JOB MARKET PAPER

Public Transit and Employment Outcomes

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Nov 21, 2001

Abstract

This study combines three national data sources in order to examine the effect of the density of public transit service on an individual's employment outcomes, while controlling for other city characteristics as well as individual characteristics. Results from a random effects regression using a sample of 62 small and mid-sized cities show that for those with no college education, the density of public transit routes has a positive effect on the probability of employment, which is significant at the 5% level. For the average city in the sample, a ten percent increase in transit route density is associated with an increase in the probability of employment of roughly three tenths of a percent (.27%) for those with no college education. This increase is approximately $1/6^{th}$ the size of the increase in the probability of employment that is predicted from a ten percent increase in the rate of car ownership. Fourteen large metropolitan areas with less precise data are added to the sample, and when this expanded sample of 76 cities is used, transit density is found to be positive and significant at 5% for those with any post-high school education as well as for the low education group. With the larger sample, the results predict an increase in employment of approximately sixth tenths of a percent for a ten percent change in transit density, for both the low and high education groups.

Public Transit and Employment Outcomes

I. Introduction

Transportation plays a key role in providing access to employment opportunities. The set of job options open to an individual depends on which jobs the person can reach with available transportation. The role of transportation is particularly important for workers who face constraints on residential location. While job growth used to be centered in inner cities, it has been gradually dispersing. For low-income households, affordable housing is often difficult to find in these new high job growth areas. Yinger (1998) and Ladd (1998), among others, provide recent evidence of racial discrimination in the housing market, indicating that residential choice is limited even further for non-whites. The decline in the availability of appropriate jobs in the central city has made getting to interviews and jobs increasingly difficult for those who face barriers to relocating to where the new jobs are being created.

One option for addressing the problems caused by mismatch between job locations and worker locations is to improve transportation. Several studies have investigated the relation between car ownership and employment outcomes, and the results suggest that car ownership improves both earnings and the probability of being employed. These results point to the potential that good transportation policies have for improving employment outcomes. While improvements in public transit are an obvious alternative to policies which promote car ownership, little research has been done so far on the effect of public transportation on employment outcomes. Research on the relative effects of various transit options would be useful for policy-makers as they decide how best to allocate funds in order to improve the links between jobs and potential workers.

Such research would be especially relevant at this time, given that there have been recent increases in funding for transportation programs and that policy makers will need to decide how to allocate these new funds. In particular, following recent welfare reforms which implement time limits for welfare assistance, funding has increased for projects designed to improve welfare recipients' access to jobs. The Transportation Equity Act for the 21st Century (TEA-21), passed by Congress in May 1998, authorized $750 million to be spent between 1999 and 2003, targeted for assisting welfare recipients and other low-income workers with transportation to work. The TEA-21 bill contains the following explanation of the motivation for the legislation:

> SEC. 3037. JOB ACCESS AND REVERSE COMMUTE GRANTS.
>
> (a) Findings.--Congress finds that--
>
> (1) two-thirds of all new jobs are in the suburbs, whereas three-quarters of welfare recipients live in rural areas or central cities;

(2) even in metropolitan areas with excellent public transit systems, less than half of the jobs are accessible by transit;

(3) in 1991, the median price of a new car was equivalent to 25 weeks of salary for the average worker, and considerably more for the low-income worker;

(4) not less than 9,000,000 households and 10,000,000 Americans of driving age, most of whom are low-income workers, do not own cars;

(5) 94 percent of welfare recipients do not own cars;

(6) nearly 40 percent of workers with annual incomes below $10,000 do not commute by car;

(7) many of the 2,000,000 Americans who will have their Temporary Assistance to Needy Families grants (under the State program funded under part A of title IV of the Social Security Act (42 U.S.C. 601 et seq.)) terminated by the year 2002 will be unable to get to jobs they could otherwise hold;

(8) increasing the transit options for low-income workers, especially those who are receiving or who have recently received welfare benefits, will increase the likelihood of those workers getting and keeping jobs; and

(9) many residents of cities and rural areas would like to take advantage of mass transit to gain access to suburban employment opportunities.

The range of transportation programs being considered is wide. These include numerous programs intended to facilitate car ownership, such as: subsidies for automobile repairs, vehicle licenses, insurance, and down-payments on cars; interest-free revolving loan programs; gasoline vouchers; car-sharing programs; and assistance with obtaining driver's licenses and establishing car maintenance schedules. Some places, such as North Carolina and Ohio, are developing programs to transfer donated cars to welfare recipients for free, or at reduced cost.

The public transit programs that are being considered are equally diverse. Funding for transit-related projects may go towards providing transit tokens or passes; extending public transit service hours, days, and areas of operation; encouraging tax credits for employers who subsidize their employees' transit use; creating or expanding vanpool services; educating welfare recipients and case workers about public transit availability; coordinating schedules between transit service providers to minimize transfer times; and guaranteeing taxi rides home in cases of emergency. Another transit oriented option which has already been tried in several cities is the development of job fairs which feature job opportunities which are accessible by public transportation.[1]

As policy-makers weigh their options for allocating funds, additional information about the relative effectiveness of different transportation programs would be useful. If current public transit systems are ineffective at linking workers to jobs, then planners should avoid programs which focus on replicating existing transit service. Conversely, if public transit service is found

[1] Community Transportation Association of America (1999).

to make a significant difference for employment outcomes, then planners might prefer to emphasize transit-based options rather than car ownership programs, depending on the cost-effectiveness of the two approaches.

This paper aims to address several questions. First, does the quality of public transit affect employment outcomes? Second, does the quality of public transit have a greater effect on the employment outcomes of low-skilled workers? This population is less likely to own a car, less able to relocate near job opportunities, and therefore more likely to be reliant on public transit. Thirdly, which modes of public transit (bus, light rail, etc.) are most effective in determining employment outcomes? An understanding of which modes are most effective would help policy makers with their decisions on how to allocate funds. While there are several aspects of transit service which may affect an individual's ability to get employed and stay employed, this paper focuses on the density of public transit routes as a measure of transit quality.

I combine three data sources in order to look at the effect of the density of public transit routes on an individual's employment outcomes, while controlling for other characteristics of the city, as well as characteristics of the individual. Using a sample of small and mid-sized cities, I find that the number of miles of public transit routes (normalized by a measure of city size) do not have a statistically significant effect for the general population. For the low education population, however, a random effects regression shows that the density of public transit routes has a positive effect on the probability of employment, which is significant at the 5% level. For a 10% increase in the transit miles variable, the probability of employment is predicted to increase by .16% for the whole population. This increase is roughly $1/10^{th}$ the size of an increase in the probability of employment which would be predicted to occur from a 10% increase in the rate of car ownership. For those individuals who have no college education, a 10% increase in the density of transit routes corresponds to an increase in the probability of employment of almost three tenths of a percent.

The initial sample of 62 small and mid-sized cities is augmented with less precise data for 14 large cities. In this larger sample, the transit measure is found to have a statistically significant effect on employment at the 5% level for the population as a whole as well as for the low education group. In contrast to the results for the smaller sample, the size of the effect is virtually identical across both education groups. A 10% increase in transit density is associated with an increase of sixth tenths of a percent in the probability of employment. This is roughly half the size of the increase in employment which is expected if the rate of car ownership increases by 10%. Several robustness checks were performed, and the conclusions remain unchanged.

The remainder of the paper is organized as follows: Section II contains a review of the related literature, followed by a discussion of relevant theoretical concepts in Section III. Section

IV describes the data and the model to be estimated, Section V presents the results, and Section VI provides my concluding remarks and recommends avenues for future research.

II. Literature Review

There is an extensive body of empirical research testing the hypothesis that there is a spatial mismatch between job locations and non-white or low-income workers. Survey articles by Holzer (1991), Kain (1992), and Ihlanfeldt and Sjoquist (1998) document the results of the empirical work done since John Kain's seminal 1968 paper. Each of these survey articles concludes that the bulk of the evidence supports the spatial mismatch hypothesis. While some earlier papers arrived at mixed results[2], recent work has shown strong evidence that employment prospects are negatively affected by the distance between a person's residence and job-rich areas, particularly for non-whites living in the inner city.

For example, Holzer, Ihlanfeldt, and Sjoquist (1994) find evidence that the duration of unemployment among African-American youths in the central city increases with the degree of job decentralization. Stoll (1998) focuses on the growth rather than the level of job decentralization, and finds that the rate of job decentralization strongly affects both the incidence and the duration of joblessness for young African-American and Latino males. The results of the study indicate that by combining full employment policies with changes in the distribution of jobs, better labor market outcomes for minority males could be achieved than by pursuing either approach separately. Raphael (1998) uses a gravity equation to measure access to net employment growth. The results of his pooled regressions indicate that differences in access explain 30 to 50 percent of the difference in employment rates between white and black male youth. In fact, the majority of the empirical evidence seems to show that, while other determinants have important roles, spatial factors also have a significant effect on employment outcomes.

