traffic vs Trade Area Size vs Social Distancing

Table 5: Margins for Trade Area Size and Social Distancing

At	Trade Area Size	Social Dis.	Margin	Delta Method Std. Error	Z	P>|z|	95% confidence interval	
1	0.15	0.10	4,035.65	434.09	9.30	0.00	3,184.84	4,886.46
2	1.35	0.10	7,273.74	699.41	10.40	0.00	5,902.92	8,644.57
3	0.15	0.30	3,606.29	376.74	9.57	0.00	2,867.89	4,344.69
4	1.35	0.30	6,973.61	737.75	9.45	0.00	5,527.64	8,419.58
5	0.15	0.50	3,111.78	316.67	9.83	0.00	2,491.12	3,732.43
6	1.35	0.50	4,722.99	495.73	9.53	0.00	3,751.38	5,694.59
7	0.15	0.70	2,552.12	250.14	10.20	0.00	2,061.85	3,042.38
8	1.35	0.70	521.87	250.88	2.08	0.04	30.16	1,013.58

Table 6: Estimation Results

Dependent Variable	**Pre-Pandemic 2018-2019**	**Pandemic 2020**	
FOOT_TRAFFIC	Model 1.1 (Equation 1)	Model 1.2 (Equation 2)	Model 1.3 (Equation 3)
Independent Variables			
Social Distancing			
SOCIAL_DISTANCE		432.58 (718.47)	-56,310.86** (19,516.41)
$(\text{SOCIAL\_DISTANCE})^2$		-6,661.10*** (900.92)	55,169.13** (18,107.35)
Trade Area Size			
TRADE_AREA_SIZE	1,168.40** (362.25)	2,475.36*** (729.51)	2,055.40** (649.56)
TRADE_AREA_SIZE · SOCIAL_DISTANCE			8,394.05*** (1,737.54)
TRADE_AREA_SIZE · $(\text{SOCIAL\_DISTANCE})^2$			-19,638.99*** (3,598.74)
Transport Modes			
TRANS_CARPOOLED	1,681.32 (3,551.31)	10,435.86** (3,931.74)	1,218.08 (2,718.14)
TRANS_CARPOOLED · SOCIAL_DISTANCE			53,556.71** (17,884.77)
TRANS_CARPOOLED · $(\text{SOCIAL\_DISTANCE})^2$			-68,182.83** (23,681.81)
TRANS_PUBLIC	-638.73 (1,495.55)	-5,350.53** (1,707.90)	-5,890.77** (1,794.91)
TRANS_PUBLIC · SOCIAL_DISTANCE			-1,978.23 (6,024.99)
TRANS_PUBLIC · $(\text{SOCIAL\_DISTANCE})^2$			5,290.72 (10,130.80)
TRANS_BICYCLE	5,277.33 (7,428.55)	14,002.81 (12,580.73)	18,068.78 (15,051.68)
TRANS_BICYCLE · SOCIAL_DISTANCE			17,120.13 (12,173.20)
TRANS_BICYCLE · $(\text{SOCIAL\_DISTANCE})^2$			-75,220.74 (45,797.04)
TRANS_WALK	-495.88 (1,102.10)	5,662.92 (6,791.53)	-5,534.48 (3,366.05)
TRANS_WALK · SOCIAL_DISTANCE			52,601.99 (54,231.57)
TRANS_WALK · $(\text{SOCIAL\_DISTANCE})^2$			-43,836.77 (78,777.88)
TRANS_OTHER	4,646.45 (6,773.24)	-6,733.83 (9,993.53)	-11,993.62 (8,553.68)
TRANS_OTHER · SOCIAL_DISTANCE			1,997.79 (19,822.00)
TRANS_OTHER · $(\text{SOCIAL\_DISTANCE})^2$			33,088.11 (35,060.01)
TRANS_HOME	4,678.00* (2,732.63)	-2,616.53 (7,388.03)	12,786.01* (7,581.59)
TRANS_HOME · SOCIAL_DISTANCE			-73,651.04*** (17,248.92)
TRANS_HOME · $(\text{SOCIAL\_DISTANCE})^2$			72,252.08*** (18,765.61)
Income			

INCOME_MEDIAN	-1.39 (37.60)	40.45 (105.45)	-30.86 (95.32)
INCOME_MEDIAN · SOCIAL_DISTANCE			293.41 (188.68)
INCOME_MEDIAN · (SOCIAL_DISTANCE)^2			-294.09* (168.55)
Gender			
FEMALE	685.40 (561.28)	-9,929.49* (4,816.20)	-12,423.42* (6,461.47)
FEMALE · SOCIAL_DISTANCE			9,367.68 (22,664.26)
FEMALE · (SOCIAL_DISTANCE)^2			-3,436.42 (31,149.96)
Age			
AGE_YOUNG_ADULT	-4,042.96 (3,891.52)	5,798.49*** (1,709.06)	2,037.22 (5,468.00)
AGE_YOUNG_ADULT · SOCIAL_DISTANCE			28,380.88 (19,337.29)
AGE_YOUNG_ADULT · (SOCIAL_DISTANCE)^2			-47,537.55** (16,862.14)
AGE_ADULT	-8,261.34* (4,992.51)	7,670.49* (4,028.92)	-6,824.54 (8,984.05)
AGE_ADULT · SOCIAL_DISTANCE			79,603.75*** (19,191.43)
AGE_ADULT · (SOCIAL_DISTANCE)^2			-95,360.88*** (14,934.94)
AGE_ELDER	-5,295.93 (3,971.88)	6,061.89** (1,850.40)	1,107.40 (2,685.25)
AGE_ELDER · SOCIAL_DISTANCE			30,527.74*** (4,321.93)
AGE_ELDER · (SOCIAL_DISTANCE)^2			-42,950.09*** (9,260.18)
Ethnicity			
ETHNICITY_WHITE	-1,630.32 (1,490.59)	-4,750.63*** (884.99)	-9,010.79*** (839.24)
ETHNICITY_WHITE · SOCIAL_DISTANCE			11,903.62*** (3,191.95)
ETHNICITY_WHITE · (SOCIAL_DISTANCE)^2			97.51 (5,280.74)
ETHNICITY_AF_AMER	-1,363.77 (1,301.33)	-1,028.92** (329.24)	-4,819.77*** (503.08)
ETHNICITY_AF_AMER · SOCIAL_DISTANCE			9,837.55*** (2,967.49)
ETHNICITY_AF_AMER · (SOCIAL_DISTANCE)^2			1,340.42 (5,434.15)
ETHNICITY_HISPANIC	-2,776.94 (3,017.61)	-2,719.38** (912.91)	-4,688.32*** (988.23)
ETHNICITY_HISPANIC · SOCIAL_DISTANCE			4,209.65** (1,379.92)
ETHNICITY_HISPANIC · (SOCIAL_DISTANCE)^2			1,959.38 (3,084.41)
ETHNICITY_OTHER	-8,025.32* (4,283.36)	-15,042.70* (7,147.93)	-9,357.86 (8,241.20)
ETHNICITY_OTHER · SOCIAL_DISTANC			-40,937.04 (35,470.56)
ETHNICITY_OTHER · (SOCIAL_DISTANCE)^2			60,784.81 (38,459.32)
Control Variables			
POPULATION	99.36 (156.79)	126.86 (142.23)	154.22 (141.81)

NETWORK_REGIONAL	-4.126 (197.37)	53.78 (146.99)	51.58 (150.24)
NETWORK_NATIONAL	-635.222 (757.85)	-455.94 (365.53)	-457.68 (362.23)
NEW_COVID19_CASES		0.00 (0.01)	0.001 (0.001)
WEEKEND_EFFECT	INCLUDED	INCLUDED	INCLUDED
STATE_EFFECT	INCLUDED	INCLUDED	INCLUDED
MONTH_EFFECT	INCLUDED	INCLUDED	INCLUDED
WEEK_EFFECT	INCLUDED	INCLUDED	INCLUDED
CONSTANT	16,921.25*** (4,197.51)	12,260.43** (3,961.01)	23,614.98*** (6,445.51)
N	853,370	391,615	391,615
Sigma_u	3,914.88	3,136.49	3,126.11
Sigma_e	1,828.45	1,673.31	1,628.49
Rho	0.82	0.78	0.79

The table shows estimated coefficients. Standard errors in parentheses. *p<0.1, **p<0.01, ***p<0.001

Notes:

1) We observe significantly positive results for WEEKEND_EFFECT with respect to the weekday base case. For the HOLIDAY_EFFECT, on the one hand, we observe that some holidays have positive and significant results on foot traffic; for example, Martin Luther's Day, President Day, Memorial Day, Labor Day, and Black Friday; on the other hand, other holidays show significantly negative relation; for example, Easter, Thanksgiving, Christmas, New Years, and Independence Day.
2) We also conducted a robustness check using natural log transformed foot traffic variable. Table 24 in the Appendix shows the regression results. Model 2.1 explores the direct impact of trade area characteristics on foot traffic during the pre-pandemic period. Model 2.2 studies the direct impact during the pandemic period, and Model 2.3 investigates the moderating effect of social distancing index during the pandemic. Overall, the estimation results are consistent with our primary findings in Table 6.

5. Results and Discussion: Social Distancing and Transport Modes

In this section, we illustrate how the interaction of transport modes and social distancing affect consumer foot traffic during the pre-pandemic and pandemic periods. Specifically, we investigate the effects of carpooled (§5.1), public transit (§5.2), bicycled and walked (§5.3), and worked-at-home (§5.4) during the pre-pandemic and pandemic periods. In the following analysis, we used drive alone as the base case.

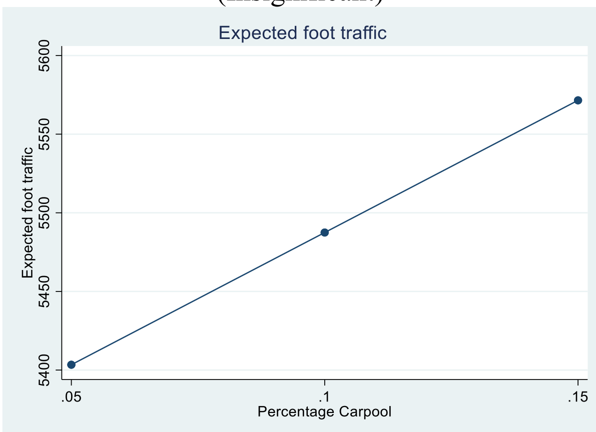
5.1 Carpooled

We first examine that how the propensity of using carpooled transport mode affect foot traffic during the pre-pandemic and pandemic periods. For variable $\mathrm{TRANS\_CARPOOLED}$ in the pre-pandemic model, Model 1.1, the coefficient is insignificant (1,681.32, $p>0.1$); while in the pandemic model, Model 1.2, the coefficient is positive and significant (10,435.86, $p<0.01$). Figure 4(a) and 4(b) show the marginal effect of carpooled on foot traffic during the pre-pandemic and pandemic periods. *The results indicate that compared to the propensity of driving alone, carpooling propensity showed little correlation with pre-pandemic foot traffic, however a positive correlation can be established between carpooling and foot traffic during the pandemic period, associated with more foot traffic.*

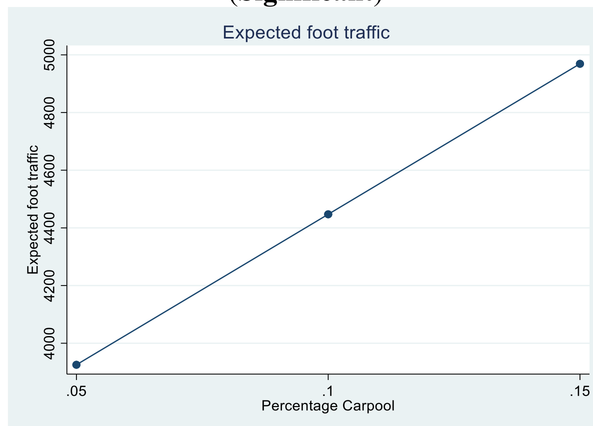
We further study the moderating effect of social distancing during the pandemic period. In Model 1.3, we find that the coefficient for $\mathrm{TRANS\_CARPOOLED} \cdot \mathrm{SOCIAL\_DISTANCE}$ is significantly positive (53,556.71, $p<0.01$) and the coefficient for $\mathrm{TRANS\_CARPOOLED} \cdot (\mathrm{SOCIAL\_DISTANCE})^2$ is significantly negative (-68,182.83, $p<0.01$). Table 7 and Figure 4(c) illustrate the combined marginal effects of carpooling and social distancing on foot traffic. On the one hand, as $\mathrm{SOCIAL\_DISTANCE}$ went up from 0.1 to 0.7, at $\mathrm{TRANS\_CARPOOLED}$ =5%, $\mathrm{FOOT\_TRAFFIC}$ decreased from 4,787 to 1,685 by 3,102; at $\mathrm{TRANS\_CARPOOLED}$ =15%, $\mathrm{FOOT\_TRAFFIC}$ decreased from 5,376 to 2,215 by 3,161. On the other hand, as $\mathrm{TRANS\_CARPOOLED}$ went up from 5% to 15%, at $\mathrm{SOCIAL\_DISTANCE}$=0.3, foot traffic increased from 4,167 to 5,281 by 1,114; at $\mathrm{SOCIAL\_DISTANCE}$=0.7, foot traffic increased from 1,685 to 2,215 by 530. *Overall, a clear positive correlation can be observed between carpooling and foot traffic during the pandemic period; however, the correlation became less established and visible as distancing measures grew tighter.*

Pre-pandemic 2018-2019	**Pandemic 2020**

(a) Direct Effects Based on Model 1.1 (Insignificant)



(b) Direct Effects Based on Model 1.2 (**Significant**)



(c) Moderating Effects Based on Model 1.3 **(Significant)**

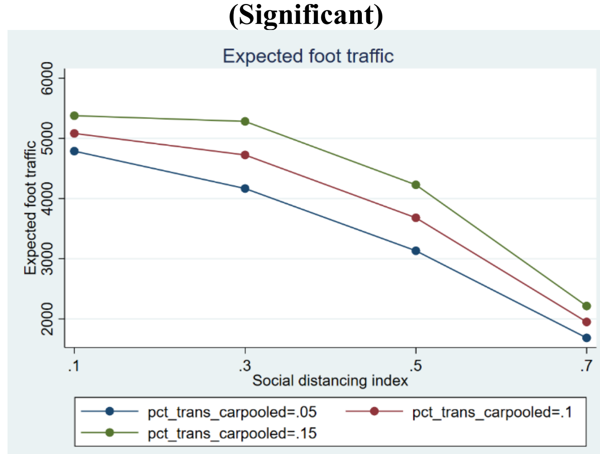


Figure 4: Foot Traffic vs Carpooled vs Social Distancing.

