Shopping Distancing: The Impact of Travel Cost on Shopping Destination Choices

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Problem Definition: Travel cost is typically assumed to reduce the probability of choosing a given shopping destination. Increases in the cost, through higher sensitivity to distance, might however increase propensity to shop. **Methodology/Results:** We develop an analytical model to explain such variations, which predicts positive impacts for the nearest shopping destinations. Using population-wide data sets of mall visits from four cities in two countries, we quantify that the COVID-19 pandemic increased the sensitivity to travel distance during the lockdowns of Spring 2020 by 35-115%, depending on the city; and by 3-60% during the reopening phases afterwards. We also identify the threshold-radius around which probability to visit increased due to a higher travel distance sensitivity. Besides temporal and location heterogeneity, customer characteristics and contextual factors that affect one's ability to choose significantly influence travel distance sensitivity changes. Specifically, the COVID shock had a larger effect on the sensitivity to distance during weekends, non-rainy days, and for wealthier consumers. **Managerial Implications:** Our model and empirical results help predict how future changes in travel cost will influence store footfall and customer mix by attracting more or less customers from different origins. The paper informs the debate around urban mobility policies and the future of physical stores and urban landscapes.

Key words: retail; travel cost; choice models; customer mobility; COVID-19

1. Introduction

In the last decade, the future of physical retail has been put into question. From claims that America is 'overstored' (Kahn 2021) to the advent of online retailing (Caro et al. 2020), stores seem to be less relevant to consumers. Indeed, footfall has been falling in recent years (Nazir 2019), even before store closures during the lockdowns in the COVID-19 pandemic. At the heart of this trend is the realization that, while stores contribute with an experiential value into the shopping process, store visit also involves a travel cost that consumers may not always be willing to incur. When the travel cost is zero, visiting a store provides a higher utility compared to shopping online (Bell et al. 2020). In contrast, when travel cost is high, consumers prefer to avoid the visit and shop in lower access cost alternatives.

To help understand the future of retail and shoppers preferences in future years, we need to quantify the role of travel cost. Travel cost is typically measured as a direct function of travel distance sensitivity and the distance between consumer origin and shopping destination (e.g., Bai et al. 2022; Gao et al. 2021). Unfortunately, travel cost is intrinsically connected to the geographical locations of customers and stores, which means that it is hard to empirically identify the impact of sensitivity to travel distance on shopping propensity. Moreover, in measuring sensitivity to distance, it is important to properly identify the shopping options that consumers have. These options are not only about the offline vs. online channel choice (Chintagunta et al. 2012; Nault and Rahman 2019), but more broadly about the different physical locations that compete for consumers' attention. Only through this broader choice set we can fully capture the choice process that consumers face and the role of travel cost.

Findings from prior literature can be extrapolated to infer that an increase (decrease) in distance sensitivity leads to customers shopping more (less) locally (e.g., Bell et al. 1998; Marshall and Pires 2018), although this has not explicitly been postulated. Indeed, the sensitivity to travel distance could structurally change for multiple reasons such as mobility restrictions imposed by regulators, increased access to public transportation, fluctuations in energy prices, or health concerns related to pollution and infection. Consequently, changes in travel distance sensitivity would influence not only the overall foot traffic but also the origin and customer profile that shops receive.

Therefore, in this paper we address the following research questions: How does a change in the sensitivity to travel distance influence customer shopping destination choices? How is distance sensitivity affected by customer characteristics and environmental factors related to individual ability to choose?

To this end, we develop a model based on the Multinomial Logit (MNL) to characterize the probability of a given consumer choosing a shopping destination based on consumer and shop characteristics, time effects, and the distance between consumer origin and shopping destinations. Namely, we include in our choice model insights from the existing literature on gravity models in retail, trade economics, and information economics. Our analytical model provides two main insights. First, by formulating how changes in travel distance sensitivity affect shopping choices, we show that increases (decreases) in the sensitivity can lead to increases (decreases) in propensity to shop for destinations that are close to the individual. Second, we identify the threshold-radius around the shopping destination around which customers increase (decrease) their visits to the destination due to the increase (decrease) in distance sensitivity.

Next, we take advantage of a major structural shock, the COVID-19 pandemic, to empirically measure the impact of distance sensitivity on consumer choices across different shopping options. The pandemic certainly triggered a major shock on both demand (e.g., economic uncertainty, lifestyle changes, type of product needs) and supply factors (e.g., product availability, store capacities, service quality). The shock reduced the overall propensity to visit shops during the period, although its magnitude cannot be accurately measured for lack of a proper control group since all markets were affected simultaneously. At the same time, COVID-19 radically changed the way consumers traveled and shopped, not only during store closures in Spring of 2020, but also afterwards with the mobility restrictions that made store visits more costly and the psychological burden from the risk of infection when travelling. For this reason, we expect the shock to have an increased effect with distance to the shop on the propensity to visit. Because some consumer origins were affected more than others –depending on the distance to the shopping destination–, we are able to identify how travel distance sensitivity changed during the different phases of COVID-19.

To estimate our model, we employ geolocated data on consumers from different origins visiting shopping malls in four cities of two countries with a total population of 5.4 million individuals. The two countries present very different shopping contexts: one in Latin America, where shopping malls are the main shopping option; and another in Europe, where street stores attract more customer attention compared to malls. We find that indeed the sensitivity to travel distance increased during the lockdown period of the pandemic between 35% and 115% depending on the city. During the reopening phase the sensitivity to travel distance reverted to between 3% and 60% above pre-pandemic levels.

Furthermore, we explore how sensitivity changes to travel distance depends on customer characteristics and environmental factors related to an individual's ability to choose. We show that in weekends, when there are fewer work obligations and consumers have more freedom to choose where to shop, travel distance sensitivity increased 14% and 6% more than in weekdays during lockdown and reopening, respectively. Similarly, during non-rainy days, when travel choice is less restricted compared to rainy days, travel distance sensitivity increased 3% more during lockdown but did not present differences during the reopening. Finally, affluent individuals who have higher freedom to choose when and where to shop experienced 10% and 5% higher travel distance sensitivity compared to less-privileged individuals during lockdown and reopening, respectively.

In sum, we quantify how sensitivity to travel distance changes over time (differences between strict lockdown and reopening period), over space (two different countries, one in Latin America, the other in Europe), and consumer contexts (weekday vs. weekend shopping, weather conditions, and socioeconomic factors). More specifically, the increase in travel cost due to the COVID-19 pandemic –through a higher sensitivity to distance– is exacerbated in contexts where consumers have more freedom to choose. We expect other shocks on travel costs to have a similar effect: they will affect more those consumers with more shopping destination options, leading them to concentrate their visits into locations with comparatively easier access.

Our research thus advances our understanding of consumer choices in the earlier stages of the purchase funnel, informs policy makers and managers on the effect of policies that affect mobility and travel costs, and provides insights for the design of store networks. Indeed, our model and empirical results help predict how future changes in travel cost will influence store footfall and customer mix by attracting more or less customers from different origins. This can inform the current, heated political debate about the survival of urban stores and the future of dense urban areas (Hu 2016; Benvenuty 2021). Our results may help policy makers better understand the externalities of city planning decisions, mobility restriction policies, and public transportation access. Specifically, our model predicts that, with mobility restrictions that increase travel costs, visitors from suburban origins will sharply fall, because they substitute city-center destinations for their local store; in contrast, local residents will find it harder to "escape" the city and thus opt for local options. Consequently, besides customer profile changes, the overall effect on footfall would depend on the population density distribution. Anecdotally, when the city center of Madrid, Spain, was closed to motor vehicles during 2019-2020, newspapers shared evidence that customer profile of local stores had changed due to an increase in visits of nearby customers and a decrease of distant customers (Aranda 2019). Finally, our results can also inform retail network design, providing a modeling tool to help evaluate the appropriate store density to attract consumers from different origins.

2. Literature Review and Contribution

In this section, we review the three literature streams in which our research is rooted. Next, we highlight the contributions of this paper over extant research.

2.1. Travel Cost and Shopping Choices

How consumers make shopping destination decisions is a topic of primary interest in retail. Marshall and Pires (2018) build a model of consumer grocery shopping that considers the decisions of where to shop and which products to shop. When making these decisions, consumers trade off between the travel cost and the prices and product assortment of each shop. The authors exploit the variation on weather, traffic, and cost of time to identify how travel cost affect store choices for a sample of 7,000 households. Their findings highlight the importance of travel cost on shopping decisions since travel cost rather than prices or assortment drives store choice. Similarly, Chan et al. (2007) study the trade off between prices and distance traveled to shop with a competition model for gasoline retailers. Using three waves of data for 226 gasoline stations, the authors estimate a travel distance demand elasticity of .106, compared to a 2.808 price elasticity.

Other studies delve deeper into quantifying travel cost in the context of all shopping costs. Bell et al. (1998) propose that consumers minimize total shopping cost and, hence, develop a store choice model that quantifies fixed and variable shopping costs. Fixed cost includes store preference and travel cost, which is modeled as a non-linear function of distance and varies by consumer. In their empirical application with 520 households, the authors find that while some segments of consumers are highly sensitive to travel cost, other segments are very insensitive. In their logit specification the sensitivity to travel distance varies between .056 and 3.738, with an average elasticity of 1.705. Dellaert et al. (1998) study how customers combine different store visits in one trip to minimize total travel costs. To this end, the authors manipulate the store type and distance in an experimental design with 144 surveyed households. The authors quantify three travel cost parameters depending on the type of shop visited, which range between .403 and .524. He et al. (2017) apply the gravity model to support the geographical network design for electric car sharing providers. The authors estimate a travel distance cost coefficient for consumers of 2.013.

Chintagunta et al. (2012) develop a channel choice model (online vs. offline) that accounts multiple transaction costs. Travel cost consists of distance and time costs. To incorporate different effects of travel cost, distance is interacted with household income and distances is scaled by a factor of two in downtown areas and during peak hours. In their application with 3,500 customers of a retailer, higher travel cost encourages households to visit the online channel. Forman et al. (2009) exploit the openings of physical stores to examine the effect of distance to store on online shopping. The authors find that both travel cost and the disutility of purchasing online influence consumer choices. We refer to Gallino and Moreno (2019) for a discussion of omnichannel retailing.

There are also analytical models that incorporate the role of distance in choices. Bai et al. (2022) highlight the importance of consumer travel sensitivity for retailer decision on where to locate an outlet store with respect to the main store locations. The authors find that an increase in consumer heterogeneity in travel sensitivity has a positive impact on retailer profitability. Finally, Gao and Su (2017a,b) and Gao et al. (2021) consider the different functions of stores in an omnichannel perspective, study how these influence channel choices and characterize effective store networks.

The literature has thus studied the sensitivity of demand to travel distance, but with very different estimated values, suggesting that we need more research to understand what drives the sensitivity parameter.

2.2. Gravity Models

The law of gravitation has been widely used to model consumer choices of retail locations. Early conceptualization and formulation work goes back to Reilly (1931), Converse (1949), and Huff (1964). Multiple studies extended the gravity model proposing the inclusion of factors that influence consumer choice. Gautschi (1981) suggests the addition in the model of retail center characteristics such as assortment, design, and pricing as well as mode of transportation characteristics such as safety, comfort, and cost. Okoruwa et al. (1988) propose the inclusion of shopper demographic attributes and retail center attributes such as various size measures. Lee and Pace (2005) develop a gravity model that accounts for spatial dependencies among consumers and retailers. Li and Liu (2012) show that incorporating spatial competition and agglomeration improves the gravity model performance.

Our geolocation data and gravity model application have some parallelism with other population-level studies. The law of gravitation characterizes the traffic flow across the 30 main cities in South Korea (Jung et al. 2008) and the phone call patterns between cities for 2.5 million people in Belgium (Krings et al. 2009). In their seminal paper, Simini et al. (2012) propose a modelling framework based on gravitation, which they call radiation model, to predict population mobility patterns that only require information on population distribution. Beiró et al. (2018) use the gravity model to investigate whether social mixing affects the decision of 380,000 people to visit 16 malls in Chile. Jia et al. (2020) document with the gravity model how the mobility of more than 11 million people in China predicts the spread of COVID-19 and the efficacy of mobility restrictions. In comparison, we combine the gravity model with a choice model over shopping destinations and use the model to identify variations in travel distance sensitivity.