The role of transportation

Recently, researchers have begun investigating the role that transportation can play in improving labor market outcomes. Danziger et al. (1999) evaluate the importance of transportation problems in comparison with 14 other employment barriers facing welfare recipients in Michigan. Among both African-American and white welfare recipients, the lack of

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[2] For example, Ellwood's influential 1986 paper on Chicago-area teenagers concluded that while many of the features of the mismatch hypothesis were evident (significant segregation, job dispersal, high black unemployment), factors other than spatial mismatch were causing the negative labor market outcomes for blacks. Kain (1992) emphasizes that for two of the three mismatch measures used in Ellwood's study, small effects in the expected direction were found. The independent variable for which Ellwood finds a negative (and insignificant) effect is the percentage of jobs within 30 minutes of the zone by public transit. Kain points out that this measure does not take into account differences in commute time that may occur if white teenagers are more likely to own cars.

a car or a driver's license was found to be the most common problem (56.1% of African-American recipients, 35.8% of white recipients). The next most common problems for African-Americans were: having less than a high school education (31.3%), having a major depressive disorder (24.3%), and having few job skills (23.9%).[3] While Danziger et al. found that the lack of a car was the most *prevalent* problem, drug dependence was the variable with the strongest negative effect on the probability of working 20 or more hours per week. Having insufficient job skills was the second most important factor in this regard, and lack of a car or a driver's license came in third. The other two statistically significant factors for the probability of employment were the level of discrimination perceived by the individual and the mother's health problems.[4] Over 60% of welfare recipients had two or more barriers, which indicates that for this population, resolving transportation problems may be valuable but not sufficient for gaining employment.

As with Danziger et al., most of the recent research on transportation and labor market outcomes has focused on automobile ownership. In "Cars for the Poor", O'Regan and Quigley (1998) report that in 1990, 24% of poor households did not own cars, whereas only 2% of non-poor households were without cars. With data from the National Personal Transportation Survey, they also find that the time advantage from commuting by car rather than public transit is greater for African-Americans than for whites. This would be consistent with the idea that African-Americans generally have further to travel because of housing location constraints.

Because of the large time advantage from using a private auto, the authors recommend policies which promote car ownership among the poor. O'Regan and Quigley applaud the change in welfare eligibility rules which eliminated the stringent restrictions for welfare recipients on the asset value of their cars. They also suggest that "programs that help job takers obtain a used car—a secured loan for purchase, a leasing scheme, a revolving credit arrangement—may offer real promise, particularly in less dense and less centralized urban areas" (p. 24). While car ownership projects may in fact be a better policy choice for a more decentralized city such as Los Angeles, the authors do not address whether improvements to public transit systems might ever be an effective alternative approach to reducing commute times.

Holzer, Ihlanfeldt and Sjoquist (1994) and Ong (1996) have shown that car ownership is associated with higher earnings and a higher probability of employment. Holzer, Ihlanfeldt, and Sjoquist found that black male youths spend more time commuting to work than white males, but cover less distance, reflecting a higher time cost per mile for blacks. Part of this higher cost is attributed to higher rates of car ownership for white youths. The authors also found positive effects of car ownership on wages, and negative effects on unemployment duration.

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[3]The other barriers that were considered were low knowledge of work norms, strong perceptions of discrimination, Post-Traumatic Stress Disorder, general anxiety disorder, alcohol dependence, drug dependence, mother's health problem, child health problem, and domestic violence.
[4] Danziger et al.(1999), Tables 6 and 7.

Ong's 1996 paper investigates the relationship between car ownership and several labor market measures--employment, monthly earnings, hours worked, and hourly wages. In this paper, the predominantly female sample is comprised of California welfare recipients. He regresses the four labor market outcomes on a set of control variables and a dummy for car ownership. With the exception of the hourly wage regression, he finds the coefficient of the car ownership dummy to be positive and statistically significant. Based on these results he argues for programs which facilitate car ownership, "including providing training for do-it-yourself maintenance, referrals to reliable and honest automobile repair services, and access to reasonable insurance" (p. 261).

Unfortunately, in this analysis the causality of the relationship between car ownership and employment outcomes is uncertain. It could be that welfare recipients who find good jobs then have the income with which to buy a car. Alternatively, there could be an underlying unobserved individual characteristic, such as motivation, which affects both the probability of employment and the probability of car ownership. These factors undermine the strength of the argument for policies promoting car ownership.

Using an instrumental variables framework to treat the causality issues, Raphael and Rice (1999) still find evidence that car ownership increases the probability of employment and the number of hours worked. State level gasoline taxes and average costs of car insurance are used as instruments for car ownership, since they are likely to be correlated with car ownership but not correlated with unobserved differences in personal characteristics like motivation. The results show that car ownership has a positive effect on employment, statistically significant at the 5 percent level. Results for hourly wages (conditional on being employed) are less clear: while OLS results show that car ownership has a significant positive effect on log-wages, the 2SLS results yield significant negative coefficients. The study also finds large differences in car ownership rates between races. Analysis of the dataset (the Survey of Income and Program Participation--SIPP) shows that 49% of blacks own cars, while 77% of whites, and 56% of Hispanics do.

Given the current empirical evidence, it seems likely that programs which aim to increase car ownership rates among the poor would have a positive influence on employment rates among this population. However, it is possible that public transit could be used to the same effect. If public transit is a viable alternative to personal automobile use for increasing employment rates, it would be worth considering the relative costs and benefits of the two options.

With respect to public transit, a few papers have looked at the effect of public transit on the racial composition of the workforce at the firm level. Ihlanfeldt and Young (1996), Holzer and Ihlanfeldt (1996), and Holzer, Quigley, and Raphael (1997) all present evidence that a firm's proximity to public transit affects the racial composition of the job applicant pool and the

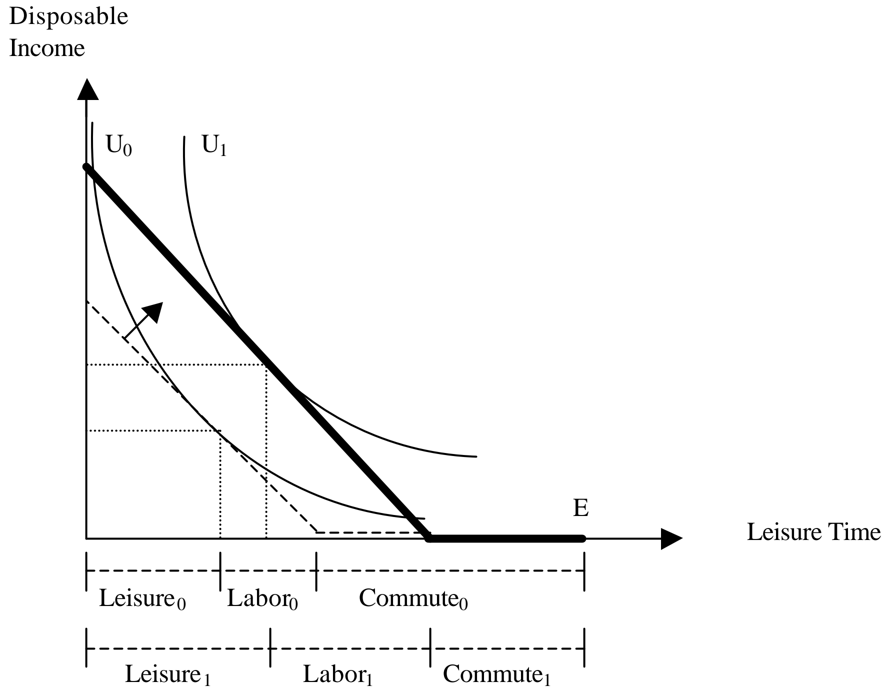
workforce at the firm. Ihlanfeldt and Young found that 35% of the central-city/suburban difference in black employment share is due to the inaccessibility of suburban firms by public transit.

Two studies have been done which look at the accessibility of jobs for welfare recipients via public transit. Coulton et al (forthcoming) and Rich and Coughlin (1998) provide in-depth, single-city analyses of Cleveland and Atlanta, respectively. Both papers find that job opportunities for welfare recipients are not accessible by public transit in these cities. Coulton et al. also highlight the need for transportation by pointing out that the areas of Cleveland which have a high percentage of entry level job openings have only a small percentage of housing units which are affordable to an entry level job holder. Conversely, central Cleveland has 56.3% of the affordable housing units in the area but only 11.8% of the entry level job openings. While these studies show that appropriate jobs are difficult to access by public transit in these two cities, they do not demonstrate whether or not employment or earnings would increase if public transit improved. The innovation of this current paper is that it looks directly at the relationship between public transit and employment outcomes.