Table 7: Margins for Percent of Carpooled

At	Carpool	Social Dis.	Margin	Delta Method Std. Error	Z	P>|z|	95% confidence interval	
1	0.05	0.10	4,787.17	219.53	21.81	0.00	4,356.89	5,217.45
2	0.15	0.10	5,376.36	485.36	11.08	0.00	4,425.07	6,327.65
3	0.05	0.30	4,166.61	127.60	32.65	0.00	3,916.51	4,416.70
4	0.15	0.30	5,281.47	508.95	10.38	0.00	4,283.94	6,279.00
5	0.05	0.50	3,132.49	162.52	19.27	0.00	2,813.95	3,451.03
6	0.15	0.50	4,227.56	435.67	9.70	0.00	3,373.67	5,081.45
7	0.05	0.70	1,684.82	313.69	5.37	0.00	1,069.99	2,299.65
8	0.15	0.70	2,214.64	257.71	8.59	0.00	1,709.53	2,719.75

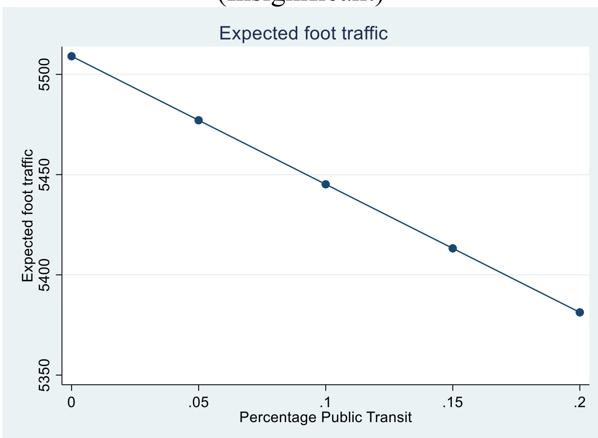
5.2 Public Transit

We first explore how propensity of using public transit affect foot traffic during the pre-pandemic and pandemic periods. We observed that, in the pre-pandemic model, Model 1.1, the coefficient for variable TRANS_PUBLIC is insignificant (-638.73, p>0.1). In the pandemic model, Model 1.2, we see a significant negative impact on foot traffic (-5,350.53, p<0.01). Figures 5(a) and 5(b) present the marginal effect of percentage using public transit on the foot traffic during the pre-pandemic and pandemic. *The results suggest that the usage of public transit has a notable negative impact on pandemic foot traffic.*

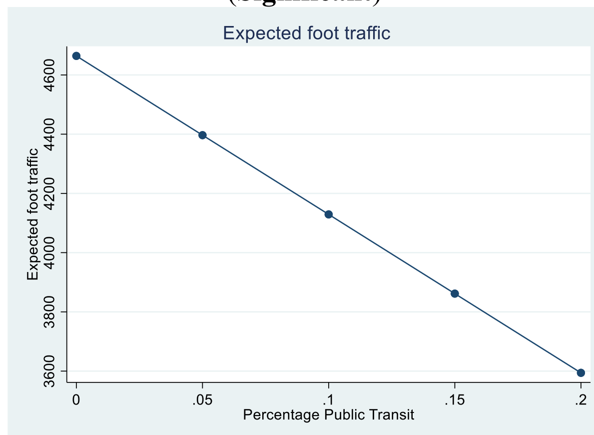
Next, we explore the moderating effects of social distancing during the pandemic period. In Model 1.3, the coefficient for $\text{TRANS\_PUBLIC} \cdot \text{SOCIAL\_DISTANCE}$ is insignificant (-1,978.23, p>0.1) and the coefficient for $\text{TRANS\_PUBLIC} \cdot (\text{SOCIAL\_DISTANCE})^2$ is insignificant (5,290.72, p>0.1). Figure 5 (c) and Table 8 illustrate the combined marginal effects of social distancing and public transit on foot traffic. First, we observe that, as SOCIAL_DISTANCE increased from 0.1 to 0.7, at TRANS_PUBLIC =0%, we see FOOT_TRAFFIC dropped from 5,362 to 2,163 by 3,199; at TRANS_PUBLIC =20%, FOOT_TRAFFIC dropped from 4,155 to 1,226 by 2,929. Moreover, we find that, as TRANS_PUBLIC went up from 0% to 20%, at SOCIAL_DISTANCE=0.3, foot traffic decreased from 4,971 to 3,770 by 1,201; at SOCIAL_DISTANCE=0.7, foot traffic decreased from 2,163 to 1,226 by 937. *In general, a considerable proportion of consumers avoided public transportation during the pandemic period, with little change throughout regardless of social distancing measures.*

Pre-pandemic 2018-2019	**Pandemic 2020**

(a) Direct Effects Based on Model 1.1 (Insignificant)



(b) Direct Effects Based on Model 1.2 (**Significant**)



(c) Moderating Effects Based on Model 1.3 (Insignificant)

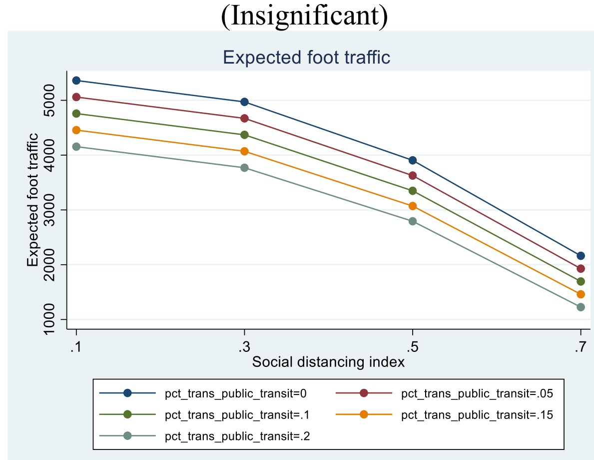


Figure 5: Foot Traffic vs Public Transit vs Social Distancing

Table 8: Margins for Percent of Public Transit and Social Distancing

At	Public Transit	Social Dis.	Margin	Delta Method Std. Error	Z	P>|z|	95% confidence interval	
1	0.00	0.10	5,361.65	380.08	14.11	0.00	4,616.71	6,106.59
2	0.20	0.10	4,154.51	299.90	13.85	0.00	3,566.71	4,742.31
3	0.00	0.30	4,971.20	313.77	15.84	0.00	4,356.22	5,586.18
4	0.20	0.30	3,769.58	338.45	11.14	0.00	3,106.24	4,432.93
5	0.00	0.50	3,904.84	256.11	15.25	0.00	3,402.87	4,406.80
6	0.20	0.50	2,793.40	311.26	8.97	0.00	2,183.33	3,403.46
7	0.00	0.70	2,162.56	299.57	7.22	0.00	1,575.41	2,749.72
8	0.20	0.70	1,225.95	230.57	5.32	0.00	774.04	1,677.86

5.3 Bicycled and Walked

We did not obtain significant results for percentage using bicycle. For Models 1.1 and 1.2, the coefficients for variable TRANS_BICYCLE are both insignificant. *Thus, we can conclude that there is no significant impact of percentage population using bicycle on foot traffic during both the pre-pandemic and pandemic periods.* In the Model 1.3, the coefficient for TRANS_BICYCLE $\cdot$ SOCIAL_DISTANCE is insignificant (17,120.13, p>0.1) and the coefficient for TRANS_BICYCLE $\cdot$ (SOCIAL_DISTANCE)^2 is insignificant (-75,220.74, p>0.1). *In short, there is no noteworthy moderating effect of social distancing upon the relationship between the usage of biking as a mode of transport and foot traffic.*

We got similar results for percentage of walked. For TRANS_WALK, the coefficients are insignificant in Model 1.1 (-495.88, p>0.1) and Model 1.2 (5,662.92, p>0.1). *Thus, we can conclude that there is no significant impact of percentage population walked on foot traffic during both the pre-pandemic and pandemic periods.* For the moderating effects of social distancing, in Model 1.3, the coefficient for TRANS_WALK $\cdot$ SOCIAL_DISTANCE is insignificant (52,601.99, p>0.1), and the coefficient for TRANS_WALK $\cdot$ (SOCIAL_DISTANCE)^{2}is insignificant (-43,836.77, p>0.1). *In summary, the impact of percentage of walking on foot traffic does not change with social distancing during the pandemic period.*

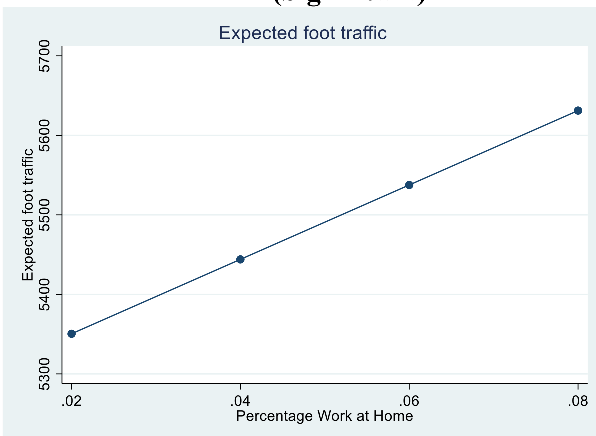
5.4 Worked at Home

We first compare the direct impact of percentage population working from home on foot traffic during the pre-pandemic and pandemic periods. In the pre-pandemic model, Model 1.1, the coefficient for variable TRANS_HOME is significantly positive (4,678.00, p<0.10). In the pandemic model, Model 1.2, the coefficient for variable TRANS_HOME is insignificant (-2,616.53, p>0.1). Figure 6(a) and 6(b) show the marginal effects of percentage working at home on foot traffic during the pre-pandemic and pandemic periods. *Compared to driving alone, the segment of the consumers working at home positively contributed to foot traffic during pre-pandemic; but has no significant effect on foot traffic during the pandemic period.*

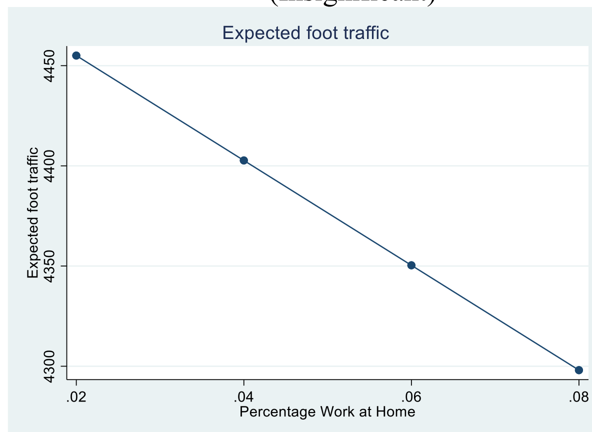
We further examine the moderating effects of social distancing during the pandemic period. In Model 1.3, the coefficient for TRANS_HOME $\cdot$ SOCIAL_DISTANCE is significantly negative (-73,651.04, p<0.001) and the coefficient for TRANS_HOME $\cdot$ (SOCIAL_DISTANCE)^2 is significantly positive (72,252.08, p<0.001). Figure 6(c) and Table 9 demonstrate the combined marginal effects of working at home and social distancing on foot traffic. We can see that, as social distancing increased from 0.1 to 0.7, at TRANS_HOME=4%, FOOT_TRAFFIC fell from 5,005 to 1,941 by 3,064; at TRANS_HOME=8%, FOOT_TRAFFIC fell from 5,251 to 1,806 by 3,445. We also find that, as TRANS_HOME increased from 2% to 8%, at SOCIAL_DISTANCE =0.3, FOOT_TRAFFIC decreased from 4,733 to 4,564 by 369; at SOCIAL_DISTANCE =0.7, FOOT_TRAFFIC decreased from 2,008 to 1,806 by 202. *Overall, the results suggest that there is a negative correlation between the work-from-home population and foot traffic in times of severe social distancing.*

Pre-pandemic 2018-2019	**Pandemic 2020**

(a) Direct Effects Based on Model 1.1 **(Significant)**



(b) Direct Effects Based on Model 1.2 (Insignificant)



