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Working Paper 2404

June 2024

11200 SW 8th Street, Miami, Florida 33199

https://economics.fiu.edu/

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January 9, 2024

Abstract

Using data on the number of visitors at the store level, this paper attempts to measure the welfare costs of traditional shopping trips for the U.S. census blocks. The investigation is based on an economic model, where individuals living in census blocks decide on which store to shop from based on the shopping-trip costs and idiosyncratic benefits. The welfare gains from removing shopping-trip costs in percentage terms are shown to depend on the weighted average of log distance measures between shopping stores and census blocks. The results show that the welfare gains from removing shopping-trip costs is about 4% for the average census block, with a range between 0.021% and 18% across census blocks that is further connected to their demographic or socioeconomic characteristics, especially their population density. Several practical policy implications follow regarding how shopping-trip costs can be reduced to achieve higher welfare gains.

JEL Classification: L81, R13, R41

Key Words: Store-Level Analysis, Census Block Groups, Shopping, Welfare

*The author would like to thank the editor Hong Sok Brian Kim and an anonymous referee for their helpful comments and suggestions. The usual disclaimer applies.

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1 Introduction

Despite the increasing trend in online shopping, 88.5% of sales in the U.S. is still through traditional shopping due several reasons including its convenience or urgency of shopping (e.g., see Hunneman, Verhoef, and Sloot (2017)).[1] Since traditional shopping requires leaving home and walking/riding/commuting to a shopping store, it results in not only travel costs but also time and opportunity costs (e.g., see Brief (1967), Bell, Ho, and Tang (1998) or Aguiar and Hurst (2007)). Nevertheless, the literature is limited on quantitative analyses regarding the corresponding welfare costs of traditional shopping trips; among others, Marshall and Pires (2018) show that travel costs impact the surplus earned by consumers in economically significant ways; Dolfen, Einav, Klenow, Klopack, Levin, Levin, and Best (2019) show evidence for gains from avoiding travel costs to local merchants; and Huang and Bronnenberg (2021) demonstrate that more than half of the total gains from e-commerce come from lower consumer transportation costs.

This paper attempts to contribute to this limited literature by measuring the welfare costs of traditional shopping trips at the U.S. census block group level.[2] The empirical investigation is based on an economic model, where individuals living in census blocks decide on which store to shop from based on the corresponding shopping-trip costs (increasing with distance to the store) and idiosyncratic benefits as in earlier studies such as by Ahlfeldt, Redding, Sturm, and Wolf (2015), Monte, Redding, and Rossi-Hansberg (2018) or Heblich, Redding,

[1]This statistic is borrowed from the U.S. Census Bureau for the first quarter of 2020 that is consistent with the sample period of the data set used in the empirical investigation of this paper.

[2]These welfare costs cover not only walking/riding/commuting costs but also time and opportunity costs related to shopping trips. Nevertheless, these welfare costs do not cover any costs related to those during shopping (e.g., time spent after arriving at the store). See Goolsbee and Klenow (2018) or Dolfen, Einav, Klenow, Klopack, Levin, Levin, and Best (2019) as alternative studies focusing on costs related to those during shopping (e.g., opportunity cost of time spent during shopping).

and Sturm (2020). The implications of the model are used to measure shopping-trip costs between individuals (residing in census blocks) and stores.

The key innovation through the economic model in this paper is to measure the welfare gains from removing bilateral shopping-trip costs (that we consider as the welfare costs of shopping trips) in percentage terms. As the empirical investigation is at the U.S. census block group level, the model-implied welfare gains are measured for each census block as the weighted average of log current bilateral distance measures between shopping stores and census blocks, where weights are the bilateral probabilities of individuals (living in certain census blocks) shopping at certain stores. This is similar to international trade studies such as by Lai, Fan, and Qi (2020) and Yilmazkuday (2021) who have obtained similar expressions for welfare gains following changes in trade costs.

The model is empirically tested by using SafeGraph cellphone location data that provide information on the total number of visitors at the store level, where the census block group of visitors regarding their residence (home) is also given. The estimation results based on about 75 million observations show that the bilateral probabilities of individuals (living in certain census blocks) shopping at certain stores decrease with the corresponding distance measures, which is consistent with earlier studies such as by Bell, Ho, and Tang (1998), Tiwari, Doi, and Kawakami (2006), Dolfen, Einav, Klenow, Klopack, Levin, Levin, and Best (2019) or Florez-Acosta and Herrera-Araujo (2020). Quantitatively, the elasticity of shopping probability from a store with respect to distance is estimated around 0.0767.

The overall estimated distance effects on the bilateral probabilities of individuals (living in certain census blocks) shopping at certain stores are removed in a counterfactual investigation to measure the welfare costs of traditional shopping, similar to studies such as by Lai, Fan, and Qi (2020) and Yilmazkuday (2021). Such an investigation is achieved for each census block in the data set. The corresponding results show that the welfare gains from removing bilateral shopping-trip costs is about 4% for the average (or median) census block, with a range between 0.021% and 18% across census blocks. As these welfare gains are calculated by removing the overall distance effects, they should be considered as the upper limit of welfare costs that can be removed.

The heterogeneity of welfare gains across census blocks is further investigated in a secondary analysis, where it is shown that the welfare costs of traditional shopping decrease with population density (defined as population divided by land area) as census blocks with higher population density currently make shopping trips to more nearby stores (or equivalently, census blocks with lower population density currently make shopping trips to more distant stores). It is also shown that the welfare costs of traditional shopping increase with cars per capita as census blocks with higher per capita number of cars currently make shopping trips to more distant stores.

Regarding heterogeneity of welfare gains across demographic or socioeconomic groups, it is depicted that census block groups with a higher share of Asian people would benefit the least from removing shopping-trip costs, whereas those with a higher share of American Indian and Alaska Native people would benefit the most from it. When the relationship between welfare costs of traditional shopping and family income is investigated, it is shown that there is evidence for a hump-shaped relationship between family income and welfare costs. Finally, it is depicted that census block groups with a higher share of an educational attainment of an elementary school diploma would benefit the least from removing shopping-trip costs, and those with a higher share of an educational attainment of a high school diploma would benefit the most from it. Based on the implications of the model used, these results suggesting that certain demographic or socioeconomic groups would benefit less from removing costs of traditional shopping can be explained by such groups currently making shopping trips to relatively close-by stores so that they gain relatively less when shopping-trip costs are removed. It is implied that alternative policies across regions can be considered to reduce shopping-trip costs and thus inequality across these groups, for which a coordination of policy makers across different regions may be essential.