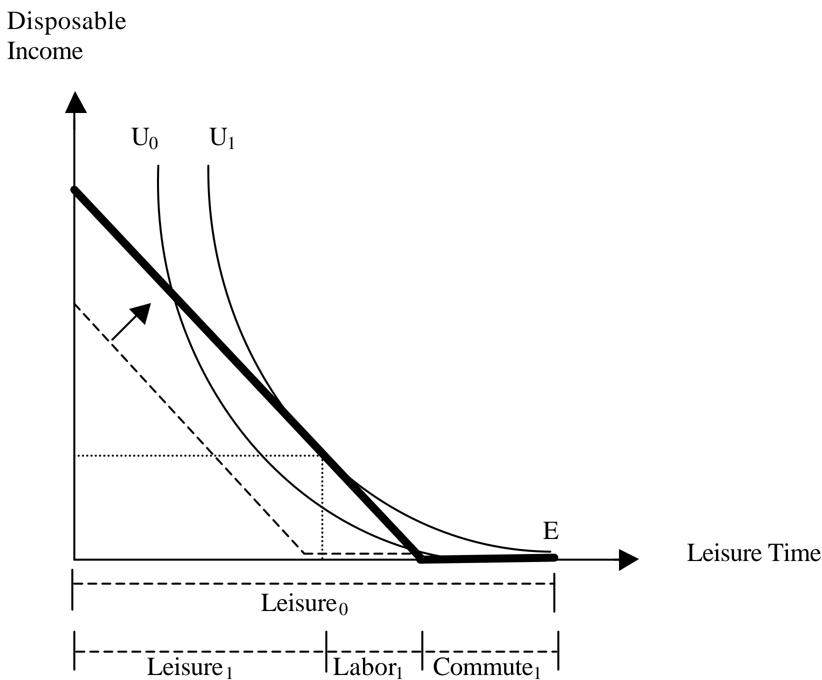
III. Theoretical Concepts

Here I present several basic concepts which capture the relationships I aim to estimate in this paper. First, an improvement in transit quality may increase labor supply. Transportation costs are a function of commute time and monetary travel expenses, TC(time, \$). If take-home pay is defined as the wage less the transportation cost, and transportation costs are reduced from TC_0 to TC_1, such that $(wage - TC_0) < wage^{reservation} < (wage - TC_1)$, then a reduction in commute time or travel expenses can be expected to draw an individual into the labor force. Secondly, an improvement in transit quality may increase earnings by increasing the number of hours worked. Both of these concepts can be depicted graphically, following the example of Raphael and Rice (1999).

The picture below shows a set of budget constraints and indifference curves. The endowment of hours is depicted by point E. The difference between this graph and the usual graphs showing a trade-off between labor and leisure is the kink in the budget constraint which appears here due to the introduction of commute time. Commute time reduces the amount of time available to be divided between leisure and labor. Leisure time and disposable income are assumed to be normal goods, and workers are assumed to be paid their marginal product. When a decrease in commute time shifts the budget constraint out, the individual can allocate more time to both leisure and work. Even though hourly wages do not change, earnings increase because the individual is working more hours.



However, an individual may have a different set of indifference curves, such that the tangency between the original budget constraint and the highest attainable indifference curve occurs at a point where all hours will be allocated to leisure and the person chooses not to work. In this case, a decrease in commute time may cause the individual to shift from providing zero hours of work to providing a positive amount of work. That is, we might expect to see an increase in employment in proportion to the fraction of the population with indifference curves like those in the graph below.



One thing these graphical examples fail to capture is the possibility that improvements in transit quality may also lead to higher hourly wages. This could be another important effect of public transit. If transportation costs decrease, then job search costs will decrease, which would lead the job seeker to expand the geographic area of the job search. By increasing the job search area, an individual is likely to arrive at a larger set of job offers and a better set of wages from which to choose. For those who would choose to work even at higher levels of transportation costs, wages are expected to be higher when transportation costs are lower. However, if there is a sizable shift in labor supply as in the second graphical example, then the marginal workers may be drawn in at low wages and the overall effect on average hourly wages is unclear.

IV. Econometric Model and Description of the Data

Econometric Model

The theoretical concepts lead me to test whether the characteristics of public transit affect the probability of being employed, the number of hours worked, and/or the hourly wages received.

My basic model is as follows:

$$EO_{ic} = \alpha + \beta' Z_{ic} + \lambda X_c + \psi' C_c + u_c + v_{ic} ,$$

where
i = individual
c = city

EO_{ic} = one of the three employment outcomes: a dummy for whether the individual is employed, hours worked per week, or the natural log of hourly wages

Z_{ic} = individual characteristics
(gender, marital status, race, ethnicity, education level, age, age^2, infant present in the home, currently enrolled in school, and car ownership)

X_c = a measure of transit density
(This measure is discussed in further detail below)

C_c = city characteristics which might affect employment outcomes
(median household income, cost of living index, population, black population, area of the city, density of census tracts, degree of clustering of black neighborhoods, degree to which blacks are concentrated in small areas, and the difference between black and non-black college attendance)

u_c = a city-specific error term

and

v_{ic} = an individual error term.

The vector of city characteristics is included to avoid a spurious correlation between public transit and employment outcomes, which could emerge if public transit were highly correlated with particular city characteristics which affect employment outcomes. For example, it could be that people who live in cities with a high cost of living feel more strongly compelled to work in order to meet their needs than people who face a low cost of living. If public transit density happens to be highly correlated with the cost of living, then the exclusion of cost of living from the model could result in omitted variables bias, wrongly attributing an employment effect to the transit variable when in fact the employment effect was related to the cost of living.

The specification also includes a city-specific error term. I estimate the regression as a random effects model, using maximum likelihood estimation.

The primary measure of transit coverage used in this study is the total miles of transit service in the city, divided by the square root of the area of the city, and multiplied by one million. The numerator is divided by the square root of the area rather than dividing simply by the area, so that the numerator and the denominator are both in terms of miles.[5] Defining the transit density measure in this manner means that two cities with identical patterns of transit will have the same value for the transit variable, regardless of the size of the cities.[6] However, this measure has the shortcoming that for two cities with the same pattern of transit routes (and therefore the same value for the transit density measure), the space between service routes is bigger in the larger of the cities. Still, in the absence of more detailed data on the layout of transit routes in different cities, this ratio seems to be one good option for measuring transit coverage. In the *Robustness Checks* section of the paper, I describe an alternate measure of transit density, which yields qualitatively similar results.

Data

The National Transit Database (NTD), compiled by the U.S. Department of Transportation, has annual data for 516 transit companies in 411 cities across the country.[7] The main variable of interest from the NTD is the number of miles of transit service.[8] The dataset also breaks down the total miles of transit service into miles by mode (i.e., bus, light rail, commuter rail, and vanpool). For each city, I have added together the miles of transit service, total and by mode, provided by each company within the city.

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[5] The measure is multiplied by one million simply so that the coefficients are scaled nicely for tables.

[6] For example, consider two circular cities, each having one bus route which crosses through the center of the city. Let the radius of one city be twice the radius of the other. Then the transit miles ratio for the smaller city is $2r/(\pi^{1/2}r)=2/\pi^{1/2}$, while the transit miles ratio for the larger city is $2(2r)/(\pi^{1/2}*2r)$, which is also $2/\pi^{1/2}$.

[7] This is meant to be a comprehensive dataset covering every transit system in the country.

[8] The actual variable used is "Vehicle Revenue Miles". This category includes miles of route where passengers pay to travel, and excludes, for example, the miles between the bus parking lot and the first stop on the bus route.

The Survey of Income and Program Participation (SIPP) is a nationally representative dataset maintained by the U.S. Census Bureau. The SIPP has individual level data on hourly wages, employment status, weekly work hours, and personal characteristics such as car ownership, age, education, race, sex, marital status, presence of an infant in the family, and the Metropolitan Statistical Area (MSA) where the individual lives. This paper uses SIPP data from 1993 and 1994. (The set of individuals interviewed changes between years.)

Cutler, Glaeser, and Vigdor have put together a dataset of city characteristics, created from Census data.[9] I include these city characteristics to help avoid omitted variables bias, as discussed in the section outlining the econometric model. These measures are available for about 332 Metropolitan Statistical Areas (MSA's). Measures are available only every ten years, so I use only the data for 1990.

The three datasets are merged together by appending the transit data and the city characteristics to the individual SIPP observations, by MSA code. Merging by MSA code results in a sample of 62 small and medium sized metropolitan areas. For the largest urban areas, the SIPP gives information only on the Consolidated Metropolitan Statistical Area (CMSA), which contains several Primary Metropolitan Statistical Areas (PMSAs)—while the other two data files provide the more specific PMSA location identifiers. For these larger metro areas, I have aggregated the transit data from the PMSA level to the CMSA level, in order to attach it to the SIPP data. This gives me a larger and more nationally representative sample of cities. The larger sample contains 14 more metropolitan areas than the sample of 62 small and mid-size cities, and it roughly doubles the number of individual observations. The additional metropolitan areas are: Boston-Worcester-Lawrence-Lowell-Brockton; Chicago-Gary-Kenosha; Cincinnati-Hamilton; Cleveland-Akron; Dallas-Fort Worth; Denver-Boulder-Greeley; Detroit-Ann Arbor-Flint; Houston-Galveston-Brazoria; Kalamazoo-Battle Creek; Los Angeles-Riverside-Orange; New York-Northern New Jersey-Long Island; Philadelphia-Wilmington-Atlantic City; Portland-Salem; San Francisco-Oakland-San Jose; Sarasota-Bradenton; Seattle-Tacoma-Bremerton; and Washington-Baltimore.