(c) Moderating Effects Based on Model 1.3 **(Significant)**

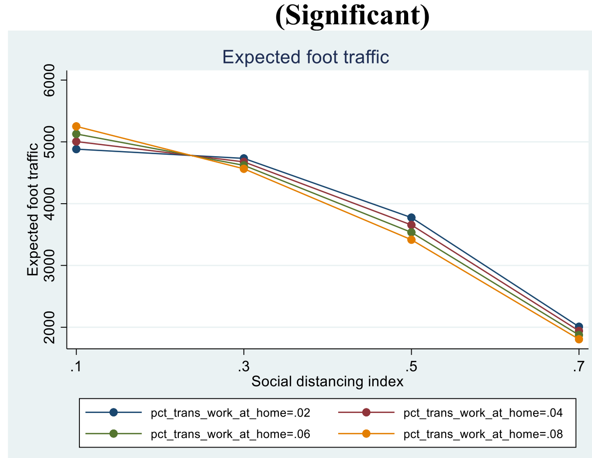


Figure 6: Foot Traffic vs Worked at Home vs Social Distancing

Table 9: Margins for Percent of Work-at-Home and Social Distancing

At	Work at home	Social Dis.	Margin	Delta Method Std. Error	Z	P>|z|	95% confidence interval	
1	0.02	0.10	4,882.38	427.93	11.41	0.00	4,043.66	5,721.11
2	0.08	0.10	5,250.99	336.47	15.61	0.00	4,591.51	5,910.46
3	0.02	0.30	4,732.76	418.99	11.30	0.00	3,911.55	5,553.97
4	0.08	0.30	4,564.36	245.39	18.60	0.00	4,083.41	5,045.32
5	0.02	0.50	3,774.71	407.97	9.25	0.00	2,975.11	4,574.31
6	0.08	0.50	3,416.12	156.87	21.78	0.00	3,108.67	3,723.58
7	0.02	0.70	2,008.23	429.29	4.68	0.00	1,166.85	2,849.62
8	0.08	0.70	1,806.26	85.85	21.04	0.00	1,638.01	1,974.52

6. Results and Discussion: Social Distancing and Socio-Demographics

In this section, we demonstrate how the interaction of social distancing and socio-demographics affect consumer foot traffic during the pre-pandemic and pandemic periods. Accordingly, we investigate the effects of income (§6.1), gender (§6.2), age (§6.3), and ethnicity (§6.4) during the pre-pandemic and pandemic periods.

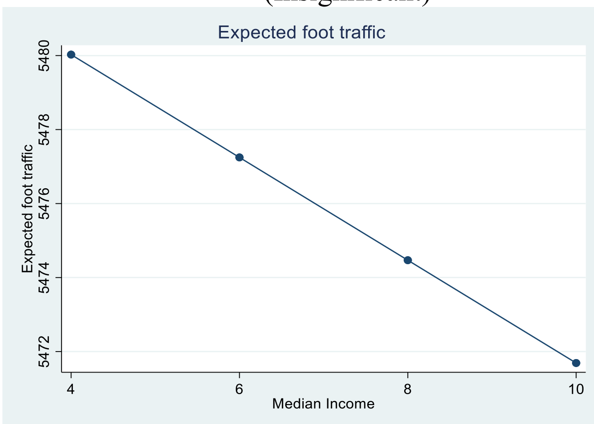
6.1 Income

Previous studies illustrated inconsistent findings on the impact of median income on consumer purchasing behavior. We first explore the direct effect of median income on foot traffic during the pre-pandemic and pandemic periods. In the pre-pandemic model, Model 1.1, the coefficient of $\mathrm{INCOME\_MEDIAN}$ is negative and insignificant (-1.39, p>0.1). In the pandemic model, Model 1.2, the coefficient of $\mathrm{INCOME\_MEDIAN}$ is positive and insignificant (40.45, p>0.1). Figure 7(a) and 7(b) present the marginal effects of median income on foot traffic, both of which are insignificant. *Overall, the median income has no significant impact on foot traffic during both periods.*

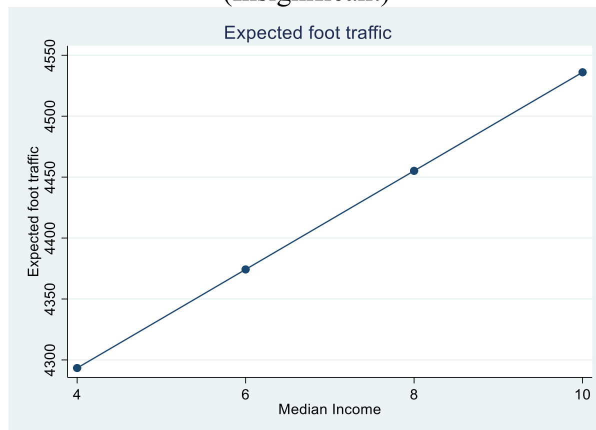
Next, we explore the moderating effect of social distancing during the pandemic. In Model 1.3, the coefficient of $\mathrm{INCOME\_MEDIAN} \cdot \mathrm{SOCIAL\_DISTANCE}$ is insignificant (293.41, p>0.1), and the coefficient of $\mathrm{INCOME\_MEDIAN} \cdot (\mathrm{SOCIAL\_DISTANCE})^2$ is significantly negative (-294.09, p<0.1). Figure 7(c) and Table 10 illustrate the combined marginal effects of median income and social distancing on foot traffic during the pandemic. For example, as $\mathrm{SOCIAL\_DISTANCE}$ increased from 0.1 to 0.7, at $\mathrm{INCOME\_MEDIAN}$ =\$40,000, foot traffic decreased from 5,057 to 1,849 by 3,208; at $\mathrm{INCOME\_MEDIAN}$=\$100,000, foot traffic decreased from 5,030 to 2,032 by 2,998. We also find that, as $\mathrm{INCOME\_MEDIAN}$ increased from \$40,000 to \$100,000, at $\mathrm{SOCIAL\_DISTANCE}$=0.3, $\mathrm{FOOT\_TRAFFIC}$ increased from 4,588 to 4,772 by 184; at $\mathrm{SOCIAL\_DISTANCE}$=0.7, $\mathrm{FOOT\_TRAFFIC}$ increased from 1,849 to 2,032 by 183. *The results suggest that the median income generally show a slightly positive association with foot traffic during the pandemic period.*

Pre-pandemic 2018-2019	Pandemic 2020

(a) Direct Effects Based on Model 1.1 (Insignificant)



(b) Direct Effects Based on Model 1.2 (Insignificant)



(c) Moderating Effects Based on Model 1.3 (**Significant**)

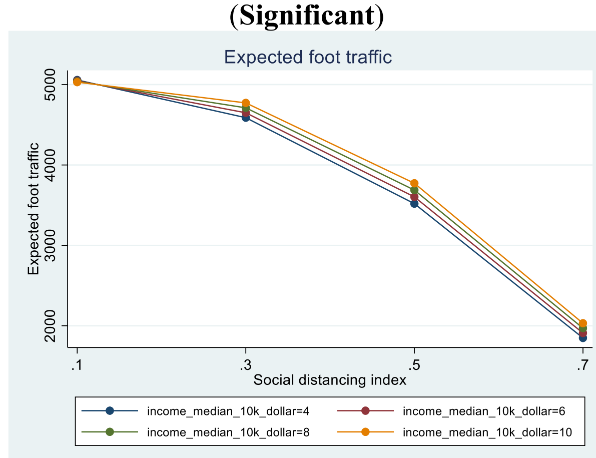


Figure 7: Foot Traffic vs Median Income vs Social Distancing

Table 10: Margins for Median Income and Social Distancing

At	Median Inc	Social Dis.	Margin	Delta Method Std. Error	z	P>|z|	95% confidence interval	
1	4.00	0.10	5,056.81	250.31	20.20	0.00	4,566.22	5,547.41
2	10.00	0.10	5,030.05	629.42	7.99	0.00	3,796.41	6,263.70
3	4.00	0.30	4,588.11	214.10	21.43	0.00	4,168.48	5,007.74
4	10.00	0.30	4,772.28	626.57	7.62	0.00	3,544.22	6,000.34
5	4.00	0.50	3,518.92	216.13	16.28	0.00	3,095.30	3,942.54
6	10.00	0.50	3,772.85	595.86	6.33	0.00	2,605.00	4,940.71
7	4.00	0.70	1,849.23	285.58	6.48	0.00	1,289.51	2,408.96
8	10.00	0.70	2,031.77	538.85	3.77	0.00	975.64	3,087.90

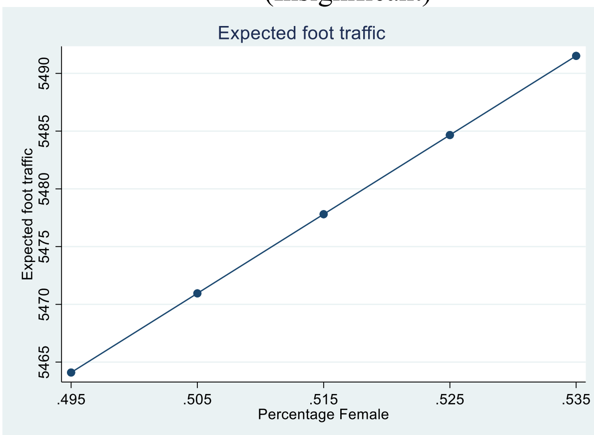
6.2 Gender

For gender, we use percentage of male population as the base case. We first investigate the direct effect of female population on foot traffic. For the pre-pandemic model, Model 1.1, the coefficient for FEMALE is insignificant (685.40, $p>0.1$). For the pandemic model, Model 1.2, the coefficient for FEMALE is significant and negative (-9,929.49, $p<0.1$). Figure 8(a) and 8(b) demonstrate the direct effect of female population on foot traffic during the pre-pandemic and pandemic periods. *Compared to the male population, there was a significant decrease in the percentage of female foot traffic during the pandemic period relative to the pre-pandemic norms.*

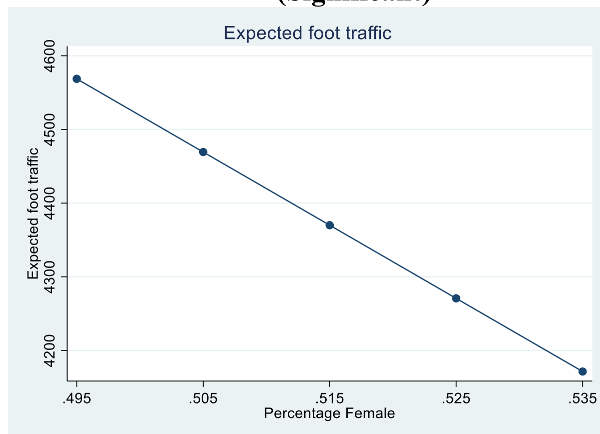
We further investigate the moderating effect of social distancing during the pandemic. In Model 1.3, the coefficient for FEMALE is negative and significant (-12,423.42, $p<0.1$), the coefficient for $\mathrm{FEMALE} \cdot \mathrm{SOCIAL\_DISTANCE}$ is insignificant (9,367.68, $p>0.1$), and the coefficient for $\mathrm{FEMALE} \cdot (\mathrm{SOCIAL\_DISTANCE})^2$ is insignificant (-3,436.42, $p>0.1$). Figure 8(c) and Table 11 demonstrate the combined marginal effect of female population and social distancing on foot traffic. We observe that, when social distancing index increased from 0.1 to 0.7, at FEMALE=50%, foot traffic dropped from 5,260 to 2,058 by 3,202; while at FEMALE=54%, foot traffic dropped from 4,799 to 1,756 by 3,043. We also find that, as FEMALE increased from 50% to 54%, at $\mathrm{SOCIAL\_DISTANCE}$=0.3, $\mathrm{FOOT\_TRAFFIC}$ decreased from 4,841 to 4,444 by 397; at $\mathrm{SOCIAL\_DISTANCE}$=0.7, $\mathrm{FOOT\_TRAFFIC}$ decreased from 2,058 to 1,756 by 302. *Overall, female population significantly decreased foot traffic during the pandemic, and the risk-averse behavior did not significantly change with the distancing measure.*

Pre-pandemic 2018-2019	Pandemic 2020

(a) Direct Effects Based on Model 1.1 (Insignificant)



(b) Direct Effects Based on Model 1.2 **(Significant)**



(c) Moderating Effects Based on Model 1.3 (Insignificant)

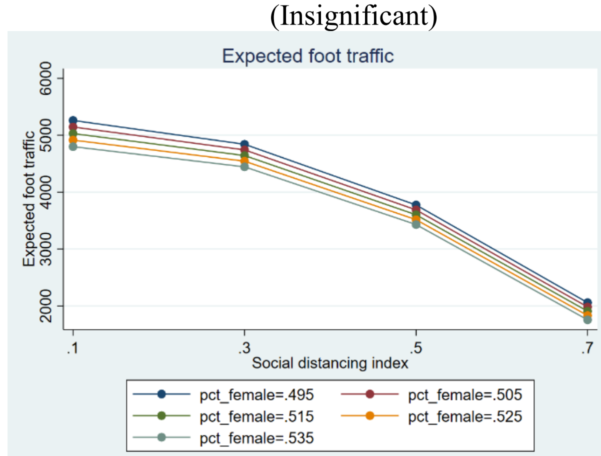


Figure 8: Foot Traffic vs Female vs Social Distancing

Table 11: Margins for Percent of Female and Social Distancing

At	Female%	Social Dis.	Margin	Delta Method Std. Error	Z	P>|z|	95% confidence interval	
1	0.50	0.10	5,259.73	317.13	16.59	0.00	4,638.16	5,881.30
2	0.54	0.10	4,798.89	378.49	12.68	0.00	4,057.06	5,540.72
3	0.50	0.30	4,841.16	297.14	16.29	0.00	4,258.77	5,423.55
4	0.54	0.30	4,444.26	302.71	14.68	0.00	3,850.96	5,037.57
5	0.50	0.50	3,773.85	249.01	15.16	0.00	3,285.79	4,261.91
6	0.54	0.50	3,429.90	254.93	13.45	0.00	2,930.24	3,929.56
7	0.50	0.70	2,057.80	269.26	7.64	0.00	1,530.05	2,585.55
8	0.54	0.70	1,755.80	257.23	6.83	0.00	1,251.64	2,259.96

6.3 Age

We expect that various population age group may alter their foot traffic during the pandemic. Specifically, we categorize the population into four age groups: minor (<18), young adult (18-35), adult (35-55), and elder (>55). And we consider percentage of minor population as the base case for our analysis.