In order to have a simplified policy suggestion, we further connect the heterogeneity of welfare gains across census blocks (in our secondary analysis) to a benchmark variable, population density, which is shown to explain the heterogeneity of welfare gains across alternative categorizations of demographic or socioeconomic groups. Specifically, as the welfare costs of traditional shopping decrease with population density, it is implied that policies reducing shopping-trip costs in regions with relatively lower population density would be more beneficial.

In the corresponding literature, Bell, Ho, and Tang (1998) have shown how the store choice of individuals depend on the lowest shopping costs, whereas Hunneman, Verhoef, and Sloot (2017) have shown that quality of service, price, and convenience are the criteria that shoppers have to shop from a certain store. Bringing stores closer to individuals (proximity) through zoning regulations or carbon taxes has also been shown to be effective in understanding the shopping behavior of individuals as discussed in studies such as by Billings and Johnson (2016), Florez-Acosta and Herrera-Araujo (2020) or Sun, Lian, and Yang (2021). Similarly, as agglomeration of stores or shopping from one supercenter can reduce shopping costs, shopping from these single locations can also affect the shopping behavior of individuals as in studies such as by Anas and Xu (1999), Konishi (2005), Hausman and Leibtag (2007) and Thomassen, Smith, Seiler, and Schiraldi (2017). Sales tax rates (across stores in alternative tax zones) have also been shown to be effective in shaping the shopping behavior of individuals as shown in studies such as by Goolsbee (2000) or Baker, Johnson, and Kueng (2021).

This paper contributes to this literature by measuring bilateral shopping-trip costs between individuals (residing in census blocks) and stores by using the corresponding distance between them, where price faced at the store is also considered; the remaining factors such as quality of service or convenience are captured by idiosyncratic benefits at the store level for each individual. Regarding methodology, to our knowledge, this is the first paper introducing a theoretical model by considering the utility of individuals living in a census block and shopping at a particular store; matching this theoretical model with the corresponding data at the U.S. census block group level has not been done in the literature before, either. Having such an investigation at the census block level is essential to have policy suggestions across demographic or socioeconomic characteristics as these measures are relatively more stable at the census block level (compared to, say, a zip code-level, a city-level, or a state-level investigation). Regarding the empirical results, shopping-trip costs have been estimated for U.S. census block groups at the store level, and the corresponding welfare costs/gains have been calculated for each U.S. census block group. As the corresponding welfare costs/gains have been further used in a secondary analysis to connect them to the corresponding demographic or socioeconomic characteristics, this paper also contributes to the literature by providing certain policy suggestions at the U.S. census block group level based on these characteristics.

The rest of this paper is organized as follows. The next section introduces an economic model to measure the costs of shopping trips and its implications for welfare. Section 3 introduces the empirical methodology and the data used. Section 4 depicts the empirical results, whereas Section 5 achieves a corresponding discussion. Section 6 concludes. The Appendix contains the technical derivations of certain results in the main text.

2 Model

We model the utility of individuals living in census blocks, where they decide on which store to shop from based on the corresponding shopping-trip costs and idiosyncratic benefits. The model draws on earlier studies such as by Ahlfeldt, Redding, Sturm, and Wolf (2015), Monte, Redding, and Rossi-Hansberg (2018) or Heblich, Redding, and Sturm (2020) who have also considered idiosyncratic benefits of living and working/shopping in alternative locations. The implications of the model are used to construct the welfare gains from removing shopping-trip costs.

2.1 Consumption

An individual i living in census block b and shopping at store s has the following utility function:

$$U_{ibs} = \frac{a_{ibs} C_{bs}}{\tau_{bs}} \tag{1}$$

where a_{ibs} is the idiosyncratic benefits of shopping at store s, C_{bs} is the amount of consumption, and $\tau_{bs} \geq 1$ represents bilateral shopping-trip costs similar to those in studies such as by Ahlfeldt, Redding, Sturm, and Wolf (2015), Monte, Redding, and Rossi-Hansberg (2018) or Heblich, Redding, and Sturm (2020). According to Equation 1, utility of an individual increases with the amount of consumption and decreases with shopping-trip costs, where both measures are census block and store specific, subject to individual-specific idiosyncratic benefits. This modeling strategy is consistent with the disaggregation level of the data set (to be introduced below) that is at the census block and store level.

Individuals are endowed with one unit of labor supply. The idiosyncratic benefit a_{ibs} is drawn from an independent Fréchet distribution given by:

$$G_{bs}(a) = e^{-A_{bs}a^{-\theta}} \tag{2}$$

where the scale parameter $A_{bs} > 0$ determines the average benefits of (preferences for) shopping at store s for individuals living in census block b, and the shape parameter $\theta > 1$ controls the dispersion of benefits. Having an idiosyncratic benefit a_{ibs} implies that individuals of census block b can shop at different stores when faced with the same prices across different stores.

The budget constraint for any individual living in census block b and shopping at store s is given by:

$$P_s C_{bs} = W \tag{3}$$

where P_s is the price per unit of C_{bs}, and W is the wage rate that is common across locations due to labor mobility. It is implied that the indirect utility function based on Equations 1 and 3 is as follows:

$$U_{ibs} = \frac{a_{ibs}W}{\tau_{bs}P_s} \tag{4}$$

which is a monotonic function of idiosyncratic benefits (a_{ibs}'s) that have a Fréchet distribution. Therefore, the indirect utility given by Equation 4 also has a Fréchet distribution as follows:

$$G_{bs}(U) = e^{-\Psi_{bs}U^{-\theta}} \tag{5}$$

where

$$\Psi_{bs} = A_{bs}(P_s\tau_{bs})^{-\theta}(W)^{\theta} \tag{6}$$

Based on this distribution, the expected utility $\overline{U}_b$ of an individual living in census block b is implied as follows:

$$\overline{U}_b = \left(\sum_s \Psi_{bs}\right)^{\frac{1}{\theta}} \Gamma\left(1 - \frac{1}{\theta}\right) \tag{7}$$

where $\Gamma(\cdot)$ is the Gamma function. The technical details of this derivation are shown in the Appendix.