For these larger metro areas, the transit density variable (as well as the city characteristics variables) may be fairly imprecise for a given individual within that CMSA. For example, the CMSA for New York City also includes Bergen, Passaic, Jersey City, Middlesex, Somerset, Hunterdon, Monmouth, Ocean, Newark, Trenton (NJ), Dutchess County, Nassau, Suffolk (NY), Newburgh (NY-PA), Fairfield County, and New Haven (CT). The miles of transit routes for all these areas are aggregated, and the same transit numbers are appended to the personal data for an individual in Passaic, New Jersey and an individual in the Bronx, New York although they clearly

[9] See Cutler and Glaeser (1997) and Cutler, Glaeser, and Vigdor (1997) for thorough descriptions of the data.

have very different local transit environments. Likewise, these same two individuals are given the same value for other city level variables such as the cost of living. Thus, the addition of the larger cities provides a more nationally representative dataset, but with less accurate data on local conditions for individuals in the larger cities. Therefore, I present results for both the large and the small sample.

The small sample provides a sample of 10,543 individuals in 62 cities. The large sample yields a sample of 25,978 individuals in 76 cities.[10] Since the smaller sample excludes the largest cities, the conclusions derived from the results may not be applicable to the biggest metropolitan areas. However, the mean population in the smaller sample is over one million, so this smaller sample should not be thought of as only containing small cities. In the smaller sample there are eighteen cities with a population over a million, the largest being Atlanta, Georgia, with a population of 2,833,500. The next largest cities in the smaller sample are, in decreasing order by size: San Diego, Minneapolis, Phoenix, Tampa, Pittsburgh, Kansas City, Sacramento, Milwaukee, Norfolk, Columbus, San Antonio, Indianapolis, New Orleans, Charlotte, Orlando, Salt Lake City, Rochester, and Nashville.

V. Results

Main Results

The first question to be examined is whether the density of public transit routes has an effect on the probability of employment. Tables 1 and 2 show the results from a first pass at the data—regressions of the employment status dummy on the transit density measure, the set of personal characteristics variables, and a dummy for the year 1993. Three different specifications are presented for comparison: an OLS linear probability model, a probit model, and a random effects linear probability model. Results are discussed for the small sample of 62 cities first (Table 1). In the OLS and probit specifications, the coefficient on transit density is positive and significant at the 1% level, while in the random effects model, it is positive and significant at the 5% level. The size of the estimated marginal effect of transit density on employment is fairly similar across specifications, ranging from .089 to .103 depending on the specification. (The interpretation of magnitude of the coefficient on the transit variable will be further discussed below.) The coefficients on the personal characteristics variables are all significant, and have the expected signs (e.g., the probability of employment increases with age and with education). The size and significance of the coefficients on the personal characteristics variables are highly robust across all the specifications presented in this paper, so the coefficients will not be presented in

[10] Miami-Fort Lauderdale was excluded from the analysis because it shows an extremely large drop in the number of transit miles between 1993 and 1994, which is vastly larger than the changes in transit seen in

later tables. A Hausman test shows that the consistency of the random effects model would be rejected at the 5% significance level, suggesting that the random effects model is inappropriate here.[11]

As reported in Table 2, results from the larger sample of 76 metropolitan areas indicate that the transit density coefficients are negative, but the coefficients are much smaller in size than the coefficients from the small sample. The transit coefficients are significant at the 1% level in the first two specifications, but insignificant in the random effects model.

This first set of regressions shows a weak indication of a relation between public transportation and employment, though the relation appears to be positive in the small sample and negative in the large sample. However, these apparent relations may be spurious. The density of public transit may be correlated with other city-level characteristics which are related to employment. Employment and public transit quality may both be affected by the same underlying factor. In order to avoid wrongly attributing an employment effect to the transit variable, the same regressions are run in Tables 3 and 4 with the addition of a set of city characteristics.[12, 13] Once these city characteristics are included, transit density shows a positive coefficient in all of the specifications, for both samples. The negative coefficients on transit in Table 2 (for the large sample) may have been due to omitted variable bias. When the city-level controls are added, transit density is no longer as significant, except in the random effects model for the large sample, where transit is now positive and significant at the 5% level.

Once the city characteristics are added in Table 3, the Hausman test fails to reject the random effects model at the 5% level for the small sample, giving evidence that the random effects model produces consistent estimates for this sample. However, for the larger sample of 76 metropolitan areas the Hausman test does identify systematic differences between the fixed effect coefficients and the random effects coefficients, as reported at the bottom of Table 4. The main difference between the fixed effects results and the random effects results is the coefficient on the transit variable. For the large sample, the transit coefficient is positive in the random effects model and negative in the fixed effects model. The fixed effects transit coefficient derives its

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the other cities. This decline is attributed to error in the transit data.

[11] The Hausman test checks for consistency by testing whether the random effects coefficients are the same as the fixed effects coefficients. If they are found to be different, then the city-specific error term may be correlated with the regressors, or the model may be otherwise misspecified.

[12] The set of city characteristics included in the model are a subset of the variables available from the Cutler, Glaeser, and Vigdor dataset. The set of city-level controls was chosen to avoid multicollinearity or endogeneity, and to achieve a parsimonious model. The variables from the Cutler, Glaeser, Vigdor dataset which were not used include other measures of segregation, the size of the hispanic population, the number of census tracts, the population density, the share of the labor force in manufacturing, a measure of single motherhood, and black/non-black difference in commute times. When individually added to the model, none of these excluded variables were statistically significant.

[13] An alternative possibility is that the city characteristics included in Table 2 help determine the quality of transit provided in a city, in which case it would be difficult to identify the effect of transit miles, per se.

identification from the change in transit between years, and since the difference in transit miles between years in any city in the sample is virtually zero, there is not enough variation in transit between years for the fixed effects model to provide a very accurate estimate of the coefficient on the transit density variable. The transit coefficient is not significant in the fixed effects model. Therefore, the remainder of the analysis will include random effects in the specification in spite of the results of the Hausman test for the large sample. For the results presented in the rest of the paper, the Hausman statistic is generally above the .05 cut-off for the regressions using the small sample, and it is generally below the .05 cut-off for the regressions using the large sample.

Tables 3 and 4 provide some evidence of a positive relation between public transit density and employment for the general population, but we might expect that public transit density has a larger effect for those who are less well off. Affluent people have more flexibility in terms of locating their residence close to work opportunities, and they are better able to purchase cars. This might suggest that it would be useful to control for the individual's income level. However, income is affected by the dependent variable (employment status), and therefore I focus instead on education level, which is less problematic with respect to endogeneity since education is largely determined before an individual enters the workforce. I expect to find that transit matters more for those who have not been to college.

The first column of Table 5 shows results for the small sample from the same regression presented in the last column of Table 3, using a random effects linear probability model. The second column of Table 5 introduces interactions with a high education dummy variable which equals one if the individual has had any education beyond high school. In this specification, the coefficient on the transit density variable is interpreted as the effect of transit on employment *for the low education population*. The effect of transit for the high education sample is found by adding the coefficient on the transit-high education interaction term to the transit density coefficient. (The interaction term itself shows the differential effect of transit for high education individuals over the baseline effect for the low education individuals.) For the small sample, I find that the transit density variable is insignificant in the first column, but is positive (.1611) and significant at 5% for the low education group, as seen by the coefficient on transit density in the model with education interactions. Testing the significance of the sum of the coefficient on transit density and the coefficient on the transit-education interaction term, I find that the effect of transit density on employment for the high education sample is positive but not significantly different from zero.

In order to better understand the meaning of the transit coefficient, Table 6 calculates the effect of a ten percent change in the transit density variable on the probability of employment,

using the results from the regressions in Table 5.[14] The marginal effect of transit density for each group (entire population, low education, or high education) is multiplied by the size of a 10% change in transit density for the average MSA in the sample. (The marginal effect for the high education population is the sum of the transit density coefficient and the interaction term coefficient.) Using the results from the smaller sample of 62 cities I find that for the population as a whole, a ten percent change in transit route density is associated with an increase in the probability of employment of approximately two tenths of a percent (.16%). For the low education population, the predicted effect of a 10% change in transit density is almost twice as large, .27%. For the high education population, a change in transit density is found to have virtually no effect on employment.