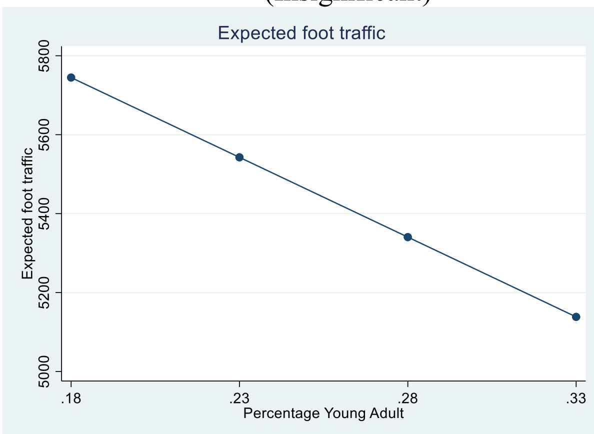
Young Adult

We first examine the direct effect of young-adult population on foot traffic before and during the pandemic. For variable AGE_YOUNG_ADULT in the pre-pandemic model, Model 1.1, we got negative and insignificant coefficient (-4,042.96, $p>0.1$); in the pandemic model, Model 1.2, we got positive and significant coefficient (5,798.49, $p<0.001$). Figure 9(a) and 9(b) show the marginal effects of young-adult population on foot traffic during the pre-pandemic and pandemic periods. *The results suggest that compared to minor population segment, young adults show no significant impacts on pre-pandemic foot traffic; however, during the pandemic period, there is a significant positive impact on the foot traffic from this age group.*

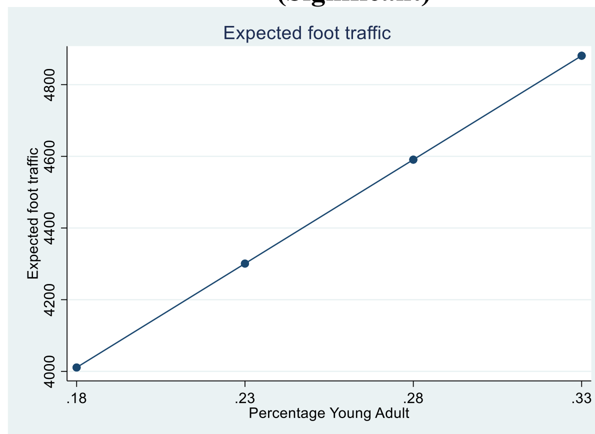
Next, we explore the moderating effect of social distancing during the pandemic. In Model 1.3, the coefficient for AGE_YOUNG_ADULT · SOCIAL_DISTANCE is insignificant (28,380.88, $p>0.1$), but the coefficient for AGE_YOUNG_ADULT · (SOCIAL_DISTANCE)^2 is significantly negative (-47,537.55, $p<0.01$). Figure 9 (c) and Table 12 present the combined marginal effects of young adult group and social distancing on foot traffic. We investigate that, as the SOCIAL_DISTANCE increased from 0.1 to 0.7, at AGE_YOUNG_ADULT = 18%, there was a fall in FOOT_TRAFFIC from 4,763 to 2,008 by 2,755; at AGE_YOUNG_ADULT = 33%, there was a fall in FOOT_TRAFFIC from 5,423 to 1,799 by 3,624. We also find that, as AGE_YOUNG_ADULT increased from 18% to 33%, at SOCIAL_DISTANCE=0.3, FOOT_TRAFFIC increased from 4,253 to 5,194 by 941; at SOCIAL_DISTANCE=0.7, FOOT_TRAFFIC decreased from 2,008 to 1,799 by 209. *Overall, the positive effect of young adult on foot traffic decreased as social distancing index increased during the pandemic.*

Pre-pandemic 2018-2019	**Pandemic 2020**

(a) Direct Effects Based on Model 1.1 (Insignificant)



(b) Direct Effects Based on Model 1.2 **(Significant)**



(c) Moderating Effects Based on Model 1.3 **(Significant)**

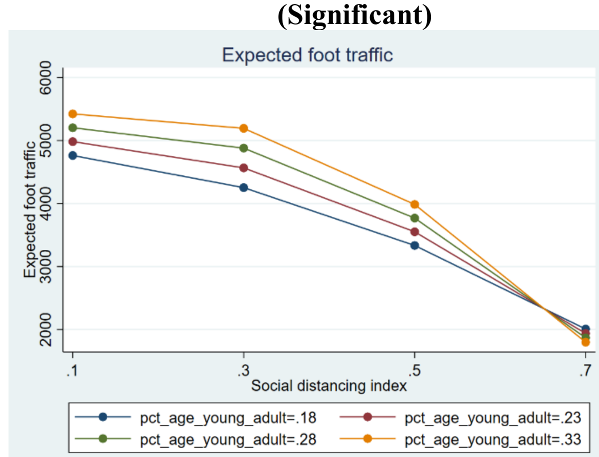


Figure 9: Foot Traffic vs Young Adult vs Social Distancing

Table 12: Margins for Percent of Young Adult and Social Distancing

At	YA %	Social Dis.	Margin	Delta Method Std. Error	Z	P>|z|	95% confidence interval	
1	0.18	0.10	4,762.77	350.50	13.59	0.00	4,075.79	5,449.75
2	0.33	0.10	5,422.76	521.70	10.39	0.00	4,400.26	6,445.26
3	0.18	0.30	4,252.88	229.10	18.56	0.00	3,803.85	4,701.92
4	0.33	0.30	5,193.85	391.86	13.25	0.00	4,425.82	5,961.88
5	0.18	0.50	3,334.58	164.07	20.32	0.00	3,013.01	3,656.16
6	0.33	0.50	3,986.07	340.20	11.72	0.00	3,319.29	4,652.86
7	0.18	0.70	2,007.87	236.10	8.50	0.00	1,545.13	2,470.61
8	0.33	0.70	1,799.43	284.78	6.32	0.00	1,241.27	2,357.59

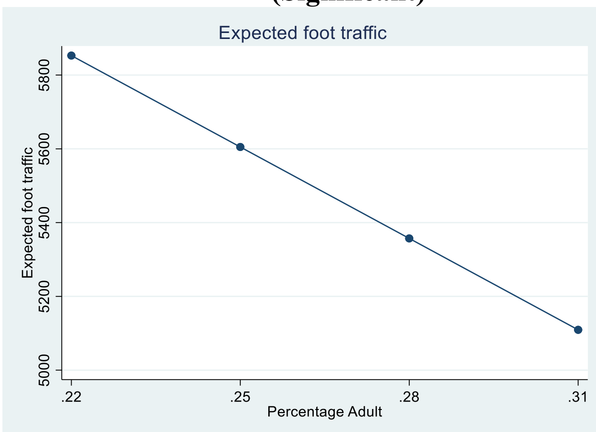
Adult

Using percentage of population less than 18 as the base case, we first analyze the direct effects of adult population on foot traffic. In the pre-pandemic model, Model 1.1, the coefficient for $\mathrm{AGE\_ADULT}$ is negative and significant (-8,261.34, $p<0.10$). However, in the pandemic model, Model 1.2, the coefficient positive and significant (7,670.49, $p<0.10$). Figure 10(a) and 10(b) demonstrate a significant reversing trend before and during the pandemic. *Compared to population of minors, the adult population contribute less foot traffic before the pandemic but contribute more foot traffic during the pandemic.*

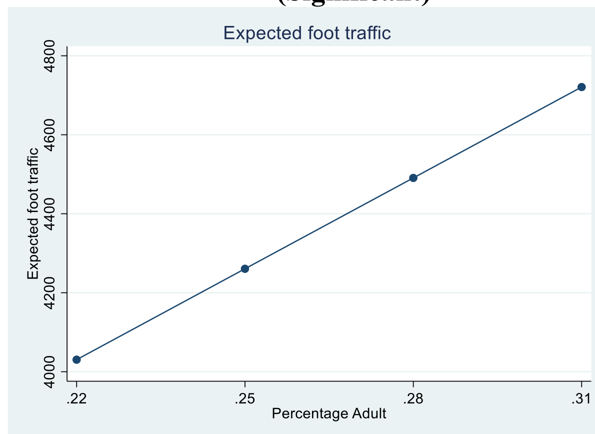
For the moderating effect of social distancing during the pandemic, we observe that, in Model 1.3, the coefficient for $\mathrm{AGE\_ADULT} \cdot \mathrm{SOCIAL\_DISTANCE}$ is significantly positive (79,603.75, $p<0.001$) and the coefficient for $\mathrm{AGE\_ADULT} \cdot (\mathrm{SOCIAL\_DISTANCE})^2$ is significantly negative (-95,360.88, $p<0.001$). Figure 10(c) and Table 13 show the combined marginal effect of adult group and social distancing on foot traffic. We find that, as $\mathrm{SOCIAL\_DISTANCE}$ increased from 0.1 to 0.7, at $\mathrm{AGE\_ADULT}$=22%, we see that the foot traffic fell from 5,038 to 1,818 by 3,220; at $\mathrm{AGE\_ADULT}$=31%, we see that the foot traffic fell from 5,055 to 2,013 by 3,042. In addition, we notice that, as $\mathrm{AGE\_ADULT}$ increased from 22% to 31%, at $\mathrm{SOCIAL\_DISTANCE}$ =0.3, $\mathrm{FOOT\_TRAFFIC}$ increased from 4,266 to 5,029 by 763; at $\mathrm{SOCIAL\_DISTANCE}$ =0.7, $\mathrm{FOOT\_TRAFFIC}$ increased from 1,818 to 2,013 by 195. *Overall, adults contribute more foot traffic during the pandemic relative to population less than 18, with decreasing impacts as social distancing index increased.*

Pre-pandemic 2018-2019	**Pandemic 2020**

(a) Direct Effects Based on Model 1.1 **(Significant)**



(b) Direct Effects Based on Model 1.2 **(Significant)**



(c) Moderating Effects Based on Model 1.3 **(Significant)**

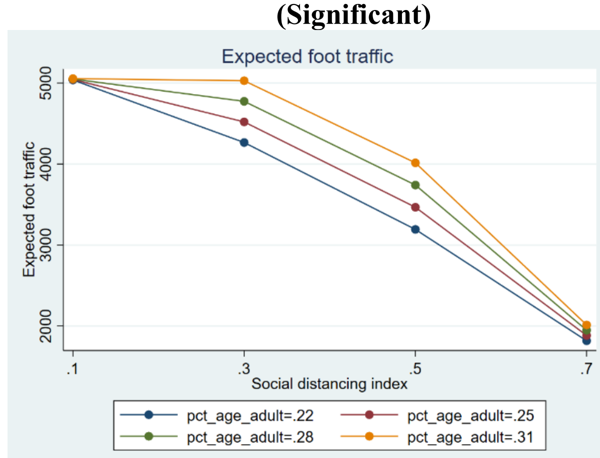


Figure 10: Foot Traffic vs Adult vs Social Distancing

Table 13: Margins for Percent of Adult and Social Distancing

At	Adult %	Social Dis.	Margin	Delta Method Std. Error	z	P>|z|	95% confidence interval	
1	0.22	0.10	5,038.28	599.01	8.41	0.00	3,864.25	6,212.31
2	0.31	0.10	5,054.68	264.91	19.08	0.00	4,535.46	5,573.90
3	0.22	0.30	4,266.01	451.87	9.44	0.00	3,380.36	5,151.67
4	0.31	0.30	5,028.68	183.27	27.44	0.00	4,669.47	5,387.89
5	0.22	0.50	3,192.53	343.25	9.30	0.00	2,519.77	3,865.29
6	0.31	0.50	4,014.87	171.57	23.40	0.00	3,678.60	4,351.14
7	0.22	0.70	1,817.84	273.13	6.66	0.00	1,282.52	2,353.16
8	0.31	0.70	2,013.25	308.06	6.54	0.00	1,409.47	2,617.03

