Commutes, Neighborhood Effects, and Earnings:  
An Analysis of Racial Discrimination and  
Compensating Differentials*

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Recent “tester” studies indicate that minority workers face restricted residential  
and employment opportunities because of racial discrimination in housing and  
labor markets. These restrictions may create a spatial mismatch between where  
urban minorities reside and where metropolitan area jobs are located, resulting in  
reduced proximity of minority workers to jobs. Prior studies of racial discrimination  
and urban spatial mismatch, however, have paid little attention to the possibility  
that differences in employment commutes may be partially offset by compensating  
variations in neighborhood amenities, quality-adjusted house prices, and earnings.  
Such effects could help to mitigate the impact of discrimination on minority  
workers.

Using a unique subset of the 1985 and 1989 American Housing Surveys, we  
estimate a fixed effects commute time model that controls for quality-adjusted  
house prices, neighborhood amenities, and earnings. Results indicate that although  
blacks have longer commutes than comparably skilled white and Asian workers,  
roughly one-third of the estimated difference is offset by neighborhood amenity  
and housing price differentials. However, even after controlling for neighborhood

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fixed effects and earnings, educated black workers have significantly longer com-
mutes than comparably skilled Asian and white workers. Additional findings
indicate that regardless of race, household mobility is an important mechanism
through which the market attains a spatial equilibrium, providing further support
for arguments that restricted proximity to residential opportunities and jobs
reduces the economic welfare of minority households. © 1996 Academic Press, Inc.

I. INTRODUCTION

Despite ongoing efforts to enforce federal fair housing legislation,
recent “tester” studies have provided convincing evidence that discrimina-
tion continues to restrict minority access to certain residential neighbor-
hoods (e.g., Yinger [30, 31], Turner [29]). Such evidence is especially
troubling given long-standing arguments that restricted minority residen-
tial opportunities may adversely affect minority employment because of an
urban “spatial mismatch” between where minority workers reside and
where metropolitan area jobs are located. Nearly 30 years ago, for exam-
ple, Kain [16] suggested that housing market discrimination in suburban
areas of Chicago and Detroit reduced minority access to increasingly
important suburban employment sites in those cities.2

While housing market discrimination almost certainly reduces the econ-
omic welfare of minority families, the magnitude of that effect is less
clear. In particular, much of the spatial mismatch literature appears to
have overlooked fundamental lessons from urban economic theory which
suggest that price adjustments could mitigate the adverse welfare effects
stemming from reduced minority access to jobs. In fact, because commut-
ing is costly, households choose where to live based in part on proximity to
their place of employment. For that reason, with competitive markets,
house prices and wage rates should adjust to compensate workers for
differential access to metropolitan area employment centers (e.g., Mills
and Hamilton [22], Brueckner [3], Henderson [13], and Hamilton [11]). In
addition, households choose where to live based in part on preferences for
local amenities (e.g., Tiebout [26], Hamilton [12], and Epple and Romer
[6]). Accordingly, house prices and wage rates should also adjust in
response to local amenity and fiscal differentials (e.g., Roback [23, 24],
Blomquist et al. [2], Gyourko and Tracy [9, 10]). Together, these principles
imply that with competitive markets, differences in proximity to employ-
ment centers should be offset by compensating variations in earnings,
neighborhood amenities, and quality-adjusted house prices. An important

1 Note that tester studies have also recently documented discrimination in labor markets as
well (e.g., Kenney and Wissoker [20] and Turner et al. [28]).
2 Since Kain’s initial work, numerous subsequent studies have sought to test the spatial
mismatch hypothesis and evaluate its policy implications. See Kain [17] for a recent review of
the spatial mismatch literature.
Implication of that argument is that compensating variations should be taken into account when the welfare effects of racial differences in proximity to jobs are analyzed. Nevertheless, that point has received almost no attention in the spatial mismatch literature.\(^3\)

Consider, for example, a white worker and a minority worker with different length commutes, but who otherwise earn the same wage and face equivalent local amenities and house prices. Assume that the minority worker has the longer commute. Then the minority worker receives a less valuable compensation package, where compensation comprises earnings, quality-adjusted house prices, a basket of neighborhood amenities, and commute time. Over time, with competitive markets and sufficiently low moving costs, undercompensated minority workers should move, change jobs, or do both, causing wage rates and house prices to adjust until a new spatial equilibrium is attained. Thus, in long-run equilibrium, with competitive markets, minorities should be fully compensated for observed differences in proximity to employment relative to majority white workers. On the other hand, if discriminatory barriers are sufficiently pronounced to render some markets less than fully competitive, then minority workers may not be fully compensated for reduced proximity to jobs. Under those conditions, discrimination would result in a loss of welfare for minority workers.

This paper revisits the spatial mismatch question by empirically examining the degree to which differences in proximity to employment across workers is offset by compensating variations in quality-adjusted house prices, local amenities, and wage rates. To conduct our analysis we exploit certain unique features of the 1985 and 1989 American Housing Surveys (AHS) that enable us to group households into different neighborhoods.\(^4\) Panel data methods are then used to estimate a commute time equation that controls for neighborhood fixed effects (such as the quality-adjusted price of housing and local amenities), earnings, and other household attributes. An additional feature of our analysis is that we impose no restrictions on where a given household lives and works, which greatly increases the generality and, therefore, the robustness of our results.

Findings indicate that although blacks have longer commutes than comparably skilled white and Asian workers, roughly one-third of the...

\(^3\) Indeed, Kain [17] notes that most spatial mismatch studies do not adequately control for the links between housing and labor markets, particularly with regard to the degree to which house prices or wages adjust to compensate minority workers for reduced proximity to jobs. An exception to Kain’s critique is Zax [33]. However, that research is limited by a lack of controls for quality-adjusted house prices and neighborhood amenities. See also Kasarda [18, 19], Zax and Kain [34, 35], and Zax [32].

\(^4\) In our data, a neighborhood is defined as a given urban household and that household’s 10 closest neighbors. Additional detail on the data is provided later in the paper.
estimated difference is offset through neighborhood amenity and housing price differentials. However, even after controlling for neighborhood fixed effects and earnings, black workers with a high school degree or some college education still have significantly longer commutes than those of comparably skilled Asian and white workers. This result supports previous claims that black workers suffer adverse economic effects because of restrictions on housing and labor market locations. On a more optimistic note, the more onerous commute burden of black workers diminishes with educational attainment. This finding supports arguments that education helps to break down racial barriers, or at least reduces the impact of racial barriers on household welfare.

Further analysis of the link between commute compensation and household mobility suggests that regardless of race, families are more likely to move if they are undercompensated for their employment commutes in a nonsystematic or idiosyncratic manner, as measured by the error term in the commute equation. Hence, families are more likely to move when welfare-improving opportunities are available, consistent with arguments that household mobility is an important mechanism through which the market attains a spatial equilibrium. In contrast, we also find that black families are less likely to move despite systematic undercompensation for their commutes. Such findings suggest that undercompensation of black employment commutes reflects persistent phenomena, such as housing or labor market discrimination, which are not necessarily ameliorated through household moves.5

To clarify these and other results the paper is organized as follows. The following section describes the theoretical underpinnings of the commute time and household mobility analysis. Section III presents the econometric model and discusses estimation procedures. Section IV describes the data and variables. The final two sections of the paper present estimation results and concluding remarks.