When the larger sample is used, transit density is found to have a positive effect which is significant at the 5% level for the general population as well as for those with no college education, as shown in the first and second columns of Table 7. A test of the significance of the sum of the transit variable and its interaction with the education dummy demonstrates that, for the large sample, the positive relation between transit density and the probability of employment is also significant for the high education group, at the 5% level.

The large sample results indicate that a 10% change in transit density leads to a predicted increase in probability of employment of about sixth tenths of a percent, regardless of education level. In contrast to the results for the smaller sample, here those with education beyond the high school level appear to benefit from public transit almost as much as their low education counterparts. One explanation for this result is that in large cities, highly educated people are more likely to take public transportation because the benefits of public transit relative to traveling by automobile may be higher in larger cities. Due to higher levels of congestion in larger cities, parking costs may be higher and commute time by car may not be substantially shorter than commute time using public transit.

In order to get some perspective on the size of the transit effect, I compare the predicted effect of a 10% change in transit density to the predicted effect of a 10% change in car ownership. Using the smaller sample results I find that for the general population, the effect of a 10% change in car ownership on the employment probability is 8.75 times greater than for a 10% change in the transit density measure. For the low education population, a 10% change in car ownership has about 6 times the effect of a 10% change in transit density. Looking at the numbers from the large sample, I find that the effect of a 10% change in car ownership has roughly twice the effect of a 10% change in transit density, for the population as a whole. For the low education group, car ownership has 2.3 times the effect of transit.

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[14] For the small sample, 10% of the mean of transit density is about 1/9th the size of a standard deviation. For the large sample, 10% of the mean is about 1/13th the size of a standard deviation.

The theoretical and graphical analysis presented earlier in the paper would predict an increase in hours worked as well as an increase in employment. The regressions presented in Tables 5 and 7 were repeated using the number of weekly hours worked as the dependent variable instead of the probability of employment. The results are presented in Tables 9 through 12. In the small sample, the transit density variable is not significant at all, regardless of education level. The (insignificant) point estimate for the coefficient for the low education group is much larger than for the population as a whole (4.76 vs. 1.78). However, for the low education population, a ten percent change in transit density still only leads to about a five minute predicted increase in time worked per week. In contrast, a 10% increase in car ownership has an effect about eight times as large, increasing the number of minutes worked per week by about 40 (for the low education group). The estimated effect of transit density is negative for the high education group (-0.73), but again insignificant.

The large sample results (Tables 11 and 12) also show positive coefficients for transit, but this time they are significant at the 5% level, both for the general population and for the low education population. (The effect of transit density on hours worked is positive and significant at 10% for the high education group.) Paralleling the employment results, there is not much difference between the transit coefficient for the low education group and the estimated effect for the high education group. The results from the large sample indicate that a 10% change in transit density will lead to 15 minutes more of work per week for both education groups. By comparison, a ten percent change in car ownership is predicted to lead to a little more than a half hour of additional work per week.

Although the theoretical analysis has no clear prediction for hourly wages, regressions for log wages are run because wages are also an important labor market outcome. Tables 13 through 16 present the results with log wages as the dependent variable. The log wage regressions only contain individuals who are employed. Here the point estimate for the transit density variable is insignificant, regardless of the sample of metropolitan areas used. This is true for both the general regression and for the regression with the education interaction term. Using the insignificant coefficient from the small sample I find that increasing transit density by 10% leads to a rise in log wage of .0011 for the low education group. The estimated positive effect of car ownership is roughly 5 times as big (and the car ownership coefficient is significant at 1%). For the low education group in the large sample, the point estimate on transit density is actually negative, while the coefficient on car ownership is still positive and significant at 1%. The density of public transit routes appears to operate mainly on the probability of employment, and not to have a clear effect on the wage rate.

The analysis presented in Tables 17 and 18 explores the question of whether miles of transit are less important for the probability of employment if an individual owns a car. The transit density variable is interacted with the car ownership variable and regressions are run separately for the entire population, the low education group and the high education group. Looking at the results from the small sample, I find that for the general population, the point estimate for the interaction term is negative, which is what would be expected. A negative coefficient suggests that the benefits of an increase in transit route density are not as strong for an individual who owns a car, or, conversely that the benefits of car ownership decrease as public transit coverage increases. However, the coefficient is insignificant. Contrary to expectation, the coefficients on the interaction term are positive in the regressions run separately for the low education and high education population,[15] but these coefficients are not significantly different from zero. For the large sample, the interaction term is positive but insignificant for all three regressions. For both samples, the coefficient on the transit density variable itself closely resembles the results presented earlier in Tables 5 and 7, where the regressions were run without the interaction between transit density and car ownership.

In addition to looking at the effect of *total* miles of transit routes (summed across bus, commuter rail, light rail, and vanpool routes), I also look at the effectiveness of each separate mode of transit. Tables 19 and 20 present the results for an analysis of the effects of each particular mode of transit on the probability of employment. The total of transit miles is broken down into its component modes, and these components are normalized in the same manner as the total transit density measure, by dividing by the square root of the area of the city. The results from the smaller sample show that the density of bus routes and the density of vanpool routes both have a positive effect for the low education population, significant at the 5% level. Commuter rail and light rail show negative coefficients for the low education group, but they are not significantly different from zero. In the larger sample, none of the individual transit modes show up significantly, although the point estimates for bus and vanpool are positive for the low education population, which mirrors the results from the small sample.

Robustness Checks

Checking the robustness of the results, I tested the sensitivity of the results to the specification of the transit density variable. Focusing on the probability of employment, I repeated the employment regression presented in the second column of Table 5, this time using

[15] One possible interpretation of this positive coefficient could be that better public transit systems lead to less congested roads and lower commute times for drivers. This decrease in commute time might make working more attractive to car owners who might otherwise choose not to work.

transit miles normalized by the area rather than square root of the area. As mentioned earlier, the transit measure used in the earlier analyses gives the same value of transit density to two cities with identical patterns of transit routes. If one city is larger than the other, then the average distance to the nearest transit route will be higher in the larger city, indicating that this is not an ideal measure for access to transit. Dividing by area instead of the square root of the area means that the denominator increases faster as area increases, and the overall measure increases at a slower rate as area increases. As a simple example, consider two circular cities, each with one transit route bisecting the city, where one city has twice the radius of the other. With the original transit density measure, these two cities had the same transit density value. With the alternative measure which divides by area, the large city will have a transit density measure which is half the size of that of the smaller city ($1/\pi r$ for the large city versus $2/\pi r$ for the smaller city, where r is the radius). This alternate measure discounts transit density in the larger cities quite heavily. The results using the two different transit density measures could be considered as rough upper and lower bounds on the actual effect of access to transit routes within a city.

For the small sample, the signs and significance levels of the previous results are closely replicated: the positive coefficient on the new transit density variable is still insignificant for the general population, and is significant at the 5% level for the low education population. However, the transit coefficient is now negative for the high education population, but very small and statistically insignificant. With the large sample, the signs and significance levels for the transit variable are again found to be similar to the previous results: with the new transit density specification, the coefficient is positive and significant at the 5% level for both the low education population and for the high education population.

For the average city in the small sample, a 10% change in this new transit density variable leads to a 0.07 percent predicted change in the probability of employment for the general population. (See Table 21.) This is roughly half the size of the 0.16 percent effect that was found with the previous density measure. For both transit measures I find that the predicted effect is approximately doubled for the low education population over the numbers for the general population. (There is a 0.15% predicted change in probability of employment for the low education group using the new measure, and a 0.27% predicted change for the low education group using the old measure).

Using the results for the large sample I find that for the average city a 10% change in the new transit density variable results in a 0.41 percent predicted increase in probability of employment for the low education group, and the numbers are very similar for the entire population. This effect is roughly two-thirds the size of that found in the earlier results when transit density was normalized using the square root of area. While the coefficients are lower

when this alternate measure of transit density is used, the results maintain their statistical significance and still indicate a fairly strong positive effect of transit miles.

VI. **Conclusion**

Summary of Results

This study uses several nationwide datasets to examine the relationship between the density of public transit routes and an individual's employment outcomes. The theoretical constructs presented earlier yielded a prediction that transit density would have a positive effect on labor market participation and on the number of hours worked. For hourly wages, the prediction was unclear. In areas with high transit density, those with strong labor market attachment may have higher hourly wages, but there is also the expectation that workers with weak labor market attachment will be drawn into the labor market, probably at low wages—hence, an uncertain effect for overall hourly wages.

Of the three labor market outcomes, employment appeared to be the outcome most influenced by the density of transit routes, followed by weekly hours worked, while the results for hourly wages were quite weak. For those without any college education, the random effects regression indicated that miles of public transit have a positive effect on the probability of employment, significant at the 5% level. Positive coefficients on transit density were also found for the low education group for the number of hours worked per week. The weekly hours result is not significant in the smaller sample of 62 cities, but is significant at the 5% level in the larger sample of 76 cities. The results for the natural log of hourly wages are small and insignificant for both education levels, regardless of the sample of cities used. There is weak evidence that miles of bus service and miles of vanpool service have the strongest positive effects on the probability of employment for the low education population. Overall, this study provides evidence that public transit plays a small but notable role in determining labor market outcomes, worth further investigation.