2.3. COVID-19 Impact

Many recent studies examine how consumer spending habits changed due to the COVID-19 employing large data sets of credit card records. Carvalho et al. (2020) analyze 2.1 billion transactions from

6 million cardholders of a bank in Spain. These authors find that mobility reduction during the lockdown is influenced by social class and day of the week, with poorer households traveling more during weekdays. Bounie et al. (2020) use 4.5 billion transactions from 70 million cards for all banks in France. They find that cardholders during lockdown reduced the distance traveled to one-quarter and concentrated spending in fewer retailers, a finding consistent with our model and empirical results. Relihan et al. (2020) analyze 450 million transactions from 11 million cardholders in US. They find that lower-income neighborhoods had a larger decline in overall spending and had a slower adoption of online grocery shopping although larger use of online restaurant ordering. Chronopoulos et al. (2020) utilize 20 million transactions from 100,000 cardholders in Great Britain. The authors identified stockpiling behavior and differences in consumption across sociodemographic groups.

Other studies employ different types of data to examine the heterogeneous impact of COVID-19. For example, Chetty et al. (2020) combine data from private companies in the USA to track multiple economic indicators at the zip code, industry, income group, and business size level. They find that high-wage individuals faced a V-shaped recession that only lasted a few weeks, while low-wage individuals suffered much larger job losses that persisted several months. Similarly, Campos-Vazquez and Esquivel (2021) use point-of-sale transaction data from Mexico to find geographic and sectorial differences in consumption declines. Alexander and Karger (2021) combine credit card spending data with county-level data on mobility and mobility restrictions to find that political affiliation is associated to differences in mobility and restaurant spending. Martínez-de-Albéniz et al. (2021) break down the impact of COVID-19 on fashion retail sales into regulatory effects, social panic, and shocks from tourism. Alé-Chilet et al. (2020) document that the shock brought by COVID-19 induced a change in mobility patterns that explain a significant portion of the overall drop in non-respiratory emergency room visits during the period. Carranza et al. (2022) use geolocated mobile phone data to document heterogeneous behaviors by socioeconomic areas in mobility reductions during COVID-19 lockdown which in turn are related to differences in infection.

2.4. Our Contribution

Previous literature highlights the importance of travel cost on shopping choices. The magnitude of the sensitivity to travel distance varies significantly across studies due to methodological and contextual differences. Notwithstanding, although it has not been explicitly postulated, an implication of previous findings is that increases (decreases) in travel cost sensitivity would lead customers to travel less (more) to shop. Our paper builds on the above studies applying the gravity law to develop a model of consumer shopping destination choices. We embed the law of gravitation in the logit framework (McFadden 1974) so that shop attractiveness is proportional to distance to the power of a negative β. Our work differs from the literature in that we analytically formulate how do changes in travel cost affect shopping destination choices. Specifically, we analytically predict that an increase in travel distance sensitivity decreases the likelihood that a consumer chooses to visit a shopping destination that is far but increases the likelihood for a destination that is near. We also identify the threshold-radius around the shopping destination around which probability to visit increases due to the increase in travel distance sensitivity.

We test empirically our predictions with customer data on daily visits during 27 months to seven malls in four cities from two countries for a total population of 5.4 million individuals. Furthermore, we quantify how the magnitude of the sensitivity to travel distance changes over time, over space, and consumer contexts examining differences by social class, weekday vs. weekend variation, and weather conditions. In line with previous studies, we employ the COVID-19 outbreak as a major shock on consumer behavior. We argue that COVID-19 caused a structural shock on both the main propensity to shop and, importantly, on the travel cost faced by consumers due to both the mobility restrictions imposed by the authorities and the health risk associated with social interactions. In our empirical application, we account for differences in the strength of the shock, which we expect to peak during the lockdown and fade away afterwards.

3. Theoretical Analysis

In this section, we provide a theoretical analysis of the effect of travel distance sensitivity on customer shopping destination choices. We first present a general model and then derive our theoretical predictions from this stylized model.

We embed the travel cost customers face into a discrete choice model framework (McFadden 1974). This is similar to papers in economics of migration that have built on the logit model to generate a gravity model of destination choices (e.g., Beine et al. 2011; Grogger and Hanson 2011). Indeed, Anderson (2011) states that "the discrete choice probability model rationalizes structural gravity equally well" (p. 148). Hence, we express the utility obtained by individual i from choosing the shopping destination j as:

$$U_i^j = \alpha_i^j + \beta log\_dist_i^j + \epsilon_i^j$$

where the individual utility obtained from traveling to a certain shopping destination depends linearly on the individual preference for the destination (α_i^j), a (dis)utility from traveling to the destination (β, which should be negative to reflect that higher distance increases travel cost and reduces utility), and a residual term (ϵ_i^j). We express the distance variable in logs ($log\_dist_i^j$) for consistency with the gravity literature to account for a concave relationship.

When the residual follows an independent and identically distributed (i.i.d.) extreme-value distribution, we can apply the results in McFadden (1974) to write the destination choice probability as:

$$P_i^j := Pr(Y_i^j = j) = \frac{exp(\alpha_i^j + \beta log\_dist_i^j)}{\sum_{k=1}^J exp(\alpha_i^k + \beta log\_dist_i^k)} = \frac{a_i^j}{a_i^1 + a_i^2 + ... + a_i^J} \tag{1}$$

where $a_i^j = exp(\alpha_i^j + \beta log\_dist_i^j)$. When complete information on possible choices is not available, these alternatives are typically grouped into an outside option (e.g., Vulcano et al. 2012; Newman et al. 2014).

Next, we evaluate how a change in travel cost –via a variation in travel distance sensitivity– would influence destination choices. Taking logs in both sides of Equation (1), we obtain

$$\log(P_i^j) = \alpha_i^j + \beta log\_dist_i^j - \log\left(a_i^1 + a_i^2 + \ldots + a_i^J\right).$$

By taking derivatives with respect to β, we find that

$$\frac{\partial log(P_i^j)}{\partial \beta} = \frac{1}{P_i^j}\frac{\partial P_i^j}{\partial \beta} = log\_dist_i^j - \frac{\left(a_i^1 + a_i^2 + ... + a_i^J\right)'}{a_i^1 + a_i^2 + ... + a_i^J},$$

where $(a_i^j)' := \frac{\partial a_i^j}{\partial \beta} = a_i^j log\_dist_i^j$. Hence, we can write

$$\frac{\partial log(P_i^j)}{\partial \beta} = log\_dist_i^j - \sum_{k=1}^{J} P_i^k log\_dist_i^k.$$

where P_i^k, defined in Equation (1), are positive weights that add to one. Hence, the probability of option j increases with respect to β if and only if its log-distance is higher than the weighted average of log-distances across other possible choices. In other words, as travel distance sensitivity increases, i.e., $\beta < 0$ becomes even more negative, the nearby shopping alternatives (lower than a threshold) see the number of visits increase while further away alternatives become less popular. In particular, $\frac{\partial (P_i^j)}{\partial \beta} < 0$ if destination j is the closest to individual i. This is formally stated next.

Theorem 1. *An increase in travel distance sensitivity increases the propensity to visit the shopping destination that is closest to the individual and reduces the propensity to visit the furthest ones.*

We now evaluate which is the threshold-radius around the shopping destination under which the probability to visit would increase (decrease) due to an increase (decrease) in travel distance sensitivity. That is, we are interested in identifying the distance from a shopping destination below which visits increase and above which visits decrease due to an increase in distance sensitivity. The indifference point for individual i with respect to destination j is characterized by a no-change in the probability to visit, or $\frac{\partial P_i^j}{\partial \beta} = 0$. Combined with the results from above, we can state:

Theorem 2. *The threshold-radius around the shopping destination under which the probability to visit increases (decreases) due to an increase (decrease) in travel distance sensitivity is*

$$TH_i^j = \sum_{k=1}^{J} P_i^k log\_dist_i^k.$$

Therefore, the threshold-radius depends on both the distance to all shopping alternatives the individual has and also on the individual preference for each shopping alternative (captured by all α_i^j). Hence, distance sensitivity and customer preferences (independent of travel or distance cost) have an effect on the threshold-radius. Importantly, this is different from the results in Theorem 1, where the direction of the change in travel distance sensitivity (increase or decrease) determines the direction of change in the visit probability for the shopping destinations independently of the individual preference for the destinations.

4. Main Empirical Analysis: City of Quito

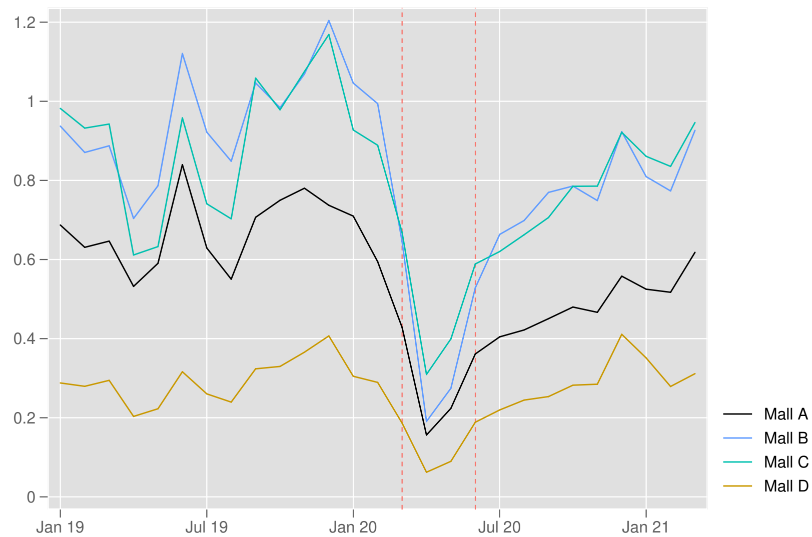
4.1. Data Description

Our primary data set was granted by a retail analytics company. The data geolocates individuals in the city of Quito, Ecuador, using their cellphone activity. For privacy reasons, individuals are aggregated into districts depending on where they live (in Ecuador called "subparroquias" (parroquias urbanas), "parroquias" (parroquias rurales), and "cantones"). The data tracks the number of visitors from each district to four main shopping malls in Quito from January 1, 2019, to March 31, 2021, for a total of 816 days (five days from 2019 are missing from the data set). We call the four malls A, B, C, and D. The number of unique visitors is measured at various time-aggregation levels ranging from daily to yearly. For our analysis, we consider the 51 districts with consumers visiting the four malls (we excluded from the analysis 10 districts that due to the combination of small population size and large distance to the malls do not have any visitor to some malls throughout the whole span of the data). These districts account for a population of 2,544,382 individuals, with a minimum of 3,224 people in Tababela district and a maximum of 173,752 people in Calderon district. The Online Appendix locates the 51 districts in the city map of Quito and provides their population (variable *population*). Figure 1 shows the evolution of monthly visits per mall (variable *visit*).

We distinguish three time periods in the data (categorical variable *Period*). The first period covers the pre-COVID-19 phase, the second covers the lockdown, and the third covers the reopening phase after the lockdown. In Quito, the lockdown started on March 17, 2020, and finished on June 3, 2020 (Gobierno de Ecuador 2020). During this period, the authorities imposed strict mobility restrictions across provinces and visits to malls were restricted to grocery shopping. From the end of the lockdown all types of shops could open with some capacity restrictions. We also call the pre-COVID-19, lockdown, and reopening periods as Periods 1, 2, and 3, respectively. Please see the Online Appendix for robustness checks with alternative period measurements including monthly periods.

We also collect data from multiple open-source platforms. First, we obtain the coordinates of the perimeter of each district from the city council of Quito, which we use to compute, for each district, the centroid and the distance to each mall. The shortest and longest distance from a district (its centroid)

Figure 1 **Evolution of Monthly Mall Visits in Quito**



Notes. The red-dashed lines indicate the lockdown period. The vertical axis reports the monthly visits in millions.