II. THEORETICAL MODEL

Household utility (V) is given by the sum of a systematic (V) and an idiosyncratic (φ) component,

$$v_{ij} = V(g_{ij}, h_{ij}, a_{ij}) + \phi_i, \quad (2.1)$$

5 Housing market discrimination may have measurable effects on minority economic welfare beyond those associated with the out-of-pocket and opportunity costs of longer commutes. For instance, restricted proximity to jobs may result in reduced knowledge of employment opportunities and/or higher housing and employment search costs on minorities. In addition, labor market discrimination could affect the willingness of employers to make job offers to minority workers for any given market wage. While such effects are important, this paper emphasizes the degree to which proximity to employment is offset by equilibrium adjustments in quality-adjusted house prices and wage rates, apart from the impact of proximity to jobs on the propensity of minority workers to obtain employment.
where $V$ increases with nonhousing consumption ($g_{ij}$), housing services ($h_{ij}$), and neighborhood amenities ($a_j$), ($V_1 > 0$, $V_2 > 0$, $V_3 > 0$) at a diminishing rate ($V_{11} < 0$, $V_{22} < 0$, $V_{33} < 0$), while $\phi_i$ is unforecastable with mean zero and finite variance. To simplify exposition, a neighborhood is defined as a spatial concentration of households that face the same set of location-specific attributes and amenities. Notationally, neighborhood-specific variables are subscripted by $j$, while household-specific variables are subscripted by $i$. Variables that are sensitive to both neighborhood and household characteristics are subscripted by $i$ and $j$.

Each worker inelastically supplies one unit of labor. All labor markets are competitive, and a given employer varies wage rates across workers only in response to differences in endowment that affect the worker's skill level. However, employers in different locations are free to offer different wages to similarly skilled workers. Accordingly, wage rates are given by $y_{ij} = y_j(m_i)$, which says that for a given level of endowment, $m_i$, wage rates can vary with the worker's location.\(^6\)

The household's budget constraint is expressed as

$$y_j(m_i) = g_{ij} + p_j h_{ij} + c(y_j(m_i)) \cdot t(D_{ij}, s_j(m_i)).$$  \hspace{1cm} (2.2)

Observe that the price of nonhousing goods ($g$) is normalized to 1. Moreover, as with amenities, quality-adjusted house prices within a given neighborhood ($p_j$) are constant across households and are subscripted only by $j$. Commute times ($t_{ij}$) increase with distance of commute ($D_{ij}$) but decrease with travel speed ($s_{ij}$). In addition, travel speed varies across households based on differences in endowment ($m_i$) that affect access to vehicles (and modal choice). Travel speed also varies with the household's location since some areas are more congested than others. Finally, unit commuting costs ($c_{ij}$) increase with the worker's wage rate as the opportunity cost of commute time goes up.

We adopt an open city, long-run model with families mobile both within and across cities. Families choose their residential and employment locations, along with $g_{ij}$ and $h_{ij}$, to maximize utility. Hence, in equilibrium, identically endowed households receive equal expected utility regardless of location,

$$E[V(g_{ij}, h_{ij}, a_j) + \phi_i] = E[V(g_{ij}, h_{ij}, a_j)] = k(m_i),$$

for $i = 1, \ldots, n$ and $j = 1, \ldots, L$.  \hspace{1cm} (2.3)

\(^6\)Although recent studies suggest that wage gradients within cities are flat (e.g., Ihlandfeldt [15]), various arguments suggest that wage rates increase with city size (e.g., Mills and Hamilton [22]).
where $k$ is the expected level of utility and $E$ is the expectations operator. Inverting (2.3), suppressing the expectations operator for convenience, and solving for $g_{ij}$ gives

$$g_{ij} = G(h_{ij}, a_j, k(m_i)).$$  \hspace{1cm} (2.4)

where $G_h$ and $G_a$ (which denote $\partial G / \partial h_{ij}$ and $\partial G / \partial a_j$, respectively) are both negative and equal the marginal rates of substitution between $g_{ij}$ and $h_{ij}$, and between $g_{ij}$ and $a_j$, respectively, since utility is held constant in $G(\cdot)$. Substituting (2.4) into the budget constraint and solving for commute times yields

$$t(D_{ij}, s_j(m_i)) = \left[ y_j(m_i) - G(h_{ij}, a_j, k(m_i)) - p_j h_{ij} \right] / c_j(y_j(m_i)).$$  \hspace{1cm} (2.5)

Differentiating (2.5), it is clear that for a given level of endowment, $m_i$, which sets the worker's level of utility, equilibrium commutes fall with an increase in house prices ($\partial t_{ij}/\partial p_i = -h_{ij}/c_{ij} < 0$) but increase with improved neighborhood amenities ($\partial t_{ij}/\partial a_j = G_a/c_{ij} > 0$). The effect of wage rates on commutes is given by $\partial t_{ij}/\partial y_{ij} = 1/c_j - \partial c_j/\partial y_j(y_j - g_{ij} - p_j h_{ij})/c_j^2$, which has an ambiguous sign, a priori. However, assuming that the effect of wages on unit commuting costs ($\partial c_j/\partial y_j$) is small, in practice one would expect wages to have a positive net effect on equilibrium commutes. Finally, assuming that housing and nonhousing consumption ($h_{ij}$ and $g_{ij}$, respectively) are chosen in an optimal manner, one can readily show that differences in housing consumption across workers have no impact on commutes ($\partial t_{ij}/\partial h_{ij} = 0$), ceteris paribus.

Thus, for any given commute, equilibrium requires that compensating variations in earnings, neighborhood amenities, and quality-adjusted house prices allow workers to achieve their exogenous expected level of utility. By extension, if two equally endowed workers earn the same wage and face the same quality-adjusted housing prices, but live in different locations with different-valued amenities ($a_j$), then in equilibrium the worker in the

\footnotesize
\begin{itemize}
  \item[7] Not that in order to convince workers to accept longer commutes, employers must offer higher wages, which implies a positive relationship between wages and commutes. On the other hand, higher wages raise the opportunity cost of time, which has a dampening effect on commutes.
  \item[8] To establish this last point, note first that $G_a = -p_j$, which says that in equilibrium the marginal rate of substitution between $h_{ij}$ and $g_{ij}$ equals minus the price ratio. Consider next that $\partial t_{ij}/\partial h_{ij} = -(G_a + p_j)$. Substituting, it is apparent that with $h_{ij}$ and $g_{ij}$ optimally chosen, $\partial t_{ij}/\partial h_{ij}$ equals zero and differences in housing consumption across workers have no impact on commutes.
\end{itemize}
more attractive location (higher $a_j$) should have a longer commute.\footnote{Alternatively, if two workers have different commutes and enjoy different values for $y$, $p$, or $a$, \textit{a priori} it is not possible to determine which worker is more highly compensated. This point is particularly relevant to spatial mismatch studies that do not properly control for neighborhood effects and are presented in Gabriel and Rosenthal [7].} Similarly, if two equally skilled workers live next door to each other (facing the same values of $p_j$ and $a_j$) and earn the same wage, they should have the same expected length commute. Otherwise, the worker with the longer commute would be undercompensated relative to his neighbor and would have an incentive to move, change jobs, or do both. In contrast, the worker with the shorter commute would be overcompensated and would have an incentive to remain stationary. Over time, however, one would expect the overcompensated worker to experience an unfavorable net adjustment in wages and house prices as other similarly skilled workers sought a comparable combination of residential and job location. With mobile households, such adjustments will continue until all arbitrage opportunities have been exhausted, thus ensuring an efficient equilibrium matching of where families live and work.