Policy Implications

The results of this study indicate that programs designed to improve public transit should be considered alongside policies promoting car ownership when looking for methods to improve access to employment. When weighing the transportation options, policymakers will need to determine the relative benefits and costs of car ownership and public transit policies. The results of this study imply that the predicted effect of a 10% increase in car ownership is much greater than the predicted effect of a 10% increase in transit density. However, for a given increase in employment, the sum of private and social costs for achieving that goal by investing in public

transit could still be less than the costs via programs promoting car ownership. For a complete comparison of the social costs and benefits, externalities such air pollution and traffic congestion would need to be taken into consideration. It is important to note, however, that increasing transit density and increasing car ownership are not necessarily mutually exclusive actions. Planners may decide to do both simultaneously, or they may decide to use one approach in some areas and the other approach elsewhere.

The effectiveness of public transit relative to car ownership is likely to depend greatly on the specific geography of a given area. The Community Transportation Association of America states, "[T]here is no single welfare-to-work transportation solution. The methods that work are responsive to the needs of local clients and employers, take into consideration the unique geography and resources of the regions they serve…"[16] Therefore, while the results of this paper indicate that public transit miles generally have a notable effect on employment probabilities, these results may not apply to a specific city, and attempts to estimate program costs and benefits should make sure to consider the particular characteristics of that city.

Another consideration is that transportation may be only one of several barriers to employment for disadvantaged individuals. Physical access to a decent job may not be enough for a worker who has inadequate job skills and child care problems, or who faces racial discrimination in the job market, for example. In this context, transportation planning should not be considered in isolation from other factors. Chicago's Suburban Job-Link program provides several services in tandem—express bus services, rideshare networks, interpersonal skill training, identification of appropriate job openings, and temporary work experience employment. While not every city or every transit agency will be willing and able to implement such a comprehensive program, planners should take into consideration not only transportation to work opportunities but also transportation to social service providers, job training programs, child care facilities, and other necessary destinations.

Future research

There are many avenues for further research on this topic. A more extensive treatment of the endogeneity of car ownership would be valuable in getting a better picture of the true effect of miles of transit service on labor market outcomes. This might be done by incorporating two stage least squares estimation, with state gasoline taxes and average insurance premiums as instruments, as done in Raphael and Rice (1999). Another option might be to use a Heckman two-step estimation approach, where the first step would be a probit for the probability of owning a car. This would correct for bias due to self-selection into car-ownership.

[16] Community Transportation Association of America (1999), Chapter V.

On a more fundamental level, miles of transit service are not the only dimension of public transit quality that might affect an individual's ability to get and keep a job. The National Transit Database also has data on the days of the week and the hours of service available. These factors may also have significant effects on job accessibility and therefore on employment outcomes. An understanding of the magnitude of these effects would be useful for comparing transit policy options. Detailed benefit-cost analyses of the various transit and car policy options available would be very valuable to public planners, as would information about how these costs and benefits vary with city characteristics such as size.

The research could also be extended by looking at the differential impact of public transit by race. Car ownership rates are lower for African-Americans than for whites, even when characteristics such as education are held constant, suggesting that public transit may well play a larger role in the labor market outcomes of African-Americans. An examination of the differences in the effectiveness of transit for cities with different levels of segregation could also provide interesting results.

Public transit may also have a greater effect for women. Past research has shown that women are less attached to the labor force, and transit may be an influential factor for women on the employment margin. In addition, women are more likely to be caring for children, and the addition of a trip to a child care center on top of the commute to work may make transportation quality a more important variable for women.

This paper is an introductory look at how public transit affects the employment outcomes of the poor. The results indicate that the density of public transit routes does make a difference. There are many unanswered questions regarding the importance of other characteristics of public transit service. Also unresolved are issues regarding the benefits of public transit expenditures relative to expenditures on other transportation alternatives. Public transit improvements may prove to be highly effective in some scenarios, but unrealistic in others. Hopefully this paper will be a catalyst for further research, leading to informed decisions on how best to improve transportation for those most in need of access to jobs.

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Table 1: Probability of Employment

(SMALL SAMPLE)

	OLS		Probit[a]		Random Effects	
Transit Density	.0887	***	.1027	***	.0915	**
	(.0255)		(.0292)		(.0430)	
Car Owner	.1924	***	.2068	***	.1913	***
	(.0104)		(.0129)		(.0104)	
High Education	.0804	***	.0888	***	.0821	***
(College)	(.0081)		(.0091)		(.0081)	
Female	-.1311	***	-.1484	***	-.1304	***
	(.0076)		(.0084)		(.0076)	
Married	-.0473	***	-.0504	***	-.0484	***
	(.0091)		(.0104)		(.0091)	
Black	-.0423	***	-.0441	***	-.0392	***
	(.0119)		(.0139)		(.0122)	
Hispanic	-.0754	***	-.0811	***	-.0594	***
	(.0136)		(.0166)		(.0144)	
Age	.0426	***	.0392	***	.0428	***
	(.0021)		(.0022)		(.0021)	
Age^2	-.0006	***	-.0005	***	-.0006	***
	(2.53 E-5)		(2.69 E-5)		(2.52 E-5)	
Infant	-.1084	***	-.1240	***	-.1063	***
	(.0132)		(.0172)		(.0132)	
In School	-.1620	***	-.1840	***	-.1608	***
	(.0128)		(.0167)		(.0128)	
1993 Dummy	-.0030		-.0059		-.0027	
	(.0076)		(.0086)		(.0076)	
R^2	.2060		.1835	a	.2059	
N	10,543		10,543		10,543	
Hausman prob>χ^2	--		--		.0090	

All regressions include a constant.

Standard errors are in parentheses.

* indicates significance at the 10% level.
** indicates significance at the 5% level.
*** indicates significance at the 1% level.

a. The numbers reported are transformations of coefficients from a probit regression. They represent the change in the probability of employment for an infinitesimal change in the continuous independent variables, or for a discrete change in probability for the dichotomous independent variables. The R^2 reported is a pseudo-R^2.

Table 2: Probability of Employment

(LARGE SAMPLE)

	OLS		Probit[a]		Random Effects	
Transit Density	-.0069	***	-.0074	***	-.0051	
	(.0020)		(.0022)		(.0074)	
Car Owner	.1760	***	.1904	***	.1750	***
	(.0065)		(.0078)		(.0065)	
High Education (College)	.0859	***	.0961	***	.0867	***
	(.0053)		(.0060)		(.0053)	
Female	-.1382	***	-.1584	***	-.1381	***
	(.0050)		(.0056)		(.0050)	
Married	-.0591	***	-.0652	***	-.0602	***
	(.0060)		(.0069)		(.0060)	
Black	-.0463	***	-.0501	***	-.0477	***
	(.0078)		(.0092)		(.0079)	
Hispanic	-.0551	***	-.0590	***	-.0384	***
	(.0077)		(.0091)		(.0081)	
Age	.0411	***	.0398	***	.0413	***
	(.0014)		(.0015)		(.0014)	
Age^2	-.0006	***	-.0005	***	-.0006	***
	(1.67 E-5)		(1.81 E-5)		(1.66 E-5)	
Infant	-.1106	***	-.1261	***	-.1087	***
	(.0086)		(.0110)		(.0086)	
In School	-.1902	***	-.2143	***	-.1892	***
	(.0085)		(.0109)		(.0085)	
1993 Dummy	.0025		4.87 E-5		.0028	
	(.0050)		(.0057)		(.0050)	
R^2	.2005		.1740	a	.2003	
N	25,978		25,978		25,978	
Hausman prob>χ^2	--		--		.0001	

All regressions include a constant.

Standard errors are in parentheses.

* indicates significance at the 10% level.
** indicates significance at the 5% level.
*** indicates significance at the 1% level.

a. The numbers reported are transformations of coefficients from a probit regression. They represent the change in the probability of employment for an infinitesimal change in the continuous independent variables, or for a discrete change in probability for the dichotomous independent variables. The R^2 reported is a pseudo-R^2.