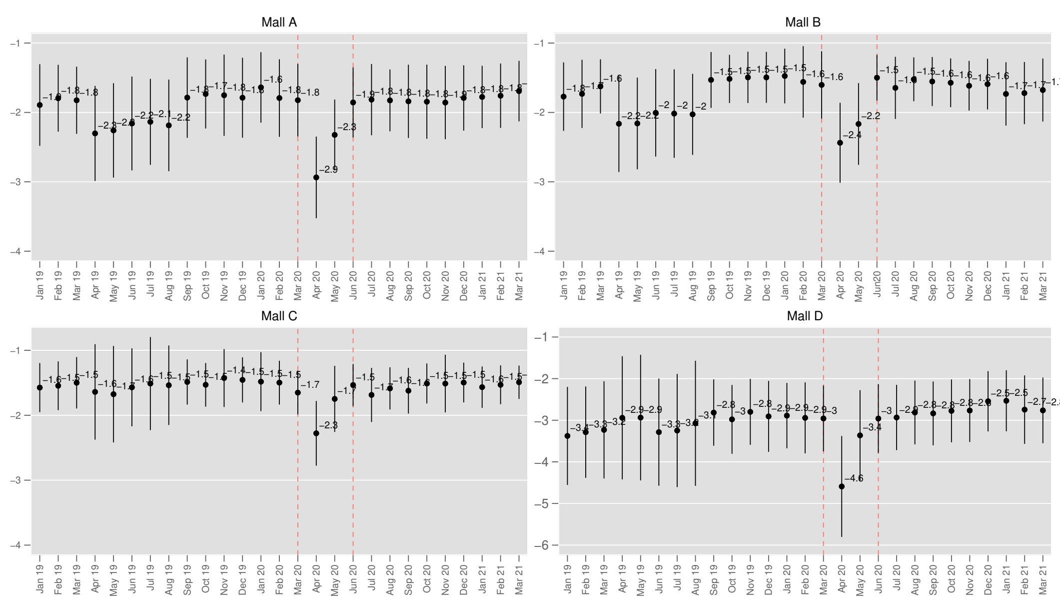
to a mall are 1.21 and 37.73 km, respectively. We take the log of distance to compute the variable *log_dist* (we consider alternative measurements for the distance variable. See the Online Appendix for non-parametric measurement. Also, distance measured in car driven time and car driven distance have correlations of .97 and .93 with our measure of bird's eye distance). Second, we collect the geographic location of the 10 malls in Quito not included in our primary data set. We compute which of the 14 malls is the closest to each district (categorical variable *closest*). Third, we gather precipitation data from NASA POWER Project (2003). The distribution of precipitation is highly skewed to the right. Although only 21 days have zero precipitation, 219 days have less than 1 millimeter (mm) of rainfall a day. The median and mean daily precipitations are 2.82 and 4.20 mm, respectively. We code precipitation as a continuous variable named *Rain*. Fourth, we collect sociodemographic data at district level from the Quito city council (Instituto de la Ciudad de Quito 2015). To evaluate the economic-well being, we standardize the measure of economic security ("Seguridad Económica" in the data) to create the continuous variable *Rich* (see Online Appendix for a distribution of the variables *Rain* and *Rich*) ("Seguridad Económica" measure is not available for Rumiñahui district). Finally, we create a dummy variable that takes value of 1 on weekend days (variable *WE*).

4.2. Model-free Evidence

Before embarking on the model estimations, we provide some model-free evidence on the strength of COVID-19 shock on travel distance sensitivity and on how changes in this sensitivity affect shopping choices differently depending on the distance, as predicted by our analytical model. We specify the linear regression in Equation (2) to evaluate how the relationship between visits and distance to shopping destination evolves. The regression evaluates the changes over time of the relationship between the number of visits to a mall ($visits_{it}$) from district i in month t and the distance from the district to the mall ($Distance_i$), controlling for seasonality (α_t) and district population ($Population_i$). We estimate the regression for each of the four malls in Quito introduced above. Figure 2 shows the estimates of the distance coefficients, β_t. During the most severe lockdown from March to May 2020, the β_t coefficients are sharply reduced, suggesting a stronger travel cost sensitivity than before the pandemic. After June 2020, the β_t coefficients return to pre-COVID-19 levels.

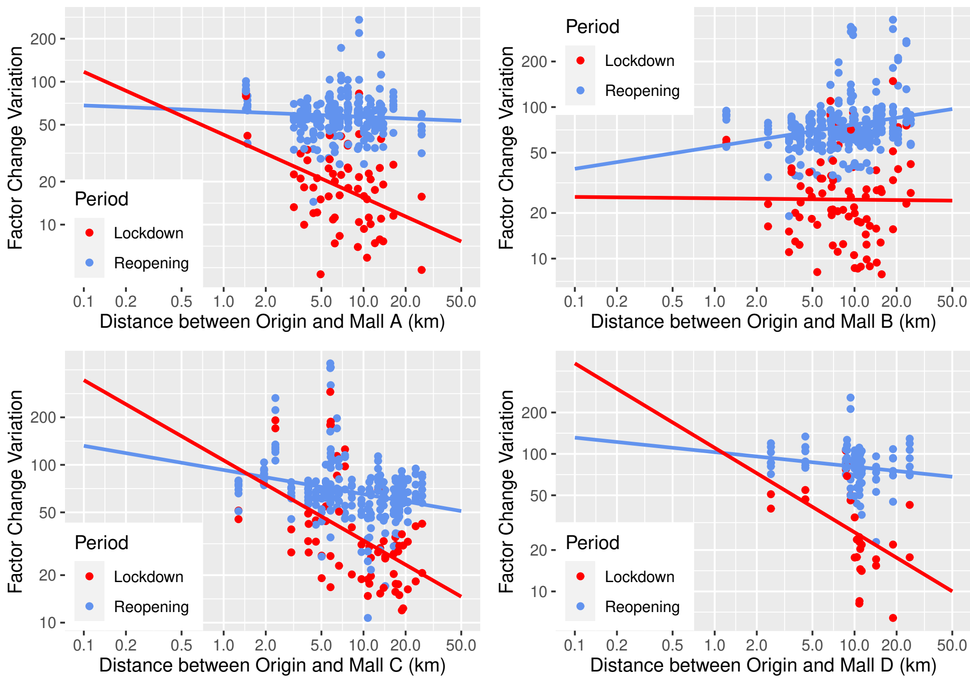
$$\log(visits_{it}) = \alpha_t + \beta_t \log(Distance_i) + \gamma_t \log(Population_i) + \varepsilon_{it} \tag{2}$$

Figure 2 Evolution of the Relationship between Distance to Mall and Visits (Malls in Quito)



Notes. The red-dashed lines indicate the period of lockdown. Vertical axis represents the coefficient and confidence interval estimates of the variable β_t in Equation (2).

Figure 3 Model-free Relationship between Distance to Mall and Variation in Visits by District (Malls in Quito)



Notes. Each dot represents the factor change variation in visits of a district-month. Factor change variation is the number of visits from each month from March to December 2020 divided by the corresponding month in 2019 multiplied by 100. A number above 100 indicates an increase in the number of visits and a decrease otherwise. The lines are the linear OLS predictions of the relationship between distance and variation in visits.

To provide a more nuanced evidence of the COVID-19 shock on travel cost, we plot in Figure 3 the variation in monthly visits to the shopping malls before vs. after COVID-19 for each district. Each dot represents the factor change in visits of a district-month. We emphasize several aspects. First, there is a sharper decline in visits across districts during lockdown compared to the reopening phase for the four malls, since almost all red dots are below the blue dots. Second, not only there is an overall decline in visits post-COVID-19 (both lockdown and reopening), except in the reopening period for Mall B, but there is a negative relationship between distance to the mall and drop in visits which is stronger in the lockdown compared to the reopening period, as indicated by the steeper red trend vs. the blue trend. Taking both results together, the shock on travel cost is related to a main reduction in visits and an increased reduction of visits with distance. Third, and most notably, the trend lines for Malls A, C, and D intersect with the 100-factor-line indicating that for short distances to the mall the number of visits would increase with respect to pre-COVID-19 period.

4.3. Model Formulation and Estimation

In this section we empirically test our predictions. We accommodate the choice model presented in Equation (1) to account for changes in travel distance sensitivity at different periods in a panel framework. The following model presents the individual level decision to visit a shopping destination on a certain day:

$$P_{it}^{j} := Pr(Y_{it}^{j} = j) = \frac{exp(\alpha_d^j + \gamma_t^j + \delta_{Period_t} + \beta_{Period_t} \times log\_dist_i^j)}{\sum_{k=1}^{J} exp(\alpha_d^k + \gamma_t^k + \delta_{Period_t} + \beta_{Period_t} \times log\_dist_i^k)} \tag{3}$$

where subscript i represents the individuals in the city of Quito ($i = 1, \ldots, 2,544,382$), subscript d represents the district to which the individual belongs ($d = 1, \ldots, 51$), subscript t represents the daily time dimension ($t = 1, \ldots, 816$), and subscript j represents the choice of visiting one of the four malls ($j = 0, \ldots, 4$, where 0 denotes the outside option, that of not visiting any of the four malls, which includes the choice of shopping online and not shopping at all). The main coefficients of interest are β_{Period_t}, which capture the incremental effect of distance in periods 2 and 3. Note that in this specification the main effect of distance, i.e., the travel distance sensitivity in period 1, is not estimated since it is collinear with district fixed effects. With α_d^j, we allow for district fixed effects to vary by mall (e.g., the product offering of certain malls might have better fit with individuals of certain districts). With γ_t^j, we allow for time effects to vary by mall (e.g., some seasonal promotions might be different in each mall). We operationalize the time effects as month of the year and day of the week fixed effects (results are robust to alternative time fixed effects operationalizations, see Online Appendix). We consider that the main effect of period is the same across malls, δ_{Period_t}, i.e., the average shock on propensity to visit (results are robust to a specification with different effects per mall, see Online Appendix). We estimate the models with maximum likelihood.

Following our analytical model, we make three assumptions implicit in the logit framework (Train 2002). First, we assume that the decision of visiting a mall is independent across individuals and time, after controlling for district and time effects. We believe this assumption is reasonable to capture the average effect across the whole population, especially given the large sample size we employ for our estimation. We recognize that at individual level there might be autocorrelation in the decisions. For example, negative autocorrelation in the short-term and positive in the long-term, because a consumer that has visited the mall today might be less likely to visit the day immediately after but more likely to visit at some point in the future. We further assume that an individual visits only one of the four malls a day and that the independence from irrelevant alternatives property (IIA) holds in our setting. We empirically examine the plausibility of these last two assumptions.

Column (1) of Table 1 presents the estimation results of Equation (3), which support our predictions. The increase in travel distance sensitivity due to COVID-19 affects shopping choices differently depending on the distance to destination, both for period 2 and 3. The negative estimates of β_{Period} (-.505 and -.056, both $p < .001$) indicate that the farther the shopping destination, the larger the decrease in visit likelihood during post-COVID-19. The negative estimates of δ_{Period} (-.459 and -.176, both $p < .001$) indicate that consumers generally reduced their likelihood to visit the malls after COVID-19. For the city of Quito, both the main shock and the distance effects are stronger in lockdown than in the reopening phase. Importantly, the ratio of the base level and the interaction coefficients is smaller for period 3 than period 2 (-.176/-.056 < -.459/-.505) suggesting that the threshold from which shorter distances increases the likelihood to visit the mall is larger for period 2. That is, in the city of Quito, the combination of a higher shock on both the main propensity to shop and the distance sensitivity during the lockdown compared to the reopening period resulted in a larger circle around the mall in which the likelihood to visit increases rather than decreases. In sum, during the lockdown it was more difficult to attract customers from far but it was easier to capture and retain near customer.