III. ECONOMETRIC MODEL

Our empirical model is based on the equation

$$\log(t_{ij}) = a_j \beta_a + p_j \beta_p + y_{ij} \beta_y + s_{ij} \beta_s + r_i \beta_r + d_i \beta_d + e_{ij}. \quad (3.1)$$

where commute times are expressed in log linear terms for simplicity, $e_{ij}$ is a mean zero normally distributed error term with variance $\sigma^2$, and $a_j$, $p_j$, $y_{ij}$, $s_{ij}$, and $t_{ij}$ are defined as before. Household race is denoted by $r_i$. Accordingly, the null hypothesis that white and nonwhite households receive equal expected compensation for commutes is equivalent to a test of whether $\beta_r$ equals zero. Expression (3.1) also includes a variety of demographic variables ($d$), such as age, education, and marital status. If all markets are perfectly competitive one would expect zero coefficients on the elements of $d_i$ and $r_i$.\footnote{We also estimated the commute model including tenure status, number of rooms, and indicators for whether the home is in a single-family detached, single-family attached, or multifamily building. As shown in Section II, with optimal housing decisions, variation in housing consumption across families should not affect commutes. Findings from the augmented commute equation were consistent with that hypothesis and are presented in Gabriel and Rosenthal [7]. Nevertheless, given that housing consumption is a choice variable, we focus here on a more parsimonious commute model that excludes housing unit descriptors in order to ensure that simultaneity problems do not arise.}
Given that $R_i$ and worker race ($r_i$) may be highly correlated, it is useful to highlight their different effects on commutes by rewriting (3.1) as

$$\log(t_{ij}) = a_j \beta_a + p_j \beta_p + y_{ij} \beta_y + s_{ij} \beta_s + r_i \beta_r + R_i \beta_R + d_i \beta_d + e_{ij},$$

(3.2)

where $R_i$ has been split out from $a_i$. Suppose now that predominantly black neighborhoods are located further away from employment centers than integrated or white neighborhoods (as argued in the spatial mismatch literature). Then individuals that live in black neighborhoods would incur longer commutes by an amount governed by $\beta_R$, ceteris paribus. Such effects are distinct from the impact of the worker's race on commutes $\beta_r$. Although it would be desirable to estimate $\beta_R$, our data do not allow us to do so. Instead, a principal goal of this study is to obtain an unbiased and consistent estimate of $\beta_r$ as defined by Eq. (3.2).

The key to our empirical approach is to recognize that $a_i$, $p_j$, and $R_i$ are all neighborhood-specific effects. Including dummy variables for each of the neighborhoods yields

$$\log(t_{ij}) = \gamma_j + y_{ij} \beta_y + s_{ij} \beta_s + r_i \beta_r + d_i \beta_d + e_{ij},$$

(3.3)

where $\gamma_j$ represents the neighborhood fixed effects. Note that all neighborhood-specific variables drop out of the model. This is convenient since one could never specify the complete vector of neighborhood amenities or obtain perfectly accurate measures of quality-adjusted house prices.

Two additional complications arise in estimating (3.3). First, our theory pertains most closely to individuals that earn positive income at a fixed job site away from the home. For that reason, controlling for sample selection effects, we restricted the sample based on two criteria: the household head must be employed and the household head's job must be located at a fixed

\[11\] In contrast, much of the spatial mismatch literature has confounded the effects of neighborhood racial composition and household race on access to employment by failing to control for both $r_i$ and $R_i$.

\[12\] Note that if the assumptions underlying the monocentric urban model held, it would not be possible to estimate the coefficient on income in (3.3). In particular, if all employment is in the downtown and all land is homogeneous, with additional mild restrictions the bid-rent function for high income housing is steeper than the bid-rent function for low income housing (e.g., Mills and Hamilton [22]). Hence, those functions would intersect at only one distance from the downtown and most urban neighborhoods would exhibit little variation in household income which would preclude identification of $\beta_r$. Note, however, that both our theoretical and empirical models allow for the possibility that jobs are located throughout the metropolitan area, and that neighborhood amenities vary with location. Under those conditions, and assuming heterogeneous preferences for locational amenities, most neighborhoods would display considerable variation in income enabling us to identify $\beta_r$. Note, however, that both our theoretical and empirical models allow for the possibility that jobs are located throughout the metropolitan area, and that neighborhood amenities vary with location. Under those conditions, and assuming heterogeneous preferences for locational amenities, most neighborhoods would display considerable variation in income enabling us to identify $\beta_r$. Note, however, that both our theoretical and empirical models allow for the possibility that jobs are located throughout the metropolitan area, and that neighborhood amenities vary with location. Under those conditions, and assuming heterogeneous preferences for locational amenities, most neighborhoods would display considerable variation in income enabling us to identify $\beta_r$. Note, however, that both our theoretical and empirical models allow for the possibility that jobs are located throughout the metropolitan area, and that neighborhood amenities vary with location. Under those conditions, and assuming heterogeneous preferences for locational amenities, most neighborhoods would display considerable variation in income enabling us to identify $\beta_r$. Note, however, that both our theoretical and empirical models allow for the possibility that jobs are located throughout the metropolitan area, and that neighborhood amenities vary with location. Under those conditions, and assuming heterogeneous preferences for locational amenities, most neighborhoods would display considerable variation in income enabling us to identify $\beta_r$. Note, however, that both our theoretical and empirical models allow for the possibility that jobs are located throughout the metropolitan area, and that neighborhood amenities vary with location. Under those conditions, and assuming heterogeneous preferences for locational amenities, most neighborhoods would display considerable variation in income enabling us to identify $\beta_r$. Note, however, that both our theoretical and empirical models allow for the possibility that jobs are located throughout the metropolitan area, and that neighborhood amenities vary with location. Under those conditions, and assuming heterogeneous preferences for locational amenities, most neighborhoods would display considerable variation in income enabling us to identify $\beta_r$. Note, however, that both our theoretical and empirical models allow for the possibility that jobs are located throughout the metropolitan area, and that neighborhood amenities vary with location. Under those conditions, and assuming heterogeneous preferences for locational amenities, most neighborhoods would display considerable variation in income enabling us to identify $\beta_r$. Note, however, that both our theoretical and empirical models allow for the possibility that jobs are located throughout the metropolitan area, and that neighborhood amenities vary with location. Under those conditions, and assuming heterogeneous preferences for locational amenities, most neighborhoods would display considerable variation in income enabling us to identify $\beta_r$.
site away from home. Second, as described earlier, earnings and commute times are both part of the worker's equilibrium compensation package, which suggests that earnings are endogenous. Accordingly, (3.3) was estimated by two-stage least squares (2SLS) to control for possible simultaneity between earnings and commute times.