2.2 Shopping Decision of Individuals

Each individual decides on which store to shop from to receive maximum utility. Using the fact that the maximum of Fréchet distributed random variables is also Fréchet distributed, the probability of any individual living in census block b and shopping at store s is as follows:

$$\lambda_{bs} = \frac{A_{bs}(P_s\tau_{bs})^{-\theta}}{\sum_r A_{br}(P_r\tau_{br})^{-\theta}} \tag{8}$$

for which the technical derivation is shown in the Appendix. It is implied that individuals in census block b are more likely to shop at store s, the higher the popularity of store s (measured by its average benefits across individuals of census block b, A_{bs}), the lower the prices at store s (P_s), and the lower the bilateral shopping-trip costs (τ_{bs}).

2.3 Production

The production at store s is achieved according to the following production function:

$$Y_s = Z_s L_s \tag{9}$$

where Z_s represents productivity, and L_s is the amount of labor used. Perfect competition across stores implies the following price at store s:

$$P_s = \frac{W}{Z_s} \tag{10}$$

where prices increase with the wage rate and decrease with productivity. Although having perfect competition across stores is consistent with earlier studies such as by Ahlfeldt, Redding, Sturm, and Wolf (2015) or Heblich, Redding, and Sturm (2020), it is different from other studies such as by Ellickson and Misra (2008) who discuss strategic interaction across stores or DellaVigna and Gentzkow (2019) who consider monopolistically competitive stores; the implications of these alternative competition structures are captured by productivity measures in this paper.

2.4 Equilibrium Conditions

Labor mobility across stores implies the following condition for the labor market:

$$\sum_s L_s = \sum_b I_b \tag{11}$$

where I_b represents the number of individuals living in census block b.

The market for the products of store s is cleared according to the following expression:

$$Y_s = \sum_b I_b \lambda_{bs} C_{bs} \tag{12}$$

which implies the following expression for the labor used in location j according to Equations 3, 8, 9 and 10:

$$L_s = \sum_b \lambda_{bs} I_b \tag{13}$$

which is consistent with Equation 11.

2.5 Implications for Welfare

We are interested in investigating the welfare effects of removing bilateral shopping-trip costs represented by τ_{bs}'s. For this investigation, we first rewrite Equation 7 using Equations 6 and 10 as follows:

$$\overline{U}_b = \left(\sum_s A_{bs} \left(\frac{\tau_{bs}}{Z_s} \right)^{-\theta} \right)^{\frac{1}{\theta}} \Gamma \left(1 - \frac{1}{\theta} \right) \tag{14}$$

In this expression, preferences represented by A_{bs}'s and productivity measures represented by Z_s's are assumed to be fixed as they are not the main focus while investigating the welfare effects of removing shopping-trip costs. In an alternative model, both A_{bs}'s and Z_s's can depend on shopping-trip costs of τ_{bs}'s, for example, through preferences of A_{bs}'s decreasing with trade costs (comparable to τ_{bs}'s in this paper) as in studies such as by Hummels and Schaur (2013) (e.g., capturing time to bring perishable products home) or increasing with trade costs as in studies such as by Yilmazkuday (2016) (e.g., capturing preferences towards exotic goods) or Z_s's decreasing with trade costs as in studies such as by Melitz and Redding (2014) (e.g., capturing a reorganization of production with higher trade that elevates productivity). Therefore, when A_{bs}'s and Z_s's change with shopping-trip costs of τ_{bs}'s, the expected utility of $\overline{U}_b$ can be lower or higher following a change in τ_{bs}'s depending on how A_{bs}'s and Z_s's are connected to τ_{bs}'s theoretically, although this paper abstracts from these additional details.

As the technical details are shown in the Appendix, taking total derivative of Equation 14 results in:

$$d\log \overline{U}_b = -\sum_s \lambda_{bs} d\log \tau_{bs} \tag{15}$$

where we used $\frac{dx}{x} \approx d\log x$ and the following version of Equation 8 based on Equation 10:

$$\lambda_{bs} = \frac{A_{bs}\left(\frac{\tau_{bs}}{Z_s}\right)^{-\theta}}{\sum_r A_{br}\left(\frac{\tau_{br}}{Z_r}\right)^{-\theta}} \tag{16}$$

According to Equation 15, welfare changes in percentage terms are connected to weighted average of log changes in bilateral shopping-trip costs, where weights are the bilateral probabilities λ_{bs}'s of individuals (living in census block b) shopping at store s.

Equation 15 is in line with earlier studies focusing on international trade such as by Lai, Fan, and Qi (2020) and Yilmazkuday (2021) who have obtained similar expressions for welfare gains following changes in trade costs. Since we are interested in the welfare effects of removing all bilateral shopping-trip costs represented by τ_{bs}'s (which we consider as the welfare costs of shopping trips in this paper), we focus on the following changes in bilateral shopping-trip costs:

$$d \log \tau_{bs} = -\log \tau_{bs} \tag{17}$$

which hypothetically removes bilateral shopping-trip costs. In other words, changes in bilateral shopping-trip costs are set equal to their existing value so that bilateral shopping-trip costs are completely removed in this hypothetical expression. Inserting Equation 17 into Equation 15 results in:

$$d \log \overline{U}_b = \sum_s \lambda_{bs} \log \tau_{bs} \tag{18}$$

which suggests that the welfare gains from removing bilateral shopping-trip costs τ_{bs}'s in percentage terms can be measured in census block b as the weighted average of log current bilateral shopping-trip costs, where weights are the bilateral probabilities λ_{bs}'s of living in census block b and shopping at store s. As these welfare gains are calculated by removing all bilateral shopping-trip costs, they should be considered as the upper limit of welfare costs that can be removed. It is important to emphasize that welfare gains based on extremely high initial shopping-trip costs may be biased up to a first order approximation as the total derivative depends on infinitesimal changes in shopping-trip costs. Nevertheless, as the empirical results (to be introduced below) show that the weighted average of shopping-trip costs are about 4% for the median census block group, the concerns for extremely high initial shopping-trip costs are highly limited.

For measurement purposes, bilateral shopping-trip costs τ_{bs}'s are further proxied by the effects of distance d_{bs} between census block b and store s according to the following expression as in international trade or regional economics studies such as by Anderson and Van Wincoop

(2003), Anderson and Van Wincoop (2004) or Yilmazkuday (2011):

$$\tau_{bs} = (d_{bs})^{\delta} \tag{19}$$

where $\delta > 0$ (i.e., shopping-trip costs increase with distance). Combining Equations 18 and 19 results in the following expression:

$$d \log \overline{U}_b = \delta \sum_s \lambda_{bs} \log d_{bs} \tag{20}$$

which suggests that the welfare gains from removing shopping-trip costs τ_{bs}'s in percentage terms can be measured in census block b as the weighted average of log current bilateral distance measures between shopping stores and block b, where weights are the bilateral probabilities λ_{bs}'s of living in census block b and shopping at store s. This expression is line with studies such as by Dolfen, Einav, Klenow, Klopack, Levin, Levin, and Best (2019), where store-specific utility of individuals depends on the distance between individuals and stores; this paper differs by showing that the overall utility changes depend on the weighted average of such distance measures due to keeping preferences and productivity measures fixed. In Equation 20, δ is the key parameter governing the welfare gains from removing bilateral shopping-trip costs, which we parametrize next.