Columns (2) to (6) of Table 1 introduce some variations in terms of variables and level of data aggregation. Although the model fit is reduced when district fixed effects are removed (LL, Pseudo R2, AIC, and BIC), the coefficients are consistent not only in terms of direction and significance but also in magnitude. In column (2), we remove the district fixed effects to estimate the main effect of distance. The comparison of the travel cost estimates in the three periods (-1.380, -1.862, and -1.433,

Table 1. Main Results on the Effect of Distance on Shopping Destination Choice

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Period=2	-.459*** (.001)	-.485*** (.001)	-1.005*** (.003)	-.718*** (.002)	-.740*** (.002)	-1.453*** (.005)
Period=3	-.176*** (.001)	-.180*** (.001)	-.462*** (.001)	-.266*** (.001)	-.267*** (.001)	-.643*** (.002)
Period=2 x *log_dist*	-.505*** (.001)	-.482*** (.001)	-.287*** (.001)	-.350*** (.001)	-.326*** (.001)	-.059*** (.002)
Period=3 x *log_dist*	-.056*** (.000)	-.053*** (.000)	.051*** (.000)	-.020*** (.001)	-.017*** (.000)	.124*** (.001)
log_dist		-1.380*** (.000)	-1.027*** (.000)		-1.238*** (.000)	-.955*** (.000)
Closest			.995*** (.001)			.846*** (.001)
Period=2 x *Closest*			.460*** (.002)			.633*** (.004)
Period=3 x *Closest*			.256*** (.001)			.346*** (.001)
Month FE	Included	Included	Included	Included	Included	Included
Day of the Week FE	Included	Included	Included	Not Included	Not Included	Not Included
District FE	Included	Not Included	Not Included	Included	Not Included	Not Included
Observations	2,076,215,712	2,076,215,712	2,076,215,712	290,059,548	290,059,548	290,059,548
Log-likelihood	-319,849,395	-334,389,672	-331,111,694	-119,352,202	-125,623,366	-124,431,021
Pseudo R2	.158	.119	.128	.163	.119	.127
AIC	639,699,343	668,779,498	662,223,548	238,704,908	251,246,838	248,862,155
BIC	639,704,712	668,780,996	662,225,105	238,709,315	251,247,765	248,863,134

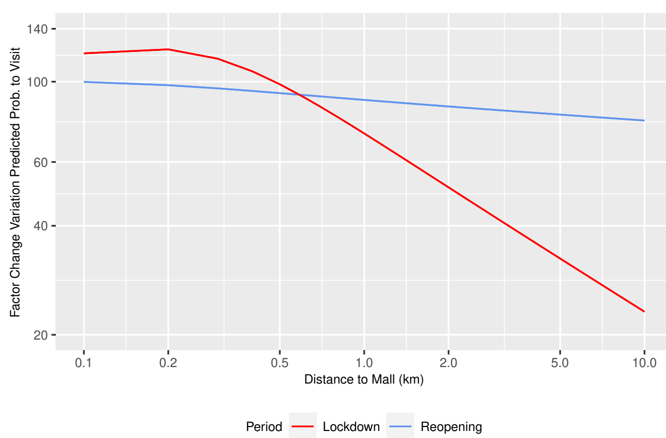
Notes: Columns (1) to (3) are estimated with daily data. Columns (4) to (6) are estimated with weekday data. FE refers to fixed effects.

$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

all $p < .001$) shows that the sensitivity increased by 35% during the lockdown and by merely 4% during the reopening. As a result, before COVID-19 for every unit increase in *log_dist* the propensity to visit decreased by a factor of .25 ($e^{-1.38}$), or, similarly, every 2.63 km away from the mall three fourths of the customers were lost. Comparatively, for every unit increase in *log_dist* the propensity to visit decreased by a factor of .15 during lockdown and by .24 in the reopening.

To ease the interpretation of the results, we plot in Figure 4 the factor change in predicted probabilities to visit a mall in periods 2 and 3 vs. period 1 of column (2) of Table 1. The combination of a higher cost of distance and a main decrease in visit likelihood during lockdown compared to the reopening phase can be noticed in that the factor change in predicted probability to visit for period 2 intersects the 100-line at the distance of around 500m, while for period 3 intersect at 100m. These intersections mark the thresholds from which the shock on travel cost provoked visits to increase for shorter distances and visits to decrease for longer distances. As distance increases, the effect of distance dominates over the main shock effect and the predictions of the different periods converge. See Online Appendix for the predicted probabilities to visit instead of the factor change. At a distance of 1 km from the mall, the predicted probability to visit decreases from 8.5% in period 1 to 6.1% in period 2 and to 7.5% in period 3. At 2 km, the predicted probability to visit decreases to half in period 2 from 4.2% to 2.1% and in period 3 to 3.5%. At 10 km, the predicted probability to visit decreases six-fold in period 2 from .6% to .1%.

Figure 4 Predicted Effect of Distance on Shopping Destination Choice



Notes. Prediction from estimates in column (2) of Table 1. Each line represents the factor change variation in the predicted probability to visit with respect to period 1. Factor change variation above 100 means an increase in the predicted probability to visit and a decrease otherwise.

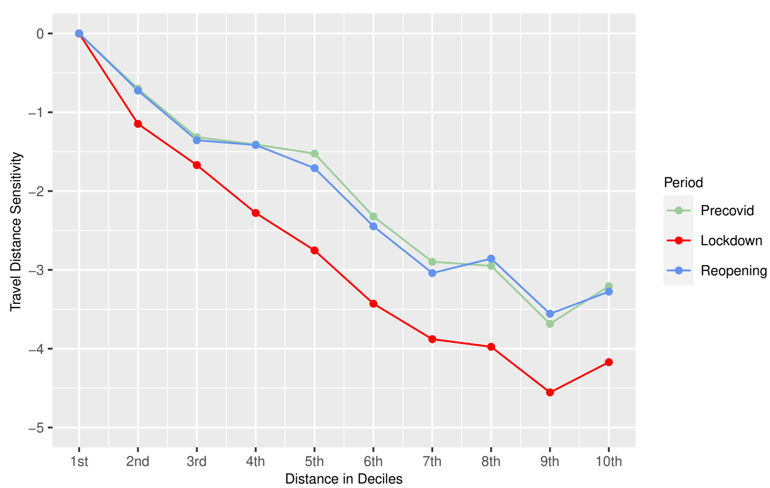
Column (3) of Table 1 introduces a variable that accounts for whether the visited mall is the closest to the consumer. The larger magnitude of the negative estimates of δ_{Period} compared to column (1)

(-1.005 vs. -.462, both $p < .001$) together with the positive interactions between having the mall as the closest and periods 2 and 3 (.460 and .256, respectively, both $p < .001$) show that the negative shock on visit likelihood when distance sensitivity increases is attenuated for the closest mall. In line with previous results, this additional variable partly captures the effect of proximity to the shopping mall, and hence the effect of distance is weakened in all periods 1, 2, and 3 (-1.027 vs. -1.380, -.287 vs. -.482, and .051 vs. -.053, respectively, all $p < .001$).

Columns (4) to (6) of Table 1 are estimated with aggregated weekly data during weekdays, i.e., unique weekly visitors from Monday to Friday (aggregated data for weekends is not available). All estimates are consistent with those in the first three columns in terms of magnitude and significance. Hence, we note some differences compared to the daily data estimation which suggest that visit frequency is also affected by the shock on travel cost. While the daily visit estimates capture the effect on visits (since daily visitors and daily visits are the same), the 5-day visit estimates capture the effect on the number of visitors during the week, thus omitting the frequency of visit of these visitors. The main effect due to COVID-19 is stronger with the 5-day aggregation than with daily data (-.718 vs. -.459, and -.266 vs. -.176, respectively, all $p < .001$). Thus, for customers nearby a shopping mall, the increase in travel cost decreased the number of visits less than the number of visitors, suggesting that frequency of visits (for those that visited) increased. In contrast, the effect of distance is attenuated for 5-day aggregation compared to daily data (-.350 vs. -.505, and -.020 vs. -.056, respectively, all $p < .001$). Thus, for customers living far from the shopping mall, the increase in travel cost comparatively reduced the number of visits more than the number of visitors, suggesting that frequency (for those that visited) decreased. Putting this in another way, the daily and weekday predicted probabilities intersect at a distance of about 1 km. As a result, for distances larger than 1 km, frequency decreased, while it increased for shorter distances. Similarly, during the reopening period, frequency increased for distances shorter than .7 km, and decreased otherwise. The Online Appendix presents the factor change in predicted probabilities to visit with 5-day data, which is flatter than with daily data.

To explore further the relationship between travel distance sensitivity and probability to visit the mall, we allow for a non-parametric functional form for distance coding the variable as categorical in intervals of deciles and quintiles (see estimates in the Online Appendix). The results are consistent with the main analysis. Figure 5 shows the estimates of the distance elasticity by decile. As expected, the effect of distance in the pre-pandemic is monotonically increasing in the whole range, except on the last decile (from -.702 to -3.206 in the first and last deciles, respectively, both $p < .001$). Similarly, the effect of distance in both post-COVID-19 periods remains largely monotonic (except the last deciles in both periods and the eight decile in period 3).

Figure 5 **Travel Distance Sensitivity with Non-parametric Measurement**



Notes. The variable *distance* is measured in deciles. First decile is set as base level. The coefficient estimates are presented in the Online Appendix.

4.4. Heterogeneity Analysis: Customer Characteristics and Environmental Factors

In this section we explore how do customer characteristics and environmental factors related to individual ability to choose influence travel distance sensitivity changes. We posit that the higher the freedom to choose, the more relevant the changes in travel cost for the consumer. We examine this proposition comparing whether the shock on travel cost has a differential effect on choices along three different factors related to ability of choice. First, we compare consumer choices during weekdays and weekends. We expect travel distance sensitivity to change more during the weekend since consumers have more alternatives to choose from during their free time and hence travel costs will be comparably more relevant in the choice process (the results are robust to the inclusion of national holidays). Second, we compare consumer choices depending on the precipitation level. Similarly, we expect travel cost sensitivity to change more in days with lower levels of rain, given that during rainy days there are fewer acceptable shopping options to choose from (Martínez-de-Albéniz and Belkaid 2021). Third, we examine the effect of social class. We expect wealthier consumers to experience higher travel distance sensitivity changes since economic well-being provides more ability to choose (Sen 2000). Of the three heterogeneity analyses, weekend (dummy variable *WE*) and precipitation (continuous variable *Rain*) vary with time while social class (continuous variable *Rich*) varies across districts. We augment Equation (3) to include the weekend dummy as follows (we do similarly with the variables rain and social class to obtain their effects):

$$P_{it}^{j} := Pr(Y_{it}^{j} = j) = \frac{exp(\phi_{it}^{j})}{\sum_{k=1}^{J} exp(\phi_{it}^{k})} \tag{4}$$

$$where \quad \phi_{it}^{j} = \alpha_{d}^{j} + \gamma_{t}^{j} + \delta_{Period_t} + \beta_{Period_t} log\_dist_{i}^{j} + \eta_{Period_t} WE_t + \theta_{Period_t} WE_t \times log\_dist_{i}^{j}.$$

Column (1) of Table 2 presents the estimation results of Equation (4) and column (2) removes the district effects to allow the estimation of the main effects. Columns (3) to (6) mirror the first two columns for rain and social class. The results support our predictions: the higher the ability to choose, the more relevant the changes in travel distance sensitivity for the consumer. That is, with the increase in travel cost brought by the COVID-19, travel distance sensitivity increases more during weekends, non-rainy days, and for wealthier people. Specifically, the sensitivity to distance increased 14% more during weekends than weekdays during the lockdown period (estimated sensitivities of -2.057 and -1.811, both $p < .001$), and 6% more during the reopening period (estimated sensitivities of -1.493 and -1.411, both $p < .001$). Given the continuous nature of the *Rain* and *Rich* variables, we establish the comparison of non-rainy vs. rainy days and wealthy vs. non-wealthy individuals at the 10th and 90th-percentiles of the *Rain* variable and at the 75th and 25th-percentiles of the *Rich* variable (see Online Appendix for a distribution of the variables *Rain* and *Rich*). We find that the

Table 2. Results on the Heterogeneity of the Effect of Distance

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Period=2	-.476*** (.001)	-.496*** (.001)	-.507*** (.002)	-.538*** (.002)	-.241*** (.002)	-.349*** (.002)
Period=3	-.205*** (.001)	-.207*** (.001)	-.188*** (.001)	-.191*** (.001)	-.128*** (.001)	-.126*** (.001)
*Period=2*log_dist*	-.475*** (.001)	-.456*** (.001)	-.540*** (.001)	-.513*** (.001)	-.610*** (.001)	-.539*** (.001)
*Period=3*log_dist*	-.059*** (.000)	-.0556*** (.000)	-.061*** (.000)	-.057*** (.000)	-.073*** (.000)	-.073*** (.000)
log_dist		-1.355*** (.000)		-1.378*** (.000)		-1.364*** (.000)
WE		-.126*** (.001)				
*Period=2*WE*	.094*** (.003)	.064*** (.003)				
*Period=3*WE*	.101*** (.001)	.101*** (.001)				
*WE*log_dist*	-.121*** (.000)	-.102*** (.000)				
*Period=2*WE*log_dist*	-.168*** (.002)	-.144*** (.002)				
*Period=3*WE*log_dist*	.019*** (.001)	.0192*** (.001)				
Rain			2,07E-04* (.000)	1,29E-04 (.000)		
*Period=2*Rain*			.012*** (.000)	.013*** (.000)		
*Period=3*Rain*			.002*** (.000)	.002*** (.000)		
*Rain*log_dist*			-.001*** (.000)	-.001*** (.000)		
*Period=2*Rain*log_dist*			.008*** (.000)	.007*** (.000)		
*Period=3*Rain*log_dist*			.001*** (.000)	.001*** (.000)		
Rich						.075*** (.000)
*Period=2*Rich*					-.143*** (.001)	-.066*** (.001)
*Period=3*Rich*					-.019*** (.001)	-.020*** (.000)
*Rich*log_dist*						.016*** (.000)
*Period=2*Rich*log_dist*					-.072*** (.001)	-.132*** (.001)
*Period=3*Rich*log_dist*					-.062*** (.000)	-.060*** (.000)
Month FE	Included	Included	Included	Included	Included	Included
Day of the Week FE	Included	Not Included	Included	Included	Included	Included
District FE	Included	Not Included	Included	Not Included	Included	Not Included
Observations	2,076,215,712	2,076,215,712	2,076,215,712	2,076,215,712	2,006,160,480	2,006,160,480
Log-likelihood	-319,768,453	-334,690,407	-319,837,366	-334,377,722	-303,741,845	-314,484,695
Pseudo R2	.158	.119	.158	.120	.155	.125
AIC	639,537,468	669,380,931	639,675,296	668,755,610	607,484,242	628,969,556
BIC	639,542,935	669,382,079	639,680,782	668,757,224	607,489,601	628,971,168