**Household Mobility and Commute Compensation**

A final empirical question concerns the link between commute compensation and household mobility. Suppose, for example, that the regressors in (3.3) capture all systematic differences in employment commutes. Then workers with a positive error term ($e_i > 0$) would be undercompensated for their commutes, while workers with a negative error term ($e_i < 0$) would be overcompensated. Among overcompensated workers, a small

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13 Two-step methods were used to control for sample selection effects. In the first stage a censored bivariate probit model was estimated that controls for the fact that job location is observed only for employed individuals. Mills ratio-type terms were then formed and included in the second-stage commute equation which was estimated by 2SLS as described below. See Maddala [21] or Tunali [27] for details on models with multiple selection criteria with censoring.

14 In principle, the fixed effects in (3.3) could also be correlated with the error term since $a_i$ and $p_i$ are part of the worker's equilibrium compensation package. This issue, however, is unlikely to affect our estimates of the slope coefficients for the following reason. Recall that for the fixed effect specification in (3.3), one can obtain identical estimates of the slope coefficients by differencing off the neighborhood means from all of the variables in the model and estimating the resulting equation by OLS (e.g., Hsiao [14]). The OLS estimates of the slope coefficients can then be written as

$$b_{OLS} = (x^*x^*)^{-1}x^*y^* = \beta_x + (x^*x^*)^{-1}x^*e^*,$$

where * indicates that the neighborhood means have been subtracted off, $x$ stands for all of the slope variables in the model, and $y$ is the dependent variable ($\log t$). Assuming that $x$ is independent of $e$ and manipulating, one can readily show that $b_{OLS}$ is consistent provided that

$$n^{-1} \sum_{i=1}^n x_i \pi_n \to 0, \quad \text{as } n \to \infty,$$

where $x_i$ and $\pi_n$ are the neighborhood means for individual $i$ living in neighborhood $j$ [see Gabriel and Rosenthal [8] for details]. This condition highlights that the fixed effect estimator (which is based on within neighborhood variation in the data) yields consistent estimates of the slope coefficients provided that households do not sort themselves across neighborhoods on the basis of unobserved human capital characteristics as reflected in the error term. In that case, the neighborhood clusters will not suffer from sample selection effects, and $\pi_n$ will be approximately zero for all neighborhoods. Given that our model controls for earnings—and hence, the propensity of families to sort across neighborhoods on the basis of income—it is difficult to imagine a scenario whereby families would further sort across neighborhoods on the basis of $e_i$. 

increase in $e_i$ should have no effect on household mobility since those workers would still be getting a “good deal.” In contrast, undercompensation for commutes can be ameliorated through a move to a new location, a change of jobs, or both, provided that the cost of moving or changing jobs is sufficiently small. Among undercompensated workers, therefore, the likelihood of moving to a new location should increase with $e_i$.

To evaluate these arguments a mobility equation is specified as

$$I_{ij} = \delta_i + y_{ij} + \theta_y + s_i + \theta_s + r_i + \theta_r + d_i + \theta_d + z_{ij} + \theta_z + N_{ij}e_{ij} + P_{ij}e_{ij} + o_{ij},$$

(3.4)

where $I_{ij}$ is a latent index underlying the discrete decision to move, $o_{ij}$ is the corresponding error term, and households move when $I_{ij}$ exceeds zero. Note that (3.4) includes all of the regressors in the commute model as described by (3.3) where $\delta_i$ now stands for the neighborhood fixed effects. In addition, the mobility model includes $z_{ij}$ which represents various housing attributes since the transaction costs of moving are considerably larger for owner-occupiers and occupants of large homes. Also included in (3.4) are two special variables, $N_{ij}e_{ij}$ and $P_{ij}e_{ij}$, where $e_i$ is the error term from the commute model (3.3), and $N_{ij}$ and $P_{ij}$ equal 1 if $e_{ij}$ is positive or negative, respectively, and 0 otherwise. Given these variable definitions, evidence that $\theta_{ne}$ equals zero and $\theta_{pe}$ is positive would be consistent with the theory above.

Under plausible assumptions for our sample, consistent estimates of (3.4) can be obtained using a fixed effect linear probability model that controls for neighborhood effects with dummy variables as in the commute model. Moreover, since by construction $e_i$ is orthogonal to all of the regressors in the model except $z_{ij}$, a simple probit model would also likely yield consistent estimates of $\theta_{pe}$ and $\theta_{ne}$ even if the neighborhood effects

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15 Although housing attributes were omitted from the commute model to avoid simultaneity problems (as previously noted), such problems are likely to be minimal in the mobility model since households choose to move conditional on the home in which they currently reside.

16 If $e_i$ also reflects measurement error in the regressors that is uncorrelated with household mobility, then estimates of $\theta_{ne}$ and $\theta_{pe}$ would be biased toward zero. Hence, evidence that $\theta_{ne}$ equals zero would not necessarily confirm the link between commute compensation and household mobility (although evidence that $\theta_{ne}$ differs from zero would refute the theory). On the other hand, evidence that $\theta_{pe}$ is positive clearly supports the theory above since measurement error causes us to underestimate $\theta_{pe}$.

17 For discrete problems in which most of the probabilities lie between 0.3 and 0.7, a linear probability model provides a good approximation of the slope coefficients (e.g., Amemiya [1]). Given that 58% of our sample moves (3.4) can be estimated using a linear probability model.
were ignored. However, such a model would likely produce inconsistent estimates of the other coefficients in (3.4) and was not preferred for that reason.

IV. DATA AND VARIABLES

Data for the study are drawn from a unique subset of the 1985 and 1989 national core files of the American Housing Survey (AHS). In 1985, the AHS selected 680 urban housing units at random from the overall core file of roughly 55,000 housing units. For each selected housing unit, the AHS then conducted a full survey of up to 10 of that unit’s “closest neighbors.” Given the dense pattern of development in most urban areas, we assume that each of the 680 housing clusters is a distinct neighborhood in which member households face the same locational attributes and amenities.

A second special feature of the AHS concerns the longitudinal structure of the neighborhood data. In 1989, the AHS resurveyed each of the neighborhood housing units. By linking these data with the 1985 surveys, it was possible to determine which families in the neighborhood clusters had moved between 1985 and 1989. That information allowed us to estimate the household move equation.