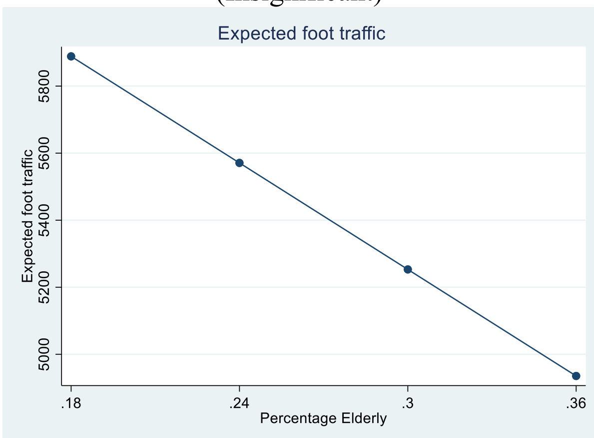
Elder

We first explore the direct effects of the elder population on the foot traffic. For $\mathrm{AGE\_ELDER}$ in the pre-pandemic period, Model 1.1, we get insignificant coefficient (-5,295.93, p>0.1). For the pandemic period, Model 1.2, we get significantly positive coefficient (6,061.89, p<0.01). Figure 11(a) and 11(b) demonstrate the marginal effect of elder population on foot traffic with respect to minor population before and during the pandemic. *We can conclude that, in comparison to minor population less than 18, the elder group has no significant impact on foot traffic during the pre-pandemic period; but has a significant positive impact on foot traffic during the pandemic period.*

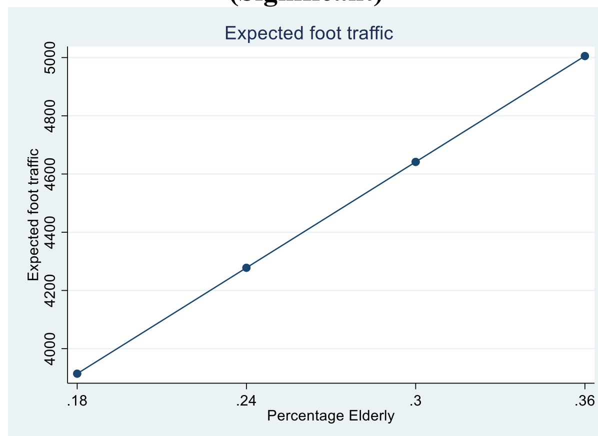
For the moderating effects of social distancing during the pandemic, in Model 1.3, the coefficient for $\mathrm{AGE\_ELDER} \cdot \mathrm{SOCIAL\_DISTANCE}$ is significantly positive (30,527.74, p<0.001) and the coefficient for $\mathrm{AGE\_ELDER} \cdot (\mathrm{SOCIAL\_DISTANCE})^2$ is significantly negative (-42,950.09, p<0.001). Figure 11(c) and Table 14 illustrate the combined marginal effects of elder population and social distancing on foot traffic. We observe that, as $\mathrm{SOCIAL\_DISTANCE}$ went up from 0.1 to 0.7, at $\mathrm{AGE\_ELDER} = 0.18$, $\mathrm{FOOT\_TRAFFIC}$ dropped from 4,757 to 1,807 by 2,950; at $\mathrm{AGE\_ELDER}$= 0.36, $\mathrm{FOOT\_TRAFFIC}$ dropped from 5,428 to 2,065 by 3,363. We also find that, as $\mathrm{AGE\_ELDER}$ increased from 18% to 36%, at $\mathrm{SOCIAL\_DISTANCE}$=0.3, $\mathrm{FOOT\_TRAFFIC}$ increased from 4,161 to 5,313 by 1,152; at $\mathrm{SOCIAL\_DISTANCE}$=0.7, $\mathrm{FOOT\_TRAFFIC}$ increased from 1,807 to 2,065 by 258. *The results suggest that, although elder population contributed to more foot traffic relative to the minor population group, the positive contribution is however negatively correlated with the social distancing index, decreasing in times of strict measures.*

Pre-pandemic 2018-2019	Pandemic 2020

(a) Direct Effects Based on Model 1.1 (Insignificant)



(b) Direct Effects Based on Model 1.2 **(Significant)**



(c) Moderating Effects Based on Model 1.3 **(Significant)**

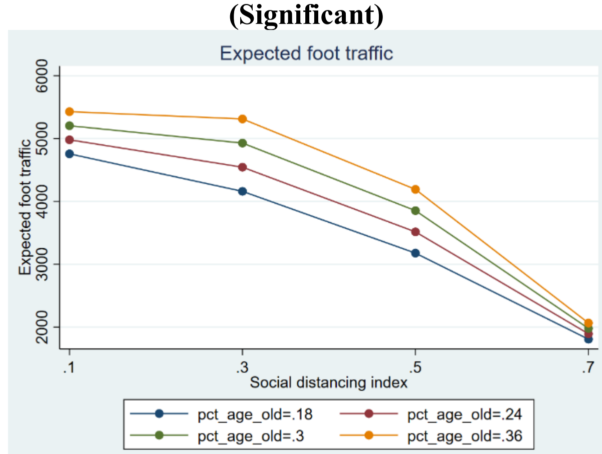


Figure 11: Foot Traffic vs Elder vs Social Distancing

Table 14: Margins for Percent of Elder and Social Distancing

At	Elder %	Social Dis.	Margin	Delta Method Std. Error	Z	P>|z|	95% confidence interval	
1	0.18	0.10	4,756.94	427.12	11.14	0.00	3,919.79	5,594.08
2	0.36	0.10	5,428.46	363.09	14.95	0.00	4,716.81	6,140.10
3	0.18	0.30	4,160.58	360.04	11.56	0.00	3,454.91	4,866.25
4	0.36	0.30	5,312.62	308.22	17.24	0.00	4,708.52	5,916.71
5	0.18	0.50	3,177.28	242.08	13.12	0.00	2,702.80	3,651.75
6	0.36	0.50	4,191.35	285.03	14.70	0.00	3,632.70	4,750.00
7	0.18	0.70	1,807.03	187.38	9.64	0.00	1,439.78	2,174.28
8	0.36	0.70	2,064.66	367.82	5.61	0.00	1,343.74	2,785.58

6.4 Ethnicity

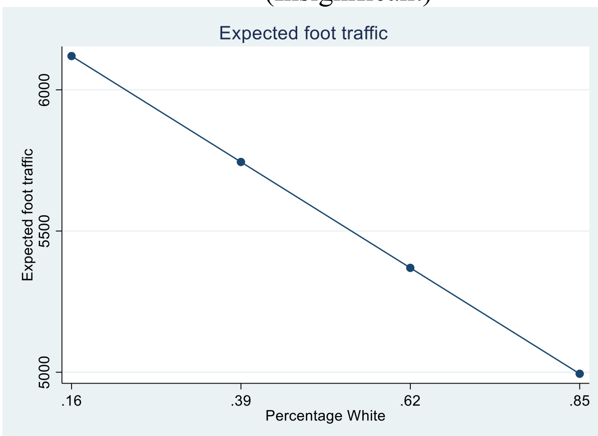
We expect that various population ethnicity group may alter their foot traffic during the pandemic. In the following analysis, we use percentage population of Asian as the base case in our analysis.

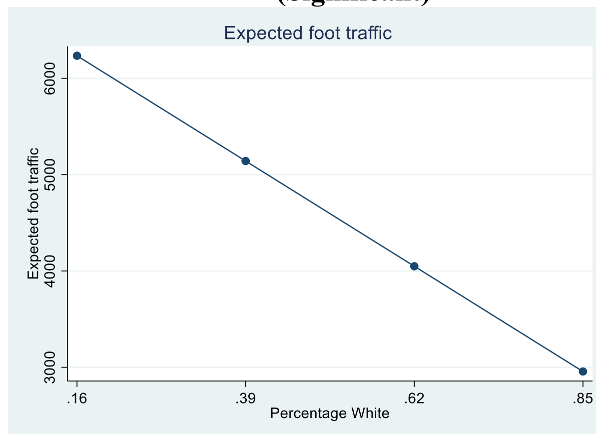
White

We first investigate the direct effect of White population on foot traffic before and during the pandemic. According to Models 1.1 and 1.2, variable ETHNICITY_WHITE does not have significant impact in the pre-pandemic period (-1,630.32, p>0.1), but has significantly negative impact in the pandemic period (-4,750.63, p<0.001). Figure 12(a) and 12(b) present the direct marginal effect of White population on the foot traffic before and during the pandemic. *The results suggests that, with respect to Asian population, there was no observable impact by the White population on the foot traffic pre-pandemic, however there was a striking decrease in foot traffic during the pandemic period.*

Next, we use Model 1.3 to examine the moderating role of social distancing during the pandemic. We find that the coefficient for $\text{ETHNICITY\_WHITE} \cdot \text{SOCIAL\_DISTANCE}$ is positive and significant (11,903.62, p<0.001) and the coefficient for $\text{ETHNICITY\_WHITE} \cdot (\text{SOCIAL\_DISTANCE})^2$ is insignificant (97.51, p>0.1). Figure 12(c) and Table 15 present the combine marginal effect of White population and social distancing on foot traffic. We find that, increasing SOCIAL_DISTANCE from 0.1 to 0.7, at ETHNICITY_WHITE= 16%, FOOT_TRAFFIC fell from 8,090 to 2,164 by 5,926; at ETHNICITY_WHITE= 85%, FOOT_TRAFFIC fell from 2,695 to 1,729 only by 966. Moreover, we also notice that, increasing ETHNICITY_WHITE from 16% to 85%, at SOCIAL_DISTANCE=0.3, FOOT_TRAFFIC decreased from 6,772 to 3,024 by 3,748; at SOCIAL_DISTANCE=0.7, FOOT_TRAFFIC decreased from 2,164 to 1,729 by 435. *The results demonstrate that the foot traffic of White population decreased as social distancing index increased during the pandemic and the effect is weakened in times of strict social distancing measures.*

Pre-pandemic 2018-2019	**Pandemic 2020**
(a) Direct Effects Based on Model 1.1 (Insignificant)	(b) Direct Effects Based on Model 1.2 **(Significant)**





(c) Moderating Effects Based on Model 1.3
(Significant)

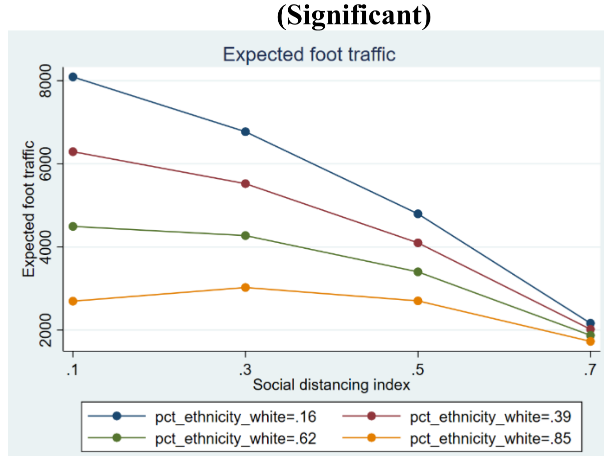


Figure 12: Foot Traffic vs White Population vs Social Distancing

Table 15: Margins for Percent of White and Social Distancing

At	White	Social Dis.	Margin	Delta Method Std. Error	z	P>|z|	95% confidence interval	
1	0.16	0.10	8,090.40	453.86	17.83	0.00	7,200.85	8979.95
2	0.85	0.10	2,694.98	381.60	7.06	0.00	1,947.06	3442.90
3	0.16	0.30	6,771.66	434.01	15.60	0.00	5,921.03	7622.30
4	0.85	0.30	3,024.32	359.95	8.40	0.00	2,318.84	3729.81
5	0.16	0.50	4,796.07	459.48	10.44	0.00	3,895.51	5696.62
6	0.85	0.50	2,702.19	364.26	7.42	0.00	1,988.26	3416.13
7	0.16	0.70	2,163.61	576.09	3.76	0.00	1,034.50	3292.72
8	0.85	0.70	1,728.58	514.80	3.36	0.00	719.59	2737.57

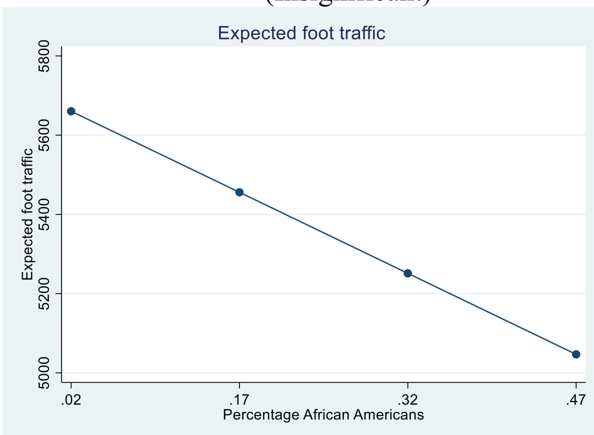
African American

We first compare the direct impact of percentage of African American population on foot traffic before and during the pandemic. For the pre-pandemic period, in Model 1.1, the coefficient for ETHNICITY_AF_AMER is insignificant (-1,363.77, $p>0.10$). For the pandemic period, in Model 1.2, the coefficient is significantly negative (-1,028.92, $p<0.01$). Figures 13(a) and 13(b) show the direct marginal effect of African American on foot traffic before and during the pandemic. *Our research suggests that, relative to Asian Americans, African Americans show a significant decrease in foot traffic during the pandemic period, with little effect prior to the pandemic.*