3 Empirical Methodology and Data

The calculation of welfare gains from removing bilateral shopping-trip costs according to Equation 20 requires knowledge on δ, λ_{bs}'s and d_{bs}'s for each b and s. This section not only depicts how we obtain these measures but also introduces the corresponding empirical methodology as well as the details of a secondary analysis to understand the heterogeneity of welfare gains across blocks based on block-specific characteristics.

The data from the U.S. on λ_{bs}'s (about 75 million of them) are obtained from SafeGraph cellphone location data collected in January 2020 (to stay away from the effects of the coronavirus disease 2019); i.e., identification in estimations (to be introduced below) is achieved through the cross-sectional dimension.[3] Specifically, SafeGraph provides information on the total number of visitors at the store level on a monthly basis, where the census block of visitors regarding their residence (home) is also given. SafeGraph collects these data by using mobile devices of consumers through its various partner mobile applications. The residence (home) census block of visitors is determined by analyzing data during nighttime hours, for which a sufficient amount of evidence (total data points and distinct days) are considered. The data set covers the U.S. census block groups covering all states of the U.S., with each census block group typically having a population between 600 and $3,000$ people. The number of stores in the data set is $4,231,572$ covering $213,302$ census blocks, whereas the number of census blocks representing the residence (home) of visitors is $220,069$. As there are totally $220,333$ census block groups according to the American Community Survey (2018), the geographical coverage of the data set is highly adequate.

Specifically, to obtain measures of λ_{bs}'s, we use the store-level visitor data provided by SafeGraph. These stores cover all sectors of the economy, including both goods and services, such as grocery stores, pharmacy stores, convenience stores, supermarket chains, coffee shops, restaurants, insurance agencies, financial services, medical services, fitness centers,

[3] The web page is https://www.safegraph.com/.

auto dealers and so on. A typical observation is for Walmart located at "720 W Pipeline Rd, Hurst, TX 76053" where the number of visitors coming from each census block (based on their residence) is depicted. Descriptive statistics based on these stores are given in Table 1, where it is shown that the average number of stores visited by individuals of a typical census block is about 446, with a range between 1 and 15,036 across blocks. The share of stores visited within the same block is about 2.9% on average across blocks, suggesting that the majority of stores visited are located in other blocks. Since this data set is at the store level, they are converted into the bilateral probabilities λ_{bs}'s of living in census block b and shopping at store s by taking into account all stores that the residents of census block b visit. The corresponding distance measures of d_{bs}'s are calculated by using the census block location of visitors and the location of stores as the great circle distance.

The key parameter of δ (subject to the knowledge of θ) is estimated according to the log versions of Equations 16 and 19 as follows:

$$\underbrace{\log \lambda_{bs}}_{\text{Data}} = - \underbrace{\theta\delta \log d_{bs}}_{\text{Shopping-Trip Costs}} + \underbrace{\theta \log Z_s}_{\text{Store Fixed Effects}} - \underbrace{\log T_b}_{\text{Block Fixed Effects}} + \underbrace{\log A_{bs}}_{\text{Residuals}} \tag{21}$$

where T_b is given by:

$$T_b = \sum_r A_{br} \left(\frac{\tau_{br}}{Z_r} \right)^{-\theta} \tag{22}$$

According to Equation 21, log bilateral shopping-trip costs represented by the fitted values of $\theta\delta \log d_{bs}$'s can be used to calculate the welfare gains from removing bilateral shopping-trip costs according to Equation 20, subject to the knowledge of the shape parameter θ. In this context, although θ is nothing more than a scale parameter in welfare calculations (that is common across census blocks), we borrow its value of $\theta = 3.3$ from Monte, Redding, and Rossi-Hansberg (2018). In sum, $\theta\delta$ is identified by the cross-sectional nature of the data set (based on census blocks and stores), and δ is further identified by using the value of $\theta = 3.3$.

Once the welfare costs of shopping trips are calculated based on Equation 20, in a secondary analysis, the heterogeneity across blocks is investigated based on the following estimation:

$$\underbrace{d\log \overline{U}_b}_{\text{Welfare Costs}} = \underbrace{\sum_i \beta_i D_{ib}}_{\text{Characteristics}} + \underbrace{\varepsilon_b}_{\text{Residuals}} \tag{23}$$

where block-specific welfare costs ($d\log \overline{U}_b$'s) are regressed on the variables (D_{ib}'s) representing block-specific characteristics. Based on the most commonly used demographic and socioeconomic groups in the literature, these variables across blocks represent (i) dummies based on percentiles of population density (defined as population divided by land area) that we accept as our benchmark variable, (ii) dummies based on percentiles of cars per capita, (iii) share of people belonging to a particular race/ethnicity, (iv) share of people having certain levels of family income, and (v) share of people having certain levels of educational attainment. The corresponding information on these characteristics are obtained from the American Community Survey (2018) 5-year estimate on the census block group level.[4]

In order to show the connection of the estimation results based on Equation 23 with the benchmark variable of population density, we also run the following supplementary regression:

$$\underbrace{pop_b}_{\text{Population Density}} = \underbrace{\sum_i \beta_i D_{ib}}_{\text{Characteristics}} + \underbrace{\varepsilon_b}_{\text{Residuals}} \tag{24}$$

[4]The web page is https://www.census.gov/programs-surveys/acs.

where block-specific population density measures (pop_b's) are regressed on the very same variables (D_{ib}'s) as in Equation 23 representing block-specific characteristics. By using Equation 24, we would like to show the population density measures corresponding to block-specific characteristics, so that the estimation results based on Equation 23 can be understood better.

4 Empirical Results

This section depicts the estimation results, the corresponding welfare costs of shopping trips and the heterogeneity across census block groups.