Unfortunately, the AHS only surveyed commute times in 1985, forcing us to limit our analysis of household commutes to that year. From those data we omit observations that could not be reliably linked to the 1989 data, and observations with household heads that are other than white, black, or Asian. The resulting sample totaled 6162 households. Focusing on labor force participants further reduced the sample by nearly 35% to 4117 families, consistent with the national household labor force participation rate which is roughly 65%. Imposing the final restriction that workers report to a fixed job site away from home left 3481 households.

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18 Adjusting for a scale factor (e.g., Amemiya [1]), estimates of \( \beta_e \) and \( \eta_e \) from such a model were nearly identical to those from the fixed effect linear probability model presented in Table 2 (see Gabriel and Rosenthal [7] for probit model results).

19 In order to obtain consistent estimates of the other slope coefficients in (3.4) one must control for neighborhood effects that may be correlated with household attributes. However, fixed effect probit models typically yield biased estimates of the coefficients on such slope variables (e.g., Hsiao [14] or Chamberlain [4, 5]). Moreover, conditional logit (e.g., Chamberlain [4]) is not computationally practical here because one would have to estimate the probabilities associated with all permutations of household actions (move/don’t move) within individual neighborhoods that yield the observed number of moves for each neighborhood. Given that our neighborhoods have up to 11 families, the number of such probabilities would be prohibitively large.

20 The ability to follow housing units over time (as opposed to households) facilitates analysis of household mobility because there is very little sample attrition that might be correlated with household moves.

21 As in the AHS, white Hispanics are coded as white and black Hispanics are coded black.
spread over 628 neighborhoods. Variable definitions and summary statistics for these data are contained in the Appendix.

As discussed earlier, the commute model includes a number of demographic descriptors. These variables enable us to test the model in Section II because if all markets are competitive, demographic characteristics should have little impact on commutes after controlling for neighborhood fixed effects and earnings. For household descriptors we include education of the household head based on a series of dichotomous variables: college degree or more (COLGRAD), high school degree or up to three years of college (HSGRAD), and less than a high school degree (LTHS). Also included are the household head’s age (AGE), sex (MALE), number of children under 18 years (CHILDREN), marital status (MARRIED), and whether a family member other than the head works (OtherWRKR).

As in Section II, commute times are expected to be inversely related to the speed of urban travel. Given the pervasive automotive bias in the U.S. urban transport system, we proxy travel speed by access to a vehicle as follows. Three dichotomous variables are constructed based on whether the household has access to one or more vehicles per adult (VEHICLE1), more than zero but less than one vehicle per adult (VEHICLE01), and zero vehicles per adult (VEHICLE0). In all of the models, VEHICLE0 is the omitted category.

Race variables are included in the model (BLACK, ASIAN) to allow for differences in commutes across black, Asian, and white workers. In addition, a vector of dichotomous variables for black households (BCOLGRAD, BHSGRAD, and BLTHS, respectively) was constructed to test whether racial differences in commute compensation vary with educational attainment.

Estimating earnings (LogEARN) as part of a 2SLS model requires instruments to ensure identification. Fortunately, under the null hypothesis that differences in commutes are offset by compensating variations in earnings and neighborhood effects, commute times should not be sensitive to demographic descriptors. Hence, all of the variables in the commute model were used in the earnings regression. In addition, the earnings

22 Controlling for vehicle access is important when evaluating questions related to spatial mismatch. In 1968, for example, the Kerner commission report suggested that inner city black households may face reduced access to suburban jobs because of low black auto-ownership rates that make reverse commutes prohibitively slow. See Kain [17] for additional details. Note, also, that in principle, vehicle access could be endogenous to commute time. In practice, however, families own vehicles for many reasons other than for commuting to work. As such, the VEHICLE variables are likely to be approximately exogenous. Nevertheless, as a robustness check, we also estimated the commute model without the VEHICLE variables. Estimates from that model were similar to those reported in Table 1 where the VEHICLE variables are included.
regression included a number of variables related to household income and wealth that have no role in the commute equation. Finally, the same variables used in the earnings regression were used to estimate the bivariate probit model of whether individuals work outside of the home (see Gabriel and Rosenthal [7] for results from the probit and earnings analyses).

V. ESTIMATION RESULTS

Table 1 presents results from the commute time models. Note that some of the models control for neighborhood fixed effects, while others reflect constrained specifications that omit the neighborhood dummy variables. In all cases, estimates were obtained by 2SLS in which earnings were treated as endogenous. Columns 1 and 2 highlight the overall impact of worker race on commute times, controlling for neighborhood effects and ignoring neighborhood effects, respectively. Columns 3 and 4 are analogous to columns 1 and 2 but allow the effect of BLACK to differ with the household head’s education. In all cases, we control for the two forms of sample selection as described earlier by including Mills ratio-type terms for whether the individual is employed (ΛEmployed) and if so, whether the individual works away from the home (ΛAway). Note, however, that the low t-ratios on ΛEmployed and ΛAway suggest that any selection effects are slight.

Comparing the relevant columns of Table 1, F-tests soundly reject the constrained specification (that ignores neighborhood location) in favor of the fixed effects model. In addition, failing to control for neighborhood fixed effects clearly leads to biased estimates given the large differences between the estimated coefficients of the fixed effects and constrained models. These results confirm that the fixed effects differ significantly across neighborhoods, and that unobserved neighborhood amenities and quality-adjusted house prices are correlated with the included regressors. Although these results are not surprising, they reinforce arguments that failing to control for neighborhood effects may lead to potentially misleading assessments of the effects of discrimination on employed minority workers.

In general, the results from the fixed effects models in columns 1 and 3 in Table 1 are consistent with the theory presented earlier. In particular, LogEARN has a positive effect on commutes, consistent with arguments

23 These variables include income other than the household head’s earnings in logs, whether the family receives social security, interest income, rental income, welfare payments, or food stamps, whether the family has any savings, and whether the family owns a home other than the primary residence.

24 Table 1 was also estimated based on an error components specification. However, Hausman tests soundly rejected the error components model in favor of the fixed effects model.
### TABLE 1
Commute Time Models with and without Neighborhood Effects