Notes: *WE* is a dummy variable, while *Rain* and *Rich* are continuous variables. *Rich* is not available for one district, hence the lower observations number in the last two columns. FE refers to fixed effects.
**p*<.05, ***p*<.01, ****p*<.001.

sensitivity to travel distance increased 3% more for non-rainy than rainy days during the lockdown period (estimated sensitivities of -1.890 and -1.831, both $p < .001$), although experienced the same change during the reopening period (both estimated sensitivities of -1.435, $p < .001$). Finally, the sensitivity to travel distance increased 10% more for wealthy than non-wealthy individuals during the lockdown period (estimated sensitivities of -1.990 and -1.810, both $p < .001$), and 5% more during the reopening period (estimated sensitivities of -1.470 and -1.402, both $p < .001$).

4.5. Robustness Checks

In this section we check the IIA assumption and the robustness of our results to a linear regression approach. IIA arises from the assumption that the error terms in Equation (3) are i.i.d. across malls. IIA may be violated if two or more of the malls are perceived by consumers as close substitutes. Hausman and McFadden (1984) demonstrate that if IIA is satisfied, then the estimated coefficients should be stable across choice sets. Therefore, we check the IIA assumption re-estimating the model with a subset of alternatives. We first examine the estimates of Equation (3) excluding from the choice set one mall at a time, that is, reducing the choice set to three malls (hence, increasing the number of individuals that choose the outside option). We explore further the IIA assumption examining consumer choices of visiting a single mall with a binary logit. Examining each mall separately, the MNL collapses to a binary logit. The results of both analyses (presented in the Online Appendix) are consistent in terms of magnitude and significance with the main results, suggesting that IIA is not violated in our setting. Specifically, all the coefficients displayed in column (1) of Table 1 are very similar to those of the eight columns on the table in the Online Appendix , except for the coefficient for period 3 for the binary logit of Mall D.

Finally, we assess the robustness of the results to a log-log linear regression specification. We examine the relationship between the log of the number of individuals that visit a mall from each district as a function of the log of distance and other variables in Equation (3). The unit of observation is district-day and the estimates can be interpreted directly as elasticities. We present the results in the Online Appendix for each mall. The effects of distance are typically not significant in the estimations with district fixed effects. However, without district fixed effects, both the main effects of distance and its interactions with period 2 are negative and significant. The magnitude of the effects suggests that for a 1% increase in the distance to the mall, the volume of visits reduces between 1.5% and 1.8% for period 1, depending on the mall, between 1.8% and 2.3% for period 2, and between 1.4% and 1.8% for period 3. In the last four columns on the table in the Online Appendix, we augment the regression to control for district population (variable *population*) and whether the mall is the closest to the district (dummy variable *closest*). The estimated travel cost elasticities are very consistent for Malls A and B, while some differences arise for Malls C and D.

5. Generalizability: Cities of Guayaquil, Manta, and Barcelona

In this section, we assess the generalizability of our empirical results to three additional cities in two distinct countries. These are the cities of Guayaquil and Manta in Ecuador and the city of Barcelona in Spain. We obtained the same data as for the analysis of Quito but for a single mall in each city. For the city of Guayaquil we considered 33 districts with a population of 1,009,117, for Manta 17 districts with a population of 233,061, and for Barcelona 73 districts with a population of 1,621,481 (note that the lockdown periods are different in each city. In Guayaquil, the lockdown went from March 17 to May 20, 2020 (Guayaquil 2020). In Manta, from March 17 to June 10, 2020 (Gobierno de Manta 2020). In Barcelona, from March 15 to June 15, 2020 (BOE 2020). See Online Appendix for a replication of the model-free analyses for these cities.

The first three columns of Table 3 present the estimates of Equation (3) for these three cities. Note that examining the choice of visiting a single mall, the MNL collapses to a binary logit. Overall, the results are consistent with our analytical predictions and empirical findings in Quito in terms of direction and significance of the estimates: (1) travel distance sensitivities are negative, (2) the shock on travel distance sensitivities due to the COVID-19 pandemic are negative with larger magnitudes during lockdown than reopening phases, (3) the main effects on visit likelihood decreases are larger also during the lockdown phases, and (4) having the mall as closest increases the likelihood of visit, more so when travel distance sensitivity increases.

Table 3. Generalizability: Logit Estimates for Guayaquil, Manta, and Barcelona

Variables	Mall Gua	Mall Man	Mall Bcn	Mall Gua	Mall Man	Mall Bcn
Period=2	-.857*** (.004)	-.555*** (.010)	-.558*** (.006)	-.087*** (.005)	-.303*** (.011)	-.775*** (.005)
Period=3	-.381*** (.001)	-.278*** (.003)	.778*** (.002)	-.306*** (.002)	-.257*** (.004)	.601*** (.002)
Period=2**log_dist*	-.666*** (.003)	-.908*** (.008)	-1.088*** (.005)	-1.157*** (.004)	-1.101*** (.009)	-.886*** (.004)
Period=3**log_dist*	-.002* (.001)	-.048*** (.002)	-.936*** (.002)	-.035*** (.001)	-.06*** (.003)	-.774*** (.002)
log_dist				-1.007*** (.001)	-1.134*** (.001)	-1.281*** (.001)
Month FE	Included	Included	Included	Included	Included	Included
Day of the Week FE	Included	Included	Included	Included	Included	Included
District FE	Included	Included	Included	Not included	Not included	Not included
Observations	823,439,472	190,177,776	1,003,696,765	823,439,472	190,177,776	1,003,696,765
Log-likelihood	-68,049,315	-14,198,222	-42,744,156	-76,315,893	-14,831,467	-43,238,011
Pseudo R2	.161	.094	.076	.059	.053	.065
AIC	136,098,739	28,396,519	85,488,500	152,631,831	29,662,980	86,476,068
BIC	136,099,739	28,397,168	85,490,260	152,632,258	29,663,372	86,476,499

Notes: FE refers to fixed effects.

*p<.05, **p<.01, ***p<.001.

Focusing on the magnitude of the effects presented in the first three columns of Table 3, we observe some interesting differences across the four cities analyzed in the paper. From a country perspective, the magnitude of the shock on distance sensitivity appears to be deeper and to last longer in Barcelona, Spain than in the three Ecuadorian cities (the interactions of distance with periods 2 and 3 are -1.088 and -.936, respectively, both $p < .001$). Interestingly, Barcelona, Spain presents a V-shaped recovery since the main effect of the shock on visit likelihood is positive for period 3 (.778, $p < .001$). Within Ecuador, the shock on distance sensitivity during the lockdown is larger in Guayaquil and Manta than in Quito (the interaction of distance with periods 2 for Guayaquil and

Manta are -.666 and -.908, respectively, both $p < .001$). However, the shock on period 3 is larger in Quito, especially compared to Guayaquil (the interaction of distance with periods 3 for Guayaquil and Manta are -.002 and -.048, respectively, both $p < .001$). Likewise, the main effect of the shock on visit likelihood is larger in Guayaquil and Manta than in Quito (periods 2 and 3 for Guayaquil and Manta are -.857 and -.381, and -.555 and -.278, respectively, all $p < .001$). See Online Appendix for an estimation that allows for different shock effects on distance sensitivity per month and for a robustness check with a log-log linear regression specification.

Following our main analysis, the last three columns of Table 3 do not present district fixed effects to estimate the main effects of distance. The travel cost estimates in the three periods (-1.007, -2.164, and -1.042 in Guayaquil, -1.134, -2.235, and -1.194 in Manta, -1.281, -2.167, and -2.055 in Barcelona, all $p < .001$) indicate that the sensitivity increased during the lockdown and the reopening by 115% and 3% in Guayaquil, by 97% and 5% in Manta, and by 69% and 60% in Barcelona, respectively.

Finally, we note some heterogeneity in the magnitudes of the thresholds around the malls in which visits increase. During lockdown, the thresholds were 900, 800, and 400 meters in Guayaquil, Manta, and Barcelona, respectively, compared to 500 meters in Quito. During the reopening, the thresholds were 100, 100, and 2,100 meters in Guayaquil, Manta, and Barcelona, respectively, compared to 100 meters in Quito. Hence, in the three Ecuadorian cities, where the shock on distance sensitivity is combined with a main decrease effect in both periods, the threshold is larger in the lockdown period than in the reopening. On the contrary, in Barcelona, Spain, the reopening period is characterized by a positive main increase effect (indication of a V-shaped recovery) which combined with a large shock on travel distance results in a larger threshold in the reopening phase compared to the lockdown.

6. Conclusions

Although the literature posits that an increase in travel distance sensitivity would reduce shopping visits, anecdotal evidence suggests that this might not always be true. To this end, we build on the gravity law to develop a model of consumer shopping destination choices. Our model predicts that with an increase in travel distance sensitivity consumers tend to substitute shopping visits at distant venues for nearby alternatives. We empirically examine our predictions in four cities from two countries with data on customer visits to seven shopping malls. We exploit the COVID-19 pandemic as a shock on travel cost to identify the relationship between distance and mall visits. Our empirical results validate our analytical predictions in that in each geography there is a threshold from the shopping destination below which visits increased due to increased travel costs. In our main empirical setting, this threshold is in the order of 500 meters during the lockdown period. Furthermore, we show that the effect of travel cost increases is strengthened in circumstances with higher ability to choose, that is, during weekends, in no-rain days, and for higher social class individuals. Our results thus provide an in-depth perspective on the drivers of consumers' sensitivity to distance, in comparison with the extant literature.

Our model and findings advance the theoretical understanding of the effect of travel cost on shopping choices by explicitly recognizing that destination substitution effects may increase visit probabilities for destinations nearby. Our work also has implications for managers and policy makers. Our findings inform retailers on what to expect when future changes on travel cost occur, not only in terms of overall customer traffic, but also customer profile depending on their origin. Moreover, our choice model helps quantify the area of influence around the retail location, hence, helping design a store networks by evaluating the appropriate store density. For policy makers, this research sheds light on the effects on local retailing of policies that affect mobility or the city landscape, for example, urban mobility restrictions or access to public transportation.

Limitations of our paper suggest useful directions for further research. First, due to privacy reasons and GDPR regulation, our mall visits data is aggregated at district level. Hence, we can make inferences at individual level on the evolution of visits and visitors, but not on visit frequency. Although our results suggest that frequency might be affected differently depending on customer location, further research could explore more in detail this phenomenon. Second, a limitation of our data is that we observe few data points at short distances from the malls. Future research with richer data on this aspect could explore more in detail the magnitude of the areas of influence around stores. Additionally, it would be interesting to compare how this area of influence changes across other geographies, and even identify factors that affect the size of the area of influence.