4.1 Estimation of Shopping-Trip Costs

The shopping-trip costs based on distance are estimated according to Equation 21. The estimation results are given in Table 2, where alternative versions of Equation 21 are considered with and without the corresponding fixed effects. As is evident, the effects of distance are negative and significant, consistent with earlier studies such as by Bell, Ho, and Tang (1998), Tiwari, Doi, and Kawakami (2006), Dolfen, Einav, Klenow, Klopack, Levin, Levin, and Best (2019) or Florez-Acosta and Herrera-Araujo (2020). The log distance has a negative and highly significant estimated coefficient of around $-\theta\delta = -0.0767$ when the full version of Equation 21 is considered in the last column of Table 2. It is implied that 1% of an increase in distance results in about -0.0767% of a reduction in the probability of an individual making a shopping trip.

4.2 Welfare Costs of Shopping Trips

Although θ is nothing more than a scale parameter in welfare calculations (that is common across census blocks), borrowing $\theta = 3.3$ from Monte, Redding, and Rossi-Hansberg (2018), it is implied based on $\theta\delta = 0.0767$ that $\delta = 0.0232$. This implied measure of $\delta = 0.0232$ is highly consistent with earlier studies such as by Dolfen, Einav, Klenow, Klopack, Levin, Levin, and Best (2019) who have estimated the effects of distance on utility with a coefficient of 0.026.

We further use this information, together with data on λ_{bs} and $\log d_{bs}$, to calculate the welfare costs of shopping trips according to Equation 20. The corresponding summary results are given in Table 3, where the welfare costs of shopping trips in percentage terms are provided across census block groups. As is evident, the average (median) welfare costs of shopping trips are about 4.4% (4.1%), suggesting that when all shopping-trip costs (based on distance) are removed, individuals could have a welfare gain of about 4.4%, on average across census blocks.

4.3 Heterogeneity across Census Block Groups

The welfare gains across census block groups have a range between 0.021% and 18.014% according to Table 3, suggesting evidence for significant heterogeneity across census block groups. We further investigate this heterogeneity across census block groups by estimating Equation 23 for alternative demographic and socioeconomic characteristics. As we pick population density as our benchmark explanatory variable, by using Equation 24, we also show the interaction between population density and demographic/socioeconomic characteristics used in Equation 23.

When dummy variables in Equation 23 are constructed based on percentiles of population density (defined as population divided by land area) across census block groups that we accept as our benchmark variable, the estimation results are given in Table 4. It is evident that the welfare costs of shopping trips decrease with population density, which implies that census block groups with lower population density benefit more from removing shopping-trip costs. Based on the implications of the model used in this paper, this can be explained by individuals living in census block groups with lower population density making shopping trips to more distant stores.

When dummy variables in Equation 23 are constructed based on percentiles of cars per capita across census block groups, the estimation results are given in Table 5. As is evident, the welfare costs of shopping trips increase with the number of cars per capita. Therefore, census block groups with higher number of cars per capita would benefit more from removing shopping-trip costs. Based on the implications of the model used in this paper, this can be explained by individuals living in census block groups with higher number of cars currently making shopping trips to more distant stores. Based on Equation 24, Table 5 also shows that the welfare costs of shopping trips decrease with population density when the dummies representing cars per capita are considered, which supports our benchmark variable of population density for having an explanatory power as an alternative to cars per capita.

Similarly, welfare costs of shopping trips across census block groups based on race/ethnicity are depicted in Table 6 (by using Equation 23), where there is evidence for heterogeneity across demographic groups. Specifically, census block groups with a higher share of Asian people would benefit the least from removing shopping-trip costs (around 1.9%), whereas those with a higher share of American Indian and Alaska Native people would benefit the most (around 8.4%) from it. Based on the implications of the model used, this result can be explained by the Asian people currently shopping from relatively close-by stores compared to the American Indian and Alaska Native people. Based on Equation 24, Table 6 also shows that the welfare costs of shopping trips decrease with population density when different shares of race/ethnicity are considered, which supports our benchmark variable of population density for having an explanatory power as an alternative to the shares of race/ethnicity.

Welfare costs of shopping trips across census block groups based on family income are depicted in Table 7 (by using Equation 23), where there is evidence for a hump-shaped relationship between family income and welfare costs. In particular, census block groups with a higher share low-income people would benefit the least from removing shopping-trip costs (of around 2.8%), and those with a higher share of middle-income people would benefit the most from it (of around 5.2%). Based on the implications of the model used, this result can be explained by low-income people (making less than $\$10,000$ as a family) currently shopping from relatively close-by stores compared to middle-income people (making between $\$50,000$ and $\$100,000$ as a family). Based on Equation 24, Table 7 also shows that the welfare costs of shopping trips decrease with population density when different shares of family income are considered, which supports our benchmark variable of population density for having an explanatory power as an alternative to the shares of family income. This result is consistent with the concept of spatial income sorting (e.g., see Diamond and Gaubert (2022)), where higher income families sort into relatively dense places with more consumer amenities (e.g., see Diamond (2016) and Handbury (2021)). Similarly, middle-income families sort into relatively sparse areas compared to high- and low-income families (e.g., see Eeckhout, Pinheiro, and Schmidheiny (2014)) as the productivity of high-skilled workers and of the providers of low-skilled services are mutually enhanced.

Finally, welfare costs of shopping trips across census block groups based on education level are depicted in Table 8 (by using Equation 23), where census block groups with a higher share of an educational attainment of an elementary school diploma would benefit the least from removing shopping-trip costs, and those with a higher share of an educational attainment of a high school diploma would benefit the most from it. Based on the implications of the model used, this result can be explained by elementary school graduates currently shopping from relatively close-by stores compared to high-school graduates. Based on Equation 24, Table 8 also shows that the welfare costs of shopping trips decrease with population density when different shares of education level are considered, which supports our benchmark variable of population density for having an explanatory power as an alternative to the shares of education level.

Overall, although the heterogeneity (of the welfare costs of shopping trips) across census block groups can be connected to alternative demographic and socioeconomic characteristics, they can all be explained by our benchmark variable of population density, where higher welfare costs of shopping trips are associated with lower population density.

5 Discussion of Results and Policy Implications

Measuring the welfare gains from removing shopping-trip costs at the census block level has been the key innovation in this paper, where connecting the heterogeneity of welfare gains across census blocks to certain demographic and socioeconomic characteristics has been a further contribution. It is important to emphasize that regarding policy implications, these welfare gains represent the upper limit that can be achieved by policy makers as they are based removing *all* shopping-trip costs. Nevertheless, in practice, it may be the case that only a certain portion of these gains are achieved by alternative policies.