<table>
<thead>
<tr>
<th></th>
<th>Race alone</th>
<th></th>
<th>Race by education</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Control for neighborhood effects</td>
<td>Ignore neighborhood effects</td>
<td>Control for neighborhood effects</td>
<td>Ignore neighborhood effects</td>
</tr>
<tr>
<td><strong>CONSTANT</strong></td>
<td>1.09521</td>
<td>(2.087)</td>
<td>1.02277</td>
<td>(1.956)</td>
</tr>
<tr>
<td><strong>LogEARN</strong></td>
<td>0.10144</td>
<td>(1.276)</td>
<td>0.08009</td>
<td>(1.004)</td>
</tr>
<tr>
<td></td>
<td>0.18323</td>
<td>(3.035)</td>
<td>0.18533</td>
<td>(3.072)</td>
</tr>
<tr>
<td><strong>COLGRAD</strong></td>
<td>0.16912</td>
<td>(3.508)</td>
<td>0.13185</td>
<td>(2.602)</td>
</tr>
<tr>
<td></td>
<td>0.06280</td>
<td>(1.152)</td>
<td>0.02549</td>
<td>(0.455)</td>
</tr>
<tr>
<td><strong>HSGRAD</strong></td>
<td>0.12862</td>
<td>(3.330)</td>
<td>0.08082</td>
<td>(1.931)</td>
</tr>
<tr>
<td></td>
<td>0.09899</td>
<td>(2.460)</td>
<td>0.05216</td>
<td>(1.222)</td>
</tr>
<tr>
<td><strong>BLACK</strong></td>
<td>0.13797</td>
<td>(2.314)</td>
<td>0.23225</td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.23225</td>
<td>(5.721)</td>
<td>0.21135</td>
<td></td>
</tr>
<tr>
<td><strong>BCOLGRAD</strong></td>
<td>—</td>
<td></td>
<td>0.14885</td>
<td></td>
</tr>
<tr>
<td></td>
<td>—</td>
<td></td>
<td>(1.557)</td>
<td></td>
</tr>
<tr>
<td><strong>BHSGRAD</strong></td>
<td>—</td>
<td></td>
<td>0.22352</td>
<td></td>
</tr>
<tr>
<td></td>
<td>—</td>
<td></td>
<td>(3.251)</td>
<td></td>
</tr>
<tr>
<td><strong>BLTHS</strong></td>
<td>—</td>
<td></td>
<td>0.11362</td>
<td></td>
</tr>
<tr>
<td></td>
<td>—</td>
<td></td>
<td>(1.044)</td>
<td></td>
</tr>
<tr>
<td><strong>ASIAN</strong></td>
<td>0.06295</td>
<td>(0.704)</td>
<td>0.08614</td>
<td>(0.961)</td>
</tr>
<tr>
<td></td>
<td>0.24824</td>
<td>(3.044)</td>
<td>0.25545</td>
<td>(3.134)</td>
</tr>
<tr>
<td><strong>AGE</strong></td>
<td>0.00145</td>
<td>(0.725)</td>
<td>0.00087</td>
<td>(2.166)</td>
</tr>
<tr>
<td></td>
<td>0.00087</td>
<td>(3.183)</td>
<td>0.00194</td>
<td>(3.345)</td>
</tr>
<tr>
<td><strong>MALE</strong></td>
<td>0.02595</td>
<td>(0.985)</td>
<td>0.04470</td>
<td>(1.310)</td>
</tr>
<tr>
<td></td>
<td>0.14540</td>
<td>(0.550)</td>
<td>0.16219</td>
<td>(0.685)</td>
</tr>
<tr>
<td><strong>MARRIED</strong></td>
<td>0.06314</td>
<td>(1.325)</td>
<td>0.08036</td>
<td>(2.588)</td>
</tr>
<tr>
<td></td>
<td>0.12378</td>
<td>(1.878)</td>
<td>0.13304</td>
<td>(4.236)</td>
</tr>
<tr>
<td><strong>OtherWRKR</strong></td>
<td>0.00099</td>
<td>(0.027)</td>
<td>0.02467</td>
<td>(0.655)</td>
</tr>
<tr>
<td></td>
<td>0.06112</td>
<td>(1.878)</td>
<td>0.08052</td>
<td>(2.436)</td>
</tr>
<tr>
<td><strong>CHILDREN</strong></td>
<td>0.01882</td>
<td>(1.592)</td>
<td>0.01746</td>
<td>(1.478)</td>
</tr>
<tr>
<td></td>
<td>0.01856</td>
<td>(1.553)</td>
<td>0.01787</td>
<td>(1.497)</td>
</tr>
<tr>
<td><strong>VEHICLE1</strong></td>
<td>0.34691</td>
<td>(4.949)</td>
<td>0.30338</td>
<td>(4.243)</td>
</tr>
<tr>
<td></td>
<td>0.40614</td>
<td>(6.355)</td>
<td>0.37949</td>
<td>(5.861)</td>
</tr>
<tr>
<td><strong>VEHICLE01</strong></td>
<td>—</td>
<td>(2.973)</td>
<td>0.22193</td>
<td>(2.907)</td>
</tr>
<tr>
<td></td>
<td>—</td>
<td>(3.466)</td>
<td>0.20146</td>
<td>(2.907)</td>
</tr>
<tr>
<td><strong>λA_Employed</strong></td>
<td>0.07491</td>
<td>(0.869)</td>
<td>0.02803</td>
<td>(0.298)</td>
</tr>
<tr>
<td></td>
<td>—</td>
<td>(0.677)</td>
<td>0.10831</td>
<td>(1.283)</td>
</tr>
<tr>
<td><strong>λA_Away</strong></td>
<td>0.11045</td>
<td>(0.442)</td>
<td>0.25847</td>
<td>(0.916)</td>
</tr>
<tr>
<td></td>
<td>0.43852</td>
<td>(2.108)</td>
<td>0.67978</td>
<td>(2.989)</td>
</tr>
<tr>
<td><strong>l_C_employed</strong></td>
<td>0.07491</td>
<td>(0.869)</td>
<td>0.02803</td>
<td>(0.298)</td>
</tr>
<tr>
<td></td>
<td>—</td>
<td>(0.677)</td>
<td>0.10831</td>
<td>(1.283)</td>
</tr>
<tr>
<td><strong>l_C_Away</strong></td>
<td>0.11045</td>
<td>(0.442)</td>
<td>0.25847</td>
<td>(0.916)</td>
</tr>
<tr>
<td></td>
<td>0.43852</td>
<td>(2.108)</td>
<td>0.67978</td>
<td>(2.989)</td>
</tr>
</tbody>
</table>

| N. observations     | 3481 3481 3481 3481          |
| N. neighborhoods    | 628   —   628   —           |
| Resid. SS           | 1313.7 1842.6 1309.5 1838.2 |
| $R^2$               | 0.324 0.055 0.326 0.057      |
| Std. error          | 0.681 0.728 0.681 0.727      |

*All models were estimated by two stage least squares (2SLS) in which LogEARN was treated as endogenous as described in the text. Numbers in parentheses are t-ratios.
that employers must offer higher wages to induce workers to accept longer
commutes, *ceteris paribus* (e.g., Mills and Hamilton [22] and Ihlanfeldt [15]).
Observe, also, that the VEHICLE access variables are negative and highly significant which confirms that driving to work reduces
commute times, reflecting the pervasive automotive bias of the U.S. urban
transportation system. Our theory also implies that if all markets are
perfectly competitive, household characteristics should have little effect on
the primary worker’s commute after controlling for neighborhood ameni-
ties, quality-adjusted house prices, and earnings. In that regard, note that
in columns 1 and 3 AGE, MALE, CHILD, and OtherWRKR are all
individually and jointly insignificant which provides support for the under-
lying hypothesis.