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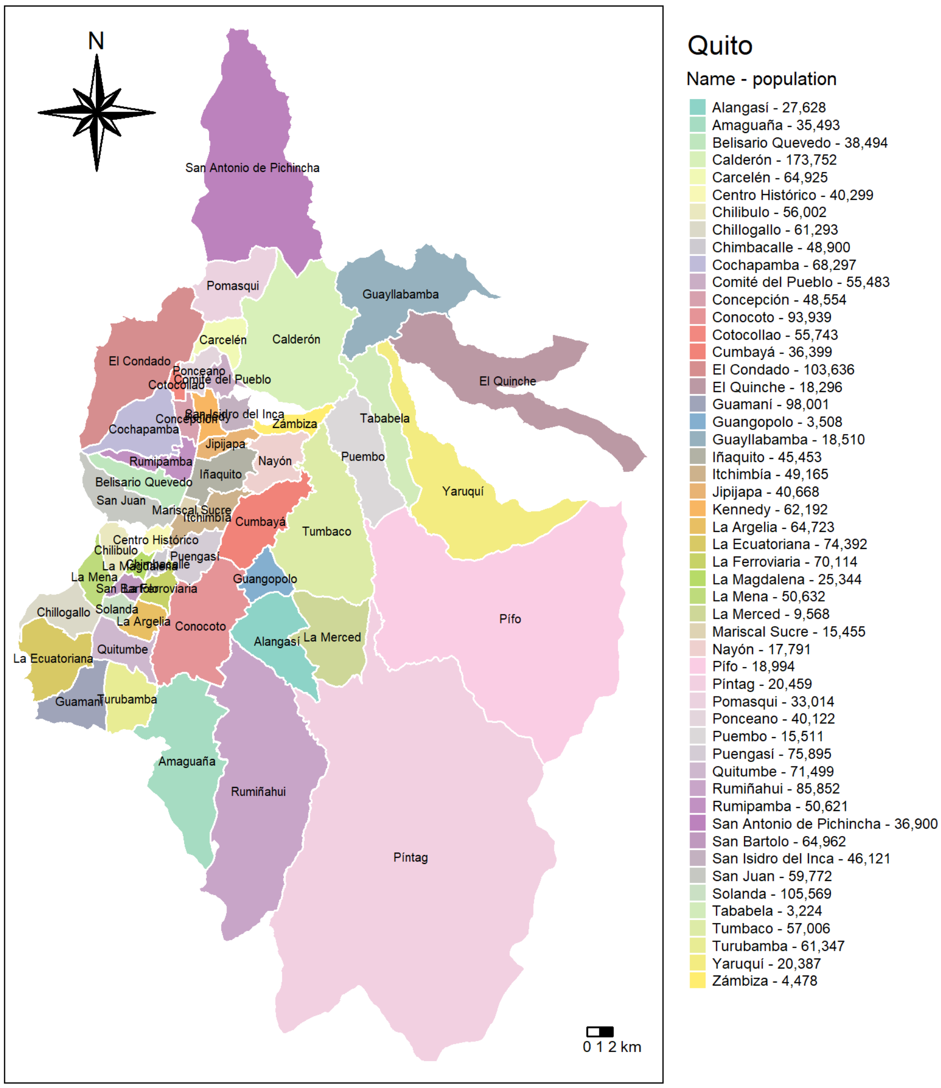
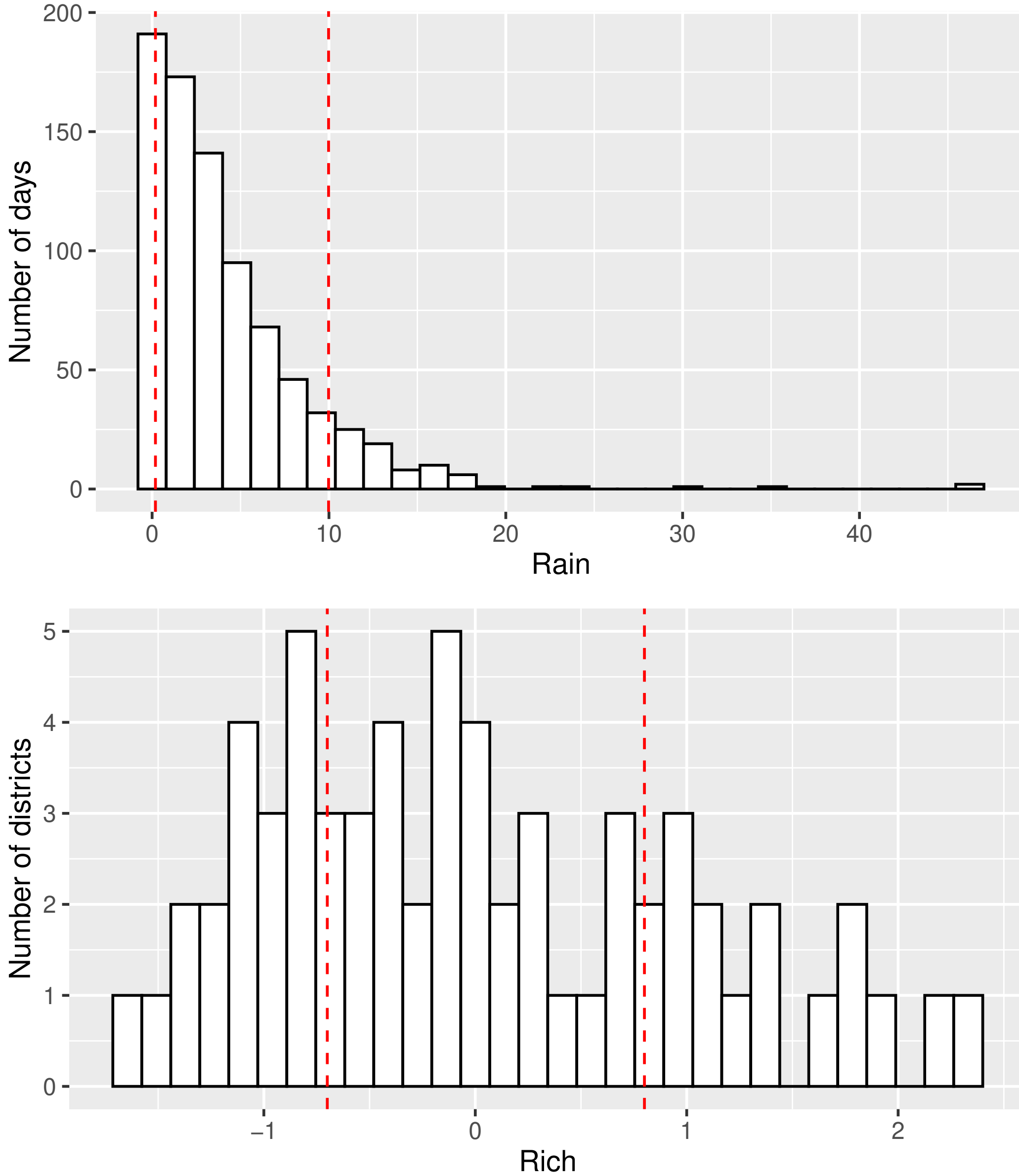
EC.1. Quito City Map and Descriptives

Figure EC.1 51 Districts Included in the Analysis.



EC.2. Distribution of Rain and Rich Variables

Figure EC.2 Histogram Rain and Rich Variables



Notes. Red-dashed lines indicate the 10th and 90th-percentiles for the variable *Rain* and the 25th and 75th-percentiles for the variable *Rich*.

EC.3. Robustness Checks: Alternative Variable Measurements

We assess the robustness of the results to alternative variable measurements. Table EC.3.1 considers four periods (instead of three as in the main analysis) which takes into account a minor change in the legal restrictions on the proportion of retail capacity allowed to be utilized. We also consider the measurement of the variable distance in levels (instead of in logs as in the main analysis). We consider two measurements for the month fixed effects: one dummy per month (27 dummies) and one dummy per calendar month (12 dummies). Finally, Table EC.3.2 considers a period measurement with a level for each month since the start of COVID-19.

Table EC.3.1 Robustness Check: Distance Effect in 4 Periods

Variables	(1)	(2)	(3)	(4)
Period=2	-.458*** (.001)	-.932*** (.002)	-.671*** (.001)	-1.161*** (.002)
Period=3	-.281*** (.001)	-1.282*** (.004)	-.346*** (.001)	-1.350*** (.003)
Period=4	-.136*** (.001)	-1.321*** (.004)	-.180*** (.004)	-1.371*** (.004)
Period=2* *dist*	-.506*** (.001)	-.510*** (.001)	-.086*** (.000)	-.083*** (.000)
Period=3* *dist*	-.079*** (.000)	-.088*** (.001)	-.009*** (.000)	-.009*** (.000)
Period=4* *dist*	-.048*** (.000)	-.061*** (.000)	-.004*** (.000)	-.005*** (.000)
Month FE	Included	Included	Included	Included
Day of the Week FE	Included	Included	Included	Included
Area FE	Included	Included	Included	Included
Observations	2,076,215,712	2,076,215,712	2,076,215,712	2,076,215,712
Log-likelihood	-319,796,334	-319,434,680	-319,839,369	-319,484,750
Pseudo R2	.157	.158	.157	.158
AIC	639,593,224	638,870,035	639,679,294	638,970,176
BIC	639,598,632	638,876,611	639,684,702	638,976,752

Notes: The variable *dist* is measured in logs in columns 1 and 2 and in levels (km) in columns 3 and 4. Columns 1 and 3 consider *Month* as categorical with periods 1-12 (Jan-Dec). Columns 2 and 4 consider *Month* as categorical with periods 1-27. FE refers to fixed effects.
**p*<.05, ***p*<.01, ****p*<.001.

Table EC.3.2 Robustness Check: Distance Effect by Month

Variables	(1)	(2)
Period=2	-.621*** (.003)	-.673*** (.003)
Period=3	-.410*** (.002)	-.440*** (.002)
Period=4	-.289*** (.002)	-.304*** (.002)
Period=5	-.600*** (.002)	-.598*** (.002)
Period=6	-.197*** (.002)	-.194*** (.002)
Period=7	-.056*** (.002)	-.058*** (.002)
Period=8	-.331*** (.002)	-.338*** (.002)
Period=9	-.211*** (.002)	-.213*** (.002)
Period=10	-.287*** (.002)	-.290*** (.002)
Period=11	-.219*** (.001)	-.217*** (.001)
Period=12	-.064*** (.001)	-.069*** (.001)
Period=13	-.032*** (.001)	-.044*** (.001)
Period=14	.032*** (.001)	.022*** (.001)
Period=2 x *log_dist*	-.721*** (.002)	-.675*** (.002)
Period=3 x *log_dist*	-.629*** (.002)	-.602*** (.001)
Period=4 x *log_dist*	-.402*** (.001)	-.388*** (.001)
Period=5 x *log_dist*	-.107*** (.001)	-.105*** (.001)
Period=6 x *log_dist*	-.077*** (.001)	-.078*** (.001)
Period=7 x *log_dist*	-.076*** (.001)	-.075*** (.001)
Period=8 x *log_dist*	-.046*** (.001)	-.040*** (.001)
Period=9 x *log_dist*	-.047*** (.001)	-.045*** (.001)
Period=10 x *log_dist*	-.062*** (.001)	-.058*** (.001)
Period=11 x *log_dist*	-.022*** (.001)	-.023*** (.001)
Period=12 x *log_dist*	-.051*** (.001)	-.047*** (.001)
Period=13 x *log_dist*	-.059*** (.001)	-.051*** (.001)
Period=14 x *log_dist*	-.050*** (.001)	-.043*** (.001)
log_dist		-1.380*** (.000)
Month FE	Included	Included
Day of the Week FE	Included	Included
District FE	Included	Not Included

Observations	2,076,215,712	2,076,215,712
Log-likelihood	-319,551,175	-334,093,852
Pseudo R2	.159	.120
AIC	639,102,947	668,187,903
BIC	639,108,744	668,189,829

Notes: Model 1 and 2 are estimated using a new variable for period defined as; *Period*=1 ("Pre-covid"), *Period*=2 (last half of March 2020), *Period*=3 for the month of April 2020 and so on. FE refers to fixed effects.
*p<.05, **p<.01, ***p<.001.