As an example to these policies, one way to reduce shopping-trip costs may be to promote online shopping by providing tax incentives, which would result in less people shopping traditionally and more people shopping online. In such a way, individuals would not only gain from removing driving/commuting costs but also gain from the opportunity cost of time. This is in line with studies such as by Goolsbee (2000) have shown that individuals living in high sales taxes locations are significantly more likely to shop online. Similarly, studies such as by Baker, Johnson, and Kueng (2021) have shown that shopping behavior (including online shopping) responds strongly to changes in sales tax rates.

Another way to reduce shopping-trip costs may be to bring stores closer to individuals (or populated areas in general) as in studies such as by Billings and Johnson (2016) or Marshall and Pires (2018) through city zoning regulations on commercial use so that individuals can shop from close-by stores with lower shopping-trip costs; e.g., Florez-Acosta and Herrera-Araujo (2020) discusses the restrictive zoning regulation in France related to the store size as a potential factor for the decentralization of stores. Within this picture, a carbon tax policy can also be considered to change the location of stores as suggested in studies such as by Sun, Lian, and Yang (2021).

Alternatively, policy makers can reduce shopping-trip costs by bringing people closer to stores. Specifically, as zoning laws and building restrictions can prevent people from moving to densely populated and attractive locations with many shopping amenities (e.g., see Gyourko and Molloy (2015) and Baum-Snow (2023)), the removal of these barriers can help bringing people closer to stores (e.g., see Hsieh and Moretti (2019)) that would result in welfare gains.

Promoting agglomeration of stores (by having policies locating them close to each other) may be another way to reduce the total shopping-trip costs of individuals as discussed in studies such as by Konishi (2005). For example, studies such as by Anas and Xu (1999) have shown how imposing congestion tolls can be used to change the agglomeration of stores. Similarly, as individuals can benefit from shopping multiple products in a single store (as in studies such as by Thomassen, Smith, Seiler, and Schiraldi (2017)), policies removing restrictions on entry and expansion of supercenters into new geographic markets (as in studies such as by Hausman and Leibtag (2007)) can further reduce total shopping-trip costs.

As this paper has shown that certain demographic or socioeconomic groups (that can mostly be explained by population density) would benefit more from removing shopping-trip costs, alternative policies (based on the discussion above) can be considered to reduce shopping-trip costs in different regions to reduce inequality across these demographic or socioeconomic groups. It is implied that a coordination of policy makers across different regions is essential to reduce shopping-trip costs for such a policy.

6 Conclusion

Traditional shopping trips result in not only travel costs but also time and opportunity costs. This paper has attempted to measure the welfare costs of traditional shopping trips by using the implications of an economic model, where individuals living in the U.S. census blocks decide on which store to shop from based on the corresponding shopping-trip costs (increasing with distance to the store) and idiosyncratic benefits (representing preferences). The implications of the model have been tested by using SafeGraph cellphone location data that provide information on the total number of visitors (living in census blocks) at the store level. The corresponding empirical results based on about 75 million observations have shown that the bilateral probabilities of individuals (living in certain census blocks) shopping at certain stores decrease with the corresponding distance measures.

The paper has continued with a counterfactual investigation at the U.S. census block level, where the negative effects of distance (through bilateral shopping-trip costs) on welfare have been removed hypothetically. The results have shown that the welfare gains from removing bilateral shopping-trip costs is about 4% for the average (or median) census block, with a range between 0.021% and 18% across census blocks.

The heterogeneity of welfare gains across census blocks has been further investigated in a secondary analysis, where it is shown that the welfare costs of traditional shopping decrease with population density (defined as population divided by land area) as census blocks with higher population density currently make shopping trips to more nearby stores (or equivalently, census blocks with lower population density currently make shopping trips to more distant stores). It has also been shown that increase with cars per capita as census blocks with higher per capita number of cars currently make shopping trips to more distant stores.

Regarding heterogeneity of welfare gains across demographic or socioeconomic groups, it has been shown that census block groups with a higher share of middle-income families would benefit the most from removing shopping-trip costs, whereas those with a higher share of low- and high-income families would benefit the least. It has also been depicted that census block groups with a higher share of Asian people would benefit the least from removing shopping-trip costs, whereas those with a higher share of American Indian and Alaska Native people would benefit the most from it. Similarly, it has been shown that census block groups with a higher share of an educational attainment of an elementary school diploma would benefit the least from removing shopping-trip costs, and those with a higher share of an educational attainment of a high school diploma would benefit the most from it.

In order to have a simplified policy suggestion, we further connect the heterogeneity of welfare gains across census blocks (in our secondary analysis) to a benchmark variable, population density, which is shown to explain the heterogeneity of welfare costs/gains across alternative categorizations of demographic or socioeconomic groups. Specifically, as the welfare costs of traditional shopping decrease with population density, it is implied that policies reducing shopping-trip costs in regions with relatively lower population density would be more beneficial.

It is important to emphasize that the welfare gains depicted in this paper represent the upper limit that can be achieved by policy makers as they are based removing *all* shopping-trip costs. However, in practice, it may be the case that only a certain portion of these gains are achieved by alternative policies such as tax incentives, zoning regulations on commercial use, or promoting agglomeration of stores and/or products. As welfare gains from removing shopping-trip costs are shown to be different across demographic or socioeconomic groups (that can mostly be explained by population density), alternative policies across regions can be considered to reduce shopping-trip costs and thus inequality across these groups, for which a coordination of policy makers across different regions may be essential.

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7 Appendix

This section contains the technical derivations of certain results in the main text.

7.1 Derivation of the Expected Utility

The number of individuals living in each location is fixed. Each individual living in any location chooses the shopping store that offers the maximum utility. Since the maximum of a sequence of Fréchet distributed random variables is itself Fréchet distributed, the distribution of utility for individuals living in census block b across all possible shopping stores is as follows:

$$1 - G_b\left(u\right) = 1 - \prod_{s} e^{-\Psi_{bs}u^{-\theta}} \tag{25}$$

where the left-hand side is the probability that an individual of census block b gets a utility higher than u, and the right hand side is one minus the probability that the individual of census block b has utility less than u for all possible shopping locations. It is implied that:

$$G_b\left(u\right) = e^{-\Psi_b u^{-\theta}} \tag{26}$$

where

$$\Psi_b = \sum_{s} \Psi_{bs} \tag{27}$$

Given this Fréchet distribution for utility in census block b, the expected utility $\overline{U}_b$ in census block b is implied as:

$$\overline{U}_b = \int_{0}^{\infty} \theta \Psi_b u^{-\theta} e^{-\Psi_b u^{-\theta}} dy \tag{28}$$

Defining the following change of variables:

$$y = \Psi_b u^{-\theta} \tag{29}$$

and

$$dy = \theta e^{-\Psi_b u^{-(\theta+1)}} \tag{30}$$

the expected utility can be rewritten as follows:

$$\overline{U}_b = \int_0^{\infty} (\Psi_b)^{\frac{1}{\theta}} y^{-\frac{1}{\theta}} e^{-y} du \tag{31}$$

which is:

$$\overline{U}_i = (\Psi_b)^{\frac{1}{\theta}} \Gamma\left(1 - \frac{1}{\theta}\right) \tag{32}$$

Using $\Psi_b = \sum_s \Psi_{bs}$, it is finally implied that:

$$\overline{U}_b = \left(\sum_s \Psi_{bs}\right)^{\frac{1}{\theta}} \Gamma\left(1 - \frac{1}{\theta}\right) \tag{33}$$

which is the expression for expected utility in the main text.