In contrast, commutes increase with education, as evidenced by the
positive and significant coefficients on COLGRAD and HSGRAD. How-
ever, skilled workers may receive considerable amounts of income in forms
that would not be reported as wage earnings (such as employer pension
contributions and the like). Under those conditions, education would proxy
unreported earnings and would be expected to have a positive effect on
commutes given the tradeoff between commutes and earnings discussed
earlier. Also, the positive and significant coefficient on marital status
(MARRIED) might reflect a more narrowly defined set of locational
preferences among married couples relative to single workers.

Turning to the race related variables, observe in column 1 that black
workers commute just under 14% longer, on average, than comparably
skilled white workers, even after controlling for neighborhood fixed effects.
These results are consistent with arguments that racial discrimination in household or workplace locations might result in longer commutes for minority workers, even after accounting for earnings, quality-adjusted house prices, and neighborhood amenities.

Additional findings in column 3, however, suggest that black commute premia differ markedly with the worker’s education. For example, blacks with a high school degree (BHSGRAD) incur roughly 22% longer commutes than their white (and Asian) counterparts. In contrast, blacks with a college degree or more (BCOLGRAD) incur a lesser commute premium (equal to roughly 15%) that is only marginally significant based on a 1-tailed test. Further, blacks with less than a high school degree do not have longer commutes given the negative and insignificant coefficient on BTHS. One explanation for this pattern of results is that unskilled jobs can be found throughout urban areas which would mitigate the impact of housing and labor market discrimination on unskilled black workers. In contrast, blacks with a high school degree may participate in a segment of the labor market characterized by a more limited geographic dispersion of jobs, leaving those workers more vulnerable to restrictions on residential and employment location choice. Higher education, however, may reduce the adverse effects of discrimination, which could account for the lesser commute premium of college-educated black workers.

Two further points should be noted in assessing the magnitude of the race effects. First, the 22% commute premium of black workers with a high school degree (BHSGRAD) translates into roughly 39 additional round trip commute hours per year, or about one week’s worth of work time. Second, when the neighborhood effects are ignored, the coefficients on BLACK (in column 2) and on BHSGRAD and BCOLGRAD (in column 4) are about one-third higher than those in the corresponding fixed effects specifications (columns 1 and 3, respectively). These results confirm that racial differences in employment commutes are at least partially offset by compensating variations in neighborhood specific qual-

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29 In contrast, there is little evidence of differences in commute compensation among white and Asian workers. Also, we should emphasize that the race coefficients are identified based on integrated neighborhoods. In our sample, 25% of the neighborhoods (or 163 neighborhoods) are integrated.

30 Note that in columns 3 and 4 the omitted education dummy variable corresponds to white and Asian households with less than a high school degree since LTHS is omitted but BTHS is included.

31 This estimate assumes that one-way commutes equal the sample mean of 21.6 minutes, and that individuals work 5 days per week for 48 weeks each year. Note, also, that the coefficient on BCOLGRAD translates into roughly 25.7 additional commute hours per year for black workers with a college degree or more.
COMMUTES AND COMPENSATING EFFECTS 77

TABLE 2
The Probability of Moving

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>t-ratio</th>
<th>Variable</th>
<th>Coefficient</th>
<th>t-ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>LogEARN</td>
<td>-0.013979</td>
<td>-1.14397</td>
<td>OtherWRKR</td>
<td>0.012463</td>
<td>0.71298</td>
</tr>
<tr>
<td>COLGRAD</td>
<td>0.004048</td>
<td>0.12376</td>
<td>CHILDREN</td>
<td>-0.001713</td>
<td>-0.21234</td>
</tr>
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<td>HSGRAD</td>
<td>-0.004753</td>
<td>-0.17016</td>
<td>VEHICLE1</td>
<td>0.008293</td>
<td>0.19605</td>
</tr>
<tr>
<td>BCOLGRAD</td>
<td>-0.106920</td>
<td>-1.70076</td>
<td>VEHICLE01</td>
<td>-0.002515</td>
<td>-0.05906</td>
</tr>
<tr>
<td>BHSGRAD</td>
<td>-0.018834</td>
<td>-0.42220</td>
<td>SFA</td>
<td>-0.041985</td>
<td>-0.62323</td>
</tr>
<tr>
<td>BLTHS</td>
<td>-0.071504</td>
<td>-1.02966</td>
<td>MF</td>
<td>0.008918</td>
<td>0.21271</td>
</tr>
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<td>ASIAN</td>
<td>0.031886</td>
<td>0.53666</td>
<td>OWN</td>
<td>-0.232940</td>
<td>-8.71853</td>
</tr>
<tr>
<td>AGE</td>
<td>-0.005826</td>
<td>-7.42410</td>
<td>ROOMS</td>
<td>-0.002477</td>
<td>-0.35047</td>
</tr>
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<td>MALE</td>
<td>-0.016912</td>
<td>-0.73342</td>
<td>EPos</td>
<td>0.051333</td>
<td>2.03974</td>
</tr>
<tr>
<td>MARRIED</td>
<td>-0.013764</td>
<td>-0.59156</td>
<td>ENeg</td>
<td>-0.021841</td>
<td>-0.92994</td>
</tr>
</tbody>
</table>

No. observations 3481
No. neighborhoods 628
Resid. SS 489.0
$R^2$ 0.425
Std. error 0.415

* Estimates based on a fixed effect linear probability model as described in the text.

ity-adjusted housing price and amenity differentials, consistent with arguments described at the outset of this paper.

Commute Compensation and Household Mobility

Table 2 presents estimates of the mobility model (3.4) based on the previously described fixed effect linear probability specification. Recall that the mobility model includes two key variables, $N_{e_t}$ and $P_{e_t}$, to facilitate evaluation of the link between commute compensation and household mobility. To simplify exposition, these variables are relabeled as $ENeg$ and $EPos$ in Table 2.

In Table 2, observe that the coefficient on $ENeg$ is small and insignificant while the coefficient on $EPos$ is larger in magnitude, positive, and significant. These results are consistent with earlier arguments that a small reduction in commute compensation should have little effect on the propensity of overcompensated workers to move, but should have a positive effect on the likelihood that undercompensated workers would move.32 Moreover, these results confirm that families are more likely to move

32 If some individuals value their time more highly than others, they would be more likely to move for any given excess commute. To test for such effects, we reran the mobility model three times and included interactive terms between $EPos$ and $ENeg$ with (i) earnings (LogEARN), (ii) education (COLGRAD, HSGRAD), and (iii) BLACK. In each case the added terms were individually and jointly insignificant.
when welfare-improving opportunities are available and that household mobility is an important mechanism through which the market attains a spatial equilibrium.