Table 3: Probability of Employment

Controlling for City Characteristics

(SMALL SAMPLE)

	OLS		Probit[a]		Random Effects	
Transit Density	.0925	**	.1093	**	.0922	
	(.0447)		(.0512)		(.0681)	
Car Owner	.1909	***	.2052	***	.1903	***
	(.0104)		(.0130)		(.0104)	
Population	1.16 E-8		1.20 E-8		8.75 E-9	
	(1.22 E-8)		(1.37 E-8)		(1.96 E-8)	
Black Population	-1.17 E-7	***	-1.22 E-7	***	-1.05 E-7	
	(3.83 E-8)		(4.37 E-8)		(6.65 E-8)	
Area of the City	9.89 E-7		9.16 E-7		1.28 E-6	
	(3.03 E-6)		(3.36 E-6)		(4.45 E-6)	
Median Household Income	3.78 E-6	***	4.17 E-6	***	4.28 E-6	*
	(1.44 E-6)		(1.61 E-6)		(2.20 E-6)	
Cost of Living Index	-.2375	***	-.2642	***	-.2524	**
	(.0641)		(.0714)		(.0997)	
Clustering of Black Neighborhoods	.0598	**	.0639	**	.0383	
	(.0236)		(.0267)		(.0341)	
Concentration of Black Residences	.0221		.0245		.0311	
	(.0191)		(.0212)		(.0271)	
Black Share of College Attendees	-.1485	***	-.1664	***	-.1560	**
	(.0453)		(.0511)		(.0641)	
R^2	.2101		.1877	a	.2100	
N	10,543		10,543		10,543	
Hausman prob>χ^2	--		--		.0985	

All regressions include a constant, and the full set of personal characteristic variables (High Education dummy, Female, Married, Black, Hispanic, Age, Age^2, Infant Present, In School, and a dummy for 1993).

Standard errors are in parentheses.

* indicates significance at the 10% level.
** indicates significance at the 5% level.
*** indicates significance at the 1% level.

a. The numbers reported are transformations of coefficients from a probit regression. They represent the change in the probability of employment for an infinitesimal change in the continuous independent variables, or for a discrete change in probability for the dichotomous independent variables. The R^2 reported is a pseudo-R^2.

Table 4: Probability of Employment

Controlling for City Characteristics

(LARGE SAMPLE)

	OLS		Probit[a]		Random Effects	
Transit Density	.0547	***	.0665	***	.0635	**
	(.0159)		(.0184)		(.0283)	
Car Owner	.1751	***	.1896	***	.1748	***
	(.0065)		(.0078)		(.0065)	
Population	-1.30 E-8	**	-1.65 E-8	**	-8.25 E-9	
	(5.98 E-9)		(6.94 E-9)		(9.89 E-9)	
Black Population	-1.93 E-8		-1.91 E-8		-3.27 E-8	
	(2.20 E-8)		(2.54 E-8)		(3.70 E-8)	
Area of the City	3.27 E-6	**	4.21 E-6	**	2.12 E-6	
	(1.53 E-6)		(1.77 E-6)		(2.62 E-6)	
Median Household Income	2.76 E-6	**	3.28 E-6	***	3.80 E-6	**
	(1.10 E-6)		(1.28 E-6)		(1.69 E-6)	
Cost of Living Index	-.0882	**	-.1067	***	-.1620	**
	(.0349)		(.0401)		(.0643)	
Clustering of Black Neighborhoods	.0551	***	.0644	***	.0421	
	(.0194)		(.0226)		(.0279)	
Concentration of Black Residences	.0369	**	.0400	**	.0369	*
	(.0154)		(.0176)		(.0216)	
Black Share of College Attendees	-.1451	***	-.1723	***	-.1516	***
	(.0406)		(.0470)		(.0558)	
R^2	.2034		.1771	a	.2031	
N	25,978		25,978		25,978	
Hausman prob>χ^2	--		--		.0014	

All regressions include a constant, and the full set of personal characteristic variables (High Education dummy, Female, Married, Black, Hispanic, Age, Age^2, Infant Present, In School, and a dummy for 1993).

Standard errors are in parentheses.

* indicates significance at the 10% level.
** indicates significance at the 5% level.
*** indicates significance at the 1% level.

a. The numbers reported are transformations of coefficients from a probit regression. They represent the change in the probability of employment for an infinitesimal change in the continuous independent variables, or for a discrete change in probability for the dichotomous independent variables. The R^2 reported is a pseudo-R^2.

Table 5: Probability of Employment

Random Effects Models with Education Interactions

(SMALL SAMPLE)

	Without Education Interactions	With Education Interactions
Transit Density	.0922	.1611 **
	(.0681)	(.0746)
Car Owner	.1903 ***	.2341 ***
	(.0104)	(.0128)
Transit Density *		-.1226 **
High Education	--	(.0510)
Car Owner *		-.1033 ***
High Education	--	(.0180)
High Education	.0826 ***	.1812 ***
(College)	(.0081)	(.0180)
R^2	.2100	.2127
N	10,543	10,543
Hausman prob>χ^2	.0985	.2366

All regressions include a constant, the set of personal characteristic variables (Female, Married, Black, Hispanic, Age, Age^2, Infant Present, In School, and a dummy for 1993) and the set of city characteristics (Population, Black Population, Area, Median Household Income, Cost of Living Index, Clustering of Black Neighborhoods, Concentration of Black Residences, and Black Share of College Attendees).

Standard errors are in parentheses.

* indicates significance at the 10% level, ** indicates significance at the 5% level, and
*** indicates significance at the 1% level.

Table 6: Percent Change in the Probability of Employment Associated with a Ten Percent Change

(SMALL SAMPLE)

	In Transit Density	In Car Ownership
Entire Population	0.16	1.40
Low Education	0.27	1.72
High Education	0.07	0.96

Table 7: Probability of Employment

Random Effects Models with Education Interactions

(LARGE SAMPLE)

	Without Education Interactions		With Education Interactions	
Transit Density	.0635	**	.0652	**
	(.0283)		(.0291)	
Car Owner	.1748	***	.2162	***
	(.0065)		(.0083)	
Transit Density *			-.0017	
High Education	--		(.0040)	
Car Owner *			-.0893	***
High Education	--		(.0111)	
High Education	.0869	***	.1506	***
(College)	(.0053)		(.0106)	
R^2	.2031		.2051	
N	25,978		25,978	
Hausman prob>χ^2	.0014		.0144	

All regressions include a constant, the set of personal characteristic variables (Female, Married, Black, Hispanic, Age, Age^2, Infant Present, In School, and a dummy for 1993) and the set of city characteristics (Population, Black Population, Area, Median Household Income, Cost of Living Index, Clustering of Black Neighborhoods, Concentration of Black Residences, and Black Share of College Attendees).

Standard errors are in parentheses.

* indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

Table 8: Percent Change in the Probability of Employment Associated with a Ten Percent Change

(LARGE SAMPLE)

	In Transit Density	In Car Ownership
Entire Population	0.61	1.19
Low Education	0.63	1.47
High Education	0.61	0.86

Table 9: Hours Worked per Week

Random Effects Models with Education Interactions

(SMALL SAMPLE)

	Without Education Interactions		With Education Interactions	
Transit Density	1.7766		4.7574	
	(2.9370)		(3.1565)	
Car Owner	8.3088	***	9.3852	***
	(.4362)		(.5383)	
Transit Density * High Education	--		-5.4868	***
			(2.1364)	
Car Owner * High Education	--		-2.5154	***
			(.7524)	
High Education (College)	3.9192	***	6.7407	***
	(.3378)		(.7563)	
R^2	.2929		.2940	
N	10,543		10,543	
Hausman prob>χ^2	.4006		.3879	

All regressions include a constant, the set of personal characteristic variables (Female, Married, Black, Hispanic, Age, Age^2, Infant Present, In School, and a dummy for 1993) and the set of city characteristics (Population, Black Population, Area, Median Household Income, Cost of Living Index, Clustering of Black Neighborhoods, Concentration of Black Residences, and Black Share of College Attendees).

Standard errors are in parentheses.

* indicates significance at the 10% level, ** indicates significance at the 5% level, and
*** indicates significance at the 1% level.

Table 10: Change in Hours Worked per Week Associated with a Ten Percent Change

(SMALL SAMPLE)

	In Transit Density	In Car Ownership
Entire Population	.0300	.6115
Low Education	.0802	.6907
High Education	-.0123	.5056

Table 11: Hours Worked per Week

Random Effects Models with Education Interactions

(LARGE SAMPLE)

	Without Education Interactions		With Education Interactions	
Transit Density	2.5185	**	2.6167	**
	(1.2596)		(1.2853)	
Car Owner	7.4538	***	8.6085	***
	(.2703)		(.3448)	
Transit Density *			-.1302	
High Education	--		(.1647)	
Car Owner *			-2.4924	***
High Education	--		(.4624)	
High Education	4.3817	***	6.2387	***
(College)	(.2214)		(.4394)	
R^2	.2867		.2875	
N	25,978		25,978	
Hausman prob>χ^2	.0305		.0686	

All regressions include a constant, the set of personal characteristic variables (Female, Married, Black, Hispanic, Age, Age^2, Infant Present, In School, and a dummy for 1993) and the set of city characteristics (Population, Black Population, Area, Median Household Income, Cost of Living Index, Clustering of Black Neighborhoods, Concentration of Black Residences, and Black Share of College Attendees).

Standard errors are in parentheses.

* indicates significance at the 10% level, ** indicates significance at the 5% level, and *** indicates significance at the 1% level.