7.2 Derivation of Shopping-Store Probabilities

The probability that an individual of census block b chooses to shop at store s out of all possible shopping locations (represented by r) is as follows:

$$\begin{aligned}
\lambda_{bs} &= \Pr\left[u_{bs} \geq \max\left\{u_{br}\right\}; \forall r\right] \\
&= \int_0^{\infty} \prod_{r \neq s} G_{br}\left(u\right) dG_{bs}\left(u\right) \\
&= \int_0^{\infty} \prod_{r} \theta \Psi_{bs} u^{-(\theta+1)} e^{-\Psi_{br} u^{-\theta}} du \\
&= \int_0^{\infty} \theta \Psi_{bs} u^{-(\theta+1)} e^{-\Psi_{b} u^{-\theta}} du
\end{aligned} \tag{34}$$

Since we have:

$$\frac{d}{du}\left[-\frac{1}{\Psi_b}e^{-\Psi_b u^{-\theta}}\right] = \theta u^{-(\theta+1)}e^{-\Psi_b u^{-\theta}} \tag{35}$$

it is implied that:

$$\lambda_{bs} = \frac{\Psi_{bs}}{\Psi_b} = \frac{A_{bs}\left(P_s\tau_{bs}\right)^{-\theta}\left(W_b\right)^{\theta}}{\sum_r A_{br}\left(P_r\tau_{br}\right)^{-\theta}\left(W_b\right)^{\theta}} = \frac{A_{bs}\left(P_s\tau_{bs}\right)^{-\theta}}{\sum_r A_{br}\left(P_r\tau_{br}\right)^{-\theta}} \tag{36}$$

where the last expression, which is the same as in in the main text, has been obtained after $(W_b)^{\theta}$'s have been effectively eliminated.

7.3 Derivation of Welfare Changes

As shown in the main text, the welfare (expected utility) $\overline{U}_b$ of an individual living in census block b is given by the following expression:

$$\overline{U}_b = \left(\sum_s A_{bs}\left(\frac{\tau_{bs}}{Z_s}\right)^{-\theta}\right)^{\frac{1}{\theta}} \Gamma\left(1-\frac{1}{\theta}\right) \tag{37}$$

Taking the total derivative of this expression can be achieved as follows:

$$d\overline{U}_b = \sum_s \frac{\partial \overline{U}_b}{\partial A_{bs}}dA_{bs} + \sum_s \frac{\partial \overline{U}_b}{\partial Z_s}dZ_s + \sum_s \frac{\partial \overline{U}_b}{\partial \tau_{bs}}d\tau_{bs} \tag{38}$$

When average benefits A_{bs}'s and productivity measures Z_s's are unchanged (i.e., $dA_{bs} = dZ_s = 0$), this expression can be simplified as follows:

$$d\overline{U}_b = \sum_s \frac{\partial \overline{U}_b}{\partial \tau_{bs}}d\tau_{bs} \tag{39}$$

which can be rewritten as follows:

$$d\overline{U}_b = \sum_s \frac{1}{\theta} \frac{\overline{U}_b \left(\frac{-\theta}{\tau_{bs}} A_{bs} \left(\frac{\tau_{bs}}{Z_s} \right)^{-\theta} \right)}{\left(\sum_s A_{bs} \left(\frac{\tau_{bs}}{Z_s} \right)^{-\theta} \right)} d\tau_{bs} \tag{40}$$

$$= - \sum_s \frac{\overline{U}_b \left(A_{bs} \left(\frac{\tau_{bs}}{Z_s} \right)^{-\theta} \right)}{\left(\sum_s A_{bs} \left(\frac{\tau_{bs}}{Z_s} \right)^{-\theta} \right)} \frac{d\tau_{bs}}{\tau_{bs}}$$

Taking $\overline{U}_b$ to the left-hand side results in:

$$\frac{d\overline{U}_b}{\overline{U}_b} = - \sum_s \frac{\left(A_{bs} \left(\frac{\tau_{bs}}{Z_s} \right)^{-\theta} \right)}{\left(\sum_s A_{bs} \left(\frac{\tau_{bs}}{Z_s} \right)^{-\theta} \right)} \frac{d\tau_{bs}}{\tau_{bs}} \tag{41}$$

which can be rewritten as follows:

$$\frac{d\overline{U}_b}{\overline{U}_b} = - \sum_s \lambda_{bs} \frac{d\tau_{bs}}{\tau_{bs}} \tag{42}$$

as the expenditure share of $\lambda_{bs} = \frac{A_{bs}(P_s \tau_{bs})^{-\theta}}{\sum_r A_{br}(P_r \tau_{br})^{-\theta}}$ in the main text can be rewritten as $\lambda_{bs} = \frac{A_{bs}\left(\frac{\tau_{bs}}{Z_s}\right)^{-\theta}}{\sum_s A_{bs}\left(\frac{\tau_{bs}}{Z_s}\right)^{-\theta}}$ by using $P_s = \frac{W}{Z_s}$ in the main text. Finally, using $\frac{dx}{x} \approx d \log x$, the following expression can be obtained:

$$d \log \overline{U}_b = - \sum_s \lambda_{bs} d \log \tau_{bs} \tag{43}$$

which represents welfare changes as in the main text.

Table 1 - Descriptive Statistics across Census Block Groups

	Stores Visited	Same Block	Other Blocks
Average	446	2.9%	97.1%
Median	361	1.8%	98.2%
Minimum	1	0.0%	0.0%
25th Percentile	236	0.8%	96.2%
75th Percentile	549	3.8%	99.2%
Maximum	15,036	100.0%	100.0%
Standard Deviation	355	3.4%	3.4%

Notes: These statistics are based on the month of January 2020. Based on residency, Same Block represents the share of stores visited within the same block, whereas Other Blocks represent the share of stores visited in other blocks.