EC.4. Robustness Checks: Different Period Effect per Mall

Table EC.4. Different Main Effect by Mall

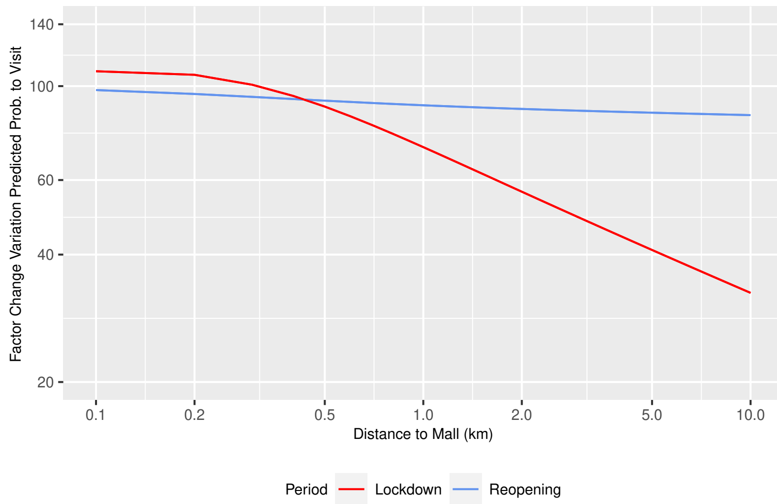
Variables	(1)
Period=2_*Mall A*	-.646*** (.002)
Period=3_*Mall A*	-.285*** (.001)
Period=2_*Mall B*	-.672*** (.002)
Period=3_*Mall B*	-.182*** (.001)
Period=2_*Mall C*	-.209*** (.002)
Period=3_*Mall C*	-.121*** (.001)
Period=2_*Mall D*	-.222*** (.003)
Period=3_*Mall D*	.045*** (.001)
Period=2*log_dist*	-.510*** (.001)
Period=3*log_dist*	-.068*** (.000)
Month FE	Included
Day of the Week FE	Included
District FE	Included
Observations	2,076,215,712
Log-likelihood	-319,752,049
Pseudo R2	.158
AIC	639,504,662
BIC	639,510,148

Notes: Variable *Period* different effect for each mall. FE refers to fixed effects.

*p<.05, **p<.01, ***p<.001.

EC.5. Distance Effect with Weekly Data

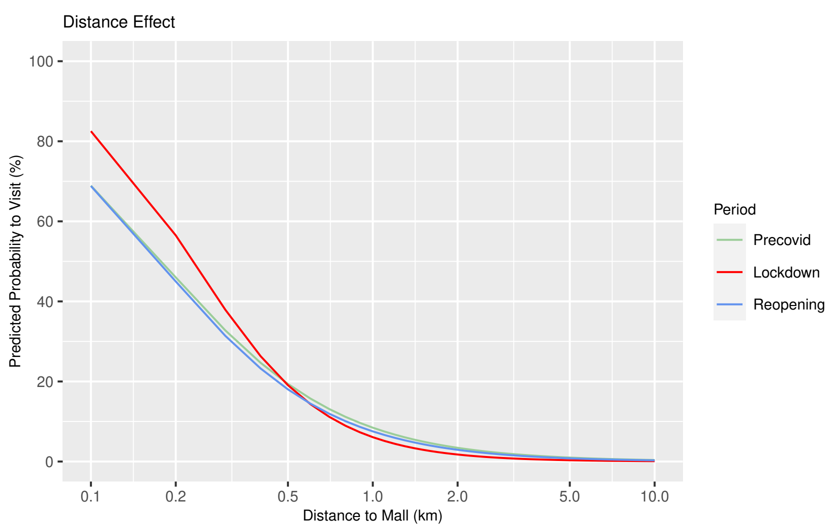
Figure EC.5 Predicted Effect of Distance on Shopping Destination Choice (Week aggregation)



Notes. Prediction from estimates in column (5) of Table 1. Each line represents the factor change variation in the predicted probability to visit with respect to period 1. Factor change variation above 100 means an increase in the predicted probability to visit and a decrease otherwise.

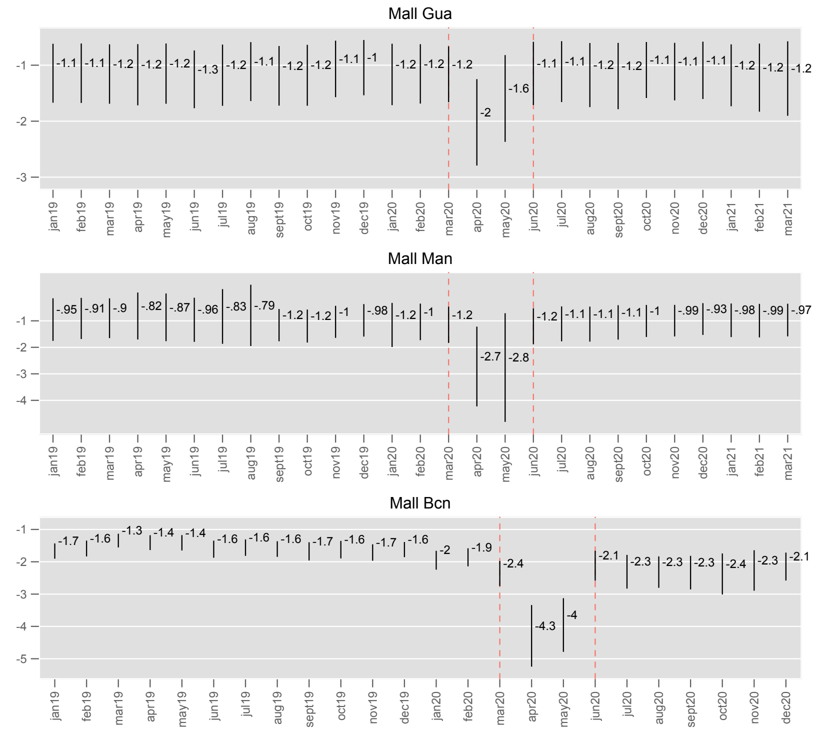
EC.6. Predicted Probabilities to Visit

Figure EC.6 Predicted Effect of Distance on Shopping Destination Choice



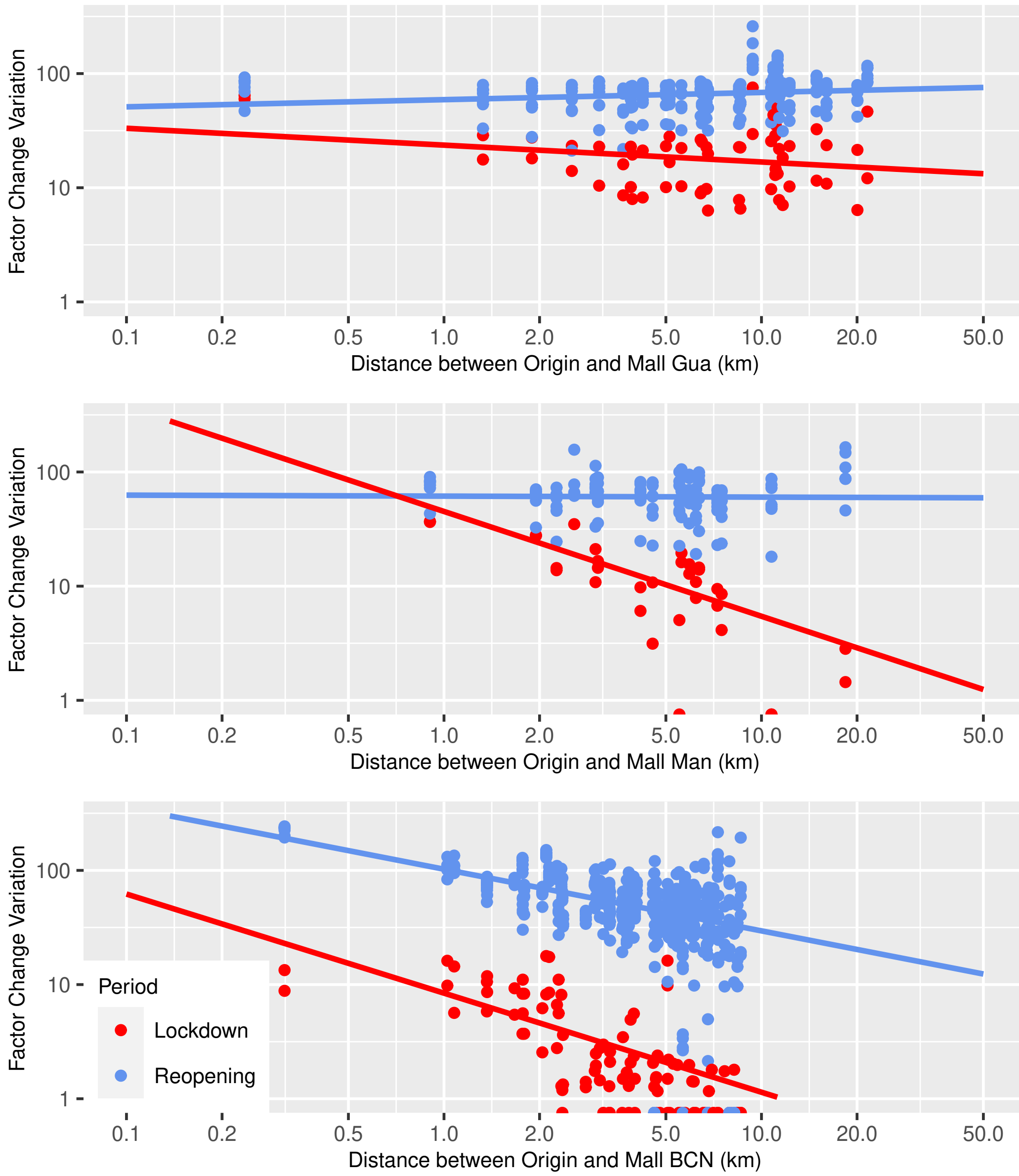
EC.7. Model-free Evidence: Cities of Guayaquil, Manta, and Barcelona

Figure EC.7 Evolution of the Relationship between Distance to the Mall and Visits.



Notes. Coefficient estimates of *log_dist* for Equation (2). Mall Gua and Mall Man include the months of Jan '21 - Mar '21.

Figure EC.8 Model-free Relationship between Distance to Mall and Variation in Visits by District.



Notes. Factor change variation represents visits post-COVID-19 divided by pre-COVID-19, A number above 100 indicates an increase in the number of visits and a decrease otherwise. The lines are the linear OLS predictions of the relationship between distance and change in visits.

EC.8. Travel Cost by Month in Guayaquil, Manta, and Barcelona

Table EC.8 Robustness Check: Distance Effect by Month for the 3 Different Cities

Variables	Mall Gua	Mall Man	Mall BCN	Mall Gua	Mall Man	Mall BCN
Period=2	-.797*** (.008)	-.442*** (.024)	-1.949*** (.027)	.077*** (.010)	-.113*** (.028)	-2.218*** (.023)
Period=3	-.885*** (.006)	-.463*** (.017)	-1.828*** (.016)	-.046*** (.007)	-.176*** (.019)	-2.103*** (.014)
Period=4	-.789*** (.005)	-.498*** (.016)	-1.405*** (.012)	-.311*** (.007)	-.253*** (.018)	-1.632*** (.010)
Period=5	-1.124*** (.004)	-.870*** (.011)	.868*** (.005)	-.965*** (.006)	-.791*** (.013)	.692*** (.004)
Period=6	-.623*** (.004)	-.251*** (.010)	.772*** (.005)	-.531*** (.005)	-.205*** (.012)	.608*** (.004)
Period=7	-.549*** (.004)	-.160*** (.010)	.645*** (.006)	-.431*** (.005)	-.116*** (.012)	.482*** (.005)
Period=8	-.367*** (.004)	-.349*** (.009)	.758*** (.005)	-.285*** (.005)	-.319*** (.011)	.581*** (.004)
Period=9	-.260*** (.004)	-.229*** (.009)	.809*** (.005)	-.186*** (.005)	-.212*** (.010)	.628*** (.004)
Period=10	-.321*** (.004)	-.359*** (.009)	.734*** (.005)	-.235*** (.005)	-.334*** (.010)	.535*** (.004)
Period=11	-.272*** (.003)	-.361*** (.008)	.971*** (.004)	-.246*** (.005)	-.360*** (.009)	.786*** (.004)
Period=12	-.071*** (.003)	-.077*** (.009)		.009 (.005)	-.064*** (.010)	
Period=13	-.123*** (.003)	-.154*** (.009)		-.084*** (.005)	-.144*** (.010)	
Period=14	-.127*** (.003)	-.180*** (.008)		-.136*** (.005)	-.178*** (.009)	
Period=2 x *log_dist*	-.851*** (.006)	-1.283*** (.021)	-1.364*** (.025)	-1.436*** (.008)	-1.547*** (.025)	1.107*** (.020)
Period=3 x *log_dist*	-.776*** (.004)	-1.075*** (.014)	-1.396*** (.015)	-1.326*** (.006)	-1.301*** (.017)	-1.133 (.012)
Period=4 x *log_dist*	-.298*** (.003)	-.881*** (.013)	-1.136*** (.011)	-.572*** (.004)	-1.069*** (.015)	-.924*** (.009)
Period=5 x *log_dist*	-.003 (.002)	-.222*** (.008)	-.943*** (.004)	-.062*** (.003)	-.271*** (.009)	-.781*** (.003)
Period=6 x *log_dist*	.015*** (.002)	-.133*** (.007)	-.871*** (.004)	-.022*** (.003)	-.164*** (.008)	-.721*** (.003)
Period=7 x *log_dist*	-.017*** (.002)	-.134*** (.007)	-.844*** (.005)	-.070*** (.003)	-.163*** (.008)	-.695*** (.004)
Period=8 x *log_dist*	-.006*** (.002)	-.078*** (.006)	-.934*** (.004)	-.043*** (.003)	-.095*** (.007)	-.772*** (.004)
Period=9 x *log_dist*	-.005** (.002)	-.039*** (.006)	-.955*** (.004)	-.041*** (.003)	-.048*** (.007)	-.789*** (.003)
Period=10 x *log_dist*	-.014*** (.002)	-.062*** (.006)	-1.050*** (.005)	-.055*** (.003)	-.076*** (.007)	-.865*** (.004)
Period=11 x *log_dist*	.020*** (.002)	.022*** (.005)	-.999*** (.004)	.013*** (.003)	.025*** (.006)	-.828*** (.003)
Period=12 x *log_dist*	-.026*** (.002)	-.032*** (.006)		-.071*** (.003)	-.041*** (.007)	
	.002	-.021***		-.018***	-.026***	