Given these findings, suppose that the systematic undercompensation of black employment commutes evidenced in 1985 was a temporary anomaly. One might then expect black households to demonstrate elevated mobility rates between 1985 and 1989. In contrast, black households were if anything less likely to move, as indicated by the negative and marginally significant coefficients on BLTHS, BHSGRAD, and BCOLGRAD. This result provides further support for arguments that the systematic undercompensation of black employment commutes may reflect persistent phenomena such as housing or labor market discrimination.33

VI. CONCLUSIONS

For nearly 30 years now, various analysts have argued that racial discrimination in the housing market adversely affects minority households by creating an urban “spatial mismatch” between where urban minorities live and where metropolitan area jobs are located. While the spatial mismatch literature has made many contributions, most studies ignore the possibility that house prices and wage rates adjust to at least partially compensate workers for differences in proximity to employment. To address that issue, this paper revisits the spatial mismatch question by analyzing the extent to which differences in employment commutes are offset by compensating variations in wages, quality-adjusted house prices, and neighborhood amenities.

Our analysis is based on an urban location model with perfectly competitive markets, in which the spatial equilibrium of households and jobs is such that equally skilled workers receive equal expected utility. Hence, in equilibrium, differences in household commutes are offset by compensating variations in earnings, neighborhood amenities, and quality-adjusted house prices. Moreover, that equilibrium is maintained, in part, through the ability of households to move when more attractive combinations of residential and employment locations are available. Given this framework, we argue that if minority households face exogenously imposed constraints on residential and employment location choice, then an inefficient matching of where those families live and where they work could result, causing household commutes to increase.

33 The remaining variables in the mobility models perform in a manner consistent with findings from other studies (e.g., Rosenthal [25]). Older households (AGE), for example, are less mobile, reflecting life-cycle effects that reduce the benefits from mobility with the individual’s age. Owner-occupiers (OWN) also are less mobile given the large transactions costs of buying and selling real estate.
Data for the analysis are drawn from a unique subset of the 1985 and 1989 American Housing Surveys that enables us to group households into different neighborhoods. A fixed effects commute time equation is then estimated that controls for neighborhood-specific variables, earnings, and other household attributes. Results indicate that although blacks have longer commutes than comparably skilled white and Asian workers, roughly one-third of the estimated difference is offset through neighborhood amenity and housing price differentials. However, even after controlling for neighborhood fixed effects and earnings, black workers with a high school degree commute roughly 22% longer (or approximately 39 additional commute hours each year) than comparably skilled Asian and white workers. On a more encouraging note, we also find that the longer commute of high school educated black workers declines with additional educational attainment, consistent with arguments that education helps to break down racial barriers, or at least reduces the adverse economic effects of such barriers.

Related analysis indicates that regardless of race, families are more likely to move if they are undercompensated for their employment commutes in a nonsystematic manner, as measured by the error term in the commute equation. This finding suggests that families tend to move when welfare improving opportunities are available, consistent with arguments that household mobility is an important mechanism through which the market attains a spatial equilibrium.

In contrast, we also find that black families are less likely to move despite systematic undercompensation for their commutes. This result further implies that the undercompensation of black employment commutes evidenced in 1985 is not a temporary aberration, but instead stems from persistent phenomena, such as housing or labor market discrimination, that restrict the residential and employment choice sets of black households. Such constraints are consistent with recent evidence of racial discrimination in housing and labor markets (e.g., Yinger [30, 31], Turner [29], Turner et al. [28], Kenney and Wissoker [20]). On a policy level, our findings point to a more vigorous enforcement of antidiscrimination laws in housing and labor markets so as to ameliorate the adverse effects of discrimination on minority households.

Finally, from a methodological perspective, we should emphasize that this is the first study to apply panel data methods to the 1985 and 1989 AHS neighborhood files. Those data, in conjunction with our empirical methods, allow us to control for quality-adjusted house prices and neighborhood characteristics in a manner that adds considerable strength to our analysis of race-related effects. As such, our approach is in contrast to the large number of studies in the housing and urban literatures—covering a wide range of topics—that base their analyses on an imprecise accounting
of quality-adjusted house prices and neighborhood amenities. Note also that the methods developed in this study could potentially be applied to other questions in which neighborhood characteristics and quality-adjusted house prices act as nuisance variables. In that regard, this paper demonstrates the value of household data that can be grouped into distinct neighborhoods. Agencies such as the U.S. Bureau of the Census should be encouraged to provide similar data in the future.

APPENDIX

Variable Definitions and Selected Summary Statistics

\textsc{Time} equals the commute time of the first wage earner in 1985.

\textsc{Move} equals 1 if the household moved between 1985 and 1989, and 0 if the household did not move.

\textsc{LogEarn} equals the log of the primary worker's earnings in 1985.

\textsc{ColGrad} equals 1 for a household head that has a college degree or more in 1985, and 0 otherwise.

\textsc{HsGrad} equals 1 for a household head that has a high school degree or up to three years of college in 1985, and 0 otherwise.

\textsc{LThs} equals 1 for a household that has less than a high school degree in 1985, and 0 otherwise.

\textsc{Black} equals 1 if the head of household was black in 1985, and 0 otherwise.

\textsc{BColGrad} equals \textsc{Black}*$\textsc{ColGrad}$.

\textsc{BHsGrad} equals \textsc{Black}*$\textsc{HsGrad}$.

\textsc{BLThs} equals \textsc{Black}*$\textsc{LThs}$.

\textsc{Asian} equals 1 if the head of household was Asian in 1985, and 0 otherwise.

\textsc{Age} equals the age of the household head in 1985.

\textsc{Male} equals 1 if the household head is male and 0 if the household head is female.

\textsc{Married} equals 1 for a household head who is married in 1985, and 0 otherwise.

\textsc{OtherWrkr} equals 1 if a family member other than the household head is employed outside the home, and 0 otherwise.

\textsc{Children} equals the number of children under 18 in the household in 1985.

\textsc{Vehicle1} equals 1 if the household had access to 1 or more vehicles per adult in the household in 1985. The vehicles could be cars, trucks, privately owned vehicles, or company vehicles.

\textsc{Vehicle01} equals 1 if the household had access to between more than 0 but less than 1 vehicles per adult in the household in 1985. The vehicles could be cars, trucks, privately owned vehicles, or company vehicles.

\textsc{Vehicle0} equals 1 if the household had access to zero vehicles in 1985.
The vehicles could have been cars, trucks, privately owned vehicles, or company vehicles.

ROOMS equals the number of rooms in the house in 1985.
SFD equals 1 if the household lives in a single-family detached dwelling in 1985, and 0 otherwise.
SFA equals 1 if the household lives in a single-family attached dwelling in 1985, and 0 otherwise.
MF equals 1 if the household lives in a multifamily dwelling in 1985, and 0 otherwise.
OWN equals 1 if the head of household lives in owner-occupied housing in 1985, and 0 otherwise.

EPos equals the error term from the commute equation $e_i$ multiplied by a dummy variable that equals 1 if $e_i$ is positive and 0 otherwise.

Eneg equals the error term from the commute equation $e_i$ multiplied by a dummy variable that equals 1 if $e_i$ is negative and 0 otherwise.

### TABLE A-1

<table>
<thead>
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<th>Variable</th>
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*Sample size equals 3481. Number of neighborhoods equals 628.
REFERENCES