Table 12: Change in Hours Worked per Week Associated with a Ten Percent Change

(LARGE SAMPLE)

	In Transit Density	In Car Ownership
Entire Population	.2432	.5068
Low Education	.2527	.5853
High Education	.2401	.4158

Table 13: Log Wages, for those Employed

Random Effects Models with Education Interactions

(SMALL SAMPLE)

	Without Education Interactions		With Education Interactions	
Transit Density	.0802		.0640	
	(.0965)		(.1052)	
Car Owner	.1313	***	.0713	***
	(.0153)		(.0198)	
Transit Density *			.0147	
High Education	--		(.0719)	
Car Owner *			.1301	***
High Education	--		(.0273)	
High Education	.2869	***	.1798	***
(College)	(.0113)		(.0277)	
R^2	.3297		.3316	
N	7,852		7,852	
Hausman prob>χ^2	.8678		.8842	

All regressions include a constant, the set of personal characteristic variables (Female, Married, Black, Hispanic, Age, Age^2, Infant Present, In School, and a dummy for 1993) and the set of city characteristics (Population, Black Population, Area, Median Household Income, Cost of Living Index, Clustering of Black Neighborhoods, Concentration of Black Residences, and Black Share of College Attendees).

Standard errors are in parentheses.

* indicates significance at the 10% level, ** indicates significance at the 5% level, and
*** indicates significance at the 1% level.

Table 14: Change in Log Wages (for those Employed) Associated with a Ten Percent Change

(SMALL SAMPLE)

	In Transit Density	In Car Ownership
Entire Population	.0014	.0097
Low Education	.0011	.0052
High Education	.0013	.0148

Table 15: Log Wages, for those Employed

Random Effects Models with Education Interactions

(LARGE SAMPLE)

	Without Education Interactions		With Education Interactions	
Transit Density	.0022		-.0102	
	(.0403)		(.0415)	
Car Owner	.1495	***	.1176	***
	(.0096)		(.0129)	
Transit Density *			.0183	***
High Education	--		(.0060)	
Car Owner *			.0639	***
High Education	--		(.0172)	
High Education	.3082	***	.2432	***
(College)	(.0077)		(.0166)	
R^2	.3309		.3316	
N	18,679		18,679	
Hausman prob>χ^2	.6894		.7764	

All regressions include a constant, the set of personal characteristic variables (Female, Married, Black, Hispanic, Age, Age^2, Infant Present, In School, and a dummy for 1993) and the set of city characteristics (Population, Black Population, Area, Median Household Income, Cost of Living Index, Clustering of Black Neighborhoods, Concentration of Black Residences, and Black Share of College Attendees).

Standard errors are in parentheses.

* indicates significance at the 10% level, ** indicates significance at the 5% level, and
*** indicates significance at the 1% level.

Table 16: Change in Log Wages (for those Employed) Associated with a Ten Percent Change

(LARGE SAMPLE)

	In Transit Density	In Car Ownership
Entire Population	.0002	.0102
Low Education	-.0010	.0080
High Education	.0008	.0123

Table 17: Probability of Employment
By Level of Education,
with Car-Transit Interaction Term
(SMALL SAMPLE)

	All		Low Education		High Education	
Transit Density	.1039		.1508		.0281	
	(.0796)		(.1088)		(.1060)	
Car Owner	.1932	***	.2229	***	.1328	***
	(.0142)		(.0204)		(.0207)	
Transit Density* Car Owner	-.0169		.0019		.0358	
	(.0572)		(.0824)		(.0853)	
R^2	.2100		.2197		.1420	
N	10,546		5,102		5,441	
Hausman prob>χ^2	.2096		.8349		.2084	

All regressions are estimated as random effects models. All regressions include a constant, the set of personal characteristic variables (High Education, Female, Married, Black, Hispanic, Age, Age^2, Infant Present, and In School), a dummy for 1993, and the set of city characteristics (Population, Black Population, Area, Median Household Income, Cost of Living Index, Clustering of Black Neighborhoods, Concentration of Black Residences, and Black Share of College Attendees).

Standard errors are in parentheses.

* indicates significance at the 10% level.
** indicates significance at the 5% level.
*** indicates significance at the 1% level.

Table 18: Probability of Employment
By Level of Education,
with Car-Transit Interaction Term
(LARGE SAMPLE)

	All		Low Education		High Education	
Transit Density	.0624	**	.0971	**	.0350	
	(.0287)		(.0421)		(.0330)	
Car Owner	.1723	***	.2062	***	.1282	***
	(.0079)		(.0115)		(.0110)	
Transit Density*	.0022		.0015		.0062	
Car Owner	(.0040)		(.0061)		(.0055)	
R^2	.2031		.2089		.1428	
N	25,978		12,491		13,487	
Hausman prob>χ^2	.0053		.6945		.3561	

All regressions are estimated as random effects models. All regressions include a constant, the set of personal characteristic variables (High Education, Female, Married, Black, Hispanic, Age, Age^2, Infant Present, and In School), a dummy for 1993, and the set of city characteristics (Population, Black Population, Area, Median Household Income, Cost of Living Index, Clustering of Black Neighborhoods, Concentration of Black Residences, and Black Share of College Attendees).

Standard errors are in parentheses.

* indicates significance at the 10% level.
** indicates significance at the 5% level.
*** indicates significance at the 1% level.

Table 19: Probability of Employment

Effects of Transit by Mode

(SMALL SAMPLE)

	Without Education Interactions		With Education Interactions	
Bus Route Density	.0888		.1711	**
	(.0709)		(.0803)	
Commuter Rail Density	-14.1408		-15.4475	
	(20.1815)		(24.7873)	
Light Rail Density	.7723		-.5666	
	(1.6309)		(1.8737)	
Vanpool Density	2.3445		5.2953	**
	(1.8350)		(2.2447)	
Car Owner	.1903	***	.2340	***
	(.0104)		(.0128)	
Bus Route Density* High Education	--		-.1446	***
			(.0555)	
Commuter Rail Density* High Education	--		5.664	
			(30.3064)	
Light Rail Density * High Education	--		2.4505	*
			(1.3126)	
Vanpool Density * High Education	--		-5.5833	**
			(2.2521)	
Car Owner* High Education	--		-.1036	***
			(.0180)	
R^2	.2103		.2139	
N	10,543		10,543	
Hausman prob>χ^2	.1849		.7122	

Both models are estimated as random effects models. Both regressions include a constant, the set of personal characteristic variables (High Education, Female, Married, Black, Hispanic, Age, Age^2, Infant Present, and In School), a dummy for 1993, and the set of city characteristics (Population, Black Population, Area, Median Household Income, Cost of Living Index, Clustering of Black Neighborhoods, Concentration of Black Residences, and Black Share of College Attendees).

Standard errors are in parentheses.

* indicates significance at the 10% level.
** indicates significance at the 5% level.
*** indicates significance at the 1% level.

Table 20: Probability of Employment

Effects of Transit by Mode

(LARGE SAMPLE)

	Without Education Interactions	With Education Interactions
Bus Route Density	.0387	.0428
	(.0368)	(.0407)
Commuter Rail Density	.6044	.5728
	(.4330)	(.4775)
Light Rail Density	-.2463	-.3302
	(.2944)	(.3484)
Vanpool Density	-.0849	.0186
	(.2678)	(.3260)
Car Owner	.1747	.2158 ***
	(.0065)	(.0083)
Bus Route Density*		-.0033
High Education	--	(.0206)
Commuter Rail Density*		.0150
High Education	--	(.2352)
Light Rail Density *		.1734
High Education	--	(.2850)
Vanpool Density *		-.2099
High Education	--	(.2791)
Car Owner*		-.0888 ***
High Education	--	(.0111)
R^2	.2035	.2054
N	25,978	25,978
Hausman prob>χ^2	.0365	.3254

Both models are estimated as random effects models. Both regressions include a constant, the set of personal characteristic variables (High Education, Female, Married, Black, Hispanic, Age, Age^2, Infant Present, and In School), a dummy for 1993, and the set of city characteristics (Population, Black Population, Area, Median Household Income, Cost of Living Index, Clustering of Black Neighborhoods, Concentration of Black Residences, and Black Share of College Attendees).

Standard errors are in parentheses.

* indicates significance at the 10% level.
** indicates significance at the 5% level.
*** indicates significance at the 1% level.

Table 21:
Comparison of the Percent Effect on the Probability of Employment of a Ten Percent Change in Transit Density Using Two Different Measures
(SMALL SAMPLE)

	$\frac{TransitMiles}{Area^{1/2}}$	$\frac{TransitMiles}{Area}$
Entire Population	0.16	0.07
Low Education	0.27	0.15
High Education	0.07	0.00

Table 22:
Comparison of the Percent Effect on the Probability of Employment of a Ten Percent Change in Transit Density Using Two Different Measures
(LARGE SAMPLE)

	$\frac{TransitMiles}{Area^{1/2}}$	$\frac{TransitMiles}{Area}$
Entire Population	0.61	0.39
Low Education	0.63	0.41
High Education	0.61	0.38