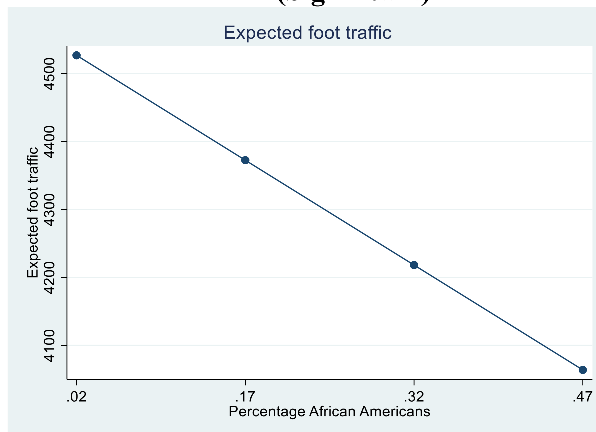
We further examine the moderating effect of social distancing during the pandemic period. We observe that, in Model 1.3, the coefficient for $\text{ETHNICITY\_AF\_AMER} \cdot \text{SOCIAL\_DISTANCE}$ is positive and significant (9,837.55, $p<0.001$) and the coefficient for $\text{ETHNICITY\_AF\_AMER} \cdot (\text{SOCIAL\_DISTANCE})^2$ is insignificant (1,340.42, $p>0.1$). Figure 13(c) and Table 16 show the combine marginal effect of African American and social distancing on foot traffic during the pandemic. We find that, as SOCIAL_DISTANCE increased from 0.1 to 0.7, at ETHNICITY_AF_AMER =2%, FOOT_TRAFFIC decreased from 5,574 to 1,543 by 4,031; at ETHNICITY_AF_AMER=47%, FOOT_TRAFFIC decreased from 3,854 to 2,768 by 1,086. We also identify that, as ETHNICITY_AF_AMER increased from 2% to 47%, at SOCIAL_DISTANCE=0.3, FOOT_TRAFFIC decreased from 4,899 to 4,112 by 787; at SOCIAL_DISTANCE =0.7, FOOT_TRAFFIC increased from 1,543 to 2,768 by 1,225. *The results indicate that, although African American decreased foot traffic during the pandemic, but high social distancing index weakened the negative effects on foot traffic.*

Pre-pandemic 2018-2019	Pandemic 2020

(a) Direct Effects Based on Model 1.1 (Insignificant)



(b) Direct Effects Based on Model 1.2 **(Significant)**



(c) Moderating Effects Based on Model 1.3 **(Significant)**

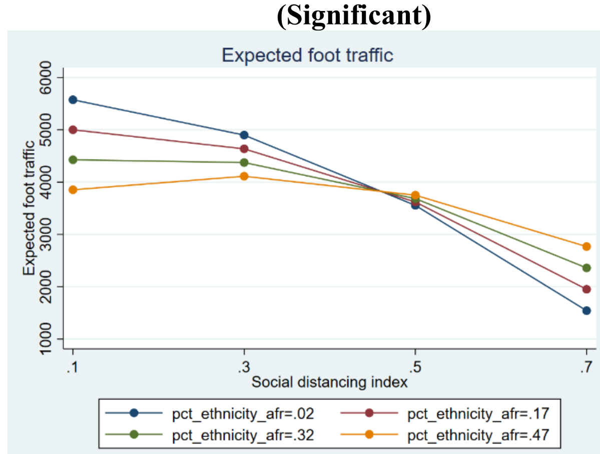


Figure 13: Foot Traffic vs African American Population vs Social Distancing

Table 16: Margins for Percent of African American and Social Distancing

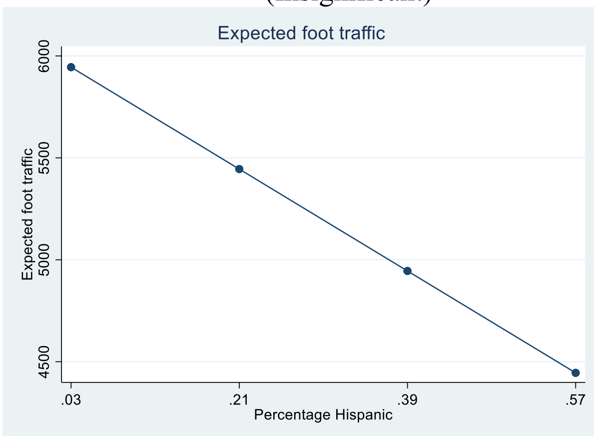
At	African American	Social Dis.	Margin	Delta Method Std. Error	z	P>|z|	95% confidence interval	
1	0.02	0.10	5,573.67	297.70	18.72	0.00	4,990.19	6,157.16
2	0.47	0.10	3,853.50	403.06	9.56	0.00	3,063.52	4,643.48
3	0.02	0.30	4,898.65	248.92	19.68	0.00	4,410.78	5,386.51
4	0.47	0.30	4,112.11	361.85	11.36	0.00	3,402.89	4,821.33
5	0.02	0.50	3,555.01	234.64	15.15	0.00	3,095.14	4,014.89
6	0.47	0.50	3,750.36	298.58	12.56	0.00	3,165.15	4,335.58
7	0.02	0.70	1,542.77	248.29	6.21	0.00	1,056.13	2,029.41
8	0.47	0.70	2,768.27	469.45	5.90	0.00	1,848.16	3,688.37

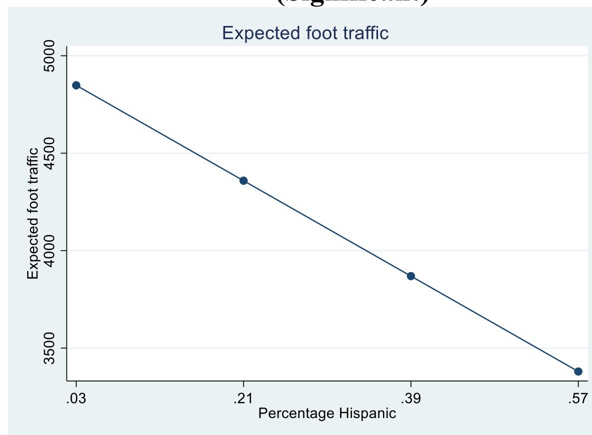
Hispanic

We continue to explore the direct impact of Hispanic population on the foot traffic. For the pre-pandemic period, in Model 1.1, $\mathrm{ETHNICITY\_HISPANIC}$ has an insignificant impact on foot traffic (-2,776.94, p>0.1). For the pandemic period, in Model 1.2, $\mathrm{ETHNICITY\_HISPANIC}$ has significantly negative impact (-2,719.38, p<0.01). Figures 14(a) and 14(b) show the marginal effects of Hispanic population on foot traffic before and during the pandemic. *The results indicate that, compared to Asian population, Hispanic population has no significant impact on foot traffic before the pandemic, with drastic reductions of foot traffic during the pandemic period.*

For the moderating effects of social distancing during the pandemic, Model 1.3 shows that the coefficient of $\mathrm{ETHNICITY\_HISPANIC} \cdot \mathrm{SOCIAL\_DISTANCE}$ is significantly postive (4,209.65, p<0.01) and the coefficient of $\mathrm{ETHNICITY\_HISPANIC} \cdot (\mathrm{SOCIAL\_DISTANCE})^2$ is insignificant (1,959.38, p>0.1). Figure 14(c) and Table 17 present the combined marginal effect of Hispanic population and social distancing on foot traffic. We can observe that, as $\mathrm{SOCIAL\_DISTANCE}$ increased from 0.1 to 0.7, at $\mathrm{ETHNICITY\_HISPANIC}$=3%, $\mathrm{FOOT\_TRAFFIC}$ fell from 5,770 to 2,051 by 3,719; at $\mathrm{ETHNICITY\_HISPANIC}$=57%, $\mathrm{FOOT\_TRAFFIC}$ fell from 3,477 to 1,629 by 1,848. Moreover, we also identify that, as $\mathrm{ETHNICITY\_HISPANIC}$ increased from 3% to 57%, at $\mathrm{SOCIAL\_DISTANCE}$ =0.3, $\mathrm{FOOT\_TRAFFIC}$ decreased from 5,211 to 3,457 by 1,754; at $\mathrm{SOCIAL\_DISTANCE}$=0.7, $\mathrm{FOOT\_TRAFFIC}$ decreased from 2,051 to 1,629 by 422. *The results demonstrate an observable decrease in foot traffic from the Hispanic population during the pandemic period, weakening in times of high social distancing index placement.*

Pre-pandemic 2018-2019	Pandemic 2020
(a) Direct Effects Based on Model 1.1 (Insignificant)	(b) Direct Effects Based on Model 1.2 **(Significant)**





(c) Moderating Effects Based on Model 1.3 **(Significant)**

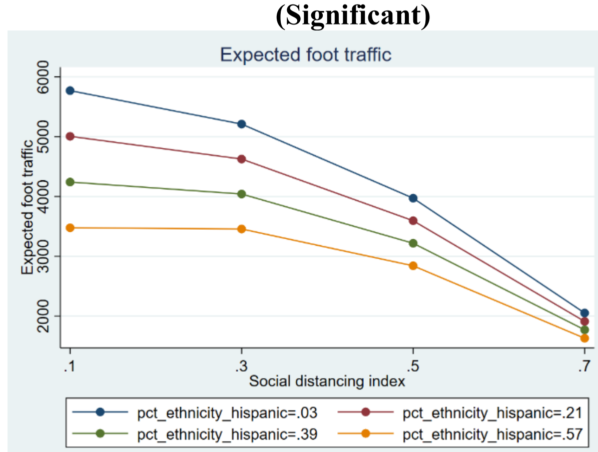


Figure 14: Foot Traffic vs Hispanic Population vs Social Distancing

Table 17: Margins for Percent of Hispanic and Social Distancing

At	Hispanic	Social Dis.	Margin	Delta Method Std. Error	z	P>|z|	95% confidence interval	
1	0.03	0.10	5,770.42	395.34	14.60	0.00	4,995.57	6,545.27
2	0.57	0.10	3,476.63	448.55	7.75	0.00	2,597.48	4,355.78
3	0.03	0.30	5,211.26	357.98	14.56	0.00	4,509.62	5,912.89
4	0.57	0.30	3,456.75	393.80	8.78	0.00	2,684.92	4,228.59
5	0.03	0.50	3,971.56	341.32	11.64	0.00	3,302.59	4,640.54
6	0.57	0.50	2,840.99	284.48	9.99	0.00	2,283.43	3,398.56
7	0.03	0.70	2,051.34	355.81	5.77	0.00	1,353.97	2,748.71
8	0.57	0.70	1,629.35	380.98	4.28	0.00	882.65	2,376.05

7. Conclusion and Limitations

Our findings are threefold. To begin with, our research indicates a significant decrease in foot traffic across the board in times of stricter distancing measures, this again can be attributed to governmental regulations and personal avoidant behaviour adopted seen commonly in the population during a pandemic. Furthermore, the impact of trading area attributes such as trade area size, transport modes, and socio-demographics have varying effects upon foot traffic before and during the pandemic. Lastly and most interestingly, the level of social distancing measures instilled itself has a strong impact on the correlation strength between trading area attributes and foot traffic volume.

7.1 Trade Area Size

Trade Area is the neighborhood or area from which most of the customers come from, which can be further categorized Primary, Secondary and Tertiary (Applebaum, 1996). The Primary Trade Area, also called the core trade area, provides 60-70% of the customers. For this study we consider the habitation area for 70 percent of consumers. We expect that under normal circumstance a larger trade area will draw higher volumes of foot traffic. From our results, trade area size played a significant role in affecting the foot traffic. We find that trade area size is positively associated with foot traffic during both the pre-pandemic and pandemic period. During the pandemic period, although foot traffic is positively related to foot traffic, the relationship weakened with increased social distancing measures. This may suggest an unwillingness in consumer to travel longer distances with increasing restrictions (EY, 2020).

Table 18: Summary of Results (Social Distancing and Trade Area Size)

Variables		Main Result		Notes
		Pre-Pandemic	Pandemic	
Trade Area Size	Direct Effects	Positive and Significant	Positive and Significant	Trade area size is positively associated with consumer foot traffic during both the pre-pandemic and pandemic periods. Overall, shopping malls with larger trade area suffers more when social distancing index is higher during the pandemic.
	Moderating Effects	-	Significant	

7.2 Transport Modes

In this research project, we also explore the impact of means of travel (drove alone, carpooled, public transit, bicycled, walked, and worked at home) on foot traffic before and during the pandemic. Compared to driving alone, there is a positive correlation between carpooling and foot traffic during the pandemic; however, the correlation became less established and visible in times of stricter social distancing. Moreover, the usage of public transit has a notable negative impact on pandemic foot traffic, with little change throughout regardless of social distancing measures. This might suggest that people avoided using public transit during the pandemic (Scorrano & Danielis, 2021). Interestingly, we find that, compared to driving alone, the segment of the consumers working at home positively contributed to foot traffic pre-pandemic, but is negatively associated with foot traffic in times of severe social distancing. The results indicate that due to their prior experience, this segment of the population was able to more easily adjust to stay-home policies, resulting in lower pandemic period traffic.