Period=13 x *log_dist*	(.002)	(.006)		(.003)	(.007)	
Period=14 x *log_dist*	.040*** (.002)	.008 (.005)		.048*** (.003)	.008 (.006)	
log_dist				-1.008*** (.001)	-1.134*** (.001)	-1.281*** (.001)
Month FE	Included	Included	Included	Included	Included	Included
Day of the Week FE	Included	Included	Included	Included	Included	Included
District FE	Included	Included	Included	Not Included	Not Included	Not Included
Observations	823,439,472	190,177,776	1,003,696,765	823,439,472	190,177,776	1,003,696,765
Log-likelihood	-67,887,096	-14,181,463	-42,604,579	-76,159,339	-14,814,655	-43,098,465
Pseudo R2	.163	.094	.079	.061	.054	.068
AIC	135,774,343	28,363,045	85,209,378	152,318,767	29,629,400	86,197,009
BIC	135,775,752	28,364,069	85,211,438	152,319,601	29,630,168	86,197,739

Notes: Model 1 and 2 are estimated using a new variable for period defined as *Period*=1 ("Pre-covid"), *Period*=2 (last half of March 2020), *Period*=3 for the month of April 2020 and so on. FE refers to fixed effects.
*p<.05, **p<.01, ***p<.001.

EC.9. Robustness Checks: Guayaquil, Manta, and Barcelona

Table EC.9 Robustness Check: Linear Regression

Variables	Mall Guay	Mall Man	Mall Bcn	Mall Guay	Mall Man	Mall Bcn
Period=2	-1.546*** (.357)	-.677* (.290)	-2.620*** (.392)	-1.931*** (.104)	-.897*** (.156)	-3.236*** (.093)
Period=3	-.392** (.110)	-.182 (.288)	.878*** (.173)	-.463*** (.065)	-.185** (.063)	.716*** (.050)
*Period=2*log_dist*	-.290 (.167)	-1.099*** (.153)	-.314 (.248)	-.128* (.052)	-.989*** (.078)	-.008 (.049)
*Period=3*Distance*	.032 (.061)	-.082 (.151)	-1.286*** (.112)	.062 (.033)	-.080* (.032)	-1.206*** (.030)
Distance				-1.257*** (.021)	-.740*** (.023)	-1.321*** (.015)
Population				-.009**** (.003)	.289*** (.009)	.595*** (.004)
Closest				-.293*** (.039)	.991*** (.035)	.531*** (.013)
*Closest*Period=2*				1.387*** (.099)	.491*** (.109)	.612*** (.059)
*Closest*Period=3*				.255*** (.062)	.007 (.046)	.161*** (.036)
Month FE	Included	Included	Included	Included	Included	Included
Day of the Week FE	Included	Included	Included	Included	Included	Included
District FE	Not Included	Not Included	Not Included	Not included	Not included	Not included
Observations	26,928	13,872	45,187	26,928	13,872	45,187
R2	.677	.649	.632	.489	.601	.774

Notes: Dependent variable measured in logs. *Population* measured in ten thousands inhabitants.

FE refers to fixed effects. In parentheses, standard errors are clustered at the district level.

*p<.05, **p<.01, ***p<.001.

EC.10. Distance in Intervals

Table EC.10 Effect of Distance in Intervals

Variables	(1)	(2)	(3)	(4)
Period=2	-.857*** (.001)	-.817*** (.001)	-.935*** (.001)	-.903*** (.001)
Period=3	-.236*** (.000)	-.227*** (.000)	-.242*** (.000)	-.231*** (.000)
Period=2**Dist*=2	-.385*** (.002)	-.445*** (.002)		
Period=2**Dist*=3	-.303*** (.002)	-.353*** (.002)	-.407*** (.002)	-.454*** (.002)
Period=2**Dist*=4	-.808*** (.003)	-.869*** (.003)		
Period=2**Dist*=5	-1.191*** (.004)	-1.229*** (.004)	-1.084*** (.003)	-1.103*** (.003)
Period=2**Dist*=6	-1.079*** (.006)	-1.107*** (.006)		
Period=2**Dist*=7	-.963*** (.008)	-.982*** (.008)	-.915*** (.005)	-.929*** (.005)
Period=2**Dist*=8	-.986*** (.008)	-1.027*** (.008)		
Period=2**Dist*=9	-.839** (.011)	-.870*** (.011)	-.831*** (.007)	-.837*** (.007)
Period=2**Dist*=10	-.955*** (.009)	-.965*** (.009)		
Period=3**Dist*=2	-.017*** (.001)	-.023*** (.001)		
Period=3**Dist*=3	-.029*** (.001)	-.038*** (.001)	-.014*** (.001)	-.020*** (.001)
Period=3**Dist*=4	-.004*** (.001)	-.007*** (.001)		
Period=3**Dist*=5	-.175*** (.001)	-.185*** (.001)	-.155*** (.001)	-.164*** (.001)
Period=3**Dist*=6	-.119*** (.002)	-.125*** (.002)		
Period=3**Dist*=7	-.135*** (.002)	-.143*** (.002)	.008*** (.001)	.001 (.001)
Period=3**Dist*=8	.101*** (.002)	.092*** (.002)		
Period=3**Dist*=9	.140*** (.003)	.128*** (.003)	.023*** (.002)	.011*** (.002)
Period=3**Dist*=10	-.060*** (.002)	-.070*** (.002)		
Dist=2		-.702*** (.000)		
Dist=3		-1.317*** (.001)		-1.176*** (.000)
Dist=4		-1.409*** (.001)		
Dist=5		-1.524*** (.001)		-1.608*** (.001)

Dist=6		-2.322*** (.001)		
Dist=7		-2.897*** (.001)		-2.596*** (.001)
Dist=8		-2.949*** (.001)		
Dist=9		-3.685*** (.002)		-3.142*** (.001)
Dist=10		-3.206*** (.001)		
Month FE	Included	Included	Included	Included
Day of the Week FE	Included	Included	Included	Not Included
District FE	Included	Not Included	Included	Not Included
Observations	2,076,215,712	2,076,215,712	2,076,215,712	2,076,215,712
Log-likelihood	-319,882,036	-346,260,696	-319,909,719	-348,053,458
Pseudo R2	.158	.088	.158	.084
AIC	639,764,655	692,521,593	639,820,002	696,107,040
BIC	639,770,336	692,523,558	639,825,488	696,108,246

Notes: For columns (1) and (2), the variable *dist* (distance) is a categorical variable grouped in deciles. For columns (3) and (4), the variable *dist* is a categorical variable grouped in quintiles. FE refers to fixed effects.
*p<.05, **p<.01, ***p<.001.

EC.11. Robustness Checks: Main Analysis City of Quito

Table EC.11.1 Robustness Check: Excluding One Mall at a Time and Binary Logit

Variables	excl. Mall A	excl. Mall B	excl. Mall C	excl. Mall D	Mall A	Mall B	Mall C	Mall D
Period=2	-.458***	-.340***	-.590***	-.444***	-.329***	-.662***	-.326***	-.468***
	(.001)	(.002)	(.002)	(.001)	(.003)	(.002)	(.002)	(.007)
Period=3	-.150***	-.146***	-.226***	-.180***	-.222***	-.219***	-.112***	.157***
	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)	(.003)
Period=2**log_dist*	-.450***	-.515***	-.517***	-.538***	-.783***	-.499***	-.391***	-.370***
	(.001)	(.001)	(.001)	(.001)	(.002)	(.002)	(.001)	(.004)
Period=3**log_dist*	-.048***	-.066***	-.037***	-.071***	-.105***	-.039***	-.073***	-.121***
	(.000)	(.000)	(.000)	(.000)	(.001)	(.001)	(.001)	(.001)
Month FE	Included	Included	Included	Included	Included	Included	Included	Included
Day of the Week FE	Included	Included	Included	Included	Included	Included	Included	Included
District FE	Included	Included	Included	Included	Included	Included	Included	Included
Observations	2,076,215,712	2,076,215,712	2,076,215,712	2,076,215,712	2,076,215,712	2,076,215,712	2,076,215,712	2,076,215,712
Log-likelihood	-245,576,970	-213,944,623	-219,109,714	-281,818,457	-74,902,876	-106,665,247	-100,971,228	-38,136,495
Pseudo R2	.157	.169	.156	.150	.157	.130	.162	.213
AIC	491,154,357	427,889,662	438,219,843	563,637,330	149,805,897	213,330,638	201,942,600	76,273,133
BIC	491,158,403	427,893,708	438,223,890	563,641,376	149,807,297	213,332,038	201,944,001	76,274,534

Notes: First four columns present MNL estimations excluding in each model one of the four malls in Quito at a time. The last four columns present Logit estimations for each of the four malls separately. FE refers to fixed effects.

*$p<.05$, **$p<.01$, ***$p<.001$.

Table EC.11.2 Robustness Check: Linear Regression

Variables	Mall A	Mall B	Mall C	Mall D	Mall A	Mall B	Mall C	Mall D
Period=2	-1.161*** (.399)	-1.042*** (.348)	-.329 (.230)	-1.407 (.812)	-1.287** (.058)	-1.229*** (.065)	-.921*** (.110)	-1.176*** (.174)
Period=3	-.573*** (.139)	-.489*** (.128)	-.148 (.200)	-.012 (.418)	-.580*** (.035)	-.584*** (.037)	-.638*** (.064)	.080 (.084)
Period=2**log_dist*	-.333 (.190)	-.306 (.167)	-.435*** (.099)	-.076 (.306)	-.281*** (.026)	-.231*** (.030)	-.239*** (.039)	-.152** (.059)
Period=3**log_dist*	.126 (.066)	.149* (.063)	-.036 (.093)	.079 (.153)	.131*** (.017)	.187*** (.018)	.126*** (.024)	.049 (.030)
log_dist					-1.855*** (.011)	-1.878*** (.012)	-1.529*** (.016)	-1.873*** (.023)
Population					.258*** (.002)	.267*** (.002)	.255*** (.002)	.231*** (.002)
Closest					.333*** (.016)	-.472 (.026)	.285*** (.025)	1.680*** (.034)
Period=2**Closest*					.515*** (.070)	.833*** (.067)	.452*** (.062)	-.237* (.105)
Period=3**Closest*					.136*** (.029)	.428*** (.039)	.374*** (.035)	-.095* (.045)
Month FE	Included	Included	Included	Included	Included	Included	Included	Included
Day of the Week FE	Included	Included	Included	Included	Included	Included	Included	Included
District FE	Not Included	Not Included	Not Included	Not Included	Not included	Not included	Not included	Not included
Observations	41,616	41,616	41,616	41,616	41,616	41,616	41,616	41,616
R2	.531	.532	.389	.371	.710	.706	.750	.599

Notes: Dependent variable measured in logs. *Population* measured in ten thousands inhabitants. FE refers to fixed effects. In parentheses, standard errors are clustered at the district level.

*p<.05, **p<.01, ***p<.001.