Table 2 - Estimation Results

	Dependent Variable: $\log \lambda_{bs}$			
	(1)	(2)	(3)	(4)
Coefficient of	-0.0514^{***}	-0.0767^{***}	-0.0631^{***}	-0.0767^{***}
Log Distance	(0.000026)	(0.000028)	(0.000028)	(0.000028)
Store Fixed Effects	NO	YES	NO	YES
Block Fixed Effects	NO	NO	YES	YES
Sample Size	$74,897,375$	$74,496,115$	$74,895,204$	$74,495,584$
Adjusted $R-$Sq.	0.047	0.212	0.128	0.212

Notes: *** stands for significance at the 0.1% level. Standard errors are in parentheses.

Table 3 - Welfare Costs of Shopping Trips across Census Block Groups

Across Census Block Groups	Welfare Costs (%)
Average	4.403
Median	4.089
Minimum	0.021
25th Percentile	3.381
75th Percentile	5.316
Maximum	18.014
Standard Deviation	1.403

Notes: *** stands for significance at the 0.1% level. Standard errors are in parentheses.

Table 4 - Welfare Costs of Shopping Trips Based on Population Density

	Dependent Variable:	
Population Density Dummies	Welfare Costs (%)	Population Density
Below 20th Percentile	6.410***	0.0212
	(0.00422)	(0.0243)
Between 20th and 40th Percentiles	4.845***	0.232***
	(0.00422)	(0.0243)
Between 40th and 60th Percentiles	3.933***	0.894***
	(0.00422)	(0.0243)
Between 60th and 80th Percentiles	3.603***	1.913***
	(0.00422)	(0.0243)
Above 80th Percentile	3.214***	8.013***
	(0.00422)	(0.0243)
Sample Size	$184,551$	$184,551$
Adjusted $R-$Squared	0.969	0.387

Notes: *** stands for significance at the 0.1% level. Standard errors are in parentheses.

The estimations are based on Equation 23 and Equation 24 in the text.

The welfare costs depicted in this table have been estimated by running the block-specific welfare costs on dummy variables presenting percentiles of population density (defined as population divided by land area) across blocks.

Table 5 - Welfare Costs of Shopping Trips Based on Cars per Capita

	Dependent Variable:	
Cars per Capita Dummies	Welfare Costs (%)	Population Density
Below 20th Percentile	3.492***	5.704***
	(0.0115)	(0.0299)
Between 20th and 40th Percentiles	4.002***	2.065***
	(0.0115)	(0.0299)
Between 40th and 60th Percentiles	4.334***	1.365***
	(0.0115)	(0.0299)
Between 60th and 80th Percentiles	4.694***	0.927***
	(0.0115)	(0.0299)
Above 80th Percentile	5.484***	0.458***
	(0.0115)	(0.0299)
Sample Size	184,724	184,551
Adjusted $R-$Squared	0.803	0.194

Notes: *** stands for significance at the 0.1% level. Standard errors are in parentheses.

The estimations are based on Equation 23 and Equation 24 in the text.

The welfare costs depicted in this table have been estimated by running the block-specific welfare costs on dummy variables presenting percentiles of cars per capita across blocks.

Table 6 - Welfare Costs of Shopping Trips Based on Race/Ethnicity

	Dependent Variable:	
Share of Race/Ethnicity	Welfare Costs (%)	Population Density
White	5.050***	0.138***
	(0.00437)	(0.0183)
Black or African American	3.409***	3.546***
	(0.0116)	(0.0485)
American Indian and Alaska Native	8.441***	−1.213***
	(0.0563)	(0.236)
Asian	1.851***	12.27***
	(0.0307)	(0.128)
Hispanic or Latino	2.236***	9.714***
	(0.0162)	(0.0678)
Sample Size	184, 190	184, 190
Adjusted $R-$Squared	0.928	0.247

Notes: *** stands for significance at the 0.1% level. Standard errors are in parentheses.

The estimations are based on Equation 23 and Equation 24 in the text.

The welfare costs depicted in this table have been estimated by running the block-specific welfare costs on the variables presenting shares of race/ethnicity across blocks.

Table 7 - Welfare Costs of Shopping Trips Based on Family Income

	Dependent Variable:	
Share of Family Income	Welfare Costs (%)	Population Density
Below \$10,000	2.796***	5.224***
	(0.0386)	(0.154)
Between \$10,000 and \$25,000	3.281***	5.695***
	(0.0265)	(0.106)
Between \$25,000 and \$50,000	4.561***	2.147***
	(0.0204)	(0.0815)
Between \$50,000 and \$100,000	5.213***	0.0259
	(0.0164)	(0.0655)
Between \$100,000 and \$200,000	4.211***	1.547***
	(0.0201)	(0.0806)
Above \$200,000	3.765***	6.679***
	(0.0312)	(0.125)
Sample Size	$183,683$	$183,683$
Adjusted $R-$Squared	0.912	0.158

Notes: *** stands for significance at the 0.1% level. Standard errors are in parentheses.

The estimations are based on Equation 23 and Equation 24 in the text.

The welfare costs depicted in this table have been estimated by running the block-specific welfare costs on the variables presenting shares of family income levels across blocks.

Table 8 - Welfare Costs of Shopping Trips Based on Education Level

	Dependent Variable:	
Share of Education Level	Welfare Costs (%)	Population Density
5th Grade	-1.503^{***}	24.30^{***}
	(0.118)	(0.470)
8th Grade	4.487^{***}	7.816^{***}
	(0.0585)	(0.233)
High School Diploma	4.925^{***}	0.424^{***}
	(0.00851)	(0.0339)
Bachelor's Degree	3.775^{***}	3.557^{***}
	(0.0174)	(0.0695)
Master's Degree	4.175^{***}	3.359^{***}
	(0.0339)	(0.135)
Doctorate Degree	4.481^{***}	1.539^{***}
	(0.0917)	(0.366)
Sample Size	$184,075$	$184,075$
Adjusted $R-$Squared	0.912	0.160

Notes: *** stands for significance at the 0.1% level. Standard errors are in parentheses.

The estimations are based on Equation 23 and Equation 24 in the text.

The welfare costs depicted in this table have been estimated by running the block-specific welfare costs on the variables presenting shares of education levels across blocks.