Table 19: Summary of Results (Social Distancing and Transport Modes)

Variables		Main Result		Notes
		Pre-Pandemic	Pandemic	
Carpooled	Direct Effects	Non-Significant	Significant and positive	Compared to driving alone, there is a positive correlation between carpooling and foot traffic during the pandemic; however, the correlation became less established and visible as distancing measures grew tighter.
	Moderating Effects	-	Significant	
Pubic-Transit	Direct Effects	Non-Significant	Significant and negative	Compared to driving alone, the usage of public transit has a notable negative impact on pandemic foot traffic, with little change throughout regardless of social distancing measures.
	Moderating Effects	-	Non-Significant	
Bicycled & Walked	Direct Effects	Non-Significant	Non-Significant	
	Moderating Effects	-	Insignificant	
Worked-at-Home	Direct Effects	Significant and positive	Non-Significant	Compared to driving alone, the segment of the consumers working at home positively contributed to foot traffic pre-pandemic, but negatively relates to foot traffic in times of severe social distancing.
	Moderating Effects	-	Significant	

7.3 Socio-Demographics

For socio-demographics, we first explore how income and gender affect foot traffic during pre-pandemic and pandemic periods. Previous literature has suggested inconsistent findings on the relationship between income and consumer purchasing behavior. In this study, we observe that there is no direct relation with foot traffic. This is comparable to another study by Russell (1957) which shows that there is no direct correlation between sales and median family income. Moreover, we observe a non-linear moderating impact of social distancing on the relation between median income and foot traffic. In terms of gender, compared to the male population, a significant decrease in female foot traffic was detected in the pandemic period relative to the pre-pandemic norms, and the risk-averse behavior did not significantly change with the distancing measure. This is consistent with the findings by Kim & Crimmins (2020). They find that women are more likely to follow regulations. Thus, we expect that women are more like to follow the staying at home orders and practise social distancing during the pandemic.

We further investigate how socio-demographics such as age and ethnicity affect foot traffic before and during the pandemic. An interesting observation is for adult age group (36-55). In comparison to minor population less than 18-year-old, adult has a negative impact on foot traffic before the pandemic, while has a significant positive impact on foot traffic during the pandemic. Overall, in comparison to the minor population, the young adult, adult, and elder age group have a significant positive impact on foot traffic during the pandemic period with decreasing effects in times of tight social distancing measures. Next, we turn our attention to different ethnicity groups. Compared to the Asian population, we see that all other ethnic groups showed a drop in foot traffic during the pandemic with the highest decrease from the White population segment. This can be attributed to higher standard of living in comparison to other minority ethnic groups. However, a high social distancing index weakened the negative effects on foot traffic. It is interesting to note that trade area with higher percentage of one ethnicity saw a lower drop in foot traffic. This suggests that heterogeneous society were more apt to observe protocol.

Table 20: Summary of Results (Social Distancing and Socio-Demographics)

Variables		Main Result		Notes
		Pre-Pandemic	Pandemic	
Income	Direct Effects	Non-significant	Non-significant	The median income generally shows a slightly positive association with foot traffic during the pandemic period.
	Moderating Effects	-	Significant	
Gender	Direct Effects	Non-significant	Significant	Compared to the male population, there was a significant decrease in the percentage of female foot traffic during the pandemic period relative to the pre-pandemic norms, and the risk-averse behavior did not significantly change with the distancing measure.
	Moderating Effects	-	Non-Significant	
Age	Direct Effects	Significant only for adult	Significant	In comparison to the minor population of less than 18, the young adult, adult, and elder age group have a significant positive impact on foot traffic during the pandemic period, decreasing in times of strict social distancing measures.
	Moderating Effects	-	Significant	
Ethnicity	Direct Effects	Non-significant	Significant	With respect to Asian population, White, African American, and Hispanic population decreased foot traffic during the pandemic, but high social distancing index weakened the negative effects on foot traffic.

7.4 Limitation and Future Research

Focusing on open-air centers, we conducted a comprehensive study to understand the role played by trade area characteristics in affecting consumer foot traffic to shopping centers. This paper has certain limitations. First, we used daily foot traffic data in this study; however, certain variables were not considered, including the impact of the weather conditions which may affect foot traffic on specific days. Hence, only the general impact of trade area characteristics on foot traffic was captured. Future research may explore how weather conditions affect foot traffic. Secondly, in this study, we use open-air centers as a case study, most of open-air centers using grocery stores as anchor stores. Future research can demonstrate the effects of various types of anchor grocery stores on foot traffic during the pandemic period. Moreover, for further in-depth study, closed malls can be included, to provide a more diverse and macroscopic picture. It is worth noting that, compared to open-air centers, most closed malls use department store or apparel stores as anchor stores, which are categorized as non-essential businesses during the pandemic. Finally, our study mainly compared consumer foot traffic in the pre-pandemic period (2018-2019) and in the pandemic period (2020). Future works can extend our research to explore how trade-area characteristics affect foot traffic during the post-pandemic period (2021-2022).

In summary, this work compares consumer foot traffic before and during the COVID-19 pandemic. From a management and policy perspective, we call for more attention to the trading area characteristics such as transport modes and socio-demographics, in order to better respond to the outbreak of the COVID-19 pandemic as well as prepare for the recovery from the COVID-19 pandemic. In this seeding work, we focus on open-air shopping centers, and for our next step, we aim to further extend this work to other formats in the retail sector.

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Appendix

Table 21: Geographic Distribution of Shopping Centers

State	State code	Brixmor	Kimco	Phillips Edison	SITE Centers	Total
Alabama	AL	1	0	0	0	1
Alaska	AK	0	0	0	0	0
Arizona	AZ	1	9	7	6	23
Arkansas	AR	0	0	0	0	0
California	CA	27	72	24	6	129
Colorado	CO	7	10	11	5	33
Connecticut	CT	11	7	4	3	25
Delaware	DE	1	1	0	0	2
District of Columbia	DC	0	0	0	0	0
Florida	FL	46	47	53	31	177
Georgia	GA	29	10	30	19	88
Hawaii	HI	0	0	0	0	0
Idaho	ID	0	0	0	0	0
Illinois	IL	15	5	13	5	38
Indiana	IN	7	2	6	1	16
Iowa	IA	2	1	3	0	6
Kansas	KS	2	0	2	1	5
Kentucky	KY	7	0	3	0	10
Louisiana	LA	0	0	0	0	0
Maine	ME	1	0	0	0	1
Maryland	MD	2	29	4	1	36
Massachusetts	MA	8	7	9	3	27
Michigan	MI	16	0	5	2	23
Minnesota	MN	9	3	9	1	22
Mississippi	MS	0	0	0	1	1
Missouri	MO	3	0	2	2	7
Montana	MT	0	0	0	0	0
Nebraska	NE	0	0	0	0	0
Nevada	NV	0	6	3	0	9
New Hampshire	NH	3	2	0	1	6
New Jersey	NJ	13	18	2	10	43
New Mexico	NM	0	0	3	0	3
New York	NY	22	32	1	1	56
North Carolina	NC	19	14	12	11	56
North Dakota	ND	0	0	0	0	0
Ohio	OH	14	0	21	17	52
Oklahoma	OK	1	0	0	0	1
Oregon	OR	0	6	4	1	11
Pennsylvania	PA	25	22	6	5	58
Rhode Island	RI	0	0	0	0	0

South Carolina	SC	7	4	9	5	25
South Dakota	SD	0	0	0	0	0
Tennessee	TN	10	1	6	2	19
Texas	TX	39	27	16	7	89
Utah	UT	0	0	0	0	0
Vermont	VT	1	0	0	0	1
Virginia	VA	7	15	13	7	42
Washington	WA	0	12	2	0	14
West Virginia	WV	2	0	0	0	2
Wisconsin	WI	4	0	7	1	12
Wyoming	WY	0	0	0	0	0
Total		362	362	290	155	1169
Properties in Chain		400	404	311	171	1286
Percentage in Estimation		90.50%	89.60%	93.25%	90.64%	90.90%

Table 22: Correlation Table (Pre-Pandemic 2018-2019)

No.	Variables	1	2	3	4	5	6	7	8	9	10
1	FOOT_TRAFFIC	1.00	0.34	0.07	0.03	0.05	0.06	0.00	-0.04	0.00	-0.05
2	TRADE_AREA_SIZE	0.34	1.00	-0.08	-0.10	-0.06	0.08	-0.05	0.05	-0.01	0.03
3	TRANS_CARPOOLED	0.07	-0.08	1.00	-0.20	-0.08	-0.21	0.12	-0.34	-0.41	-0.12
4	TRANS_PUBLIC	0.03	-0.10	-0.20	1.00	0.17	0.52	0.02	-0.12	0.22	0.11
5	TRANS_BICYCLE	0.05	-0.06	-0.08	0.17	1.00	0.48	0.04	0.13	0.00	-0.17
6	TRANS_WALK	0.06	0.08	-0.21	0.52	0.48	1.00	-0.01	-0.05	0.05	-0.06
7	TRANS_OTHER	0.00	-0.05	0.12	0.02	0.04	-0.01	1.00	-0.02	-0.08	-0.10
8	TRANS_HOME	-0.04	0.05	-0.34	-0.12	0.13	-0.05	-0.02	1.00	0.55	-0.12
9	INCOME_MEDIAN	0.00	-0.01	-0.41	0.22	0.00	0.05	-0.08	0.55	1.00	-0.24
10	FEMALE	-0.05	0.03	-0.12	0.11	-0.17	-0.06	-0.10	-0.12	-0.24	1.00
11	AGE_YOUNG_ADULT	0.12	0.15	0.11	0.14	0.42	0.55	0.01	-0.19	-0.21	-0.19
12	AGE_ADULT	0.01	0.00	-0.13	0.06	-0.30	-0.32	-0.02	0.34	0.56	-0.17
13	AGE_ELDER	-0.11	-0.11	-0.25	-0.05	0.04	-0.05	-0.05	0.05	-0.10	0.29
14	ETHNICITY_WHITE	-0.13	0.09	-0.47	-0.27	0.08	0.09	-0.19	0.30	0.18	-0.11
15	ETHNICITY_AF_AMER	0.00	0.08	0.08	0.17	-0.14	-0.03	0.03	-0.21	-0.28	0.54
16	ETHNICITY_HISPANIC	0.09	-0.17	0.47	0.05	-0.02	-0.14	0.21	-0.23	-0.16	-0.24
17	ETHNICITY_OTHER	0.04	0.01	0.13	-0.02	0.13	0.03	-0.02	0.04	0.07	-0.15
18	POPULATION	0.33	0.49	-0.04	0.43	0.10	0.24	0.03	-0.03	0.10	-0.04
19	NETWORK_REGIONAL	-0.01	-0.20	0.12	0.03	0.00	-0.20	0.12	0.03	0.04	-0.01
20	NETWORK_NATIONAL	-0.10	-0.11	0.07	0.10	0.04	0.07	-0.01	-0.10	0.06	-0.07

No.	Variables	11	12	13	14	15	16	17	18	19	20
1	FOOT_TRAFFIC	0.12	0.01	-0.11	-0.13	0.00	0.09	0.04	0.33	-0.01	-0.10
2	TRADE_AREA_SIZE	0.15	0.00	-0.11	0.09	0.08	-0.17	0.01	0.49	-0.20	-0.11
3	TRANS_CARPOOLED	0.11	-0.13	-0.25	-0.47	0.08	0.47	0.13	-0.04	0.12	0.07
4	TRANS_PUBLIC	0.14	0.06	-0.05	-0.27	0.17	0.05	-0.02	0.43	0.03	0.10
5	TRANS_BICYCLE	0.42	-0.30	0.04	0.08	-0.14	-0.02	0.13	0.10	0.00	0.04
6	TRANS_WALK	0.55	-0.32	-0.05	0.09	-0.03	-0.14	0.03	0.24	-0.20	0.07
7	TRANS_OTHER	0.01	-0.02	-0.05	-0.19	0.03	0.21	-0.02	0.03	0.12	-0.01
8	TRANS_HOME	-0.19	0.34	0.05	0.30	-0.21	-0.23	0.04	-0.03	0.03	-0.10
9	INCOME_MEDIAN	-0.21	0.56	-0.10	0.18	-0.28	-0.16	0.07	0.10	0.04	0.06
10	FEMALE	-0.19	-0.17	0.29	-0.11	0.54	-0.24	-0.15	-0.04	-0.01	-0.07
11	AGE_YOUNG_ADULT	1.00	-0.36	-0.56	-0.20	0.12	0.08	0.16	0.20	-0.16	0.03
12	AGE_ADULT	-0.36	1.00	-0.40	-0.16	-0.02	0.09	0.04	0.11	0.05	-0.02
13	AGE_ELDER	-0.56	-0.40	1.00	0.44	-0.17	-0.28	-0.21	-0.20	0.13	0.00
14	ETHNICITY_WHITE	-0.20	-0.16	0.44	1.00	-0.47	-0.69	0.02	-0.33	-0.32	-0.09
15	ETHNICITY_AF_AMER	0.12	-0.02	-0.17	-0.47	1.00	-0.22	-0.08	0.05	-0.08	-0.06
16	ETHNICITY_HISPANIC	0.08	0.09	-0.28	-0.69	-0.22	1.00	-0.15	0.23	0.36	0.11
17	ETHNICITY_OTHER	0.16	0.04	-0.21	0.02	-0.08	-0.15	1.00	0.03	-0.09	-0.01
18	POPULATION	0.20	0.11	-0.20	-0.33	0.05	0.23	0.03	1.00	0.06	0.00
19	NETWORK_REGIONAL	-0.16	0.05	0.13	-0.32	-0.08	0.36	-0.09	0.06	1.00	0.29
20	NETWORK_NATIONAL	0.03	-0.02	0.00	-0.09	-0.06	0.11	-0.01	0.00	0.29	1.00

Table 23: Correlation Table (Pandemic 2020)

NO.	Variables	1	2	3	4	5	6	7	8	9	10	11
1	FOOT_TRAFFIC	1.00	-0.14	0.25	0.08	0.02	0.05	0.07	0.01	-0.07	-0.04	-0.04
2	SOCIAL_DISTANCE	-0.14	1.00	-0.07	0.00	0.14	0.03	0.07	0.03	-0.04	0.07	-0.01
3	TRADE_AREA_SIZE	0.25	-0.07	1.00	-0.07	-0.10	-0.06	0.05	-0.05	0.01	-0.03	0.03
4	TRANS_CARPOOLED	0.08	0.00	-0.07	1.00	-0.21	-0.07	-0.17	0.12	-0.33	-0.41	-0.12
5	TRANS_PUBLIC	0.02	0.14	-0.10	-0.21	1.00	0.17	0.58	0.06	-0.12	0.19	0.12
6	TRANS_BICYCLE	0.05	0.03	-0.06	-0.07	0.17	1.00	0.48	0.06	0.12	-0.01	-0.15
7	TRANS_WALK	0.07	0.07	0.05	-0.17	0.58	0.48	1.00	0.03	-0.09	0.03	-0.06
8	TRANS_OTHER	0.01	0.03	-0.05	0.12	0.06	0.06	0.03	1.00	-0.01	-0.07	-0.10
9	TRANS_HOME	-0.07	-0.04	0.01	-0.33	-0.12	0.12	-0.09	-0.01	1.00	0.55	-0.14
10	INCOME_MEDIAN	-0.04	0.07	-0.03	-0.41	0.19	-0.01	0.03	-0.07	0.55	1.00	-0.23
11	FEMALE	-0.04	-0.01	0.03	-0.12	0.12	-0.15	-0.06	-0.10	-0.14	-0.23	1.00
12	AGE_YOUNG_ADULT	0.11	-0.02	0.08	0.15	0.16	0.44	0.52	0.05	-0.23	-0.27	-0.21
13	AGE_ADULT	-0.02	0.00	0.01	-0.17	0.04	-0.31	-0.31	-0.04	0.37	0.58	-0.15
14	AGE_ELDER	-0.09	0.04	-0.08	-0.25	-0.05	0.00	-0.06	-0.05	0.07	-0.07	0.30
15	ETHNICITY_WHITE	-0.11	-0.07	0.11	-0.45	-0.28	0.05	0.02	-0.20	0.30	0.19	-0.11
16	ETHNICITY_AF_AMER	0.03	-0.05	0.08	0.07	0.19	-0.12	-0.01	0.03	-0.22	-0.28	0.55
17	ETHNICITY_HISPANIC	0.08	0.08	-0.18	0.46	0.06	-0.01	-0.09	0.21	-0.22	-0.16	-0.24
18	ETHNICITY_OTHER	0.03	0.02	0.01	0.11	-0.02	0.14	0.06	-0.02	0.03	0.05	-0.17
19	POPULATION	0.23	0.06	0.46	-0.05	0.45	0.10	0.28	0.06	-0.05	0.09	-0.03
20	NETWORK_REGIONAL	-0.02	0.14	-0.21	0.11	0.03	0.00	-0.16	0.12	0.04	0.05	-0.02
21	NETWORK_NATIONAL	-0.08	0.06	-0.10	0.06	0.11	0.03	0.07	-0.01	-0.10	0.06	-0.07
22	NEW_COVID19_CASES	0.01	0.14	-0.08	0.09	-0.05	0.00	-0.12	0.06	0.02	0.00	-0.06

NO.	Variables	12	13	14	15	16	17	18	19	20	21	22
1	FOOT_TRAFFIC	0.11	-0.02	-0.09	-0.11	0.03	0.08	0.03	0.23	-0.02	-0.08	0.01
2	SOCIAL_DISTANCE	-0.02	0.00	0.04	-0.07	-0.05	0.08	0.02	0.06	0.14	0.06	0.14
3	TRADE_AREA_SIZE	0.08	0.01	-0.08	0.11	0.08	-0.18	0.01	0.46	-0.21	-0.10	-0.08
4	TRANS_CARPOOLED	0.15	-0.17	-0.25	-0.45	0.07	0.46	0.11	-0.05	0.11	0.06	0.09
5	TRANS_PUBLIC	0.16	0.04	-0.05	-0.28	0.19	0.06	-0.02	0.45	0.03	0.11	-0.05
6	TRANS_BICYCLE	0.44	-0.31	0.00	0.05	-0.12	-0.01	0.14	0.10	0.00	0.03	0.00
7	TRANS_WALK	0.52	-0.31	-0.06	0.02	-0.01	-0.09	0.06	0.28	-0.16	0.07	-0.12
8	TRANS_OTHER	0.05	-0.04	-0.05	-0.20	0.03	0.21	-0.02	0.06	0.12	-0.01	0.06
9	TRANS_HOME	-0.23	0.37	0.07	0.30	-0.22	-0.22	0.03	-0.05	0.04	-0.10	0.02
10	INCOME_MEDIAN	-0.27	0.58	-0.07	0.19	-0.28	-0.16	0.05	0.09	0.05	0.06	0.00
11	FEMALE	-0.21	-0.15	0.30	-0.11	0.55	-0.24	-0.17	-0.03	-0.02	-0.07	-0.06
12	AGE_YOUNG_ADULT	1.00	-0.40	-0.55	-0.25	0.14	0.13	0.18	0.19	-0.12	0.03	-0.03
13	AGE_ADULT	-0.40	1.00	-0.37	-0.11	-0.04	0.06	0.01	0.09	0.03	-0.02	0.00
14	AGE_ELDER	-0.55	-0.37	1.00	0.46	-0.17	-0.29	-0.20	-0.19	0.13	0.01	0.00
15	ETHNICITY_WHITE	-0.25	-0.11	0.46	1.00	-0.48	-0.68	0.02	-0.32	-0.30	-0.08	-0.16
16	ETHNICITY_AF_AMER	0.14	-0.04	-0.17	-0.48	1.00	-0.23	-0.08	0.05	-0.09	-0.06	-0.08
17	ETHNICITY_HISPANIC	0.13	0.06	-0.29	-0.68	-0.23	1.00	-0.15	0.22	0.36	0.11	0.23
18	ETHNICITY_OTHER	0.18	0.01	-0.20	0.02	-0.08	-0.15	1.00	0.04	-0.10	-0.02	-0.04
19	POPULATION	0.19	0.09	-0.19	-0.32	0.05	0.22	0.04	1.00	0.06	0.01	0.04
20	NETWORK_REGIONAL	-0.12	0.03	0.13	-0.30	-0.09	0.36	-0.10	0.06	1.00	0.29	0.32
21	NETWORK_NATIONAL	0.03	-0.02	0.01	-0.08	-0.06	0.11	-0.02	0.01	0.29	1.00	0.03
22	NEW_COVID19_CASES	-0.03	0.00	0.00	-0.16	-0.08	0.23	-0.04	0.04	0.32	0.03	1.00

Table 24: Robustness Check

Dependent Variable	Pre-Pandemic (2018-2019)	Pandemic (2020)	
Log FOOT_TRAFFIC	Model 2.1	Model 2.2	Model 2.3
Independent Variables			
Social Distancing			
SOCIAL_DISTANCE		0.12 (0.29)	-14.98*** (3.68)
$(\text{SOCIAL\_DISTANCE})^2$		-1.82*** (0.42)	24.04*** (6.21)
Trade Area Size			
TRADE_AREA_SIZE	0.29* (0.15)	0.33** (0.12)	0.28 (0.18)
TRADE_AREA_SIZE · SOCIAL_DISTANCE			2.22*** (0.35)
TRADE_AREA_SIZE · $(\text{SOCIAL\_DISTANCE})^2$			-5.75*** (0.33)
Transport Modes			
TRANS_CARPOOLED	0.65 (0.91)	1.19* (0.52)	-0.50 (0.47)
TRANS_CARPOOLED · SOCIAL_DISTANCE			8.40** (2.69)
TRANS_CARPOOLED · $(\text{SOCIAL\_DISTANCE})^2$			-9.00* (4.43)
TRANS_PUBLIC	0.78 (1.09)	-1.30*** (0.11)	-1.58*** (0.30)
TRANS_PUBLIC · SOCIAL_DISTANCE			2.77* (1.64)
TRANS_PUBLIC · $(\text{SOCIAL\_DISTANCE})^2$			-5.51* (2.71)
TRANS_BICYCLE	1.38 (1.48)	3.37* (1.97)	3.70* (1.53)
TRANS_BICYCLE · SOCIAL_DISTANCE			-1.03 (9.99)
TRANS_BICYCLE · $(\text{SOCIAL\_DISTANCE})^2$			-1.52 (11.98)
TRANS_WALK	-0.87 (0.55)	0.26 (0.87)	-0.26 (0.43)
TRANS_WALK · SOCIAL_DISTANCE			5.27* (2.71)
TRANS_WALK · $(\text{SOCIAL\_DISTANCE})^2$			-6.80* (3.98)
TRANS_OTHER	1.77 (2.28)	-0.44 (1.64)	-1.20 (1.29)
TRANS_OTHER · SOCIAL_DISTANCE			-2.78 (10.54)
TRANS_OTHER · $(\text{SOCIAL\_DISTANCE})^2$			11.91 (17.90)
TRANS_HOME	3.07*** (0.79)	-0.69 (1.99)	1.72 (2.05)
TRANS_HOME · SOCIAL_DISTANCE			-8.52*** (1.63)
TRANS_HOME · $(\text{SOCIAL\_DISTANCE})^2$			2.84 (3.38)
Income			

INCOME_MEDIAN	0.00 (0.01)	-0.01 (0.02)	0.02 (0.03)
INCOME_MEDIAN · SOCIAL_DISTANCE			-0.15* (0.09)
INCOME_MEDIAN · $(\text{SOCIAL\_DISTANCE})^2$			0.18 (0.15)
Gender			
FEMALE	1.48* (0.87)	-0.981 (1.48)	-1.95* (0.99)
FEMALE · SOCIAL_DISTANCE			8.60*** (1.76)
FEMALE · $(\text{SOCIAL\_DISTANCE})^2$			-14.31* (7.21)
Age			
AGE_YOUNG_ADULT	-1.99 (1.98)	0.65*** (0.16)	0.16 (0.40)
AGE_YOUNG_ADULT · SOCIAL_DISTANCE			6.49** (2.13)
AGE_YOUNG_ADULT · $(\text{SOCIAL\_DISTANCE})^2$			-14.13*** (3.09)
AGE_ADULT	-4.57 (3.58)	0.04 (1.64)	-2.73 (1.71)
AGE_ADULT · SOCIAL_DISTANCE			20.090** (6.556)
AGE_ADULT · $(\text{SOCIAL\_DISTANCE})^2$			-31.43*** (8.85)
AGE_ELDER	-2.75 (2.33)	0.64 (0.45)	-0.11 (0.29)
AGE_ELDER · SOCIAL_DISTANCE			6.96** (2.47)
AGE_ELDER · $(\text{SOCIAL\_DISTANCE})^2$			-12.91* (5.18)
Ethnicity			
ETHNICITY_WHITE	0.35* (0.21)	-0.91** (0.32)	-1.54* (0.60)
ETHNICITY_WHITE · SOCIAL_DISTANCE			2.69 (1.86)
ETHNICITY_WHITE · $(\text{SOCIAL\_DISTANCE})^2$			-2.33 (2.25)
ETHNICITY_AF_AMER	0.57*** (0.07)	-0.27* (0.16)	-0.64 (0.50)
ETHNICITY_AF_AMER · SOCIAL_DISTANCE			0.22 (1.64)
ETHNICITY_AF_AMER · $(\text{SOCIAL\_DISTANCE})^2$			1.89 (1.52)
ETHNICITY_HISPANIC	-0.09 (0.78)	-0.45* (0.18)	-0.43 (0.34)
ETHNICITY_HISPANIC · SOCIAL_DISTANCE			-0.40 (1.71)
ETHNICITY_HISPANIC · $(\text{SOCIAL\_DISTANCE})^2$			0.48 (1.97)
ETHNICITY_OTHER	-1.97 (1.47)	-3.39* (1.93)	-2.00 (1.35)
ETHNICITY_OTHER · SOCIAL_DISTANCE			-8.39 (6.46)
ETHNICITY_OTHER · $(\text{SOCIAL\_DISTANCE})^2$			11.88* (5.96)
Control Variables			
POPULATION	-0.02 (0.05)	0.01 (0.03)	0.02 (0.03)

NETWORK_REGIONAL	-0.03 (0.04)	-0.02 (0.03)	-0.02 (0.03)
NETWORK_NATIONAL	-0.06 (0.12)	-0.07 (0.07)	-0.07 (0.07)
NEW_COVID19_CASES		-0.00** (0.00)	-0.00 (0.00)
WEEKEND_EFFECT	INCLUDED	INCLUDED	INCLUDED
STATE_EFFECT	INCLUDED	INCLUDED	INCLUDED
MONTH_EFFECT	INCLUDED	INCLUDED	INCLUDED
WEEK_EFFECT	INCLUDED	INCLUDED	INCLUDED
CONSTANT	10.07*** (1.45)	10.04*** (1.18)	11.85*** (1.05)
N	853,370	391,615	391,615
Sigma_u	0.62	0.70	0.69
Sigma_e	0.35	0.47	0.46
Rho	0.75	0.69	0.70

The table shows estimated coefficients. Standard errors in parentheses. *p<0.1, **p<0.01, ***p<0.001